# FIT1043 Introduction to Data Science Assignment 2

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## Introduction

In this assignment, I will be predictive analysis on a dataset that consists of essays with a lot of varying attributes.</br>
My approach will be to do research on different techniques and attempting to create the best model I am able to.</br>
References will also be provided at the end of the assignment.

## **Importing Libraries**

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, cohen_kappa_score
from IPython.display import display, Markdown, Latex
```

## **Reading The Files**

```
In [2]: dataset = pd.read_csv('FIT1043-Essay-Features.csv')
```

## **Reading The Data**

## Reading data from FIT1043 Essay Features

#### Displaying the data

```
In [3]: dataset
Out[3]: essayid chars words commas apostrophes punctuations avg_word_length sentences question
```

	essayid	chars	words	commas	apostrophes	punctuations	avg_word_length	sentences	questio
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	
•••	•••		•••						
1327	1151	2404	467	16	10	0	5.147752	22	
1328	1015	1182	241	0	14	0	4.904564	16	
1329	1345	1814	363	5	11	0	4.997245	13	
1330	344	1427	287	5	8	0	4.972125	13	
1331	1077	2806	542	24	6	0	5.177122	22	

1332 rows × 19 columns

	4									,		
In [4]:	dataset.head()											
Out[4]:		essayid	chars	words	commas	apostrophes	punctuations	avg_word_length	sentences	questions		
	0	1457	2153	426	14	6	0	5.053991	16	0		
	1	503	1480	292	9	7	0	5.068493	11	0		
	2	253	3964	849	19	26	1	4.669022	49	2		
	3	107	988	210	8	7	0	4.704762	12	0		
	4	1450	3139	600	13	8	0	5.231667	24	1		
	4									•		

#### Checking the dimensions of the data

```
In [5]: dataset.shape

Out[5]: (1332, 19)
```

## Checking how the column headers are stored

## Displaying more detailed parts of the data

<pre><bound \<="" ations="" dataframe.ir="" method="" pre=""></bound></pre>			ne.info of		essayi	d chars	words	commas	apostrophes
0	•					6		0	
1	503	1480	292	14 9		7		0	
2	253		849	19		26			
		3964						1	
3 4	107 1450	988 3139	210 600	8 13		7 8		0	
							•		
1327	1151	2404	467	16		10		0	
1328	1015	1182	241	0		14		0	
1329	1345	1814	363	5		11		0	
1330	344	1427	287	5		8		0	
1331	1077	2806	542	24		6		0	
	avg word	d length	sentence	s qu	estions	avg wor	d sentend	ce	POS \
0		5.053991	16		0	<b>5</b> _	26.62500		.995272
1		5.068493	1:		0		26.54545		.993103
2		1.669022	49		2		17.32653		.990544
3		1.704762	12		0		17.50000		.653784
4		5.231667	24		1		25.0000		.652150
							•		
1327	5	5.147752	22	2	0		21.22727	73 462	.987069
1328	4	1.904564	10	6	0		15.06250	00 238	.655462
1329	4	1.997245	13	3	3		27.92307	77 362	.329640
1330	4	1.972125	13	3	1		22.07692	23 284	.657277
1331		5.177122	22	2	3		24.63636	54 538	.988889
	POS/tota	al_words	prompt_w	ords	prompt	words/to	tal_words	s synor	nym_words \
0		_ 9.995294		207			0.48591	-	105
1		996552		148			0.506849		77
2		0.994100		285			0.335689		130
3		9.988828		112			0.533333		62
4		9.991087		255			0.425000		165
	,								
1327		 0.991407		200			0.428266		113
1328							0.390043		67
		0.990272		94					
1329		0.998153		170			0.468320		107
1330 1331		0.991837 0.994444		144 284			0.501742 0.523985		83 155
synonym_words/total_		ntal words	line	temmed	stemmed	score			
0	Jy.ioiiyiii_	43/ ((	0.246479		424	412	4		
1			0.263699		356	345	4		
2			0.153121		750	750	4		
3			0.133121		217	209			
4					702		3 4		
			0.275000			677	4		
1227			0 241070			· · ·			
1327			0.241970		529	519	4		
1328			0.278008		293	283	3		
1329			0.294766		427	415	3		
1330			0.289199		323	312	3		
1331			0.285978		596	575	4		

[1332 rows x 19 columns]>

In [13]:

Out[13]:

```
In [8]:
           dataset.describe()
Out[8]:
                                     chars
                                                 words
                                                                                     punctuations avg_word_length
                     essayid
                                                             commas
                                                                       apostrophes
                                                         1332.000000
                  1332.00000
                              1332.000000
                                            1332.000000
                                                                       1332.000000
                                                                                        1332.00000
                                                                                                         1332.000000
          count
                                                                                           0.47973
                   905.27027
                              2101.745495
                                             424.485736
                                                            14.667417
                                                                           8.141141
                                                                                                            4.939762
          mean
            std
                   526.68760
                               865.963750
                                             171.873730
                                                            10.920781
                                                                           6.124520
                                                                                           1.27168
                                                                                                            0.231071
                     0.00000
                               169.000000
                                              36.000000
                                                             0.000000
                                                                           2.000000
                                                                                           0.00000
                                                                                                            2.231322
            min
            25%
                   442.75000
                              1527.250000
                                             310.000000
                                                             7.000000
                                                                           4.000000
                                                                                           0.00000
                                                                                                            4.791679
                                                                           6.000000
            50%
                   914.50000
                                                            13.000000
                                                                                           0.00000
                                                                                                            4.946059
                              2029.500000
                                             411.000000
            75%
                  1369.75000
                                                            21.000000
                                                                          11.000000
                                                                                           0.00000
                                                                                                            5.092938
                              2613.500000
                                             525.000000
                 1799.00000
                              6142.000000
                                            1170.000000
                                                            72.000000
                                                                          51.000000
                                                                                          26.00000
                                                                                                            5.681429
```

## **Describing The Data**

dataset['words'].mean()

424.4857357357357

## Measures of Central Tendency (Mean and Median)

