SVM method(以下以linear演示,後面有標註與RBF之差異)

1. 先將檔案分類的資料讀入後,把所有內容轉存為整數

2. 讀入作業一中所有求出的tfldf檔案,並存入一個總存的二維ndarray中

3. 將所有tfidf檔案按照是否為訓練檔做分裝,同時以testLabel存取

```
In [8]: x_train = np.empty([195, 19130])
x_test = np.empty([900, 19130])
testLabel = []
In [9]: countTest = 0
          for k in range(1, len(tfidfTest) + 1):
    check = 0
               for i in range(13):
                    for j in range(15):
    if k == test[i][j]:
                              x_{train}[i * 15 + j] = tfidfTest[k - 1]
                              break
               if check == 0:
                    x_test[countTest] = tfidfTest[k - 1]
                    testLabel.append(k)
          x_train
Out[9]: array([[0.
                                , 0.
],
                                               , 0.
                                                                                    , 0.
                                                               , ..., 0.
                                , 0.
],
, 0.
],
                   [0.
                                               , 0.
                                                               , ..., 0.
                                                                                    , 0.
                    0.
                   [0.
                                                , 0.
                                                               , ..., 0.
                                                                                    , 0.
                    0.
                                , 0.03412166, 0.
                   [0.
                                                               , ..., 0.
                                                                                    , 0.
                                , 0.
],
, 0.
                                               , 0.
                                                              , ..., 0.
                                                                                    , 0.
                   [0.
                                              , 0.
                                                               , ..., 0.
                                                                                    , 0.
                                , ø.
]])
```

4. 將訓練資料的結果存入一個一維list

```
In [10]: y_train = []
    for i in range(13):
        for k in range(15):
            y_train.append(i + 1)
```

5. 導入SVM method做資料訓練(以linear演示,若要做RBF則改變kernel係數)

```
In [11]: from sklearn.svm import SVC
SVM_model = SVC(kernel='linear', C=1.0)
In [12]: SVM_model.fit(x_train,y_train)
Out[12]: SVC(kernel='linear')
```

6. 將測試資料丟入訓練完的分類器中,再以csv檔將內容輸出

下面為有關precision的操作

7. 將訓練資料以1:9的比率做切割(stratify=y_train)

```
In [15]: from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(x_train, y_train, test_size=0.1, random_state=3, stratify = y_train
```

8. 將切割完的訓練資料丟入前面的分類器中,並以原正解設為expected_result

9. 將訓練結果與正解做fi-score, precision,並輸出結果

```
In [20]: from sklearn.metrics import precision_score
         precision = precision_score(predicted_result, expected_result, average='micro')
In [21]: from sklearn import metrics
         print(metrics.classification_report(expected_result, predicted_result))
                        precision
                                      recall f1-score
                                                          support
                              1.00
                                        1.00
                     1
                                                   1.00
                     2
                              1.00
                                        1.00
                                                   1.00
                                                                 1
                     3
                              1.00
                                        1.00
                                                   1.00
                                                                 1
                     4
                                                                 2
                              1.00
                                        1.00
                                                   1.00
                     5
                              1.00
                                        1.00
                                                   1.00
                                                                 1
                     6
                                                                 1
                              1.00
                                        1.00
                                                   1.00
                                                                 1
2
                     7
                              1.00
                                        1.00
                                                   1.00
                     8
                              1.00
                                        1.00
                                                   1.00
                                                                 2
2
                     9
                              1.00
                                        1.00
                                                   1.00
                    10
                                        1.00
                              1.00
                                                   1.00
                    11
                              1.00
                                        1.00
                                                   1.00
                                                                 2
                                                                 2
                    12
                              1.00
                                        1.00
                                                   1.00
                              1.00
                                        1.00
                                                                 1
                    13
                                                   1.00
                                                   1.00
                                                                20
              accuracy
                              1.00
                                        1.00
                                                   1.00
                                                                20
             macro avo
         weighted avg
                              1.00
                                        1.00
                                                   1.00
                                                                20
```

以下為畫Precision-Recall Curve

10. 調用訓練器OneVsRestClassifier將目前的20個訓練資料訓練成multi-class的機率

```
In [28]: from sklearn.preprocessing import label_binarize

# Use label_binarize to be multi-label like settings
Y = label_binarize(expected_result, classes=[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13])
n_classes = Y.shape[1]

In [33]: from sklearn.multiclass import OneVsRestClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import StandardScaler
from sklearn.svm import LinearSVC

classifier = OneVsRestClassifier(make_pipeline(StandardScaler(), LinearSVC()))
classifier.fit(X_test, Y_test)
y_score = classifier.decision_function(X_test)
```

