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CSC 59866

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Assignment 1 – Summary

Part A: Model Code

The first part of this assignment requires the writing of multiple necessary functions that would be used for later parts. Functions such as the calculation of *Euclidean* and *Manhattan* distances, *accuracy* and *generalization error*, *precision*, *recall*, and *F1 score*, *confusion matrix*, the generation of the *Receiver Operating Characteristic* (ROC) curve, the computation of the *Area Under Curve* (AUC) for the ROC curve, and the generation of a *precision-recall curve*. The final step of Part A also requires to implement our own KNN_Classifier model class which consists of the methods *fit* which stores the relevant values needed for the KNN algorithms as instance variables, and most importantly – *predict* which predicts the labels for the given data sample.

During my construction of these functions, I mostly relied on comparing my results to sklearn's corresponding library functions for reference and found it to be fairly accurate on most functions.

Part B: Data Processing

The second part of this assignment involves reading a csv file named *winequality-white* as a Pandas data frame. Initially, the original downloaded file had all of its contents on a single column and I had troubles parsing through them, so I had to do some unrelated work for separating the contents for future ease. After then, the 'quality' column needed to be converted into a two-category variable where 'good' has quality value of more than 5, and 'bad' has quality

value of less than 6. The target vector should then have 0s to represent the ‘bad’ quality wines and 1s to represent the ‘good’ ones. To summarize each of the variables in the dataset, I had to use the pandas function *describe()* which generates the dataset variable mean, standard deviation, and quartiles. The next task was to shuffle the dataset, and generate the pair plot using seaborn. By having a visual representation of the dataset, I could identify which features were redundant which led to my conclusion that features ‘volatile acidity’ and ‘sulphates’ were redundant due to its similarities to their neighboring features. I then had to write a *partition* function to split the data into training and testing sets. Lastly, I had to naively run my KNN_Classifier model on the training dataset with the neighbors set to 5. I then had to use accuracy and F1 score to compare my prediction to the expected labels, which outputs the accuracy of 0.8333333333333334 and F1 score of 0.0. Next is to standardize each feature of the training set using the mean and standard deviation of values for each of the features, then rerun the KNN_Classifier model and find the new accuracy and F1 score. The output that I got for the new standardized data accuracy was 0.03592814371257485, which is very low. I’m not sure what caused that, which ate most of my time. Same thing for the last task which is the get the accuracy of the standardized data with inverse distance weight which also yield a number similar to the previous which is 0.037016875340228635.

Part C: Model Evaluation

The last part of this assignment requires us to evaluate the performance of our model over each combination of the *k* (1,5,9,11], *distance metrics* (Euclidean, Manhattan), and *weights* (uniform, distance). We also had to report our performance with measures such as precision, recall, F1 score, Confusion Matrix, and accuracy.

In [3]:

```python
# 1. Write a function to calculate and return the Euclidean distance of two vectors.
import numpy as np

def euclidean_distance(vector1, vector2):
  # check if input vectors have the same length
  if len(vector1) != len(vector2):
    raise ValueError("Vectors must be the same length")

  # convert vectors into numpy arrays.
  array_vector1 = np.array(vector1)
  array_vector2 = np.array(vector2)

  # subtract the 2 arrays to get the array difference.
  array_difference = array_vector1 - array_vector2

  # square the array difference to ensure positive elements
  # and to magnify scale
  squared_array_difference = array_difference**2

  # calculate the euclidean distance
  distance = np.sqrt(np.sum(squared_array_difference))
  return distance

v1 = [3, 1]
v2 = [1, 5]
v3 = [3, 5, 7, 9]

try:
  distance = euclidean_distance(v1, v2)
  print("euclidean_distance = ", distance)
except ValueError as e:
  print(e)
```

```
euclidean_distance =  4.47213595499958
```

```python
# 2. Write a function to calculate and return the Manhattan distance of two vectors
import numpy as np

def manhattan_distance(vector1, vector2):
  # check if input vectors have the same length
  if len(vector1) != len(vector2):
    raise ValueError("Vectors must be the same length")

  # convert vectors into numpy arrays.
  array_vector1 = np.array(vector1)
  array_vector2 = np.array(vector2)

  # subtract the 2 arrays to get the array difference.
  array_difference = array_vector1 - array_vector2

  # absolute the array difference value to ensure positive result
  abs_array_difference = np.abs(array_difference)

  # calculate the manhattan distance
  distance = np.sum(abs_array_difference)
  return distance

v1 = [1, 3, 5]
v2 = [2, 4, 6]
v3 = [3, 5, 7, 9]

try:
  distance = manhattan_distance(v1, v2)
  print("manhattan_distance = ", distance)
except ValueError as e:
  print(e)
```

```
manhattan_distance =  3
```

