Programming Assignment 3

執行環境: Visual Studio Code 程式語言:Python 3.11.5 作業架構: R12725048 |— report.pdf |— training.txt |— pa3.py |— data/

執行方式

- 使用VS code跑pa3.py檔
- 需要下載的套件有:
 - pip install stop words:刪除不太帶有資訊的單詞所需
 - pip install nltk: 使用Porter's algorithm.所需
- 直接按全部執行即可

• Step 1: import 所需套件

- Step 2: 根據HW2 一樣先依據上次的news dataset建立class TF_TFIDF(),並建立其 object : tf_idf
 - ▶ 此步驟會做資料的前處理、建好dictionary、tf-idf table
 - ▶ 皆是上次作業的內容,因此簡報就不多花篇幅敘述

```
# step1:藉由HW2先根據所有data建立dictionary&tfidf table
file_path = "./IRTM"
num_docs = 1095
tf idf = TF IDF(file path, num docs)
```

- Step 3: 讀取training.txt,並將內容分別儲存成以下形式
- training_dataset = [1,2,3,...700,730,...,1019] → 將所有要拿來訓練的文章id儲存起來並照id大小排序
- training_list = {1:[11,19,29,113,...],2:[1,2,3,...],...} → 用dict儲存每個class各別需要訓練的doc有哪些
- classes = [1,2,3,...13] → 用list紀錄所有的類別

```
training dataset = [] #用list來儲存所有要拿來training的doc id
217
     training list = {} #用dict分別儲存每個class中有那些training的doc id
218
     classes = [] #用list來儲存class有哪些
219
     f = open('training.txt')
220
     for line in f.readlines():
221
         input = line.split(' ')
222
         if '\n' in input:
223
224
             input.remove('\n')
         input = [int(i) for i in input]
225
         training_list[input[0]] = input[1:]
226
         training dataset.extend(input[1:])
227
         classes.append(input[0])
228
      f.close
229
      training dataset.sort()
230
```

• Step 4(1): 重要features挑選

- ➤ 採取Log likelihood ratio的方式來挑features
- ➤ 而又因為作業為Multiple Classifiers,所以使用select the top k/n features for each n classifiers的方式來挑選500個features
- ▶ 要把最後的features union起來,因為不同類別可能挑到相同的feature

```
# step2: 根據training dataset先做重要term的篩選
  232
          selected_features = FeaturesSelection(training_list, classes, int(500/13
  233
          selected features = set(selected features)
  234
▶ 198 ∨ def FeaturesSelection(training list:dict,classes:list, k:int) -> list:
          vocabulary = []
 199
          score list = {} #用來儲存每個class中的每個term的llr score e.g.score list={'apple':0.025,'banana':3.521,...}
 200
          #針對各個class各挑k個重要features最後合併起來
 201
          for c in classes:
 202 \
             V = ExtractVocabulary(training list[c])
 203
             score list = likelihood ratio(c, V)
 204
             #將score list依照values(llr score)排序
 205
             sorted score = dict(sorted(score_list.items(), key=lambda item: item[1], reverse=True))
 206
             #每個class挑最高分的k個features合併起來
 207
             vocabulary.extend(list(sorted score.keys())[:k])
 208
 209
          return vocabulary
 210
```

• Step 4(2):

likelihood ratio

```
def likelihood ratio(c:int, V:list) -> dict:
          score = {}
          for term in V:
173
              n11 = 0
174
175
              n01 = 0
              n10 = 0
176
177
              n00 = 0
              for doc in training dataset:
178
                  #若此doc為此類別(on topic)
179
                  if doc in training list[c]:
180
                      #若term為present
181
                      if term in ExtractTokensFromDoc(doc):
182
                          n11+=1
183
                      #若term為absent
184
185
                      else:
186
                          n10+=1
                  #若此doc為不屬於此類別(off topic)
187
                  else:
188
                      #若term為present
189
                      if term in ExtractTokensFromDoc(doc):
190
191
                          n01+=1
                      #若term為absent
192
                      else:
193
                          n00+=1
194
              pt = (n11+n01)/len(training_dataset)
195
              p1 = n11/(n11+n10)
196
              p2 = n01/(n01+n00)
197
              H1 likelihood = (math.pow(pt,n11)) * (math.pow((1-pt),n10)) * (math.pow(pt,n01)) * (math.pow((1-pt),n00))
198
              H2 likelihood = (math.pow(p1,n11)) * (math.pow((1-p1),n10)) * (math.pow(p2,n01)) * (math.pow((1-p2),n00))
199
              llr = (-2)*(math.log(H1 likelihood)-math.log(H2 likelihood))
200
              score[term] = 11r
201
202
          return score
```

