final-project-spam-email

May 14, 2021

[1]:
```
%config Completer.use_jedi = False

import os
os.chdir('data')
print(os.listdir())
```

```
['ham', 'spam', '.DS_Store']
```

[2]:
```
print('number of email in ham folder: ',len(os.listdir('ham')))
print('number of email in spam folder: ',len(os.listdir('spam')))
```

```
number of email in ham folder:  3672
number of email in spam folder:  1500
```

[3]:
```
# open python and nltk packages needed for processing
import sys
import random
import nltk
import pandas as pd
from nltk.corpus import stopwords
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer,␣
↪TfidfTransformer
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import MultinomialNB
from sklearn.pipeline import Pipeline
from sklearn.metrics import classification_report, ConfusionMatrixDisplay,␣
↪confusion_matrix
import matplotlib.pyplot as plt
import re
from collections import defaultdict
```

[4]:
```
# function to read spam and ham files, train and test a classifier
def processspamham(spam_limit = 1500, ham_limit = 3672):
    # convert the limit argument from a string to an int
    # limit = int(limitStr)

    # start lists for spam and ham email texts
    hamtexts = []
```

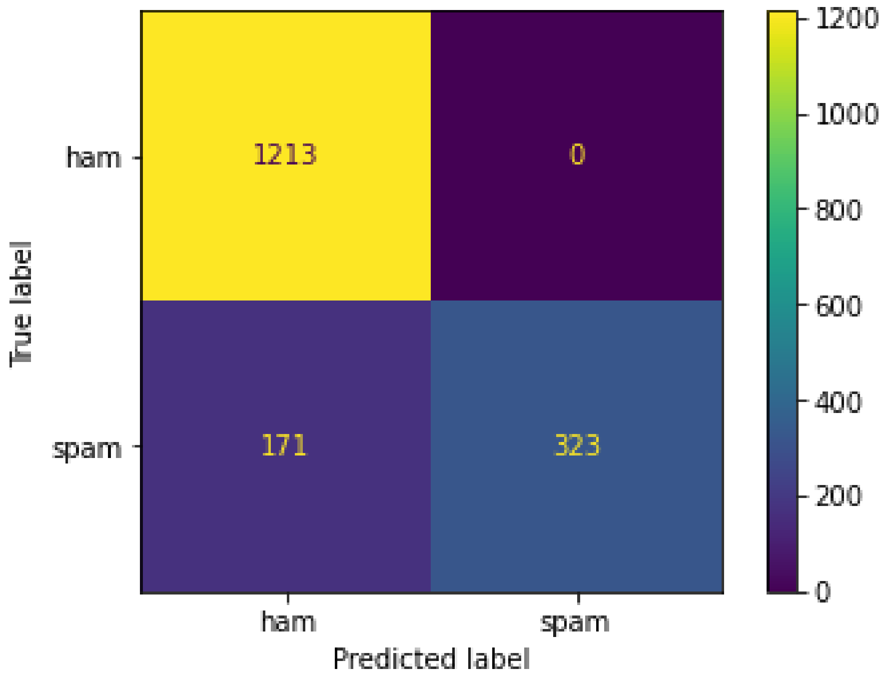
```python
    spamtexts = []
    # process all files in directory that end in .txt up to the limit
    #    assuming that the emails are sufficiently randomized
    for file in os.listdir("./spam"):
         if (file.endswith(".txt")) and (len(spamtexts) < spam_limit):
            # open file for reading and read entire file into a string
            f = open("./spam/" + file, 'r', encoding="latin-1")
            spamtexts.append(f.read())
            f.close()
    for file in os.listdir("./ham"):
         if (file.endswith(".txt")) and (len(hamtexts) < ham_limit):
            # open file for reading and read entire file into a string
            f = open("./ham/" + file, 'r', encoding="latin-1")
            hamtexts.append(f.read())
            f.close()

    # possibly filter tokens
    regex = re.compile('[\W+]|[\d+]')
    stop_words = set(stopwords.words('english'))

    # create list of mixed spam and ham email documents as (list of words,␣
↪label)
    emaildocs = []
    # add all the spam
    for spam in spamtexts:
        tokens = nltk.word_tokenize(regex.sub(' ',spam))
        clean_tokens = [w for w in tokens if not w in stop_words]
        emaildocs.append((clean_tokens, 'spam'))
    # add all the regular emails
    for ham in hamtexts:
        tokens = nltk.word_tokenize(regex.sub(' ', ham))
        clean_tokens = [w for w in tokens if not w in stop_words]
        emaildocs.append((clean_tokens, 'ham'))

    # randomize the list
    random.shuffle(emaildocs)
    return pd.DataFrame(emaildocs,columns=["tokens","label"])
```

