Lab : Detecting Spam Email with Naive Bayes

As promised, in this chapter, we kick off our supervised learning journey with machine learning classification, specifically, binary classification. We will be learning with the goal of building a high-performing spam email detector. It is a good starting point to learn classification with a real-life example—our email service providers are already doing this for us, and so can we. We will be learning the fundamental concepts of classification, including what it does and its various types and applications, with a focus on solving spam detection using a simple yet powerful algorithm, Naïve Bayes. One last thing: we will be demonstrating how to fine-tune a model, which is an important skill for every data science or machine learning practitioner to learn.

We will get into detail on the following topics:

- What is machine learning classification?
- Types of classification
- Applications of text classification
- The Naïve Bayes classifier
- The mechanics of Naïve Bayes
- The Naïve Bayes implementations
- Spam email detection with Naïve Bayes
- Classification performance evaluation
- Cross-validation
- Tuning a classification model

Pre-reqs:

- Docker

Lab Environment

We will run Jupyter Notebook as a Docker container. This setup will take some time because of the size of the image. Run the following commands one by one:

`docker run -d --user root -p 8888:8888 --name jupyter -e GRANT_SUDO=yes jupyter/tensorflow-notebook:2ce7c06a61a1 start-notebook.sh`

`docker exec -it jupyter bash -c 'cd /home/jovyan/work && git clone https://github.com/athertahir/python-machine-learning-by-example.git && sudo && chmod +x ~/work/prepareContainer.sh && ~/prepareContainer.sh'`

`docker restart jupyter`

Note: After completing these steps, jupyter notebook will be accessible at port 8888 of the host machine.

All Notebooks are present in `work` folder.

Login

When the container is running, execute this statement:
`docker logs jupyter 2>&1 | grep -v "HEAD"`

This will show something like:

```
Copy/paste this URL into your browser when you connect for the first time, to login with a token:
    http://localhost:8888/?token=f89b02dd78479d52470b3c3a797408b20cc5a11e067e94b8
    THIS IS NOT YOUR TOKEN.  YOU HAVE TO SEARCH THE LOGS TO GET YOUR TOKEN
```

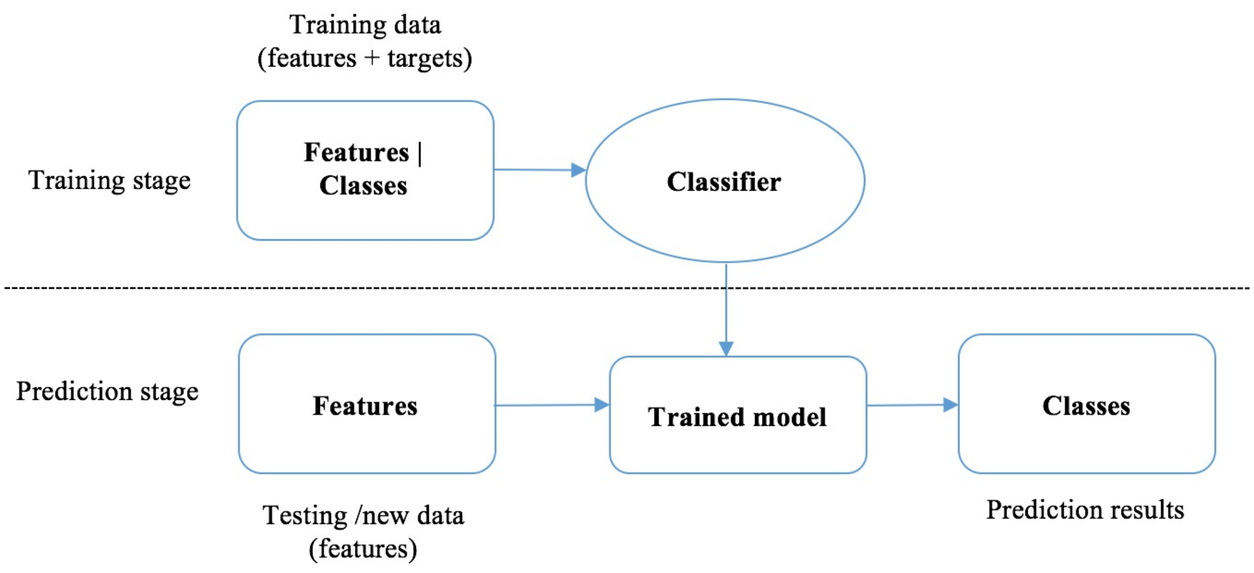
The token is the value behind `/?token=`. You need that for logging in.

Note: You can also run follow ing command to get token directly:

```
docker exec -it jupyter bash -c 'jupyter notebook list' | cut -d'=' -f 2 | cut -d' ' -f 1
```

Getting started with classification

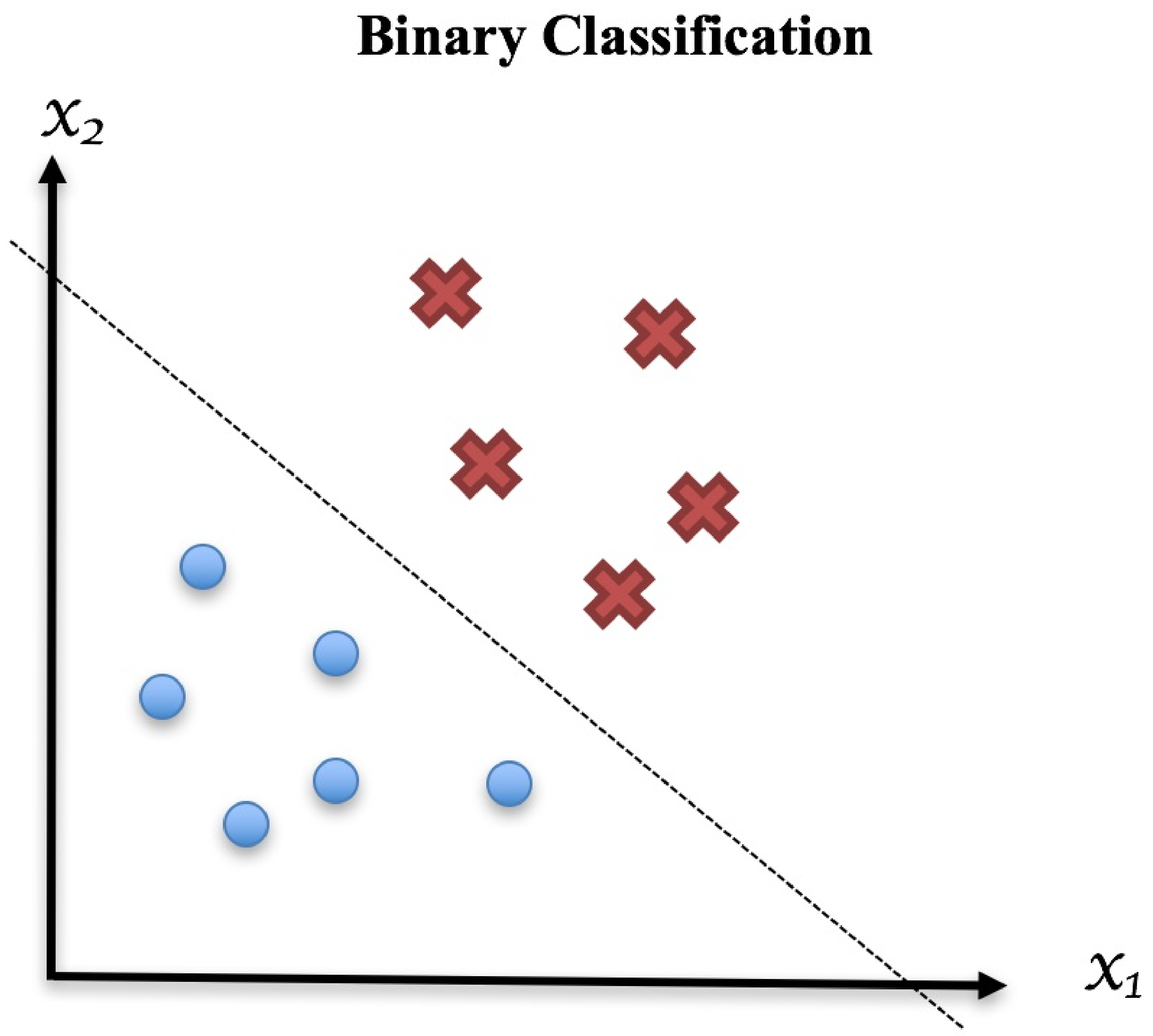
Spam email detection is basically a machine learning classification problem. Let's get started by learning important concepts of machine learning classification. Classification is one of the main instances of supervised learning. Given a training set of data containing observations and their associated categorical outputs, the goal of classification is to learn a general rule that correctly maps the observations (also called features or predictivevariables) to the target categories (also called labels or classes). Put another w ay, a trained classification model w ill be generated after learning from features and targets of training samples, as show n in the first half of the follow ing diagram. When new or unseen data comes in, the trained model w ill be able to determine their desired memberships. Class information w ill be predicted based on the know n input features using the trained classification model, as displayed in the second half of the follow ing diagram:



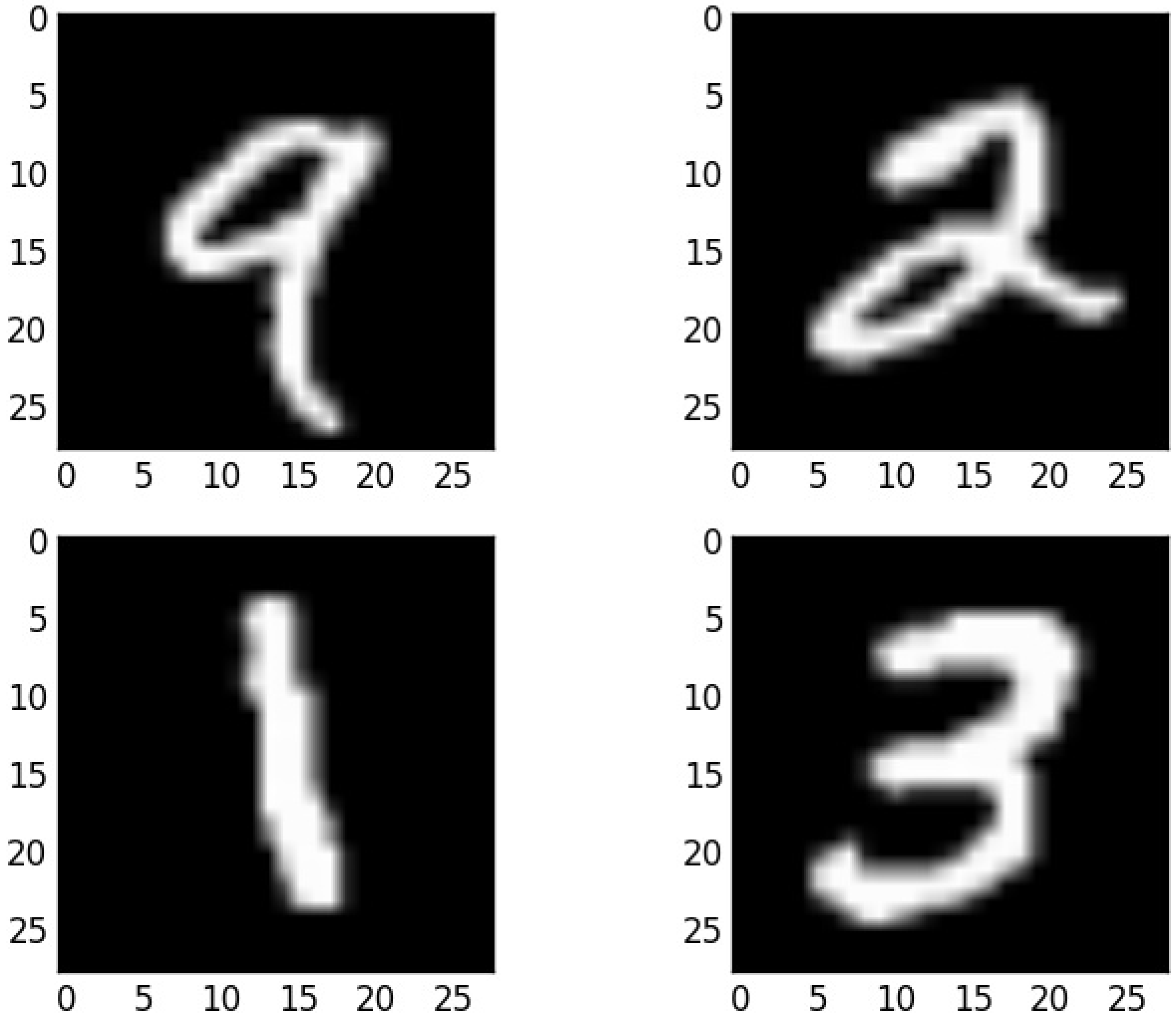
Types of classification

Based on the possibility of class output, machine learning classification can be categorized into binary classification, multiclass classification, and multilabel classification, as follow s:

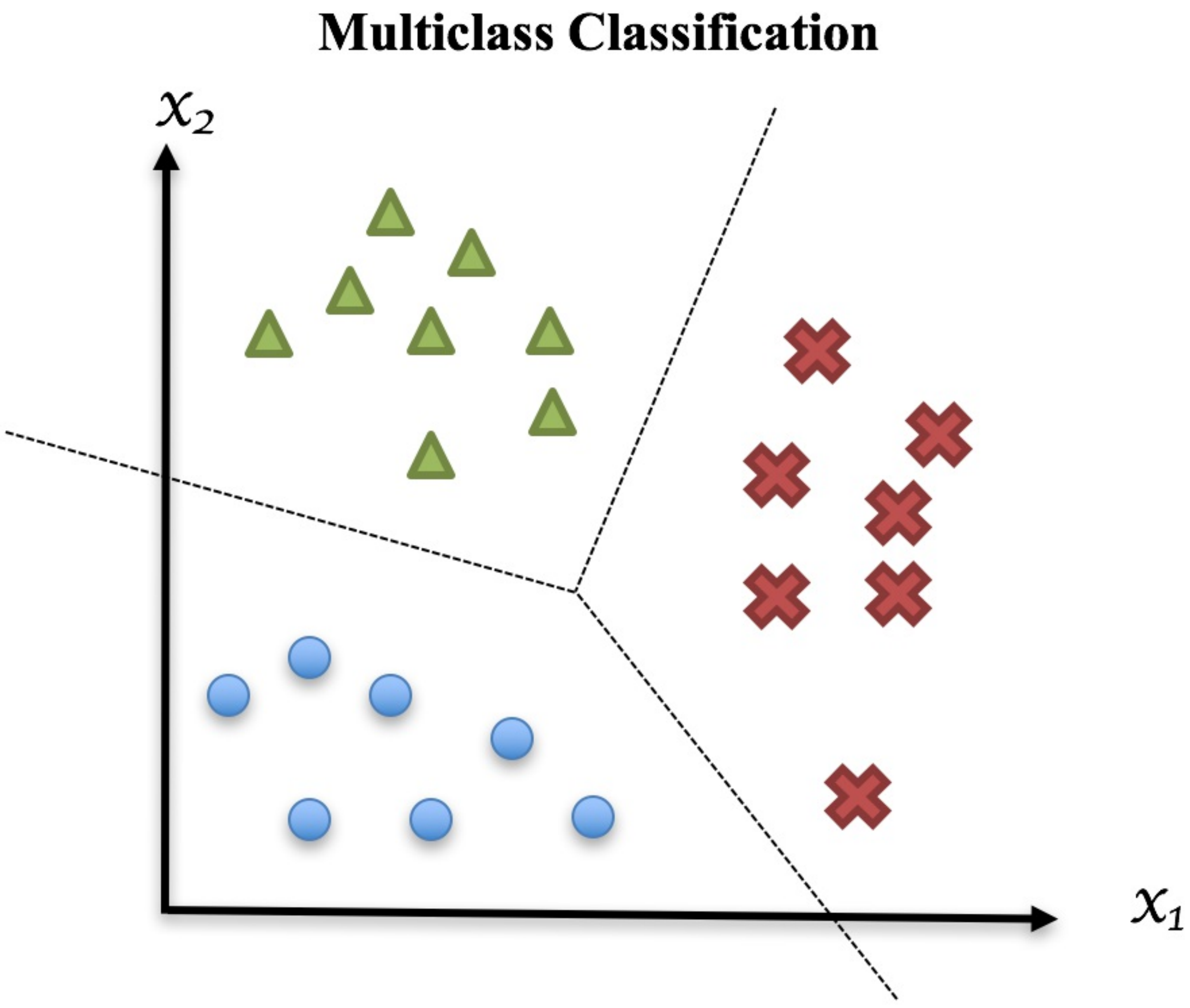
Binary classification: This classifies observations into one of tw o possible classes. The example of spam email filtering w e mentioned earlier is a typical use case of binary classification, w hich identifies email messages (input observations) as spam or not spam (output classes). Customer churn prediction is another frequently mentioned example, w here the prediction system takes in customer segment data and activity data from CRM systems and identifies w hich customers are likely to churn. Another application in the marketing and advertising industry is click-through prediction for online ads—that is, w hether or not an ad w ill be clicked, given users' cookie information and brow sing history. Last, but not least, binary classification has also been employed in biomedical science, for example, in early cancer diagnosis, classifying patients into high or low risk groups based on MRI images. As demonstrated in the follow ing example, binary classification tries to find a w ay to separate data from tw o classes:



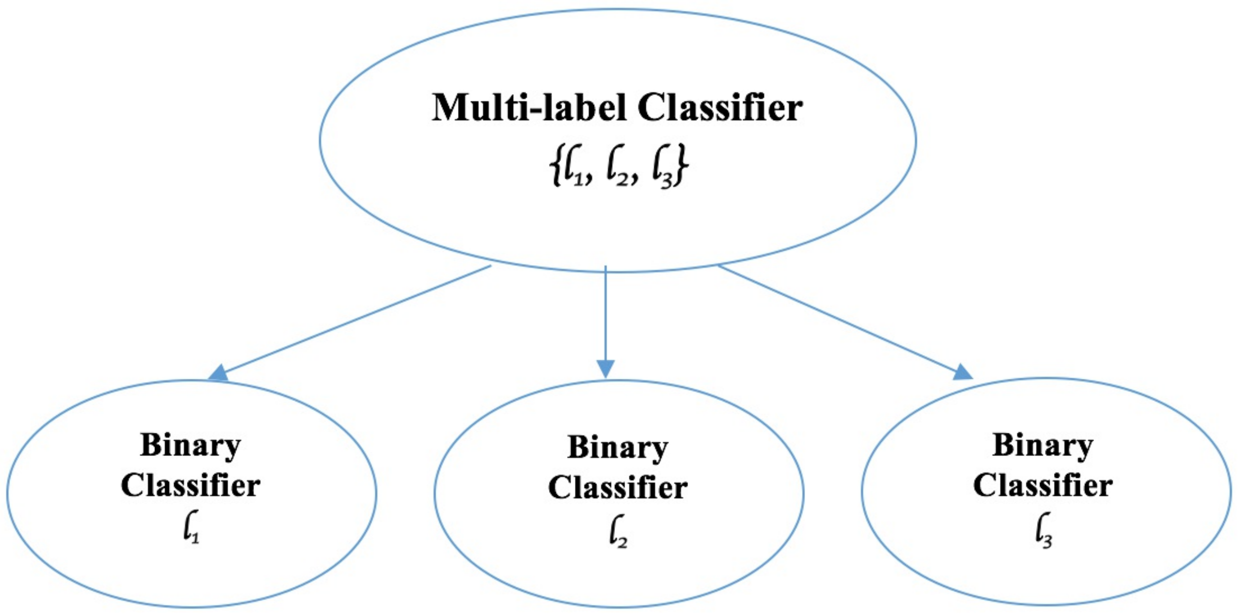
Multiclass classification: This classification is also called multinomial classification, and allow s more than tw o possible classes, as opposed to only tw o in binary cases. Handw ritten digit recognition is a common instance of classification and has a long history of research and development since the early 1900s. A classification system, for example, learns to read and understand handw ritten ZIP codes (digits from 0 to 9 in most countries) by w hich envelopes are automatically sorted.
Handw ritten digit recognition has become a hello w orld in the journey of studying machine learning, and the scanned document dataset constructed from the National Institute of Standards and Technology, called MNIST (short for Modified National Institute of Standards and Technology), is a benchmark dataset frequently used to test and evaluate multiclass classification models. The follow ing screenshot show s the four samples taken from the MNIST dataset:



In the follow ing example, the multiclass classif ication model tries to f ind segregation boundaries to separate data from the follow ing three dif ferent classes:



Multi-label classification: This classification is different from the first tw o types of classification, w here target classes are disjointed. Research attention to this field has been increasingly draw n by the nature of the omnipresence of categories in modern applications. For example, a picture that captures a sea and sunset can simultaneously belong to both conceptual scenes, w hereas it can only be an image of either cat or dog in a binary case, or one type of fruit among oranges, apples, and bananas in a multiclass case. Similarly, adventure films are often combined w ith other genres, such as fantasy, science fiction, horror, and drama. Another typical application is protein function classification, as a protein may have more than one function—storage, antibody, support, transport, and so on. One approach to solve an n label classification problem is to transform it into a set of n binary classifications problem, w hich is then handled by individual binary classifiers. Refer to the follow ing diagram of restructuring a multi-label classification problem into multiple binary classification problems:



Applications of text classification

As w as discussed in Chapter 3, Mining the 20 New sgroups Dataset w ith Clustering and Topic Modeling Algorithms, unsupervised learning, including clustering and topic modeling, can be applied to text data. We w ill continue to see how supervised learning, specifically classification, is used in the text domain.

In fact, classification has been w idely used in text analysis and new s analytics. For instance, classification algorithms are used to identify new s sentiment, positive or negative in a binary case, or positive, neutral, or negative in a multiclass classification case. New s sentiment analysis provides a significant signal to trading in the stock market.

Another example that comes to mind is new s topic classification, w here classes may or may not be mutually exclusive. In the new sgroup example that w e just w orked on, classes are mutually exclusive (despite slight overlapping), such as computer graphics, motorcycles, baseball, hockey, space, and religion. We w ill demonstrate how to use machine learning algorithms to solve such multiclass classification problems in Chapter 5, Classifying New sgroup Topic w ith Support Vector Machine. It is, how ever, good to realize that a new s article is occasionally assigned multiple categories, w here, properly speaking, multi-label classification is more suitable. For example, an article about the Olympic Games may be labeled as both sports and politics if there is an unexpected political involvement.

Finally, a text classification application that is perhaps difficult to realize is named-entity recognition (NER). Named entities are phrases of definitive categories, such as names of persons, companies, geographic locations, dates and times, quantities, and monetary values. NER is an important subtask of information extraction, to seek and identify such entities. For example, w e can conduct NER on the follow ing sentence: SpaceX[Organization], a California[Location]-based company founded by a famous tech entrepreneur Elon Musk[Person], announced that it w ould manufacture the next-generation, 9[Quantity]-meter-diameter launch vehicle and spaceship for the first orbital flight in 2020[Date].

To solve these problems, researchers have developed many pow er classification algorithms, among w hich Naïve Bayes and support vector machine (SVM) models are often used for text classification. In the follow ing sections, w e w ill cover the mechanics of Naïve Bayes and its in-depth implementation, along w ith other important concepts, including classifier tuning and classification performance evaluation.

Exploring Naïve Bayes

The Naïve Bayes classifier belongs to the family of probabilistic classifiers that computes the probabilities of each predictive feature (also called attribute) of the data belonging to each class in order to make a prediction of probability distribution over all classes (of course, including the most likely class that the data sample is associated w ith). What it does, as its name indicates, is as follow s:

- **Bayes:** As in, it maps the probabilities of observing input features given belonging classes, to the probability distribution over classes based on Bayes' theorem. We w ill explain Bayes' theorem w ith the later examples in this chapter
- **Naïve:** As in, it simplifies probability computation by assuming that predictive features are mutually independent.

Learning Bayes' theorem by examples

It is important to understand Bayes' theorem before diving into the classifier. Let A and B denote tw o events. Events could be that it w ill rain tomorrow ; 2 kings are draw n from a deck of cards; or a person has cancer. In Bayes' theorem, P(A |B) is the probability that A occurs given that B is true. It can be computed as follow s:

$$P(A\,|B) = \frac{P(B|A)P(A)}{P(B)}$$

Here, P(B|A) is the probability of observing B given that A occurs, w hile P(A) and P(B) are the probability that A and B occur, respectively. Too abstract? Let's look at some of the follow ing concrete examples:

- **Example 1:** Given tw o coins, one is unfair w ith 90% of flips getting a head and 10% getting a tail, w hile the other one is fair. Randomly pick one coin and flip it. What is the probability that this coin is the unfair one, if w e get a head?

We solve it by first denoting U for the event of picking the unfair coin, F for the fair coin, and H for the event of getting a head. So the probability that the unfair has been picked w hen w e get a head, P(U|H) can be calculated w ith the follow ing:

$$P(U\,|H) = \frac{P(H|U)P(U)}{P(H)}$$

As w e know P(H|U) is 90% . P(U) is 0.5 because w e randomly pick a coin out of tw o. How ever, deriving the probability of getting a head P(H) is not that straightforw ard, as tw o events can lead to the follow ing, w here U is w hen the unfair one is picked and F is w hen the fair coin is picked:

$$P(H) = P(H|U)P(U) + P(H|F)P(F)$$

So P(U |H) becomes the follow ing:

$$P(U\,|H) = \frac{P(H|U)P(U)}{P(H)} = \frac{P(H|U)P(U)}{P(H|U)P(U) + P(H|F)P(F)} = \frac{0.9 * 0.5}{0.9 * 0.5 + 0.5 * 0.5} = 0.64$$

- **Example 2:** Suppose a physician reported the follow ing cancer screening test scenario among 10,000 people:

| Cancer | No cancer | Total
--- | --- | --- | ---

`Text positive` | 80 | 900 | 980
`Text negative` | 20 | 9,000 | 9,020
`Total` | 100 | 9,900 | 10,000

It indicates for example 80 out of 100 cancer patients are correctly diagnosed, w hile the other 20 are not; cancer is falsely detected in 900 out of 9,900 healthy people.

If the result of this screening test on a person is positive, w hat is the probability that they actually has cancer?

Let's assign the event of having cancer and positive testing result as C and Pos respectively. Apply Bayes' theorem to calculate P(C|Pos):

$$P(C|Pos) = \frac{P(Pos|C)P(C)}{P(Pos)} = \frac{\frac{80}{100} * \frac{100}{10000}}{\frac{980}{10000}} = 8.16\%$$

Given a positive screening result, the chance that the subject has cancer is 8.16%, w hich is significantly higher than the one under general assumption (100/10000=1%) w ithout undergoing the screening.

Example 3: Three machines A, B, and C in a factory account for 35%, 20%, and 45% of the bulb production. And the fraction of defective bulbs produced by each machine is 1.5%, 1%, and 2% respectively. A bulb produced by this factory w as identified defective, w hich is denoted as event D. What are the probabilities that this bulb w as manufactured by machine A, B, and C respectively?
Again, simply just follow Bayes' theorem, as follow s:

$$\begin{aligned} P(A|D) &= \frac{P(D|A)P(A)}{P(D)} = \frac{P(D|A)P(A)}{P(D|A)P(A) + P(D|B)P(B) + P(D|C)P(C)} \\ &= \frac{0.015 * 0.35}{0.015 * 0.35 + 0.01 * 0.2 + 0.02 * 0.45} = 0.323 \end{aligned}$$

$$\begin{aligned} P(B|D) &= \frac{P(D|B)P(B)}{P(D)} = \frac{P(D|B)P(B)}{P(D|A)P(A) + P(D|B)P(B) + P(D|C)P(C)} \\ &= \frac{0.01 * 0.2}{0.015 * 0.35 + 0.01 * 0.2 + 0.02 * 0.45} = 0.123 \end{aligned}$$

$$\begin{aligned} P(C|D) &= \frac{P(D|C)P(C)}{P(D)} = \frac{P(D|C)P(C)}{P(D|A)P(A) + P(D|B)P(B) + P(D|C)P(C)} \\ &= \frac{0.02 * 0.45}{0.015 * 0.35 + 0.01 * 0.2 + 0.02 * 0.45} = 0.554 \end{aligned}$$

Also, either w ay, w e do not even need to calculate P(D) since w e know that the follow ing is the case:

$$P\left(A|D\right) : P\left(B|D\right) : P\left(C|D\right) = P\left(D|A\right)P\left(A\right) : P\left(D|B\right)P\left(B\right) : P\left(D|C\right)P\left(C\right) = 21 : 8 : 36$$

We too know the follow ing concept:

$$P\ (A|D) + P\ (B|D) + P\ (C|D) = 1$$

So w e have the follow ing formula:

$$P(A|D) = \frac{21}{21+8+36} = 0.323, P(B|D) = \frac{8}{21+8+36} = 0.133$$

After making sense of Bayes' theorem as the backbone of Naïve Bayes, w e can easily move forw ard w ith the classifier itself.

