Assignment 4: Spam classification using Naïve Bayes

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In [1]:

```
import pandas as pd
import tarfile
import matplotlib.pyplot as plt
import seaborn as sns #seaborn is a package for nice-looking graphics
import numpy as np
import email.policy
from sklearn.naive_bayes import MultinomialNB
from sklearn.naive_bayes import BernoulliNB
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
#Import scikit-learn dataset library
from sklearn import datasets
# Import train_test_split function
from sklearn.model_selection import train_test_split
#Import scikit-learn metrics module for accuracy calculation
from sklearn import metrics
from IPython.display import display_html
from itertools import chain,cycle
from email import message_from_string
```

In [2]:

```
# functions
# display_side_by_side function:
# https://stackoverflow.com/questions/38783027/jupyter-notebook-display-two-pandas-tables-
def display_side_by_side(*args,titles=cycle([''])):
    html_str=''
    for df,title in zip(args, chain(titles,cycle(['</br>'])) ):
        html_str+='<th style="text-align:center"><td style="vertical-align:top">'
        html_str+=f'<h2>{title}</h2>'
        html_str+=df.to_html().replace('table','table style="display:inline"')
        html_str+='</td></th>'
    display_html(html_str,raw=True)

# converting bz2 file to dataframe
def bz2_to_df(bz2, label):
    dataframe = []
    for bz2_file in bz2:
        tfile = tarfile.open(bz2_file, 'r:bz2')
        for file in tfile.getmembers():
            df = tfile.extractfile(file)
            if df is not None:
                df = df.read()
                dataframe.append({'email': df.decode('latin-1'), 'filetype': label,
                                  'policy': message_from_string(df.decode('latin-1'),polic
        tfile.close()
    return pd.DataFrame(dataframe)

# Naïve Bayes classifier, classifies the test sets and reports the percentage of ham
# and spam test sets that were classified correctly in a confusion matrix.
# includes some code from notebook naïve_bayes_intro
def naive_bayes(ham,spam,word_filter): #word_filter range [0.0,0.5)
    # concatinate the two dataframes and split into data ('email') and target ('filetype',
    dataframe = pd.concat([ham,spam])
    vectorizer = CountVectorizer(max_df=(1.0-word_filter), min_df=word_filter)
    data = vectorizer.fit_transform(dataframe['email'])
    target = dataframe['filetype']
    # Split dataset into training set and test set (70-30)
```

```
    datatrain, datatest, targettrain, targettest = train_test_split(data, target, test_si

    #Multinominal classifier
    mulinominal = MultinomialNB()
    mulinominal.fit(datatrain,targettrain)
    multinominal_pred = mulinominal.predict(datatest)
    multinominal_score = metrics.accuracy_score(targettest, multinominal_pred)
    multinominal_cm = metrics.confusion_matrix(targettest, multinominal_pred, normalize =

    #Bernoulli classifier
    bernoulli = BernoulliNB(binarize=0.0)
    bernoulli.fit(datatrain,targettrain)
    bernoulli_pred = bernoulli.predict(datatest)
    bernoulli_score = metrics.accuracy_score(targettest, bernoulli_pred)
    bernoulli_cm = metrics.confusion_matrix(targettest, bernoulli_pred, normalize = 'true'

    #plot the two confusion matrices as subplots
    fig, (ax1,ax2) = plt.subplots(1, 2,figsize=(18,6))
    sns.heatmap(multinominal_cm, ax = ax1, annot=True, fmt=".3f", linewidths=.5, square =
    sns.heatmap(bernoulli_cm, ax = ax2, annot=True, fmt=".3f", linewidths=.5, square = Tru
    label = ['ham','spam']
    ax1.set_title('Multinominal accuracy score: {0}'.format(multinominal_score))
    ax1.set_xticklabels(label)
    ax1.set_yticklabels(label)
    ax1.set_ylabel('Actual label');
    ax1.set_xlabel('Predicted label');
    ax2.set_title('Bernoulli accuracy score: {0}'.format(bernoulli_score))
    ax2.set_xticklabels(label)
    ax2.set_yticklabels(label)
    ax2.set_ylabel('Actual label');
    ax2.set_xlabel('Predicted label');
    plt.show()

# Extract message part of email
# https://stackoverflow.com/questions/30517621/python-get-the-body-of-an-multipart-email
def cutEmail(message):
    if message.is_multipart():
        for part in message.get_payload():
            body = part.get_payload().__str__()
    else:
        body = message.get_payload().__str__()
    return body
```

1. Preprocessing:

a.

