```
1 # -*- coding: utf-8 -*-
 2 """Bernoulli NB Testing.ipynb
 4 Automatically generated by Colaboratory.
 6 Original file is located at
       https://colab.research.google.com/drive/199uJ4b4t-1xxUSn2onGApxLUPMPofQDt
 9 <center><h1>Mini Project 2 - Bernoulli Naïve Bayes</h1>
10 <h4>This file tests the performance of the Bernoulli Naïve Bayes implemented by
    ourselves.</h4></center>
11
12 <h3>Team Members:</h3>
13 <center>
14 Yi Zhu, 260716006<br>
15 Fei Peng, 260712440<br>
16 Yukai Zhang, 260710915
17 </center>
18 """
19
20 from google.colab import drive
21 drive.mount('/content/drive')
22
23 # make path = './' in-case you are running this locally
24 path = '/content/drive/My Drive/ECSE_551_F_2020/Mini_Project_02/'
25
26 import numpy as np
27 import pandas as pd
28 import matplotlib.pyplot as plt
29
30 from time import time
31 from sklearn.model_selection import train_test_split
32 from sklearn.preprocessing import Normalizer
33 from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
34 from sklearn.feature_extraction import text
35 from sklearn import metrics
36 from sklearn.model_selection import GridSearchCV, cross_val_score, KFold
37 from sklearn.pipeline import make_pipeline
38 from sklearn.preprocessing import LabelEncoder
39
40 !pip install nltk
41 import nltk
42 nltk.download('punkt')
43 nltk.download('wordnet')
44 nltk.download('averaged_perceptron_tagger')
46 from nltk.stem import PorterStemmer
47 from nltk import word_tokenize
48 from nltk import word_tokenize
49 from nltk.stem import WordNetLemmatizer
50 from nltk.corpus import wordnet
51
52 """# Import Data"""
53
54 reddit_dataset = pd.read_csv(path+"train.csv")
55 reddit_test = pd.read_csv(path+"test.csv")
56
57 X = reddit_dataset['body']
58 y = reddit_dataset['subreddit']
59
60 """# Define Vectorizer
61 ### (To vectorize the text-based data to numerical features)
62
```

```
63 1. CountVectorizer
 64 1) Use "CountVectorizer" to transform text data to feature vectors.
 65 2) Normalize your feature vectors
 67
 68 def count_vectorizer(X_train, X_test):
        vectorizer = CountVectorizer(binary=True)
 70
        vectors_train = vectorizer.fit_transform(X_train)
 71
        vectors_test = vectorizer.transform(X_test)
 72
 73
        return vectors_train, vectors_test
 74
 75 """2. CountVectorizer with stop word
 76 1) Use "CountVectorizer" with stop word to transform text data to vector.
 77 2) Normalize your feature vectors
78 """
79
 80 def count_vec_with_sw(X_train, X_test, max_features):
 81
        stop_words = text.ENGLISH_STOP_WORDS
 82
        if max_features:
 83
            vectorizer = CountVectorizer(stop_words=stop_words, binary=True,
    max_features=5000)
 84
        else:
 85
            vectorizer = CountVectorizer(stop_words=stop_words, binary=True)
 86
        vectors_train_stop = vectorizer.fit_transform(X_train)
 87
        vectors_test_stop = vectorizer.transform(X_test)
 88
 89
        return vectors_train_stop, vectors_test_stop
 90
 91 """3. TF-IDF
 92 1) use "TfidfVectorizer" to weight features based on your train set.
 93 2) Normalize your feature vectors
 94 """
 95
 96 def tfidf_vectorizer(X_train, X_test):
 97
        tf_idf_vectorizer = TfidfVectorizer(binary=True)
        vectors_train_idf = tf_idf_vectorizer.fit_transform(X_train)
 98
99
        vectors_test_idf = tf_idf_vectorizer.transform(X_test)
100
101
        return vectors_train_idf, vectors_test_idf
102
103 """4. CountVectorizer with stem tokenizer
104 1) Use "StemTokenizer" to transform text data to vector.