```
Essay ID
 In [9]:
          dataset['essayid'].mean()
          905.2702702702703
 Out[9]:
In [10]:
          dataset['essayid'].median()
          914.5
Out[10]:
         Characters
In [11]:
          dataset['chars'].mean()
          2101.7454954954956
Out[11]:
In [12]:
           dataset['chars'].median()
          2029.5
Out[12]:
         Words
```

```
In [14]:
          dataset['words'].median()
         411.0
Out[14]:
         Commas
In [15]:
          dataset['commas'].mean()
         14.667417417417417
Out[15]:
In [16]:
          dataset['commas'].median()
         13.0
Out[16]:
         Apostrophes
In [17]:
          dataset['apostrophes'].mean()
         8.14114114114114
Out[17]:
In [18]:
          dataset['apostrophes'].median()
Out[18]:
         Punctuations
In [19]:
          dataset['punctuations'].mean()
         0.4797297297297297
Out[19]:
In [20]:
          dataset['punctuations'].median()
         0.0
Out[20]:
         Average Word Length
In [21]:
          dataset['avg_word_length'].mean()
         4.939762160950457
Out[21]:
In [22]:
          dataset['avg_word_length'].median()
         4.946059456
Out[22]:
         Sentences
```

dataset['POS/total\_words'].median()

In [32]:

Out[32]: 0.9915724335

#### **Prompt Words**

```
In [33]: dataset['prompt_words'].mean()
Out[33]: 198.91366366366367

In [34]: dataset['prompt_words'].median()
Out[34]: 193.0
```

#### Ratio of Prompt Words to Total Number Of Words

#### **Synonym Words**

## Ratio of Synonym Words to Total Number Of Words

#### **Unstemmed Words**

```
In [41]: dataset['unstemmed'].mean()
Out[41]: 468.987987988
```

```
In [42]:
          dataset['unstemmed'].median()
         463.0
Out[42]:
         Stemmed Words
In [43]:
          dataset['stemmed'].mean()
         455.5075075075075
Out[43]:
In [44]:
          dataset['stemmed'].median()
         448.0
Out[44]:
         Score
In [45]:
          dataset['score'].mean()
          3.4271771771771773
Out[45]:
In [46]:
          dataset['score'].median()
Out[46]:
         Measures of Variability (Range and Variance)
         Essay ID
In [47]:
          dataset['essayid'].max() - dataset['essayid'].min()
         1799
Out[47]:
In [48]:
          dataset['essayid'].var()
         277399.8277255469
Out[48]:
         Characters
In [49]:
          dataset['chars'].max() - dataset['chars'].min()
         5973
Out[49]:
In [50]:
```

749893.2161705282

dataset['chars'].var()

Out[50]:

```
Words
```

```
In [51]:
          dataset['words'].max() - dataset['words'].min()
         1134
Out[51]:
In [52]:
          dataset['words'].var()
         29540.57906008939
Out[52]:
         Commas
In [53]:
          dataset['commas'].max() - dataset['commas'].min()
         72
Out[53]:
In [54]:
          dataset['commas'].var()
         119.26346049279931
Out[54]:
        Apostrophes
In [55]:
          dataset['apostrophes'].max() - dataset['apostrophes'].min()
Out[55]:
In [56]:
          dataset['apostrophes'].var()
         37.50974114610453
Out[56]:
         Punctuations
In [57]:
          dataset['punctuations'].max() - dataset['punctuations'].min()
Out[57]:
In [58]:
          dataset['punctuations'].var()
         1.6171695737811695
Out[58]:
        Average Word Length
In [59]:
          dataset['avg_word_length'].max() - dataset['avg_word_length'].min()
```

3.4501067320000005

Out[59]:

```
In [60]:
          dataset['avg_word_length'].var()
         0.05339401973194578
Out[60]:
         Sentences
In [61]:
          dataset['sentences'].max() - dataset['sentences'].min()
         642
Out[61]:
In [62]:
          dataset['sentences'].var()
         368.74489591018533
Out[62]:
         Questions
In [63]:
          dataset['questions'].max() - dataset['questions'].min()
Out[63]:
In [64]:
          dataset['questions'].var()
         3.4130556176010507
Out[64]:
         Average Words Per Sentence
In [65]:
          dataset['avg_word_sentence'].max() - dataset['avg_word_sentence'].min()
          301.91588785
Out[65]:
In [66]:
          dataset['avg word sentence'].var()
         124.54604743033157
Out[66]:
         Part-Of-Speech
In [67]:
          dataset['POS'].max() - dataset['POS'].min()
         1123.33750418
Out[67]:
In [68]:
          dataset['POS'].var()
         29235.908018788636
Out[68]:
```

#### Ratio of Part-Of-Speech to Total Number Of Words

```
4/29/22, 4:07 PM
                                                  32713339_FIT1043_Assignment2
              dataset['POS/total_words'].max() - dataset['POS/total_words'].min()
    In [69]:
              0.07522861199999997
    Out[69]:
    In [70]:
              dataset['POS/total_words'].var()
              5.3412047135317936e-05
    Out[70]:
             Prompt Words
    In [71]:
              dataset['prompt_words'].max() - dataset['prompt_words'].min()
              655
    Out[71]:
    In [72]:
              dataset['prompt_words'].var()
              6844.131533674911
    Out[72]:
             Ratio of Prompt Words to Total Number Of Words
    In [73]:
              dataset['prompt_words/total_words'].max() - dataset['prompt_words/total_words'].min()
              0.672318008
    Out[73]:
    In [74]:
              dataset['prompt_words/total_words'].var()
              0.0027526862975129464
    Out[74]:
             Synonym Words
    In [75]:
              dataset['synonym words'].max() - dataset['synonym words'].min()
              344
    Out[75]:
    In [76]:
              dataset['synonym words'].var()
              1932.6503791545117
    Out[76]:
             Ratio of Synonym Words to Total Number Of Words
    In [77]:
               dataset['synonym_words/total_words'].max() - dataset['synonym_words/total_words'].min()
              0.43821839
    Out[77]:
    In [78]:
               dataset['synonym_words/total_words'].var()
```

Out[78]: 0.0015109093517610816

#### **Unstemmed Words**