Note that the email files contain a lot of extra information, besides the actual message. Ignore that for now and run on the entire text. Further down (in the higher grade part), you will be asked to filter out the headers and footers.

b.

We don't want to train and test on the same data. Split the spam and the ham datasets in a training set and a test set.

In [3]:

```
#Using both easy_ham and hard_ham to get a different result than in question 3.
easy_ham = bz2_to_df(['datasets/20021010_easy_ham.tar.bz2'], 'ham')
hard_ham = bz2_to_df(['datasets/20021010_hard_ham.tar.bz2'], 'ham')
ham = pd.concat([easy_ham,hard_ham])
```

```
spam = bz2_to_df(['datasets/20021010_spam.tar.bz2'], 'spam')
# Splitting dataset into training set and test set in the function
```

2. Write a Python program that:

a.

Uses four datasets (hamtrain, spamtrain, hamtest, and spamtest)

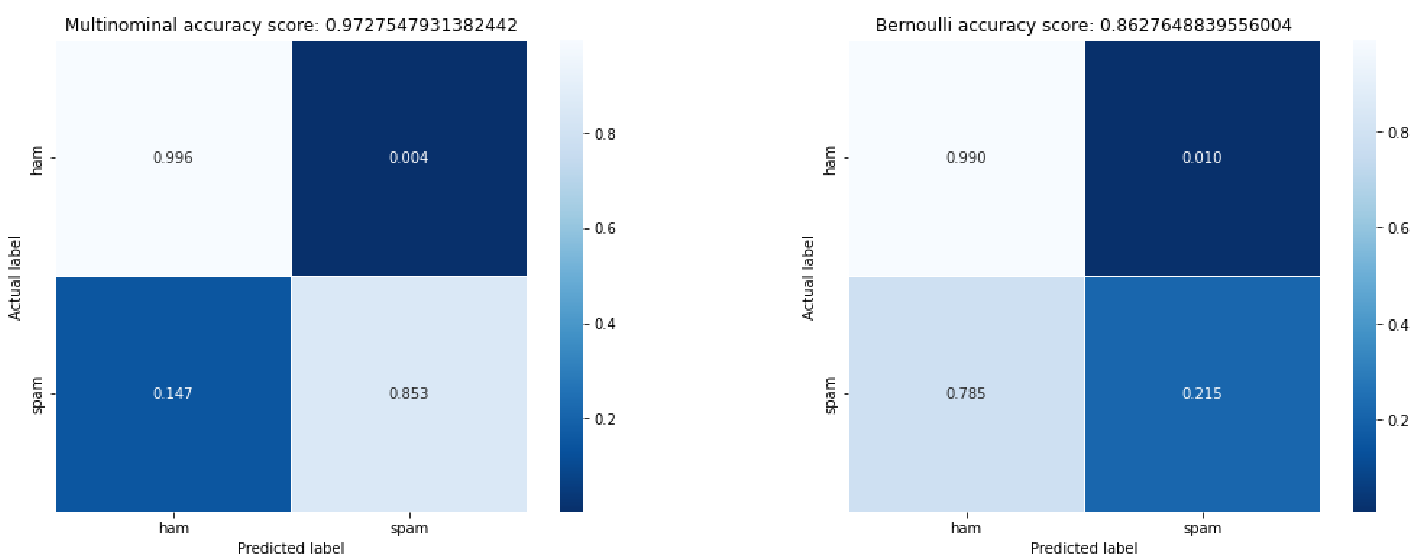
Splitting the data into four datasets (hamtrain, spamtrain, hamtest, and spamtest) seems like a wierd aproach to the problem. Because then the AI would train and test on ham-mails and spam-mails separatly, instead of training and testing on both spam-mails and ham-mails at the same time.

So instead of using four datasets (hamtrain, spamtrain, hamtest, and spamtest), two dataframes (ham, spam) are used. The function concatinates the two dataframes and split it into two datasets called data and target. Data contains all the emails (both spam and ham) and target contains the filetypes (both spam and ham). Then the two datasets are split into training sets and test sets (datatrain, datatest, targettrain, targettest).

b.

