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EE219 Project 2 – Classification Analysis

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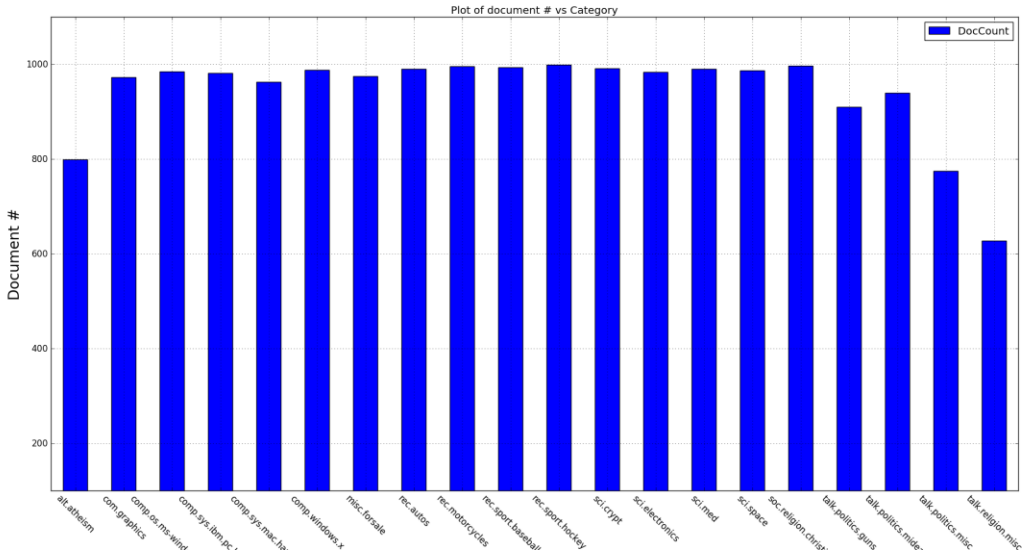
Dataset and Problem Statement:

A) The number of documents in ***Recreational Activity*** are ***3979***.
The number of documents in ***Computer Technology*** are ***3903***.
Histogram of the number of documents per topic is shown below. We see that the distribution of the training samples is almost the same, except for tapering down on the sides for a few categories (which are not included in the later questions).



Modeling Text Data and Feature Extraction:

B) The final number of terms extracted equals **70465**

C) The most significant terms for the different classes are as follows:

comp.sys.ibm.pc.hardware		**comp.sys.mac.hardware**		**misc.forsale**		**soc.religion.christian**	
Words	**Counts**	**Words**	**Counts**	**Words**	**Counts**	**Words**	**Counts**
edu	1423	*edu*	1899	*edu*	1751	*god*	2577
Drive	1403	*line*	1073	*00*	1215	*christian*	1760
line	1101	*mac*	1020	*line*	1044	*edu*	1638
com	1080	*subject*	997	*subject*	1008	*church*	937
subject	1024	*organ*	934	*Sale*	955	*subject*	1176
use	1010	*use*	803	*Organ*	981	*jesus*	904
scsi	1000	*quadra*	270	*univers*	564	*Homosexu*	653
organ	972	*appl*	664	*com*	548	*peopl*	1073

card	769	*Problem*	611	*new*	542	*Sin*	795
ide	573	*centri*	223	*10*	509	*Line*	1052

Learning Algorithms

We first load the training and test dataset for the categories which need to be classified. Classifiers need to classify documents into two classes: Computer technology and Recreational activity.
Computer technology (indicated as class 0) include subcategories *comp.graphics , comp.os.ms-windows.misc, comp.sys.ibm.pc.hardware, comp.sys.mac.hardware*.
Recreational activity (indicated as class 1) include subcategories *rec.autos, rec.motorcycles, rec.sport.baseball, rec.sport.hockey*

Ans e) Linear Support Vector Machine

In this problem, Linear Support Vector Machine is trained to fit the test dataset. We used linear kernel to train the classifier. Statistics obtained are as follows:

Confusion matrix

	Predicted : Computer technology (Class 0)	*Predicted : Recreational activity (Class 1)*
Actual : Computer technology (Class 0)	1501	59
Actual : Recreational activity (Class 1)	38	1552

