# EE 219
# Large-Scale Data Mining: Models and Algorithms

## Project 2
## Classification Analysis
## Winter 2017

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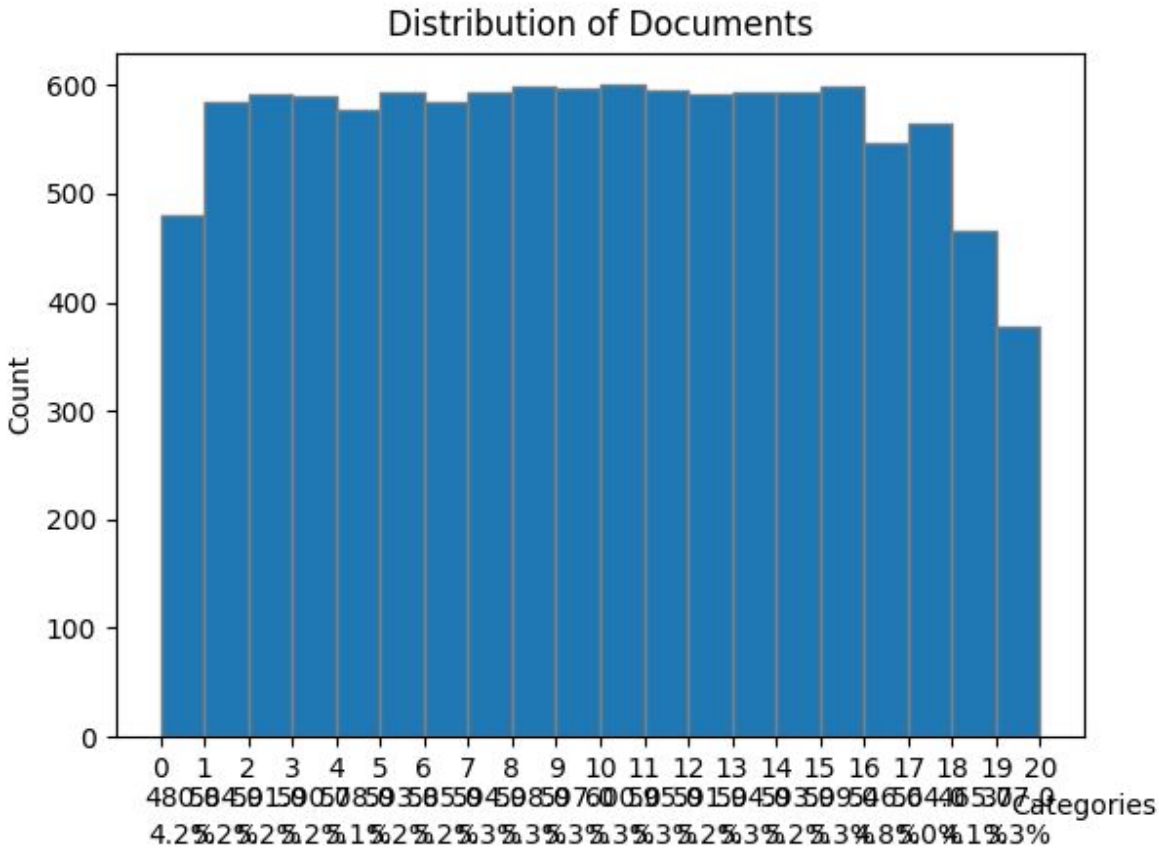
**a. Dataset and Problem Statement**

The 20newsgroups dataset has about 18000 newsgroups posts on 20 topics split into two subsets: one for training and the other for testing. The split is based on the message posted before and after a specific date. There are 2354 documents of computer technology and 2389 documents of recreational activity. The numbers are fairly close, therefore there is no need to adjust the number of documents in preprocessing.

To make the datasets more balanced, we need to sample the data randomly and reduce the the number of classes to the lowest number of original classes. Here we plot a histogram (Figure 1) of the number of documents per topic to make sure they are evenly distributed.