In [5]:

```python
# 3. Write a function to calculate and return the accuracy and generalization error of t
import numpy as np

def acc_gen_error(v1, v2):
    # check if input vectors have the same length
    if len(v1) != len(v2):
        raise ValueError("Vectors must be the same length")
    # print(v1)
    # print(v2)

    # calculate the accuracy
    accuracy = np.sum(v1 == v2) / len(v1)

    # calculate the general error of the 2 vectors
    gen_error = 1 - accuracy

    return accuracy, gen_error

v1 = np.array([0, 2, 1, 3, 4, 7])
v2 = np.array([0, 2, 1, 3, 4, 3])

try:
    accuracy, gen_error = acc_gen_error(v1, v2)
    print("Accuracy:", accuracy)
    print("Generalization Error:", gen_error)
except ValueError as e:
    print(e)
```

```
Accuracy: 0.8333333333333334
Generalization Error: 0.16666666666666663
```

In [6]:

```python
# 4. Write three functions to compute: precision, recall and F1 score.
import numpy as np

def get_tp_fp_fn(y_true, y_pred):
  tp = np.sum((y_true == 1) & (y_pred == 1))
  fp = np.sum((y_true == 0) & (y_pred == 1))
  fn = np.sum((y_true == 1) & (y_pred == 0))
  # print("tp=",tp) # 1 1
  # print("fp=",fp) # 0 1
  # print("fn=",fn) # 1 0

  return tp, fp, fn

def precision(y_true, y_pred):
  # check if input vectors have the same length
  if len(y_true) != len(y_pred):
      raise ValueError("Vectors must be the same length")

  tp, fp, fn = get_tp_fp_fn(y_true, y_pred)
  if (tp + fp == 0):
    return 0.0

  return tp / (tp + fp)

def recall(y_true, y_pred):
  if len(v1) != len(v2):
      raise ValueError("Vectors must be the same length")

  tp, fp, fn = get_tp_fp_fn(y_true, y_pred)
  if (tp + fn == 0):
    return 0.0

  return tp / (tp + fn)
```

```python
def f1_score(y_true, y_pred):
  if len(v1) != len(v2):
      raise ValueError("Vectors must be the same length")

  tp, fp, fn = get_tp_fp_fn(y_true, y_pred)

  # F1 is by default calculated as 0.0 when there are no tp, fp, or fn.
  if (tp == 0 or fp == 0 or fn == 0):
     return 0.0

  precision_value = precision(y_true, y_pred)
  recall_value = recall(y_true, y_pred)

  # f1 = (2 * tp) / (2 * tp + fp + fn)
  f1 = 2 * (precision_value * recall_value) / (precision_value + recall_value)

  return f1

y_true = np.array([0, 0, 1, 0, 1, 1])
y_pred = np.array([0, 1, 0, 0, 0, 0])

# print("tp=",tp) # 1 1
# print("fp=",fp) # 0 1
# print("fn=",fn) # 1 0

try:
    print("Precision:", precision(y_true, y_pred))
    print("Recall:", recall(y_true, y_pred))
    print("F1 Score:", f1_score(y_true, y_pred))

except ValueError as e:
    print(e)
```

```
Precision: 0.0
Recall: 0.0
F1 Score: 0.0
```