Recall and Precision score

CLASS	PRECISION	RECALL	F1-SCORE	SUPPORT
0	0.98	0.96	0.97	1560
1	0.96	0.98	0.97	1590
avg / total	0.97	0.97	0.97	3150

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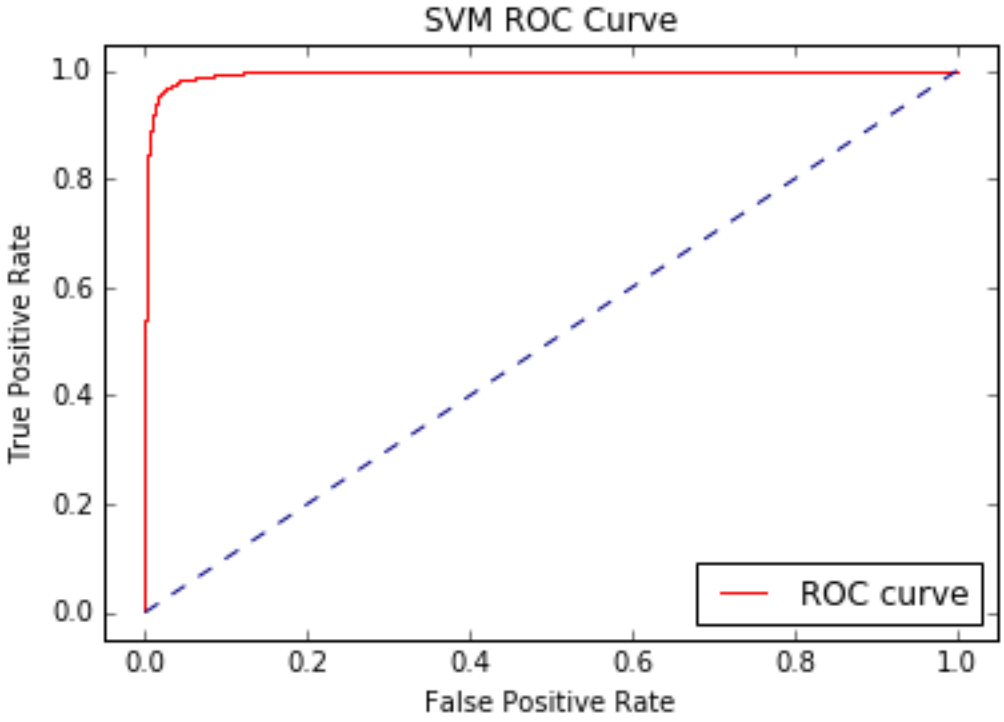
Accuracy: **0.969206349206 (96.92%)**

ROC Curve



Ans f) Soft Margin Support Vector Machine with 5-fold cross validation

In this problem, Soft margin Support Vector Machine with different values of gamma is trained to fit the test dataset. It is done in order to minimize training error and avoid overfitting of data. To obtain best results, 5-fold cross validation is performed.

The best results were obtained at gamma = 0.1

Confusion matrix

	Predicted : Computer technology (Class 0)	*Predicted : Recreational activity (Class 1)*