```
In [79]:
          dataset['unstemmed'].max() - dataset['unstemmed'].min()
Out[79]:
In [80]:
          dataset['unstemmed'].var()
         25423.48896153852
Out[80]:
         Stemmed Words
In [81]:
          dataset['stemmed'].max() - dataset['stemmed'].min()
          700
Out[81]:
In [82]:
          dataset['stemmed'].var()
         24258.44246801268
Out[82]:
         Score
In [83]:
          dataset['score'].max() - dataset['score'].min()
Out[83]:
In [84]:
          dataset['score'].var()
```

# **Supervised Learning**

0.5995012668566343

Out[84]:

## What is Supervised Learning?

Supervised Learning which is also known as Supervised Machine Learning, is a subcategory of machine learning and artificial intelligence. Through the cross</br>-validation process, which is a technique where an untrained sample of the provided dataset is used to assess the machine learning model's performance, all the input data that is fed into the model will contribute towards the approximation of the desired output. [1] [2]

#### What is the notion of labeled data?

Labeled data is essentially data that have been labeled to be made identifiable according to specific

properties, characteristics or classifications. In terms of supervised machine learning, labeled data acts as the starting point for training and testing machine learning models. It is used by models to perform analysis and comparisons betweem them to determine the nature of the data and sort them into their own individual categories. The result of this operation will be useful in the predictive analysis of unlabeled data wherein we will be able to predict the labels for these unlabeled data or in other words be able to categorize them. [3]

#### What are the purpose of training and test datasets?

The training and test datasets make up the one dataset in which they have been split into training and test datasets individually with different ratios for different purposes. It is very important that the training and test datasets are derived from the same dataset and that the test dataset is large enough to ensure that the results of the machine learning process are justifiable. In terms of the purpose of the datasets, the training dataset will be used to train the model while the test dataset will be used to test the trained model. Most importantly, the test dataset should never be used to train the model as this will result in a very high accuracy when the test dataset is tested using this kind of model, this scenario would be considered as overfitting. [4]

## **Splitting of Features and Labels**

#### Explanation for choice of features and labels:

After looking at the dataset, it can be easily concluded that the labels would be the scores which we will be attempting to perform predictive analysis on, and the features would be the rest of the data in the dataset. However, it can be seen that the amount of data for the features is quite bloated, hence I will be trimming it down later on.

#### Obtaining the features (All data besides score)

```
In [85]:
          data_features = dataset.iloc[:,:-1].values
In [86]:
          data features
         array([[1.45700000e+03, 2.15300000e+03, 4.26000000e+02, ...,
Out[86]:
                  2.46478873e-01, 4.24000000e+02, 4.12000000e+02],
                 [5.03000000e+02, 1.48000000e+03, 2.92000000e+02, ...,
                  2.63698630e-01, 3.56000000e+02, 3.45000000e+02],
                 [2.53000000e+02, 3.96400000e+03, 8.49000000e+02, ...,
                 1.53121319e-01, 7.50000000e+02, 7.50000000e+02],
                 [1.34500000e+03, 1.81400000e+03, 3.63000000e+02, ...,
                  2.94765840e-01, 4.27000000e+02, 4.15000000e+02],
                 [3.44000000e+02, 1.42700000e+03, 2.87000000e+02, ...,
                  2.89198606e-01, 3.23000000e+02, 3.12000000e+02],
                 [1.07700000e+03, 2.80600000e+03, 5.42000000e+02, ...,
                  2.85977860e-01, 5.96000000e+02, 5.75000000e+02]])
```

#### Obtaining the labels (Score)

```
In [87]: data_labels = dataset.iloc[:,-1].values
```

```
In [88]: data_labels
Out[88]: array([4, 4, 4, ..., 3, 3, 4], dtype=int64)
```

#### Trimming down the Features (Using Feature Selection Methods)

#### Recursive Feature Elimination (RFE)

Recursive Feature Elimination essentially selects features by recursively considering smaller and smaller sets of features. It selects features based on the importance of the feature with regards to the predicting the output of the model. It eliminates features that are of less importance and selects the top features indicated. Along with RFE, I will also be using the Logistic Regression Algorithm which is a linear model for classification despite its name. In this model, a logistic function is used to model the probabilities describing the possible outcomes of a single trial, which in our case will be the features. [5] [6] [7]

Explanation: Here I will be using Recursive Feature Elimination (RFE) to identify the top 9 features which is approximately half the features that contribute the most to predicting the Score. These 9 features will be used to train the model.

```
In [89]:
          #the 'lbfqs' solver is used here as it is the most robust solver
          model = LogisticRegression(solver='lbfgs')
          rfe = RFE(model, n features to select=9)
          fit = rfe.fit(data_features, data_labels)
          d = {'Feature':dataset.columns[:-1], 'Contribution': fit.support , 'Ranking': fit.ranki
          df = pd.DataFrame(data=d)
          df
         C:\Users\andre\anaconda3\lib\site-packages\sklearn\linear model\ logistic.py:814: Conver
         genceWarning: lbfgs failed to converge (status=1):
         STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
         Increase the number of iterations (max_iter) or scale the data as shown in:
             https://scikit-learn.org/stable/modules/preprocessing.html
         Please also refer to the documentation for alternative solver options:
             https://scikit-learn.org/stable/modules/linear model.html#logistic-regression
           n_iter_i = _check_optimize_result(
         C:\Users\andre\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:814: Conver
         genceWarning: lbfgs failed to converge (status=1):
         STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
         Increase the number of iterations (max_iter) or scale the data as shown in:
             https://scikit-learn.org/stable/modules/preprocessing.html
         Please also refer to the documentation for alternative solver options:
             https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
           n_iter_i = _check_optimize_result(
         C:\Users\andre\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:814: Conver
         genceWarning: lbfgs failed to converge (status=1):
         STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
         Increase the number of iterations (max_iter) or scale the data as shown in:
```