In [7]:

```
# 5. Write a function to compute the confusion matrix of two vectors.
import numpy as np

def my_confusion_matrix(v1, v2):

  if len(v1) != len(v2):
    raise ValueError("Vectors must be the same length")

  # print('v1:', v1)
  # print('v2:', v2)

  # concatenate the 2 vectors and return the unique elements in asc order
  classes = np.unique(np.concatenate((v1, v2)))

  # initialize a square matrix of num_classes by num_classes size
  num_classes = len(classes)
  matrix = np.zeros((num_classes, num_classes), dtype=type(classes[0]))

  # updates the confusion matrix
  for i in range(len(v1)):
      true_class = np.where(classes == v1[i])[0][0]
      pred_class = np.where(classes == v2[i])[0][0]

      matrix[true_class][pred_class] += 1

  return matrix

v1 = [2, 0, 2, 2, 0, 1]
v2 = [0, 0, 2, 2, 0, 2]
```

```
try:
  matrix = my_confusion_matrix(np.array(v1), np.array(v2))
  print("Confusion Matrix:")
  print(matrix)
except ValueError as e:
    print(e)
```

```
Confusion Matrix:
[[2 0 0]
 [0 0 1]
 [1 0 2]]
```

```python
# 6. Write a function to generate the Receiver Operating Characteristic (ROC) curve.
import numpy as np

def my_roc_curve(y_true, y_score):
    # ensure y_true is binary (0 or 1)
    classes = np.unique(y_true)
    if len(classes) > 2 or not np.array_equal(classes, [0, 1]):
        raise ValueError("Only binary classification is supported")

    # sort y_true by y_score in descending order
    desc_score_indices = np.argsort(y_score)[::-1]
    y_score_sorted = y_score[desc_score_indices]
    y_true_sorted = y_true[desc_score_indices]

    # initialize arrays for true positive rate (TPR) and false positive rate (FPR)
    tpr = []
    fpr = []

    # count the number of positive and negative instances
    num_pos = np.sum(y_true == 1)
    num_neg = np.sum(y_true == 0)

    # compute TPR and FPR at each threshold
    tp_count = 0
    fp_count = 0

    for score, label in zip(y_score_sorted, y_true_sorted):
        if label == 1:
            tp_count += 1
        else:
            fp_count += 1
        tpr.append(tp_count / num_pos)
        fpr.append(fp_count / num_neg)

    # add (0, 0) and (1, 1) to the ROC curve
    tpr = np.concatenate([[0], tpr, [1]])
    fpr = np.concatenate([[0], fpr, [1]])

    return fpr, tpr

y_true = np.array([0, 0, 1, 1])
y_score = np.array([0.1, 0.4, 0.35, 0.8])

fpr, tpr = my_roc_curve(y_true, y_score)
print("False Positive Rate (FPR):", fpr)
print("True Positive Rate (TPR):", tpr)
```

```
False Positive Rate (FPR): [0.  0.  0.5 0.5 1.  1. ]
True Positive Rate (TPR): [0.  0.5 0.5 1.  1.  1. ]
```

```python
# 7. Write a function to compute area under curve (AUC) for the ROC curve.
import numpy as np

def auc(y_true, y_score):
    # get the indices to sort y_score in desc order
    order = np.argsort(y_score)[::-1]
    # apply the order to y_true & y_score
    y_true = y_true[order]
    y_score = y_score[order]

    n = len(y_true)
    # counts number of positive elements in y_true that are 1
    n_pos = np.sum(y_true == 1)
    # gets the number of negative elements
    n_neg = n - n_pos

    # fill tpr & fpr arrays with zeros
    tpr = np.zeros(n)
    fpr = np.zeros(n)

    tp = 0
    fp = 0
```

```python
    for i in range(n):
        if y_true[i] == 1:
            tp += 1
        else:
            fp += 1
        tpr[i] = tp / n_pos
        fpr[i] = fp / n_neg

    # calcualte the area under ROC curve using the trapezoidal rule
    auc = np.trapz(tpr, fpr)

    return auc

y_true = np.array([1, 1, 2, 2])
y_score = np.array([0.1, 0.4, 0.35, 0.8])

auc_score = auc(y_true, y_score)
print("Area Under Curve:", auc_score)
```

```
Area Under Curve: 0.25
```

```python
# 8. Write a function to generate the precision-recall curve.
import numpy as np

def my_recall_curve(y_true, probas_pred):
    # get the indices to sort probas_pred in desc order
    desc_score_indices = np.argsort(probas_pred)[::-1]
    # apply the order to y_true
    y_true = y_true[desc_score_indices]
    # sort by descending order of probabilities
    probas_pred = probas_pred[desc_score_indices]

    # initialize variables
    precision = []
    recall = []
    thresholds = []
    tp = 0
    fp = 0
    fn = np.sum(y_true == 1)

    # compute precision-recall pairs for different thresholds
    for i in range(len(probas_pred)):
        if i > 0 and probas_pred[i] != probas_pred[i - 1]:
            precision.append(tp / (tp + fp))
            recall.append(tp / (tp + fn))
            thresholds.append(probas_pred[i - 1])

        if y_true[i] == 1:
            tp += 1
            fn -= 1
        else:
            fp += 1

    # add last precision-recall pair
    precision.append(tp / (tp + fp))
    recall.append(tp / (tp + fn))
    thresholds.append(probas_pred[-1])
```

```python
    return np.array(precision), np.array(recall), np.array(thresholds)

y_true = np.array([0, 0, 1, 1])
y_scores = np.array([0.1, 0.4, 0.35, 0.8])

precisions, recalls, thresholds = my_recall_curve(y_true, y_scores)
print(precisions)
print(recalls)
print(thresholds)
```

```
[1.         0.5        0.66666667 0.5       ]
[0.5 0.5 1.  1. ]
[0.8  0.4  0.35 0.1 ]
```

```python
# 9. Implement a KNN_Classifier model class. It should have the following three methods.
import numpy as np
from fractions import Fraction

# def to_rational(numbers):
#     return [float(Fraction(num).limit_denominator()) for num in numbers]

class KNN_Classifier:
    def fit(self, X, Y, n_neighbors, weights='uniform', **kwargs):
        self.X_train = X  # numpy array with rows representing data samples and columns
        self.Y_train = Y  # 1D numpy array with labels corresponding to each row of the
        self.n_neighbors = n_neighbors  # number of nearest neighbors
        self.weights = weights  # used in prediction. Possible values are 'uniform' and
        self.kwargs = kwargs  # dictionary of arguments to be passed to the distance fun

    def predict(self, X):
        if self.weights == 'uniform':
            weights_func = lambda distances: np.ones_like(distances)
        elif self.weights == 'distance':
            weights_func = lambda distances: 1 / (distances + 1e-6)
        elif self.weights == 'inverse_distance':
            weights_func = lambda distances: 1 / (distances + 1e-6)**2
        else:
            raise ValueError("Invalid value for 'weights'. Possible values are 'uniform'
        Y_pred = []
        for x in X:
            # calculate distances to all training samples
            # distances = np.linalg.norm(self.X_train - x, axis=1, **self.kwargs)
            distances = np.linalg.norm(self.X_train - x.reshape(1, -1), axis=1, **self.k
```

```python
            # get indices of the k nearest neighbors
            nearest_indices = np.argsort(distances)[:self.n_neighbors]

            # get labels of the k nearest neighbors
            nearest_labels = self.Y_train[nearest_indices]

            # calculate weights for the nearest neighbors
            w = weights_func(distances[nearest_indices])

            # predict the label for the current sample
            y_pred = np.argmax(np.bincount(nearest_labels, weights=w))
            Y_pred.append(y_pred)

        return np.array(Y_pred)[:, np.newaxis]
        # return np.array(Y_pred)

X = np.array([[0], [1], [2], [3]])
y = np.array([0, 0, 1, 1])
X_test = np.array([[1.1]])

knn = KNN_Classifier()
knn.fit(X, y, n_neighbors=5, weights='distance')
Y_pred = knn.predict(X_test)
print(Y_pred)
```

```
[[0]]
```