[5]:
```python
def vectorize(tokens):
    features = defaultdict(int)
    for token in tokens:
        features[token] += 1
    return features
```

```
def vectorlizedspamham(spam_limit = 1500, ham_limit = 3672):
    emails = processspamham(spam_limit, ham_limit)
    vector = map(vectorize, emails.tokens.tolist())

    return pd.DataFrame(vector).fillna(0), emails.label.tolist()
```

[6]:
```
X, y = vectorlizedspamham()

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33)

pipeline = Pipeline([('tfid', TfidfTransformer()),
                     ('nbc', MultinomialNB())]).fit(X_train,y_train)

y_pred = pipeline.predict(X_test)

print(classification_report(y_test, y_pred))

labels = pipeline.steps[-1][1].classes_
cm = confusion_matrix(y_test, y_pred, labels=labels)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=labels)
disp.plot()
plt.show()
```

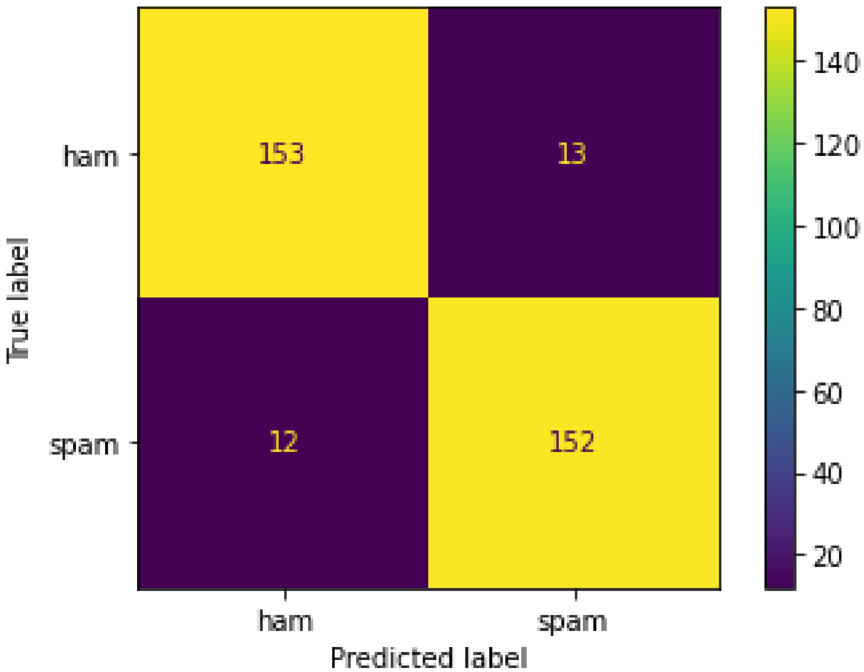
```
              precision    recall  f1-score   support

         ham       0.88      1.00      0.93      1213
        spam       1.00      0.65      0.79       494

    accuracy                           0.90      1707
   macro avg       0.94      0.83      0.86      1707
weighted avg       0.91      0.90      0.89      1707
```



