Daga_03

November 29, 2020

1 Assignment 03

[1]:
```
%matplotlib inline
```

[2]:
```
from Data import Data
from NBC import Model, average_accuracy
from Vocabulary import Vocabulary
import pandas as pd
import matplotlib.pyplot as plt
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\harsh\AppData\Roaming\nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
```

Reading the vocabulary file included with the data folder. See `Vocabulary.py`

[3]:
```
vocab = Vocabulary(r'aclImdb\\imdb.vocab')
```

[4]:
```
print(f'Stopwords: {vocab.stopwords}')
```

```
Stopwords: {'because', 'haven', 'than', 'll', 'needn', 'in', 'her', 'into',
'hers', "doesn't", "you're", 'off', 'wouldn', 'were', 'ours', 'wasn', 'here',
"don't", 'as', 'where', "should've", 'then', 'our', 'himself', 'no', 'through',
'just', 'having', 'up', 'each', 'd', 'i', 'don', 'should', 'does', 'so',
"you've", 'o', 'had', 'own', 'that', "won't", "shan't", 'more', "wasn't",
'from', 'didn', 'down', 'to', 'out', 'while', "mightn't", 'hadn', 'other', 'is',
'been', 'most', 'did', 'yours', 'yourself', 'm', 'now', 'doing', "shouldn't",
'isn', 'after', 'ain', 'shouldn', 'any', 'again', 'theirs', 'itself', 'a', 'be',
'ma', 'are', 'has', 'few', 'me', 'same', 've', 'against', 'too', 'my', 'which',
'or', 'it', 'only', "didn't", 'but', 'ourselves', "that'll", 'during', 'how',
'not', 'whom', 'yourselves', "hadn't", 'who', 'at', 'some', 'for', 's', 'this',
'he', 'by', 'about', 'both', 'do', 't', 'before', 'above', 'once', 'when',
'will', "isn't", 'if', 'mightn', 'all', 'have', 'with', 'herself', 'we', 'what',
"you'd", 'nor', 'hasn', 'them', 'an', 'they', 'over', 'on', 'him', 'doesn',
'was', "wouldn't", "needn't", 'themselves', 'their', 'can', 'until', 'further',
'am', 'these', "haven't", 're', 'your', "aren't", 'those', 'between', 'shan',
'myself', 'weren', "she's", "couldn't", 'couldn', 'under', 'there', 'its',
'such', 'aren', 'his', "you'll", 'being', "hasn't", 'of', 'you', 'the', 'below',
'why', 'and', 'she', 'very', "mustn't", 'won', 'y', 'mustn', "it's", "weren't"}
```

Reading the train reviews file using 5 fold cross-validation.

See `Data.py` and `Reviews.py`

[5]:
```
k = 5
data_sets = list(Data.read_train('aclImdb', k))
```

Creating NBC models for each of the data set that was produced by 5 fold cross-validation. See `NBC.py`

[6]:
```
models = [Model(x.train, vocab) for x in data_sets]
```

[7]:
```
reviews = data_sets[0].all_train
index_the = vocab.get_index('the')
```

Calculating $P[\text{“}the\text{”}]$ = num of documents containing 'the' / num of all documents

[8]:
```
print(f'P["the"] = {reviews.count(index_the) / len(reviews.all)}')
```

```
P["the"] = 0.99168
```

Calculating $P[\text{“}the\text{”}|Positive]$ = # of positive documents containing "the" / num of all positive review documents

[9]:
```
print(f'P["the" | Positive] = {reviews.count_positive(index_the) / len(reviews.
↪positive)}')
```

```
P["the" | Positive] = 0.99048
```

Calculating the average accuracy of these models without any smoothing and ignoring stop words only.

[10]:
```
dev_data = [x.dev for x in data_sets]
accuracy = average_accuracy(models, dev_data, smoothen=0, min_occurrence=0)
print(f'Average accuracy = {accuracy:.4%}')
```

```
Average accuracy = 74.7840%
```

Calculating the accuracy using smoothing hyperparameters in the range $[0, 1]$ with step size 0.1

[11]:
```
h_params = {}
for i in (x * 0.1 for x in range(0, 11)):
    h_params[i] = average_accuracy(models, dev_data, i, 0)
smoothing_accuracies = pd.DataFrame.from_dict(h_params, orient='index',␣
↪columns=['Accuracy'])
```