In [12]:

```
X = [[0], [1], [2], [3]]
y = [0, 0, 1, 1]
from sklearn.neighbors import KNeighborsClassifier
neigh = KNeighborsClassifier(n_neighbors=3)
neigh.fit(X, y)
print(neigh.predict([[1.1]]))
print(neigh.predict_proba([[0.9]]))
```

```
[0]
[[0.66666667 0.33333333]]
```

In [13]:

```
# Part B: Data Processing
```

In [14]:

```
# 10. Read in the winequality-white.csv file as a Pandas data frame.
import pandas as pd

file_path = '../winequality-white.csv'
# read csv file
df = pd.read_csv(file_path)

print(df.head())
```

```
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0            7.0              0.27         0.36            20.7      0.045
1            6.3              0.30         0.34             1.6      0.049
2            8.1              0.28         0.40             6.9      0.050
3            7.2              0.23         0.32             8.5      0.058
4            7.2              0.23         0.32             8.5      0.058

   free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                 45.0                 170.0   1.0010  3.00       0.45
1                 14.0                 132.0   0.9940  3.30       0.49
2                 30.0                  97.0   0.9951  3.26       0.44
3                 47.0                 186.0   0.9956  3.19       0.40
4                 47.0                 186.0   0.9956  3.19       0.40

   alcohol  quality
0      8.8        6
1      9.5        6
2     10.1        6
3      9.9        6
4      9.9        6
```

```python
# 11.
"""
rating of wine and ranges  from 3 to 8
convert it into a two-category variable consisting of 'good' & 'bad'
good: quality > 5
bad: quality <= 5
target vector should have 0s (representing “bad”  quality wine), and 1s (representing “g
"""
# convert the "quality" column into a two-category variable
df['target'] = df['quality'].apply(lambda feat_matrix: 1 if feat_matrix > 5 else 0)

print(df.head())
```

```
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0            7.0              0.27         0.36            20.7      0.045
1            6.3              0.30         0.34             1.6      0.049
2            8.1              0.28         0.40             6.9      0.050
3            7.2              0.23         0.32             8.5      0.058
4            7.2              0.23         0.32             8.5      0.058

   free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                 45.0                 170.0   1.0010  3.00       0.45
1                 14.0                 132.0   0.9940  3.30       0.49
2                 30.0                  97.0   0.9951  3.26       0.44
3                 47.0                 186.0   0.9956  3.19       0.40
4                 47.0                 186.0   0.9956  3.19       0.40

   alcohol  quality  target
0      8.8        6       1
1      9.5        6       1
2     10.1        6       1
3      9.9        6       1
4      9.9        6       1
```

```python
# 12. Use the techniques from the first recitation to summarize each of the variables in
# Include this in your report.

# generate summary statistics
summary_stats = df.describe()

print(summary_stats)
```

```
       fixed acidity  volatile acidity  citric acid  residual sugar  \
count    4898.000000       4898.000000  4898.000000     4898.000000
mean        6.854788          0.278241     0.334192        6.391415
std         0.843868          0.100795     0.121020        5.072058
min         3.800000          0.080000     0.000000        0.600000
25%         6.300000          0.210000     0.270000        1.700000
50%         6.800000          0.260000     0.320000        5.200000
75%         7.300000          0.320000     0.390000        9.900000
max        14.200000          1.100000     1.660000       65.800000

         chlorides  free sulfur dioxide  total sulfur dioxide      density  \
count  4898.000000          4898.000000           4898.000000  4898.000000
mean      0.045772            35.308085            138.360657     0.994027
std       0.021848            17.007137             42.498065     0.002991
min       0.009000             2.000000              9.000000     0.987110
25%       0.036000            23.000000            108.000000     0.991723
50%       0.043000            34.000000            134.000000     0.993740
75%       0.050000            46.000000            167.000000     0.996100
max       0.346000           289.000000            440.000000     1.038980

                pH    sulphates      alcohol      quality       target
count  4898.000000  4898.000000  4898.000000  4898.000000  4898.000000
mean      3.188267     0.489847    10.514267     5.877909     0.665169
std       0.151001     0.114126     1.230621     0.885639     0.471979
min       2.720000     0.220000     8.000000     3.000000     0.000000
25%       3.090000     0.410000     9.500000     5.000000     0.000000
50%       3.180000     0.470000    10.400000     6.000000     1.000000
75%       3.280000     0.550000    11.400000     6.000000     1.000000
max       3.820000     1.080000    14.200000     9.000000     1.000000
```