11. 針對每一個class的訓練資料做precision_recall_curve的處理

```
In [30]: y_score = np.array(y_score)

In [31]: from sklearn.metrics import precision_recall_curve
    from sklearn.metrics import average_precision_score

# For each class
precision = dict()
recall = dict()
average_precision = dict()
for i in range(n_classes):
    precision[i], recall[i], _ = precision_recall_curve(Y[:, i], y_score[:, i])
    average_precision[i] = average_precision_score(Y[:, i], y_score[:, i])
```

12. 利用matplotlib做圖

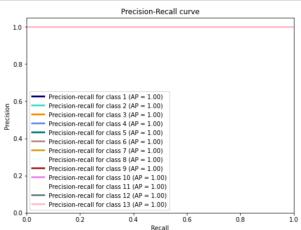
```
In [32]: import matplotlib.pyplot as plt
from itertools import cycle

# setup plot details
colors = cycle(["navy", "turquoise", "darkorange", "cornflowerblue", "teal", "rosybrown", "goldenrod", "azure", "bro
_, ax = plt.subplots(figsize=(8, 6))

for i, color in zip(range(n_classes), colors):
    display = PrecisionRecallDisplay(recall=recall[i], precision=precision[i], average_precision=average_precision[i])
    display.plot(ax=ax, name=f"Precision-recall for class {i + 1}", color=color, linewidth=3)

handles, labels = display.ax_.get_legend_handles_labels()
ax.axis([0.0, 1.0, 0.0, 1.05])
ax.legend(handles=handles, labels=labels, loc="best")
ax.set_title("Precision-Recall curve")

plt.show()
```



Bernoulli Naïve Bayes method

1. 先將檔案分類的資料讀入後,把所有內容轉存為整數

2. 重新讀取所有文字檔,並存入files

```
In [5]: files = []
In [6]: for i in range(1, 1096):
    with open('PA1-data/' + str(i) + '.txt', mode='r', encoding='utf-8') as f:
        file = [f.read()]
        files += file
```

3. 將所有檔案做Multi-hot vector,並存入x_total

```
In [7]: from sklearn.preprocessing import MultiLabelBinarizer
import numpy as np

In [8]: x_total = np.empty([0])

In [9]: processTrain = MultiLabelBinarizer()
x_total = processTrain.fit_transform(files)
```

4. 判讀檔案是否為訓練檔,並將Multi-hot vector分裝於兩個ndarray中

```
In [10]: x_{train} = np.empty([195, 85])
          x_{\text{test}} = \text{np.empty}([900, 85])
          testLabel = []
In [11]: countTest = 0
          for k in range(1, len(x_total) + 1):
               check = 0
               for i in range(13):
                   for j in range(15):
                        if k == test[i][j]:
                            x_{train}[i * 15 + j] = x_{total}[k - 1]
                            \overline{check} = 1
                            break
               if check == 0:
                   x_{test[countTest]} = x_{total[k - 1]}
                   countTest += 1
                   testLabel.append(k)
```

5. 將將訓練資料的結果存入一個一維list後,導入BernoulliNB做資料訓練

```
In [12]: from sklearn. naive_bayes import BernoulliNB
In [13]: y_train = []
    for i in range(13):
        for k in range(15):
            y_train.append(i + 1)

In [14]: train = BernoulliNB()
In [15]: train.fit(x_train, y_train)
Out[15]: BernoulliNB()
```

6. 將測試資料丟入分類器中,並以list存取

```
In [16]: predicted_results = []
In [17]: predicted_results.extend(train.predict(x_test))
          predicted_results
Out[17]:
          [2,
           13,
           8,
          8,
           8,
           13,
           9,
           8,
           2,
           8,
           10,
           8,
           5,
           13,
           13,
           8,
           8,
           5,
```

7. 將測試資料丟入訓練完的分類器中,再以csv檔將內容輸出

```
In [18]: import csv

In [19]: with open('hw2_b09704078.csv', mode='w', encoding='utf-8') as outcome:
    writer = csv.writer(outcome)
    writer.writerow(["Id","Value"])
    for i in range(len(testLabel)):
        writer.writerow([testLabel[i], predicted_results[i]])
```

下面為有關precision的操作

8. 將訓練資料以1:9的比率做切割(stratify=y_train)

```
In [20]: from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(x_train, y_train, test_size=0.1, random_
```

