EE219 Project-1
Classification Analysis on Textual Data

Sneha Shankar – 404946026

Devanshi Patel – 504945601

Contents

1. Introduction

This project focusses on statistical classification of textual data. The term classification involves categorizing a data set into its respective class based on the known categories. We have performed various classification techniques on the same dataset to draw a definitive comparison about their performances. We analyzed classifiers like Linear Support Vector Machines, Naïve Bayes and Logistic Regression to gain better insight into their working.

2. Dataset and Problem Statement

Here, we use the '20 Newsgroups' dataset provided by the scikit-learn package in Python. In this dataset, the documents are categorized into 20 different classes or newsgroups. Some of the classes are closely related to each other and can also be grouped together as a super-category (e.g. comp.graphics, comp.os.ms-windows.misc, comp.sys.ibm.pc.hardware can be grouped together into a category of 'computer technology').

Question (a)

In any classification problem, it is very important to have a balanced relative size of the data sets corresponding to different categories. In case of an imbalance, we can either reduce the number of samples in the majority classes to match those in the minority ones or use an appropriate penalty function to assign more weights to the errors of minority classes. Here we have plotted a histogram of the number of documents obtained in each category for 8 such categories. The observations from this histogram eliminates the possibility of an imbalance in the dataset.

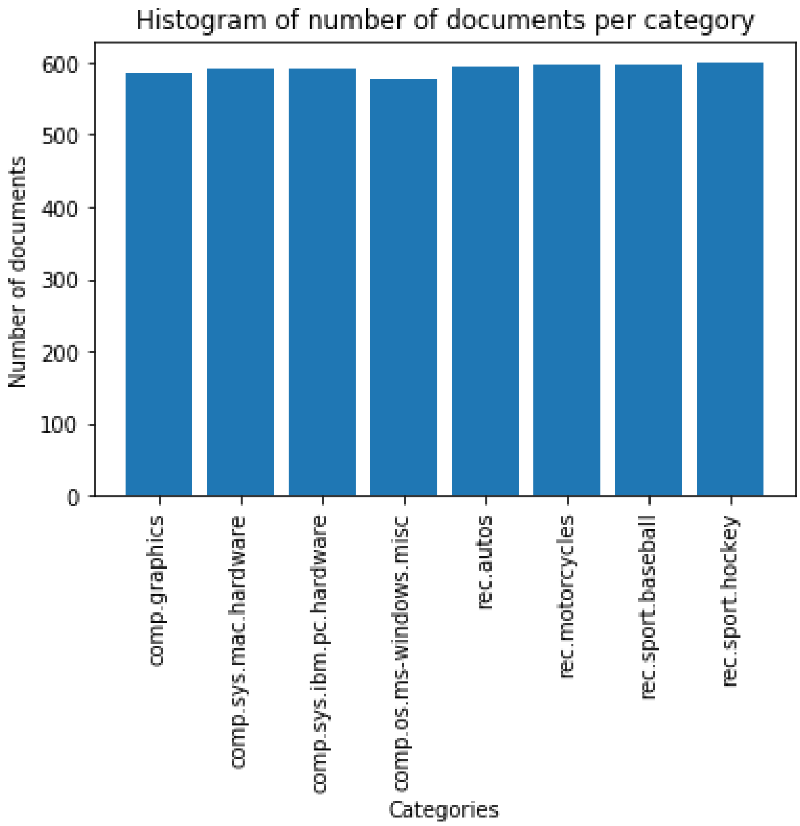


Fig.1 Histogram of Number of Documents per category

3. Modeling Text Data and Feature Extraction

Question (b)

To classify a document, it is very important to represent it properly with its appropriate set of features. This representation should contain only as much relevant information which will avoid the problem of overfitting. The problem of overfitting can be avoided by removing frequently occurring stop words, stemming and also eliminating highly in-frequent words. This also ensures that we do not have to deal with extremely large feature vector which may contain irrelevant information. For this purpose we have tokenized the documents into words and then used the Porter Stemmer to stem the words to their base words and finally we excluded the stop words and punctuations. We have used Python's NLTK library for the same.

After this pre-processing, it is important to determine the relevance of a word within a document. We have used the TFIDF measure to capture it. Here, TF stands for the 'Term Frequency' which denotes the number of times a particular term occurs in a given document. This is used to determine the frequent words. In our project, we set the threshold for words using the min_df parameter. IDF stands for 'Inverse Document Frequency' which is used to denote the relevance of rare words. TFIDF of a particular term is the multiplication of the TF and IDF of that term.

After applying TFIDF transformation on the training dataset, we obtain a document – term matrix in which each row represents a document and each column a term. We have made the following observations by setting min_df as 2 and 5 respectively.

Minimum Document Frequency	Number of Terms Extracted
2	25342
5	10726

This was observed for a set of 4732 documents and with default value of max_df in the TFIDF transformer.

Question (c)

Like TFIDF measures the relevance of a word to a particular document, TFICF is a measure which denotes how relevant a word is to a particular class. It is computed by multiplying frequency of a term in a particular class with its inverse class frequency. Here we use all 20 classes of the dataset to determine the 10 most significant terms with respect to the TFICF measure in each of the following classes:

comp.sys.ibm.pc.hardware, comp.sys.mac.hardware, misc.forsale, soc.religion.christian.

The 10 most significant terms observed as tabulated as follows:

i. **For minimum document frequency = 2**

comp.sys.ibm.pc.hardware	comp.sys.mac.hardware	misc.forsale	soc.religion.christian
bio	monitor	printer	faith
ide	duo	pc	christian
monitor	quadra	manual	bibl
motherboard	centri	sale	jesu
pc	nubu	cd	atho
floppi	fpu	packag	truth
scsi	mac	forsal	church

disk	scsi	ship	scriptur
isa	simm	disk	sin
jumper	lc	wolverin	christ

ii. For minimum document frequency = 5

comp.sys.ibm.pc.hardware	comp.sys.mac.hardware	misc.forsale	soc.religion.christian
bio	machin	printer	faith
ide	lc	pc	rutger
monitor	ram	manual	christian
motherboard	fpu	sale	bibl
pc	mac	cd	jesu
floppi	se	packag	truth
scsi	scsi	window	church
disk	vram	forsal	scriptur
isa	simm	ship	sin
jumper	monitor	disk	christ

4. Feature Selection

Question (d) Decomposition

The extracted TFIDF matrix is a high dimensional matrix which comprises of documents and terms (i.e. rows and columns) in the order of thousands. Such a high dimensional matrix should not be used for classification as learning algorithms generally perform poorly in such a scenario. As a result, LSI dimensionality reduction method is used to get the best rank-k approximation of the original matrix by minimizing the sum of squared errors. This is known as feature selection. The steps followed are:

- Pre-process training and testing datasets
- Apply TFIDF transformation
- Select best features using LSI Decomposition with k=50

The above steps were performed for min_df=2 and min_df=5 respectively.

Alternatively, it is also possible to reduce the dimensionality of the original TFIDF matrix using NMF (Non-negative matrix factorization).

We will compare the results of the following sections using both the aforementioned methods.

5. Learning Algorithms

From this section onwards, we will be classifying the documents into two broad categories namely ‘Computer Technology’ and ‘Recreational Activity’. Therefore, we have divided the 8 categories into two groups which belong to the previously mentioned categories.

Question (e) Linear Support Vector Machines

SVM classifies documents based on the sign of vector representation of the document multiplied by the weights that are learnt by the classifier. A positive sign signifies that the document belongs to one class while the one with negative sign belongs to the other. The amount of error the classifier permits for a given data sample is controlled by gamma. There are two types of SVM based on the values of gamma fed to the classifier:

- Hard Margin SVM with large values of γ (i.e. $\gamma >> 1$) highly penalizes the incorrect classification of documents.
- Soft Margin SVM (when $\gamma << 1$) is very lenient towards incorrect classification of some documents provided that the majority of them are well separated.

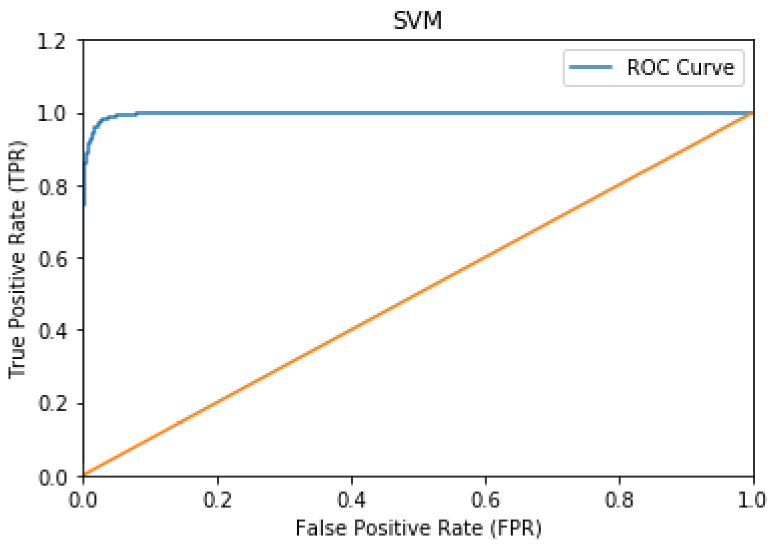
When we use the Linear Kernel to train our classifier on the training dataset, we get the following results.

Minimum Document frequency	γ	Type of decomposition	Accuracy
2	1000	SVD	97.3015873016
		NMF	96.1587301587
5	1000	SVD	97.1428571429
		NMF	96.2222222222
2	0.001	SVD	50.4761904762
		NMF	50.4761904762
5	0.001	SVD	50.4761904762
		NMF	50.4761904762

- **min_df=2; γ=1000; with SVD**

Statistic	Result
Accuracy	97.3015873016
Precision	97.3252190977
Recall	97.2925737784

	Predicted: Computer Technology	Predicted: Recreational Activity
Actual: Computer Technology	1503	57
Actual: Recreational Activity	28	1562

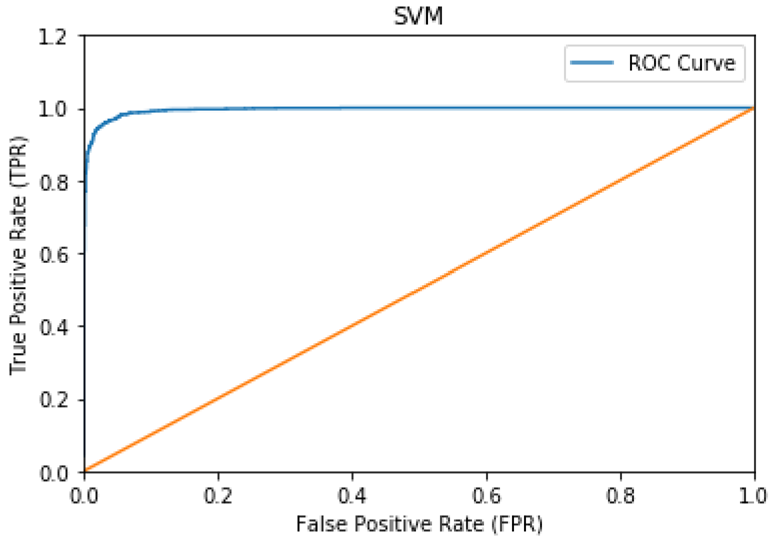


The ROC curve is created by plotting True Positive Rate(TPR) against False Positive Rate(FPR) for different values of threshold. The ideal ROC curve has an area of 1 hence, if a ROC curve shows classes having area of approximately 1, it indicates that the test data is correctly classified.

- **min_df=2; γ=1000; with NMF**

Statistic	Result
Accuracy	96.1587301587
Precision	96.1719683027
Recall	96.1520319303

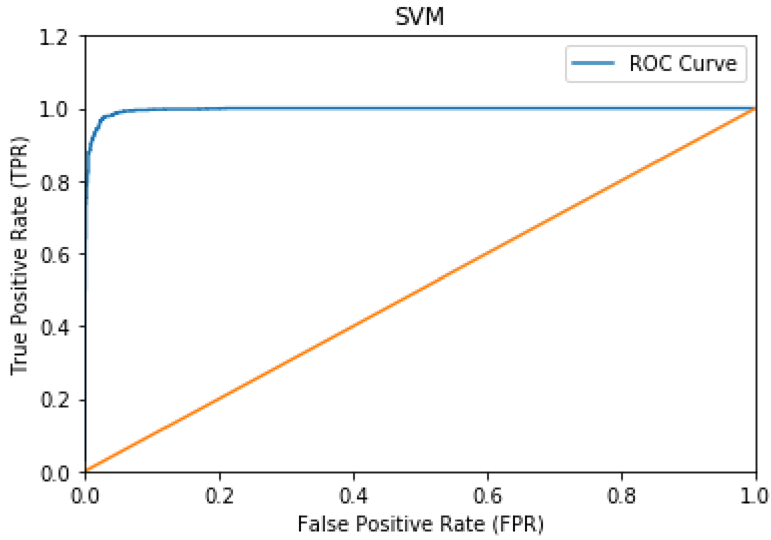
	Predicted: Computer Technology	Predicted: Recreational Activity
Actual: Computer Technology	1489	71
Actual: Recreational Activity	50	1540



- **min_df=5; γ=1000; with SVD**

Statistic	Result
Accuracy	97.1428571429
Precision	97.1576956958
Recall	97.1359458152

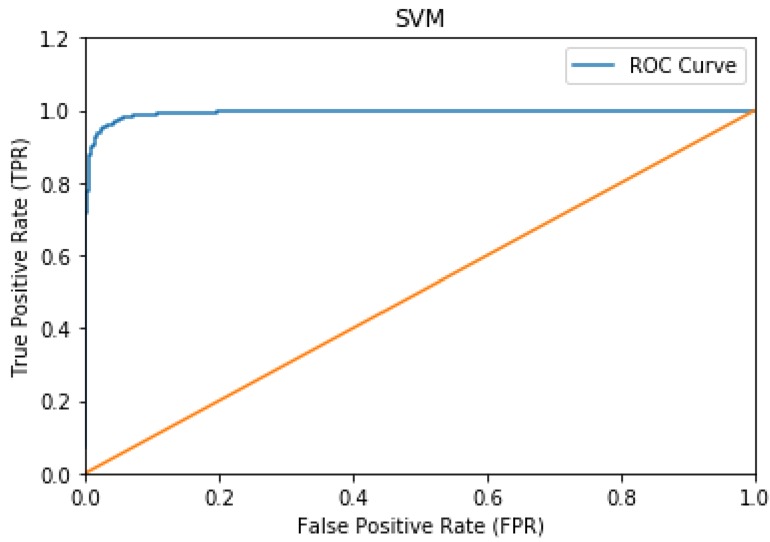
	Predicted: Computer Technology	Predicted: Recreational Activity
Actual: Computer Technology	1504	56
Actual: Recreational Activity	34	1556



- **min_df=5; γ=1000; with NMF**

Statistic	**Result**
Accuracy	96.2222222222
Precision	96.2283670606
Recall	96.2179487179

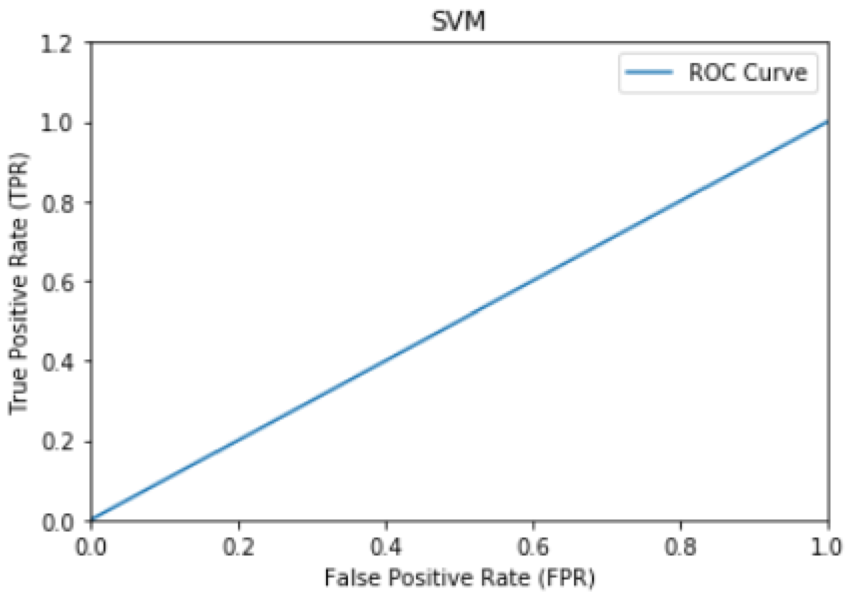
	Predicted: Computer Technology	**Predicted: Recreational Activity**
Actual: Computer Technology	1494	66
Actual: Recreational Activity	53	1537