Using a Naïve Bayes classifier (e.g. Sklearn), classifies the test sets and reports the percentage of ham and spam test sets that were classified correctly. You can use CountVectorizer to transform the email texts into vectors. Please note that there are different types of Naïve Bayes Classifier in SKlearn (Document is available here). Test two of these classifiers: 1. Multinomial Naive Bayes and 2. Bernoulli Naive Bayes that are well suited for this problem. For the case of Bernoulli Naive Bayes you should use the parameter binarize to make the features binary. Discuss the differences between these two classifiers.

In [4]:
```
naive_bayes(ham,spam,0.0) # 0.0 = no word filter
```



The multinominal classifier performs well, since it almost predicts all the ham mails correctly and predicts 85% of the spam correctly. The bernoulli classifier, however, performs rather ill, since it predicts almost all ham mails correctly but missclassifies 78% of the spam mails. In other words, the bernoulli classifier misses alot of the spam mails.

Multinominal is a model that counts every occurance of a word in a document compared to the model Bernoulli that in a binary way checks if a feature is present or absent.

Multinominal naïves bayes works by traversing through the train dataset while counting every feature and calculating the probability for that feature to either be in "ham" or "spam", depending on the label of the feature. When all features have been processed and the likelihoods have been calculated the model is ready to be tested. The model calculates a score by multiplying the prior probability with the probability for each feature found in the test input. This is done for both "spam" and "ham". These two scores are then comapred and the greater gets picked.

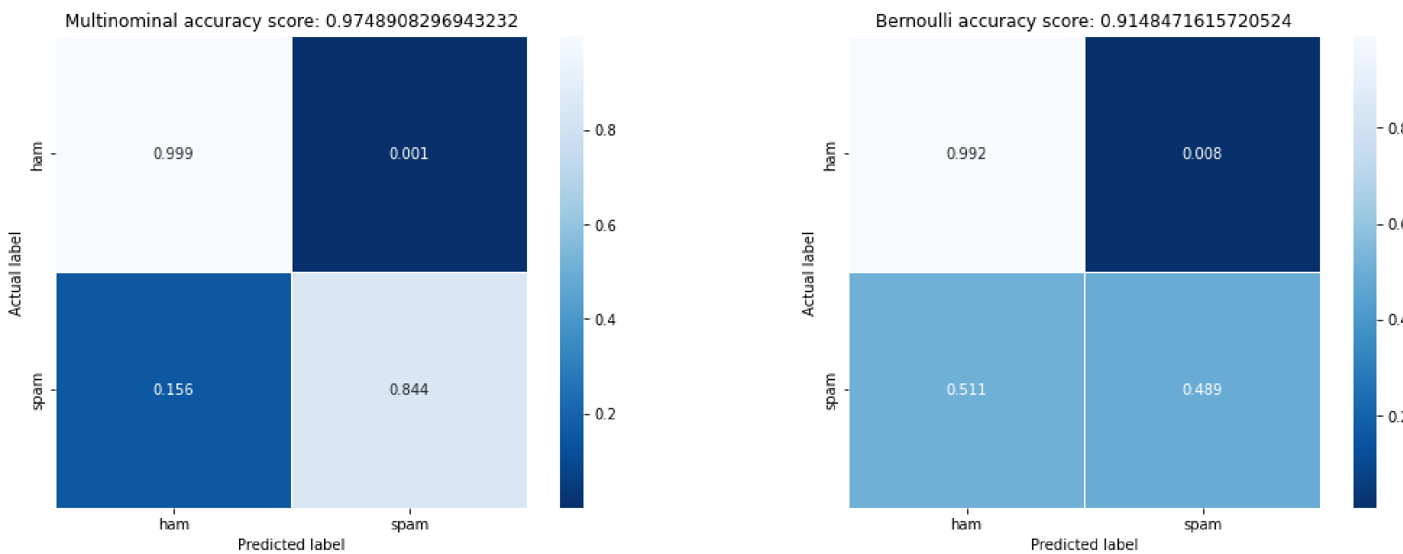
Bernoulli naïves bayes instead check if features are present or absent. This trains the model to select "spam" when features are found.