There is one intesting things I have noted while editing the preprocessing function given with the homework. The function will take a limit with apply to both `spam` and `ham` emails. This would make sense if we are trying to save processing power. However we also will run in to problems like different distribution of the input data. Natually the number of spam we get will be much lesser than real emails. 1500/3672, in this case. If we munipulate the ratio, the model won't be less accuarte in real production environment. Here is an example:

[7]:
```
X2, y2 = vectorlizedspamham(500,500)



X_train2, X_test2, y_train2, y_test2 = train_test_split(X2, y2, test_size=0.33)

pipeline2 = Pipeline([('tfid', TfidfTransformer()),
                      ('nbc', MultinomialNB())]).fit(X_train2,y_train2)

y_pred2 = pipeline2.predict(X_test2)

print(classification_report(y_test2, y_pred2))

cm2 = confusion_matrix(y_test2, y_pred2, labels=labels)
disp2 = ConfusionMatrixDisplay(confusion_matrix=cm2,
                               display_labels=labels)
disp2.plot()
plt.show()
```

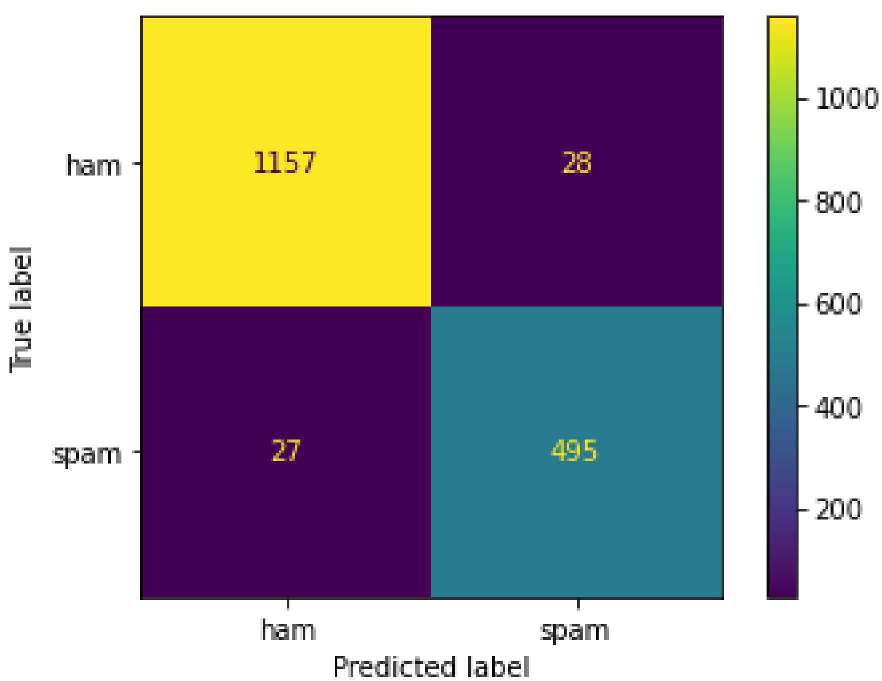
```
              precision    recall  f1-score   support

         ham       0.93      0.92      0.92       166
        spam       0.92      0.93      0.92       164

    accuracy                           0.92       330
   macro avg       0.92      0.92      0.92       330
weighted avg       0.92      0.92      0.92       330
```



[8]:
```
def dummy(tokens):
    return tokens

downsampled_emails = processspamham(500,500)

X3 = downsampled_emails.tokens.tolist()
y3 = downsampled_emails.label.tolist()

emails = processspamham()
X4 = emails.tokens.tolist()
y4 = emails.label.tolist()

X_train3, X_test3, y_train3, y_test3 = train_test_split(X3, y3, test_size=0.33)
X_train4, X_test4, y_train4, y_test4 = train_test_split(X4, y4, test_size=0.33)
```

```
pipeline3 = Pipeline([('count', CountVectorizer(tokenizer=dummy,␣
↪preprocessor=dummy)),
                      ('tfid', TfidfTransformer()),
                      ('nbc', MultinomialNB())]).fit(X_train3,y_train3)

y_pred4 = pipeline3.predict(X_test4)

print(classification_report(y_test4, y_pred4))

cm4 = confusion_matrix(y_test4, y_pred4, labels=labels)
disp4 = ConfusionMatrixDisplay(confusion_matrix=cm4,
                            display_labels=labels)
disp4.plot()
plt.show()
```

```
              precision    recall  f1-score   support

         ham       0.98      0.98      0.98      1185
        spam       0.95      0.95      0.95       522

    accuracy                           0.97      1707
   macro avg       0.96      0.96      0.96      1707
weighted avg       0.97      0.97      0.97      1707
```