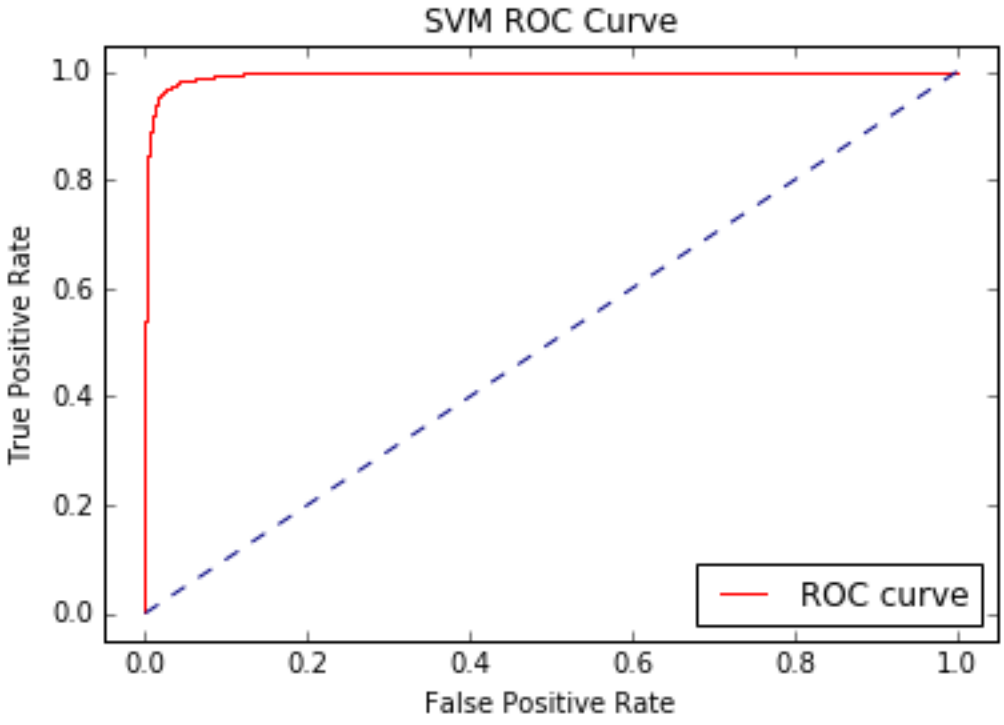
Actual : Computer technology (Class 0)	1501	59
Actual : Recreational activity (Class 1)	38	1552

Recall and Precision score

CLASS	PRECISION	RECALL	F1-SCORE	SUPPORT
0	0.98	0.96	0.97	1560
1	0.96	0.98	0.97	1590
avg / total	0.97	0.97	0.97	3150

Accuracy: 0.969206349206 (96.92%)

ROC Curve



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Ans g) Naïve Bayes Algorithm

Confusion matrix

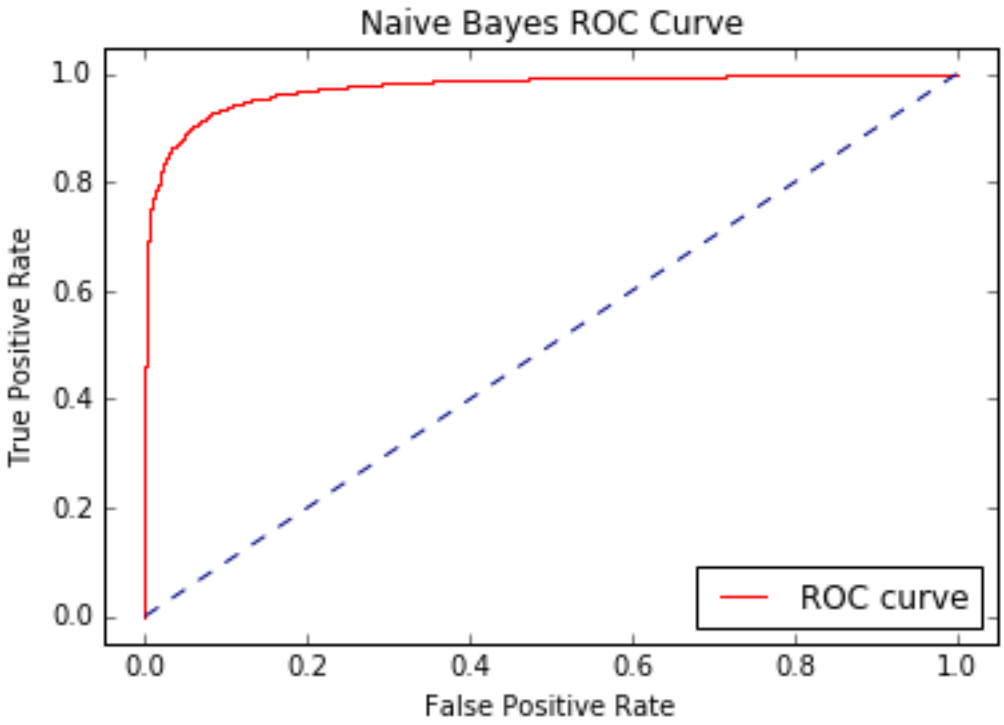
	Predicted : Computer technology (Class 0)	*Predicted : Recreational activity (Class 1)*
Actual : Computer technology (Class 0)	1293	267
Actual : Recreational activity (Class 1)	56	1534

Recall and Precision score

CLASS	PRECISION	RECALL	F1-SCORE	SUPPORT
0	0.96	0.83	0.89	1560
1	0.85	0.96	0.90	1590
avg / total	0.90	0.90	0.90	3150

Accuracy : 0.89746031746 (89.74 %)

ROC Curve



Ans h) Logistic Regression Classifier

In this problem, Logistic Regression Classifier with different penalty function is trained to fit the test dataset.
Statistics for Logistic Regression Classifier with **'l2' penalty function** are as follows:

Confusion matrix

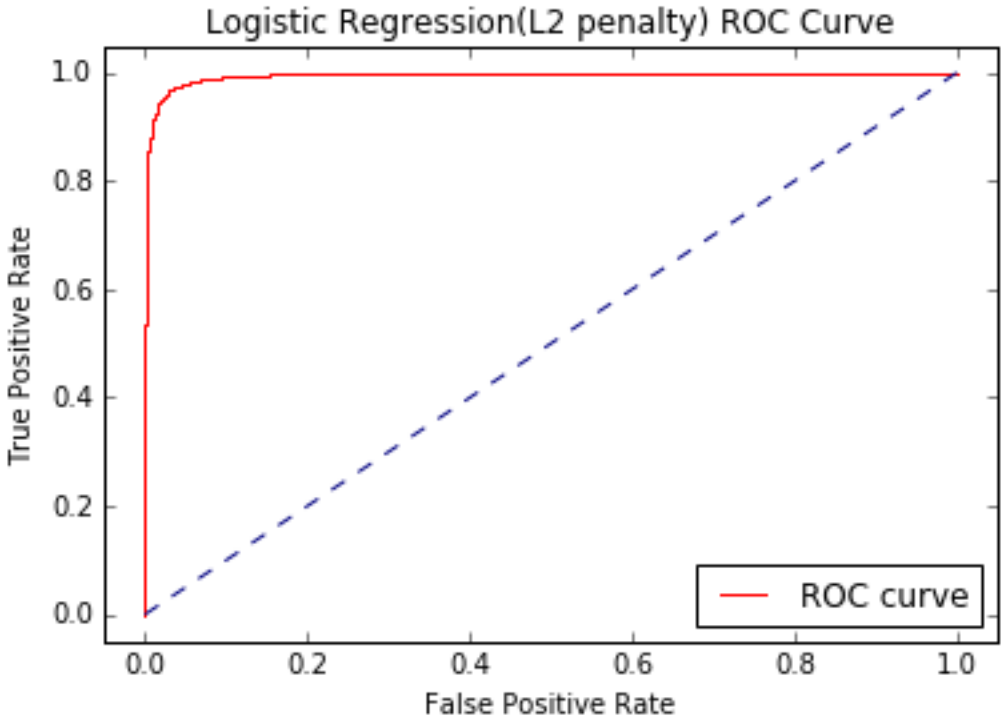
	Predicted : Computer technology (Class 0)	*Predicted : Recreational activity (Class 1)*
Actual : Computer technology (Class 0)	1486	74
Actual : Recreational activity (Class 1)	35	1555

Recall and Precision score

CLASS	PRECISION	RECALL	F1-SCORE	SUPPORT
0	0.98	0.95	0.96	1560
1	0.95	0.98	0.97	1590
avg / total	0.97	0.97	0.97	3150

Accuracy: 0.965396825397 (96.53 %)

ROC Curve



Statistics for Logistic Regression Classifier with **'l1' penalty function** are as follows:

Confusion matrix

	Predicted : Computer technology (Class 0)	*Predicted : Recreational activity (Class 1)*

