FIT1043 Introduction to Data Science

Assignment 2

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1. Introduction

Machine Learning has been a trending topic since the 20th century and is becoming more and more demanding in the world regarding which field. In this assignment, we will be dealing with machine learning model which is classifications on predicting marks on essay on several features. For example, number of character, stemmed word and average word length

Importing necessary libraries

StandardScaler() from sklearn.preprocessing

In [1]:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import LocalOutlierFactor
from sklearn.svm import SVC
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn import metrics
```

Read CSV File

In [2]:

```
essay_features = pd.read_csv("FIT1043-Essay-Features.csv")
#essay_features.head()
essay_features.head()
```

Out[2]:

	essayid	chars	words	commas	apostrophes	punctuations	avg_word_length	sentences
0	1457	2153	426	14	6	0	5.053991	16
1	503	1480	292	9	7	0	5.068493	11
2	253	3964	849	19	26	1	4.669022	49
3	107	988	210	8	7	0	4.704762	12
4	1450	3139	600	13	8	0	5.231667	24

```
→
```

In [3]:

```
features, label = essay_features.iloc[:, :-1], essay_features.iloc[:,[-1]]
```

In [4]:

```
import numpy as np
unique_elements, counts_elements = np.unique(label, return_counts=True)
print("Frequency of unique values:")
print(np.asarray((unique_elements, counts_elements)))
```

```
Frequency of unique values: [[ 1 2 3 4 5 6] [ 18 110 557 583 60 4]]
```

Descriptive Statistic

In [5]:

essay_features.describe()

Out[5]:

	essayid	chars	words	commas	apostrophes	punctuations	avg_w
count	1332.00000	1332.000000	1332.000000	1332.000000	1332.000000	1332.00000	1
mean	905.27027	2101.745495	424.485736	14.667417	8.141141	0.47973	
std	526.68760	865.963750	171.873730	10.920781	6.124520	1.27168	
min	0.00000	169.000000	36.000000	0.000000	2.000000	0.00000	
25%	442.75000	1527.250000	310.000000	7.000000	4.000000	0.00000	
50%	914.50000	2029.500000	411.000000	13.000000	6.000000	0.00000	
75%	1369.75000	2613.500000	525.000000	21.000000	11.000000	0.00000	
max	1799.00000	6142.000000	1170.000000	72.000000	51.000000	26.00000	
4							•

In [6]:

essay_features.corr()

Out[6]:

	essayid	chars	words	commas	apostrophes	punctuatic
essayid	1.000000	0.020961	0.021810	0.025137	-0.020580	-0.0082
chars	0.020961	1.000000	0.991998	0.647711	0.437508	0.1840
words	0.021810	0.991998	1.000000	0.647159	0.456932	0.1899
commas	0.025137	0.647711	0.647159	1.000000	0.397497	0.2067
apostrophes	-0.020580	0.437508	0.456932	0.397497	1.000000	0.1230
punctuations	-0.008286	0.184317	0.189927	0.206741	0.123361	1.0000
avg_word_length	-0.025634	0.236563	0.123142	0.126595	-0.060541	-0.002§
sentences	0.016737	0.366223	0.422922	0.207493	0.153522	0.0738
questions	0.019837	0.328230	0.336836	0.316261	0.261627	0.1869
avg_word_sentence	-0.027987	-0.040719	-0.042562	-0.025439	-0.041249	0.0012
POS	0.021576	0.992162	0.999907	0.648915	0.458441	0.1898
POS/total_words	-0.024392	0.317080	0.305294	0.288851	0.239325	0.0547
prompt_words	0.020400	0.948406	0.960853	0.656856	0.399875	0.1540
prompt_words/total_words	-0.024958	-0.034214	-0.026602	0.128626	-0.126017	-0.0977
synonym_words	0.016857	0.912003	0.924474	0.535154	0.384010	0.115
synonym_words/total_words	-0.023628	-0.286498	-0.273979	-0.316782	-0.203050	-0.1886
unstemmed	0.017443	0.953534	0.948491	0.620890	0.418899	0.2066
stemmed	0.018011	0.955315	0.950299	0.625511	0.420205	0.2109
score	0.033463	0.683983	0.662091	0.525055	0.322052	0.1579
4						•

- 1. Total 1332 of essays in this file.
- 2. The maximum word wrote for the essay is 1170 words.
- 3. The average score obtained by the 1332 people is 3.427 marks.
- 4. prompt words/total words may not relate to the score
- 5. Both unstemmed and stemmed are highly related to the score

2. Supervised Learning

Supervised Machine Learning

- Supervised Learning
- Part of Machine Learning & Artificial Intelligence
- Train algorithms in classifying data/prediciting outcomes by labelled datasets
- user insert data to the model/algorithms -> model/algorithms adjust weight and come out with a output
- Regression/Classifications/Support Vector Machine(SVM)/Random Forest Model

Notion of labelled data

- Have a set of unlabelled data, augmenting it with some meaningful tag that easy to know
- Process of having a set of raw data -> add a meaningful name/label (informative) -> model learn from it
- · Datasets about Fruits:
 - Columns: length , weight , shape , percentage of vitamin C
 - Rows will be each unique fruit

Training and test datasets

Training datasets

- · Datasets used to train the model
- · Usually taking 80% or 70% of the dataset to train the model
- · Data will split to features and labels

Test datasets

- · Datasets to test the outcome of the prediction
- · Independent with training datasets
- · Same features columns but not having the label

Roughly visualize the score

In [7]:

```
sns.set(font_scale=1.5)
countplt=sns.countplot(x='score', data=essay_features, palette ='hls')
plt.show()
```



Codes of splitt features and labels

```
In [8]:
```

```
features, label = essay_features.iloc[:, :-1], essay_features.iloc[:,[-1]]
print(features)
print(label)
```

0 1 2 3 4 1327 1328 1329 1330 1331	essayid 1457 503 253 107 1450 1151 1015 1345 344 1077	chars 2153 1480 3964 988 3139 2404 1182 1814 1427 2806	words 426 292 849 210 600 467 241 363 287 542	commas 14 9 19 8 13 16 0 5 5	apostro	6 7 26 7 8 10 14 11 8 6	punctuations 0 0 1 0 0 0 0 0 0 0	
\	avg_word	_length	senter	nces qu	estions	avg_ı	word_sentence	POS
0 1 2 3 4	5 4 4	.053991 .068493 .669022 .704762		16 11 49 12 24	0 0 2 0 1		26.625000 26.545455 17.326531 17.500000 25.000000	290.993103 843.990544
1327 1328 1329 1330 1331	5 4 4 4	 .147752 .904564 .997245 .972125		22 16 13 13 22	 0 0 3 1 3		21.227273 15.062500 27.923077 22.076923 24.636364	 462.987069 238.655462 362.329640 284.657277
	POS/tota	1_words	prompt	_words	prompt_	_words,	/total_words	synonym_wor
ds \ 0 05	0	.995294		207			0.485915	1
1	0	.996552		148			0.506849	
77 2 30	0	.994100		285			0.335689	1
3 62	0	.988828		112			0.533333	
4 65	0	.991087		255			0.425000	1
		• • •		• • •			•••	
1327 13	0	.991407		200			0.428266	1
1328 67	0	.990272		94			0.390041	
1329 07	0	.998153		170			0.468320	1
1330 83	0	.991837		144			0.501742	
1331 55	0	.994444		284			0.523985	1
0 1 2 3 4 1327 1328	synonym_	words/t	0.2464 0.2636 0.1531 0.2952 0.2756	179 599 121 238 900 	temmed 424 356 750 217 702 529 293	34 7! 20 6: • 5:	ed 12 45 50 39 77 	

1329	0.294766	427	415	
1330	0.289199	323	312	
1331	0.285978	596	575	
[1332 rows x 18 o	columns]			

```
0
          4
1
          4
2
          4
3
          3
4
1327
          4
          3
1328
1329
          3
          3
1330
1331
          4
```

```
[1332 rows x 1 columns]
```

In [9]:

```
essay_features.corr()
```

Out[9]:

	essayid	chars	words	commas	apostrophes	punctuatic
essayid	1.000000	0.020961	0.021810	0.025137	-0.020580	-0.0082
chars	0.020961	1.000000	0.991998	0.647711	0.437508	0.1843
words	0.021810	0.991998	1.000000	0.647159	0.456932	0.1899
commas	0.025137	0.647711	0.647159	1.000000	0.397497	0.2067
apostrophes	-0.020580	0.437508	0.456932	0.397497	1.000000	0.1230
punctuations	-0.008286	0.184317	0.189927	0.206741	0.123361	1.0000
avg_word_length	-0.025634	0.236563	0.123142	0.126595	-0.060541	-0.0029
sentences	0.016737	0.366223	0.422922	0.207493	0.153522	0.0738
questions	0.019837	0.328230	0.336836	0.316261	0.261627	0.1869
avg_word_sentence	-0.027987	-0.040719	-0.042562	-0.025439	-0.041249	0.0012
POS	0.021576	0.992162	0.999907	0.648915	0.458441	0.1898
POS/total_words	-0.024392	0.317080	0.305294	0.288851	0.239325	0.0547
prompt_words	0.020400	0.948406	0.960853	0.656856	0.399875	0.1540
prompt_words/total_words	-0.024958	-0.034214	-0.026602	0.128626	-0.126017	-0.0977
synonym_words	0.016857	0.912003	0.924474	0.535154	0.384010	0.115
synonym_words/total_words	-0.023628	-0.286498	-0.273979	-0.316782	-0.203050	-0.1886
unstemmed	0.017443	0.953534	0.948491	0.620890	0.418899	0.2066
stemmed	0.018011	0.955315	0.950299	0.625511	0.420205	0.2109
score	0.033463	0.683983	0.662091	0.525055	0.322052	0.1579
4						>

Codes of split of training and test datasets

In [10]:

features_train, features_test, label_train, label_test = train_test_split(features, labe
l,test_size=0.2,random_state=0)
print(features_train)
print(label_train)

568 1273 49 1165 1268 	essayid 1724 895 657 1468 362 	chars 1881 5013 1445 1027 3207 	words 378 953 287 207 663 372	commas 15 24 3 4 27 6	apostro	pphes 2 16 8 2 7 5	punctuations 0 0 0 0	\
835	1161	2473	457	23		6	0	
1216	489	2952	581	12		27	0	
559 684	243 513	3316 591	716 124	21 3		25 3	0	
	avg_word				estions		ord_sentence	POS
\ 568	4	.976190		15	0		25.200000	374.994652
1273		.260231		32	6		29.781250	945.987368
49		.034843		8	2		35.875000	280.328554
1165		.961353		6	0		34.500000	203.990148
1268	4	.837104		33	3		20.090909	657.987879
 763	4	.927419		25			14.880000	367.983740
835		.411379		21	0		21.761905	456.330403
1216		.080895		29	4		20.034483	578.324122
559		.631285		31	2		23.096774	712.991597
684	4	.766129		6	0		20.666667	120.322129
ds \	POS/tota	l_words	prompt	t_words	prompt_	words/	total_words	synonym_wor
568 07	0	.992049		209			0.552910	1
1273 15		.992642		454			0.476390	2
49 94	0	.976755		129			0.449477	
1165 54	0	.985460		98			0.473430	
1268 89	0	.992440		322			0.485671	1
• • •		• • •		• • •			•••	
763 16	0	.989204		213			0.572581	1
835 07	0	.998535		243			0.531729	1
1216 68	0	.995394		318			0.547332	1
559 55	0	.995798		275			0.384078	1
684 35	0	.970340		51			0.411290	
	synonym_	words/t	otal wor	rds uns	temmed	stemme	ed	
568	<i>y</i> y		0.2836		445	42		
1273			0.2256		750	75		
49			0.3275		330	31		
1165 1268			0.2608 0.2850		273 658	26 63		
1208						•••		
763 835			0.3118 0.2341	328	364 534	35 52	1	

```
un_ele, count_ele = np.unique(label_test, return_counts=True)
print("Frequency of unique values of label testing datasets: ")
print(np.asarray((un_ele, count_ele)))
```

```
Frequency of unique values of label testing datasets: [[ 1 2 3 4 5 6] [ 2 20 115 119 10 1]]
```

Classification

3a. Binary & Multi-Class Classification

Binary Classifications

- Binary meaning is 0 or 1 (False or True) in computer. From the word binary, the meaning of binary classifications is easy to know, which is classifying the input data into 2 groups.
- For example in the Titanic dataset, we can classfied the passengers into survived or not survived

Multi-Class Classifications

- Multi-Class classifications is a machine learning classfications that it consists of two or more output or classes
- · For example given images of fruits, identify them into which type of fruit
- A machine learning model to predict the input data/classes and come out with 2 or more output

3b. Normalisation

Why Normalise Data

- · Help Improve data cleaning
- · Reduce Duplicating Data
- · Improve speed and effiency of models
- · Raw Data ranges widely hence ML algorithms can't work as it expected

```
In [13]:
```

```
scaler = StandardScaler()
```

In [14]:

```
# fit & transform training data
scaled_train = scaler.fit_transform(features_train)
# transform test data
scaled_test = scaler.transform(features_test)
```

3c. SVM

Explain SVM (must have some reference comparison to linear regression)

- · supervised machine learning algorithms.
- · classification or regression but mostly used in classifications
- Implemented by plotting data item as a point in the n-dimensional space,
 - n is number of features
 - with value of each feature being the value of a coordinate.
- Eg 2 features
 - A group of point gathered at a side, another group gather at a side
 - Seperated by a hyper-plane
- · Perform non-linear classification by implementing different kernel in the codes
- SVM application
 - Speech Recognition
 - Cancer Diagnosis
 - Text Classification
 - Facial Expression

Kernel in SVM / SVR

- Kernel is used due to mathematicals functions used in SVM
- · A kernel take input data and transform into a output by a series of formula
- · Generally transform training set of data
 - Non-Linear decision to Linear decision
 - Higher number of dimensional space
- · Default kernel is rbf
- Types of Kernel
 - Linear
 - Poly
 - Rbf
 - Sigmoid
 - Pre-Computed

Code to Build the Model by training dataset

```
In [15]:
```

```
sv = SVC(kernel='linear').fit(scaled_train,label_train)
```

C:\Users\KIAT\Anaconda3\lib\site-packages\sklearn\utils\validation.py:724: DataConversionWarning: A column-vector y was passed when a 1d array was ex pected. Please change the shape of y to (n_samples,), for example using r avel().

```
y = column_or_1d(y, warn=True)
```

3d. Prediction

In [16]:

```
y_pred = sv.predict(scaled_test)
```

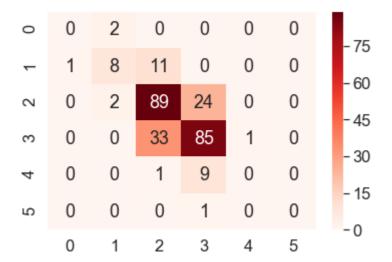
Confusion Matrix

- · Also known as Error Matrix
- · A table layout to visualize the performance of an algorithms
- · Typically used in Supervised Learning
- A confusion matrix is a square matrix or a nxn matrix
 - Each column of the matrix shows the instances in the predicted class
 - Each row of the matrix show the instances in an actual class
- Diagonal is the correct prediction
- · Terms of Confusion Matrix:
 - TP: True Positive
 - TN: True Negative
 - FP: False Positive
 - FN: False Negative
- · Measuring with Confusion Matrix:
 - Precision: TP / (TP+FP)
 - Recall: TP / (TP+FN)
 - Accuracy: (TP+TN)/ (TP+TN+FP+FN)
 - Specificity: TN/ (TN+FP)

Confusion Matrix in plotted by seaborn (visualization)

In [17]:

```
cmatrix = metrics.confusion_matrix(label_test,y_pred)
# plt.figure(figsize=(8,8))
ax = sns.heatmap(cmatrix,annot=True,cmap='Reds')
ax.set_ylim(sorted(ax.get_xlim(), reverse=True))
plt.show()
```



Normal Confusion Matrix

In [18]:

```
0 = metrics.confusion_matrix(label_test,y_pred)
print ('Confusion Matrix:')
print(0)
```

Confusion Matrix:

```
[[ 0 2 0 0 0 0]
[ 1 8 11 0 0 0]
[ 0 2 89 24 0 0]
[ 0 0 33 85 1 0]
[ 0 0 1 9 0 0]
[ 0 0 0 1 0 0]]
```

Quadratic Weighted Kappa

- · Also know as QWK
- Varies from -1 to 1
 - 1 is a perfect score (prediction and actual are the same)
 - -1 is worst (predictions are furthest away from actual)
 - Generally, a score above 0.6 is considered as a good score
- · Calculated between known score and predicted score
- · Good in imbalanced datasets & classifications problems

QWK Score

```
In [19]:
```

```
print(metrics.cohen_kappa_score(y_pred,label_test, weights ='quadratic'))
```

0.6215007866901376

4. Kaggle Submission

In [20]:

```
score_1 = essay_features[essay_features['score'] == 1]
score_2 = essay_features[essay_features['score'] == 2]
score_3 = essay_features[essay_features['score'] == 3]
score_4 = essay_features[essay_features['score'] == 4]
score_5 = essay_features[essay_features['score'] == 5]
score_6 = essay_features[essay_features['score'] == 6]
essay_features = score_1
essay_features = essay_features.append(score_2)
essay_features = essay_features.append(score_3[:150])
essay_features = essay_features.append(score_4[:150])
essay_features = essay_features.append(score_5)
essay_features = essay_features.append(score_6)
print(essay_features)
```

	essayid	chars	words	commas	apostro		punctuations	\
27	901	257	61	0		6	1	
154	263	218	44	0		2	0	
327	181	916	194	3		4	0	
337	401	2254	457	19		9	1	
341	88	389	78	4		2	0	
• • •	• • •	• • •	• • •	• • •		• • •	• • •	
1321	910	2409	479	25		15	0	
294	1654	3850	767	31		8	1	
758	450	3014	567	13		4	0	
1030	1239	5881	1170	43		19	1	
1119	1083	3096	580	21		10	1	
	avg_word	_length	sente	nces qu	estions	avg_	word_sentence	PO
S \								
27	4	.213115		3	4		20.333333	60.00000
0								
154	4	.954545		2	0		22.000000	43.00000
0								
327	4	.721649		8	1		24.250000	192.65277
8								
337	4	.932166		24	0		19.041667	454.66079
3								
341	4	.987179		1	0		78.000000	75.65765
8								
		•••		• • •	• • •		•••	
1321	5	.029228		25	2		19.160000	474.64849
8	,	.023220		23	2		13.100000	777.07072
294	-	.019557		30	17		25 566667	761.98692
8	5	.019337		30	17		25.566667	701.90092
	-	215607		26	2		15 75000	FF0 200CF
758 1	5	.315697		36	3		15.750000	558.30965
1	-	026406		7.4	0		15 010011	1150 00456
1030	5	.026496		74	8		15.810811	1158.98456
3	_	227024		22	-		25 247204	F7F 00060
1119	5	.337931		23	7		25.217391	575.98960
1								
		1_words	promp	t_words	prompt_v	words	/total_words	synonym_wor
ds \								
27	0	.983607		22			0.360656	
20								
154	0	.977273		25			0.568182	
14								
327	0	.993056		90			0.463918	
51								
337	0	.994881		210			0.459519	
99								
341	0	.969970		40			0.512821	
22								
							• • •	
1321	а	.990915		224			0.467641	1
14	O			r			3.107041	-
294	ρ	.993464		350			0.456323	1
70	V	•••••		שכנ			0.430323	1
76 758	۵	.984673		236			0.416226	1
	0	. 2040/3		230			0.410220	1
34 1020	^	000505		E 43			0 464102	2
1030	0	.990585		543			0.464103	2
66 1110	^	002006		244			0.430600	
1119	0	.993086		244			0.420690	1

	synonym_words/total_words	unstemmed	stemmed	score
27	0.327869	81	81	1
154	0.318182	64	64	1
327	0.262887	245	240	1
337	0.216630	490	457	1
341	0.282051	106	106	1
• • •	•••	• • •		
1321	0.237996	527	510	5
294	0.221643	750	750	6
758	0.236332	696	680	6
1030	0.227350	750	750	6
1119	0.224138	681	666	6

[492 rows x 19 columns]

```
In [21]:
```

```
X, y = essay_features.iloc[:, :-1], essay_features.iloc[:,[-1]]
print(X)
print(y)
```

27 154 327 337 341 1321 294	essayid 901 263 181 401 88 910 1654	chars 257 218 916 2254 389 2409 3850	words 61 44 194 457 78 479 767	commas 0 0 3 19 4 25		ophes 6 2 4 9 2 15 8	punctuations 1 0 1 0 0 1	\
758 1030	450	3014	567	13		4	0	
1030 1119	1239 1083	5881 3096	1170 580	43 21		19 10	1 1	
S \	avg_word	_length	sente	nces q	uestions	avg_	word_sentence	PO
27	4	.213115		3	4		20.333333	60.00000
0 154 0	4	.954545		2	0		22.000000	43.00000
327 8	4	.721649		8	1		24.250000	192.65277
337 3	4	.932166		24	0		19.041667	454.66079
341 8	4	.987179		1	0		78.000000	75.65765
• • •		• • •		•••	• • •		•••	
1321 8	5	.029228		25	2		19.160000	474.64849
8 294 8	5	.019557		30	17		25.566667	761.98692
758 1	5	.315697		36	3		15.750000	558.30965
1030	5	.026496		74	8		15.810811	1158.98456
3 1119 1	5	.337931		23	7		25.217391	575.98960
ds \		l_words	promp	t_words	prompt_	words	/total_words	synonym_wor
27 20		.983607		22			0.360656	
154 14	0	.977273		25			0.568182	
327 51	0	.993056		90			0.463918	
337 99	0	.994881		210			0.459519	
341 22	0	.969970		40			0.512821	
• • •		• • •					• • •	
 1321 14	0	.990915		224			0.467641	1
294 70	0	.993464		350			0.456323	1
758 34	0	.984673		236			0.416226	1
1030 66	0	.990585		543			0.464103	2
1119	0	.993086		244			0.420690	1

synonym_words/total_words	unstemmed	stemmed
0.327869	81	81
0.318182	64	64
0.262887	245	240
0.216630	490	457
0.282051	106	106
•••		
0.237996	527	510
0.221643	750	750
0.236332	696	680
0.227350	750	750
0.224138	681	666
	0.327869 0.318182 0.262887 0.216630 0.282051 0.237996 0.221643 0.236332 0.227350	0.327869 81 0.318182 64 0.262887 245 0.216630 490 0.282051 106 0.237996 527 0.221643 750 0.236332 696 0.227350 750

[492 rows x 18 columns]

L		_	 -	
	score			
27	1			
154	1			
327	1			
337	1			
341	1			
1321	5			
294	6			
758	6			
1030	6			
1119	6			

[492 rows x 1 columns]

In [22]:

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,random_state=6)
print(X_train)
print(y_test)

670 556 203 150 107 1110 809 219 164 266	essayid 1632 299 988 941 981 399 1187 1120 904 599	chars 794 4173 977 2926 2938 1593 3339 1326 778 2156	words 156 829 216 573 602 335 638 255 172 425	commas 4 41 4 12 25 13 21 1 6 20	apostro	ophes 10 17 8 12 7 3 3 4	punctuations 0 2 0 2 0 0 1 0 0	
\	avg_word	_length	senter	nces qu	estions	avg_w	ord_sentence	POS
670 556 203 150 107 1110 809 219 164	5 4 5 4 5 5	.089744 .033776 .523148 .106457 .880399 .755224 .233542 .200000		5 42 8 32 32 16 42 9	0 6 0 3 0 0 0		31.200000 19.738095 27.000000 17.906250 18.812500 20.937500 15.190476 28.333333 24.571429	153.662281 824.661010 213.644860 569.989492 597.989983 331.658610 633.321785 253.664021 170.325444
266		.072941		18	0		23.611111	422.655634
ds \ 670		l_words .985015	prompt	t_words 71	prompt_	words/	total_words 0.455128	synonym_wor
42 556 95	0	.994766		398			0.480097	1
203 68	0	.989097		75			0.347222	
150 46	0	.994746		264			0.460733	1
107 55	0	.993339		306			0.508306	1
• • •		•••		• • •			•••	
1110 91	0	.990026		187			0.558209	
809 33	0	.992667		285			0.446708	1
219 60	0	.994761		117			0.458824	
164 58	0	.990264		75			0.436047	
266 05	0	.994484		196			0.461176	1
670 556 203 150 107 1110 809	synonym_	words/t	0.2692 0.2352 0.3148 0.2547	231 223 315 799 475 	temmed 208 750 262 639 557 396 718	stemme 20 75 26 61 54 38 70	01 00 08 8 3	

```
219
                          0.235294
                                            311
                                                      302
164
                          0.337209
                                            225
                                                      217
                          0.247059
                                            490
                                                      475
266
[393 rows x 18 columns]
     score
317
          5
173
          4
          4
38
225
          4
320
          3
403
          2
18
          4
340
          3
          3
265
240
          4
[99 rows x 1 columns]
```

In [23]:

```
lof = LocalOutlierFactor()
yhat = lof.fit_predict(X_train)
# select all rows that are not outliers
mask = yhat != -1
X_train, y_train = X_train.iloc[mask, :], y_train.iloc[mask]
print(X_train.shape, y_train.shape)
```

(353, 18) (353, 1)

C:\Users\KIAT\Anaconda3\lib\site-packages\sklearn\neighbors\lof.py:236: Fu
tureWarning: default contamination parameter 0.1 will change in version 0.
22 to "auto". This will change the predict method behavior.
 FutureWarning)

In [24]:

```
# define scaler used
#scaler = StandardScaler()
# fit & transform training data
scaled_Xtrain = scaler.fit_transform(X_train)
scaled_Xtest = scaler.transform(X_test)
```

In [25]:

```
sv = SVC(C=0.05,kernel='linear',gamma=100)
sv.fit(scaled_Xtrain,y_train)
y_pred = sv.predict(scaled_Xtest)
print('QWK score:',metrics.cohen_kappa_score(y_test, y_pred,weights="quadratic"))
```

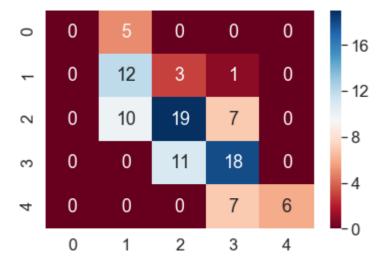
QWK score: 0.7532219570405727

C:\Users\KIAT\Anaconda3\lib\site-packages\sklearn\utils\validation.py:724: DataConversionWarning: A column-vector y was passed when a 1d array was ex pected. Please change the shape of y to (n_samples,), for example using r avel().

```
y = column_or_1d(y, warn=True)
```

In [26]:

```
cmatrix = metrics.confusion_matrix(y_test,y_pred)
# plt.figure(figsize=(8,8))
ax = sns.heatmap(cmatrix,annot=True,cmap='RdBu')
ax.set_ylim(sorted(ax.get_xlim(), reverse=True))
plt.show()
```



In [27]:

```
submission_features = pd.read_csv("FIT1043-Essay-Features-Submission.csv")
submission_features.shape
```

Out[27]:

(199, 18)

In [28]:

```
scaleX = scaler.transform(submission_features)
y_pred = sv.predict(scaleX)
```

In [29]:

```
import numpy as np
unique_elements, counts_elements = np.unique(y_pred, return_counts=True)
print("Frequency of unique values of the said array:")
print(np.asarray((unique_elements, counts_elements)))
```

```
Frequency of unique values of the said array: [[ 2 3 4 5] [20 83 84 12]]
```

```
In [30]:
```

```
draft = pd.read_csv('99999999-YourName-1.csv')
draft.head()
```

Out[30]:

	essayid	score
0	1623	NaN
1	1143	NaN
2	660	NaN
3	1596	NaN
4	846	NaN

In [31]:

```
for i in range(len(draft)):
    draft.iloc[i,-1] = int(y_pred[i])
```

In [32]:

```
draft.head()
```

Out[32]:

	essayid	score
0	1623	4.0
1	1143	4.0
2	660	3.0
3	1596	4.0
4	846	4.0

In [33]:

```
draft['score']=draft.score.astype('int64')
draft.head()
draft = draft.set_index('essayid')
#draft = draft.droplevel()
```

In [34]:

```
sub = draft.to_csv('32142773-TanYoongKiat-1.csv')
```