- **min_df=2; γ=0.001; with SVD**

Statistic	Result
Accuracy	50.4761904762
Precision	25.2380952381
Recall	50.0

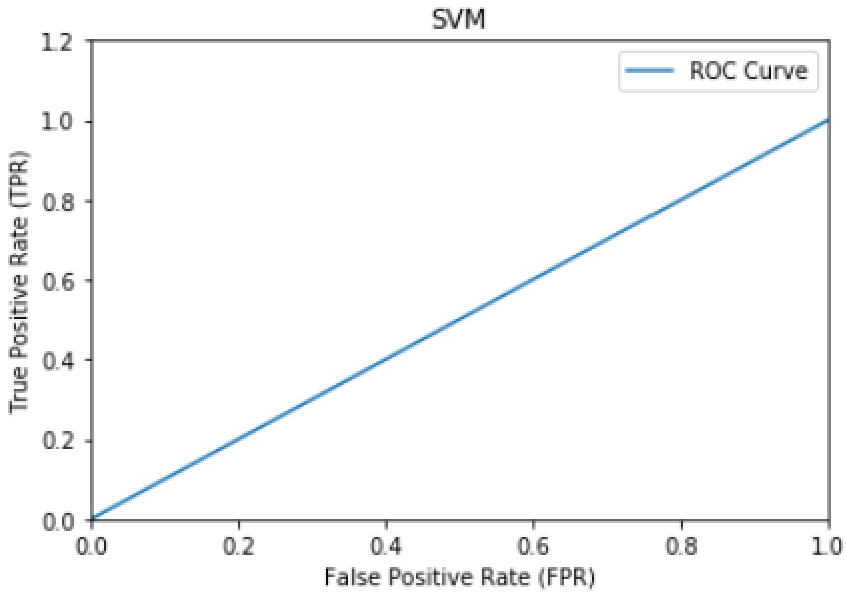
	Predicted: Computer Technology	Predicted: Recreational Activity
Actual: Computer Technology	0	1560
Actual: Recreational Activity	0	1590



- **min_df=2; γ=0.001; with NMF**

Statistic	Result
Accuracy	50.4761904762
Precision	25.2380952381
Recall	50.0

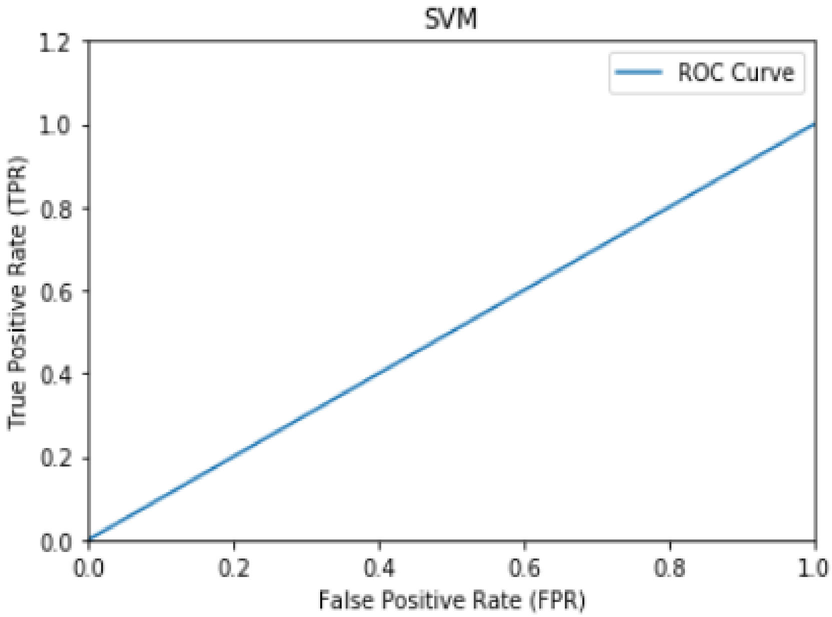
	Predicted: Computer Technology	Predicted: Recreational Activity
Actual: Computer Technology	0	1560
Actual: Recreational Activity	0	1590



- **min_df=5; γ=0.001; with SVD**

Statistic	Result
Accuracy	50.4761904762
Precision	25.2380952381
Recall	50.0

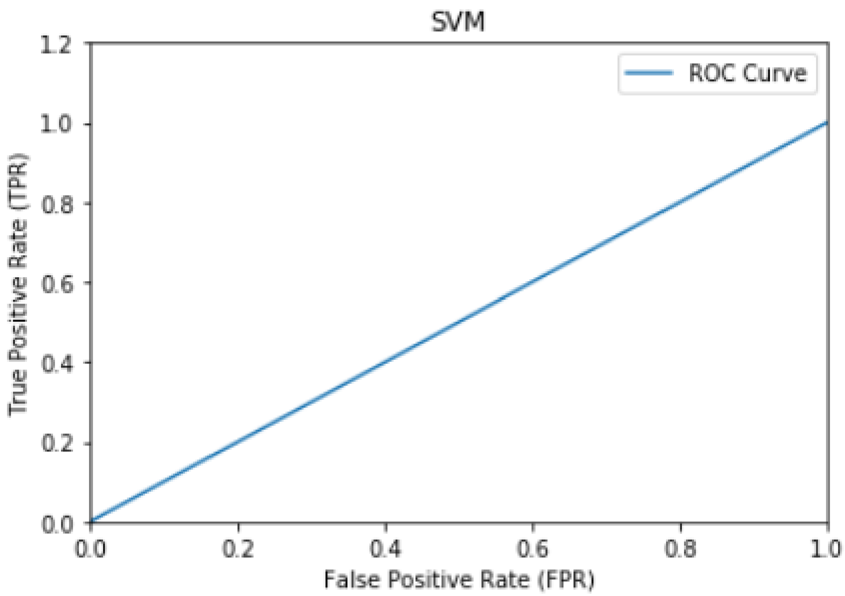
	Predicted: Computer Technology	Predicted: Recreational Activity
Actual: Computer Technology	0	1560
Actual: Recreational Activity	0	1590



- **min_df=5; γ=0.001; with NMF**

Statistic	Result
Accuracy	50.4761904762
Precision	25.2380952381
Recall	50.0

	Predicted: Computer Technology	Predicted: Recreational Activity
Actual: Computer Technology	0	1560
Actual: Recreational Activity	0	1590



Observations:

By observing the above statistics, we can say that we get the best accuracy using SVD decomposition with min_df=2. Overall, decomposition by SVD gives better accuracy than that of NMF for same values of min_df and γ.

Hence it is proved that Linear Support Vector Machines are efficient when dealing with textual data which involves high dimensionality and sparsity.

Question (f) 5-fold cross validation

Cross-validation is a useful technique that helps in assessing and improving the performance of a model. It also helps to check for overfitting and to determine whether a model will generalize well to unseen data.

In this part, we use 5-fold cross validation to obtain the best value for the parameter γ. **The best value** obtained for min_df=2 and 5 with both SVD and NMF decomposition is **100**. We get the following results (approximated to 2 digits) by trying different values of γ and clearly we observe that the **best accuracy was obtained for γ=100 (i.e. k=2)**

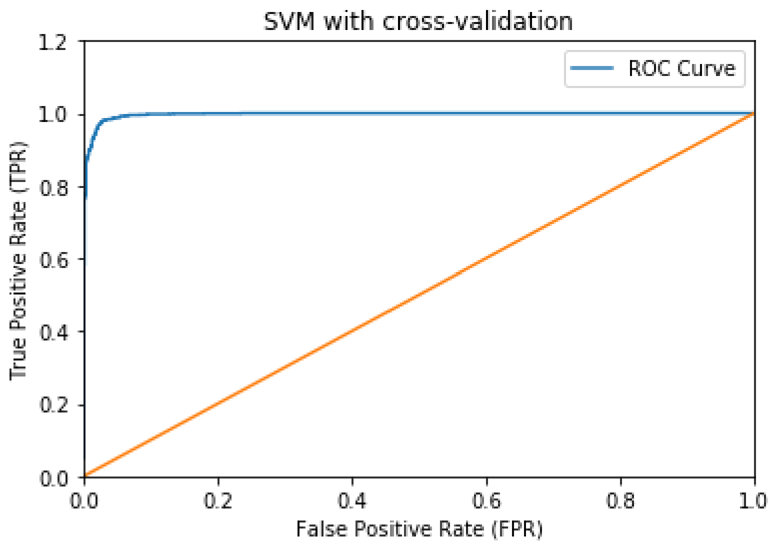
Minimum Document Frequency	Type of Decomposition	Accuracy						
		γ=0.001	γ=0.01	γ =0.1	γ =0	γ=10	γ =100	γ =1000
2	SVD	50.48	51.39	96.06	97.01	97.3	97.43	97.30
	NMF	50.48	50.48	50.47	93.52	95.4	96.10	96.15
5	SVD	50.48	53.20	95.96	97.11	97.4	97.27	97.14
	NMF	50.48	50.48	61.61	94.28	95.3	95.78	96.22

Following are the results obtained for the best value of γ chosen i.e. 100

- **min_df=2; with SVD**

Statistic	Result
Accuracy	97.4285714286
Precision	97.4447004878
Recall	97.4213836478

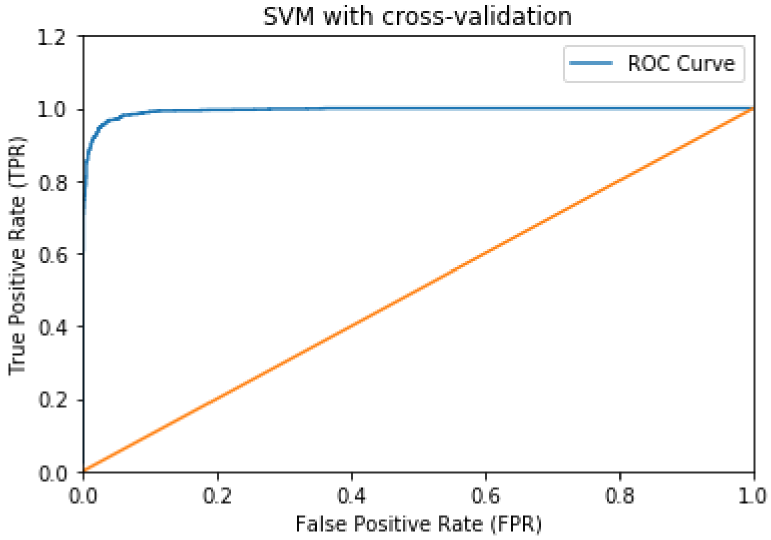
	Predicted: Computer Technology	Predicted: Recreational Activity
Actual: Computer Technology	1508	52
Actual: Recreational Activity	29	1561



- **min_df=2; with NMF**

Statistic	Result
Accuracy	96.0634920635
Precision	96.0848418736
Recall	96.0546686018

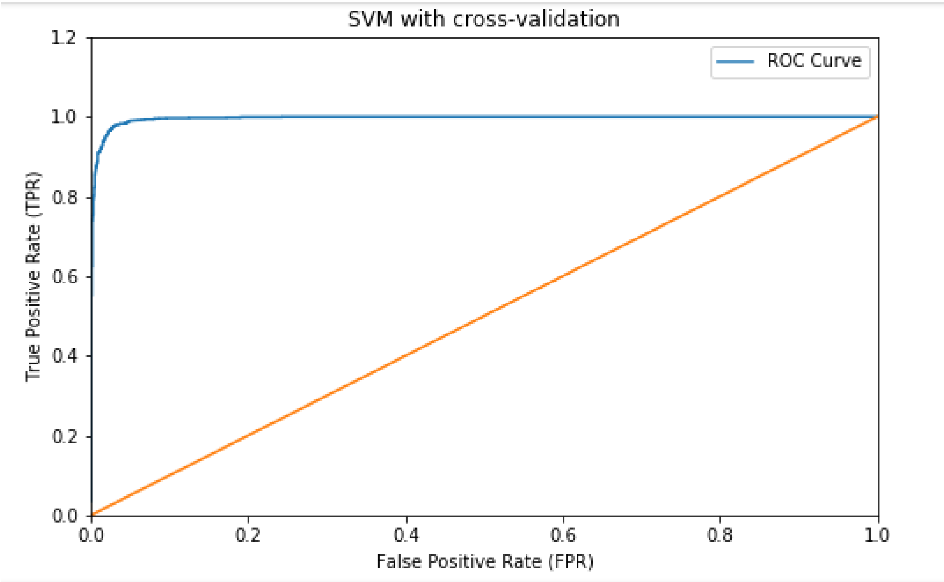
	Predicted: Computer Technology	Predicted: Recreational Activity
Actual: Computer Technology	1484	76
Actual: Recreational Activity	48	1542



- **min_df=5; with SVD**

Statistic	Result
Accuracy	97.2698412698
Precision	97.2870440288
Recall	97.2623367199

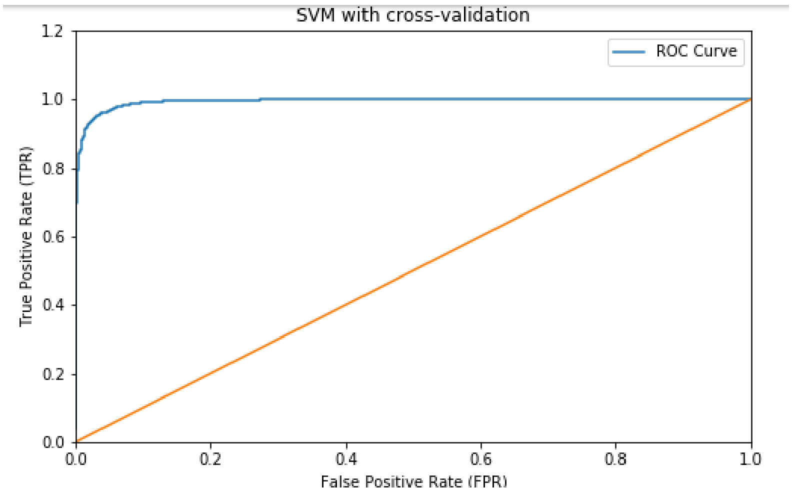
	Predicted: Computer Technology	Predicted: Recreational Activity
Actual: Computer Technology	1505	55
Actual: Recreational Activity	31	1559



- **min_df=5; with NMF**

Statistic	Result
Accuracy	95.7777777778
Precision	95.7952219118
Recall	95.7698355104

	Predicted: Computer Technology	Predicted: Recreational Activity
Actual: Computer Technology	1481	79
Actual: Recreational Activity	54	1536



Observations:

Thus, we observe that the best accuracy is obtained for min_df=2 with SVD decomposition and γ=100.

Question (g) Naive Bayes

Next, we perform the same classification using Naive Bayes algorithm. This algorithm uses Bayes rule to estimate the maximum likelihood probability of a class based on given feature set of a document. Here we are assuming that the features are statistically independent given the class.