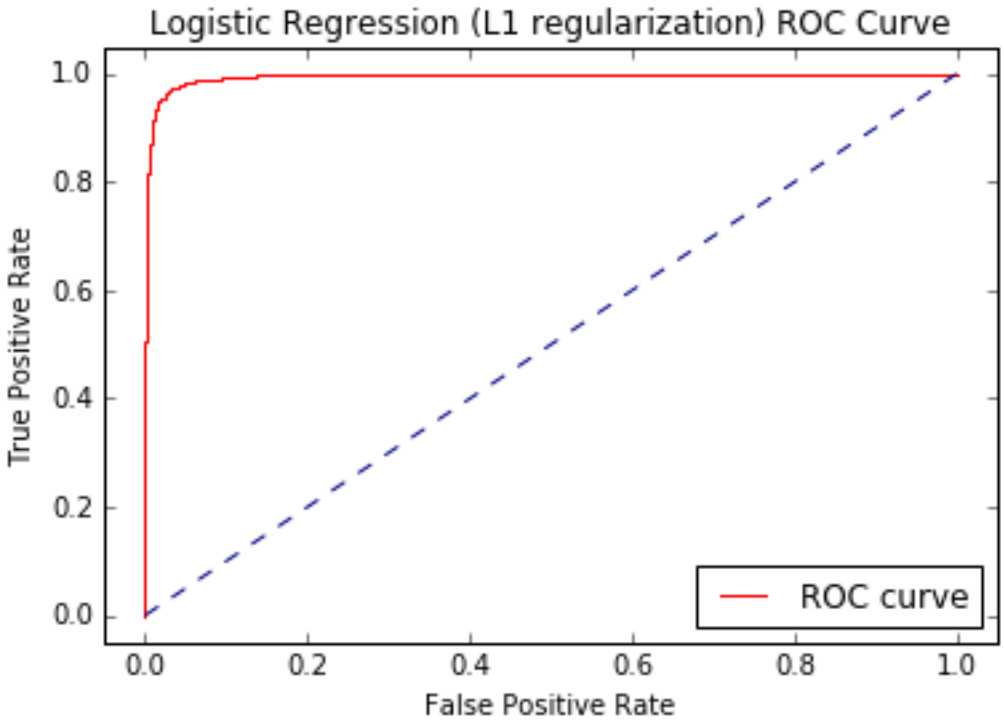
Actual : Computer technology (Class 0)	1491	69
Actual : Recreational activity (Class 1)	35	1555

Recall and Precision score

CLASS	PRECISION	RECALL	F1-SCORE	SUPPORT
0	0.98	0.96	0.97	1560
1	0.96	0.98	0.97	1590
avg / total	0.97	0.97	0.97	3150

Accuracy: **0.966984126984 (96.69 %)**

ROC Curve



Using 'L1' penalty function provides slight improvement in accuracy only when C=1, but reduces when C=0.01 as discussed below.

i) Discussion:

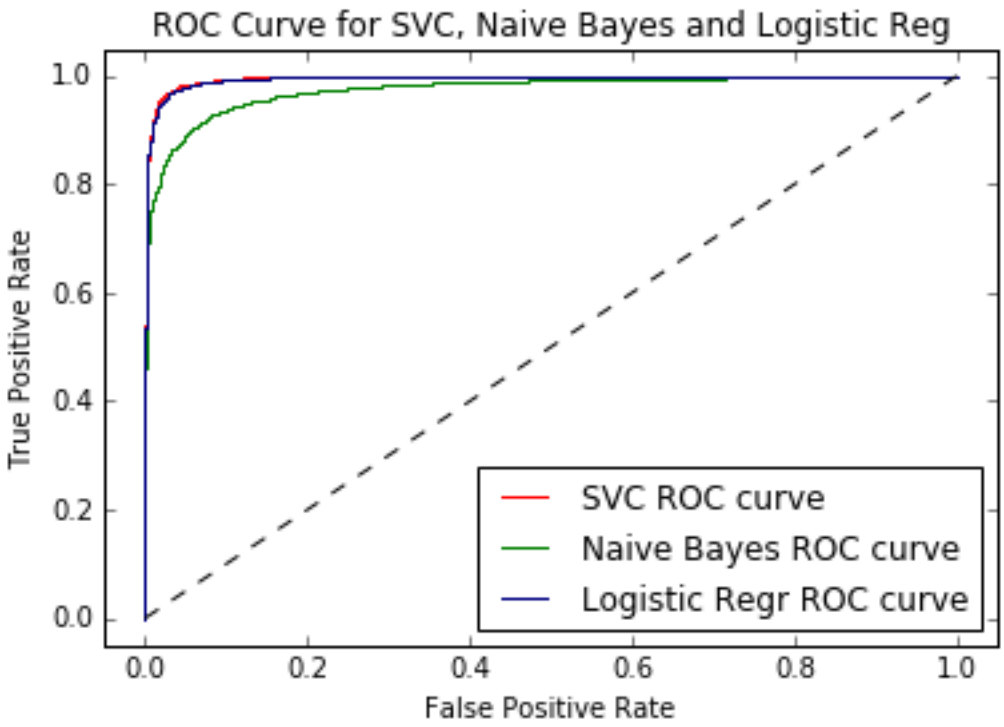
We enumerated through different values of regularization parameters for both 'L1' and 'L2' regularization. The accuracy results are summarized in the table below: (C is the inverse of the regularization strength)

PENALTY TYPE	C=0.01	C=1	C=100
L1	90.317	96.698	97.11
L2	94.793	96.539	97.11
L1 SPARSITY	96%	22%	0

Large values of C give more freedom to the model, while smaller values of C constrain the model. This leads to sparser solution in the L1 penalty case. As the value of C decreases, the coefficients of the fitted hyperplane become more and more sparse (for L1) affecting the performance of the model. L2 model, by its inherent design, remains almost unaffected by changing values of C as sparseness for all cases is 0.

As discussed above, using the L1 regularization improved the accuracy a bit in our case (for C=1). Both L1 and L2 regularizations aim to prevent overfitting in the data and make more generalized model which can perform better given a test data point. L2 regularization penalizes large values more than small values, thereby spreading the error across the training vector X. L1 regularization on the other hand, tries to have a sparse training vector, where some of the values are exactly zeros, and others may be large enough. L1 penalties are great at recovering truly sparse signals. In most cases where prediction is the ultimate goal, L2 regularization is preferred over L1 regularization; since if say two predictors are correlated, L1 simply picks any one, but L2 takes both of them and jointly shrinks the corresponding coefficients. That being said, L1 regularization is mostly used for feature selection in sparse feature spaces.

Comparison of performance between different Regressors



As seen in the figure, SVM and Logistic Regression classify documents with almost similar accuracy while Naïve Bayes is less accurate for this type of classification as compared to other two algorithms.

MultiClass Classification

Ans(i) – Naïve Bayes and SVM

The classifiers were trained for the following classes:

1. comp.sys.ibm.pc.hardware
2. comp.sys.mac.hardware
3. misc.forsale
4. soc.religion.christian.

OneVsOne and OneVsRest classification techniques used to train our classifiers.

Results for OneVsOne Classification:

1) *Naïve Bayes Classifier*

	Result*100
Recall	73.5025918685
Accuracy	73.6741214058
Precision	77.0457299961

Confusion Matrix:

278	18	94	2
70	186	125	4
47	19	323	1
0	0	32	366

2) *SVM*

	Result*100
Recall	88.2601047851
Accuracy	88.3067092652
Precision	88.4576980617

Confusion Matrix:

333	44	15	0
40	323	22	0
29	14	346	1
9	4	5	380

Results for OneVsRestClassifier

1) *Naïve Bayes Classifier*

	Result*100
Recall	72.4044929407
Accuracy	72.5878594249
Precision	76.7645816972

Confusion Matrix:

257	16	118	1
63	177	140	5
40	17	330	3
0	0	26	372

2) SVM

	Result*100
Recall	88.8913870886
Accuracy	88.945686901
Precision	88.8656279393

Confusion Matrix:

322	47	20	3
32	324	27	2
20	13	355	2
3	1	3	391