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# CS4487 - Machine Learning

## Lecture 2b - Naive Bayes Classifier

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### Outline

1. Naive Bayes Gaussian Classifier - Iris dataset
  2. Naive Bayes Spam Classifier - Spam dataset
- 

### Naive Bayes Classifier

- How to deal with multiple features?
    - e.g.,  $\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$
  - **Naive Bayes assumption**
    - assume each feature dimension is modeled independently.
      - e.g., for 2 dimensions,  $p(x_1, x_2|y) = p(x_1|y)p(x_2|y)$
      - accumulates evidence from each feature dimension:
        - $\log p(x_1, x_2|y) = \log p(x_1|y) + \log p(x_2|y)$
    - allows us to model each dimension of the observation with a simple univariate distribution.
  - **Example: Gaussian classifier**
    - We will consider the 2-dimensional iris data shown in the beginning of lecture.
- 

### Setup Python

```

In [1]: %matplotlib inline
import IPython.core.display
# setup output image format (Chrome works best)
IPython.core.display.set_matplotlib_formats("svg")
import matplotlib.pyplot as plt
import matplotlib
from numpy import *
from sklearn import *
from scipy import stats
random.seed(100)           # specify a seed so results are reproducible

/anaconda3/lib/python3.5/importlib/_bootstrap.py:222: RuntimeWarning: numpy.
dtype size changed, may indicate binary incompatibility. Expected 96, got 88
    return f(*args, **kwargs)
/anaconda3/lib/python3.5/importlib/_bootstrap.py:222: RuntimeWarning: numpy.
dtype size changed, may indicate binary incompatibility. Expected 96, got 88
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/anaconda3/lib/python3.5/importlib/_bootstrap.py:222: RuntimeWarning: numpy.
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/anaconda3/lib/python3.5/importlib/_bootstrap.py:222: RuntimeWarning: numpy.
dtype size changed, may indicate binary incompatibility. Expected 96, got 88
    return f(*args, **kwargs)
/anaconda3/lib/python3.5/site-packages/sklearn/cross_validation.py:41: Depre
cationWarning: This module was deprecated in version 0.18 in favor of the mo
del_selection module into which all the refactored classes and functions are
moved. Also note that the interface of the new CV iterators are different fr
om that of this module. This module will be removed in 0.20.
    "This module will be removed in 0.20.", DeprecationWarning)
/anaconda3/lib/python3.5/site-packages/sklearn/ensemble/weight_boosting.py:2
9: DeprecationWarning: numpy.core.umath_tests is an internal NumPy module an
d should not be imported. It will be removed in a future NumPy release.
    from numpy.core.umath_tests import inner1d
/anaconda3/lib/python3.5/site-packages/sklearn/grid_search.py:42: Deprecatio
nWarning: This module was deprecated in version 0.18 in favor of the model_s
election module into which all the refactored classes and functions are move
d. This module will be removed in 0.20.
    DeprecationWarning)
/anaconda3/lib/python3.5/site-packages/sklearn/learning_curve.py:22: Depreca
tionWarning: This module was deprecated in version 0.18 in favor of the mode
l_selection module into which all the functions are moved. This module will
be removed in 0.20
    DeprecationWarning)

```

## Load data

```
In [2]: # load iris data each row is (petal length, sepal width, class)
irisdata = loadtxt('iris2.csv', delimiter=',', skiprows=1)

X = irisdata[:,0:2] # the first two columns are features (petal length, sepal width)
Y = irisdata[:,2]   # the third column is the class label (versicolor=1, virginica=2)

print(X.shape)

(100, 2)
```

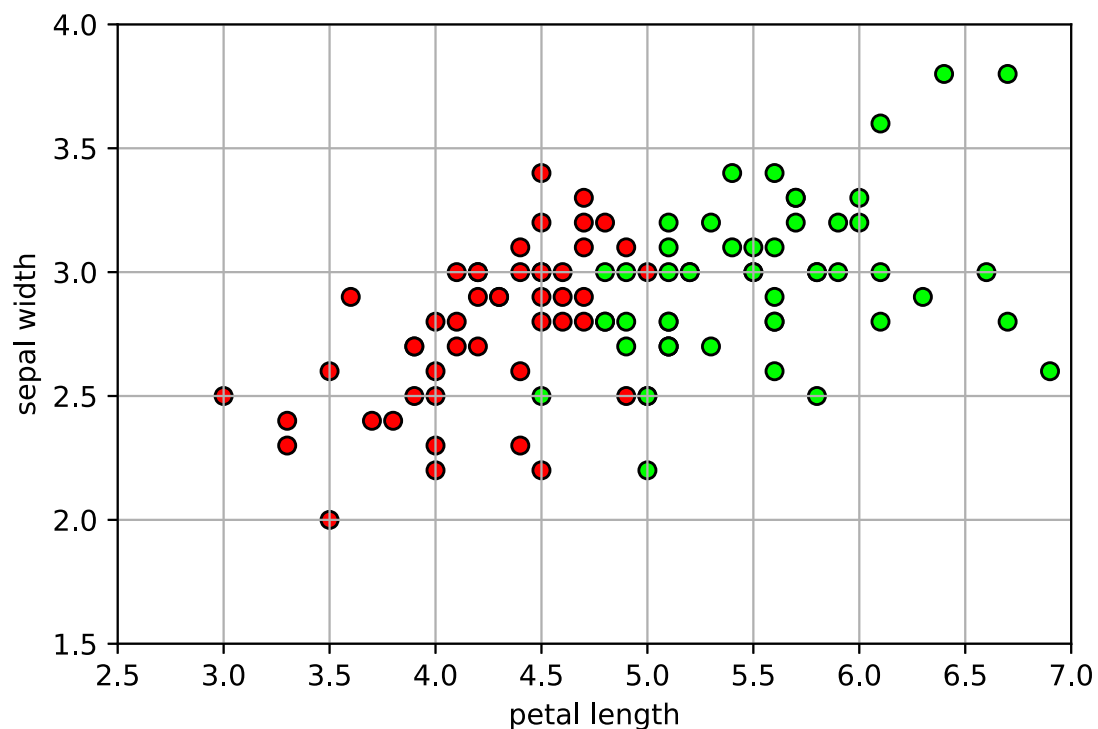
## View data

```
In [3]: # a colormap for making the scatter plot: class 1 will be red, class 2 will be green
mycmap = matplotlib.colors.LinearSegmentedColormap.from_list('mycmap', ["#FF0000", "#FFFFFF", "#00FF00"])

axbox = [2.5, 7, 1.5, 4] # common axis range

# a function for setting a common plot
def irisaxis():
    plt.xlabel('petal length'); plt.ylabel('sepal width')
    plt.axis([2.5, 7, 1.5, 4]); plt.grid(True)

In [4]: # show the data
plt.figure()
plt.scatter(X[:,0], X[:,1], c=Y, cmap=mycmap, edgecolors='k')
# c is the color value, drawn from colormap mycmap
irisaxis()
```