3. Run your program on

i. Spam versus easy-ham

In [5]:

```
ham = bz2_to_df(['datasets/20021010_easy_ham.tar.bz2'], 'ham')
spam = bz2_to_df(['datasets/20021010_spam.tar.bz2'], 'spam')

naive_bayes(ham,spam,0.0) # 0.0 = no word filter
```

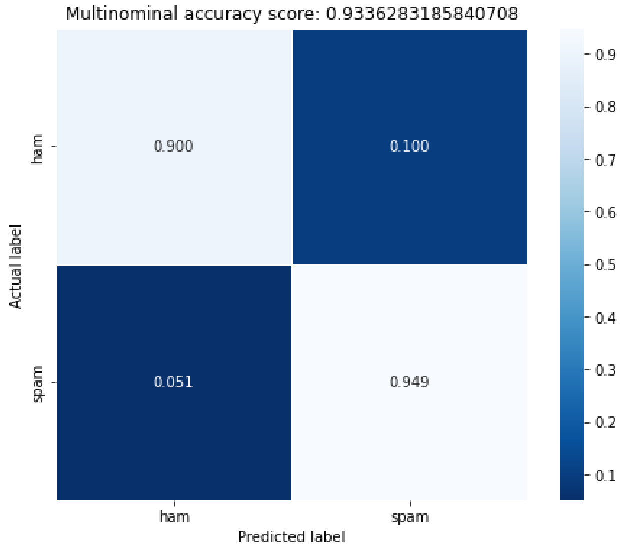


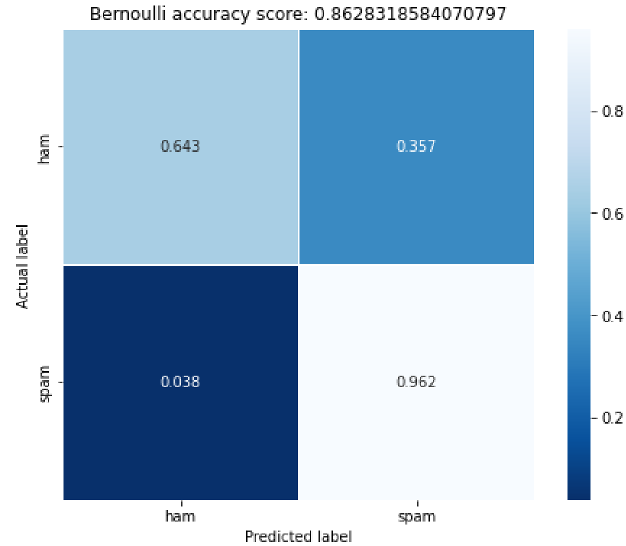
When only using the easy_ham dataset, similar results as in question 2b can be seen. The multinominal classifier performs almost exactly the same, but the bernoulli classifier performs slightly better and "only" missclassifies 51% of the spam mail. However, this is still a pretty bad result since it misses over half of the spam mails.

ii. Spam versus hard-ham

In [6]:

```
ham = bz2_to_df(['datasets/20021010_hard_ham.tar.bz2'], 'ham')
spam = bz2_to_df(['datasets/20021010_spam.tar.bz2'], 'spam')

naive_bayes(ham,spam,0.0) # 0.0 = no word filter
```





When only using the hard_ham dataset, some interesting results can be seen. The multinominal classifier performs even better than it did with the easy_ham dataset and almost classifies all of the ham and spam mails correclty. However, compared to prior results, it missclassifies more ham mails than spam mails. So whether this is a better result or not could be up for discussion. The bernoulli, on the other hand, still has rather ill performance but did the exact oppisite of what it did with the easy_ham dataset. Now it classifies almost all of the spam mails correctly but missclassifies 35% of the ham mails.

In conclusion, the multinominal classifier performs better than the bernoulli classifier in all cases. Hence, the multinominal classifier should be used to get the best results.

4.

To avoid classification based on common and uninformative words it is common to filter these out.

a.

Argue why this may be useful. Try finding the words that are too common/uncommon in the dataset.