9. 將切割完的訓練資料丟入前面的分類器中,並以原正解設為expected_result

10. 將訓練結果與正解做fl-score, precision,並輸出結果

```
In [26]: from sklearn.metrics import precision_score
         precision = precision_score(predicted_result, expected_result, average='micro')
In [27]: from sklearn import metrics
         print(metrics.classification_report(expected_result, predicted_result))
                        precision
                                      recall f1-score
                                                          support
                                        1.00
                     1
                              0.67
                                                   0.80
                     2
                              0.00
                                        0.00
                                                   0.00
                                                                 1
                     3
                              0.00
                                        0.00
                                                   0.00
                                                                 1
                     4
                              0.00
                                        0.00
                                                   0.00
                                                                2
                     5
                              0.33
                                        1.00
                                                   0.50
                     6
                                                                1
                              1.00
                                        1.00
                                                   1.00
                     7
                                                                 1
                              0.00
                                        0.00
                                                   0.00
                     8
                              0.40
                                        1.00
                                                   0.57
                                                                2
2
                     9
                              1.00
                                        0.50
                                                   0.67
                    10
                              0.00
                                        0.00
                                                   0.00
                              0.00
                                        0.00
                                                   0.00
                                                                2
                    11
                                                                2
                              0.50
                                        0.50
                                                   0.50
                    12
                    13
                              0.00
                                        0.00
                                                   0.00
                                                                1
                                                   0.40
                                                               20
              accuracy
                              0.30
                                        0.38
                                                   0.31
                                                                20
             macro avg
         weighted avg
                              0.32
                                        0.40
                                                   0.33
                                                               20
```

以下為畫Precision-Recall Curve

11. 調用訓練器OneVsRestClassifier將目前的20個訓練資料訓練成multi-class的機率

```
In [27]: from sklearn.preprocessing import label_binarize

# Use label_binarize to be multi-label like settings
Y = label_binarize(expected_result, classes=[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13])
n_classes = Y.shape[1]

In [36]: from sklearn.multiclass import OneVsRestClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline
from sklearn.svm import LinearSVC

classifier = OneVsRestClassifier(make_pipeline(StandardScaler(), LinearSVC()))
classifier.fit(X_test, Y_test)
y_score = classifier.decision_function(X_test)
```

12. 針對每一個class的訓練資料做precision recall curve的處理

```
In [37]: y_score = np.array(y_score)

In [38]: from sklearn.metrics import precision_recall_curve
    from sklearn.metrics import average_precision_score

# For each class
    precision = dict()
    recall = dict()
    average_precision = dict()
    for i in range(n_classes):
        precision[i], recall[i], _ = precision_recall_curve(Y[:, i], y_score[:, i])
        average_precision[i] = average_precision_score(Y[:, i], y_score[:, i])
```

13. 利用matplotlib做圖

```
In [31]: import matplotlib.pyplot as plt
            from itertools import cycle
            # setup plot details
            colors = cycle(["navy", "turquoise", "darkorange", "cornflowerblue", "teal", "rosybrown", "goldenrod", "azure", "bro
            _, ax = plt.subplots(figsize=(8, 6))
            for i, color in zip(range(n_classes), colors):
                 display = PrecisionRecallDisplay(recall=recall[i],precision=precision[i],average_precision=average_precision[i])
                 display.plot(ax=ax, name=f"Precision-recall for class {i + 1}", color=color, linewidth=3)
            handles, labels = display.ax_.get_legend_handles_labels()
            ax.axis([0.0, 1.0, 0.0, 1.05])
            ax.legend(handles=handles, labels=labels, loc="best")
            ax.set_title("Precision-Recall curve")
            plt.show()
                                            Precision-Recall curve
               1.0
               0.8
                         Precision-recall for class 1 (AP = 1.00)
               0.6
                         Precision-recall for class 2 (AP = 1.00)
                         Precision-recall for class 3 (AP = 1.00)
Precision-recall for class 4 (AP = 1.00)
                        Precision-recall for class 5 (AP = 1.00)
                       Precision-recall for class 6 (AP = 1.00)

Precision-recall for class 7 (AP = 1.00)
                         Precision-recall for class 8 (AP = 1.00)
                         Precision-recall for class 9 (AP = 1.00)
                        Precision-recall for class 10 (AP = 1.00)
                         Precision-recall for class 11 (AP = 1.00)
Precision-recall for class 12 (AP = 1.00)
                         Precision-recall for class 13 (AP = 1.00)
                                02
                                              04
                                                                           08
```