105 2) Normalize your feature vectors
106 """
107
108 class StemTokenizer:
109
         def __init__(self):
110
           self.wnl =PorterStemmer()
111
         def __call__(self, doc):
112
           return [self.wnl.stem(t) for t in word_tokenize(doc) if t.isalpha()]
113
114
115 def count_vec_stem(X_train, X_test):
116
        vectorizer = CountVectorizer(tokenizer=StemTokenizer(), binary=True)
117
        vectors_train_stem = vectorizer.fit_transform(X_train)
118
        vectors_test_stem = vectorizer.transform(X_test)
119
120
        return vectors_train_stem, vectors_test_stem
121
122 """5. CountVectorizer with lemma tokenizer
123 1) Use "LemmaTokenizer" to transform text data to vector.
124 2) Normalize your feature vectors
```

```
125 """
126
127 def get_wordnet_pos(word):
        """Map POS tag to first character lemmatize() accepts"""
128
129
        tag = nltk.pos_tag([word])[0][1][0].upper()
130
        tag_dict = {"J": wordnet.ADJ,
                    "N": wordnet.NOUN,
131
                    "V": wordnet.VERB,
132
                    "R": wordnet.ADV}
133
134
        return tag_dict.get(tag, wordnet.NOUN)
135
136
137 class LemmaTokenizer:
138
         def __init__(self):
           self.wnl = WordNetLemmatizer()
139
         def __call__(self, doc):
140
141
           return [self.wnl.lemmatize(t,pos =get_wordnet_pos(t)) for t in
    word_tokenize(doc) if t.isalpha()]
142
143
144 def count_vec_lemma(X_train, X_test):
145
        vectorizer = CountVectorizer(tokenizer=LemmaTokenizer(), binary=True)
146
        vectors_train_lemma = vectorizer.fit_transform(X_train)
147
        vectors_test_lemma = vectorizer.transform(X_test)
148
149
        return vectors_train_lemma, vectors_test_lemma
150
151 """# Bernoulli Naïve Bayes Classifier"""
152
153 # Bernoulli Naïve Bayes
154 class BernoulliNB:
155
156
            This is the Bernoulli Naïve Bayes class, containing fit, perdict and
    accu_eval functions,
157
            as well as many other useful functions.
158
159
160
        def __init__(self, laplace):
161
            self.laplace = laplace # true for performing Laplace smoothing
162
            self.le = LabelEncoder() # encoder for classes
163
164
        def fit(self, X, y):
165
166
                This function takes the training data X and its corresponding
    labels vector y as input,
167
                and execute the model training.
168
169
                X - features of traning data
                y - class labels
170
171
172
            # Laplace smoothing paramerters
173
            num = 0
174
            den = 0
175
            if self.laplace:
176
                num += 1
177
                den += 2
178
179
            # encode the text-based class type to numerical values
180
            le = self.le
181
            le.fit(y)
182
            y_label = le.transform(y)
            n_k = len(le.classes_) # number of classes
183
184
            n_j = X.shape[1] # number of feαtures
```

```
185
                         N = len(v) # number of samples
186
187
                         theta_k = np.zeros(n_k) # probability of class k
188
                         theta_j_k = np.zeros((n_k, n_j)) # probability of feature j given
        class k
189
190
                         # compute theta values
191
                         for k in range(n_k):
192
                                 count_k = (y_label==k).sum()
193
                                 theta_k[k] = count_k / N
194
                                 for j in range(n_j):
195
                                         theta_j_k[k][j] = (X[y_label==k, j].sum()+num) / (count_k+den)
196
197
                         # store the theta values to this instance
198
                         self.theta_k = theta_k
199
                         self.theta_j_k = theta_j_k
200
                         # print("Finished fitting...")
201
202
                def predict(self, X):
203
204
                                 This function takes a set of data as input and outputs predicted
         labels for the input points.