In [7]:

```
# Import and concatinate dataframes
easy_ham = bz2_to_df(['datasets/20021010_easy_ham.tar.bz2'], 'ham')
hard_ham = bz2_to_df(['datasets/20021010_hard_ham.tar.bz2'], 'ham')
spam = bz2_to_df(['datasets/20021010_spam.tar.bz2'], 'spam')
dataframe = pd.concat([easy_ham,hard_ham,spam])

# Count words and append to a list
mails = dataframe['email']
vectorizer = CountVectorizer().fit(mails)
matrix = vectorizer.transform(mails)
sums = np.sum(matrix,axis=0)
words = []
for word,i in vectorizer.vocabulary_.items():
    words.append({'word': word, 'sum': sums[0, i]})

# Create dataframe from list and sort from highest to lowest sum
word_df = pd.DataFrame(words)
word_df = word_df.sort_values(by='sum',ascending=False)
word_df.index = np.arange(1,len(word_df)+1)

n=25
titles=['Top {} words'.format(n),'Bottom {} words'.format(n)]
display_side_by_side(word_df[0:n],word_df[len(word_df)-n:len(word_df)], titles=titles)
```

Top 25 words

	word	sum
1	com	69898
2	the	40824
3	to	38179
4	http	34048
5	from	28715
6	td	28399
7	2002	28275
8	3d	25415
9	for	23845
10	net	22839
11	font	22609
12	with	22181
13	by	21436
14	width	20932
15	of	20336
16	and	20232
17	localhost	18916
18	id	18226
19	received	17800
20	www	17481
21	example	16310
22	list	15478
23	in	15093
24	org	14914
25	11	14820

Bottom 25 words

	word	sum
109746	4gaciiiiiiiii	1
109747	aiiiiiiih	1
109748	h3d3	1
109749	iieihwciiicagaiaiicaiaaaiiiiiiiif4iiiaaab	1
109750	4ehh4ehcigiciiaiiiacigicaiaiiiigiiigiiiiigiiiiiiiiiid3	1
109751	iiiiiaiigiiiiiiiih	1
109752	iid3iaciiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiii	1
109753	giiiiiiigaaaaadwiiiiiiiiciiiiih4h3	1
109754	ehj	1
109755	4ihciia	1
109756	4iiaiiiiif4iiiif	1
109757	ieiciiiiiiici	1
109758	d3dwiiiiiif	1
109759	iiiiihihd	1
109760	if4j4eiiiiiiib4h3d3dwiiiaiiiiiiiaiigiiiiiiigaciiiiiihh3d3eiciiiiiiiaa	1
109761	iiiiiid3d3d3d3b3ciiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiii	1
109762	iiihd3ciiaaigigiiaiaiiciiiiiiiih	1
109763	d3ciiiiiih	1
109764	iigiiaiigiiiciiiiiiiiih4	1
109765	93f3d4hwiigaiigiiiiicicigiiiii	1
109766	iiaciiagigicaiiiiaigiiiiiiiiiiif	1
109767	4d4	1
109768	93ciiaiiii	1
109769	3ihiaiiiiiiif	1
109770	7b1b73cf36cf9dbc3d64e3f2ee2b91f1	1

The most common/uncommon words could be considered as noise, since they do not provide any information that could be relevant when deciding if an email is ham or spam. Hence, removing them could improve the performance of the classifiers. When looking at the top 25 words it can be seen that they are very uninformative and irrelavant when deciding if an email is ham or spam. When looking at the bottom 25 words is can be seen that they only appear once in all of the emails and are therefor irrelavant when deciding if an email is ham or spam.