We get the following results upon using Multinomial Naive Bayes classifier. Since Multinomial NB does not work with SVD decomposition because of the presence of negative values, we have used two approaches for this problem:

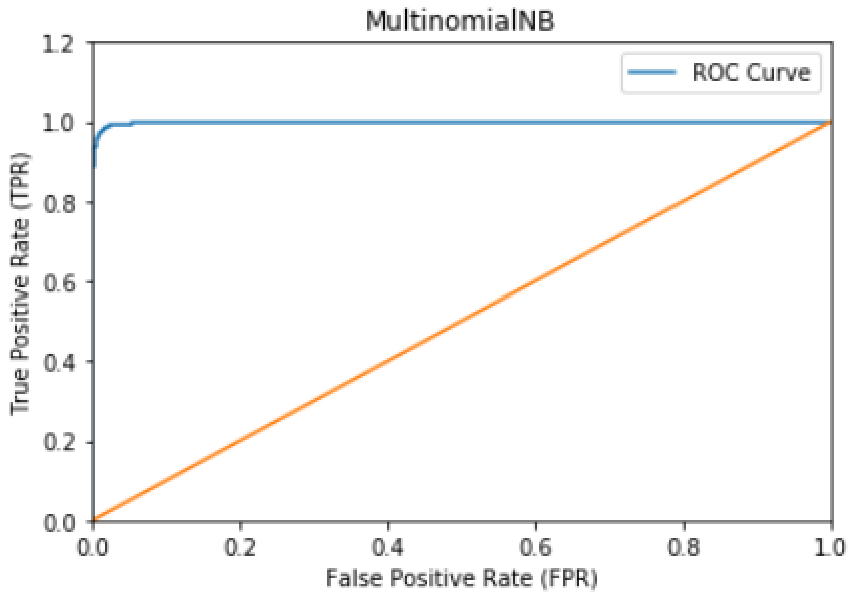
- Without decomposition (using the original TFIDF matrix to predict)
- With decomposition by NMF

Minimum Document Frequency	Type of Decomposition	Accuracy
2	None	98.1587301587
	NMF	93.5873015873
5	None	98.3174603175
	NMF	94.380952381

- **min_df=2; without decomposition**

Statistic	Result
Accuracy	98.1587301587
Precision	98.1874310043
Recall	98.1488872762

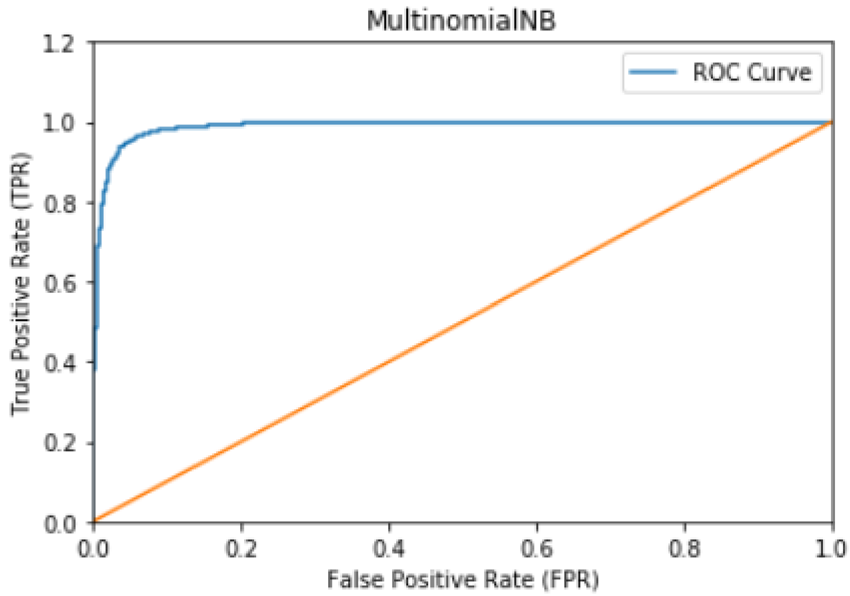
	Predicted: Computer Technology	Predicted: Recreational Activity
Actual: Computer Technology	1515	45
Actual: Recreational Activity	13	1577



- **min_df=2; with NMF**

Statistic	Result
Accuracy	93.5873015873
Precision	94.02054292
Recall	93.5413642961

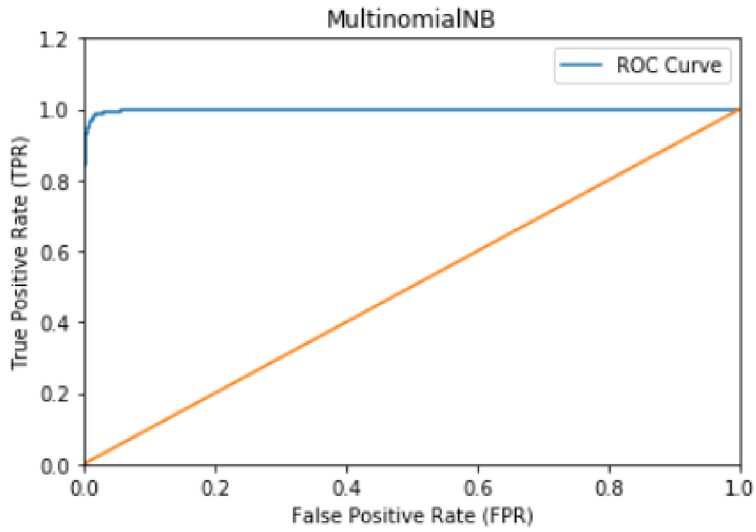
	Predicted: Computer Technology	Predicted: Recreational Activity
Actual: Computer Technology	1384	176
Actual: Recreational Activity	26	1564



- **min_df=5; without decomposition**

Statistic	Result
Accuracy	98.3174603175
Precision	98.3192049108
Recall	98.3157958394

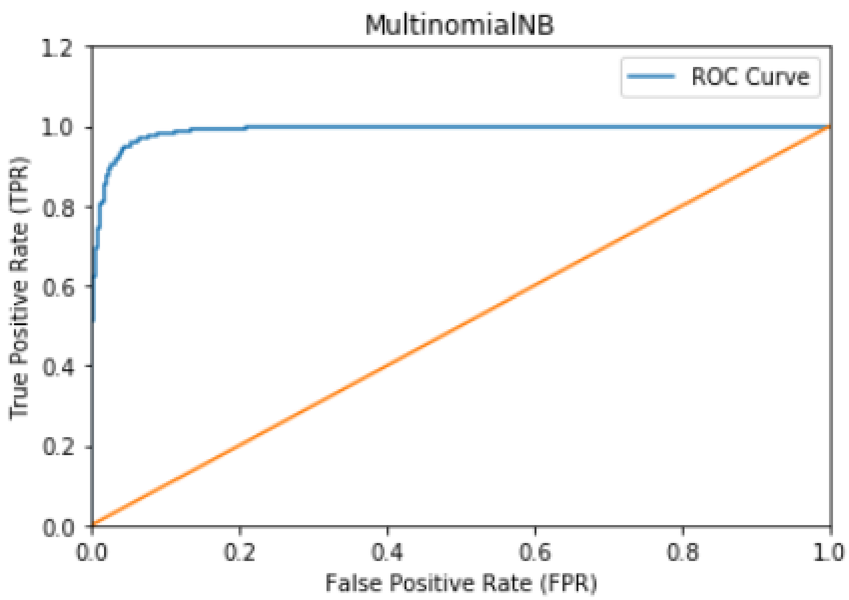
	Predicted: Computer Technology	Predicted: Recreational Activity
Actual: Computer Technology	1531	29
Actual: Recreational Activity	24	1566



- **min_df=5; with NMF**

Statistic	Result
Accuracy	94.380952381
Precision	94.637070806
Recall	94.3462747944

	Predicted: Computer Technology	Predicted: Recreational Activity
Actual: Computer Technology	1415	145
Actual: Recreational Activity	32	1558



Question (h) Logistic Regression

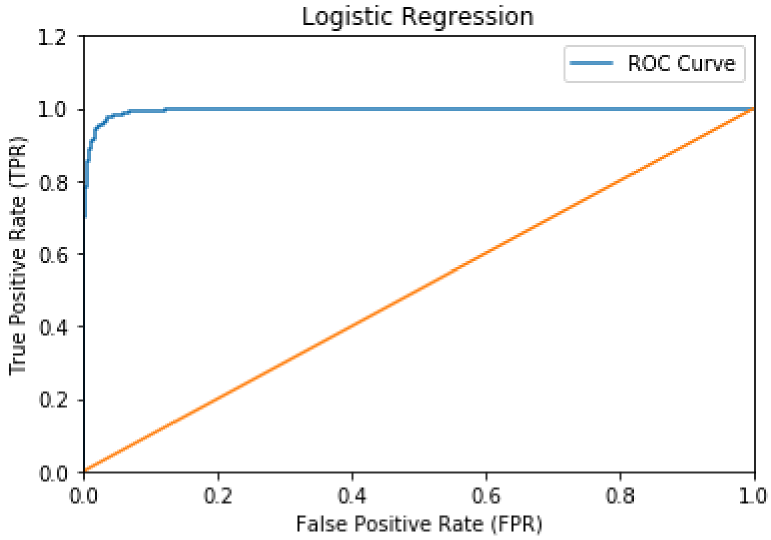
Next we use Logistic Regression classifier for the same task. Logistic Regression is used to obtain the best fitting model that describes the relationship between the categorical outcome variable and one or more independent variables by using a logistic function to estimate the probabilities. We get the following results when using a LR classifier (default). Since the default LR classifier object operates with L2 regularization, following results are tabulated for Logistic Regression with L2 regularization.

Minimum Document Frequency	Type of Decomposition	Accuracy
2	SVD	96.6666666667
	NMF	93.9365079365
5	SVD	96.7936507937
	NMF	93.7777777778

- **min_df=2; with SVD**

Statistic	Result
Accuracy	96.6666666667
Precision	96.6955249138
Recall	96.6563860668

	Predicted: Computer Technology	Predicted: Recreational Activity
Actual: Computer Technology	1491	69
Actual: Recreational Activity	36	1554

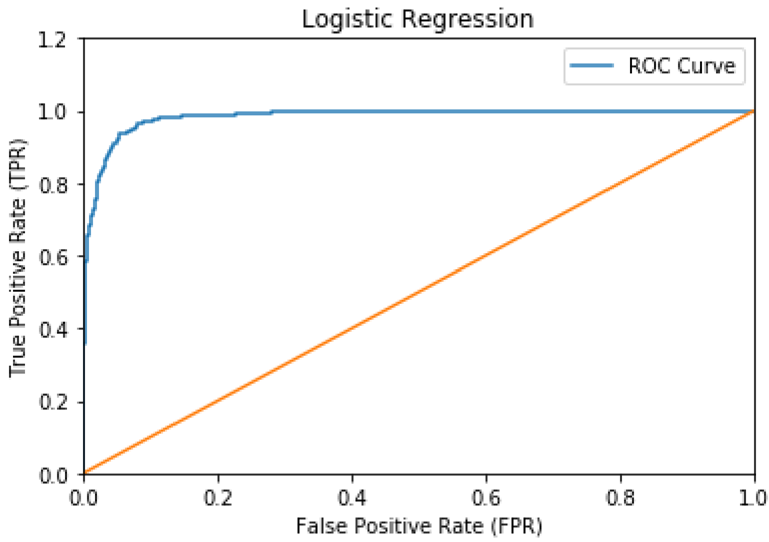


- **min_df=2; with NMF**

Statistic	Result
Accuracy	93.9365079365
Precision	94.0650476234

Recall	93.9120706338

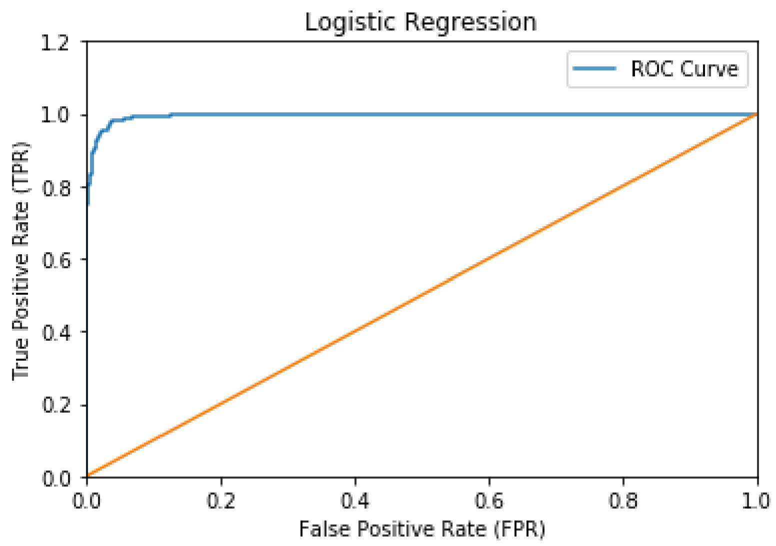
	Predicted: Computer Technology	**Predicted: Recreational Activity**
Actual: Computer Technology	1425	135
Actual: Recreational Activity	56	1534



- **min_df=5; with SVD**

Statistic	**Result**
Accuracy	96.7936507937
Precision	96.8289747736
Recall	96.7821722303

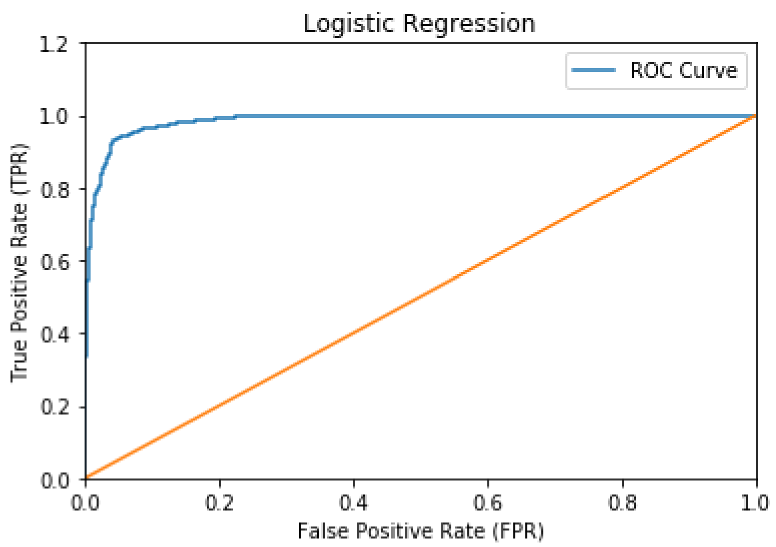
	Predicted: Computer Technology	**Predicted: Recreational Activity**
Actual: Computer Technology	1491	69
Actual: Recreational Activity	32	1558



- **min_df=5; with NMF**

Statistic	Result
Accuracy	93.7777777778
Precision	93.9088040136
Recall	93.7530237059

	Predicted: Computer Technology	Predicted: Recreational Activity
Actual: Computer Technology	1422	138
Actual: Recreational Activity	58	1532



Observations:

Here, we observe that SVD decomposition performs better as compared to NMF and the best accuracy is obtained with min_df=5 using SVD decomposition. We also observe from the above ROC curves that the area is similar to the one in SVM.