[12]:
```
smoothing_accuracies
```

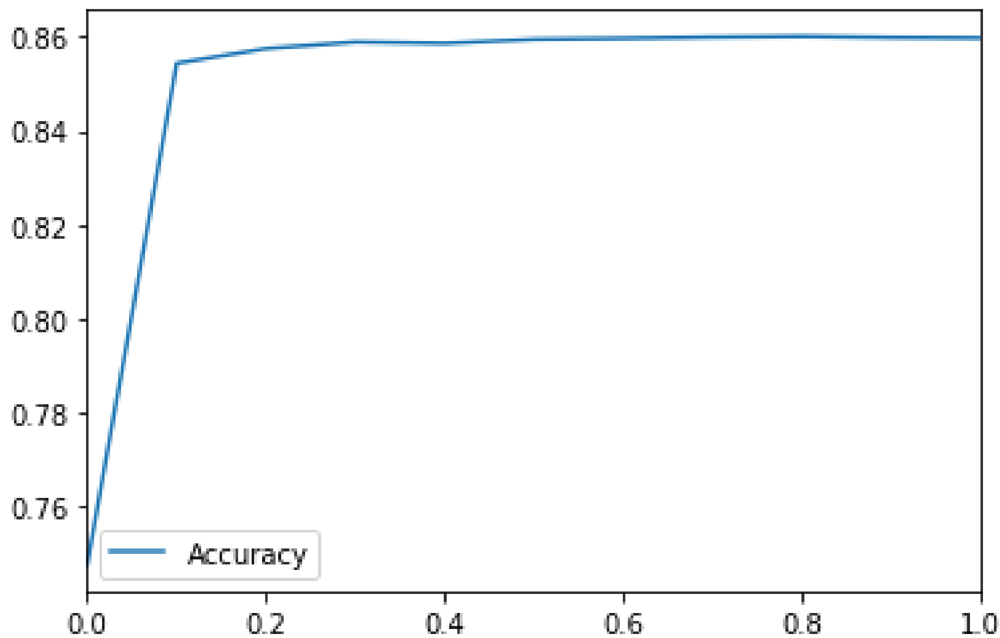
[12]:

	Accuracy
0.0	0.74784
0.1	0.85432
0.2	0.85744

```
0.3    0.85884
0.4    0.85856
0.5    0.85940
0.6    0.85960
0.7    0.85988
0.8    0.86004
0.9    0.85980
1.0    0.85968
```

[13]:
```
smoothing_accuracies.plot()
```

[13]: <matplotlib.axes._subplots.AxesSubplot at 0x16a1296cc88>



It's worth noting that increase the smoothing parameter from `0` even in the slightest increases accuracy considerably. This is because a lot of the words were forcing the probability calculation to be `0` rendering any other words in the same review useless.

[14]:
```
h_params = {}
for i in (x * 0.00025 for x in range(0, 11)):
    h_params[i] = average_accuracy(models, dev_data, 0, i)
min_occurrence_accuracies = pd.DataFrame.from_dict(h_params, orient='index',␣
 ↪columns=['Accuracy'])
```

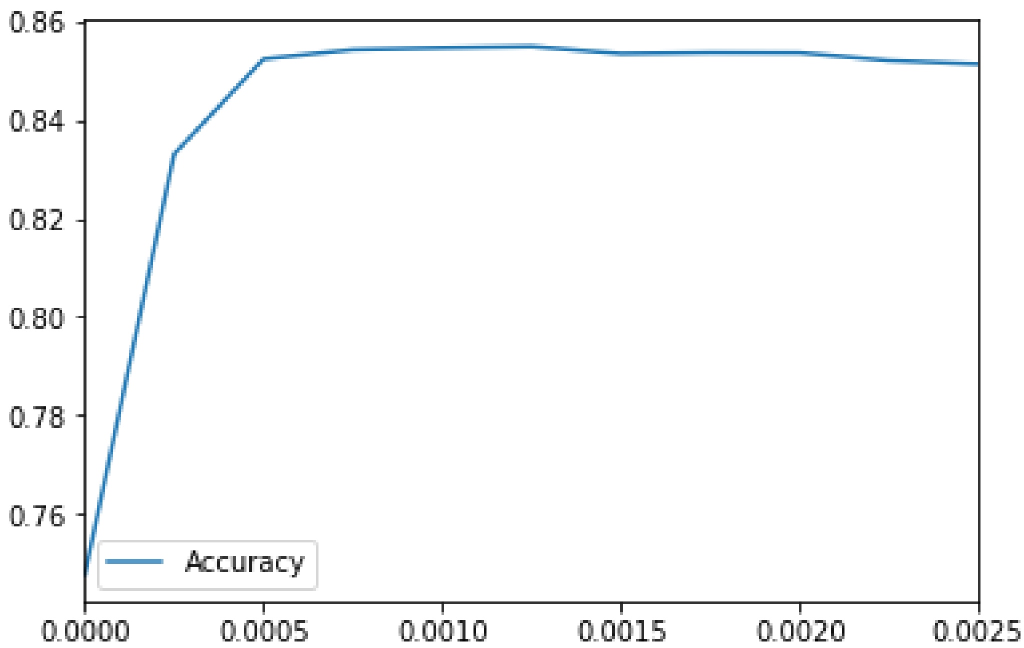
[15]:
```
min_occurrence_accuracies
```

[15]:

	Accuracy
0.00000	0.74784
0.00025	0.83300
0.00050	0.85224
0.00075	0.85412
0.00100	0.85448
0.00125	0.85476
0.00150	0.85332
0.00175	0.85352
0.00200	0.85348
0.00225	0.85192
0.00250	0.85120