205
206
                        le = self.le
207
                         theta_k = self.theta_k
208
                        theta_j_k = self.theta_j_k
209
210
                        # this part works the same as the pseudo-code provided in Lecture 12
211
                        # but matrix multiplication is much faster than nested loops
212
                        i_m = np.zeros_like(X) # identity matrix
213
                         # predict classes
                        y_pred = np.argmax(X.dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(1-y_pred = np.argmax(X.dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(1-y_pred = np.argmax(X.dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.log(theta_j_k).T)+(i_m-X).dot(np.l
214
         theta_j_k).T)+theta_k, axis=1)
215
216
                         # transform back to text-based values
217
                        y_pred = le.inverse_transform(y_pred)
218
                        return y_pred
219
220 """### 1. K-fold validation using CountVectorizer"""
221
222 tic = time()
223 accuracies = []
224 clf = BernoulliNB(laplace=True)
225 kf = KFold(n_splits=5, shuffle=True)
 226 for train_index, test_index in kf.split(X):
227
                vectors_train, vectors_test = count_vectorizer(X[train_index], X[
         test_index])
 228
                clf.fit(vectors_train, y[train_index])
                 a_s = metrics.accuracy_score(y[test_index], clf.predict(vectors_test))
 229
230
                print(a_s)
231
                 accuracies.append(a_s)
232
233 print("\t- Bernoulli Naïve Bayes + CountVectorizer -\nAccuracy: {}%\tTime
         Spent: {}s".format(np.mean(accuracies), time()-tic))
 234
 235 """### 2. K-fold validation using CountVectorizer with stop word, max_features
         =5000"""
 236
237 # with max_features=5000
238 tic = time()
239 accuracies = []
240 clf = BernoulliNB(laplace=True)
241 kf = KFold(n_splits=5, shuffle=True)
```

```
242 for train_index, test_index in kf.split(X):
243
        vectors_train, vectors_test = count_vec_with_sw(X[train_index], X[
    test_index], max_features=True)
244
        clf.fit(vectors_train, y[train_index])
        a_s = metrics.accuracy_score(y[test_index], clf.predict(vectors_test))
245
246
        print(a_s)
247
        accuracies.append(a_s)
248
249 print("\t- Bernoulli Naïve Bayes + CountVectorizer with stop word, Max
    Features = 5000 -\nAccuracy: {}%\tTime Spent: {}s".format(np.mean(accuracies
    ), time()-tic))
250
251 """### 3. K-fold validation using CountVectorizer with stop word"""
252
253 tic = time()
254 accuracies = []
255 clf = BernoulliNB(laplace=True)
256 kf = KFold(n_splits=5, shuffle=True)
257 for train_index, test_index in kf.split(X):
258
        vectors_train, vectors_test = count_vec_with_sw(X[train_index], X[
    test_index])
259
        clf.fit(vectors_train, y[train_index])
260
        a_s = metrics.accuracy_score(y[test_index], clf.predict(vectors_test))
261
        print(a_s)
262
        accuracies.append(a_s)
263
264 print("\t- Bernoulli Naïve Bayes + CountVectorizer with stop word -\nAccuracy
    : {}%\tTime Spent: {}s".format(np.mean(accuracies), time()-tic))
265
266 """### 4. K-fold validation using CountVectorizer with stem tokenizer"""
267
268 tic = time()
269 accuracies = []
270 clf = BernoulliNB(laplace=True)
271 kf = KFold(n_splits=5, shuffle=True)
272 for train_index, test_index in kf.split(X):
273
        vectors_train, vectors_test = count_vec_stem(X[train_index], X[test_index
    ])
274
        clf.fit(vectors_train, y[train_index])
275
        a_s = metrics.accuracy_score(y[test_index], clf.predict(vectors_test))
276
        print(a_s)
277
        accuracies.append(a_s)
278
279 print("\t- Bernoulli Naïve Bayes + CountVectorizer with stem tokenizer -\n
    Accuracy: {}%\tTime Spent: {}s".format(np.mean(accuracies), time()-tic))
280
281 """### 5. K-fold validation using CountVectorizer with lemma tokenizer"""
282
283 tic = time()
284 accuracies = []
285 clf = BernoulliNB(laplace=True)
286 kf = KFold(n_splits=5, shuffle=True)
287 for train_index, test_index in kf.split(X):
288
        vectors_train, vectors_test = count_vec_lemma(X[train_index], X[test_index
    ])
289
        clf.fit(vectors_train, y[train_index])
290
        a_s = metrics.accuracy_score(y[test_index], clf.predict(vectors_test))
291
        print(a_s)
292
        accuracies.append(a_s)
293
294 print("\t- Bernoulli Naïve Bayes + CountVectorizer with lemma tokenizer -\n
    Accuracy: {}%\tTime Spent: {}s".format(np.mean(accuracies), time()-tic))
```