## Split training/test data

- We will select 50% of the data for training, and 50% for testing
  - use `model_selection` module
    - `train_test_split` - give the percentage for training and testing.
    - `StratifiedShuffleSplit` - also preserves the percentage of examples for each class.

```
In [5]: # randomly split data into 50% train and 50% test set
trainX, testX, trainY, testY = \
    model_selection.train_test_split(X, Y,
                                     train_size=0.5, test_size=0.5, random_state=4487)

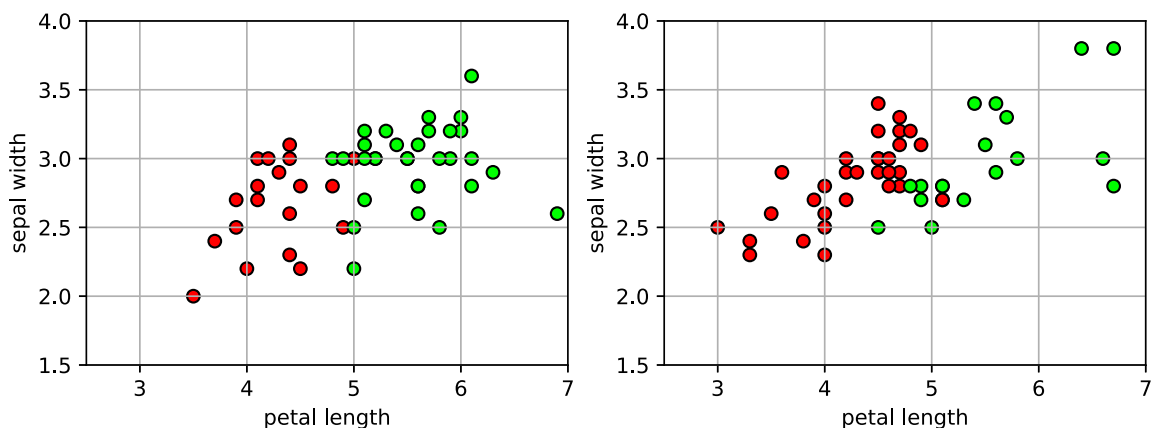
print(trainX.shape)
print(testX.shape)
```

(50, 2)  
(50, 2)

```
In [6]: # view train & test data
plt.figure(figsize=(9,3))

plt.subplot(1,2,1) # put two subplots in the same figure
# scatter plot - Y value selects the color
plt.scatter(trainX[:,0], trainX[:,1], c=trainY, cmap=mycmap, edgecolors='k')
irisaxis()

plt.subplot(1,2,2)
plt.scatter(testX[:,0], testX[:,1], c=testY, cmap=mycmap, edgecolors='k')
irisaxis()
```



## Learn Gaussian NB model

- treat each dimension as an independent Gaussian

```
In [7]: # get the NB Gaussian model from sklearn
model = naive_bayes.GaussianNB()

# fit the model to training data
model.fit(trainX, trainY)

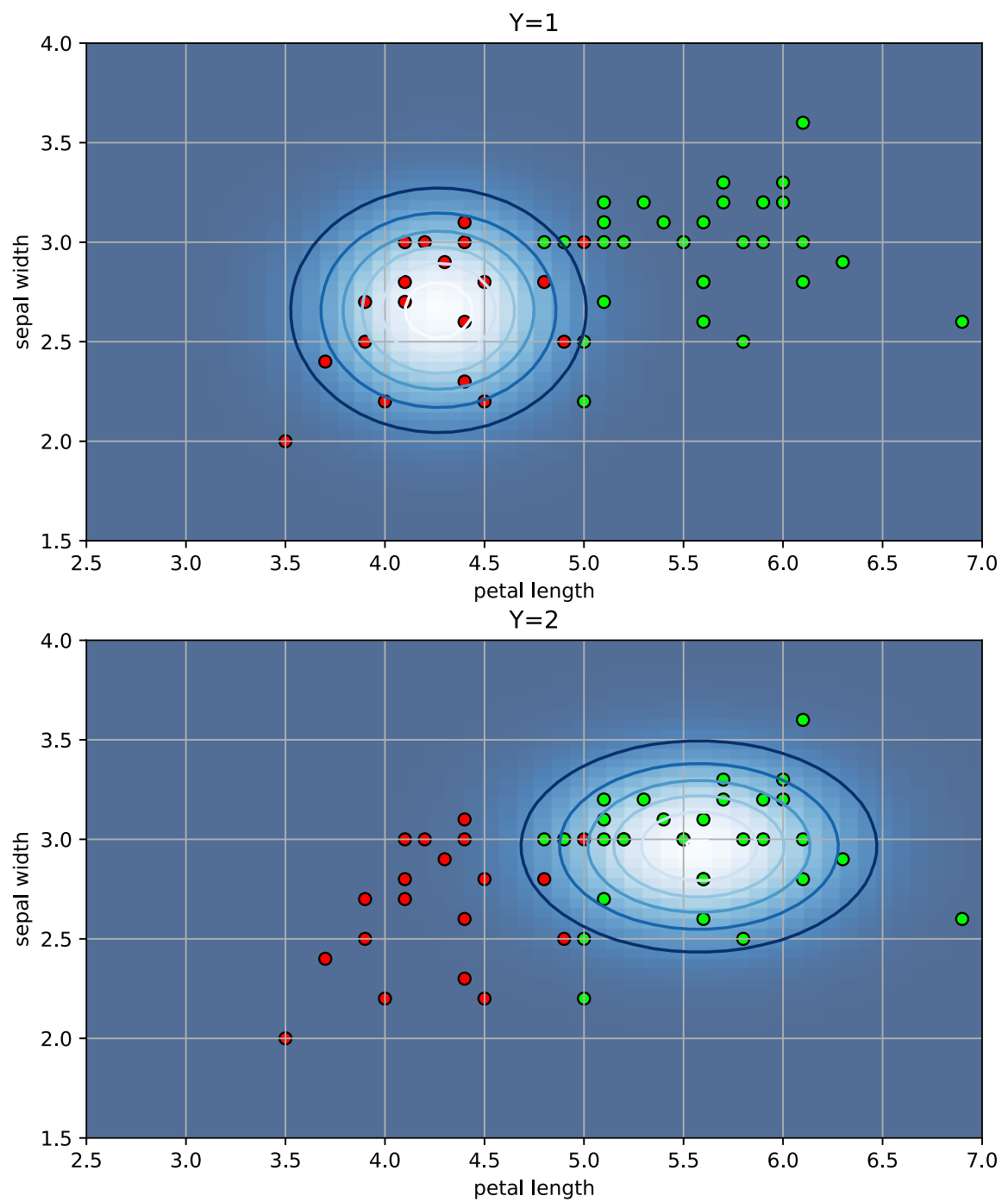
# see the parameters
print("class prior: ", model.class_prior_)
print("class 1 mean: ", model.theta_[0,:])
print("class 1 var: ", model.sigma_[0,:])
print("class 2 mean: ", model.theta_[1,:])
print("class 2 var: ", model.sigma_[1,:])
```

```
class prior: [0.38 0.62]
class 1 mean: [4.26842105 2.65789474]
class 1 var: [0.14426593 0.09927978]
class 2 mean: [5.57741935 2.96451613]
class 2 var: [0.22045786 0.07777315]
```