The mechanics of Naïve Bayes

Let's start w ith understanding the magic behind the algorithm—how Naïve Bayes w orks. Given a data sample x w ith n features, x1, x2, …, xn (x represents a feature vector and x = (x1, x2, …, xn)), the goal of Naïve Bayes is to determine the probabilities that this sample belongs to each of K possible classes y1, y2, …, yK, that is P(yk |x) or P(x1, x2, …, xn), w here k = 1, 2, …, K. It looks no different from w hat w e have just dealt w ith: x, or x1, x2, …, xn, is a joint event that the sample has features w ith valuesx1, x2, …, xn respectively, ykis an event that the sample belongs to class k. We can apply Bayes' theorem right aw ay:

$$P(y_k|x) = \frac{P(x|y_k)P(y_k)}{P(x)}$$

Let's look at each component in detail:

- P (yk) portrays how classes are distributed, provided w ith no further know ledge of observation features. Thus, it is also called prior in Bayesian probability terminology. Prior can be either predetermined (usually in a uniform manner w here each class has an equal chance of occurrence) or learned from a set of training samples.
- P(yk |x), in contrast to prior P (yk), is the posterior w ith extra know ledge of observation.
- P(x | yk), or P(x1, x2, …, xn|yk) is the joint distribution of n features, given the sample belongs to class yk. This is how likely the features w ith such values co-occur. This is named likelihood in Bayesian terminology. Obviously, the likelihood w ill be difficult to compute as the number of features increases.
  In Naïve Bayes, this is solved thanks to the feature independence assumption. The joint conditional distribution of n features can be expressed as the joint product of individual feature conditional distributions:

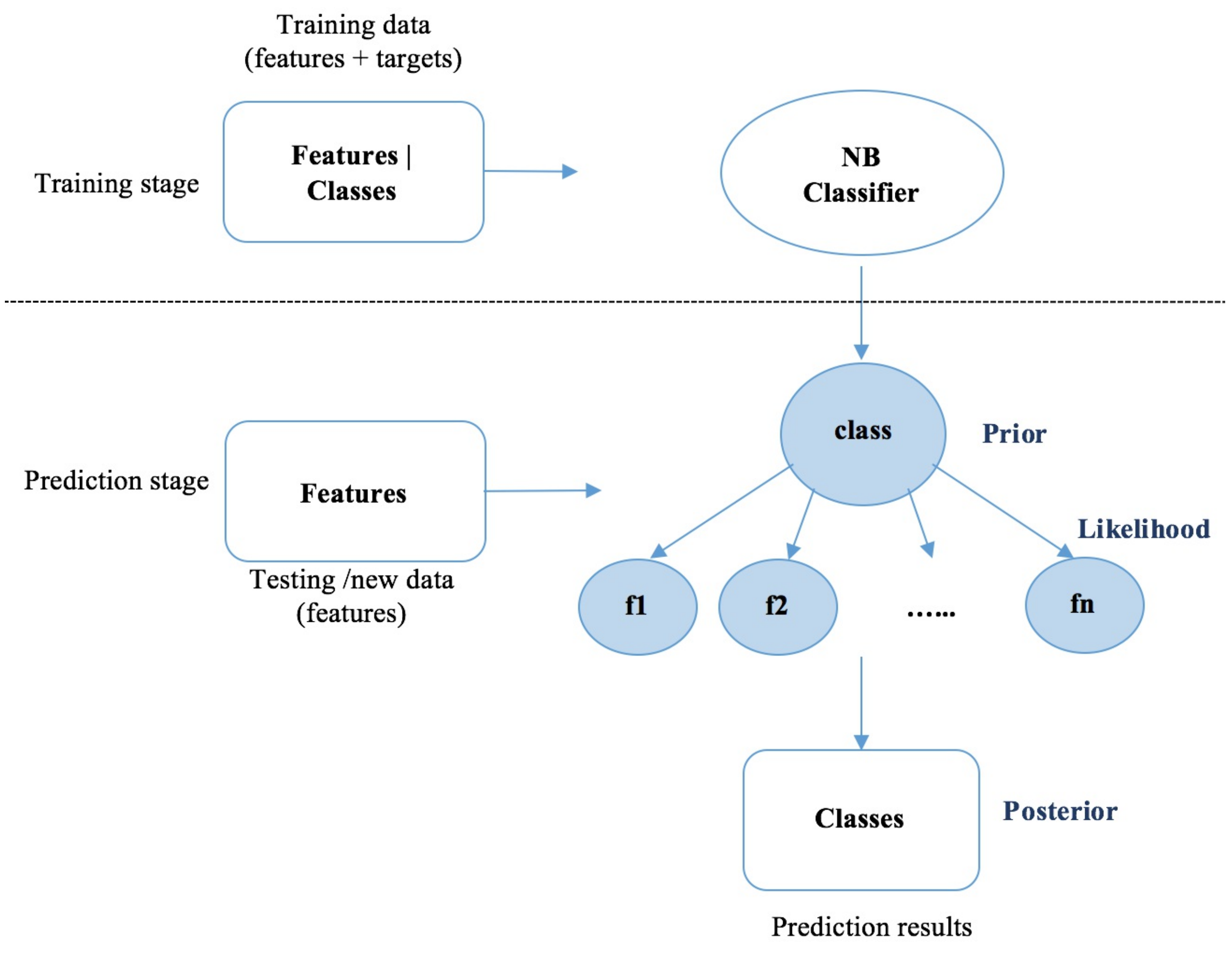
$$P(x|y_k) = P(x_1|y_k) * P(x_2|y_k) * \cdots * P(x_n|y_k)$$

Each conditional distribution can be efficiently learned from a set of training samples.

- P(x), also called evidence, solely depends on the overall distribution of features, w hich is not specific to certain classes and is therefore constant. As a result, posterior is proportional to prior and likelihood:

$$P(y_k|x) \propto P(x|y_k)P(y_k) = P(x_1|y_k) * P(x_2|y_k) * \cdots * P(x_n|y_k) * P(y_k)$$

The follow ing diagram summarizes how a Naïve Bayes classification model is trained and applied to new data:



Let's see a Naïve Bayes classifier in action through an example before w e jump to its implementations. Given four (pseudo) emails show n in the follow ing table, w e are asked to predict how likely it is that a new email is spam:

	ID	Terms in email	Is spam
Training data	1	click win prize	yes
	2	click meeting setup meeting	no
	3	prize free prize	yes
	4	click prize free	yes
Testing case	5	free setup meeting free	?

First, define the S and NS events as an email being spam or not spam respectively. From the training set, w e can easily get the follow ing:

$$P\left(S\right)=3/4$$
$$P\left(NS\right)=1/4$$

Or w e can also impose an assumption of prior that P (S)= 1%.

To calculate P(S |x) w here x = (free, setup, meeting, free), the first step is to compute P(free |S), P(setup |S), and P(meeting |S) based on the training set; that is, the ratio of the occurrence of a term to that of all terms in the S class. How ever, as the term free w as not seen in the NS class training set, P(free |NS) w ill become 0, so w ill P(x |NS) and P(NS |x). It w ill be predicted as spam email, falsely. To eliminate the zero multiplication factor, the unseen term, w e usually set each term frequency an initial value 1, that is, w e start counting term occurrence from one. This technique is also called Laplacesmoothing. With this amendment, now w e have the follow ing:

$$P(free|S) = \frac{2+1}{9+6} = \frac{3}{15}$$
$$P(free|NS) = \frac{0+1}{4+6} = \frac{1}{10}$$

Here, 9 is the total number of term occurrences from the S class (3+3+3), 4 is the total term occurrences from the NS class, and 6 comes from the 1 additional count per term (click, w in, prize, meeting, setup, free). Similarly, w e can compute the follow ing:

$$P(free|S) = \frac{0+1}{9+6} = \frac{1}{15}$$
$$P(free|NS) = \frac{1+1}{4+6} = \frac{2}{10}$$
$$P(meeting|S) = \frac{0+1}{9+6} = \frac{1}{15}$$
$$P(meeting|NS) = \frac{2+1}{4+6} = \frac{3}{10}$$

Hence w e have the follow ing formula:

$$\frac{P(S|x)}{P(NS|x)} = \frac{P(free|S) * P(setup|S) * P(meeting|S) * P(free|S) * P(S)}{P(free|NS) * P(setup|NS) * P(meeting|NS) * P(free|NS) * P(NS)} = 8/9$$

Also, remember this:

$$P(S|x) + P(NS|x) = 1$$

So, finally, w e have the follow ing:

$$P(S|x) = \frac{8}{8+9} = 47.1$$

There is 47.1% chance that the new email is spam.