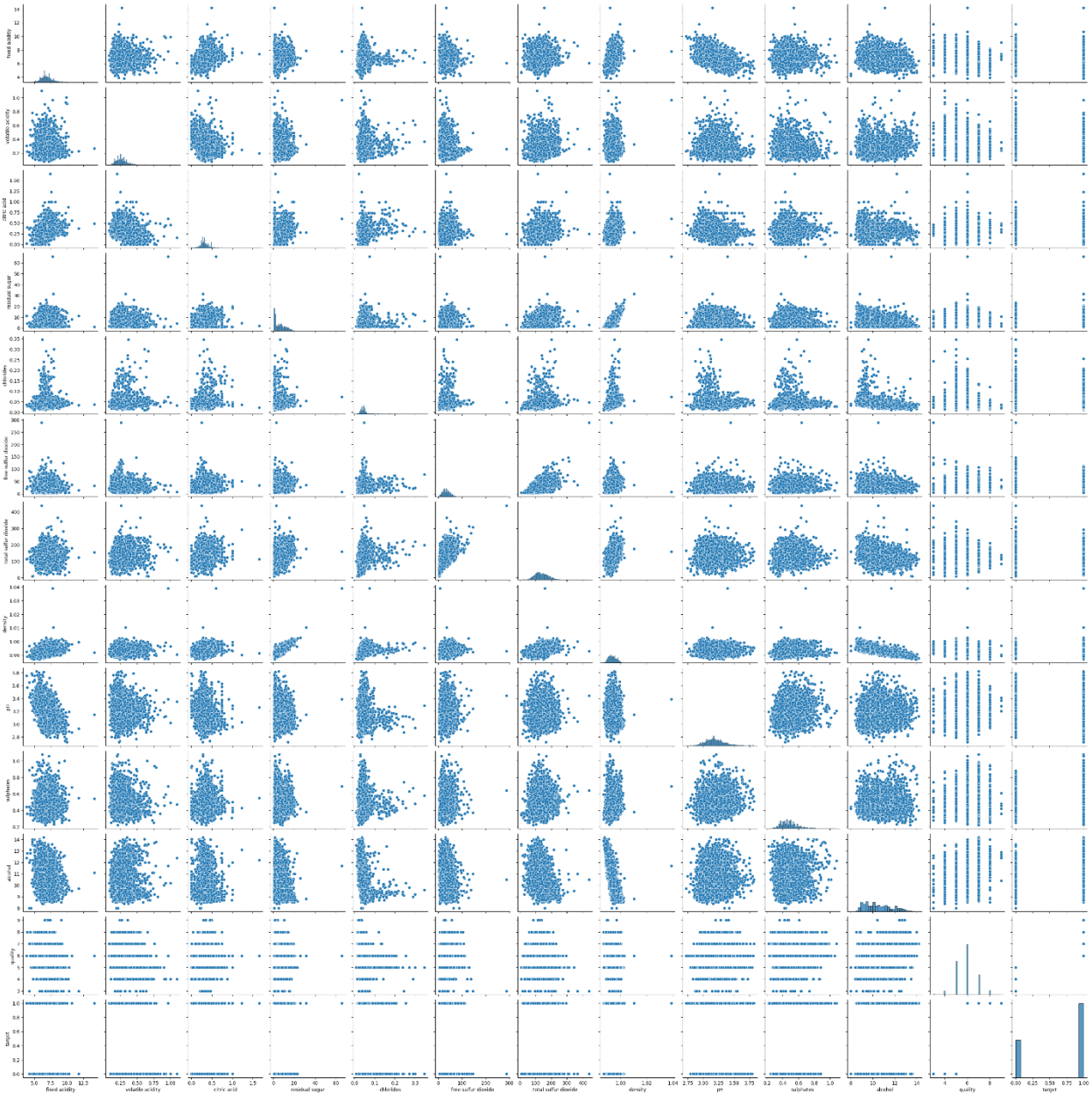
In [17]:

```
# 13. Shuffle the rows of your data. You can use def = df.sample(frac=1) as an idiomatic
df_shuffled = df.sample(frac=1)

print(df_shuffled.head())
```

```
      fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
1238            7.1              0.44         0.37             2.7      0.041
1840            6.9              0.18         0.33             1.0      0.054
4348            7.6              0.31         0.52            13.2      0.042
3502            6.7              0.29         0.45            14.3      0.054
1397            7.3              0.25         0.36            13.1      0.050

      free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
1238                 35.0                 128.0  0.98960  3.07       0.43
1840                 24.0                 164.0  0.99260  3.42       0.51
4348                 61.0                 148.0  0.99839  2.98       0.47
3502                 30.0                 181.0  0.99869  3.14       0.57
1397                 35.0                 200.0  0.99860  3.04       0.46

      alcohol  quality  target
1238     13.5        7       1
1840     10.5        5       0
4348      9.1        6       1
3502      9.1        5       0
1397      8.9        7       1
```

