```
1 # -*- coding: utf-8 -*-
 2 """Bernoulli Naïve Bayes.ipynb
 4 Automatically generated by Colaboratory.
 6 Original file is located at
       https://colab.research.google.com/drive/19asN10XEleCYuHFT9Yao8DAXamARVxFy
 9 <center><h1>Mini Project 2 - Bernoulli Naïve Bayes</h1>
10 <h4>The hyperparameters and models used in this file are chosen based on the
  findings in the testing file.</h4></center>
12 <h3>Team Members:</h3>
13 <center>
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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 sklearn.model_selection import train_test_split
31 from sklearn.preprocessing import Normalizer
32 from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
33 from sklearn.feature_extraction import text
34 from sklearn import metrics
35 from sklearn.model_selection import GridSearchCV, cross_val_score, KFold
36 from sklearn.pipeline import make_pipeline
37 from sklearn.preprocessing import LabelEncoder
38
39 !pip install nltk
40 import nltk
41 nltk.download('punkt')
42 nltk.download('wordnet')
43 nltk.download('averaged_perceptron_tagger')
44
45 from nltk.stem import PorterStemmer
46 from nltk import word_tokenize
47 from nltk import word_tokenize
48 from nltk.stem import WordNetLemmatizer
49 from nltk.corpus import wordnet
50
51 """# Import Data"""
52
53 reddit_dataset = pd.read_csv(path+"train.csv")
54 reddit_test = pd.read_csv(path+"test.csv")
55
56 X = reddit_dataset['body']
57 y = reddit_dataset['subreddit']
58
59 """# Define Vectorizer
60 ### (To vectorize the text-based data to numerical features)
61
62 1. CountVectorizer
```

```
63 1) Use "CountVectorizer" to transform text data to feature vectors.
 64 2) Normalize your feature vectors
65 """
 66
 67 def count_vectorizer(X_train, X_test):
 68
        vectorizer = CountVectorizer(binary=True)
        vectors_train = vectorizer.fit_transform(X_train)
 69
 70
        vectors_test = vectorizer.transform(X_test)
 71
 72
        return vectors_train, vectors_test
 73
 74 """2. CountVectorizer with stop word
 75 1) Use "CountVectorizer" with stop word to transform text data to vector.
 76 2) Normalize your feature vectors
77 """
 78
 79 def count_vec_with_sw(X_train, X_test):
 80
        stop_words = text.ENGLISH_STOP_WORDS
 81
        vectorizer = CountVectorizer(stop_words=stop_words, binary=True)
 82
        vectors_train_stop = vectorizer.fit_transform(X_train)
 83
        vectors_test_stop = vectorizer.transform(X_test)
 84
 85
        return vectors_train_stop, vectors_test_stop
 86
 87 """3. TF-IDF
 88 1) use "TfidfVectorizer" to weight features based on your train set.
 89 2) Normalize your feature vectors
 90 """
 91
 92 def tfidf_vectorizer(X_train, X_test):
 93
        tf_idf_vectorizer = TfidfVectorizer(binary=True)
 94
        vectors_train_idf = tf_idf_vectorizer.fit_transform(X_train)
 95
        vectors_test_idf = tf_idf_vectorizer.transform(X_test)
 96
 97
        return vectors_train_idf, vectors_test_idf
 98
99 """4. CountVectorizer with stem tokenizer
100 1) Use "StemTokenizer" to transform text data to vector.
101 2) Normalize your feature vectors
102 """
103
104 class StemTokenizer:
105
         def __init__(self):
106
           self.wnl =PorterStemmer()
107
         def __call__(self, doc):
108
           return [self.wnl.stem(t) for t in word_tokenize(doc) if t.isalpha()]
109
110
111 def count_vec_stem(X_train, X_test):
        vectorizer = CountVectorizer(tokenizer=StemTokenizer(), binary=True)
112
113
        vectors_train_stem = vectorizer.fit_transform(X_train)
114
        vectors_test_stem = vectorizer.transform(X_test)
115
116
        return vectors_train_stem, vectors_test_stem
117
118 """5. CountVectorizer with lemma tokenizer
119 1) Use "LemmaTokenizer" to transform text data to vector.
120 2) Normalize your feature vectors
121 """
122
123 def get_wordnet_pos(word):
124
        """Map POS tag to first character lemmatize() accepts"""
125
        tag = nltk.pos_tag([word])[0][1][0].upper()
```

```
126
        tag_dict = {"J": wordnet.ADJ,
127
                    "N": wordnet.NOUN,
                    "V": wordnet.VERB,
128
                    "R": wordnet.ADV}
129
130
        return tag_dict.get(tag, wordnet.NOUN)
131
132
133 class LemmaTokenizer:
         def __init__(self):
134
135
           self.wnl = WordNetLemmatizer()
136
         def __call__(self, doc):
137
           return [self.wnl.lemmatize(t,pos =get_wordnet_pos(t)) for t in
    word_tokenize(doc) if t.isalpha()]
138
139
140 def count_vec_lemma(X_train, X_test):
        vectorizer = CountVectorizer(tokenizer=LemmaTokenizer(), binary=True)
141
142
        vectors_train_lemma = vectorizer.fit_transform(X_train)
143
        vectors_test_lemma = vectorizer.transform(X_test)
144
145
        return vectors_train_lemma, vectors_test_lemma
146
147 """# Bernoulli Naïve Bayes Classifier"""
148
149 # Bernoulli Naïve Bayes
150 class BernoulliNB:
151
152
            This is the Bernoulli Naïve Bayes class, containing fit, perdict and
    accu_eval functions,
153
            as well as many other useful functions.
154
155
        def __init__(self, laplace):
156
157
            self.laplace = laplace # true for performing Laplace smoothing
158
            self.le = LabelEncoder() # encoder for classes
159
160
        def fit(self, X, y):
161
162
                This function takes the training data X and its corresponding
    labels vector y as input,
163
                and execute the model training.
164
165
                X - features of traning data
                y - class labels
166
            111
167
168
            # Laplace smoothing paramerters
169
            num = 0
170
            den = 0
171
            if self.laplace:
172
                num += 1
173
                den += 2
174
175
            # encode the text-based class type to numerical values
176
            le = self.le
177
            le.fit(y)
178
            y_label = le.transform(y)
179
            n_k = len(le.classes_) # number of classes
180
            n_j = X.shape[1] # number of feαtures
181
            N = len(y) # number of samples
182
183
            theta_k = np.zeros(n_k) # probability of class k
            theta_j_k = np.zeros((n_k, n_j)) # probability of feature j given
184
    class k
```

```
185
186
                         # compute theta values
187
                         for k in range(n_k):
188
                                 count_k = (y_label==k).sum()
189
                                 theta_k[k] = count_k / N
190
                                 for j in range(n_j):
                                          \label{eq:count_k+den}  \mbox{theta\_j\_k[k][j] = (X[y\_label==k, j].sum()+num) / (count\_k+den)} 
191
192
193
                         # store the theta values to this instance
194
                         self.theta_k = theta_k
195
                         self.theta_j_k = theta_j_k
196
                         print("Finished fitting...")
197
198
                 def predict(self, X):
199
200
                                 This function takes a set of data as input and outputs predicted
         labels for the input points.
201
202
                         le = self.le
203
                         theta_k = self.theta_k
204
                         theta_j_k = self.theta_j_k
205
206
                         # this part works the same as the pseudo-code provided in Lecture 12
207
                         # but matrix multiplication is much faster than nested loops
208
                         i_m = np.zeros_like(X) # identity matrix
209
                         # predict classes
210
                         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
         theta_j_k).T)+theta_k, axis=1)
211
212
                         # transform back to text-based values
213
                         y_pred = le.inverse_transform(y_pred)
214
                         return y_pred
215
216 """### 1. K-fold validation using CountVectorizer"""
217
218 accuracies = []
219 clf = BernoulliNB(laplace=True)
220 kf = KFold(n_splits=5, shuffle=True)
221 for train_index, test_index in kf.split(X):
                 vectors_train, vectors_test = count_vectorizer(X[train_index], X[
222
         test_index])
 223
                 clf.fit(vectors_train, y[train_index])
 224
                 a_s = metrics.accuracy_score(y[test_index], clf.predict(vectors_test))
 225
                 print(a s)
                 accuracies.append(a_s)
 226
227
 228 print(np.mean(accuracies))
 229
 230 """### 2. K-fold validation using CountVectorizer with stop word, max_features
         =5000"""
 231
232 # with max_features=5000
233 accuracies = []
234 clf = BernoulliNB(laplace=True)
235 kf = KFold(n_splits=5, shuffle=True)
236 for train_index, test_index in kf.split(X):
237
                 vectors_train, vectors_test = count_vec_with_sw(X[train_index], X[
         test_index])
 238
                 clf.fit(vectors_train, y[train_index])
 239
                 a_s = metrics.accuracy_score(y[test_index], clf.predict(vectors_test))
240
                 print(a_s)
241
                 accuracies.append(a_s)
242
```

```
243 print(np.mean(accuracies))
244
245 """### 3. K-fold validation using CountVectorizer with stop word"""
246
247 accuracies = []
248 clf = BernoulliNB(laplace=True)
249 kf = KFold(n_splits=5, shuffle=True)
250 for train_index, test_index in kf.split(X):
251
        vectors_train, vectors_test = count_vec_with_sw(X[train_index], X[
    test_index])
252
        clf.fit(vectors_train, y[train_index])
253
        a_s = metrics.accuracy_score(y[test_index], clf.predict(vectors_test))
254
        print(a_s)
255
        accuracies.append(a_s)
256
257 print(np.mean(accuracies))
258
259 """### 4. K-fold validation using CountVectorizer with stem tokenizer"""
260
261 accuracies = []
262 clf = BernoulliNB(laplace=True)
263 kf = KFold(n_splits=5, shuffle=True)
264 for train_index, test_index in kf.split(X):
265
        vectors_train, vectors_test = count_vec_stem(X[train_index], X[test_index
    ])
266
        clf.fit(vectors_train, y[train_index])
        a_s = metrics.accuracy_score(y[test_index], clf.predict(vectors_test))
267
268
        print(a_s)
269
        accuracies.append(a_s)
270
271 print(np.mean(accuracies))
272
273 """### 5. K-fold validation using CountVectorizer with lemma tokenizer"""
274
275 accuracies = []
276 clf = BernoulliNB(laplace=True)
277 kf = KFold(n_splits=5, shuffle=True)
278 for train_index, test_index in kf.split(X):
279
        vectors_train, vectors_test = count_vec_lemma(X[train_index], X[test_index
    ])
280
        clf.fit(vectors_train, y[train_index])
281
        a_s = metrics.accuracy_score(y[test_index], clf.predict(vectors_test))
282
        print(a_s)
283
        accuracies.append(a_s)
284
285 print(np.mean(accuracies))
```