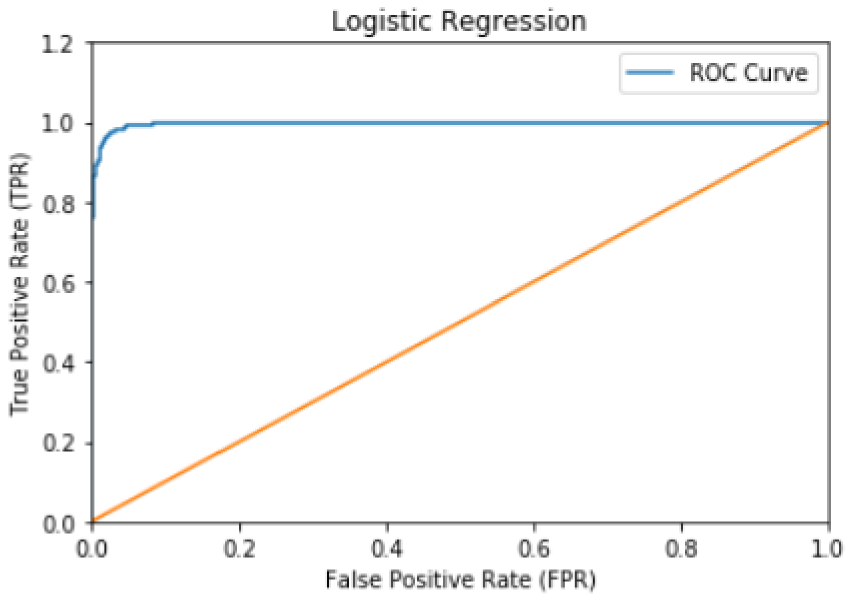
Now, since the default classifier works with L2 regularization, we changed the C to a very large value (C=10000) and recorded the following observations:

Minimum Document Frequency	Type of Decomposition	Accuracy
2	SVD	97.3968253968
	NMF	96.2857142857
5	SVD	97.3333333333
	NMF	96.0000000000

- **min_df=2; SVD decomposition**

Statistic	Result
Accuracy	97.3968253968
Precision	97.4141060641
Recall	97.3893323657

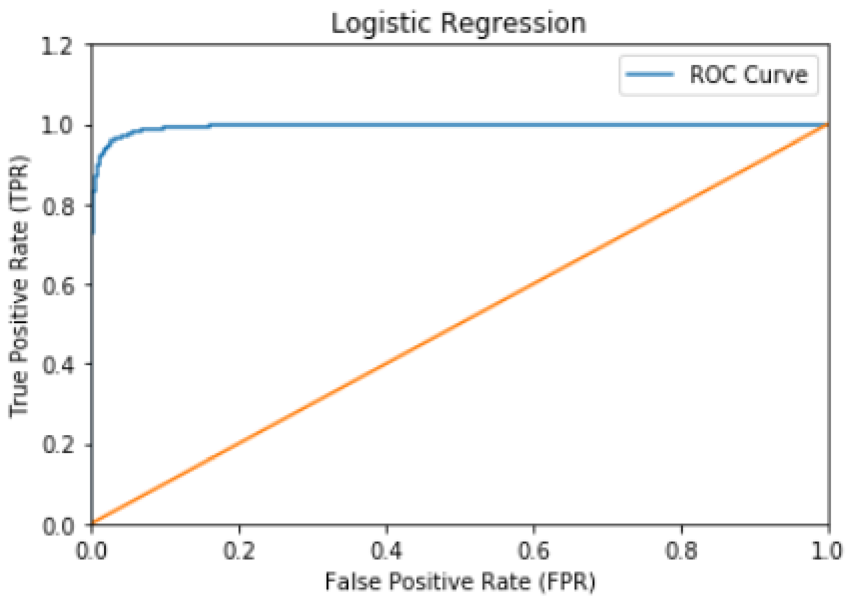
	Predicted: Computer Technology	Predicted: Recreational Activity
Actual: Computer Technology	1507	53
Actual: Recreational Activity	29	1561



- **min_df=2; NMF decomposition**

Statistic	Result
Accuracy	96.2857142857
Precision	96.2970095613
Recall	96.2796323174

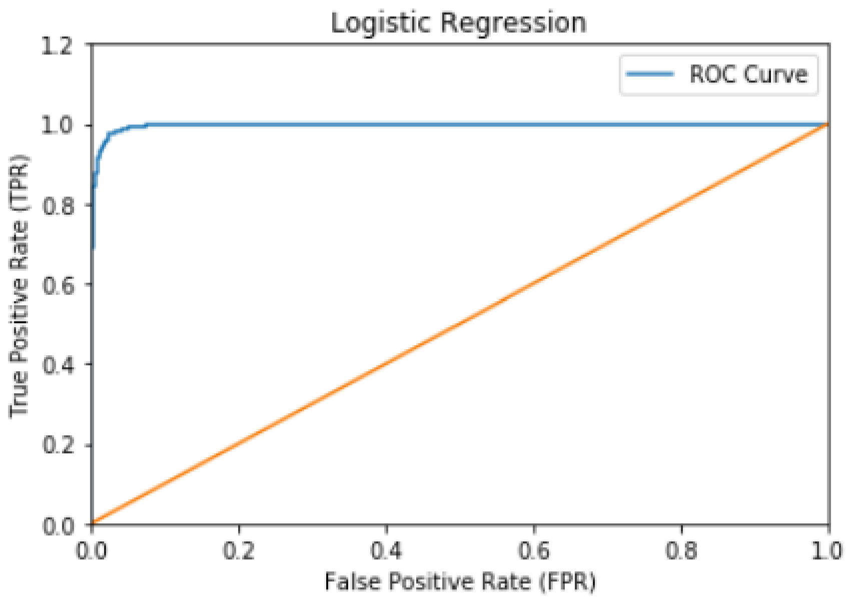
	Predicted: Computer Technology	Predicted: Recreational Activity
Actual: Computer Technology	1492	68
Actual: Recreational Activity	49	1541



- **min_df=5; SVD decomposition**

Statistic	Result
Accuracy	97.3333333333
Precision	97.3461321287
Recall	97.3270440252

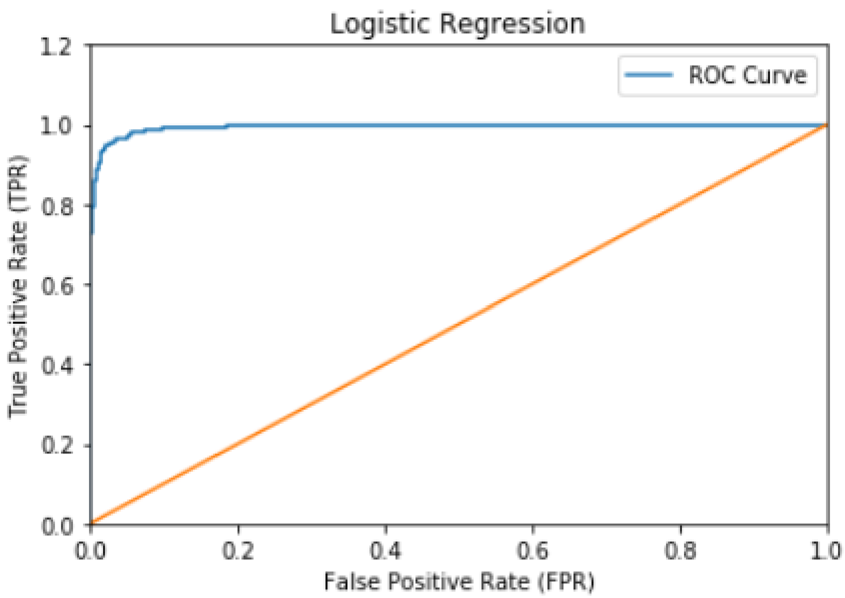
	Predicted: Computer Technology	Predicted: Recreational Activity
Actual: Computer Technology	1508	52
Actual: Recreational Activity	32	1558



- **min_df=5; NMF decomposition**

Statistic	Result
Accuracy	96.0
Precision	96.0068296271
Recall	95.9954039671

	Predicted: Computer Technology	Predicted: Recreational Activity
Actual: Computer Technology	1490	70
Actual: Recreational Activity	56	1534



Observations:

By overcoming the effect of L2 regularization (by setting C to very large value), we find that SVD decomposition still gives better results than NMF. The best value of accuracy is found for min_df=2 using SVD decomposition.

Question (i1) Logistic Regression with Regularization

In this part, we add a regularization term to optimize the LR classifier and to improve generalization performance. We use both L1 and L2 norm regularizations and vary the values of regularization coefficients from 0.001 to 1000 to obtain the results as shown below.

The combined results obtained by performing **SVD decomposition** are as follows:

Min_df	k	L1 Regularization		L2 Regularization	
		Testing Error	Mean of Coeff	Testing Errors	Mean of Coeff
2	0.001	50.48	0.0	31.36	-0.0
	0.01	10.57	-0.1	5.9	-0.0
	0.1	5.23	-0.35	4.12	0.01
	10	2.67	-0.41	2.73	0.14
	100	2.60	-0.39	2.47	-0.06
	1000	2.60	-0.39	2.60	-0.31
5	0.001	50.47	0.0	26.82	-0.00
	0.01	9.77	-0.12	5.74	-0.02
	0.1	5.27	-0.94	4.12	-0.13
	10	2.60	-1.32	2.60	-0.59
	100	2.67	-1.60	2.57	-1.04
	1000	2.67	-1.5	2.69	-1.5

Thus, we can see from above table that for k=100, the test error stabilizes for min_df=2 and min_df=5 both. The best value of test error (i.e. least) using l1 regularization is observed for k=100 in case of min_df=2 and for k=10 for min_df=5. While, the best value of test error (i.e. least) using l2 regularization is observed for k=100 for both values of min_df.

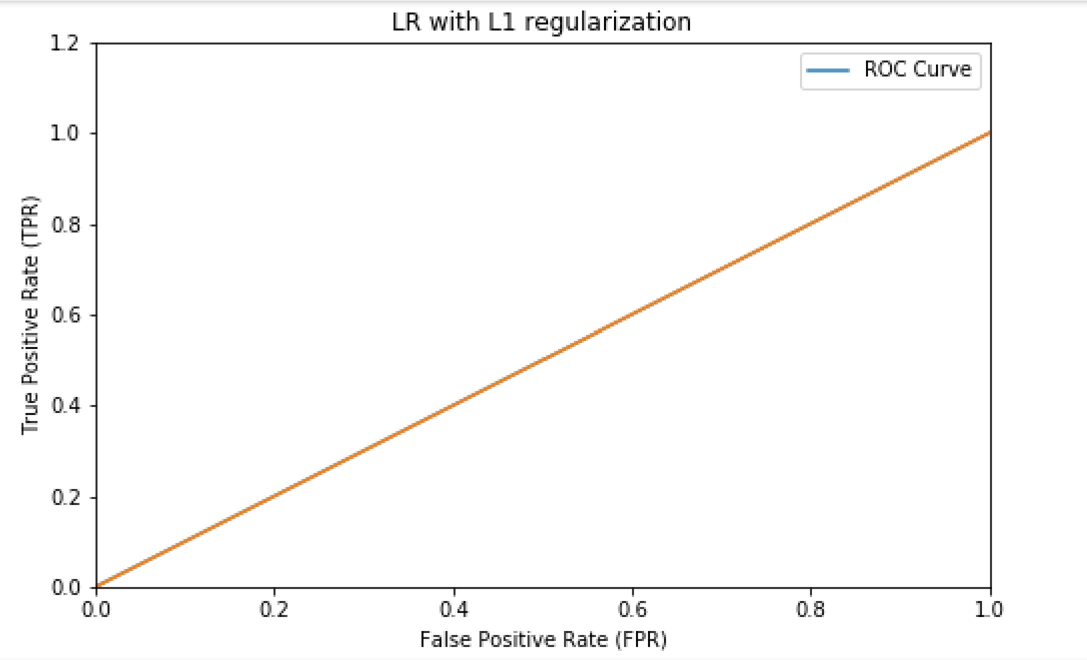
The results obtained by doing **NMF decomposition** were as follows:

Min_df	k	L1 Regularization		L2 Regularization	
		Testing Error	Mean of Coeff	Testing Errors	Mean of Coeff
2	0.001	50.48	0.0	49.52	-0.0
	0.01	50.47	0.0	48.98	-0.0
	0.1	31.3	-0.07	12.22	-0.02
	10	3.59	-6.9	4.92	-0.78
	100	3.71	-13.63	4.16	-1.98
	1000	3.74	-16.2	3.68	-5.14
5	0.001	50.47	0.0	49.52	-0.0
	0.01	50.47	0.0	38.06	-0.0
	0.1	18.16	0.001	9.26	-0.05
	10	3.94	-5.99	5.14	-1.27
	100	3.96	-8.88	4.38	-3.19
	1000	3.93	-9.7	3.97	-5.97

The following ROC curves were obtained using SVD decomposition with min_df=2 and 5 by varying k.

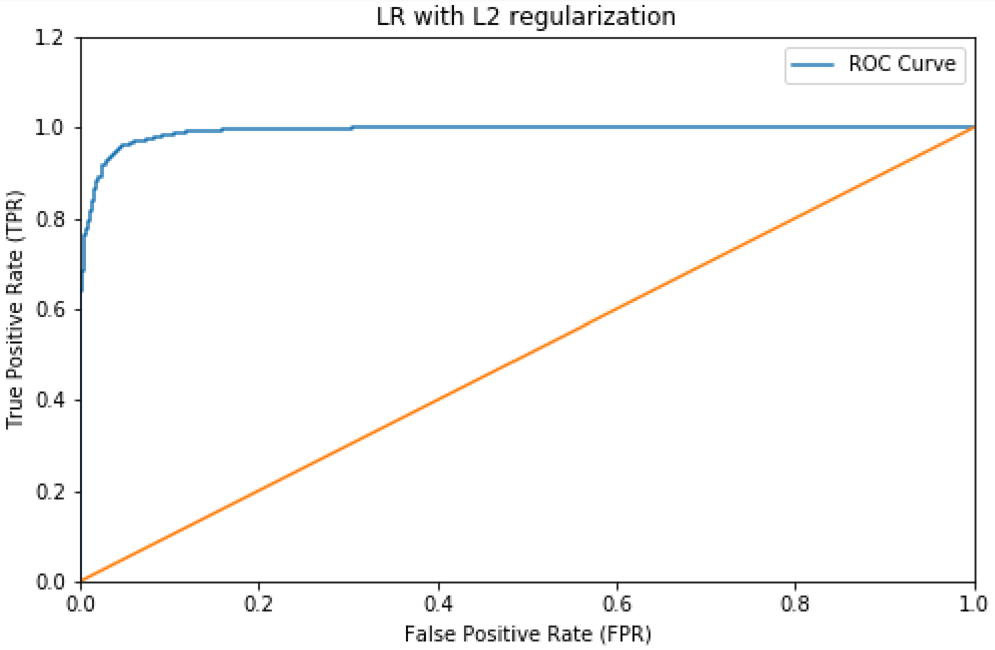
- **min_df=2; k=0.001; l1**

Statistic	Result
Accuracy	49.5238095238
Precision	24.7619047619
Recall	50.0



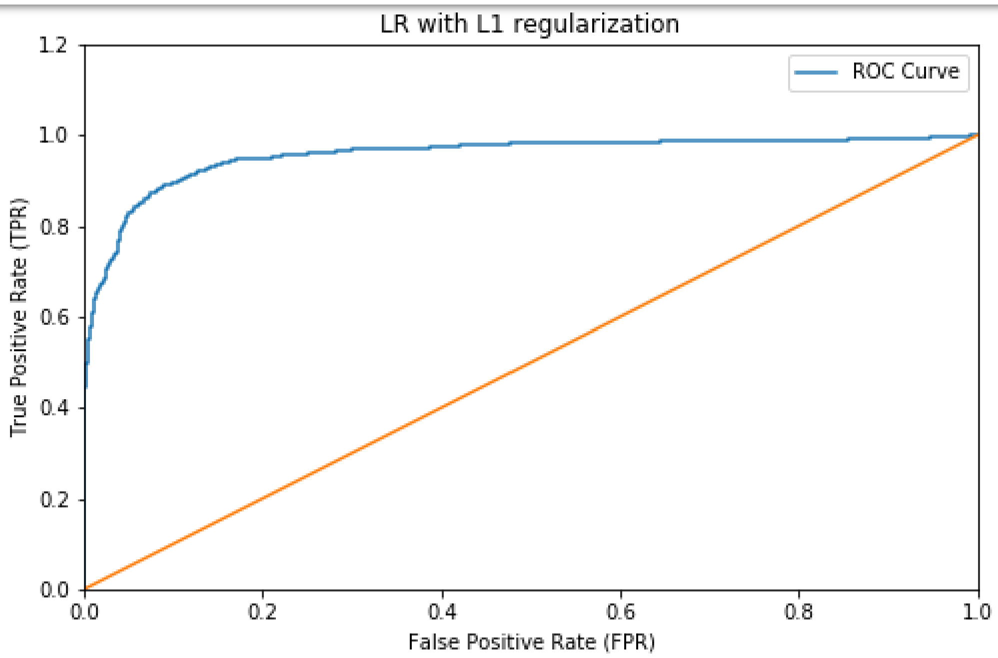
- **min_df=2; k=0.001; l2**

Statistic	Result
Accuracy	68.6349206349
Precision	80.8378588053
Recall	68.3333333333



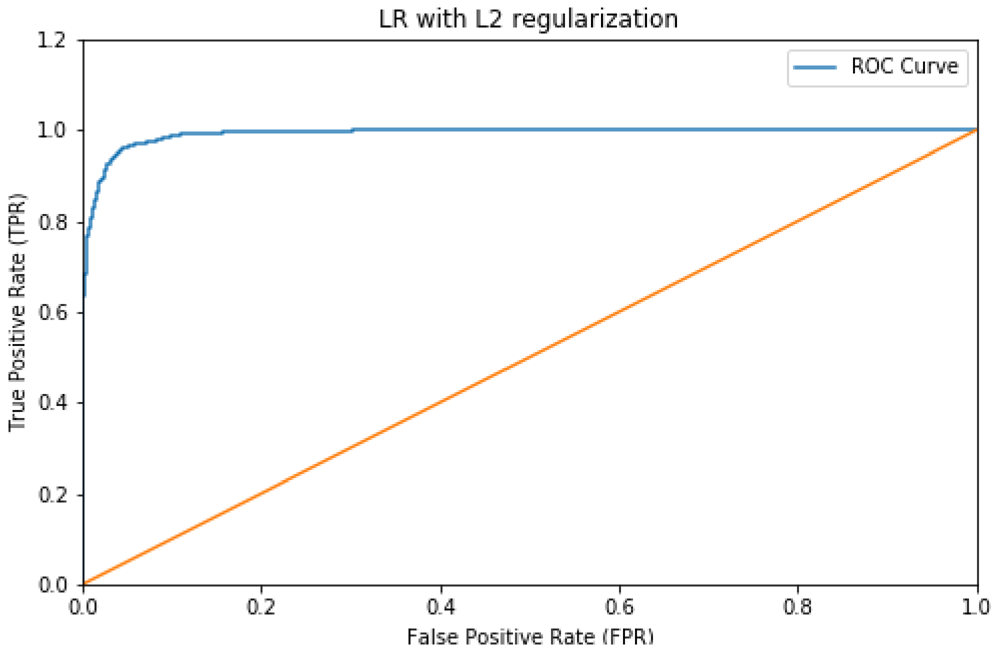
- **min_df=2; k=0.01; l1**

Statistic	Result
Accuracy	89.4285714286
Precision	89.6047355982
Recall	89.4611756168



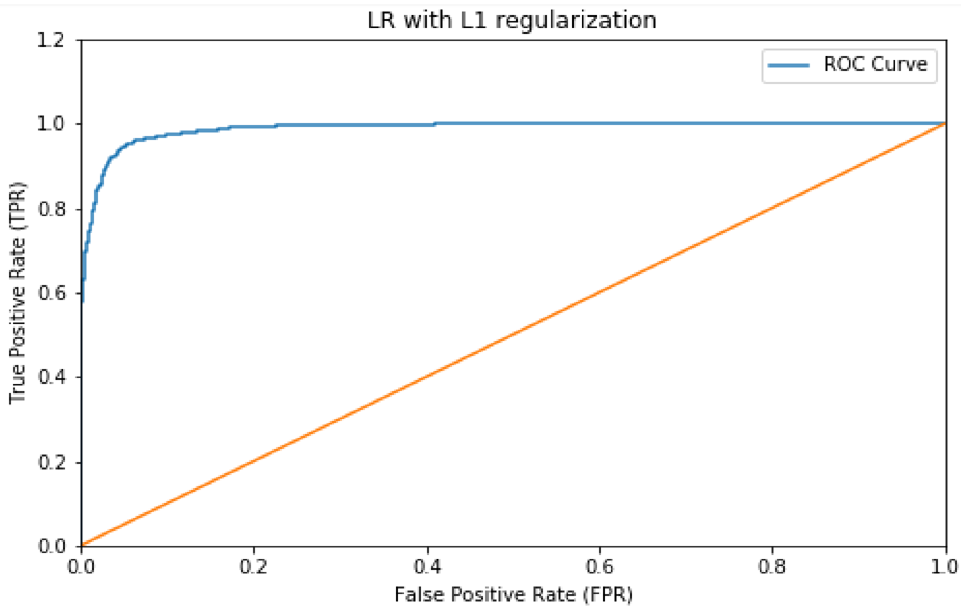
- **min_df=2; k=0.01; l2**

Statistic	Result
Accuracy	94.0952380952
Precision	94.5455605495
Recall	94.0487421384



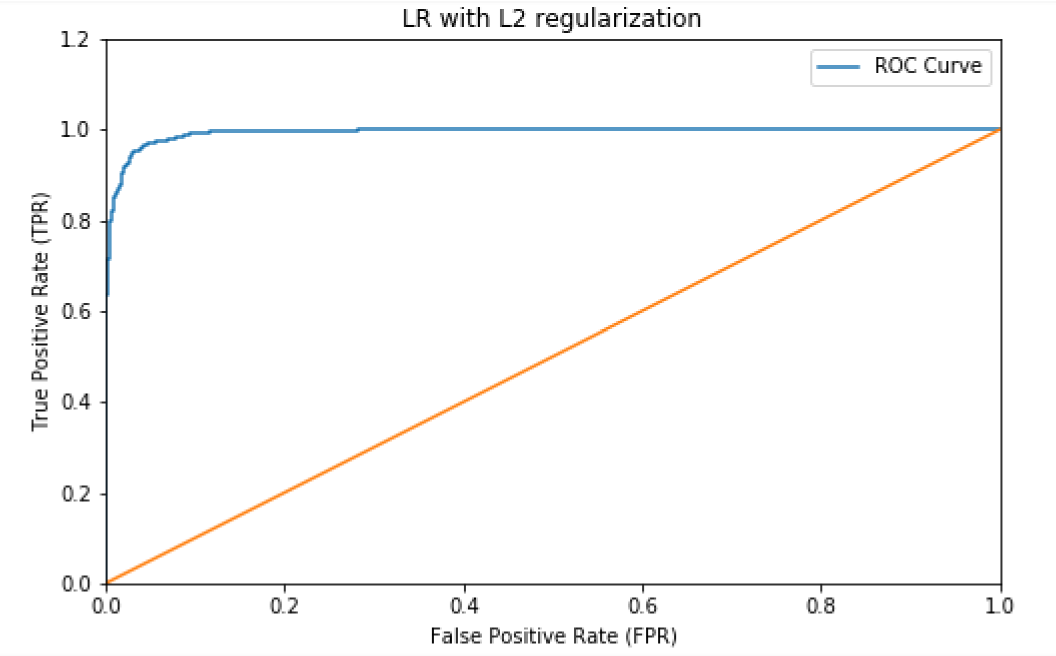
- **min_df=2; k=0.1; l1**

Statistic	**Result**
Accuracy	94.7619047619
Precision	94.7724895935
Recall	94.755684567



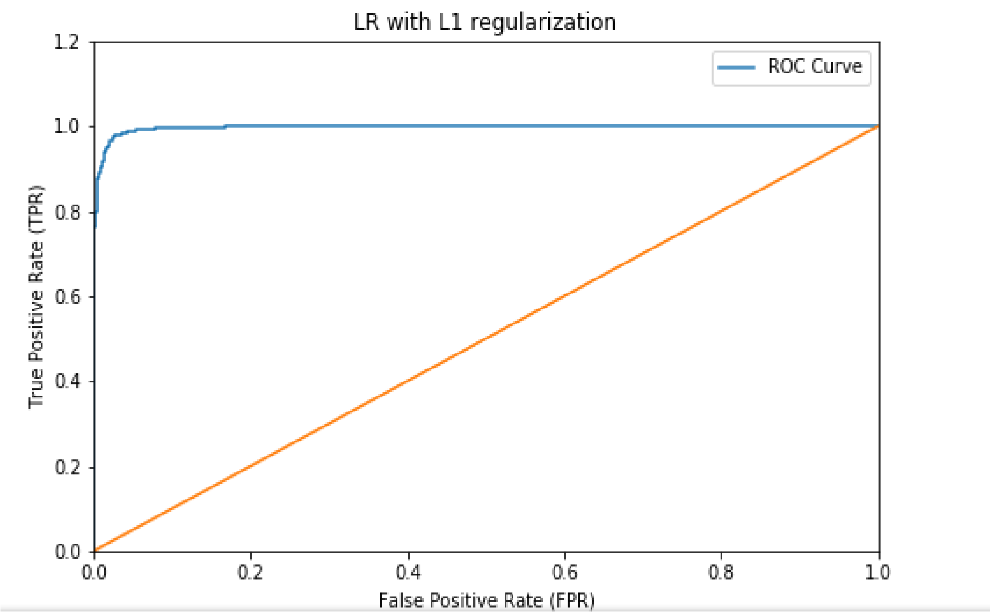
- **min_df=2; k=0.1; l2**

Statistic	Result
Accuracy	95.873015873
Precision	95.9123748789
Recall	95.860546686



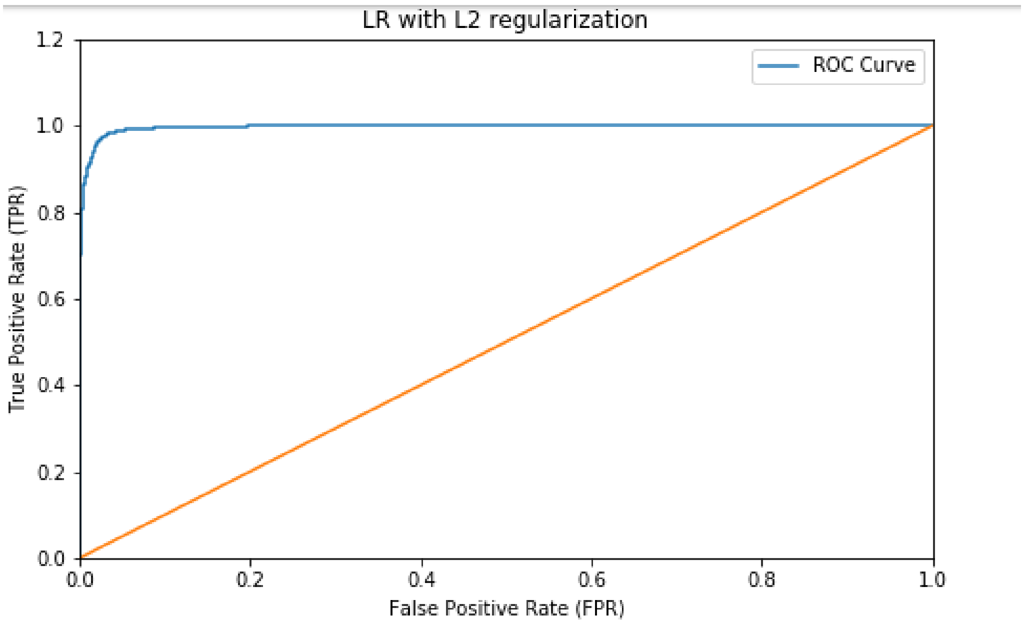
- **min_df=2; k=10; l1**

Statistic	Result
Accuracy	97.3333333333
Precision	97.3556303595
Recall	97.3246250605



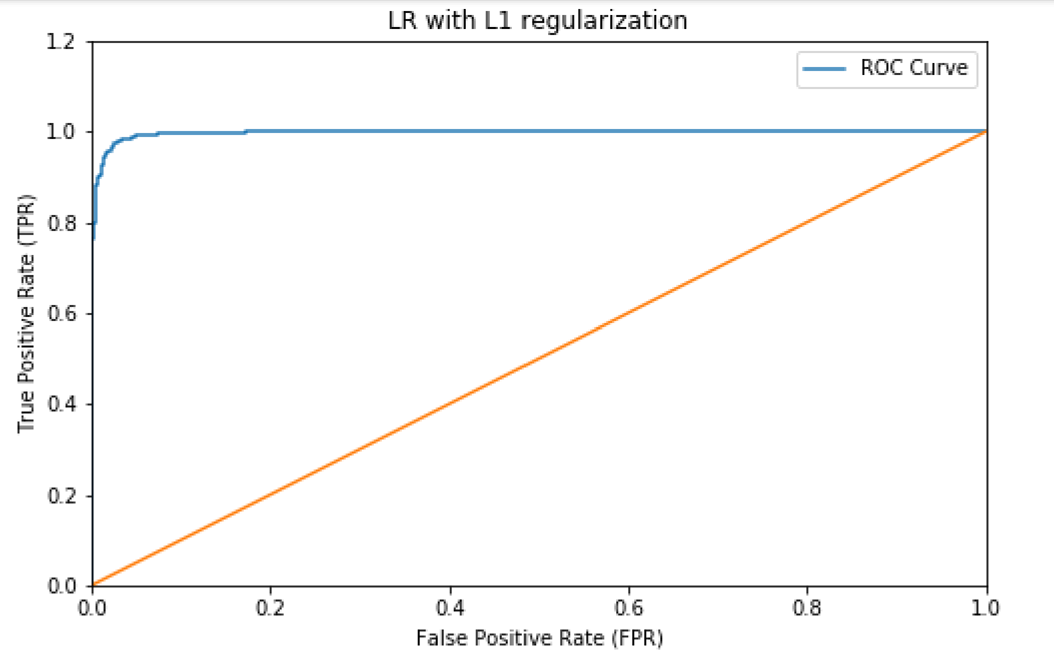
- **min_df=2; k=10; l2**

Statistic	Result
Accuracy	97.2698412698
Precision	97.2977498531
Recall	97.2599177552



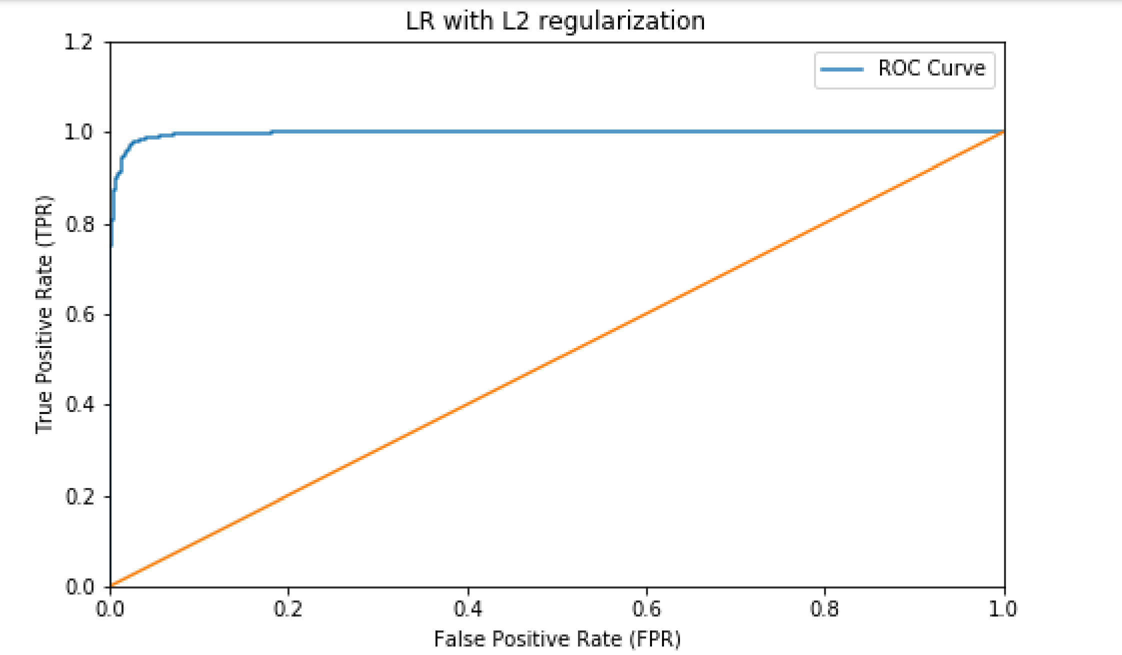
- **min_df=2; k=100; l1**

Statistic	Result
Accuracy	97.3968253968
Precision	97.4141060641
Recall	97.3893323657



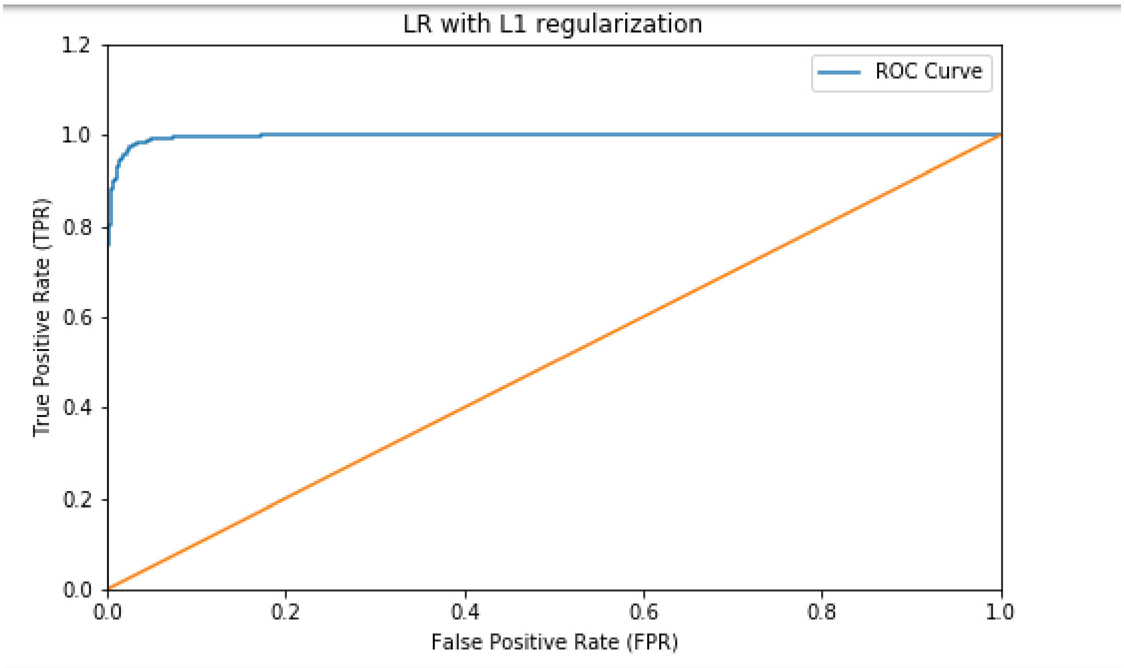
- **min_df=2; k=100; l2**

Statistic	Result
Accuracy	97.5238095238
Precision	97.5411680994
Recall	97.5163280116



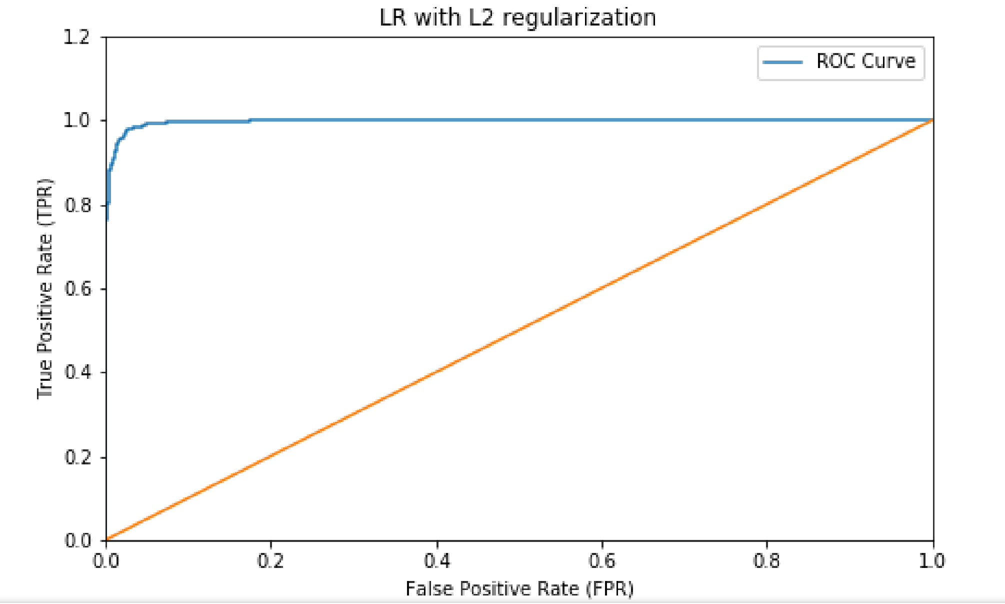
- **min_df=2; k=1000; l1**

Statistic	Result
Accuracy	97.3968253968
Precision	97.4141060641
Recall	97.3893323657



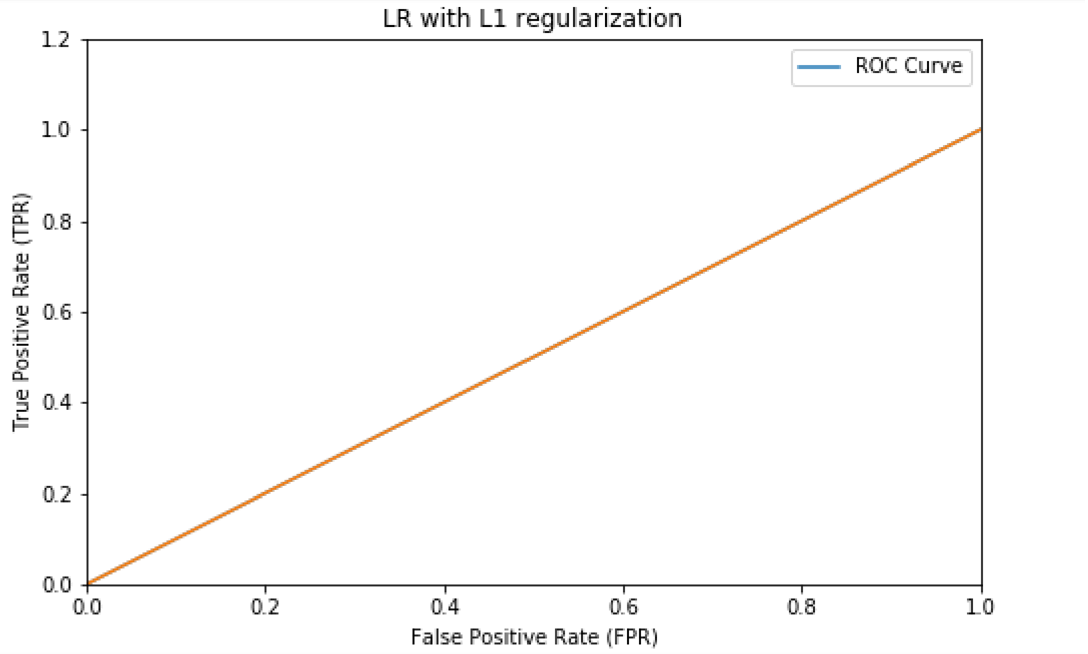
- **min_df=2; k=1000; l2**

Statistic	Result
Accuracy	97.3968253968
Precision	97.4141060641
Recall	97.3893323657



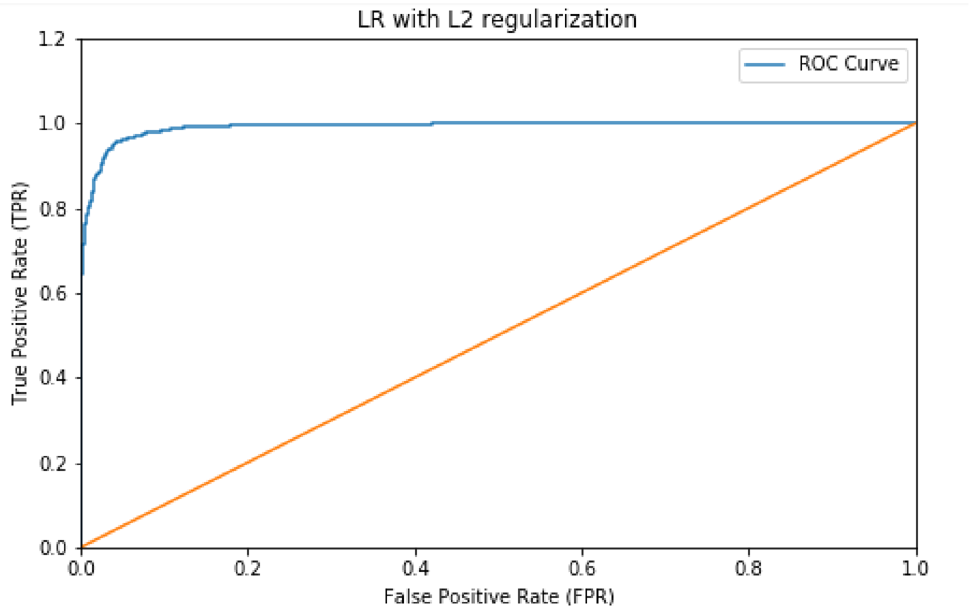
- **min_df=5; k=0.001; l1**

Statistic	**Result**
Accuracy	49.5238095238
Precision	24.7619047619
Recall	50.0



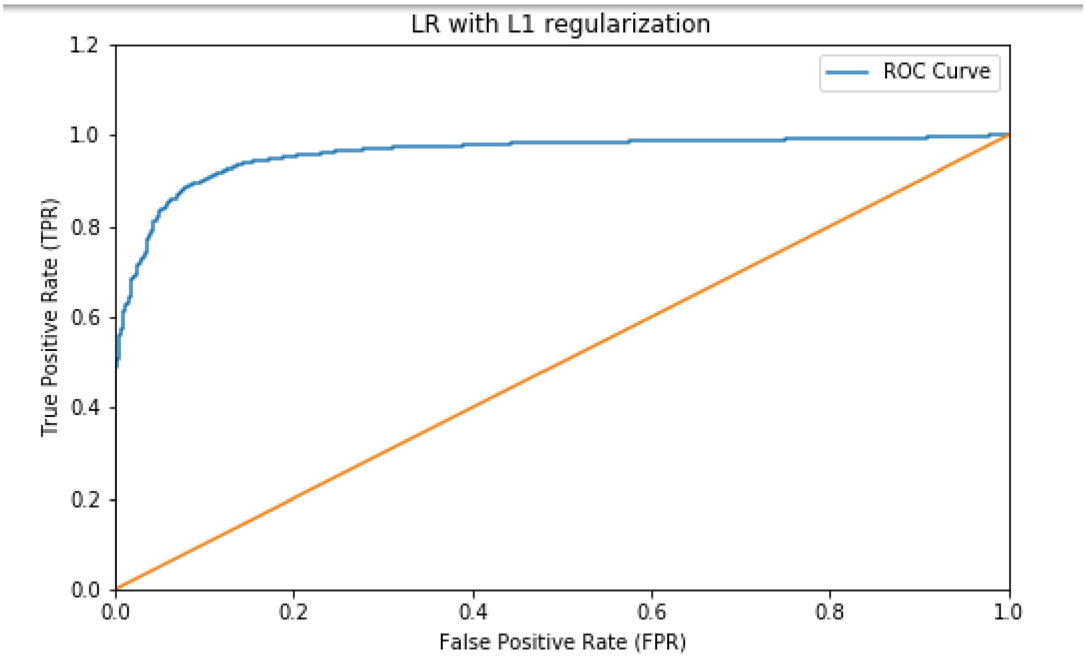
- **min_df=5; k=0.001; l2**

Statistic	**Result**
Accuracy	73.1746031746
Precision	82.6488706366
Recall	72.9166666667



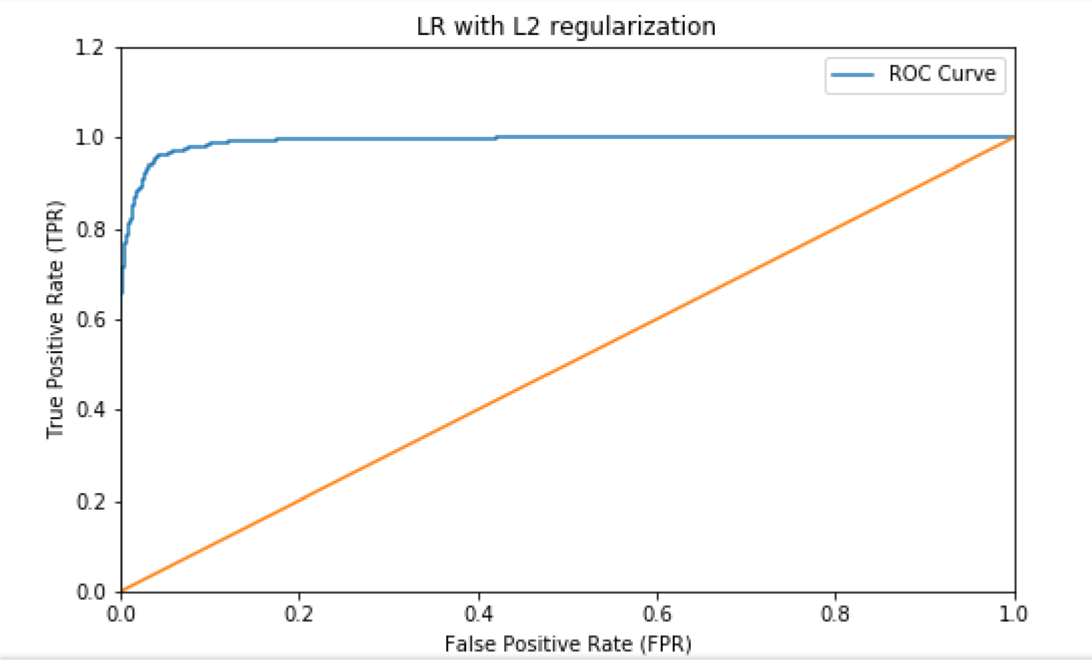
- **min_df=5; k=0.01; l1**

Statistic	Result
Accuracy	90.2222222222
Precision	90.2922285515
Recall	90.2431059507



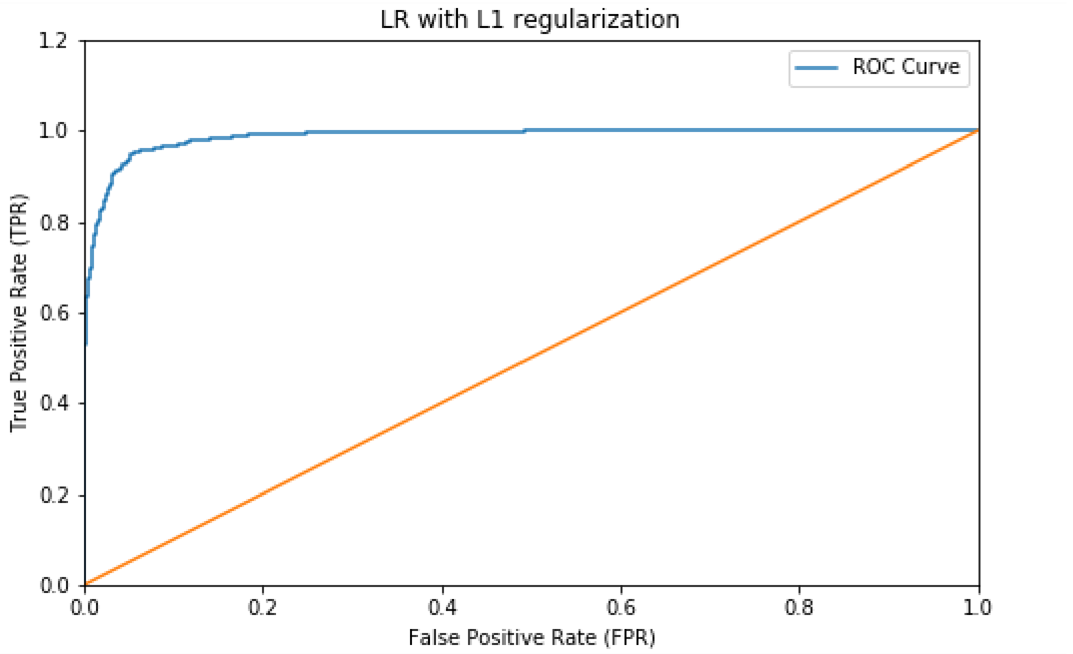
- **min_df=5; k=0.01; l2**

Statistic	Result
Accuracy	94.253968254
Precision	94.6132723112
Recall	94.2126269956



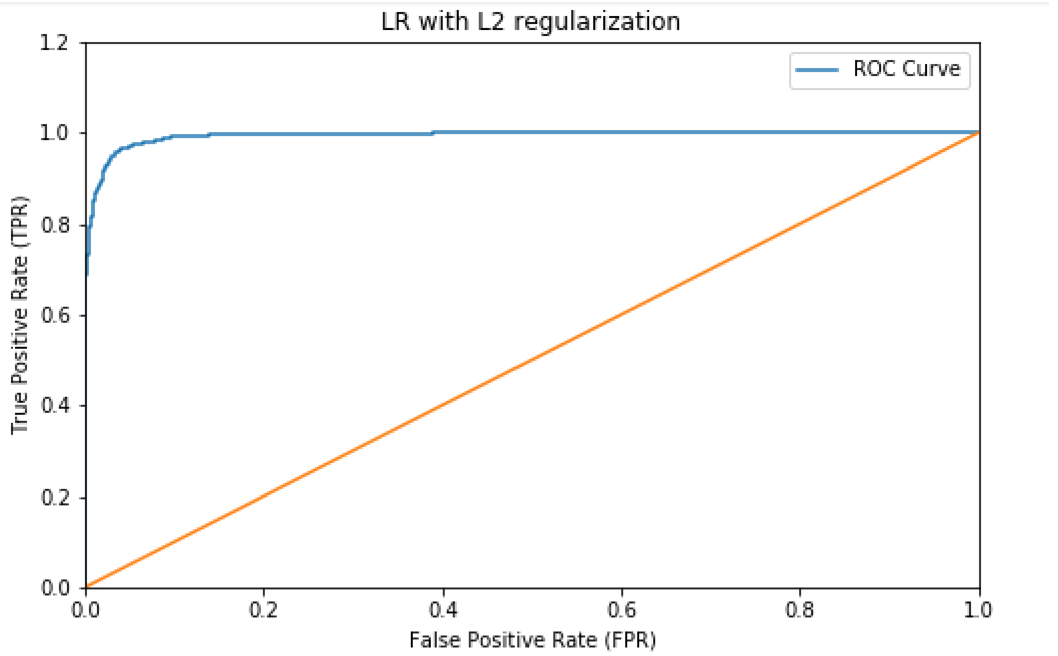
- **min_df=5; k=0.1; l1**

Statistic	Result
Accuracy	94.7301587302
Precision	94.7416713721
Recall	94.723633285



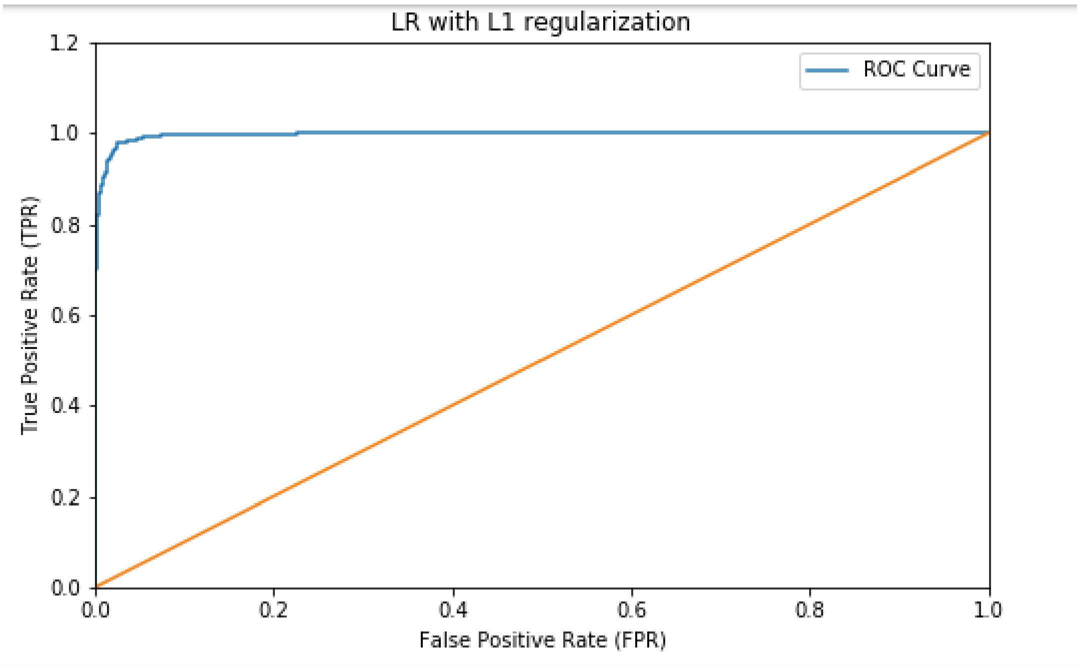
- **min_df=5; k=0.1; l2**

Statistic	Result
Accuracy	95.873015873
Precision	95.9196154927
Recall	95.8593372037



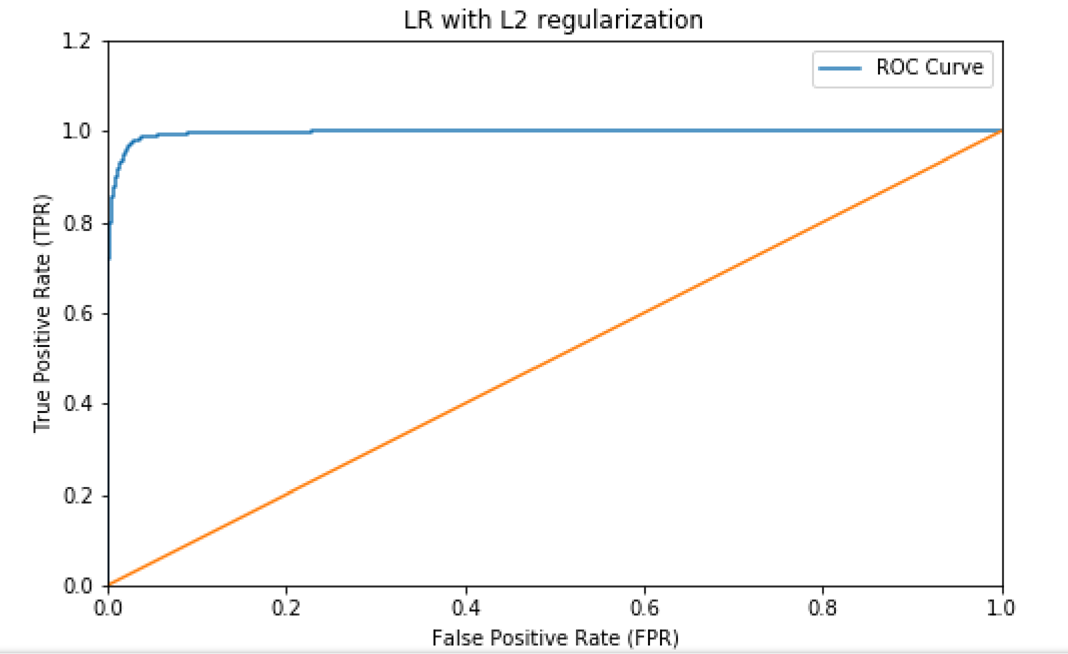
- **min_df=5; k=10; l1**

Statistic	Result
Accuracy	97.3968253968
Precision	97.4165612454
Recall	97.3887276246



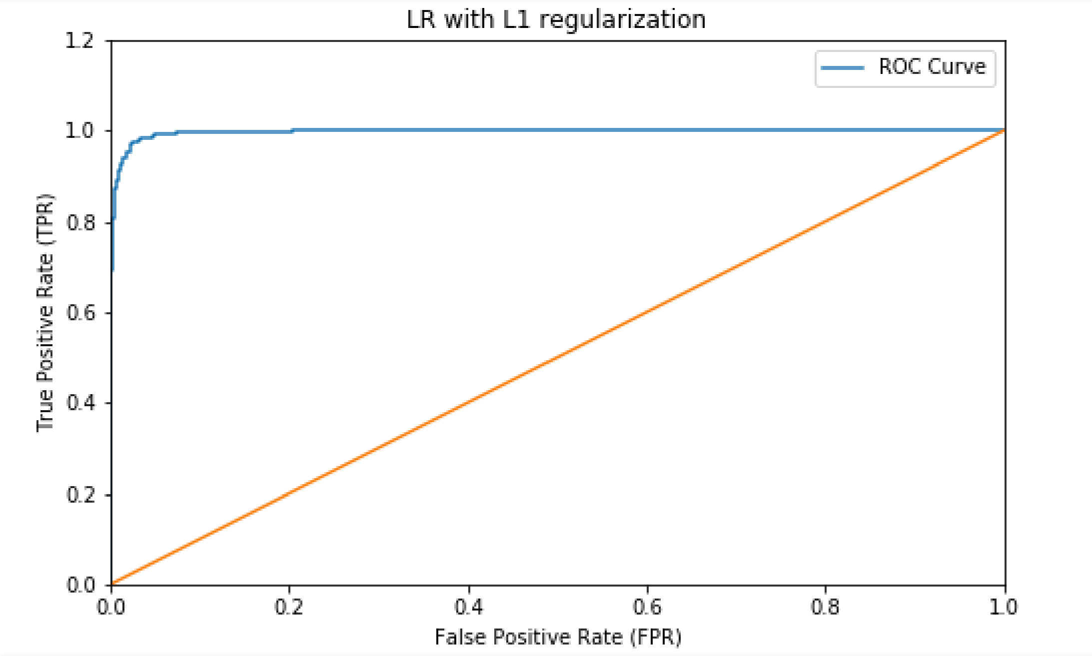
- **min_df=5; k=10; l2**

Statistic	Result
Accuracy	97.3968253968
Precision	97.4279161206
Recall	97.3863086599



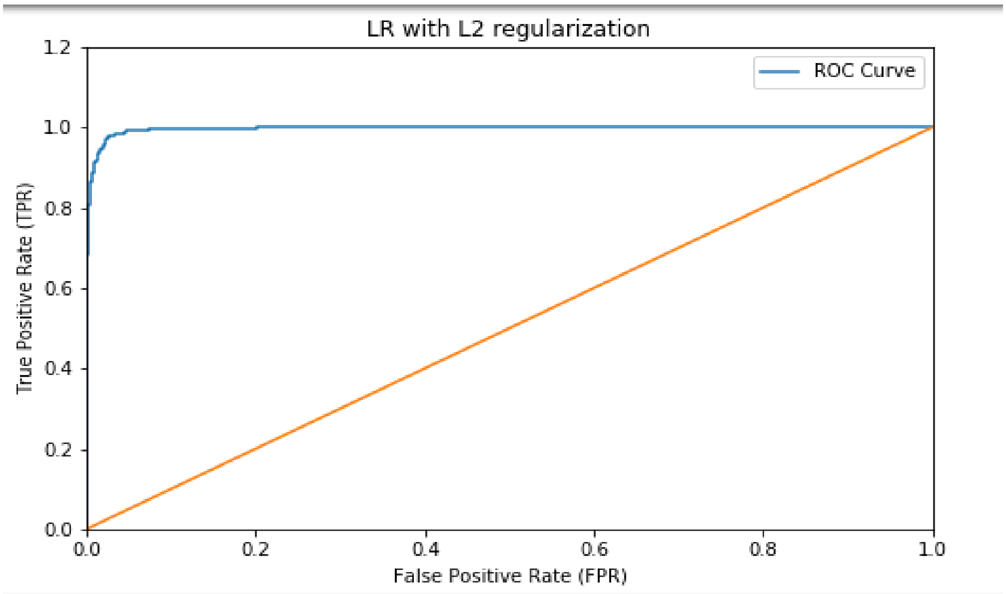
- **min_df=5; k=100; l1**

Statistic	Result
Accuracy	97.3333333333
Precision	97.3461321287
Recall	97.3270440252



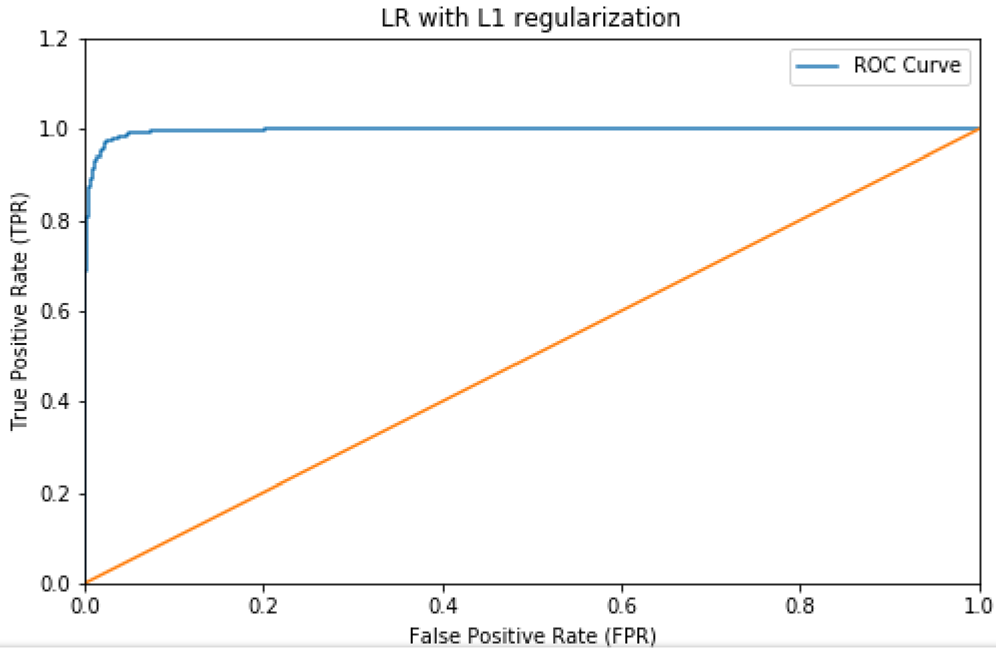
- **min_df=5; k=100; l2**

Statistic	Result
Accuracy	97.4285714286
Precision	97.4496149643
Recall	97.4201741655



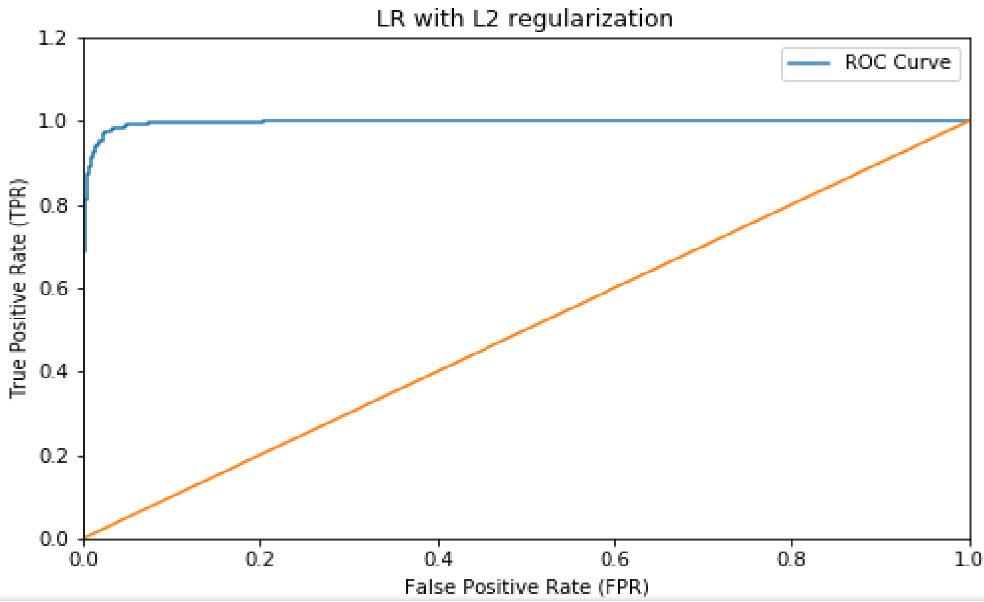
- **min_df=5; k=1000; l1**

Statistic	Result
Accuracy	97.3333333333
Precision	97.3461321287
Recall	97.3270440252



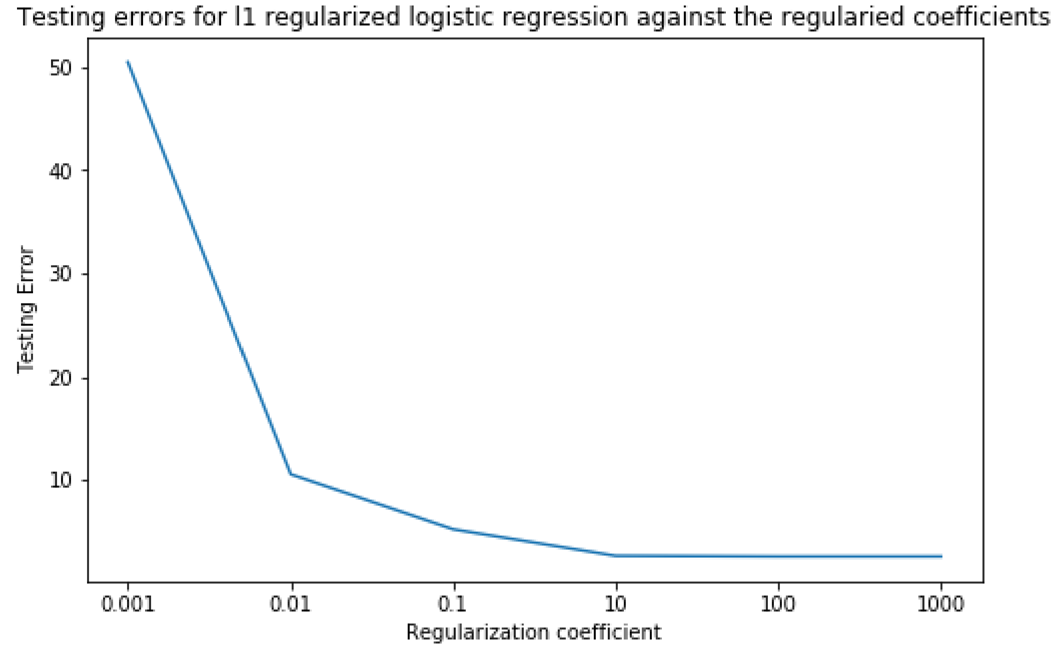
- **min_df=5; k=1000; l2**

Statistic	Result
Accuracy	97.3015873016
Precision	97.3154228422
Recall	97.2949927431

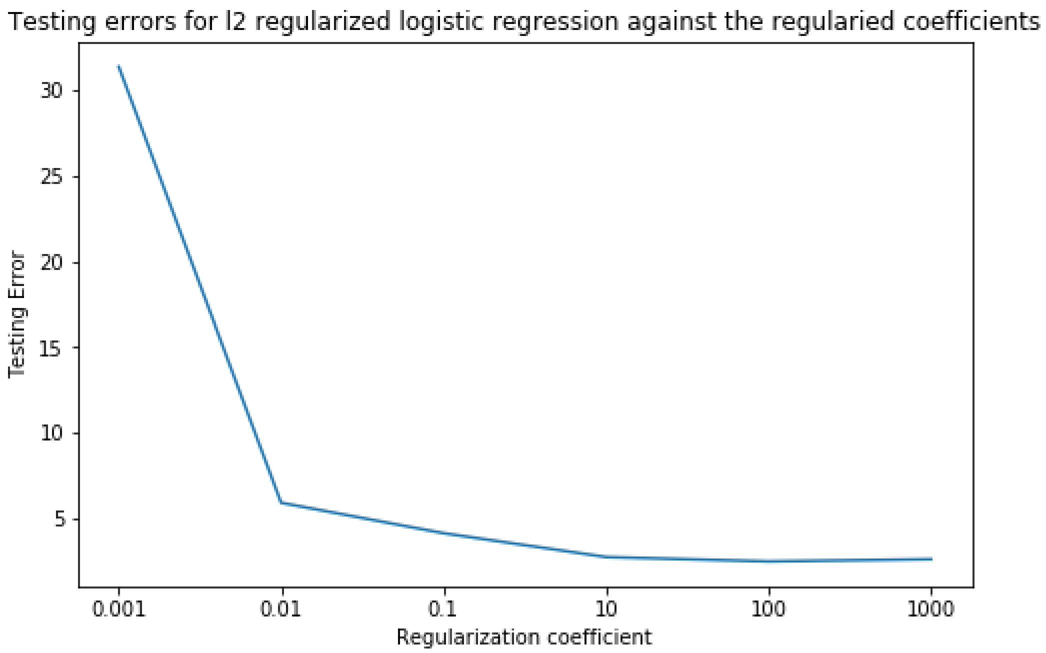


Testing Errors:

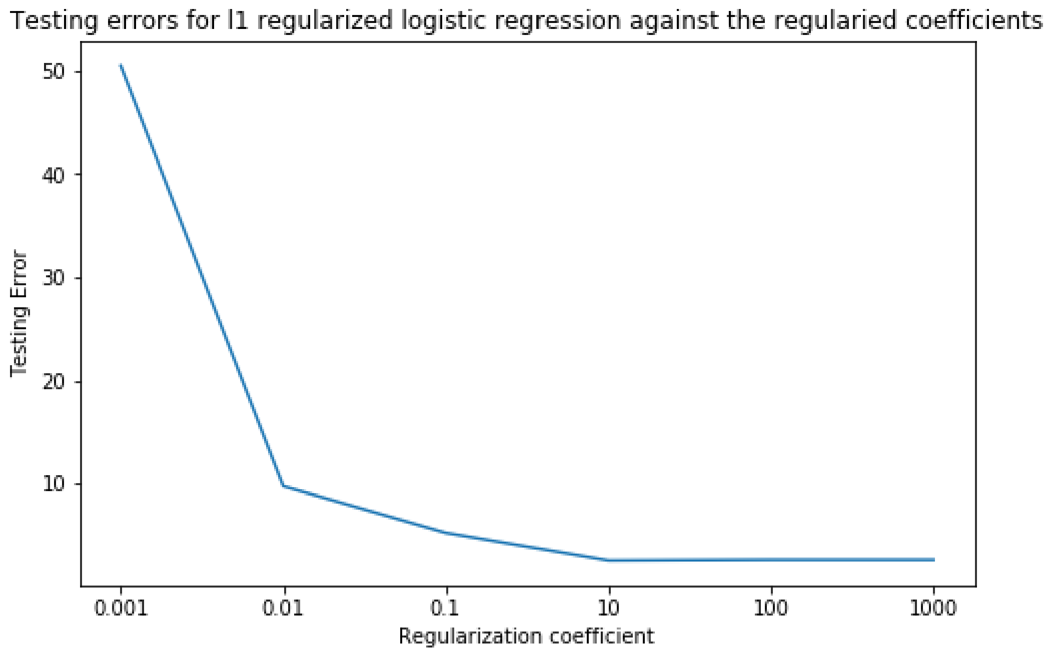
- **min_df=2; l1 regularization**



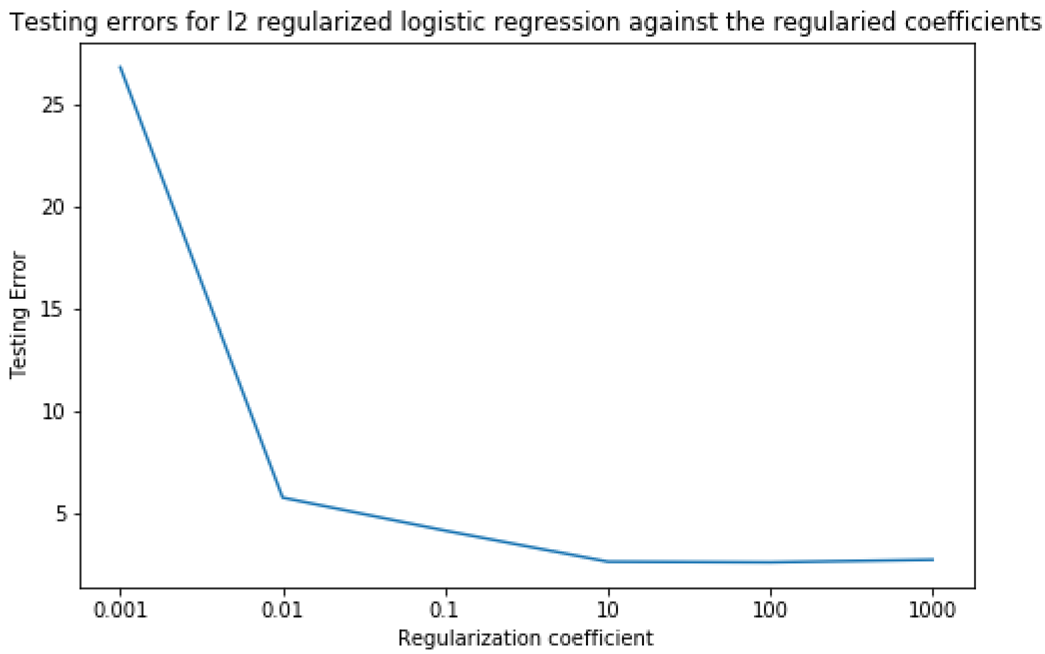
- **min_df=2; l2 regularization**



- **min_df=5; l1 regularization**



- **min_df=5; l2 regularization**



<u>Observations:</u>

We observe that for smaller values of regularization parameter, the testing error is high due to excessive regularization. However, the error decreases steadily on increasing regularization up to a certain point. As we increase the regularization parameter, the fitted hyperplane moves away from the origin.

The L1-norm should be used when we need a robust solution and can tolerate multiple stable solutions. It is better to go with L2 norm when we need to obtain a single stable solution. Moreover, L1 norm can be used when we have good computational power. But if not, L2 norm is a better option.

6. Multiclass Classification

Question (i2) Naive Bayes and SVM

Here, we perform classification on multiple classes and train classifiers on the documents belonging to the following classes:
A: comp.sys.ibm.pc.hardware
B: comp.sys.mac.hardware
C: misc.forsale
D: soc.religion.christian

We use two classification techniques namely One vs One and One vs Rest. The first technique trains nC2 different classifiers and each classifier trains individual classes against each other. On the contrary, the second technique trains n classifiers and trains each one against the rest. We obtain the following results for Naive Bayes and multiclass SVM classification when performed with both One vs One and One vs Rest methods.

- **min_df=2; OneVsOne- SVM; SVD**

Statistic	Result
Accuracy	88.7539936102
Precision	88.8377177276
Recall	88.7004676945

	Predicted: A	Predicted: B	Predicted: C	Predicted: D
Actual: A	334	40	18	0
Actual: B	43	318	23	1
Actual: C	22	14	354	0
Actual: D	9	2	4	383

- **min_df=2; OneVsRest- SVM; SVD**

Statistic	Result
Accuracy	89.0734824281
Precision	88.985634018
Recall	89.0188288919

	Predicted: A	Predicted: B	Predicted: C	Predicted: D
Actual: A	319	44	25	4
Actual: B	32	325	27	1
Actual: C	18	13	357	2
Actual: D	3	0	2	393

- **min_df=2; OneVsOne- SVM; NMF**

Statistic	Result
Accuracy	76.7412140575
Precision	80.7026663405
Recall	76.5714274957

	Predicted: A	Predicted: B	Predicted: C	Predicted: D
Actual: A	352	33	7	0
Actual: B	166	210	9	0
Actual: C	78	42	270	0
Actual: D	20	7	2	369

- **min_df=2; OneVsRest- SVM; NMF**

Statistic	Result
Accuracy	83.2587859425
Precision	83.0502894791
Recall	83.1386670879

	Predicted: A	Predicted: B	Predicted: C	Predicted: D
Actual: A	290	46	39	17
Actual: B	58	262	43	22
Actual: C	18	8	355	9
Actual: D	0	0	2	396

- **min_df=2; OneVsOne- NB; SVD**

Statistic	Result
Accuracy	73.4185303514
Precision	77.2340704709
Recall	73.2025930518

	Predicted: A	Predicted: B	Predicted: C	Predicted: D
Actual: A	280	10	100	2
Actual: B	97	153	131	4
Actual: C	35	16	338	1
Actual: D	1	0	19	378

- **min_df=2; OneVsRest- NB; SVD**

Statistic	Result
Accuracy	73.482428115
Precision	77.3389900505
Recall	73.2669134527

	Predicted: A	Predicted: B	Predicted: C	Predicted: D
Actual: A	274	10	107	1
Actual: B	85	154	139	7
Actual: C	29	18	342	1
Actual: D	0	0	18	380

- **min_df=2; OneVsOne- NB; NMF**

Statistic	Result
Accuracy	78.4664536741
Precision	78.4683685221
Recall	78.316198488

	Predicted: A	Predicted: B	Predicted: C	Predicted: D
Actual: A	285	48	53	6
Actual: B	74	233	74	4
Actual: C	38	26	320	6
Actual: D	5	1	2	390

- **min_df=2; OneVsRest- NB; NMF**

Statistic	Result
Accuracy	80.1277955272
Precision	80.1200312273
Recall	79.990297899

	Predicted: A	Predicted: B	Predicted: C	Predicted: D
Actual: A	281	52	52	7
Actual: B	66	245	70	4
Actual: C	35	16	335	4
Actual: D	3	1	1	393

- **min_df=5; OneVsOne- SVM; SVD**

Statistic	Result
Accuracy	88.8817891374
Precision	89.0114995819
Recall	88.8191385069

	Predicted: A	Predicted: B	Predicted: C	Predicted: D
Actual: A	340	37	15	0
Actual: B	51	312	22	0
Actual: C	20	16	354	0
Actual: D	9	1	3	385

- **min_df=5; OneVsRest- SVM; SVD**

Statistic	Result
Accuracy	89.2651757188
Precision	89.1745679853
Recall	89.2062404872

	Predicted: A	Predicted: B	Predicted: C	Predicted: D
Actual: A	321	42	25	4
Actual: B	32	323	29	1
Actual: C	15	15	358	2
Actual: D	2	0	1	395

- **min_df=5; OneVsOne- SVM; NMF**

Statistic	Result
Accuracy	84.6645367412
Precision	87.7697522033
Recall	84.5526627297

	Predicted: A	Predicted: B	Predicted: C	Predicted: D
Actual: A	375	9	8	0
Actual: B	117	255	13	0
Actual: C	49	13	328	0
Actual: D	28	1	2	367

- **min_df=5; OneVsRest- SVM; NMF**

Statistic	Result
Accuracy	88.3706070288
Precision	88.2696100182
Recall	88.2917480342

	Predicted: A	Predicted: B	Predicted: C	Predicted: D
Actual: A	322	30	30	10
Actual: B	39	306	31	9
Actual: C	17	13	358	2
Actual: D	0	0	1	397

- **min_df=5; OneVsOne- NB; SVD**

Statistic	Result
Accuracy	77.6357827476
Precision	78.8057048768
Recall	77.4429645791

	Predicted: A	Predicted: B	Predicted: C	Predicted: D
Actual: A	295	18	66	13
Actual: B	74	189	109	13
Actual: C	23	24	341	2
Actual: D	0	1	7	390

- **min_df=5; OneVsRest- NB; SVD**

Statistic	Result
Accuracy	76.357827476
Precision	77.6406457814
Recall	76.1585741669

	Predicted: A	Predicted: B	Predicted: C	Predicted: D
Actual: A	279	20	79	14
Actual: B	72	183	115	15
Actual: C	17	26	341	6
Actual: D	0	0	6	392

- **min_df=5; OneVsOne- NB; NMF**

Statistic	Result
Accuracy	79.8722044728
Precision	79.9884809317
Recall	79.7379709606

	Predicted: A	Predicted: B	Predicted: C	Predicted: D
Actual: A	303	34	50	5
Actual: B	55	257	68	5
Actual: C	56	28	298	8
Actual: D	4	0	2	392

- **min_df=5; OneVsRest- NB; NMF**

Statistic	Result
Accuracy	82.1086261981
Precision	82.183039153
Recall	81.9917982831

	Predicted: A	Predicted: B	Predicted: C	Predicted: D
Actual: A	302	33	52	5
Actual: B	53	272	56	4
Actual: C	44	23	317	6
Actual: D	2	1	1	394