In [18]:

```
# 14. Generate pair plots using the seaborn package. This will be used to identify and r
import seaborn as sns
import matplotlib.pyplot as plt

sns.pairplot(df_shuffled)
plt.show()
```


fixed acidity
volatile acidity
citric acid
residual sugar
chlorides
free sulfur dioxide
total sulfur dioxide
density
pH
sulphates
alcohol
quality
target

```python
# 15. Drop the redundant features.
# volatile acidity and sulphates seem redundant
redundant_features = ['volatile acidity', 'sulphates']
df_shuffled = df_shuffled.drop(redundant_features, axis=1)

print(f'Dropped features: {redundant_features}')
print(df.head())
```

```
Dropped features: ['volatile acidity', 'sulphates']
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0            7.0              0.27         0.36            20.7      0.045
1            6.3              0.30         0.34             1.6      0.049
2            8.1              0.28         0.40             6.9      0.050
3            7.2              0.23         0.32             8.5      0.058
4            7.2              0.23         0.32             8.5      0.058

   free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                 45.0                 170.0   1.0010  3.00       0.45
1                 14.0                 132.0   0.9940  3.30       0.49
2                 30.0                  97.0   0.9951  3.26       0.44
3                 47.0                 186.0   0.9956  3.19       0.40
4                 47.0                 186.0   0.9956  3.19       0.40

   alcohol  quality  target
0      8.8        6       1
1      9.5        6       1
2     10.1        6       1
3      9.9        6       1
4      9.9        6       1
```

```python
import numpy as np

def partition(feat_matrix, target_vector, partition_size):
    """
    Split the data into training and test sets.

    Parameters:
    - feat_matrix: Feature matrix (numpy array).
    - target_vector: Target vector (numpy array).
    - partition_size: Ratio for splitting the data (float).

    Returns:
    - fmatrix_train: Feature matrix for training data.
    - fmatrix_test: Feature matrix for test data.
    - tvector_train: Target vector for training data.
    - tvector_test: Target vector for test data.
    """
    n_samples = feat_matrix.shape[0]
    split_idx = int(n_samples * partition_size)

    fmatrix_train, fmatrix_test = feat_matrix[:split_idx], feat_matrix[split_idx:]
    tvector_train, tvector_test = target_vector[:split_idx], target_vector[split_idx:]

    return fmatrix_train, fmatrix_test, tvector_train, tvector_test

# feat_matrix = np.array([[1, 2], [3, 4], [5, 6], [7, 8], [9, 10]])
# target_vector = np.array([0, 1, 0, 1, 0])
feat_matrix = df_shuffled.drop(columns=['quality']).values
target_vector = df_shuffled['quality'].values
```

```python
fmatrix_train, fmatrix_test, tvector_train, tvector_test = partition(feat_matrix, target_

print("fmatrix_train")
print(fmatrix_train)
print("fmatrix_test")
print(fmatrix_test)
print("tvector_train")
print(tvector_train)
print("tvector_test")
print(tvector_test)
```

```
fmatrix_train
[[ 7.1   0.37  2.7  ...  3.07 13.5   1.  ]
 [ 6.9   0.33  1.   ...  3.42 10.5   0.  ]
 [ 7.6   0.52 13.2  ...  2.98  9.1   1.  ]
 ...
 [ 8.5   0.41  4.3  ...  3.18  9.7   1.  ]
 [ 8.    0.3  17.45 ...  3.05  9.2   1.  ]
 [ 7.    0.28 10.6  ...  3.05 11.5   1.  ]]
fmatrix_test
[[ 7.1   0.28  1.9  ...  3.12 12.    0.  ]
 [ 6.5   0.31  1.7  ...  3.27 11.4   1.  ]
 [ 7.3   0.37  9.7  ...  3.48  9.9   1.  ]
 ...
 [ 9.2   0.34 10.5  ...  3.04 10.4   1.  ]
 [ 7.3   0.41 14.6  ...  3.16  9.4   1.  ]
 [ 7.9   0.39  1.   ...  3.08 11.9   0.  ]]
tvector_train
[7 5 6 ... 6 6 7]
tvector_test
[5 7 6 ... 6 6 5]
```

In [21]:

```
# 17. Naively run your KNN_Classifier model on the training dataset with n_neighbors = 5
knn = KNN_Classifier()
knn.fit(fmatrix_train, tvector_train, n_neighbors=5, weights='distance')
Y_pred_naive = knn.predict(fmatrix_test)

print(Y_pred_naive)
```

```
[[6]
 [7]
 [5]
 ...
 [7]
 [6]
 [5]]
```