Implementing Naïve Bayes from scratch

After a hand-calculating spam email detection example, as promised, w e are going to code it through a genuine dataset, taken from the Enron email dataset http://w w w.aueb.gr/users/ion/data/enron-spam/. The specific dataset w e are using can be directly dow nloaded via http://w w w.aueb.gr/users/ion/data/enron-spam/preprocessed/enron1.tar.gz. You can either unzip it using softw are, or run the follow ing command line on your terminal:

`tar -xvz enron1.tar.gz`

The uncompressed folder includes a folder of ham, or non-spam, email text files, and a folder of spam email text files, as w ell as a summary description of the database:

```
enron1/
  ham/
    0001.1999-12-10.farmer.ham.txt
       0002.1999-12-13.farmer.ham.txt
       ……
       ……
    5172.2002-01-11.farmer.ham.txt
  spam/
    0006.2003-12-18.GP.spam.txt
       0008.2003-12-18.GP.spam.txt
       ……
       ……
       5171.2005-09-06.GP.spam.txt
  Summary.txt
```

Given a dataset for a classification problem, it is alw ays good to keep in mind the number of samples per class and the proportion of samples from each class before applying any machine learning techniques. As w ritten in the Summary.txt file, there are 3,672 ham (legitimate) emails and 1,500 spam emails so the spam: the legitimate-to-spam ratio is approximately 1:3 here. If such information w as not given, you can also get the numbers by running the follow ing commands:

```
ls -1 enron1/ham/*.txt | wc -l
3672
ls -1 enron1/spam/*.txt | wc -l
1500
```

Note
Class imbalance is critical to classification performance. Imagine if most samples are from one class—the classifier tends to only learn from the dominant class and neglect the minorities. Hence, paying extra attention to class imbalance is alw ays recommended. If it does occur, w e need to either dow nsample the majority class, or upsample the minor class, in order to mitigate the disproportion.

Let's have a look at a legitimate and a spam email by running the follow ing scripts from the same path w here the unzipped folder is located:

```
>>> file_path = 'enron1/ham/0007.1999-12-14.farmer.ham.txt'
>>> with open(file_path, 'r') as infile:
...     ham_sample = infile.read()
>>> print(ham_sample)
Subject: mcmullen gas for 11 / 99
jackie ,
since the inlet to 3 river plant is shut in on 10 / 19 / 99 ( the
last day of flow ) :
at what meter is the mcmullen gas being diverted to ?
at what meter is hpl buying the residue gas ? ( this is the gas
from teco ,vastar , vintage , tejones , and swift )
i still see active deals at meter 3405 in path manager for teco ,
vastar ,vintage , tejones , and swift
i also see gas scheduled in pops at meter 3404 and 3405 .
please advice . we need to resolve this as soon as possible so
settlement can send out payments .
thanks
```

Similarly, the spam sample is as follow s:

```
>>> file_path = 'enron1/spam/0058.2003-12-21.GP.spam.txt'
>>> with open(file_path, 'r') as infile:
...    spam_sample = infile.read()
>>> print(spam_sample)
Subject: stacey automated system generating 8 k per week parallelogram
people are
getting rich using this system ! now it ' s your
turn !
we ' ve
cracked the code and will show you . . . .
this is the
only system that does everything for you , so you can make
money
. . . . . . . .
because your
success is . . . completely automated !
let me show
you how !
click
here
to opt out click here % random _ text
```

Next, w e read all of the email text files and keep the ham/spam class information in the labels variable, w here 1 represents spam emails, and 0 is for ham.

First, import the necessary modules, glob and os, in order to find all the .txt email files, and initialize the variables, keeping the text data and labels:

```
>>> import glob
>>> import os
>>> emails, labels = [], []
Then, to load the spam email files, run the following commands:
```

> > > file_path = 'enron1/spam/'
> > > for filename in glob.glob(os.path.join(file_path, '*.txt')):
> > > … w ith open(filename, 'r', encoding="ISO-8859-1") as infile:
> > > … emails.append(infile.read())
> > > … labels.append(1)
> > > Load the legitimate email files by running the follow ing commands:

```
>>> file_path = 'enron1/ham/'
>>> for filename in glob.glob(os.path.join(file_path, '*.txt')):
...     with open(filename, 'r', encoding="ISO-8859-1") as infile:
...         emails.append(infile.read())
...         labels.append(0)
>>> len(emails)
5172
>>> len(labels)
5172
```

The next step is to preprocess and clean the raw text data. To briefly recap, this includes the follow ing:

- Number and punctuation removal
- Human name removal (optional)
- Stop-w ord removal
- Lemmatization

We herein reuse the code w e developed in the previous tw o chapters:

```
>>> from nltk.corpus import names
>>> from nltk.stem import WordNetLemmatizer
>>> def is_letter_only(word):
...     return word.isalpha()
>>> all_names = set(names.words())
>>> lemmatizer = WordNetLemmatizer()
```

Put together a function performing text cleaning as follow s:

```
>>> def clean_text(docs):
...     docs_cleaned = []
...     for doc in docs:
...         doc = doc.lower()
...         doc_cleaned = ' '.join(lemmatizer.lemmatize(word)
                    for word in doc.split() if is_letter_only(word)
                    and word not in all_names)
...         docs_cleaned.append(doc_cleaned)
...     return docs_cleaned
>>> emails_cleaned = clean_text(emails)
```

This leads to stop-w ord removal and term feature extraction, as follow s:

```
>>> from sklearn.feature_extraction.text import CountVectorizer
>>> cv = CountVectorizer(stop_words="english", max_features=1000,
                                             max_df=0.5, min_df=2)
>>> docs_cv = cv.fit_transform(emails_cleaned)
```

The max_features parameter is set to 1000, so it only considers the 1,000 most frequent terms, excluding those that are too common (50% max_df) and too rare (2 min_df). We can definitely tw eak this parameter later on in order to achieve higher classification accuracy.

In case you forget w hat the resulting term vectors look like, let's take a peek:

```
>>> print(docs_cv[0])
 (0, 932) 1
 (0, 968) 1
 (0, 715) 1
 (0, 151) 1
 (0, 585) 1
 (0, 864) 1
 (0, 506) 1
 (0, 691) 1
 (0, 897) 1
 (0, 476) 1
 (0, 72)  1
 (0, 86)  2
 (0, 997) 1
 (0, 103) 1
 (0, 361) 2
 (0, 229) 1
 (0, 363) 2
 (0, 482) 2
 (0, 265) 2
```

The sparse vector is in the form of the follow ing:

```
  (row index, term index) term_frequency
```

We can also see w hat the corresponding terms are, as follow s:

```
>>> terms = cv.get_feature_names()
>>> print(terms[932])
unsubscribe
>>> print(terms[968])
website
>>> print(terms[715])
read
```

With the docs_cv feature matrix just generated, w e can now develop and train our Naïve Bayes model, from scratch as alw ays.

Starting w ith the prior, w e first group the data by label and record the index of samples:

```
>>> def get_label_index(labels):
...     from collections import defaultdict
...     label_index = defaultdict(list)
...     for index, label in enumerate(labels):
...         label_index[label].append(index)
...     return label_index
>>> label_index = get_label_index(labels)
```

The resulting label_index looks like {0: [3000, 3001, 3002, 3003, …… 6670, 6671], 1: [0, 1, 2, 3, …., 2998, 2999]}, w here training sample indices are grouped by class. With this, w e calculate prior:

```
>>> def get_prior(label_index):
...     """
...     Compute prior based on training samples
...     @param label_index: grouped sample indices by class
...     @return: dictionary, with class label as key, corresponding
                                                  prior as the value
...     """
...     prior = {label: len(index) for label, index in
                                      label_index.items()}
...     total_count = sum(prior.values())
...     for label in prior:
...         prior[label] /= float(total_count)
...     return prior
>>> prior = get_prior(label_index)
>>> print('Prior:', prior)
Prior: {1: 0.2900232018561485, 0: 0.7099767981438515}
```

With prior calculated, w e continue w ith likelihood:

```
>>> import numpy as np
>>> def get_likelihood(term_matrix, label_index, smoothing=0):
...     """
...     Compute likelihood based on training samples
...     @param term_matrix: sparse matrix of the term frequency features
...     @param label_index: grouped sample indices by class
...     @param smoothing: integer, additive Laplace smoothing parameter
...     @return: dictionary, with class as key, corresponding conditional
                 probability P(feature|class) vector as value
...     """
...     likelihood = {}
...     for label, index in label_index.items():
...         likelihood[label] = term_matrix[index, :].sum(axis=0) +
                                                            smoothing
...         likelihood[label] = np.asarray(likelihood[label])[0]
...         total_count = likelihood[label].sum()
...         likelihood[label] = likelihood[label] /
                                            float(total_count)
```

```
...     return likelihood
```

We set the smoothing value to 1 here, w hich can also be 0 for no smoothing, and any other positive value, as long as high classification performance is achieved:

```
>>> smoothing = 1
>>> likelihood = get_likelihood(docs_cv, label_index, smoothing)
>>> len(likelihood[0])
1000
```

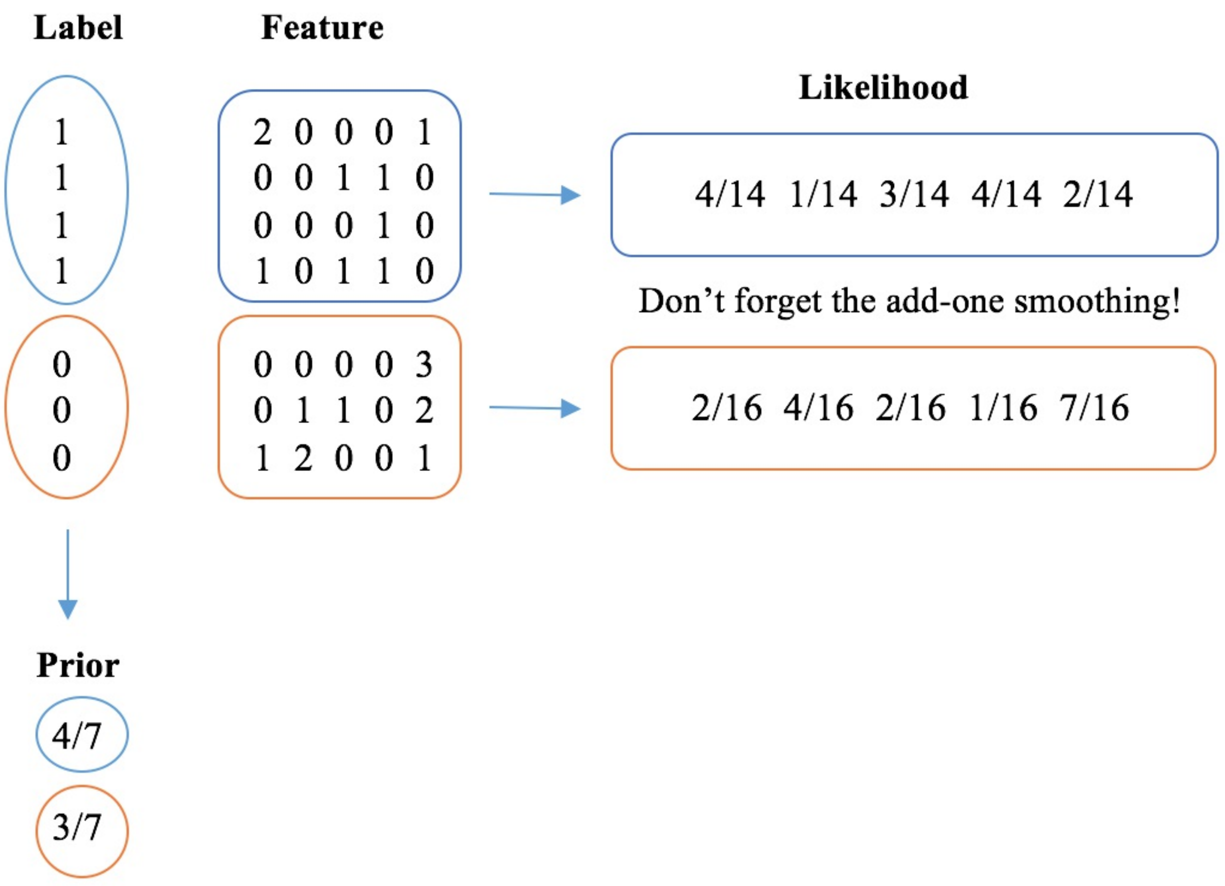
The likelihood[0] parameter is the conditional probability P(feature | legitimate) vector of length 1,000 (1,000 features) for the legitimate class. Probabilities P(feature | legitimate) for the first five features are as follow s:

```
>>> likelihood[0][:5]
[0.00024653 0.00090705 0.00080007 0.00032096 0.00073495]
```

And you can probably guess that likelihood[1] w ould be for the spam class. Similarly, the first five conditional probabilities P(feature | spam)are:

```
>>> likelihood[1][:5]
[0.00063304 0.00078026 0.00101581 0.00022083 0.00326826]
```

If you ever find any of these confusing, feel free to check the follow ing toy example to refresh (14 comes from 2 + 1 + 1 + 1 + 1 + 1 + 1 + smoothing 1 * 5, 16 comes from 1 + 1 + 2 + 1 + 3 + 2 + 1 + smoothing 1 * 5):



With prior and likelihood ready, w e can now compute the posterior for the testing/new samples. There is a trick w e use: instead of calculating the multiplication of hundreds of thousands of small value conditional probabilities of P(feature | class) (for example, 0.00024653, as w e just saw), w hich may cause overflow error, w e instead calculate the summation of their natural logarithms, then convert it back to its natural exponential value:

```
>>> def get_posterior(term_matrix, prior, likelihood):
...     """
...     Compute posterior of testing samples, based on prior and likelihood
...     @param term_matrix: sparse matrix of the term frequency features
...     @param prior: dictionary, with class label as key,
                                  corresponding prior as the value
...     @param likelihood: dictionary, with class label as key,
                     corresponding conditional probability vector as value
...     @return: dictionary, with class label as key, corresponding
                                                  posterior as value
...     """
...     num_docs = term_matrix.shape[0]
...     posteriors = []
...     for i in range(num_docs):
...         # posterior is proportional to prior * likelihood
...         # = exp(log(prior * likelihood))
...         # = exp(log(prior) + log(likelihood))
...         posterior = {key: np.log(prior_label) for key,
                                      prior_label in prior.items()}
...         for label, likelihood_label in likelihood.items():
...             term_document_vector = term_matrix.getrow(i)
...             counts = term_document_vector.data
...             indices = term_document_vector.indices
...             for count, index in zip(counts, indices):
...                 posterior[label] +=
                         np.log(likelihood_label[index]) * count
...         # exp(-1000):exp(-999) will cause zero division error,
...         # however it equates to exp(0):exp(1)
...         min_log_posterior = min(posterior.values())
...         for label in posterior:
...             try:
...                 posterior[label] = np.exp(
                            posterior[label] - min_log_posterior)
...             except:
...                 posterior[label] = float('inf')
...         # normalize so that all sums up to 1
...         sum_posterior = sum(posterior.values())
...         for label in posterior:
...             if posterior[label] == float('inf'):
...                 posterior[label] = 1.0
...             else:
...                 posterior[label] /= sum_posterior
...         posteriors.append(posterior.copy())
...     return posteriors
```

The prediction function is finished. Let's take one ham and one spam sample from another Enron email dataset to quickly verify our algorithm:

```
>>> emails_test = [
...     '''Subject: flat screens
...     hello ,
...     please call or contact regarding the other flat screens
...     requested .
...     trisha tlapek - eb 3132 b
...     michael sergeev - eb 3132 a
...     also the sun blocker that was taken away from eb 3131 a .
...     trisha should two monitors also michael .
...     thanks
...     kevin moore''',
...     '''Subject: let ' s stop the mlm insanity !
...     still believe you can earn $ 100 , 000 fast in mlm ? get real !
...     get emm , a brand new system that replaces mlm with something that works !
...     start earning 1 , 000 ' s now ! up to $ 10 , 000 per week doing simple
...     online tasks .
...     free info - breakfree @ luxmail . com - type " send emm info " in the
...     subject box .
...     this message is sent in compliance of the proposed bill section 301 . per
...     section 301 , paragraph ( a ) ( 2 ) ( c ) of s . 1618 . further transmission
...     to you by the sender of this e - mail may be stopped at no cost to you by
...     sending a reply to : " email address " with the word remove in the subject
...     line .''',
... ]
```

Go through the same cleaning and preprocessing steps as in training stage:

```
>>> emails_cleaned_test = clean_text(emails_test)
>>> term_docs_test = cv.transform(emails_cleaned_test)
>>> posterior = get_posterior(term_docs_test, prior, likelihood)
>>> print(posterior)
[{1: 5.958269329017321e-08, 0: 0.9999999404173067},
{1: 0.9999999999999948, 0: 5.2138625988879895e-15}]
```

For the first email, 99.5% legitimate; the second email nearly 100% spam. Both are predicted correctly.

Further, to comprehensively evaluate our classifier's performance, w e can randomly split the original dataset into tw o sets, the training and testing sets, w hich simulate learning data and prediction data respectively. Generally, the proportion of the original dataset to include in the testing split can be 25%, 33.3%, or 40%. We use the train_test_split function from scikit-learn to do the random splitting and to preserve the percentage of samples for each class:

```
>>> from sklearn.model_selection import train_test_split
>>> X_train, X_test, Y_train, Y_test =
              train_test_split(emails_cleaned, labels, test_size=0.33,
              random_state=42)
```

Note
It is a good practice to assign a fixed random_state (for example, 42) during experiments and exploration in order to guarantee that the same training and testing sets are generated every time the program runs. This allow s us to make sure that the classifier functions and performs w ell on a fixed dataset before w e incorporate randomness and proceed further.

Check the training size and testing size as follow s:

```
>>> len(X_train), len(Y_train)
(3465, 3465)
>>> len(X_test), len(Y_test)
(1707, 1707)
```

Retrain the term frequency CountVectorizer based on the training set and recompute prior and likelihood accordingly:

```
>>> term_docs_train = cv.fit_transform(X_train)
>>> label_index = get_label_index(Y_train)
>>> prior = get_prior(label_index)
>>> likelihood = get_likelihood(term_docs_train, label_index, smoothing)
```

We then convert the testing documents into term matrix as follow s:

```
>>> term_docs_test = cv.transform(X_test)
```

Note
It is noted that w e can't train CountVectorizer using both the training and testing sets. Otherw ise, it w ill cause data leakage, as the testing set is supposed to be unknow n beforehand to all feature extractors. Hence, the term pool and the term counter should be built solely on the training set.