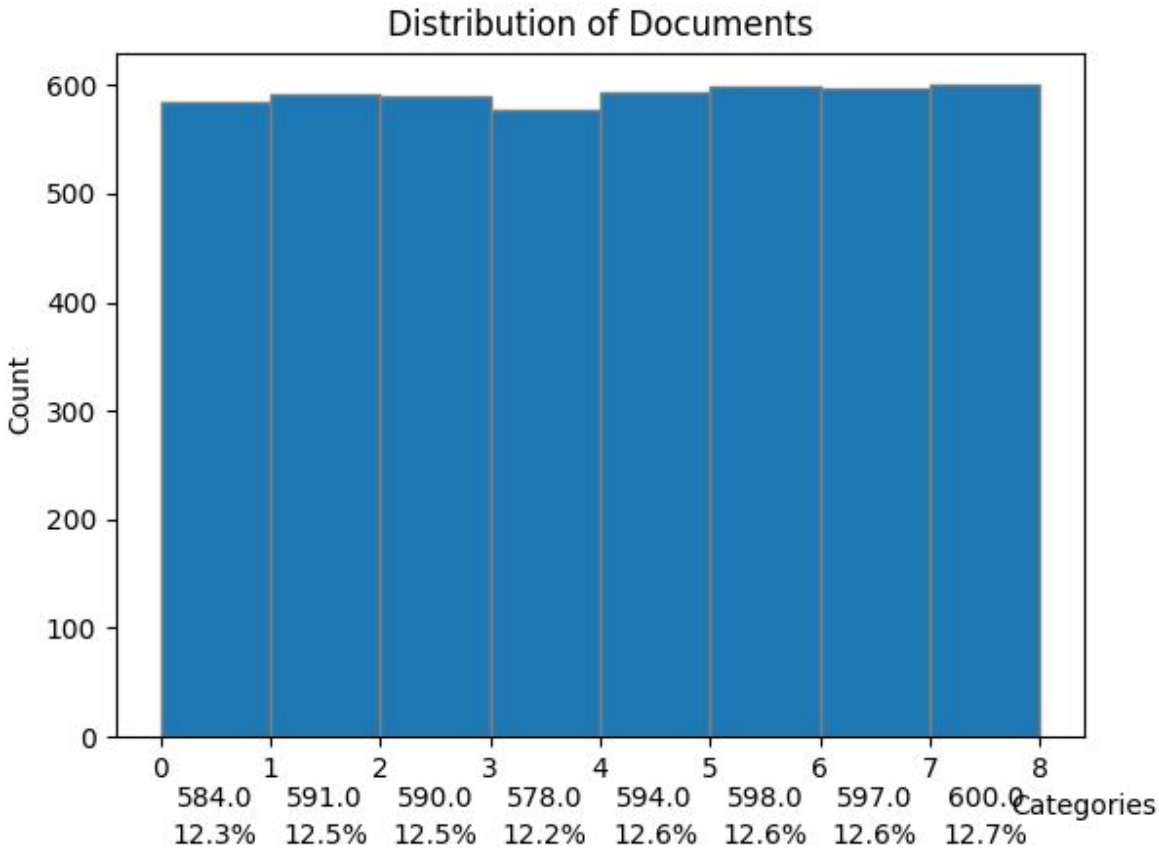



Figure 1 Histogram of the Number of Documents

**b. TFxIDF Vector Representations**

For this part, we use "Bag of Words" assumption. This model is a simplifying representation used in natural language processing and information retrieval. It is commonly used in document classification, where the frequency of occurrence of every word is treated as a feature for traning classifiers. The documents in our datasets will be represented as the bag of words, regardless of the grammar and word orders. The different stems of verbs, stop words and punctuations should be removed. In addition, special characters and words containing numbers will also be removed as they rarely occur.

TFxIDF is the short for Frequency Inverse Document Frequency. It is a numerical statistic intended to reflect how significant a words is to a document in a corpus of text. Given this, it is often used as a weight factor in information retrieval and text mining. The TFxIDF value is proportional to the number of times a word appears in a document, but is offset by the frequency

of the word in the corpus, which helps to adjust for the fact that some words appear more frequently than others.

We use TfidfVectorizer of the sklearn package to calculate all 11314 documents in 20 classes. In the end there are 54357 features.

**c. TFxICF and 10 Significant Terms**

In part c, we find out whether a term is significant to a class in order to treat the whole set of documents in the same class as one document and calculate its TFxICF value. To calculate the 10 most significant terms in the following four classes: comp.sys.ibm.pc.hardware , comp.sys.mac.hardware, misc.forsale, and soc.religion.christian, we use CountVectorizer instead of fidfVectorizer in sklearn, as TFxICF is not an viable option in this package. The 10 most significant terms are listed in Table 1:

| Rank | comp.sys.ibm.pc.hardware | comp.sys.mac.hardware | misc.forsale | soc.religion.christian |
|---|---|---|---|---|
| 1 | balog | powerbook | sabretoo | clh |
| 2 | penev | lcii | liefeld | liturgy |
| 3 | scsiha | iis | hobgoblin | kulikauska |
| 4 | husak | adb | uccxkvb | mmalt |
| 5 | korenek | bmug | radley | copt |
| 6 | buslog | iivx | kou | caralv |
| 7 | laton | iifx | keown | monophysit |
| 8 | fasst | jartsu | koutd | mussack |
| 9 | mbyet | firstclass | spiderm | sspx |
| 10 | schaufenbuel | macus | mcfarlane | atterlep |

Table 1: 10 Most Significant Terms in 4 Classes

**d. Latent Semantic Indexing**

Latent Semantic Indexing (LSI) is a dimension reducing transform that finds the optimal representation of the data in a lower dimensional space in the mean squared error sense. It can

be obtained by computing eigenvectors corresponding to the largest eigen values of the term-document matrix. The new low dimensional representations are the magnitudes of the projections of the documents into these latent topics. In this part, LSI is applied to the TFxIDF matrix with k = 50. Each document is mapped to a 50-dimensional vector. The selected features will then be used in our learning algorithm.

**e. Hard Margin SVM**

In the binary classification problem, we choose eight classes and separate the into two classes: Computer Technology and Recreational Activity, with 0 and 1 assigned to them correspondingly. The number of each subclass is close enough, therefore we do not need to balance the datasets.

In the hard margin SVM, the objective function is

$$min\frac{1}{2}\|W\|_2^2$$

And the constraint is

$$y_i(W^T\overrightarrow{x_i}+b)\geq 1, i\in\{1,...,n\}$$

We set C to 100000 to make sure that the effect of hard margin is shown. The average precision is 96.83%, the average recall is 98.11% and the accuracy is 97.43%. The confusion table and the ROC curve are shown in Table 2 and Figure 2 respectively.

| | Predicted comp | Predicted rect |
|---|---|---|
| Actual comp | 1509 | 51 |
| Actual rect | 30 | 1560 |

Table 2

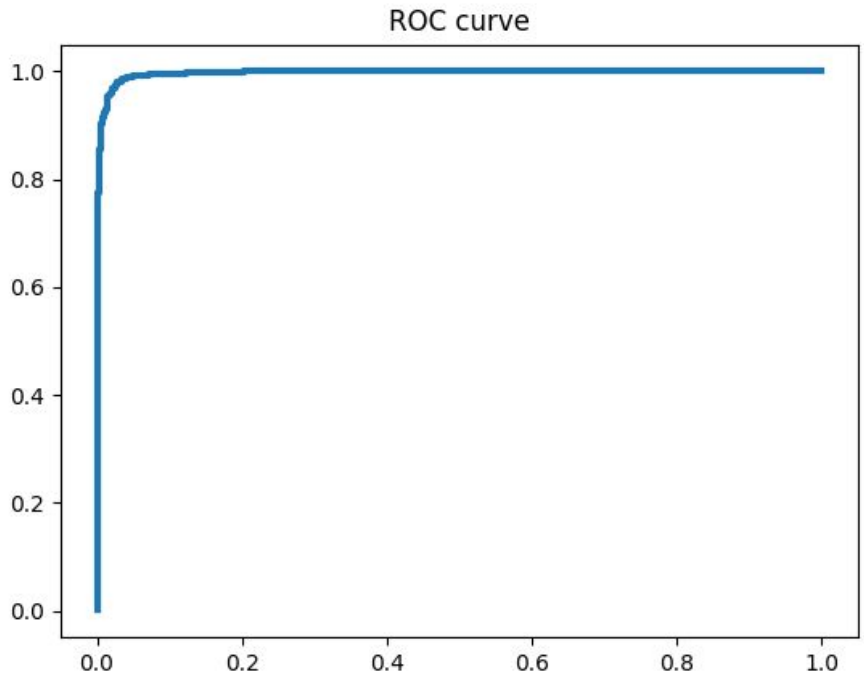



Figure 2

**f. Soft Margin SVM**

Although the hard margin SVM gives fairly good precision, average recall and accuracy for our classifier, it may create overfitting for our data. One alternative is to use the soft margin SVM. In this model, we add error parameter in the objective function and the constraints:

$$min\frac{1}{2}\|W\|_2^2 + \gamma\sum_{i=1}^{n}\xi_i$$

Accordingly, the constraints are:

$$y_i(W^T\overrightarrow{x_i} + b) \geq 1 - \xi_i, \xi_i \geq 0, i \in \{1, ..., n\}$$