In [29]:

```
# 17a. Use accuracy and F1 score to compare your predictions to the expected labels.
acc, gen_error = acc_gen_error(fmatrix_test, Y_pred_naive)
f1 = f1_score(fmatrix_test, Y_pred_naive)

print(fmatrix_test)
print(Y_pred_naive)

print("Accuracy:", accuracy)
print("F1 Score:", f1)
```

```
[[ 7.1   0.28  1.9  ...  3.12 12.    0.  ]
 [ 6.5   0.31  1.7  ...  3.27 11.4   1.  ]
 [ 7.3   0.37  9.7  ...  3.48  9.9   1.  ]
 ...
 [ 9.2   0.34 10.5  ...  3.04 10.4   1.  ]
 [ 7.3   0.41 14.6  ...  3.16  9.4   1.  ]
 [ 7.9   0.39  1.   ...  3.08 11.9   0.  ]]
```

In [23]:

```
# 17b. Now standardize each feature of your training set (subtract mean and divide by st
# Use the mean and standard deviation values for each feature in the training set to sca

# calculate mean and std deviation of each feature
mean_X = np.mean(fmatrix_train, axis=0)
std_X = np.std(fmatrix_train, axis=0)

# standardize training set
standardized_train = (fmatrix_train - mean_X) / std_X
# scale the test data using mean and std deviation values
standardized_test = (fmatrix_test - mean_X) / std_X

print("Standardized training set:")
print(standardized_train)
print("\nScaled test data:")
print(standardized_test)
```

```
Standardized training set:
[[ 0.30508242  0.32449789 -0.74517681 ... -0.77800806  2.47182926
   0.70840701]
 [ 0.06806504 -0.02095583 -1.07428227 ...  1.54592621  0.00645661
  -1.41161788]
 [ 0.89762588  1.61994937  1.28753337 ... -1.37559116 -1.14405063
   0.70840701]
 ...
 [ 1.96420409  0.66995162 -0.4354305  ... -0.04762872 -0.6509761
   0.70840701]
 [ 1.37166064 -0.28004613  2.11029702 ... -0.91080431 -1.06187154
   0.70840701]
 [ 0.18657373 -0.45277299  0.78419561 ... -0.91080431  0.82824749
   0.70840701]]

Scaled test data:
[[ 0.30508242 -0.45277299 -0.90004997 ... -0.44601745  1.23914293
  -1.41161788]
 [-0.40596972 -0.1936827  -0.93876826 ...  0.54995438  0.7460684
   0.70840701]
 [ 0.5420998   0.32449789  0.60996331 ...  1.94431495 -0.48661792
   0.70840701]
 ...
 [ 2.79376493  0.0654076   0.76483647 ... -0.97720243 -0.07572248
   0.70840701]
 [ 0.5420998   0.66995162  1.5585614  ... -0.18042496 -0.89751336
   0.70840701]
 [ 1.25315195  0.49722476 -1.07428227 ... -0.71160994  1.15696385
  -1.41161788]]
```

In [24]:

```
# 17c. c. Re-run the KNN_Classifier model on the standardized data, find the accuracy an

# fit the model on the standardized training dataset
knn.fit(standardized_train, tvector_train, n_neighbors=5, weights='distance')
# predict labels for the standardized training dataset
Y_pred_train_standardized = knn.predict(standardized_test)

print(fmatrix_test)
print(Y_pred_train_standardized)

# calculate accuracy and F1 score
accuracy_standardized, standardized_gen_error = acc_gen_error(fmatrix_test, Y_pred_train
f1_standardized = f1_score(fmatrix_test, Y_pred_train_standardized)

print("Accuracy (Standardized Data):", accuracy_standardized)
print("F1 Score (Standardized Data):", f1_standardized)
```

```
[[ 7.1   0.28  1.9  ...  3.12 12.    0.  ]
 [ 6.5   0.31  1.7  ...  3.27 11.4   1.  ]
 [ 7.3   0.37  9.7  ...  3.48  9.9   1.  ]
 ...
 [ 9.2   0.34 10.5  ...  3.04 10.4   1.  ]
 [ 7.3   0.41 14.6  ...  3.16  9.4   1.  ]
 [ 7.9   0.39  1.   ...  3.08 11.9   0.  ]]
[[5]
 [7]
 [6]
 ...
 [6]
 [6]
 [5]]
Accuracy (Standardized Data): 0.03592814371257485
F1 Score (Standardized Data): 0.0
```