```
https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear model.html#logistic-regression
 n_iter_i = _check_optimize_result(
C:\Users\andre\anaconda3\lib\site-packages\sklearn\linear model\ logistic.py:814: Conver
genceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear model.html#logistic-regression
  n_iter_i = _check_optimize_result(
C:\Users\andre\anaconda3\lib\site-packages\sklearn\linear model\ logistic.py:814: Conver
genceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
C:\Users\andre\anaconda3\lib\site-packages\sklearn\linear model\ logistic.py:814: Conver
genceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear model.html#logistic-regression
  n iter i = check optimize result(
C:\Users\andre\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:814: Conver
genceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
Increase the number of iterations (max iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear model.html#logistic-regression
  n_iter_i = _check_optimize_result(
C:\Users\andre\anaconda3\lib\site-packages\sklearn\linear model\ logistic.py:814: Conver
genceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear model.html#logistic-regression
 n iter i = check optimize result(
C:\Users\andre\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:814: Conver
genceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
Increase the number of iterations (max iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear model.html#logistic-regression
  n_iter_i = _check_optimize_result(
C:\Users\andre\anaconda3\lib\site-packages\sklearn\linear model\ logistic.py:814: Conver
genceWarning: lbfgs failed to converge (status=1):
```

STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max\_iter) or scale the data as shown in:
 https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
 https://scikit-learn.org/stable/modules/linear\_model.html#logistic-regression
 n\_iter\_i = \_check\_optimize\_result(

			_ `	
Out[89]:		Feature	Contribution	Ranking
	0	essayid	False	4
	1	chars	True	1
	2	words	True	1
	3	commas	True	1
	4	apostrophes	False	5
	5	punctuations	False	8
	6	avg_word_length	False	3
	7	sentences	False	2
	8	questions	False	6
	9	avg_word_sentence	True	1
•	10	POS	True	1
	11	POS/total_words	False	7
•	12	prompt_words	True	1
•	13	prompt_words/total_words	False	9
	14	synonym_words	True	1
	15	synonym_words/total_words	False	10
	16	unstemmed	True	1
	17	stemmed	True	1

Result: The 9 features selected that will be used for training the model are 'chars', 'words', 'commas', avg\_word\_sentence', 'POS', 'prompt\_words', 'synonym\_words', 'unstemmed' and 'stemmed'.

## **Selecting The Features**

```
In [90]: table = df[df['Ranking'] == 1]
  table
```

Out[90]:		Feature	Contribution	Ranking
	1	chars	True	1
	2	words	True	1
	3	commas	True	1

		Feature	Contribution	Ranking				
	9	avg_word_sentence	e True	1				
	10	POS	5 True	1				
	12	prompt_words	True	1				
	14	synonym_words	True	1				
	16	unstemmed	I True	1				
	17	stemmed	I True	1				
In [91]:	ne	l_feat = ['char w_features = da w_features				d_sentence'	, 'POS', 'pı	rompt_words', 'syn
Out[91]:	arr	[3964., 84 , [1814., 36 [1427., 28	6., 14., 2., 9., 9., 19., 3., 5., 7., 5., 2., 24.,	., 77. ., 130. ., 107.	, 356., , 750., , 427., , 323.,	345.], 750.], 415.], 312.],		

## **Splitting the Training and Test Dataset**

Here the dataset will be split into training and test datasets using the sklearn.model selection.train test split function. </br>

As a reminder for later on:</br>

Features\*</br>
\*train\_feat = Training dataset for Features\*

</br>
\*train\_label = Training dataset for Labels\*</br>
| Labels\*

```
In [92]:
          train feat, test feat, train label, test label = train test split(new features, data la
In [93]:
          train feat
         array([[1.900e+03, 3.580e+02, 9.000e+00, ..., 8.000e+01, 4.460e+02,
Out[93]:
                 4.320e+02],
                 [1.929e+03, 3.640e+02, 3.000e+00, ..., 1.160e+02, 3.400e+02,
                 3.240e+021,
                 [1.589e+03, 3.040e+02, 1.500e+01, ..., 8.300e+01, 2.840e+02,
                  2.700e+02],
                 [1.676e+03, 3.320e+02, 1.200e+01, ..., 9.700e+01, 3.990e+02,
                 3.880e+021,
                 [3.154e+03, 6.790e+02, 3.200e+01, ..., 2.000e+02, 6.960e+02,
                 6.780e+02],
                 [3.344e+03, 6.200e+02, 2.400e+01, ..., 1.380e+02, 6.180e+02,
                 6.000e+02]])
```

```
In [94]:
          test feat
         array([1.841e+03, 3.700e+02, 2.100e+01, ..., 9.100e+01, 4.560e+02,
Out[94]:
                 4.480e+021,
                [1.491e+03, 3.280e+02, 0.000e+00, ..., 9.800e+01, 3.890e+02,
                 3.750e+02],
                [2.404e+03, 4.670e+02, 1.600e+01, ..., 1.130e+02, 5.290e+02,
                 5.190e+021,
                [1.965e+03, 4.220e+02, 2.300e+01, ..., 1.000e+02, 4.770e+02,
                 4.640e+02],
                [2.228e+03, 4.550e+02, 2.100e+01, ..., 1.270e+02, 5.410e+02,
                 5.310e+02],
                [1.174e+03, 2.320e+02, 2.000e+00, ..., 7.600e+01, 2.350e+02,
                 2.290e+0211)
In [95]:
          train label
         array([4, 3, 3, 4, 3, 4, 4, 4, 3, 4, 4, 4, 2, 5, 3, 2, 4, 3, 3, 4, 2, 3,
Out[95]:
                4, 4, 3, 3, 4, 1, 3, 4, 3, 4, 4, 4, 3, 4, 4, 3, 5, 4, 3, 4, 4, 4,
                3, 1, 3, 5, 3, 4, 3, 4, 3, 3, 3, 4, 3, 4, 3, 4,
                                                                4, 4,
                                                                       2,
                                                                          2,
                3, 3, 3, 3, 1, 4, 2, 4, 3, 4, 1, 4, 4, 3, 4, 4,
                                                                3, 3,
                                                                       3,
                                                                          2,
                3, 4, 3, 3, 2, 3, 3, 3, 3, 3, 4, 4, 4, 4, 4, 3, 3, 3,
                3, 5, 3, 4, 3, 4, 1, 4, 4, 3, 3, 4, 4, 5, 4,
                                                             3,
                                                                 3,
                                                                    3,
                                                                       3,
                4, 4, 1, 4, 4, 3, 3, 4, 3, 4, 5, 5, 3, 3, 4,
                                                                4,
                                                                      3,
                3, 5, 3, 3, 3, 2, 4, 3, 3, 4, 3, 4, 4, 4, 2, 3, 3, 4, 3,
                3, 3, 3, 4, 3, 4, 4, 4, 3, 3, 4, 3, 4, 4, 3, 4,
                                                                 3,
                                                                    5,
                                                                       2,
                         1, 5, 3, 4, 3, 4, 4, 5, 4, 3, 4, 4,
                                                             4,
                                                                 3,
                                                                   4,
                                                                       3,
                                                                          3,
                3, 3, 3, 3, 4, 4, 3, 2, 4, 4, 5, 4, 2, 4, 3, 4,
                                                                2, 4, 3,
                                                                 3,
                3, 3, 4, 4,
                            2, 4, 4, 4, 3, 4, 3, 4,
                                                    2, 3, 5, 4,
                                                                   4,
                                                                       3,
                                        3,
                                           3,
                                              3,
                                                 4,
                                                    4,
                                                       2,
                                                          2,
                                  4,
                4, 2, 3, 4, 4, 3, 4, 4, 4, 4, 3, 4, 3, 5, 3, 4, 3, 4, 3, 4, 5, 4,
                4, 4, 3, 3, 4, 4, 4, 3, 3, 3, 3, 3, 3, 4, 4, 4, 4, 2, 4, 4, 3,
                      2, 4, 4, 3, 4, 3, 3, 2, 4,
                                                  2,
                                                                4,
                                                    3,
                                                       3,
                                                          3,
                                                             4,
                                                                    1,
                                                                       3,
                3, 4, 3, 5, 2, 3, 4, 5, 2, 3, 4, 3, 3, 3, 4, 3, 4,
                                                                       2,
                4, 4, 3, 3, 2, 2, 4, 3, 4, 4, 4, 4, 4, 4, 4, 3, 4, 4, 4,
                3, 2, 4, 4, 3, 3, 3, 3, 2, 3, 3,
                                                 3, 4,
                                                       4,
                                                          4,
                                                             4,
                                                                 2,
                                                                       3,
                                                                          3,
                         2, 4, 2, 4, 3, 3, 3, 4, 3, 5, 3, 5,
                                                                3,
                4, 4, 4, 4, 4, 3, 3, 3, 4, 3, 4, 3, 2, 4, 4, 4, 4, 2, 5,
                1, 4, 3, 3, 4, 2, 4, 2, 3, 4, 4, 3, 3, 4, 4, 4,
                                                                 3,
                                                                    3, 4,
                                                          4,
                                                                4,
                      4, 4, 4, 2, 2, 3, 4, 2, 3, 1, 3, 3,
                                                             4,
                                                                   3,
                                                                      4,
                4, 2, 3, 2, 3, 4, 4, 3, 3, 3, 3, 5, 3, 3, 3, 4,
                                                                   5,
                3, 4, 3, 4, 4, 4, 5, 2, 4, 3, 4, 2, 3, 3, 4, 4, 4, 3, 4,
                                  5, 3, 4,
                                           3,
                                              3,
                                                 3, 5, 4,
                                                          3,
                3, 4, 4, 3, 3, 4, 3, 4, 3, 3, 3, 3, 4, 4, 4, 2, 4, 3, 3, 3, 3, 3,
                3, 2, 3, 4, 3, 4, 4, 3, 6, 3, 5, 3, 4, 3, 3, 5, 4, 3,
                                                                       3, 4,
                                                                             3, 4,
                2, 4, 2, 4, 4, 3, 4, 3, 2, 3, 4, 3, 4, 4, 3, 4,
                                                                 3,
                                                                   4,
                                                                       3,
                3, 3, 4, 3, 5, 4, 4, 3, 4, 3, 2, 4, 3, 4, 4, 3, 2, 2, 5,
                                                                             2, 4,
                3, 5, 3, 4, 3, 5, 3, 3, 4, 2, 4, 5, 4, 3, 4, 3, 6, 4, 3,
                3, 4, 4, 4, 5,
                                                             4,
                               2, 3, 3, 3,
                                           3, 4, 4,
                                                    3,
                                                        3,
                                                          2,
                                                                3,
                                                                   3,
                                                                             3,
                3, 3, 3, 2, 4, 4, 4, 3, 4, 4, 4, 4, 3, 3, 2, 4,
                                                                5, 3, 3, 3,
                3, 3, 4, 4, 2, 3, 3, 3, 4, 2, 4, 3, 3, 4, 2, 4, 5, 4, 4, 3, 3, 4,
                4, 4, 3, 3, 4, 3, 5, 3, 2, 4, 4, 4, 3, 3, 4, 3,
                                                                 3, 3, 4, 4, 4, 4,
                   2, 3, 3, 4, 3, 3, 3, 3, 4, 3, 4, 3, 3, 4,
                                                                3,
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                                                                         3,
                                                                             3, 3,
                4, 4, 3, 4, 3, 4, 3, 3, 1, 3, 4, 3, 3, 3, 4, 4, 3, 2, 3, 3, 4,
                3, 3, 4, 4, 3, 4, 3, 4, 3, 3, 3, 4, 4, 4, 4, 4, 3, 3, 4, 5, 4, 4,
                      3, 4, 4, 4, 3, 4, 4, 3, 3, 4, 3, 4, 3, 3, 3, 3, 4, 4,
                2, 3, 4, 4, 3, 4, 6, 5, 3, 4, 4, 4, 3, 4, 3, 3, 3, 3, 3, 3, 4, 3,
```

```
3, 4, 4, 3, 3, 3, 2, 3, 2, 4, 4, 4, 3, 3, 4, 2, 5, 4, 3, 4, 4, 4,
                4, 3, 4, 3, 2, 5, 3, 4, 4, 3, 2, 5, 3, 4, 4, 3, 4, 3, 4, 4, 2, 4,
                3, 3, 4, 4, 3, 5, 3, 4, 3, 4, 4, 4, 5, 3, 2, 4, 4, 2, 3, 2, 3, 3,
                3, 3, 3, 3, 3, 4, 3, 3, 4, 5, 4, 3, 4, 5, 4, 4, 4, 3, 4, 3, 3, 4,
                4, 4, 3, 2, 4, 3, 4, 4, 4], dtype=int64)
In [96]:
          test label
         array([4, 3, 4, 4, 3, 4, 4, 3, 3, 3, 4, 4, 3, 3, 3, 3, 4, 4, 3,
Out[96]:
                4, 4, 3, 4, 3, 2, 3, 3, 4, 3, 3, 4, 3, 3, 3, 3, 4, 3, 3,
                3, 4, 4, 4, 4, 4, 3, 4, 4, 3, 4, 5, 4, 4, 3, 2, 4, 3, 4, 2, 1, 3,
                2, 4, 3, 3, 3, 3, 4, 4, 2, 3, 3, 3, 4, 4, 3,
                3, 2, 3, 4, 5, 3, 4, 4, 3, 4, 3, 4, 4, 4, 4, 4, 3, 3, 3, 4, 4,
                3, 3, 3, 3, 4, 3, 4, 4, 3, 5, 3, 2, 4, 3, 5, 3, 3, 2, 2, 5, 4, 4,
                4, 3, 4, 3, 3, 4, 3, 6, 4, 4, 4, 1, 4, 4, 3, 4, 3, 2, 4, 4,
                4, 4, 4, 3, 3, 3, 4, 4, 4, 3, 3, 3, 3, 3, 3, 4, 4, 4, 3, 4, 4, 3,
                4, 3, 4, 3, 2, 4, 3, 4, 4, 4, 3, 4, 4, 3, 2, 4, 5, 2, 3, 4, 3, 1,
                3, 3, 3, 4, 3, 4, 4, 4, 5, 4, 3, 4, 4, 4, 3, 5, 3, 3, 4,
                4, 4, 4, 3, 3, 3, 4, 4, 4, 2, 4, 3, 4, 2, 2, 4, 4, 4, 3,
                3, 3, 3, 4, 4, 4, 4, 2, 4, 3, 4, 4, 3, 4, 4, 3, 3, 3, 3, 4, 5, 3,
                4, 4, 4, 4, 4, 4, 3, 2, 3, 3, 4, 3, 3, 5, 3, 4, 3, 3, 4, 4, 3,
                3, 4, 4, 3, 3, 2, 4, 3, 4, 3, 4, 3, 3, 3, 3, 3, 3, 4, 2,
                4, 4, 4, 3, 4, 3, 3, 3, 4, 3, 3, 4, 4, 1, 3, 4, 3, 3, 3, 3, 3,
                4, 4, 3], dtype=int64)
```

3, 3, 3, 4, 5, 3, 4, 4, 2, 5, 4, 3, 3, 2, 4, 4, 4, 3, 3, 4, 5, 4,

## Classification

# What is the difference between binary and multi-class classification?

Classification is the act of classifying data into different classes which is used to predict from which classes the input data are derived from. Binary classification and multi-class classification are two different types of classification.</br>

\_\*Binary classification\*\_ is the classification of a dataset into two distinct classes. For example, you are presented a basket of fruits and vegetables which act as the dataset here and you will have to sort them into two batches, the two distinct classes here would obviously be Fruits and the other Vegetables. In fact, I have already performed binary classification earlier in this assignment which would be the application of Logistic Regression during Feature Selection. Other examples of algorithms used by binary classification are Decision Trees and Support Vector Machines, the latter of which we will be exploring later in the assignment as well.

\_\*Multi-class classification\*\_ is the classification of a dataset into many distinct classes, many being more than two. For example, instead of just a basket of fruits and vegetables from earlier, this time you are presented a basket of groceries to sort instead, there would be many distinct classes to sort them into, from Toiletries, to different types of Food classes, to Beverages and possibly to Meats. This is the main difference that sets multi-class classification from binary-classification wherein multi-class classification classifies a dataset into many distinct classes while binary classification just

classifies a dataset into two distinct classes. Examples of algorithms used by multi-class classification are Decision Trees and Random Forests. [8]

## **Data Normalisation**

## What is the purpose of normalised / scaling of data?

Data Normalisation is the process of scaling data to a standard scale. Due to the possibly broad range of values in given data, objective functions may not work properly in some machine learning algorithms without normalising data. Certain features may lose their effectiveness if their data is on a different scale when compared to other features. Hence, normalising data is important to ensure that all data is on a similar scale so that a good machine learning model can be produced. [9]

## **Feature Scaling**

Use StandardScaler to normalise the data

```
sc = StandardScaler()
train_feat = sc.fit_transform(train_feat)
test_feat = sc.transform(test_feat)
```

#### Checking if the data has been normalised appropriately

```
In [98]:
          train_feat
         array([[-0.23062001, -0.38254297, -0.51644799, ..., -0.67255429,
Out[98]:
                 -0.139495 , -0.14675677],
                [-0.19750726, -0.34795727, -1.08164595, ..., 0.14280868,
                 -0.79744712, -0.83384211],
                [-0.58572572, -0.69381424, 0.04874997, ..., -0.60460738,
                 -1.14504447, -1.17738478],
                [-0.48638746, -0.53241432, -0.23384901, ..., -0.28752178,
                 -0.43122849, -0.42668043],
                [ 1.20122102, 1.46779183, 1.6501442 , ..., 2.04532228,
                  1.41227888, 1.41827095],
                [1.41816663, 1.12769914, 0.89654692, ..., 0.64108605,
                  0.92812543, 0.92204265]])
In [99]:
          test feat
         array([[-0.29798733, -0.31337157, 0.61394794, ..., -0.42341561,
Out[99]:
                 -0.07742404, -0.04496635],
                [-0.69762398, -0.55547145, -1.36424493, ..., -0.26487281,
                 -0.49329944, -0.50938515],
                [0.34485677, 0.24576386, 0.14294964, ..., 0.07486177,
                  0.37569393, 0.40672864],
                [-0.15640177, -0.01362886, 0.80234726, ..., -0.21957486,
                  0.05292496, 0.05682407],
                [0.14389663, 0.17659247, 0.61394794, ..., 0.39194737,
```

```
0.45017908, 0.48307146],
[-1.0595806, -1.10884261, -1.17584561, ..., -0.76315018,
-1.44919215, -1.43822274]])
```

## **SVM Classification Model**

#### What is SVM?

Support Vector Machines (SVMs) are supervised machine learning models that are used for classification and regression but mainly for classification. For classification, the main objective of the SVM algorithm is to find the most optimal hyperplane in an N-dimensional space that best classifies the input data where N is the number of features. To achieve this, the SVM algorithm finds the hyperplane with the maximum margin which is described as the maximum distance between input data of two classes. The hyperplanes mentioned are decision boundaries that help classify the input data, they are supported by support vectors which determine the position the hyperplanes are in. This very similar to a bridge supported by girders. **[10]** 

#### How does SVM/SVR compare to Linear Regression?

Linear Regression are also supervised machine learning models but are conversely used for regression only, hence their purposes are entirely different. Linear Regression is used to minimise the sum of squared errors while Support Vector Regression (SVR) minimises the coefficients instead of the squared error which is handled in the constraints where the absolute error is set to less than or equal to the maximum error. This gives SVR a flexibility advantage over Linear Regression as errors are disregarded within a certain limits. **[11]** 

#### What is the kernel in SVM/SVR?

The kernel is a function used in SVM that transforms input data to the desired output data. It utilises pre-defined mathematical functions to perform complex calculations of datasets of any dimension to help the SVM algorithm decide on the hyperplane or in other terms the decision boundary. The kernel is also referred to as the kernel trick in which it will tend to solve a non-linearly separable problem with the help of linear classifying features. The kernel has values such as linear or polynomial that can be modified at will, this means that kernel can transmit the decision boundary to datasets of higher dimensions. The Radial Basis Function is the most commonly used kernel due to its robustness of being able to efficiently work with different sizes of datasets, however overfitting may occur on smaller datasets. Hence, linear or polynomial kernels should be used on smaller datasets instead. [12]

## **Building The SVM Model**

**Approach**: Here I will be using the sklearn.svm.SCV function to build the SVM model. The parameters for the function will be changed with different combinations and submitted to Kaggle for testing, the code here will be for the combination with the best results. The only parameters that will be tested are 'C' which is a regularization parameter and 'kernel' which is the type of kernel. My approach will be to take different numbers of different scales and changing values in small intervals

once I obtain a value that is comparatively quite higher than others. The kernel will be interchanged between linear and and rbf as they are most suitable for the model that I will be building. [13]

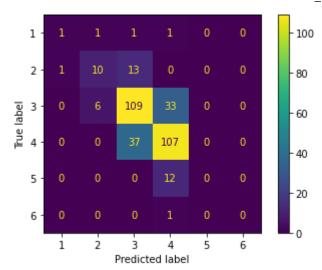
```
In [100... svm = SVC(C = 8.5, kernel = 'linear', random_state = 7)
    svm.fit(train_feat, train_label)
Out[100... SVC(C=8.5, kernel='linear', random_state=7)
```

## **Model Testing**

#### Predicting the Score using test data