[16]:
```
min_occurrence_accuracies.plot()
```

[16]: <matplotlib.axes._subplots.AxesSubplot at 0x16a12acd488>



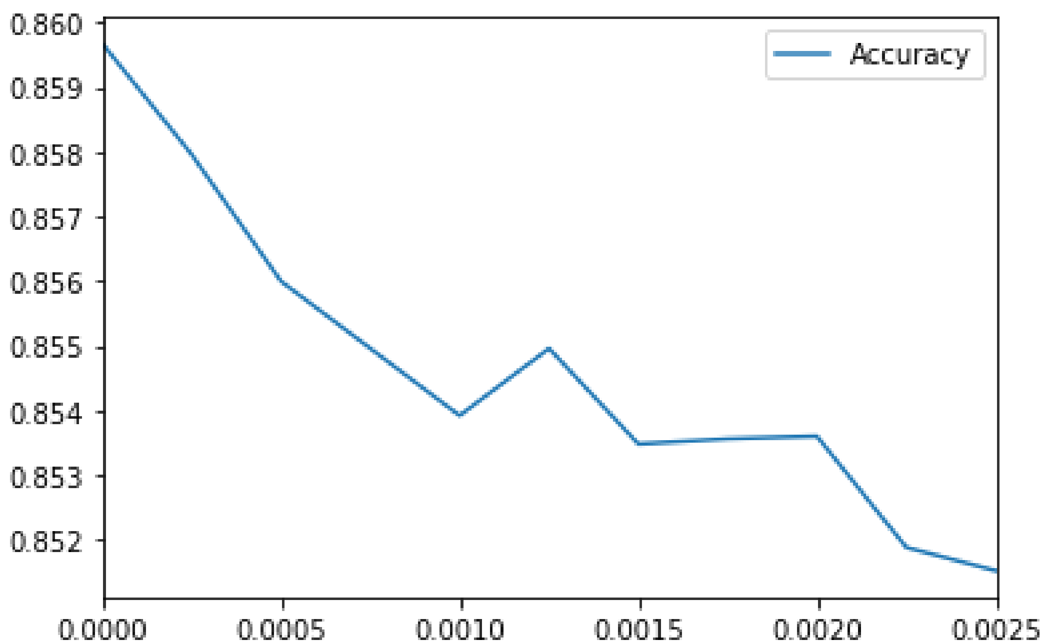
The accuracy improves significantly if we ignore words that occur rarely, specially those that occur 0 times in either `Positive` or `Negative` class. The above plot is for varying values of `min_occurences` with `smoothen=0`.

Redrawing the same plot with `smoothen=1`.

[17]:
```
h_params = {}
for i in (x * 0.00025 for x in range(0, 11)):
    h_params[i] = average_accuracy(models, dev_data, 1, i)
```

```
min_occurrence_accuracies = pd.DataFrame.from_dict(h_params, orient='index',␣
↪columns=['Accuracy'])
min_occurrence_accuracies.plot()
```

[17]: <matplotlib.axes._subplots.AxesSubplot at 0x16a15b531c8>



The accuracy is now decereasing but the absolute change in accuracy is rather small in comparison to before. Simply maximizing both the hyperparameters does not yield better results. The ideal model is a balance between the 2 hyperparameters which is rather expensive to compute in this example.

For the final accuracy calculation, `smoothen=1` and `min_occurrence=0.00025` is used. train and test reviews are combined and used in 5 fold cross-validation for the final models.

[18]:
```
data_sets = list(Data.read_all('aclImdb', k))
```

[19]:
```
models = [Model(x.train, vocab) for x in data_sets]
```

[20]:
```
test_data = [x.test for x in data_sets]
accuracy = average_accuracy(models, test_data, smoothen=1, min_occurrence=0.
↪00025)
print(f'Average accuracy = {accuracy:.4%}')
```

```
Average accuracy = 85.7680%
```

[21]:
```
pos_words, neg_words = models[0].top_words(top_count=10, min_occurrence=0)
print(f'Top 10 positive predicting words:\n{pos_words}')
```

```
print()
print(f'Top 10 negative predicting words:\n{neg_words}')
```

```
Top 10 positive predicting words:
['gundam', 'gunga', 'gypo', 'yokai', 'creasy', 'gackt', 'blandings', 'kells',
'gino', 'brashear']

Top 10 negative predicting words:
['sarne', 'gram', 'mraovich', 'domergue', 'toolbox', 'slaughterhouse', 'sade',
'hamiltons', 'triton', 'advani']
```

The top words seem like typos or otherwise meaningless because these words occured just once in their prediction class and never occured again.

[22]:
```
pos_words, neg_words = models[0].top_words(top_count=10, min_occurrence=0.01)
print(f'Top 10 positive predicting words:\n{pos_words}')
print()
print(f'Top 10 negative predicting words:\n{neg_words}')
```

```
Top 10 positive predicting words:
['wonderfully', 'beautifully', 'superb', 'outstanding', 'gem', 'finest',
'touching', 'excellent', 'magnificent', 'terrific']

Top 10 negative predicting words:
['waste', 'worst', 'laughable', 'awful', 'redeeming', 'poorly', 'pointless',
'sucks', 'lame', 'whatsoever']
```

The top words now seem meaningful after filtering out words that occur too rarely (in less than 1% of the reviews).