Now, predict the posterior of the testing/new dataset as follow s:

```
>>> posterior = get_posterior(term_docs_test, prior, likelihood)
```

Finally, w e evaluate the model's performance w ith classification accuracy, w hich is the proportion of correct prediction:

```
>>> correct = 0.0
>>> for pred, actual in zip(posterior, Y_test):
...     if actual == 1:
...         if pred[1] >= 0.5:
...             correct += 1
...     elif pred[0] > 0.5:
...         correct += 1
>>> print('The accuracy on {0} testing samples is:
         {1:.1f}%'.format(len(Y_test), correct/len(Y_test)*100))
```

The accuracy on 1707 testing samples is: 93.0%
The NaïveBayesclassifier w e just developed line by line correctly classifies 93% emails!

Implementing Naïve Bayes w ith scikit-learn
Coding from scratch and implementing on your ow n solutions is the best w ay to learn about machine learning model. Of course, w e can take a shortcut by directly using the MultinomialNB class from the scikit-learn API:

```
>>> from sklearn.naive_bayes import MultinomialNB
```

Let's initialize a model w ith a smoothing factor (specified as alpha in scikit-learn) of 1.0, and prior learned from the training set (specified as fit_prior in scikit-learn):

```
>>> clf = MultinomialNB(alpha=1.0, fit_prior=True)
```

To train the Naïve Bayes classifier w ith the fit method, use the follow ing command:

```
>>> clf.fit(term_docs_train, Y_train)
```

And to obtain the prediction results w ith the predict_proba method, use the follow ing commands:

```
>>> prediction_prob = clf.predict_proba(term_docs_test)
>>> prediction_prob[0:10]
[[1.00000000e+00 3.96500362e-13]
[1.00000000e+00 2.15303766e-81]
[6.59774100e-01 3.40225900e-01]
[1.00000000e+00 2.28043493e-15]
[1.00000000e+00 1.77156705e-15]
[5.53261316e-05 9.99944674e-01]
[0.00000000e+00 1.00000000e+00]
[1.00000000e+00 3.49697719e-28]
[1.00000000e+00 4.43498548e-14]
[3.39263684e-01 6.60736316e-01]]
```

Do the follow ing to directly acquire the predicted class values w ith the predict method (0.5 is the default threshold; if the predicted probability of class 1 is great than 0.5, class 1 is assigned, otherw ise, 0 is used):

```
>>> prediction = clf.predict(term_docs_test)
>>> prediction[:10]
[0 0 0 0 0 1 1 0 0 1]
```

Finally, w e measure the accuracy performance by calling the score method:

```
>>> accuracy = clf.score(term_docs_test, Y_test)
>>> print('The accuracy using MultinomialNB is:
                                {0:.1f}%'.format(accuracy*100))
```

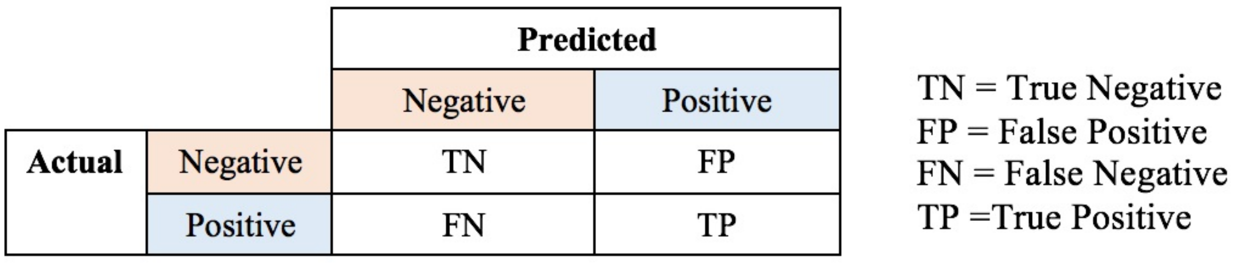
The accuracy using MultinomialNB is: 93.0%

Classification performance evaluation

So far, w e have covered in depth the first machine learning classifier and evaluated its performance by prediction accuracy. Beyond accuracy, there are several measurements that give us more insight and allow us to avoid class imbalance effects. They are as follow s:

- Confusion matrix
- Precision
- recall
- F1 score
- AUC

A confusion matrix summarizes testing instances by their predicted values and true values, presented as a contingency table:



		Predicted	
		Negative	Positive
Actual	Negative	TN	FP
	Positive	FN	TP

TN = True Negative
FP = False Positive
FN = False Negative
TP =True Positive

To illustrate this, w e compute the confusion matrix of our Naïve Bayes classifier. Herein, the confusion_matrix function of scikit-learn is used, but it is very easy to code it ourselves:

```
>>> from sklearn.metrics import confusion_matrix
>>> confusion_matrix(Y_test, prediction, labels=[0, 1])
[[1102   89]
[  31 485]]
```

Note that w e consider 1, the spam class, to be positive. From the confusion matrix, for example, there are 93 false-positive cases (w here it misinterprets a legitimate email as a spam one), and 43 false-negative cases (w here it fails to detect a spam email). So, classification accuracy is just the proportion of all true cases:

$$\frac{TN+TP}{TN+TP+FP+FN} = \frac{1098+473}{1707} = 92.0\%$$

Precision measures the fraction of positive calls that are correct, w hich is

$$\frac{TP}{TP+FP}$$

and

$$\frac{473}{473+93} = 0.836$$

in our case.

Recall, on the other hand, measures the fraction of true positives that are correctly identified, w hich is

$$\frac{TP}{TP + FN}$$

and

$$\frac{473}{473 + 43} = 0.917$$

in our case. Recall is also called true positive rate.

The f1 score comprehensively includes both the precision and the recall, and equates to their harmonic mean:

$$f1 = 2 * \frac{precision * recall}{precision + recall}$$

. We tend to value the f1 score above precision or recall alone.

Let's compute these three measurements using corresponding functions from scikit-learn, as follow s:

```
>>> from sklearn.metrics import precision_score, recall_score, f1_score
>>> precision_score(Y_test, prediction, pos_label=1)
0.8449477351916377
>>> recall_score(Y_test, prediction, pos_label=1)
0.939922480620155
>>> f1_score(Y_test, prediction, pos_label=1)
0.889908256880734
```

0, the legitimate class, can also be view ed as positive, depending on the context. For example, assign the 0 class as pos_label:

```
>>> f1_score(Y_test, prediction, pos_label=0)
0.9483648881239244
```

To obtain the precision, recall, and f1 score for each class, instead of exhausting all class labels in the three function calls above, a quicker w ay is to call the classification_report function:

```
>>> from sklearn.metrics import classification_report
>>> report = classification_report(Y_test, prediction)
>>> print(report)
          precision  recall f1-score support

      0       0.97    0.93     0.95    1191
      1       0.84    0.94     0.89     516

 micro avg    0.93    0.93     0.93    1707
 macro avg    0.91    0.93     0.92    1707
weighted avg  0.93    0.93     0.93    1707
```

Here, avg is the w eighted average according to the proportions of the class.

The measurement report provides a comprehensive view on how the classifier performs on each class. It is, as a result, useful in imbalanced classification, w here w e can easily obtain a high accuracy by simply classifying every sample as the dominant class, w hile the precision, recall, and f1 score measurements for the minority class how ever w ill be significantly low.

Precision, recall, and f1 score are also applicable to the multiclass classification, w here w e can simply treat a class w e are interested in as a positive case, and any other classes as negative cases.

During the process of tw eaking a binary classifier (that is, trying out different combinations of hyperparameters, for example, term feature dimension, a smoothing factor in our spam email classifier), it w ould be perfect if there w as a set of parameters in w hich the highest averaged and class individual f1 scores achieve at the same time. It is, how ever, usually not the case. Sometimes, a model has a higher average f1 score than another model, but a significantly low f1 score for a particular class; sometimes, tw o models have the same average f1 scores, but one has a higher f1 score for one class and low er score for another class. In situations like these, how can w e judge w hich model w orks better? Area under the curve (AUC) of the receiver operating characteristic (ROC) is a united measurement frequently used in binary classification.

The ROC curve is a plot of the true positive rate versus the false positive rate at various probability thresholds, ranging from 0 to 1. For a testing sample, if the probability of a positive class is greater than the threshold, then a positive class is assigned; otherw ise, w e use negative. To recap, the true positive rate is equivalent to recall, and the false positive rate is the fraction of negatives that are incorrectly identified as positive. Let's code and exhibit the ROC curve (under thresholds of 0.0, 0.1, 0.2, …, 1.0) of our model:

```
>>> pos_prob = prediction_prob[:, 1]
>>> thresholds = np.arange(0.0, 1.2, 0.1)
>>> true_pos, false_pos = [0]*len(thresholds), [0]*len(thresholds)
>>> for pred, y in zip(pos_prob, Y_test):
...     for i, threshold in enumerate(thresholds):
...         if pred >= threshold:
               # if truth and prediction are both 1
...             if y == 1:
...                 true_pos[i] += 1
               # if truth is 0 while prediction is 1
...             else:
...                 false_pos[i] += 1
...         else:
...             break
```

Then calculate the true and false positive rates for all threshold settings (remember, there are 516.0 positive testing samples and 1191 negative ones):

```
>>> true_pos_rate = [tp / 516.0 for tp in true_pos]
>>> false_pos_rate = [fp / 1191.0 for fp in false_pos]
Now we can plot the ROC curve with matplotlib:
```

> > > import matplotlib.pyplot as plt
> > > plt.figure()
> > > lw = 2
> > > plt.plot(false_pos_rate, true_pos_rate, color='darkorange', lw =lw)
> > > plt.plot([0, 1], [0, 1], color='navy', lw =lw , linestyle='--')
> > > plt.xlim([0.0, 1.0])
> > > plt.ylim([0.0, 1.05])
> > > plt.xlabel('False Positive Rate')
> > > plt.ylabel('True Positive Rate')
> > > plt.title('Receiver Operating Characteristic')
> > > plt.legend(loc="low er right")
> > > plt.show ()

```
Refer to the following screenshot for the resulting ROC curve:

![](./33.png)

In the graph, the dashed line is the baseline representing random guessing where the true positive rate increases linearly
```

```
>>> from sklearn.metrics import roc_auc_score
>>> roc_auc_score(Y_test, pos_prob)
0.965361984912685
```

Model tuning and cross-validation

Having learned w hat metrics to use to measure a classification model, w e'll now study how to measure it properly. We simply can avoid adopting the classification results from one fixed testing set, w hich w e did in experiments previously. Instead, w e usually apply the k-fold cross-validation technique to assess how a model w ill generally perform in practice.

In the k-fold cross-validation setting, the original data is first randomly divided into the k equal-sized subsets, in w hich class proportion is often preserved. Each of these k subsets is then successively retained as the testing set for evaluating the model. During each trial, the rest k -1 subsets (excluding the one-fold holdout) form the training set for driving the model. Finally, the average performance across all k trials is calculated to generate an overall result:

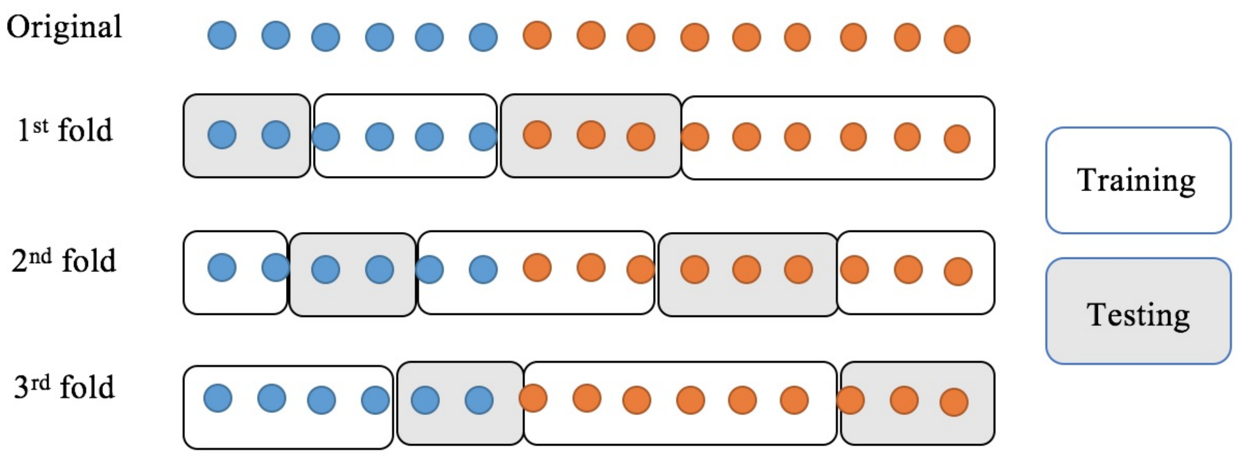


Diagram of 3-fold cross-validation

Statistically, the averaged performance of k-fold cross-validation is an accurate estimate of how a model performs in general. Given different sets of parameters pertaining to a machine learning model and/or data preprocessing algorithms, or even tw o or more different models, the goal of model tuning and/or model selection is to pick a set of parameters of a classifier so that the best averaged performance is achieved. With these concepts in mind, w e can now start to tw eak our Naïve Bayes classifier, incorporating cross-validation and AUC of ROC measurement.

Note
In k-fold cross-validation, k is usually set 3, 5, or 10. If the training size is small, a large k (5 or 10) is recommended to ensure enough training samples in each fold. If the training size is large, a small value (such 3 or 4) w orks fine since a higher k w ill lead to even higher computational cost of training on large dataset.

We herein use the split() method from the StratifiedKFold class of scikit-learn to divide the data into chunks w ith preserved class fractions:

```
>>> from sklearn.model_selection import StratifiedKFold
>>> k = 10
>>> k_fold = StratifiedKFold(n_splits=k, random_state=42)
>>> cleaned_emails_np = np.array(cleaned_emails)
>>> labels_np = np.array(labels)
```

After initializing a 10-fold generator, w e choose to explore the follow ing values for the follow ing parameters:

max_features: This represents the n most frequent terms used as feature space
alpha: This represents the smoothing factor, the initial count for a term
fit_prior: This represents w hether or not to use prior tailored to the training data
We start w ith the follow ing options:

```
>>> max_features_option = [2000, 8000, None]
>>> smoothing_factor_option = [0.5, 1.0, 2.0, 4.0]
>>> fit_prior_option = [True, False]
>>> auc_record = {}
```

Then, for each fold generated by the split() method of the k_fold object, repeat the process of term count feature extraction, classifier training, and prediction w ith one of the aforementioned combinations of parameters, and record the resulting AUCs:

```
>>> for train_indices, test_indices in k_fold.split(emails_cleaned,
                                                     labels):
...     X_train, X_test = cleaned_emails_np[train_indices],
                                cleaned_emails_np[test_indices]
```

```
...     Y_train, Y_test = labels_np[train_indices],
                          labels_np[test_indices]
...     for max_features in max_features_option:
...         if max_features not in auc_record:
...             auc_record[max_features] = {}
...         cv = CountVectorizer(stop_words="english",
                    max_features=max_features, max_df=0.5, min_df=2)
...         term_docs_train = cv.fit_transform(X_train)
...         term_docs_test = cv.transform(X_test)
...         for alpha in smoothing_factor_option:
...             if alpha not in auc_record[max_features]:
...                 auc_record[max_features][alpha] = {}
...             for fit_prior in fit_prior_option:
...                 clf = MultinomialNB(alpha=alpha, fit_prior=fit_prior)
...                 clf.fit(term_docs_train, Y_train)
...                 prediction_prob = clf.predict_proba(term_docs_test)
...                 pos_prob = prediction_prob[:, 1]
...                 auc = roc_auc_score(Y_test, pos_prob)
...                 auc_record[max_features][alpha][fit_prior] =
                            auc+ auc_record[max_features][alpha].get(
                            fit_prior, 0.0)
```

Finally, w e present the results as follow s:

```
>>> print('max features  smoothing fit prior auc')
>>> for max_features, max_feature_record in auc_record.items():
...     for smoothing, smoothing_record in max_feature_record.items():
...         for fit_prior, auc in smoothing_record.items():
...             print(' {0}      {1}   {2}
                   {3:.5f}'.format(
                   max_features, smoothing, fit_prior, auc/k))
max features  smoothing   fit prior   auc
        2000      0.5      False     0.97421
        2000      1.0      True      0.97237
        2000      1.0      False     0.97238
        2000      2.0 .    True      0.97043
        2000      2.0      False     0.97057
        2000      4.0      True      0.96853
        2000      4.0      False     0.96843
        8000      0.5      True      0.98533
        8000      0.5      False     0.98530
        8000      1.0      True      0.98428
        8000      1.0      False     0.98430
        8000      2.0      True      0.98338
        8000      2.0      False     0.98337
        8000      4.0      True      0.98291
        8000      4.0      False     0.98296
        None      0.5      True      0.98890
        None      0.5      False     0.98884
        None      1.0      True      0.98899
        None      1.0      False     0.98904
        None      2.0      True      0.98906
        None      2.0      False     0.98915
        None      4.0      True      0.98965
        None      4.0      False     0.98969
```

The (None, 4.0, False) set enables the best AUC, at 0.98969. In fact, not limiting the maximal number of features outperforms doing so, as 4.0, the highest smoothing factor, alw ays beats other values. Hence, w e conduct a second tw eak, w ith the follow ing options for greater values of smoothing factor:

```
>>> max_features_option = [None]
>>> smoothing_factor_option = [4.0, 10, 16, 20, 32]
>>> fit_prior_option = [True, False]
```

Repeat the cross-validation process and w e get the follow ing results:

```
max features  smoothing   fit prior   auc
      None       4.0        True    0.98965
      None       4.0        False   0.98969
      None       10         True    0.99208
      None       10         False   0.99211
      None       16         True    0.99329
      None       16         False   0.99329
      None       20         True    0.99362
      None       20         False   0.99362
      None       32         True    0.99307
      None       32         False   0.99307
```

The (None, 20, False) set enables the best AUC, at 0.99362!

Summary

In this chapter, w e acquired the fundamental and important concepts of machine learning classification, including types of classification, classification performance evaluation, cross-validation, and model tuning,as w ell as learning about the simple yet pow erful classifier, Naïve Bayes. We w ent in depth through the mechanics and implementations of Naïve Bayes w ith couple of examples and the most important one, the spam email detection project. In the end, w e developed a high-performing spam detector w ith AUC score close to 1.

Binary classification is our main talking point of this chapter, and as you can imagine, multiclass classification w ill be that of the next chapter. Specifically, w e w ill talk about support vector machines (SVMs) for classification.