

CSI4107 Assignment 2 Report

Part 1

In the first part of the experiment, we used Python to read the twitter messages from the text file. Using Scikit-learn, a machine learning toolkit for Python, we are able to create a $n \times m$ matrix for n documents with m features of words using a `CountVectorizer` object.

The `CountVectorizer` object takes an array of text objects representing documents and creates an appropriate matrix representing the counts of token words for each document. Documents are first preprocessed with a preprocess object, and then tokenized with a tokenizer object. Together, these form an analyzer that is called to process every document. We decided to extend the basic analyzer by stemming all the words produced by the preprocessor and tokenizer using the `EnglishStemmer` provided by Natural Language Toolkit (NLTK).

Using the matrix created from this preprocessing, tokenization, and stemming, we were then able to produce a sparse arff file for use in Weka. In the sparse arff file, a twitter document is represented by the index of the token in the bag of words list and the count of that token in that document. Tokens are only specified if they are present in the document. This reduces arff file size as features (i.e. words) not present are not included and it is implied that they are 0 for a given document.

With this arff file, the first run in Weka resulted in the following results from a 10-fold cross validation with the three different classifiers:

Decision Tree:

=== Stratified cross-validation ===

Correctly Classified Instances	3455	47.7936 %
Incorrectly Classified Instances	3774	52.2064 %
Kappa statistic	0.2297	
Mean absolute error	0.28	
Root mean squared error	0.4545	
Relative absolute error	80.8692 %	
Root relative squared error	109.2265 %	
Total Number of Instances	7229	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
e	0.692	0.365	0.612	0.692	0.649	0.704	positive
e	0.354	0.127	0.379	0.354	0.366	0.636	negative
	0.224	0.155	0.282	0.224	0.249	0.556	neutral
ve	0.344	0.115	0.351	0.344	0.348	0.641	objective
Weighted Avg.	0.478	0.239	0.46	0.478	0.467	0.651	

=== Confusion Matrix ===

a	b	c	d	<-- classified as
2271	363	387	263	a = positive
486	458	214	135	b = negative
634	263	346	304	c = neutral
319	125	281	380	d = objective

Naive Bayes:

=== Stratified cross-validation ===

Correctly Classified Instances	3368	46.5901 %
Incorrectly Classified Instances	3861	53.4099 %
Kappa statistic	0.244	
Mean absolute error	0.2824	
Root mean squared error	0.445	
Relative absolute error	81.5583 %	
Root relative squared error	106.9465 %	
Total Number of Instances	7229	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
e	0.582	0.279	0.635	0.582	0.607	0.705	positive
e	0.452	0.183	0.35	0.452	0.395	0.698	negative
	0.219	0.13	0.315	0.219	0.258	0.597	neutral
ve	0.482	0.153	0.363	0.482	0.414	0.745	objective
Weighted Avg.	0.466	0.211	0.474	0.466	0.465	0.687	

=== Confusion Matrix ===

a	b	c	d	<-- classified as
1911	596	363	414	a = positive
369	585	184	155	b = negative
480	361	339	367	c = neutral
251	130	191	533	d = objective

Support Vector Machine (SMO):

```
=== Stratified cross-validation ===
```

Correctly Classified Instances	3698	51.1551 %
Incorrectly Classified Instances	3531	48.8449 %
Kappa statistic	0.2741	
Mean absolute error	0.3202	
Root mean squared error	0.4063	
Relative absolute error	92.476 %	
Root relative squared error	97.6539 %	
Total Number of Instances	7229	

```
=== Detailed Accuracy By Class ===
```

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
e	0.725	0.36	0.626	0.725	0.672	0.716	positiv
e	0.371	0.103	0.439	0.371	0.402	0.718	negativ
	0.299	0.162	0.334	0.299	0.316	0.579	neutral
ve	0.338	0.094	0.394	0.338	0.364	0.718	objecti
Weighted Avg.	0.512	0.231	0.495	0.512	0.5	0.688	

```
=== Confusion Matrix ===
```

a	b	c	d	<-- classified as
2382	291	396	215	a = positive
462	480	253	98	b = negative
601	223	463	260	c = neutral
359	100	273	373	d = objective

Clearly, the SVM classifier produced the best results with 51.15% correctly classified instances and a precision of 49.5%.

Part 2

When adding features to the bag of words feature set, we first began by counting the amount of smiley-based emoticons and sad-based emoticons. The analysis was carried out on each document using the following code:

```

additional_features["smilies"] = twitter_document.msg_text.count("(:") + twitter_document.msg_text.count(":)") + twitter_document.msg_text.count(":-)") + twitter_document.msg_text.count(":o)") + twitter_document.msg_text.count(":]") + twitter_document.msg_text.count(":3") + twitter_document.msg_text.count(":c)") + 2*twitter_document.msg_text.count(":D") + 2*twitter_document.msg_text.count("C:")
additional_features["exclamations"] = twitter_document.msg_text.count("!")
additional_features["questions"] = twitter_document.msg_text.count("?")
additional_features["sadfaces"] = twitter_document.msg_text.count("):") + twitter_document.msg_text.count(":(") + twitter_document.msg_text.count(":-(") + twitter_document.msg_text.count(":c") + twitter_document.msg_text.count(":[") + 2*twitter_document.msg_text.count("D8") + twitter_document.msg_text.count("D;") + 2*twitter_document.msg_text.count("D=") + twitter_document.msg_text.count("DX");

```

The following emoticons representing smilies were seached for:

```
(: , :) , :-) , o) , :] , :3 , :c , :D, C:
```

The following emoticons representing sad faces were searched for:

```
): , :( , :-( , :c , :[ , D8 , D; , D=, DX
```

In addition, the amount of question marks and exclamations were added to each document as features.

This resulted in the following results from the three classifiers:

Decision Tree:

=== Stratified cross-validation ===

Correctly Classified Instances	3578	49.4951 %
Incorrectly Classified Instances	3651	50.5049 %
Kappa statistic	0.254	
Mean absolute error	0.2737	
Root mean squared error	0.4489	
Relative absolute error	79.036 %	
Root relative squared error	107.8775 %	
Total Number of Instances	7229	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
e	0.716	0.346	0.633	0.716	0.672	0.721	positiv
e	0.351	0.13	0.371	0.351	0.361	0.614	negativ
	0.262	0.154	0.316	0.262	0.286	0.572	neutral
ve	0.333	0.105	0.364	0.333	0.348	0.633	objecti
Weighted Avg.	0.495	0.229	0.477	0.495	0.484	0.657	

=== Confusion Matrix ===

a	b	c	d	<-- classified as
2351	354	358	221	a = positive
461	454	242	136	b = negative
566	291	405	285	c = neutral
336	125	276	368	d = objective

Naive Bayes:

=== Stratified cross-validation ===

Correctly Classified Instances	3459	47.8489 %
Incorrectly Classified Instances	3770	52.1511 %
Kappa statistic	0.271	
Mean absolute error	0.2747	
Root mean squared error	0.443	
Relative absolute error	79.3219 %	
Root relative squared error	106.4743 %	
Total Number of Instances	7229	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
e	0.581	0.224	0.684	0.581	0.628	0.73	positive
e	0.5	0.198	0.355	0.5	0.415	0.709	negative
	0.218	0.124	0.325	0.218	0.261	0.605	neutral
ve	0.512	0.165	0.359	0.512	0.422	0.753	objective
Weighted Avg.	0.478	0.189	0.499	0.478	0.48	0.703	

=== Confusion Matrix ===

a	b	c	d	<-- classified as
1909	613	334	428	a = positive
303	646	174	170	b = negative
393	404	338	412	c = neutral
186	159	194	566	d = objective

SVM:

=== Stratified cross-validation ===

Correctly Classified Instances	3773	52.1926 %
Incorrectly Classified Instances	3456	47.8074 %
Kappa statistic	0.2935	
Mean absolute error	0.3183	
Root mean squared error	0.4041	
Relative absolute error	91.9333 %	
Root relative squared error	97.1217 %	
Total Number of Instances	7229	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
e	0.732	0.33	0.649	0.732	0.688	0.736	positiv
e	0.394	0.107	0.446	0.394	0.419	0.724	negativ
	0.305	0.165	0.335	0.305	0.32	0.586	neutral
ve	0.351	0.096	0.398	0.351	0.373	0.724	objecti
Weighted Avg.	0.522	0.219	0.507	0.522	0.513	0.7	

=== Confusion Matrix ===

a	b	c	d	<-- classified as
2403	282	391	208	a = positive
426	510	250	107	b = negative
555	249	472	271	c = neutral
321	102	294	388	d = objective

As you can see this increased the average precision for all classifiers. Most notably, the SVM classifier increased from **49.5% to 50.7%**. This classifier continued to be the most accurate, correctly classifying **3773** twitter messages or 52.2%.

In trying to continue the improvement of the classifiers, we used senti wordnet to add positive, negative, and objective scores for each document. Iterating through each document, each word was analyzed using senti wordnet and the positive, negative, and objective score for the word (in all of the synsets in which it belongs) was added to the total positive, negative and objective score for the document. This was achieved using the following code:


```

for word in twitter_document.msg_text.split():
    for synset in swin.senti_synsets(word):
        additional_features["posscore"] += synset.pos_score()
        additional_features["negscore"] += synset.neg_score()
        additional_features["objscore"] += synset.obj_score()

```

3 features were added to the arff file: `posscore`, `negscore`, `objscore`

The three classifiers then provided the following results with these new features:

Decision Tree:

=== Stratified cross-validation ===

Correctly Classified Instances	3613	49.9793 %
Incorrectly Classified Instances	3616	50.0207 %
Kappa statistic	0.2636	
Mean absolute error	0.2698	
Root mean squared error	0.4552	
Relative absolute error	77.9164 %	
Root relative squared error	109.3981 %	
Total Number of Instances	7229	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
e	0.715	0.332	0.642	0.715	0.676	0.714	positive
e	0.364	0.125	0.388	0.364	0.376	0.612	negative
	0.266	0.156	0.317	0.266	0.289	0.565	neutral
ve	0.348	0.111	0.362	0.348	0.355	0.627	objective
Weighted Avg.	0.5	0.224	0.484	0.5	0.49	0.651	

=== Confusion Matrix ===

a	b	c	d	<-- classified as
2347	344	356	237	a = positive
442	471	242	138	b = negative
557	277	411	302	c = neutral
312	123	286	384	d = objective

Naive Bayes:

```
=== Stratified cross-validation ===

Correctly Classified Instances      3419      47.2956 %
Incorrectly Classified Instances    3810      52.7044 %
Kappa statistic                     0.2739
Mean absolute error                  0.2728
Root mean squared error              0.4476
Relative absolute error              78.7973 %
Root relative squared error          107.5843 %
Total Number of Instances           7229

=== Detailed Accuracy By Class ===

      TP Rate  FP Rate  Precision  Recall  F-Measure  ROC Area  Class
e      0.548    0.183    0.714    0.548    0.62      0.736    positiv
e      0.491    0.191    0.36     0.491    0.415    0.722    negativ
e      0.239    0.136    0.323    0.239    0.275    0.601    neutral
ve     0.555    0.193    0.342    0.555    0.423    0.757    objecti
Weighted Avg.  0.473    0.176    0.51     0.473    0.479    0.708

=== Confusion Matrix ===

      a      b      c      d  <-- classified as
1801  606  362  515 |      a = positive
 242  635  210  206 |      b = negative
 326  390  370  461 |      c = neutral
 155  135  202  613 |      d = objective
```

SVM:

=== Stratified cross-validation ===

Correctly Classified Instances	3792	52.4554 %
Incorrectly Classified Instances	3437	47.5446 %
Kappa statistic	0.2979	
Mean absolute error	0.3175	
Root mean squared error	0.4031	
Relative absolute error	91.7069 %	
Root relative squared error	96.8872 %	
Total Number of Instances	7229	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
positive	0.731	0.328	0.65	0.731	0.688	0.738	positive
negative	0.398	0.103	0.456	0.398	0.425	0.73	negative
neutral	0.31	0.164	0.34	0.31	0.324	0.588	neutral
objective	0.361	0.098	0.4	0.361	0.38	0.728	objective
Weighted Avg.	0.525	0.218	0.511	0.525	0.516	0.703	

=== Confusion Matrix ===

a	b	c	d	<-- classified as
2400	274	392	218	a = positive
426	514	249	104	b = negative
550	242	479	276	c = neutral
318	98	290	399	d = objective

Again, we saw an increase in precision and correctly classified instances for all classifiers. Most notably, the SVM classifier increased from **50.7% to 51.1%**. This classifier continued to be the most accurate, correctly classifying **3792** twitter messages or 52.45%.

With these results we noticed that combining bag of words with counting exclamations, question marks, smile emoticons, sad emoticons, and analyzing the sentiment of each individual word in a Twitter document can in fact increase precision for classifiers. The remaining investigation tested different features and approaches that did not increase precision past 51.1%.