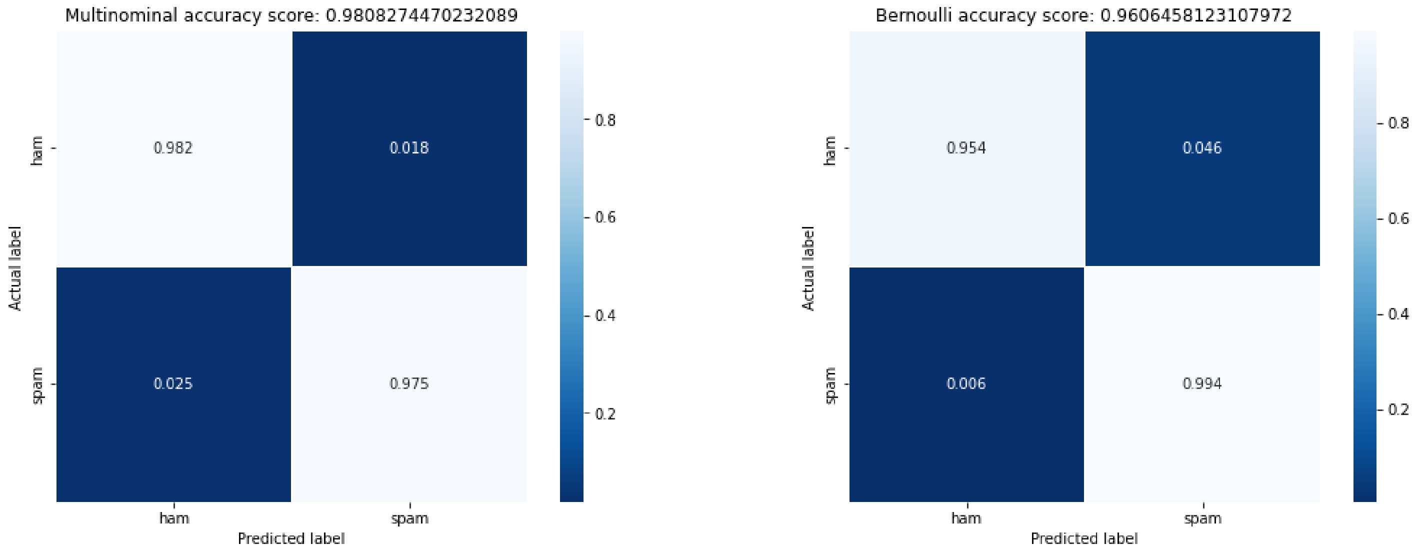
b.

Use the parameters in Sklearn's CountVectorizer to filter out these words. Run the updated program on your data and record how the results differ from 3. You have two options to do this in Sklearn: either using the words found in part (a) or letting Sklearn do it for you.

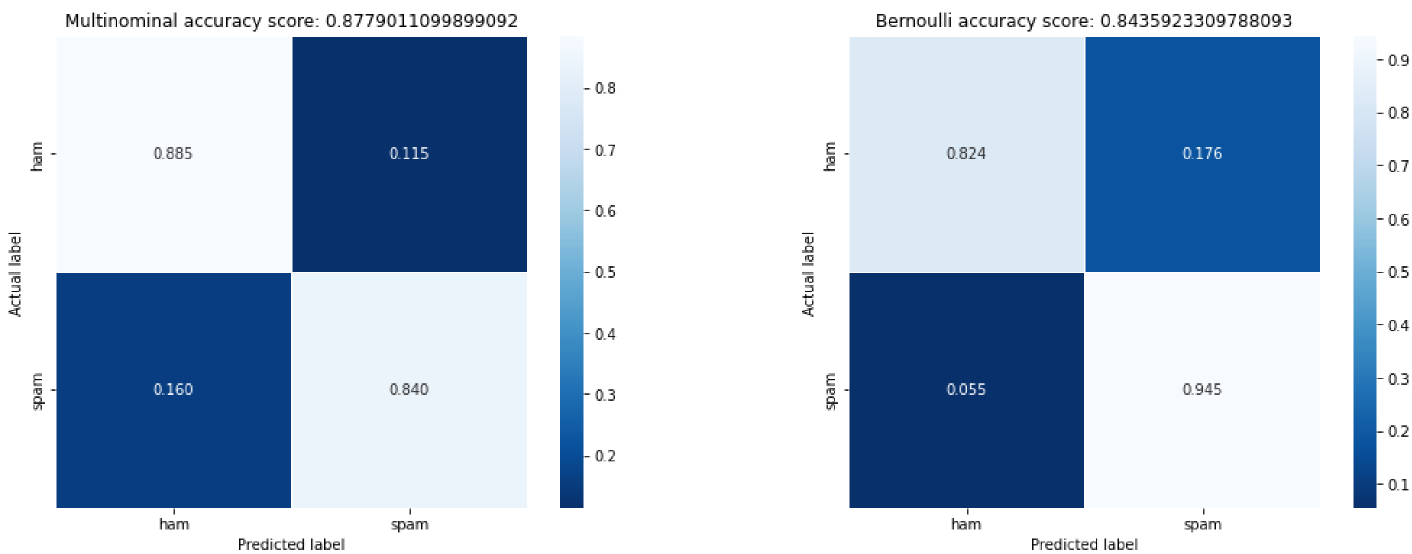
In [8]:
```
easy_ham = bz2_to_df(['datasets/20021010_easy_ham.tar.bz2'], 'ham')
hard_ham = bz2_to_df(['datasets/20021010_hard_ham.tar.bz2'], 'ham')
```

```
ham = pd.concat([easy_ham,hard_ham])
spam = bz2_to_df(['datasets/20021010_spam.tar.bz2'], 'spam')

print('Filtering top 1% and bottom 1%:')
naive_bayes(ham,spam,0.01) # 0.01 = filter top 1% and bottom 1%
print('Filtering top 30% and bottom 30%:')
naive_bayes(ham,spam,0.3) # 0.3 = filter top 30% and bottom 30%
```

```
Filtering top 1% and bottom 1%:
```




```
Filtering top 30% and bottom 30%:
```