- View 2d class conditionals:
  - $p(x_1, x_2 | y = c) = p(x_1 | y = c)p(x_2 | y = c)$

```
In [9]: ccd
```

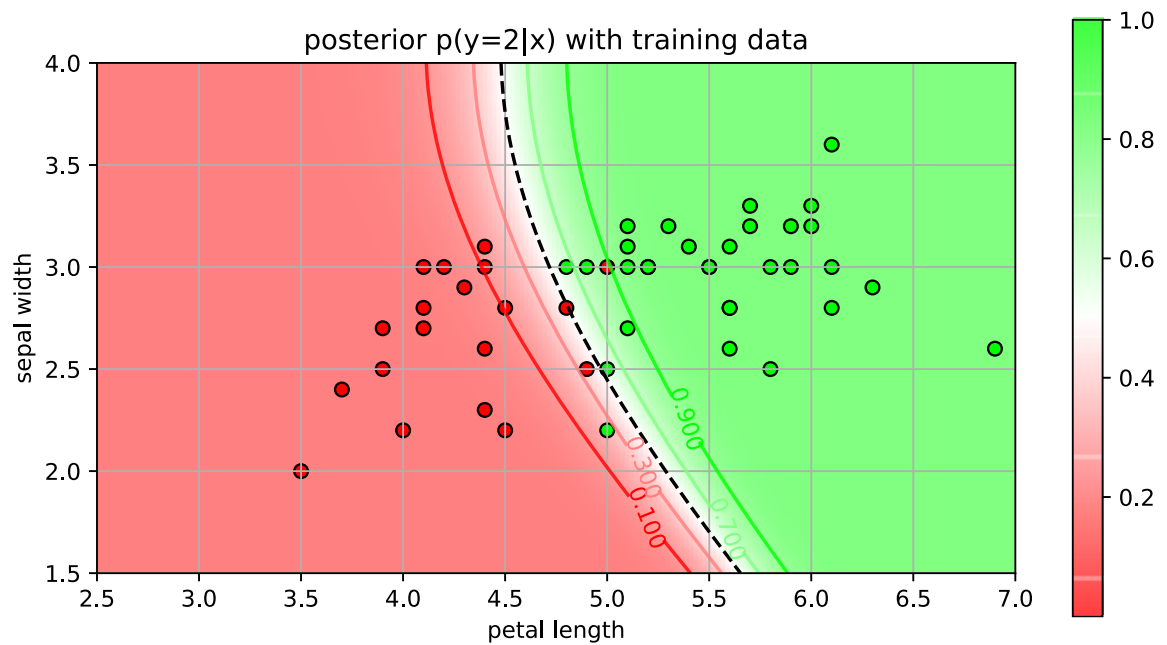
```
Out[9]:
```



**View the Posterior**

```
In [12]: pfig
```

```
Out[12]:
```



## Evaluate on the test set

```
In [13]: # predict from the model
predY = model.predict(testX)
print("pred: ", predY)
print("true: ", testY)

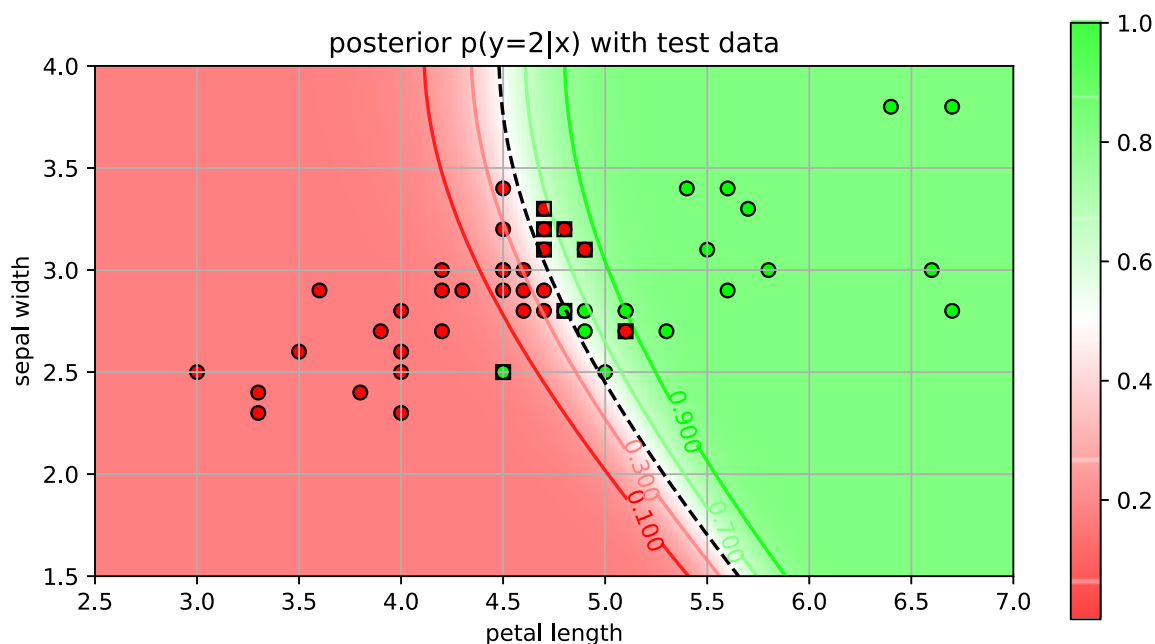
# calculate accuracy
acc = metrics.accuracy_score(testY, predY)
print("accuracy=", acc)
```

```
pred: [2. 2. 1. 2. 1. 2. 1. 1. 1. 2. 2. 2. 2. 2. 2. 1. 2. 2. 1. 2. 1. 1. 1.
1.
1. 1. 1. 1. 2. 1. 2. 1. 2. 2. 1. 1. 1. 1. 1. 2. 1. 2. 2. 2. 1. 2. 2.
1. 1.]
true: [2. 2. 1. 2. 1. 2. 1. 1. 1. 1. 1. 2. 2. 2. 2. 1. 2. 2. 1. 1. 1. 1. 2.
1.
1. 1. 1. 1. 2. 1. 2. 1. 2. 2. 1. 1. 2. 1. 1. 1. 1. 1. 2. 2. 1. 1. 2.
1. 1.]
accuracy= 0.84
```