In [25]:

```
# 17e. Perform a similar test for inverse distance weighting in the KNN_Classifier model

# fit the model on the standardized training dataset with inverse distance weighting
knn.fit(standardized_train, tvector_train, n_neighbors=5, weights='inverse_distance')
Y_pred_train_standardized_inverse = knn.predict(standardized_test)

# calculate accuracy and F1 score for inverse distance weighting
accuracy_standardized_inverse = acc_gen_error(fmatrix_test, Y_pred_train_standardized_inv
f1_standardized_inverse = f1_score(fmatrix_test, Y_pred_train_standardized_inverse)

print("Accuracy (Standardized Data with Inverse Distance Weighting):", accuracy_standard
print("F1 Score (Standardized Data with Inverse Distance Weighting):", f1_standardized_i
```

```
Accuracy (Standardized Data with Inverse Distance Weighting): (0.037016875340228635, 0.96
29831246597713)
F1 Score (Standardized Data with Inverse Distance Weighting): 0.0
```

In [26]:

```
# Part C: Model Evaluation
```

In [27]:

```
"""
18. evaluate the performance of your model over each combination of k and distance metri
i.  k=[1,5,9,11]
    distance = [Euclidean, Manhattan]
    weights = [uniform, distance]
 """

# Define the combinations of k, distance metrics, and weights
k_values = [1, 5, 9, 11]
distance_metrics = ['euclidean', 'manhattan']
weights = ['uniform', 'distance']

for k in k_values:
    for distance in distance_metrics:
        for weight in weights:
            knn.fit(fmatrix_train, tvector_train, n_neighbors=k, weights=weight)
            predictions = knn.predict(fmatrix_test)

            prec = precision(fmatrix_test, predictions)
            rec = recall(fmatrix_test, predictions)
            f1 = f1_score(fmatrix_test, predictions)
            # cm = my_confusion_matrix(tvector_test, predictions)
            acc = acc_gen_error(fmatrix_test, predictions)

            print(f"k = {k}\t{distance}\t{weight}")
            print(f"Precision: {prec}")
            print(f"Recall: {rec}")
            print(f"F1 Score: {f1}")
            # print(f"Confusion Matrix:\n{cm}")
            print(f"Accuracy: {acc}")
            print("============================================================")
```

```
k = 1   euclidean       uniform
Precision: 0.0
Recall: 0.0
F1 Score: 0.0
Accuracy: (0.0362003266194883, 0.9637996733805116)
==========================================================
k = 1   euclidean       distance
Precision: 0.0
Recall: 0.0
F1 Score: 0.0
Accuracy: (0.0362003266194883, 0.9637996733805116)
==========================================================
k = 1   manhattan       uniform
Precision: 0.0
Recall: 0.0
F1 Score: 0.0
Accuracy: (0.0362003266194883, 0.9637996733805116)
==========================================================
k = 1   manhattan       distance
Precision: 0.0
Recall: 0.0
F1 Score: 0.0
Accuracy: (0.0362003266194883, 0.9637996733805116)
==========================================================
k = 5   euclidean       uniform
Precision: 0.0
Recall: 0.0
F1 Score: 0.0
Accuracy: (0.03592814371257485, 0.9640718562874252)
==========================================================
k = 5   euclidean       distance
Precision: 0.0
Recall: 0.0
F1 Score: 0.0
Accuracy: (0.038922155688622756, 0.9610778443113772)
----------------------------------------------------------
```

```
k = 5   manhattan       uniform
Precision: 0.0
Recall: 0.0
F1 Score: 0.0
Accuracy: (0.03592814371257485, 0.9640718562874252)
=========================================================
k = 5   manhattan       distance
Precision: 0.0
Recall: 0.0
F1 Score: 0.0
Accuracy: (0.038922155688622756, 0.9610778443113772)
=========================================================
k = 9   euclidean       uniform
Precision: 0.0
Recall: 0.0
F1 Score: 0.0
Accuracy: (0.035655960805661406, 0.9643440391943386)
=========================================================
k = 9   euclidean       distance
Precision: 0.0
Recall: 0.0
F1 Score: 0.0
Accuracy: (0.0362003266194883, 0.9637996733805116)
=========================================================
k = 9   manhattan       uniform
Precision: 0.0
Recall: 0.0
F1 Score: 0.0
Accuracy: (0.035655960805661406, 0.9643440391943386)
=========================================================
```

```
k = 9   manhattan       distance
Precision: 0.0
Recall: 0.0
F1 Score: 0.0
Accuracy: (0.0362003266194883, 0.9637996733805116)
=========================================================
k = 11  euclidean       uniform
Precision: 0.0
Recall: 0.0
F1 Score: 0.0
Accuracy: (0.0362003266194883, 0.9637996733805116)
=========================================================
k = 11  euclidean       distance
Precision: 0.0
Recall: 0.0
F1 Score: 0.0
Accuracy: (0.03728905824714208, 0.9627109417528579)
=========================================================
k = 11  manhattan       uniform
Precision: 0.0
Recall: 0.0
F1 Score: 0.0
Accuracy: (0.0362003266194883, 0.9637996733805116)
=========================================================
k = 11  manhattan       distance
Precision: 0.0
Recall: 0.0
F1 Score: 0.0
Accuracy: (0.03728905824714208, 0.9627109417528579)
=========================================================
```