```
In [101...
          prediction = svm.predict(test feat)
In [102...
          prediction
         array([4, 3, 4, 4, 3, 3, 3, 3, 3, 3, 4, 4, 4, 4, 2, 4, 3, 4, 3, 3, 3,
Out[102...
                4, 3, 4, 4, 3, 2, 3, 3, 4, 3, 3, 4, 3, 3, 3, 4, 3, 3, 3, 4, 3,
                4, 4, 3, 4, 3, 4, 3, 3, 4, 4, 3, 4, 4, 4, 3, 3, 4, 3, 4, 2,
                3, 4, 4, 3, 2, 3, 3, 4, 4, 3, 3, 3, 4, 4, 4, 3, 3, 4, 4, 4, 4,
                3, 3, 3, 3, 4, 3, 3, 4, 3, 4, 4, 4, 4, 4, 4, 4, 3, 4, 3, 4, 4, 4,
                4, 3, 3, 3, 4, 3, 4, 4, 3, 4, 3, 3, 4, 4, 4, 3, 4, 1, 3, 4,
                4, 3, 3, 3, 3, 3, 4, 4, 3, 4, 2, 4, 4, 3, 4, 3,
                4, 4, 3, 4, 4, 3, 4, 4, 4, 4, 3, 3, 3, 4, 3, 4, 4, 3, 3, 4, 3, 3,
                4, 4, 4, 3, 3, 4, 3, 4, 4, 4, 3, 3, 4, 3, 2, 4, 4, 2, 4, 3, 4, 4,
                3, 3, 3, 4, 4, 3, 4, 4, 4, 4, 3, 3, 3, 4, 3, 4, 3, 3,
                4, 4, 4, 3, 3, 4, 4, 4, 3, 2, 4, 3, 4, 2, 3, 4, 4, 4, 2, 2, 4, 3,
                3, 3, 4, 4, 4, 4, 3, 3, 3, 3, 4, 4, 3, 4, 4, 3, 3, 4, 3, 4, 4, 3,
                4, 4, 4, 4, 4, 4, 3, 2, 3, 3, 4, 3, 3, 4, 4, 3, 4, 4, 3, 4, 4, 3,
                3, 4, 4, 3, 3, 2, 3, 3, 3, 3, 4, 3, 3, 3, 2, 3, 3, 4, 2, 3, 4, 4,
                4, 4, 3, 3, 3, 4, 3, 2, 3, 3, 3, 3, 1, 3, 3, 2, 3, 3, 3, 3, 4,
                4, 4, 3], dtype=int64)
```

## **Displaying the Confusion Matrix**



**Result**: From the confusion matrix, it can be seen that most of the wrong predicted labels are just bordering the actual true labels, although not the best case scenario, it is still a decent outcome. However, there are 3 values that are outside of bordering the true labels which are the values in row 1 column 3 and 4, and the value in row 6 column 4. It can also been seen that most of the predicted values are for the scores 3 and 4, and fortunately for us, a lot of them seem to be correct or close predictions. However, you can also seen from the confusion matrix that the model did not predict any of the scores for 5 or 6 correctly which is quite the problem.

## **Quadratic Weighted Kappa (QWK)**

#### What is QWK?

The Quadratic Weight Kappa (QWK) is a metric used to measure the agreement between two ratings. These ratings which can range from 0 to 5 are given according to how accurate the predicted data is to the actual data. QWK is calculated between the predicted scores and the actual scores. When calculating QWK, the main goal is to get as close to 1 as possible which is the maximum you can get, but there are also cases where the calculated QWK can fall below 0 and that is when there is less agreement between the ratings than expected. **[14]** 

**Explanation**: Here I will be using the sklearn.metrics.cohen\_kappa\_score function with the parameter 'weights' set to 'Quadratic' to calculate the QWK which has been noted to be the same as QWK by the author in [14]. [15]

```
In [104... cohen_kappa_score(test_label, prediction, weights='quadratic')

Out[104... 0.6116089652625236
```

**Result**: Here I received a QWK of 0.6116089652625236 which should be really good score as according to **[14]** a score of 0.6 or more is generally considered really good.

# **Kaggle Submission**

## **Kaggle Submission Preparation**

### Reading the competition data file

In [105	Sub_uata = pu.reau_csv( F111043-ESSay-reatures-Submission.csv )												
In [106													
Out[106		essayid	chars	words	commas	apostrophes	punctuations	avg_word_length	sentences	question			
	0	1623	4332	900	28	13	0	4.813333	39	•			
	1	1143	1465	280	11	3	1	5.232143	14	:			
	2	660	1696	325	17	2	0	5.218462	19				
	3	1596	2640	555	20	17	0	4.756757	28	(			
	4	846	2844	596	33	4	1	4.771812	24	!			
	•••	•••											
	194	1226	1208	242	8	8	0	4.991736	13	(			
	195	862	4039	817	24	11	1	4.943696	47	ï			
	196	1562	2448	468	22	7	0	5.230769	22	(			
	197	1336	1081	214	14	5	0	5.051402	11	(			
	198	1171	2094	433	11	12	0	4.836028	19	(			
	199 rd	ows × 18	3 colum	ıns									

Doing the prediction

Note: sel\_feat = ['chars', 'words', 'commas', 'avg\_word\_sentence', 'POS', 'prompt\_words', 'synonym\_words', 'unstemmed', 'stemmed'] from earlier in the assignment

```
In [107...
          sub_feat = sub_data[sel_feat].values
          kag feat = sc.transform(sub feat)
In [108...
          kag pred = svm.predict(kag feat)
In [109...
          kag pred
         array([4, 3, 4, 4, 4, 4, 3, 3, 3, 3, 3, 3, 4, 3, 4, 4, 4, 4, 3, 3, 3, 3,
Out[109...
                4, 4, 4, 4, 4, 4, 4, 3, 2, 4, 3, 3, 4, 3, 4, 4, 3, 3, 3, 3, 3, 3,
                1, 3, 3, 4, 4, 3, 3, 4, 4, 4, 3, 4, 3, 3, 4, 4, 2, 3, 3, 4, 3, 3,
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3], dtype=int64)
```

## Reading the provided submission file

```
In [110...
          kag_sub = pd.read_csv('32713339-OoiYuZhang-29.csv')
          kag_sub
```

```
Out[110...
                essayid score
                   1623
             1
                   1143
```

199 rows × 2 columns

In [111... kag\_sub['score'] = kag\_pred kag\_sub

199 rows × 2 columns

#### Output to the submission file

In [112...

kag\_sub.to\_csv("32713339-0oiYuZhang-29.csv", index=False)

## Conclusion

Through this assignment, I have learnt a lot of new techniques and information, some I have applied in this assignment, and others that I know exist which may or may not be useful to me in the future. What I have learnt are the many different ways of feature selection, feature scaling, what a SVM and QWK are and how they work, and I had the opportunity to participate in my very first Kaggle competition which was quite interesting. Overall, I feel that the model I built could have been better, which is quite apparent when comparing my score to the rest of the leaderboard in the Kaggle competition.

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