## Viewing test results

```
In [15]: tfig
```

```
Out[15]:
```



## Example: Naive Bayes Spam Classifier

- Goal: given an input email, predict whether it is spam or not
  - input: text string

A home based business opportunity is knocking at your door. Don't be rude and let this chance go by. You can earn a great income and find your financial life transformed. Learn more Here. To Your Success. Work From Home Finder Experts

- output: spam, not spam (or ham)

## Text Document Representation

- Text document is a string!
  - we need to pick a suitable representation.
- **Bag-of-Words (BoW) model**
  - Let  $\mathcal{V} = \{w_1, w_2, \dots, w_V\}$  be a list of  $V$  words (called a **vocabulary**).
  - represent a text document as a vector  $\mathbf{x} \in \mathbb{R}^V$ .
    - each entry  $x_j$  represents the number of times word  $w_j$  appears in the document.
- **Example:**
  - Document: "This is a test document"
  - Vocabulary:  $\mathcal{V} = \{"this", "test", "spam", "foo"\}$
  - Vector representation:  $\mathbf{x} = [1, 1, 0, 0]$



- **NOTE:**
  - the order of the words is not used!
  - rearranging words leads to the same representation!
- Example:
  - "this is spam" →  $x = [1, 0, 1, 0]$
  - "is this spam" →  $x = [1, 0, 1, 0]$
- This is why it is called "bag-of-words"



## Steps to make BoW

1. Build a vocabulary  $\mathcal{V}$ 
  - remove *stopwords*
    - the most common words that provide little information
    - examples: "the", "a", "on"
  - convert to all lower case
2. Calculate the vector for each document
  - count the occurrence of each word in the vocabulary

```
In [16]: # Load text data from directories
# each sub-directory contains text files for 1 class
textdata = datasets.load_files("email", encoding="utf8", decode_error="replace")

# target names
print("class names = ", textdata.target_names)
print("classes = ", unique(textdata.target))
print("num samples = ", len(textdata.target))

class names = ['ham', 'spam']
classes = [0 1]
num samples = 50
```

```
In [17]: # look at first sample
print("Sample 1 is Class " + str(textdata.target[0]) + \
      "(" + textdata.target_names[textdata.target[0]] + ")")
print("----")
print(textdata.data[0])
```

Sample 1 is Class 1(spam)

----

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- \* Gucci Bags
- \* Tiffany & Co Jewelry

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You will 100% recieve your order

```
In [18]: # randomly split data into 50% train and 50% test set
traintext, testtext, trainY, testY = \
    model_selection.train_test_split(textdata.data, textdata.target,
                                     train_size=0.5, test_size=0.5, random_state=11)

print(len(traintext))
print(len(testtext))
```

25

25

```
In [19]: # setup the document vectorizer to make BoW
# - use english stop words
# - only use the most frequent 100 words in the dataset
cntvect = feature_extraction.text.CountVectorizer(stop_words='english', max_features=100)

# create the vocabulary, and return the document vectors
# NOTE: we only use the training data!
trainX = cntvect.fit_transform(traintext)

# calculate vectors for the test data
testX = cntvect.transform(testtext)

# print the vocabulary
# - (key,value) pairs correspond to (word,vector index)
print(cntvect.vocabulary_)

{'day': 31, 'close': 21, 'brand': 18, 'thanks': 90, 'chief': 19, 'phone': 71,
 'microsoft': 61, 'york': 99, 'wilson': 96, 'new': 66, 'frank': 41, 'account': 11,
 'john': 52, 'windows': 97, 'states': 88, 'republic': 79, 'financial': 38,
 'status': 89, 'commented': 24, 'days': 32, 'today': 91, 'man': 58, 'names': 64,
 'just': 53, 'send': 85, 'let': 55, 'nations': 65, 'pricing': 73, 'number': 68,
 '30mg': 8, '000': 1, 'wilmott': 95, '30': 7, 'provide': 74, 'enabled': 35,
 'release': 77, 'email': 34, 'mandelbrot': 59, 'nigeria': 67, '70': 10,
 'compensation': 25, 'required': 80, 'contact': 26, 'details': 33, 'federal': 37,
 'following': 39, 'funds': 44, 'representative': 78, 'inheritance': 50,
 'benoit': 17, 'forward': 40, 'info': 47, 'mr': 63, '60': 9, 'receive': 75,
 'united': 92, 'inform': 48, 'current': 29, 'office': 69, 'soon': 86, 'extended': 36,
 '2010': 6, 'freeviagra': 42, 'source': 87, 'model': 62, '20': 5, 'scifinance': 84,
 'address': 12, 'wheeler': 94, 'codeine': 23, 'choice': 20, '10': 2, 'gpu': 46,
 'information': 49, 'ryan': 83, 'right': 81, 'going': 45, 'code': 22, '00': 0,
 'working': 98, 'mg': 60, 'risk': 82, 'country': 28, 'fund': 43, 'andrew': 15,
 'payment': 70, 'adobe': 13, 'bank': 16, 'cost': 27, 'major': 56, 'regards': 76,
 'interesting': 51, 'make': 57, 'watson': 93, '15mg': 4, 'pills': 72, 'david': 30,
 '120': 3, 'agaliofu': 14, 'know': 54}
```

```
In [20]: # define a function for prettier output...
def showVocab(vocab, counts=None):
    "print out the vocabulary. if counts specified, then only print the words w/
    non-zero entries"
    allwords = list(vocab.keys())
    allwords.sort() # sort vocabulary by index
    wordlist = []
    for word in allwords:
        ind = vocab[word]
        if (counts is None):
            mystr = "{:3d}. {}".format(ind, word)
        elif (counts[0,ind]>0):
            mystr = "{:3d}. ({:0.4f}) {}".format(ind, counts[0,ind], word)
        else:
            continue # skip it
        wordlist.append(mystr)

    # print 2 columns
    it = iter(wordlist)
    for i in it:
```

```
print('{:<30}{}'.format(i, next(it)))
```

```
# show the vocabulary
```

```
showVocab(cntvect.vocabulary_)
```

