DATA MINING TECHNOLOGY FOR BUSINESS AND SOCIETY HW3

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Introduction

In this work we have to solve a classification problem using different models and comparing the results.

1. First Part

In this part we have to classify comments as spam or ham.

1.1 Train/Test

	Training Set	Test Set
Spam(0)	122	53
Ham(1)	120	52

1.2 The list of all parameters to tune with the corresponding set of values.

TfidfVectorizer:

```
'ngram_range' : [(1,1),(1,2)]
'tokenizer' : [None, stemming_tokenizer]
'stop_words' : [None, 'english']
```

KNeighborsClassifier:

```
'n_neighbors' : [1,3,5,7,9,11]
'leaf size' : [2,3]
```

(we use a short list for leaf_size because the optimal value is always small and less dominant respect the other parameters.)

1.3 A simply and short description on how to perform the training-validation process using more than one CPU core.

To optimize the 10-fold-cross-validation step we can use the flag -1 for the parameter n_jobs in the function GridSearchCV: in this way we use all the available cores in the CPU for our jobs and we reduce the total time for the model tuning.

1.4 The best configuration of parameters found by the GridSearchCV object at the end of the 10-Fold-Cross-Validation process.

TfidfVectorizer:

```
'ngram_range': (1, 2)
'tokenizer': None
'stop words': None
```

KNeighborsClassifier:

```
'n_neighbors': 11
'leaf_size': 2
```

Usually the model works better with stemming and removing the stopwords. In this particular case, the outcomes are better when we do not preprocess the words: we think that this happens because the comments are extremely short (normally < 10 words) and, instead to remove noise, we lose information: it seems that stopwords and inflections help the classification task, probably capturing some semantic inside the short texts.

1.5 The output of the metrics.classification_report tool.

	precision	recall	f1-score	support
0	0.92	0.85	0.88	53 52
avg / total	0.89	0.89	0.89	105

1.6 The Confusion-Matrix with labels on columns and rows.

	Predicted – Spam	Predicted – Ham
Tested - Spam	45	8
Tested – Ham	4	48

1.7 The Normalized-Accuracy value.

0.8857

1.8 The Matthews-Correlation-Coefficient value.

0.7738

2. Second-Part

In this part we have to classify comments as positive or negative.

We decided to use a Support Vector Machine with exponential kernel and a Stochastic Gradient Descent algorithm with linear SVM as classifier (they have similar names but they are two distinct classifier with different hyperparameters and different fitting procedure) to compare the results with the KNN classifier.

2.1 Train/Test

	Training Set	Test Set
Negative(0)	308	308
Positive(1)	249	250

'penalty': ['11', '12']

2.2 The list of all parameters to tune with the corresponding set of values.

2.3	The best configuration of parameters found by the GridSearchCV object at the end of
	the 10-Fold-Cross-Validation process.

Neigh------TfidfVectorizer: 'ngram_range': (1, 2)
'stop_words': 'english' 'tokenizer': stemming tokenizer KNeighborsClassifier: 'leaf size': 2 'n neighbors': 3 SVM RBF-----TfidfVectorizer: 'ngram_range': (1, 1)
'stop_words': 'english' 'tokenizer': stemming_tokenizer SVC: 'C': 50 'gamma': 0.1 SGD-----TfidfVectorizer: 'ngram_range': (1, 1) 'stop words': 'english' 'tokenizer': stemming tokenizer SGDClassifier: 'alpha': 0.001

2.4 The output of the metrics.classification_report tool.

'penalty': 'l1'

Neigh				
	precision	recall	f1-score	support
0	0.94	0.83	0.88	250
1	0.88	0.96	0.91	308
avg / total	0.90	0.90	0.90	558

SVM_RBF					
	precision	recall	f1-score	support	
0	0.96 0.96	0.96 0.97	0.96 0.97	250 308	
avg / total	0.96	0.96	0.96	558	

SGD

	precision	recall	f1-score	support	
0 1	0.97 0.98	0.98 0.97	0.97 0.98	250 308	
avg / total	0.98	0.98	0.98	558	

2.5 The Confusion-Matrix with labels on columns and rows.

Neigh-----

	Predicted – Negative	Predicted – Positive
Tested - Negative	208	42
Tested – Positive	13	295

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SVM	KKK
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	Predicted – Negative	Predicted – Positive
Tested - Negative	239	11
Tested – Positive	9	299

SGD------

	Predicted – Negative	Predicted – Positive
Tested - Negative	245	5
Tested – Positive	8	300

Neigh-----

0.9014

2.6 The Normalized-Accuracy value.

SVM_RBF-----

0.9641

SGD------

0.9767

Neigh
0.8030
SVM_RBF
0.9275
SGD
0.9530

2.7 The Matthews-Correlation-Coefficient value.