• Step 5:建立class NaiveBayes(),並建立其object: NB,將NB的attributes&methods初始化

```
# step3: 用Naive Bayes進行training
    239
           NB = NaiveBayes(tf_idf, classes, training_dataset, training_list)
    240
           prior, condprob = NB.TrainMultinomialNB(selected features)
    241
    class NaiveBayes():
82
        def init (self, tf idf:TF IDF, classes:list, training dataset:list, training list:dict):
83
            self.tf idf = tf idf
84
            self.classes = classes
85
            self.training dataset = training dataset
86
            self.training list = training list
87
88
```

• Step 6: 進行training

```
# step3: 用Naive Bayes進行training

NB = NaiveBayes(tf_idf, classes, training_dataset, training_list)

prior, condprob = NB.TrainMultinomialNB(selected_features)
```

```
def TrainMultinomialNB(self, V:list) -> list | dict :
89
             #宣告prior陣列存放各類別的P(C)值
 90
             prior = [0 for i in range(0, len(self.classes)+1)]
 91
             condprob = {}
 92
             N = len(self.training dataset)
 93
 94
             for c in self.classes:
95
                 Nc = CountDocsInClass(c)
 96
                 prior[c] = Nc/N
 97
                                                                                            紀錄每個term在每個class的分數,並做
                 text c = ConcatenateTextOfAllDocsInClass(self.training list[c])
 98
                                                                                            smoothing處理
 99
                 num of term in class c = sum(list(text c.values()))
100
101
                 for term in V:
102
103
                     T ct = CountTokensOfTerm(text c, term)
104
                     if term not in condprob:
105
                         condprob[term] = [1/(num of term in class c+len(V)) for i in range(0, len(self.classes)+1)]
106
107
                     condprob[term][c] = (T ct+1)/(num of term in class c+len(V))
108
                                                                                                                                   9
109
             return prior, condprob
```

```
# step4: 將剩下的資料集進行apply
mapping_class_of_doc = [0 for i in range(1, num_docs+2)]
for doc in range(1, num_docs+1):
mapping_class_of_doc[doc] = NB.ApplyMultinomialNB(selected_features, classes, prior, condprob, doc)
```

• Step 7: 將所有dataset拿去驗證

```
___
112
          def ApplyMultinomialNB(self, V:list, categories:list, prior:list, condprob:dict, d:int) -> int:
              word in d = ExtractTokensFromDoc(d)
113
              score = [0 for i in range(0, len(categories)+1)]
114
115
              \max \ \text{score} = -10000000
              mapping = 0
116
              for c in categories:
117
                  score[c] = math.log(prior[c])
118
                  for term in word in d:
119 V
                      #只計算selected features裡的字,其他不用算分數
120
                      if term in V:
121 V
                          score[c] += math.log(condprob[term][c]) * tf idf.tf[d][term]
122
                  #紀錄最高分的類別是哪個
123
                  if score[c] > max score:
124 V
                      max score = score[c]
125
                      mapping = c
126
              return mapping
127
```

• Step 8: 將result寫到csv檔

```
# step5: write result to 'HW3 csv.csv'
256
257
      header = ['Id','Value']
      data = []
258
      for i in range(1,num docs+1):
259
          if i not in training_dataset:
260
              data.append([i,mapping class of doc[i]])
261
262
263
      with open('HW3 csv.csv', 'w', encoding='UTF8', newline='') as f:
264
265
          writer = csv.writer(f)
266
          # write the header
267
          writer.writerow(header)
268
269
270
          # write multiple rows
          writer.writerows(data)
271
```

Kaggle 分數