0. 00	1. 000
2. 10	3. 120
4. 15mg	5. 20
6. 2010	7. 30
8. 30mg	9. 60
10. 70	11. account
12. address	13. adobe
14. agaliofu	15. andrew
16. bank	17. benoit
18. brand	19. chief
20. choice	21. close
22. code	23. codeine
24. commented	25. compensation
26. contact	27. cost
28. country	29. current
30. david	31. day
32. days	33. details
34. email	35. enabled
36. extended	37. federal
38. financial	39. following
40. forward	41. frank
42. freeviagra	43. fund
44. funds	45. going
46. gpu	47. info
48. inform	49. information
50. inheritance	51. interesting
52. john	53. just
54. know	55. let
56. major	57. make
58. man	59. mandelbrot
60. mg	61. microsoft
62. model	63. mr
64. names	65. nations
66. new	67. nigeria
68. number	69. office
70. payment	71. phone
72. pills	73. pricing
74. provide	75. receive
76. regards	77. release
78. representative	79. republic
80. required	81. right
82. risk	83. ryan
84. scifinance	85. send
86. soon	87. source
88. states	89. status
90. thanks	91. today
92. united	93. watson
94. wheeler	95. wilmott
96. wilson	97. windows
98. working	99. york

```
In [21]: # show a document vector
# - only the non-zero entries are printed
print(trainX[0])
```

```
(0, 40)      1
(0, 44)      1
(0, 80)      1
(0, 49)      1
(0, 12)      1
(0, 68)      1
(0, 71)      1
(0, 26)      2
(0, 64)      1
(0, 47)      1
(0, 74)      1
(0, 50)      1
(0, 16)      1
(0, 70)      5
(0, 88)      1
(0, 78)      1
(0, 65)      1
(0, 92)      2
(0, 41)      2
(0, 52)      2
(0, 63)      2
(0, 31)      2
```

```
In [22]: # show the actual words
showVocab(cntvect.vocabulary_, trainX[0])
print("----")
print(traintext[0])
```

```
12. (1.0000) address      16. (1.0000) bank
26. (2.0000) contact     31. (2.0000) day
40. (1.0000) forward     41. (2.0000) frank
44. (1.0000) funds       47. (1.0000) info
49. (1.0000) information 50. (1.0000) inheritance
52. (2.0000) john        63. (2.0000) mr
64. (1.0000) names       65. (1.0000) nations
68. (1.0000) number      70. (5.0000) payment
71. (1.0000) phone       74. (1.0000) provide
78. (1.0000) representative 80. (1.0000) required
88. (1.0000) states      92. (2.0000) united
```

---

Attn:Good Day,

Compliment of the day to you, my name is Mr John Frank Harmon a UNITED NATIONS Representative here in UNITED STATES this year 2014 last payment quarter for all outstanding payment from World Bank on overdue contracts,inheritance and all other payment has commenced,you are to provide the below info asap so that the payment processing can start off.

Your full names  
Contact phone number  
Contact Address

The above information is required so as to go through your payment file and start the processing of this long and overdue funds.

looking forward to hearing from you

Mr John Frank Harmon

## Naive Bayes model for Boolean vectors

- Model each word independently
  - absence/presence of a word  $w_j$  in document
  - Bernoulli distribution
    - present:  $p(x_j = 1|y) = \pi_j$
    - absent:  $p(x_j = 0|y) = 1 - \pi_j$
  - MLE parameters:  $\pi_j = N_j/N$ ,
    - $N_j$  is the number of documents in class  $y$  that contain word  $j$ .
    - $N$  is the number of documents in class  $y$ .

- Class-conditional distribution

$$p(x_1, \dots, x_V | y = \text{spam}) = \prod_{j=1}^V p(x_j | y = \text{spam})$$

$$\log p(x_1, \dots, x_V | y = \text{spam}) = \sum_{j=1}^V \log p(x_j | y = \text{spam})$$

- for a document, the log-probabilities of the words being in a spam message adds.
  - accumulate evidence over all words in the document.
  - more words that are associated with spam --> more likely the document is spam