When filtering out the top 1% and the bottom 1% the best result is attained. Both the multinominal classifier and the bernoulli classifier performs really well now, with an accuracy score of 98% for the multinominal classifier and an accuracy score of 96% for the bernoulli classifier. Even after filtering out the top 30% and the bottom 30% both of the classifiers still performs decent.

5.

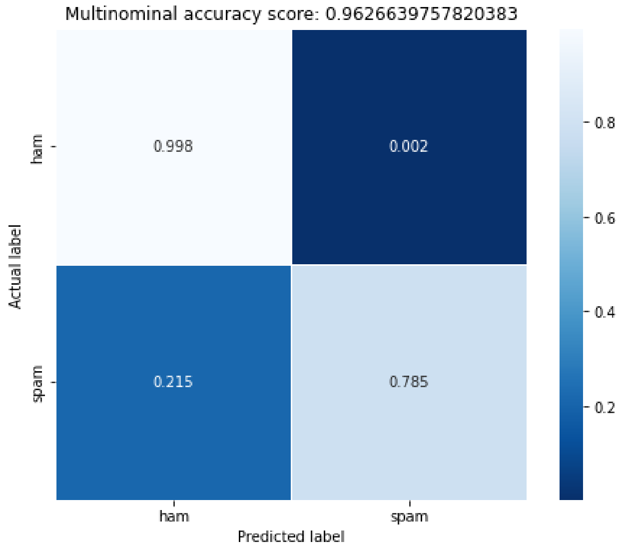
Filter out the headers and the footers of the emails before you run on them. The format may vary somewhat between emails, which can make this a bit tricky, so perfect filtering is not required. Run your program again and answer the following questions:

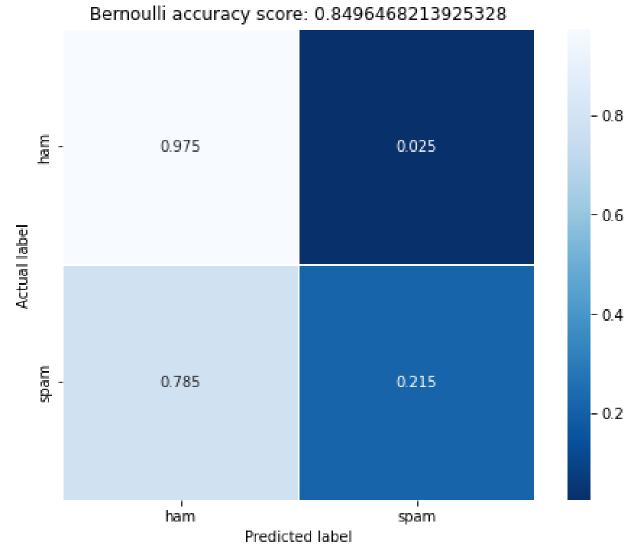
In [9]:

```
# Import and concatenate dataframes
easy_ham = bz2_to_df(['datasets/20021010_easy_ham.tar.bz2'], 'ham')
hard_ham = bz2_to_df(['datasets/20021010_hard_ham.tar.bz2'], 'ham')
ham = pd.concat([easy_ham,hard_ham])
```