[9]:
```
X2
```

[9]:
```
     Subject  investment  idea   oi   gas  advisory   oil  entered  ong  term  \
0          1         3.0   1.0  7.0  15.0       2.0  10.0      1.0  2.0   1.0
1          1         0.0   0.0  0.0   0.0       0.0   0.0      0.0  0.0   0.0
2          1         0.0   0.0  0.0   0.0       0.0   0.0      0.0  0.0   0.0
3          1         0.0   0.0  0.0   0.0       0.0   0.0      0.0  0.0   0.0
4          1         0.0   0.0  0.0   1.0       0.0   0.0      0.0  0.0   0.0
..       …           …    …   …    …       …     …      …   …    …
995        1         0.0   0.0  0.0   0.0       0.0   0.0      0.0  0.0   0.0
996        1         0.0   0.0  0.0   0.0       0.0   1.0      0.0  0.0   0.0
997        1         2.0   0.0  9.0  15.0       2.0   8.0      1.0  1.0   1.0
998        1         0.0   0.0  0.0   0.0       0.0   0.0      0.0  0.0   0.0
999        1         0.0   0.0  0.0   0.0       0.0   0.0      0.0  0.0   0.0

     …  pot  phoenican  ino  drunk  progressive  pots  refuse  phoenicianl  \
0    …  0.0        0.0  0.0    0.0          0.0   0.0     0.0          0.0
1    …  0.0        0.0  0.0    0.0          0.0   0.0     0.0          0.0
2    …  0.0        0.0  0.0    0.0          0.0   0.0     0.0          0.0
3    …  0.0        0.0  0.0    0.0          0.0   0.0     0.0          0.0
4    …  0.0        0.0  0.0    0.0          0.0   0.0     0.0          0.0
..   …  …        …  …    …          …   …     …          …
995  …  0.0        0.0  0.0    0.0          0.0   0.0     0.0          0.0
996  …  0.0        0.0  0.0    0.0          0.0   0.0     0.0          0.0
997  …  0.0        0.0  0.0    0.0          0.0   0.0     0.0          0.0
998  …  1.0        1.0  1.0    1.0          1.0   1.0     1.0          1.0
999  …  0.0        0.0  0.0    0.0          0.0   0.0     0.0          0.0

     marcia  resumel
0       0.0      0.0
1       0.0      0.0
2       0.0      0.0
3       0.0      0.0
4       0.0      0.0
..      …      …
995     0.0      0.0
996     0.0      0.0
997     0.0      0.0
998     0.0      0.0
999     1.0      1.0

[1000 rows x 19176 columns]
```

[10]:
```
downsampled_emails
```

[10]:
```
                                                tokens label
0    [Subject, list, dirty, list, let, know, lookin…   ham
```