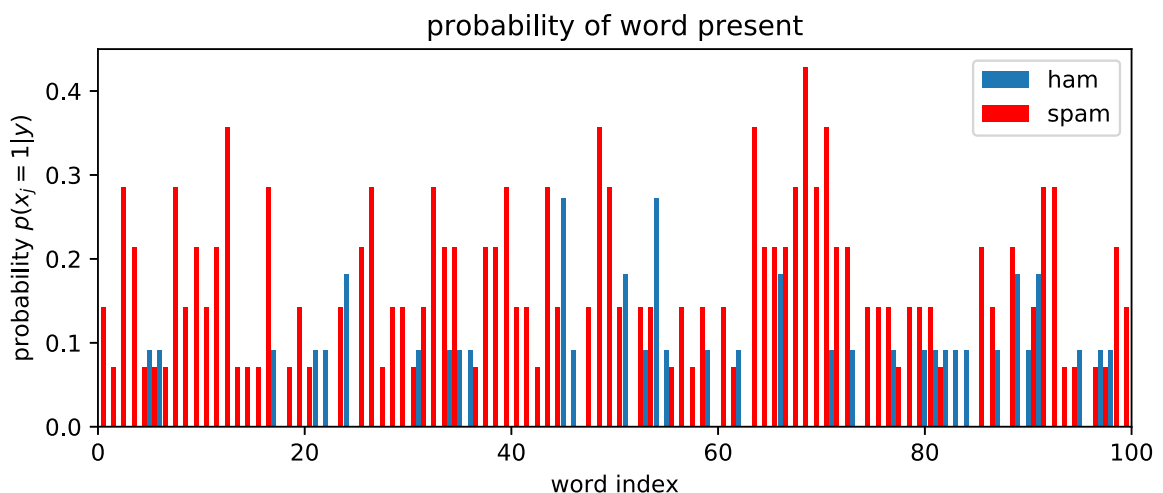
```
In [23]: # fit the NB Bernoulli model.
# the model automatically converts count vector into binary vector
bmodel = naive_bayes.BernoulliNB(alpha=0.0)
bmodel.fit(trainX, trainY)
```

```
/anaconda3/lib/python3.5/site-packages/sklearn/naive_bayes.py:472: UserWarning:
alpha too small will result in numeric errors, setting alpha = 1.0e-10
'setting alpha = %.1e' % _ALPHA_MIN)
```

```
Out[23]: BernoulliNB(alpha=0.0, binarize=0.0, class_prior=None, fit_prior=True)
```

```
In [24]: # a function for plotting the word probabilities
def plotWordProb(model):
    xr = arange(0, len(cntvect.vocabulary_))
    plt.figure(figsize=(8,3))
    plt.bar(xr, exp(model.feature_log_prob_[0,:]), width=0.4, label=textdata.target_names[0])
    plt.bar(xr+0.5, exp(model.feature_log_prob_[1,:]), width=0.4, color='r', label=textdata.target_names[1])
    plt.legend()
    plt.xlabel('word index'); plt.ylabel('probability $p(x_j=1|y)$');
    plt.xlim(min(xr), max(xr)+1)

# make plot
plotWordProb(bmodel)
plt.title('probability of word present');
```



```
In [25]: # prediction
predY = bmodel.predict(testX)
print("predictions: ", predY)
print("actual:      ", testY)

# calculate accuracy
acc = metrics.accuracy_score(testY, predY)
print(acc)

predictions: [0 1 1 1 1 1 1 1 0 1 0 0 0 0 0 0 0 1 1 0 0 0 1 1 1]
actual:      [0 1 1 1 0 1 1 0 0 1 0 0 1 0 0 0 0 0 1 1 0 1 0 0 1]
0.68
```

```
In [26]: # show examples of misclassified
inds = where(predY != testY)
print(inds)
for i in inds[0]:
    print("---- true={}, pred={}".format(testY[i], predY[i]))
    print(testtext[i])
```

```
(array([ 4,  7, 12, 17, 19, 21, 22, 23]),)
```

```
---- true=0, pred=1
```

```
LinkedIn
```

```
Julius O requested to add you as a connection on LinkedIn:
```

```
Hi Peter.
```

```
Looking forward to the book!
```

```
Accept View invitation from Julius O
```

```
---- true=0, pred=1
```

```
Hi Peter,
```

```
The hotels are the ones that rent out the tent. They are all lined up on the
hotel grounds : )) So much for being one with nature, more like being one wi
th a couple dozen tour groups and nature.
```

```
I have about 100M of pictures from that trip. I can go through them and get
you jpgs of my favorite scenic pictures.
```

```
Where are you and Jocelyn now? New York? Will you come to Tokyo for Chinese
New Year? Perhaps to see the two of you then. I will go to Thailand for wint
er holiday to see my mom : )
```

```
Take care,
```

```
D
```

```
---- true=1, pred=0
```

```
Get Up to 75% OFF at Online WatchesStore
```

```
Discount Watches for All Famous Brands
```

```
* Watches: aRolexBvlgari, Dior, Hermes, Oris, Cartier, AP and more brands
```

```
* Louis Vuitton Bags & Wallets
```



- \* Gucci Bags
- \* Tiffany & Co Jewelry

Enjoy a full 1 year WARRANTY

Shipment via reputable courier: FEDEX, UPS, DHL and EMS Speedpost

You will 100% receive your order

Save Up to 75% OFF Quality Watches

---- true=0, pred=1

This e-mail was sent from a notification-only address that cannot accept incoming e-mail. Please do not reply to this message.

Thank you for your online reservation. The store you selected has located the item you requested and has placed it on hold in your name. Please note that all items are held for 1 day. Please note store prices may differ from those online.

If you have questions or need assistance with your reservation, please contact the store at the phone number listed below. You can also access store information, such as store hours and location, on the web at [http://www.borders.com/online/store/StoreDetailView\\_98](http://www.borders.com/online/store/StoreDetailView_98).

---- true=1, pred=0

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- \* Louis Vuitton Bags & Wallets
- \* Gucci Bags
- \* Tiffany & Co Jewelry

Enjoy a full 1 year WARRANTY

Shipment via reputable courier: FEDEX, UPS, DHL and EMS Speedpost

You will 100% receive your order

---- true=1, pred=0

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- \* Watches: aRolexBulgari, Dior, Hermes, Oris, Cartier, AP and more brands
- \* Louis Vuitton Bags & Wallets
- \* Gucci Bags
- \* Tiffany & Co Jewelry

Enjoy a full 1 year WARRANTY

Shipment via reputable courier: FEDEX, UPS, DHL and EMS Speedpost

You will 100% receive your order

---- true=0, pred=1

Ok I will be there by 10:00 at the latest.

---- true=0, pred=1

Hello,

Since you are an owner of at least one Google Groups group that uses the customized welcome message, pages or files, we are writing to inform you that we will no longer be supporting these features starting February 2011. We made this decision so that we can focus on improving the core functionalities of Google Groups -- mailing lists and forum discussions. Instead of these features, we encourage you to use products that are designed specifically for

file storage and page creation, such as Google Docs and Google Sites.

For example, you can easily create your pages on Google Sites and share the site (<http://www.google.com/support/sites/bin/answer.py?hl=en&answer=174623>) with the members of your group. You can also store your files on the site by attaching files to pages (<http://www.google.com/support/sites/bin/answer.py?hl=en&answer=90563>) on the site. If you're just looking for a place to upload your files so that your group members can download them, we suggest you try Google Docs. You can upload files (<http://docs.google.com/support/bin/answer.py?hl=en&answer=50092>) and share access with either a group (<http://docs.google.com/support/bin/answer.py?hl=en&answer=66343>) or an individual (<http://docs.google.com/support/bin/answer.py?hl=en&answer=86152>), assigning either edit or download only access to the files.

you have received this mandatory email service announcement to update you about important changes to Google Groups.

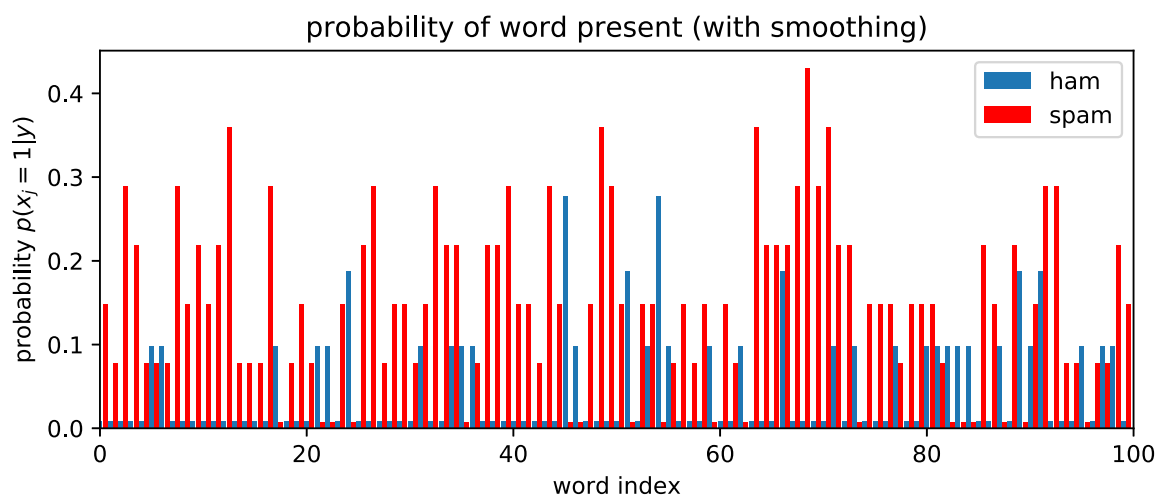
## Smoothing

- Some words are not present in any documents for a given class.
  - $N_j = 0$ , and thus  $\pi_j = 0$ .
    - i.e., the document in the class **definitely** will not contain the word.
    - can be a problem since we simply may not have seen an example with that word.
- Smoothed MLE
  - add a smoothing parameter  $\alpha$  that adds a "virtual" count
  - parameter:  $\pi_j = (N_j + \alpha) / (N + 2\alpha)$ ,
  - this is called *Laplace smoothing*
- In general, *regularizing* or *smoothing* of the estimate helps to prevent *overfitting* of the parameters.

```
In [27]: # fit the NB Bernoulli model w/ smoothing (0.1)
         bmodels = naive_bayes.BernoulliNB(alpha=0.1)
         bmodels.fit(trainX, trainY)
```

```
Out[27]: BernoulliNB(alpha=0.1, binarize=0.0, class_prior=None, fit_prior=True)
```

```
In [28]: # make plot
plotWordProb(bmodels)
plt.title('probability of word present (with smoothing)');
# note the small probabilities are all slightly above 0.
```



```
In [29]: # prediction
predY = bmodels.predict(testX)
print("predictions: ", predY)
print("actual:      ", testY)

# calculate accuracy
acc = metrics.accuracy_score(testY, predY)
print(acc)
# a little better!
```

```
predictions: [0 1 1 0 0 1 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 1]
actual:      [0 1 1 1 0 1 1 0 0 1 0 0 1 0 0 0 0 1 1 0 1 0 0 1]
0.72
```

## Most informative words

- The most informative words are those with high probability of being in one class, and low probability of being in other classes.
  - e.g., For class 1, find large values of  $\log p(w_j|y = 1) - \log p(w_j|y = 0)$

```
In [30]: # get the word names
fnames = asarray(cntvect.get_feature_names())
# coef_ contains the scores for each word
# (higher means more informative)
# sort the coefficients in ascending order, and take the 10 largest.
tmp = argsort(bmodel.coef_[0])[-10:]

for i in tmp:
    print("{:3d}. {:15s} ({:.5f})".format(i, fnames[i], bmodel.coef_[0][i]))
```

```
16. bank          (-1.25276)
67. nigeria       (-1.25276)
26. contact       (-1.25276)
69. office        (-1.25276)
32. days          (-1.25276)
48. inform        (-1.02962)
70. payment       (-1.02962)
63. mr            (-1.02962)
12. address       (-1.02962)
68. number        (-0.84730)
```

## Naive Bayes for Count Vectors

- Now we consider using the number of times each word appears in the document  $D$ .
- Two ways to create a document vector  $x$  based on the word counts.
- **Term-Frequency (TF)**
  - handles documents with different lengths (number of words).
  - normalize the count to a frequency, by dividing by the number of words in the document.
    - $x_j = \frac{w_j}{|D|}$ 
      - $w_j$  is the number of times word  $j$  appears in the document
      - $|D|$  is the number of words in the document.
- **Term-Frequency Inverse Document Frequency (TF-IDF)**
  - some words are common among many documents
    - common words are less informative because they appear in both classes.
  - **inverse document frequency (IDF)** - measure rarity of each word
    - $IDF(j) = \log \frac{N}{N_j}$ 
      - $N$  is the number of documents.
      - $N_j$  is the number of documents with word  $j$ .
    - IDF is:
      - 0 when a word is common to all documents
      - large value when the word appears in few documents
  - **TF-IDF vector:** downscale words that are common in many documents
    - multiply TF and IDF terms
    - $x_j = \frac{w_j}{|D|} \log \frac{N}{N_j}$

```
In [31]: # TF-IDF representation
# (For TF, pass use_idf=False)
tf_trans = feature_extraction.text.TfidfTransformer(use_idf=True, norm='l1')
# 'l1' - entries sum to 1

# setup the TF-IDF representation, and transform the training set
trainXtf = tf_trans.fit_transform(trainX)

# transform the test set
testXtf = tf_trans.transform(testX)

print(trainXtf[0])
```

```
(0, 31)      0.06423955966673985
(0, 63)      0.055169680057832474
(0, 52)      0.07067474166045794
(0, 41)      0.07067474166045794
(0, 92)      0.059248044723895436
(0, 65)      0.03211977983336992
(0, 78)      0.03533737083022897
(0, 88)      0.03211977983336992
(0, 70)      0.13792420014458118
(0, 16)      0.029624022361947718
(0, 50)      0.03533737083022897
(0, 74)      0.03533737083022897
(0, 47)      0.03533737083022897
(0, 64)      0.03211977983336992
(0, 26)      0.059248044723895436
(0, 71)      0.029624022361947718
(0, 68)      0.025860735932526902
(0, 12)      0.027584840028916237
(0, 49)      0.029624022361947718
(0, 80)      0.03211977983336992
(0, 44)      0.03533737083022897
(0, 40)      0.03533737083022897
```

```
In [32]: showVocab(cntvect.vocabulary_, trainXtf[0])
```

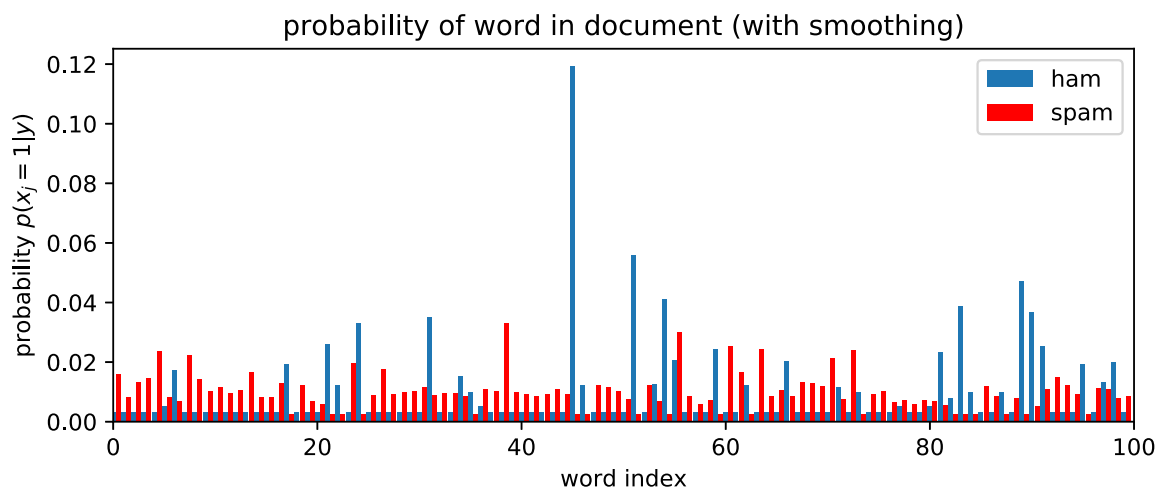
12. (0.0276) address	16. (0.0296) bank
26. (0.0592) contact	31. (0.0642) day
40. (0.0353) forward	41. (0.0707) frank
44. (0.0353) funds	47. (0.0353) info
49. (0.0296) information	50. (0.0353) inheritance
52. (0.0707) john	63. (0.0552) mr
64. (0.0321) names	65. (0.0321) nations
68. (0.0259) number	70. (0.1379) payment
71. (0.0296) phone	74. (0.0353) provide
78. (0.0353) representative	80. (0.0321) required
88. (0.0321) states	92. (0.0592) united

# Naive Bayes Multinomial

- TF or TF-IDF representation
  - Document word vector  $\mathbf{x}$ 
    - $x_j$  is the frequency of word  $j$  occurring in the document.
    - vector  $\mathbf{x}$  sums to 1, i.e.  $\sum_j x_j = 1$ .
- Use a multinomial distribution as the class conditional
  - based on the frequency that a word appears in a document of a class.

```
In [33]: # fit a multinomial model (with smoothing)
mmmodel_tf = naive_bayes.MultinomialNB(alpha=0.05)
mmmodel_tf.fit(trainXtf, trainY)

# show the word probabilities
plotWordProb(mmmodel_tf)
plt.title('probability of word in document (with smoothing)');
```



```
In [34]: # prediction
predYtf = mmmodel_tf.predict(testXtf)
print("prediction: ", predYtf)
print("actual:      ", testY)

# calculate accuracy
acc = metrics.accuracy_score(testY, predYtf)
print(acc)

prediction:  [0 1 1 1 1 1 1 1 0 1 0 0 1 1 1 0 0 1 1 1 1 1 1 1 1]
actual:      [0 1 1 1 0 1 1 0 0 1 0 0 1 0 0 0 0 1 1 0 1 0 0 1]
0.68
```

```
In [35]: # most informative words for TF-IDF
fnames = asarray(cntvect.get_feature_names())
tmp = argsort(mmodel_tf.coef_[0])[-10:]
for i in tmp:
    print("{:3d}. {:15s} ({:.5f})".format(i, fnames[i], mmodel_tf.coef_[0][i]))
```

```
26. contact          (-4.03474)
23. codeine          (-3.92301)
70. payment          (-3.85287)
 7. 30               (-3.80167)
 4. 15mg             (-3.74496)
72. pills            (-3.72604)
63. mr               (-3.71758)
60. mg               (-3.68161)
55. let              (-3.49983)
38. financial        (-3.40804)
```

## Summary

- **Generative classification model**
    - estimate probability distributions of features generated from each class.
    - given feature observation predict class with largest posterior probability.
  - **Advantages:**
    - works with small amount of data.
    - works with multiple classes.
  - **Disadvantages:**
    - accuracy depends on selecting an appropriate probability distribution.
      - if the probability distribution doesn't model the data well, then accuracy might be bad.
- 
- **Other text preprocessing**
    - *Stemming*
      - convert related words into a common root word
      - example: testing, tests --> "test"
      - see NLTK toolbox (<http://www.nltk.org>)
    - *Lemmatisation*
      - similar to stemming
      - groups inflections of word together (gone, going, went -> go)
      - see NLTK
    - Removing numbers and punctuation.
- 
- **Other word models**
    - *N-grams*
      - similar to BoW except look at pairs of consecutive words (or N consecutive words in general)
    - *word vectors*
      - each word is a real vector, where direction indicates the "concept"
      - words about similar things point in the same direction
      - adding and subtracting word vectors yield new word vectors