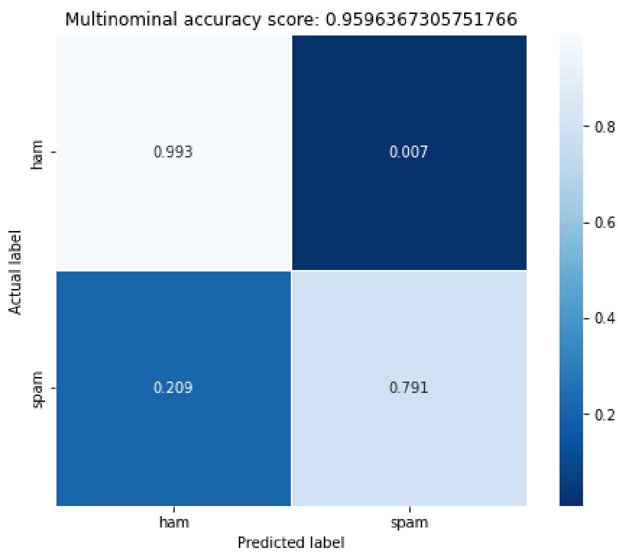
```python
spam = bz2_to_df(['datasets/20021010_spam.tar.bz2'], 'spam')

# Extract message part of email in ham
# and place in collumn 'email'.
p = []
for i in ham['policy']:
#     print(i)
    a = cutEmail(i)
    p.append(a)
ham['email'] = p

# Extract message part of email in spam
# and place in collumn 'email'.
p = []
for i in spam['policy']:
#     print(i)
    a = cutEmail(i)
    p.append(a)
spam['email'] = p

print('Example mail without header: \n')
print(ham['email'].iloc[4])

print('No filter:') # compare to question 3
naive_bayes(ham,spam,0.0)
print('Filtering top 1% and bottom 1%:') # compare to question 4
naive_bayes(ham,spam,0.01)
```

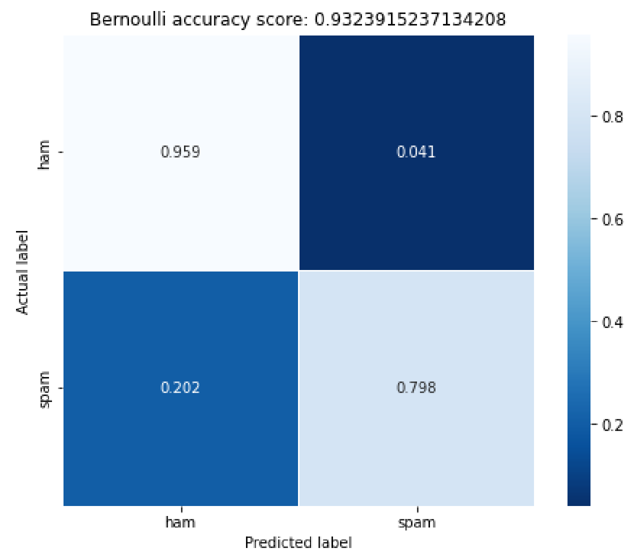
```
Example mail without header:

Hi, I'm building an rpm for the resin webserver, and I basically want to
install the entire tarball under a diretory, but, the tarball includes
subdirectorys, in my spec i have:


install -s -m 755 %{name}-%{version}.%{release}/* \
  $RPM_BUILD_ROOT/usr/local/resin

and I'm getting:

install: `resin-2.0.5/bin' is a directory
install: `resin-2.0.5/conf' is a directory

Is there a proper/nice way I should handle this?


                                    -- \m/ --
  "...if I seem super human I have been misunderstood." (c) Dream Theater
         mark@talios.com - ICQ: 1934853 JID: talios@myjabber.net



_______________________________________________
RPM-List mailing list <RPM-List@freshrpms.net>
http://lists.freshrpms.net/mailman/listinfo/rpm-list


No filter:
```






```
Filtering top 1% and bottom 1%:
```





a.

Does the result improve from 3 and 4?

The result does not improve from question 3 and 4. When not filtering the data, like in question 3, similiar but worse results are attained. When filtering the data, the result improves significantly for the bernoulli method but it's still lower then in question 4.

b.

The split of the data set into a training set and a test set can lead to very skewed results. Why is this, and do you have suggestions on remedies?

When splitting the data into training and test sets the training set can by randomness include more ham messages than spam messages, thus learning the AI to determine ham messages better than spam. The test set on the other hand, would then include more spam messages than ham messages and the AI would not perform well since it's better at determining ham messages.

A solution to this would be to utilize the parameter stratify in the train_test_split function. Stratify would ensure that there is balance in the train and test sets regarding the distribution between ham and spam.

c.

What do you expect would happen if your training set were mostly spam messages while your test set were mostly ham messages?

In this scenario, the AI would be well trained on spam messages. When being tested with ham it would perform poorly since it's better at determining spam messages.