The $\gamma$ is the hyperparameter. Different values of $\gamma$ will affect the classification results. We implement 5-fold cross validation to fit the model and choose the optimal $\gamma$ value. The best $\gamma$ value we could obtain is 100. The average precision is 98.11%, the average recall is 98.36% and the accuracy is 98.22%. The confusion matrix and the ROC curve are shown in Table 3.

| | Predicted Comp | Predicted Rect |
|---|---|---|
| Actual Comp | 769 | 15 |
| Actual Rect | 13 | 779 |

Table 3

**g. Naive Bayes Classifier**

In this part, we perform the same classification task but with naive Bayes algorithm. This algorithm estimates the maximum likelihood probability of a class given a document with feature set based on the assumption that given the class, the features are statistically independent. The assumption may seem too simple, but this algorithm actually performs well for many practical problems and operates fast.

score= 0.900317460317
precision= 0.915364583333
recall= 0.88427672956
auc= 0.952333293017

We first use our matrix to train a Gaussian naive Bayes classifier. The precision is 91.54%, the recall is 88.43% and the accuracy is 90.03%. The confusion matrix and the ROC curve are shown in Table 4 and Figure 4 respectively. The area under the curve is 0.9523.

| | Predicted Comp | Predicted Rect |
|---|---|---|
| Actual Comp | 1430 | 130 |
| Actual Rect | 184 | 1406 |

Table 4

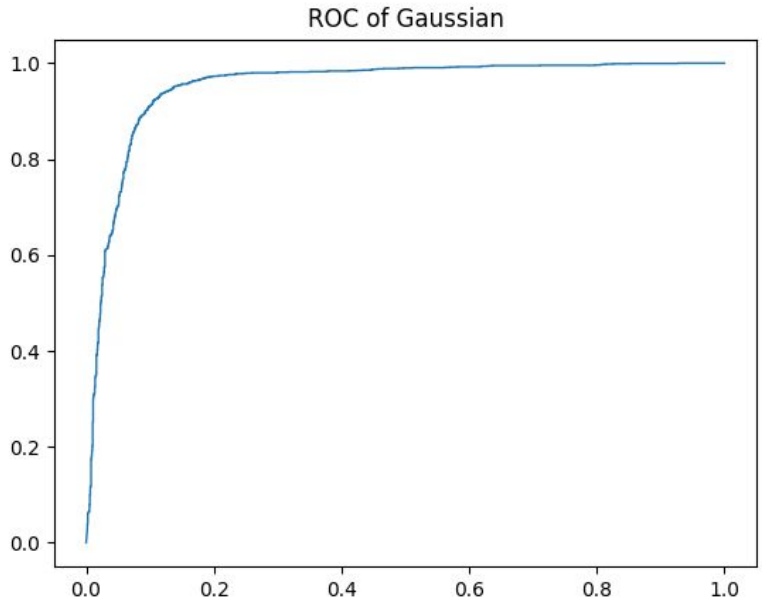



Figure 4

We also implement a Bernoulli naive Bayes classifier, which is suitable for text classification as well and may be better than the multinomial one. The main difference is that Bernoulli penalizes the non-occurrence of a feature explicitly. However, it should be noted that Bernoulli is only suitable for binary-value features. Therefore we first need to binarize the features before training the classifier.

The precision is 91.46%, the recall is 91.57% and the accuracy is 91.43%. The confusion matrix and the ROC curve are shown in Table 5 and Figure 5. The area under the curve is 0.9639.

| | Predicted Comp | Predicted Rect |
|---|---|---|
| Actual Comp | 1424 | 136 |
| Actual Rect | 134 | 1456 |

Table 5

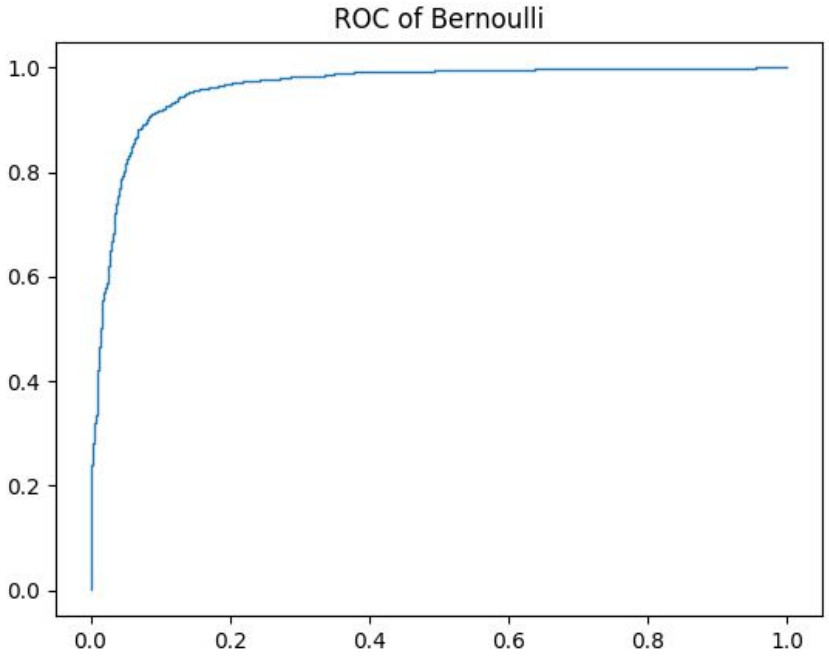



Figure 5

The result tells us that the performance of both kinds of classifiers are similar to each other and both can achieve accuracy of about 90%.

**h. Logistic Regression Classifier**

In this part, we perform the same task as in g but with the logistic regression classifier. Logistic regression measures the relationship between the categorical dependent variable and one or more independent variables by estimating probabilities using a logistic function, which is the cumulative logistic distribution. Thus it's analogous to a regression function. Our data are as follows.

The accuracy is 97.27%, the precision is 96.48% and the recall is 98.18%. The area under the curve is 99.66%.

| | Predicted Comp | Predicted Rect |
|---|---|---|
| Actual Comp | 1503 | 57 |
| Actual Rect | 29 | 1561 |

Table 5

We also plot the ROC curve of Logistic Regression along with the ROC curves of other algorithms in Figure 6.

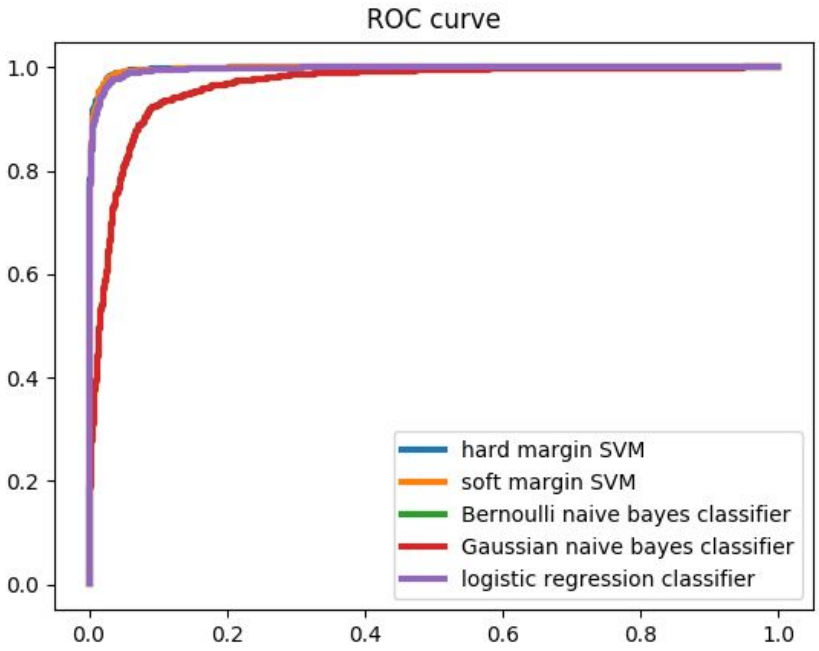



Figure 6

From Figure 6, we can see that Logistic Regression and SVM have almost the same area under the ROC, which implies that they classify the records correctly, while Naive Bayes has the least amongst all algorithms, which implies that some records are not correctly classified by it.

**i-1. Logistic Regression with Regulation**

In this part we again apply the logistic regression algorithm, but this time we add a regularization term to the optimization objective. There are two alternatives, L1 and L2 regularization. Both provide some sort of penalization function to optimize logistic regression algorithm. We will first try both l1 and l2 norm regularization and then sweep through different regularization coefficients, ranging from very small ones to large ones.

Under L1 norm regularization, the precision is 95.98%, the accuracy is 96.73% and the recall is 97.61%. The confusion matrix and the ROC curve are shown in Table 6 and Figure 6. The area under curve is 0.9956.

| | Predicted Comp | Predicted Rect |
|---|---|---|
| Actual Comp | 1495 | 65 |
| Actual Rect | 38 | 1552 |

Table 6

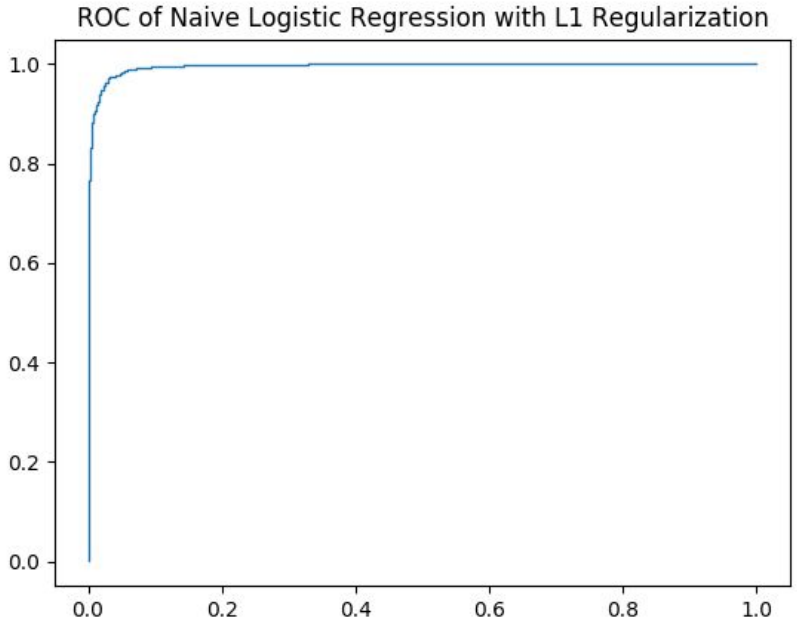



Figure 7

Under L2 regularization, the precision is 95.34%, the accuracy is 96.54% and the recall is 97.92%. The confusion matrix and the ROC curve are shown in Table 7 and Figure 7. The area under curve is 0.9950.

| | Predicted Comp | Predicted Rect |
|---|---|---|
| Actual Comp | 1484 | 76 |
| Actual Rect | 33 | 1557 |

Table 8

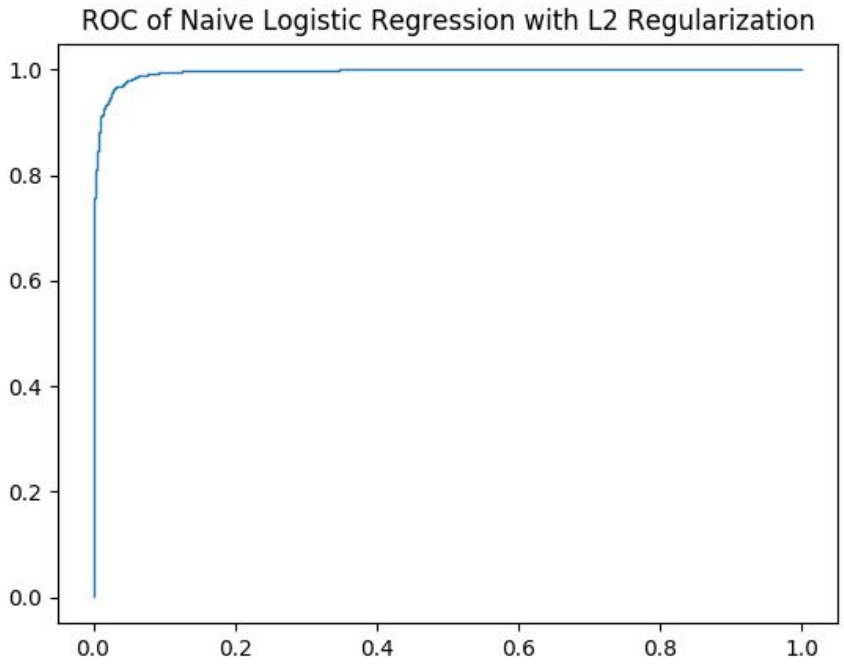



Figure 9

The results we obtained show that when trained with data after LSI processing, the form of norm regularization do not have a very obvious effect on the performance of the logistic regression classifier.

To better observe the effect of the regularization parameter, we try to sweep through different values of coefficients, from 0.01 to 10000. The corresponding measurements are as follows.

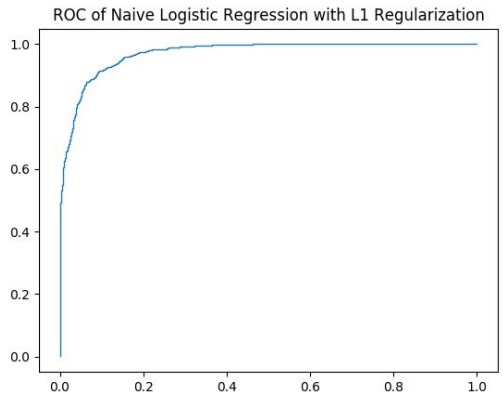
For l1 regularization:

| coefficient | Confusion matrix | Accuracy | Precision | Recall | Area under the curve |
|---|---|---|---|---|---|
| 0.01 | [[1495 65]<br>[ 304 1286]] | 88.29% | 95.19% | 80.88% | 0.9715 |
| 0.1 | [[1477 83]<br>[ 45 1545]] | 95.94% | 94.90% | 97.17% | 0.9931 |
| 1 | [[1494 66]<br>[ 38 1552]] | 96.70% | 95.92% | 97.61% | 0.9956 |

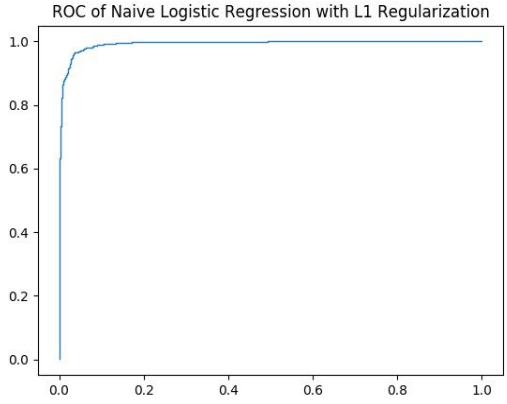
| | | | | | |
|---|---|---|---|---|---|
| 10 | [[1509 51]<br>[ 30 1560]] | 97.43% | 96.83% | 98.11% | 0.9970 |
| 100 | [[1509 51]<br>[ 32 1558]] | 97.37% | 96.83% | 98.00% | 0.9970 |
| 1000 | [[1508 52]<br>[ 33 1557]] | 97.30% | 96.77% | 97.92% | 0.9970 |
| 10000 | [[1508 52]<br>[ 33 1557]] | 97.30% | 96.77% | 97.92% | 0.9970 |

Table 9 L1 Regularization Measurements

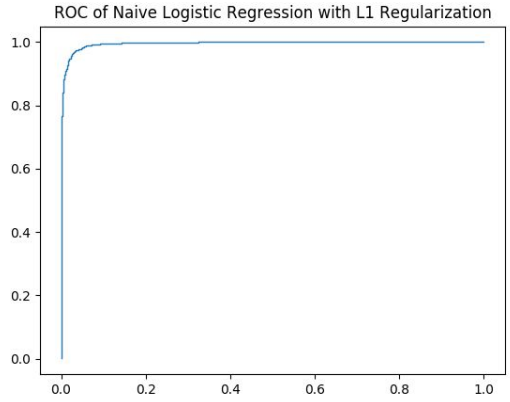
C = 0.01



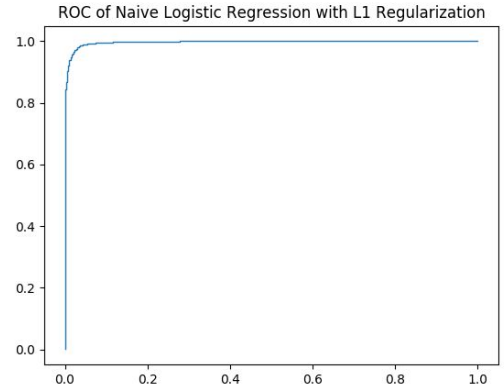

C = 0.1



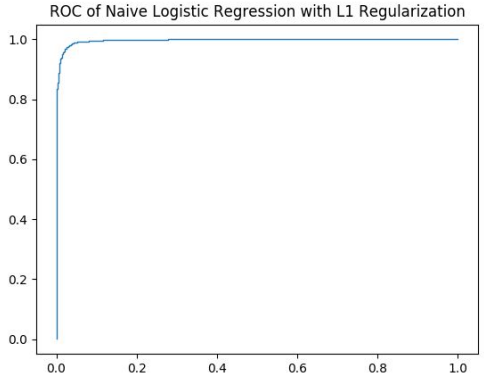

C = 1



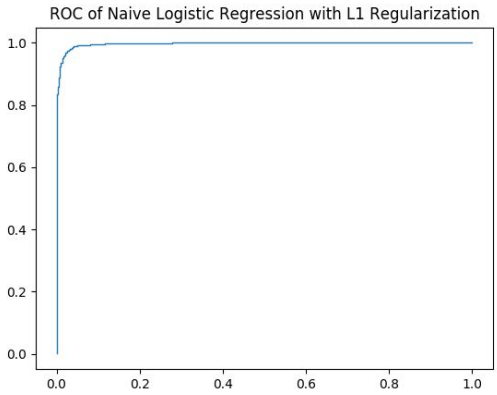

C = 10



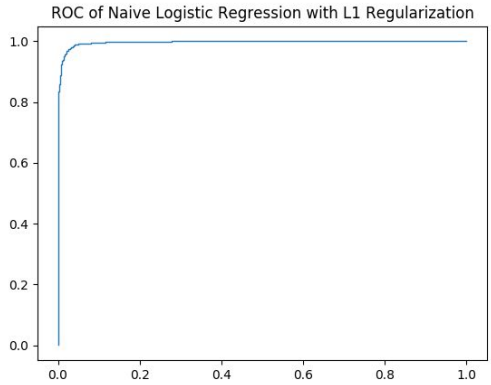
C = 100




C = 1000




C = 10000




We can see that the choice of coefficients affect the results significantly. When the regularization coefficient is too small (0.01, 0.1, 1), or too large(1000, 10000), the results are not very ideal. When the coefficient is some middle values like 10 and 100, all measurements are fairly good and the fitted hyperplane is able to classify data more accurately.

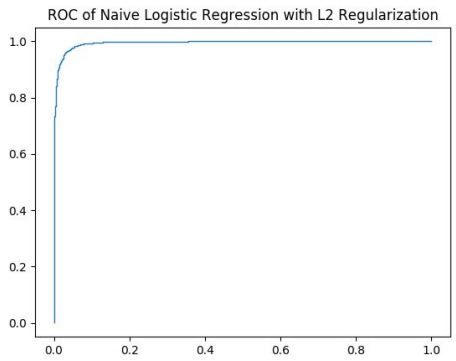
For l2 regularization:

| coefficient | Confusion matrix | Accuracy | Precision | Recall | Area under the curve |
|---|---|---|---|---|---|
| 0.01 | [[1384 176]<br>[ 8 1582]] | 94.16% | 90.00% | 99.50% | 0.9946 |
| 0.1 | [[1484 76]<br>[ 33 1557]] | 96.54% | 95.35% | 97.92% | 0.9950 |

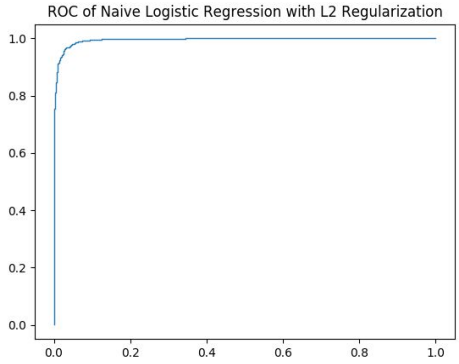
| | | | | | |
|---|---|---|---|---|---|
| 1 | [[1497 63]<br>[ 36 1554]] | 96.86% | 96.10% | 97.74% | 0.9957 |
| 10 | [[1503 57]<br>[ 28 1562]] | 97.30% | 96.48% | 98.24% | 0.9965 |
| 100 | [[1505 55]<br>[ 29 1561]] | 97.33% | 96.60% | 98.18% | 0.9968 |
| 1000 | [[1508 52]<br>[ 32 1558]] | 97.33% | 96.77% | 97.99% | 0.9969 |
| 10000 | [[1508 52]<br>[ 33 1557]] | 97.30% | 96.77% | 97.92% | 0.9969 |

Table 10 L2 Regularization Measurements

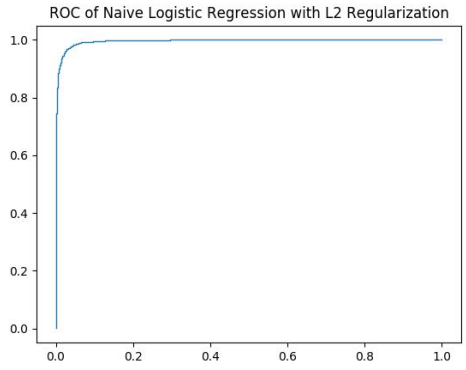
C = 0.01



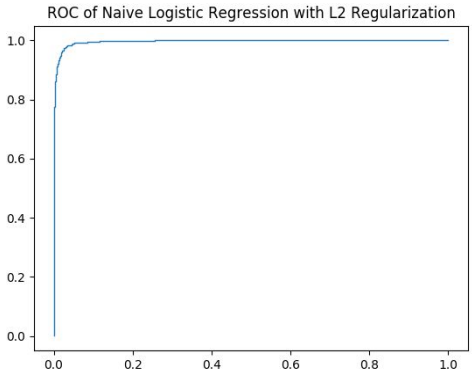

C = 0.1




C = 1

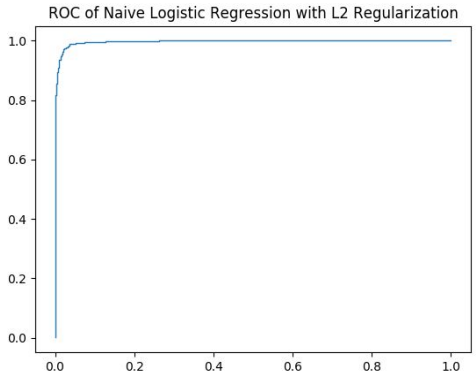


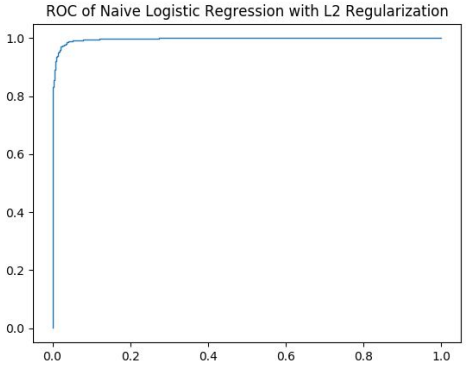

C = 10



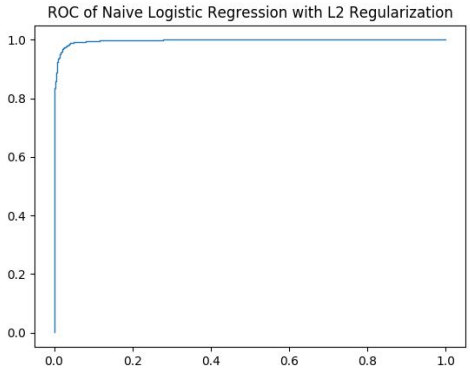

C = 100

C = 1000




C = 10000




Similarly for l2 regularization, the choice of coefficients also affect the results: values too small or too large will generate non-ideal results. For l2 regularization, 10 and 100 tend to make a better fitted hyperplane.

To sum up, by applying both l1 and l2 norm regularizations and sweeping through different regularization coefficients, it appears that small (but not too small) values for parameters correspond to a simpler hypothesis and a simpler hypothesis is less prone to overfitting. In other words, smaller values tend to have fewer test errors and larger ones more. The coefficients of the fitted hyperplane are supposed to be those that separate the two target classes. When we have less error, it means the separation of two classes are good and the coefficients of the fitted hyperplane will decrease. In the reverse case where the separation of two classes is not handled well the coefficients will increase. Thus the choice of coefficient values will affect the final results of logistic regression.

We also observe that L1 regularization works well for recovering truly sparse data points, as they are computationally tractable but still capable of recovering the exact sparse solution. L2 regularization is preferable for data that is not at all sparse, i.e. where we do not expect

regression coefficients to show a decaying property. Therefore, depending on the characteristics of the data, we may be interested in different types of regularization.

**i-2. Multiclass Classification**

In this part we perform naive Bayes classification and multiclass SVM classification. Here we first discuss the unbalancing strategy between the 4 target classes. The number of files in each class is shown in Table 8. All 4 c lasses have about 390 files. Thus it is well-balanced.

| Class Name | Number of Files |
|---|---|
| comp.sys.ibm.pc.hardware | 392 |
| comps.sys.mac.hardware | 385 |
| misc.forsale | 390 |
| soc.religion.christian | 398 |

Table 8 Number of Files

The naive Bayes classifier performs the multiclass classification inherently. It finds the class with the maximum likelihood given the datasets. We implement both Gaussian and Bernoulli naive Bayes classifiers.

**Gaussian**

For Gaussian classifier, the precision is 70.22%, the accuracy is 67.09% and the recall is 67.09%. The confusion matrix is shown in Table 9. The performance of Gaussian classifier is much worse than the binary case. Most of the errors occur between the first two classes - this may suggest that the content of these classes are quite similar. Thus, this classifier can not distinguish them.

| Predicted | pc.hardware | mac.hardware | forsale | christian |
|---|---|---|---|---|
| Actual pc.hardware | 244 | 36 | 112 | 0 |
| Actual mac.hardware | 98 | 142 | 144 | 1 |
| Actual forsale | 41 | 36 | 313 | 0 |
| Actual christian | 4 | 0 | 43 | 351 |

Table 9

**Bernoulli**

For Bernoulli classifier, the precision is 83.33%, the accuracy is 83.19% and the recall is 83.19%. The confusion matrix is shown in Table 10. The matrix show that the Bernoulli gives much better performance than the Gaussian classifier. Although there are still errors in the first two classes, the total number has decreased. This may be due to the feature binarization, with which we can distinguish between the ibm pc and mac.

| Predicted | pc.hardware | mac.hardware | forsale | christian |
|---|---|---|---|---|
| Actual pc.hardware | 296 | 69 | 25 | 2 |
| Actual mac.hardware | 62 | 299 | 21 | 3 |
| Actual forsale | 43 | 28 | 313 | 6 |
| Actual christian | 2 | 1 | 1 | 394 |

Table 10

**One VS One SVM**

To implement SVM for multiclass classification, one way is to create a set of one-to-one SVMs between each pair of target classes, each of which vote for one of the two classes for a given piece of data. The class with highest votes will be picked.

We implement soft margin SVMs and set $\gamma$ to 100. The precision is 88.29%, the accuracy is 88.24% and the recall is 88.24%. The confusion matrix is shown in Table 11.

| Predicted | pc.hardware | mac.hardware | forsale | christian |
|---|---|---|---|---|
| Actual pc.hardware | 318 | 50 | 24 | 0 |
| Actual mac.hardware | 35 | 324 | 26 | 0 |
| Actual forsale | 26 | 16 | 348 | 0 |

| | | | | |
|---|---|---|---|---|
| Actual christian | 4 | 1 | 2 | 391 |

Table 11

**One VS Rest SVM**

Another way to implement SVM for multiclass classification is to create a set of one vs. rest SVMs for every class. We only need n classifiers for n classes for efficiency. Since each class is represented by a classifier, it is convenient for us to gain insight into the classes.

We implement soft margin SVMs and set $\gamma$ to 100. The precision is 88.65%, the accuracy is 88.63% and the recall is 88.63%. The confusion matrix is shown in Table 12.

| Predicted | pc.hardware | mac.hardware | forsale | christian |
|---|---|---|---|---|
| Actual pc.hardware | 318 | 45 | 27 | 2 |
| Actual mac.hardware | 32 | 326 | 26 | 1 |
| Actual forsale | 19 | 15 | 354 | 2 |
| Actual christian | 5 | 1 | 3 | 389 |

Table 12

We learn from the results that SVM classifiers outperform the naive Bayes classifiers and achieve an accuracy of near 90%. The first two classes are very similar to each other while the last class is most different from all other classes.

**Appendices**

C:
number of terms: 54357

comp.sys.ibm.pc.hardware
[u'balog', u'penev', u'scsiha', u'husak', u'korenek', u'buslog', u'laton', u'fasst', u'mbyet', u'schaufenbuel']

comp.sys.mac.hardware
[u'powerbook', u'lcii', u'iis', u'adb', u'bmug', u'iivx', u'iifx', u'jartsu', u'firstclass', u'macus']

misc.forsale
[u'sabretoo', u'liefeld', u'hobgoblin', u'uccxkvb', u'radley', u'kou', u'keown', u'koutd', u'spiderm', u'mcfarlane']

soc.religion.christian
[u'clh', u'liturgy', u'kulikauska', u'mmalt', u'copt', u'caralv', u'monophysit', u'mussack', u'sspx', u'atterlep']

E
[[1509   51]
 [  30 1560]]
score =  0.974285714286
precision =  0.96834264432
recall =  0.981132075472

G
GaussianNB
confusion matrix:
[[1430  130]
 [ 184 1406]]
score= 0.900317460317
precision= 0.915364583333
recall= 0.88427672956
auc= 0.952333293017

BernoulliNB, -0.007
confusion matrix:
[[1430  130]
 [ 152 1438]]
score= 0.910476190476
precision= 0.917091836735
recall= 0.904402515723
auc= 0.96217989034

BernoulliNB, -0.0075
confusion matrix:
[[1429  131]
 [ 142 1448]]
score= 0.913333333333
precision= 0.917036098797
recall= 0.910691823899
auc= 0.962514916949

BernoulliNB, -0.008
confusion matrix:
[[1424  136]
 [ 134 1456]]
score= 0.914285714286
precision= 0.914572864322
recall= 0.91572327044
auc= 0.963884857281

H1

LR1
confusion matrix:
[[1495   65]
 [  38 1552]]
score= 0.967301587302
precision= 0.959802102659
recall= 0.976100628931
auc= 0.99559425899

LR2
confusion matrix:
[[1484   76]
 [  33 1557]]
score= 0.965396825397
precision= 0.953459889773

recall= 0.979245283019
auc= 0.995007660055

LR1: 0.01
confusion matrix:
[[1495   65]
 [ 304 1286]]
score= 0.882857142857
precision= 0.951887490748
recall= 0.808805031447
auc= 0.971544912111

LR2: 0.01
confusion matrix:
[[1384  176]
 [   8 1582]]
score= 0.941587301587
precision= 0.899886234357
recall= 0.994968553459
auc= 0.994629495243

LR1: 0.1
confusion matrix:
[[1477   83]
 [  45 1545]]
score= 0.959365079365
precision= 0.949017199017
recall= 0.971698113208
auc= 0.993092646347

LR2: 0.1
confusion matrix:
[[1484   76]
 [  33 1557]]
score= 0.965396825397
precision= 0.953459889773

recall= 0.979245283019
auc= 0.995002418965

LR1: 1
confusion matrix:
[[1494   66]
 [  38 1552]]
score= 0.966984126984
precision= 0.959208899876
recall= 0.976100628931
auc= 0.995603934849

LR2: 1
confusion matrix:
[[1497   63]
 [  36 1554]]
score= 0.968571428571
precision= 0.961038961039
recall= 0.977358490566
auc= 0.995669246896

LR1: 10
confusion matrix:
[[1509   51]
 [  30 1560]]
score= 0.974285714286
precision= 0.96834264432
recall= 0.981132075472
auc= 0.99696298984

LR2: 10
confusion matrix:
[[1503   57]
 [  28 1562]]
score= 0.973015873016

precision= 0.964793082149
recall= 0.982389937107
auc= 0.996448959845

LR1: 100
confusion matrix:
[[1509   51]
 [  32 1558]]
score= 0.973650793651
precision= 0.968303293971
recall= 0.979874213836
auc= 0.99690574101

LR2: 100
confusion matrix:
[[1505   55]
 [  29 1561]]
score= 0.973333333333
precision= 0.965965346535
recall= 0.981761006289
auc= 0.99683357523

LR1: 1000
confusion matrix:
[[1508   52]
 [  33 1557]]
score= 0.973015873016
precision= 0.967681789932
recall= 0.979245283019
auc= 0.996894452508

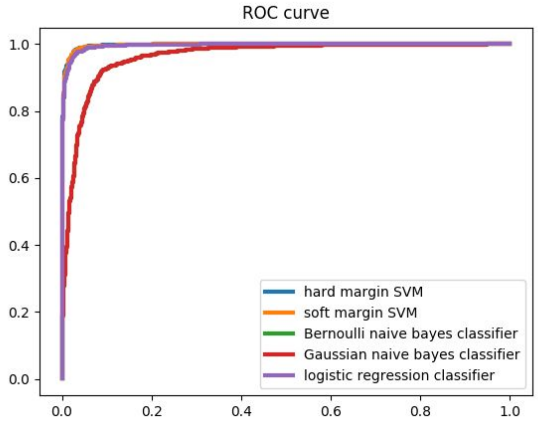
LR2: 1000
confusion matrix:
[[1508   52]
 [  32 1558]]

score= 0.973333333333
precision= 0.967701863354
recall= 0.979874213836
auc= 0.996897274633

LR1: 10000
confusion matrix:
[[1508  52]
 [ 33 1557]]
score= 0.973015873016
precision= 0.967681789932
recall= 0.979245283019
auc= 0.99689566199

LR2: 10000
confusion matrix:
[[1508  52]
 [ 33 1557]]
score= 0.973015873016
precision= 0.967681789932
recall= 0.979245283019
auc= 0.996892839865

H2




I

1 VS 1 SVC
confusion matrix:
[[318  50  24   0]
 [ 35 324  26   0]
 [ 26  16 348   0]
 [  4   1   2 391]]
score= 0.882428115016
precision= 0.882939755814
recall= 0.882428115016

1 VS Rest SVC
confusion matrix:
[[318  45  27   2]
 [ 32 326  26   1]
 [ 19  15 354   2]
 [  5   1   3 389]]
score= 0.886261980831
precision= 0.886454315788
recall= 0.886261980831

GaussianNB
confusion matrix:
[[244  36 112   0]
 [ 98 142 144   1]
 [ 41  36 313   0]
 [  4   0  43 351]]
score= 0.670926517572
precision= 0.702204375077
recall= 0.670926517572

BernoulliNB
confusion matrix:
[[296  69  25   2]
 [ 62 299  21   3]
 [ 43  28 313   6]
 [  2   1   1 394]]

score= 0.831948881789
precision= 0.833326689424
recall= 0.831948881789