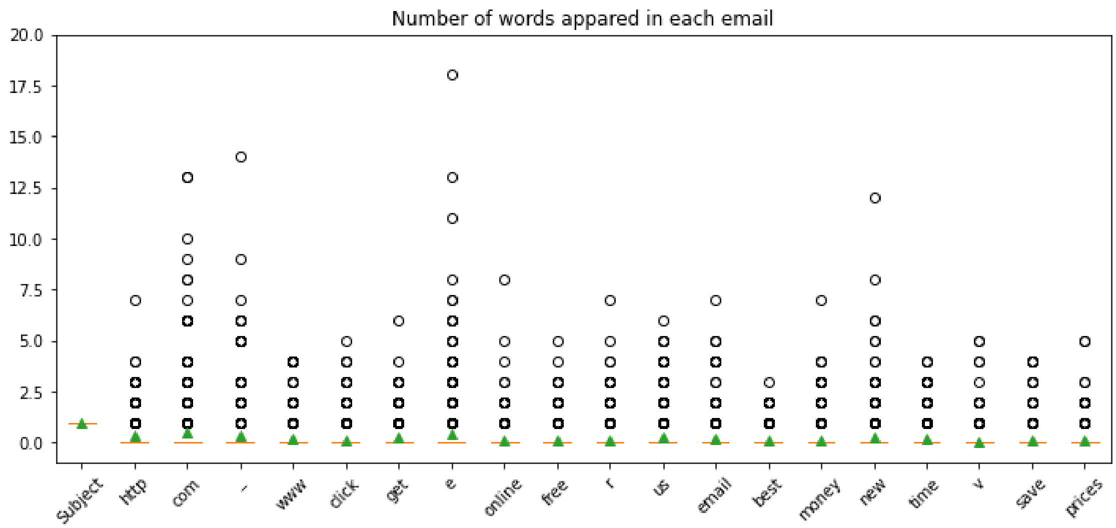
```
1     [Subject, epgt, gloria, difference, two, pipes…   ham
2     [Subject, cornhusker, plants, become, external…   ham
3            [Subject, free, report, euro, tells, gain]  spam
4     [Subject, eastrans, nomination, change, effect…   ham
..                                                 …    …
995  [Subject, ad, felt, stiffen, goo, hair, face, …  spam
996  [Subject, urgent, reply, overseas, stake, lott…  spam
997  [Subject, dating, service, nauuughty, minded, …  spam
998  [Subject, may, activity, survey, daren, please…   ham
999  [Subject, cancel, payment, n, dear, paliourg, …  spam

[1000 rows x 2 columns]
```

Also one important things I have realized is that words like Subject, To, CC, etc., which come with all the e-mails. Would be included in all the documents.

[11]:
```
pipeline4 = Pipeline([('count', CountVectorizer(tokenizer=dummy,␣
 ↪preprocessor=dummy)),
                      ('tfidf', TfidfTransformer()),
                      ('nbc', MultinomialNB())]).fit(X_train4,y_train4)

def show_most_informative_features(vectorizer, clf, n=20):
    feature_names = vectorizer.get_feature_names()
    coefs_with_fns = sorted(zip(clf.coef_[0], feature_names))
    top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
    word_list = []
    for (coef_1, fn_1), (coef_2, fn_2) in top:
        word_list.append(fn_2)
        print ("\t%.4f\t%-15s" % ( coef_2, fn_2))
    plt.figure(figsize=(12,5))
    plt.title('Number of words appared in each email')
    plt.boxplot(X2[word_list],showmeans=True,vert=True)
    plt.xticks(ticks=list(range(1,21)),labels=word_list,rotation=45)
    plt.ylim(-1,20)
show_most_informative_features(pipeline4['count'],pipeline4['nbc'])
```

```
/home/jim/anaconda3/lib/python3.7/site-
packages/sklearn/utils/deprecation.py:101: FutureWarning: Attribute coef_ was
deprecated in version 0.24 and will be removed in 1.1 (renaming of 0.26).
  warnings.warn(msg, category=FutureWarning)

        -7.0714 Subject
        -7.3682 http
        -7.5554 com
        -7.6032 _
        -7.7624 www
        -7.8423 click
        -7.8490 get
        -8.0086 e
```

```
-8.0665 online
-8.0987 free
-8.1242 r
-8.1465 us
-8.1589 email
-8.1598 best
-8.1863 money
-8.2063 new
-8.2174 time
-8.2479 v
-8.2505 save
-8.3105 prices
```



[ ]: