Part A: Classification

A1. Supervised learning

1) Explain supervised machine learning, the notion of labelled data, and train and test datasets.

Supervised machine learning uses labelled data as inputs, to train the machine learning model to obtain a desired output. The correct outputs are given to the model so that the model can learn over time using the labelled dataset. Labelled data is data that is given meaningful tags or labels which corresponds to the data's element. Labelling is usually done by a human operator and the labelled data is used to train supervised machine learning models. Training is done on a model for it to learn from a training dataset and make new predictions on new instances. Test datasets are datasets that are not used in the training of the model and is used to test the performance of the trained machine learning model.

2) Read the 'FIT1043-Essay-Features.csv' file and separate the features and the label (Hint: the label, in this case, is the 'score')

In [56]:
```
import pandas as pd
import matplotlib.pylab as plt
%matplotlib inline
```

In [57]:
```
essay = pd.read_csv("FIT1043-Essay-Features.csv")
```

In [58]:
```
essay
```

Out[58]:

	essayid	chars	words	commas	apostrophes	punctuations	avg_word_length	sentences	questions	avg_word_sentence	POS	POS/total_words	prompt_words	prompt_words/total_words	synonym_words	synonym_
0	1457	2153	426	14	6	0	5.053991	16	0	26.625000	423.995272	0.995294	207	0.485915	105	
1	503	1480	292	9	7	0	5.068493	11	0	26.545455	290.993103	0.996552	148	0.506849	77	
2	253	3964	849	19	26	1	4.669022	49	2	17.326531	843.990544	0.994100	285	0.335689	130	
3	107	988	210	8	7	0	4.704762	12	0	17.500000	207.653784	0.988828	112	0.533333	62	
4	1450	3139	600	13	8	0	5.231667	24	1	25.000000	594.652150	0.991087	255	0.425000	165	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
1327	1151	2404	467	16	10	0	5.147752	22	0	21.227273	462.987069	0.991407	200	0.428266	113	
1328	1015	1182	241	0	14	0	4.904564	16	0	15.062500	238.655462	0.990272	94	0.390041	67	
1329	1345	1814	363	5	11	0	4.997245	13	3	27.923077	362.329640	0.998153	170	0.468320	107	
1330	344	1427	287	5	8	0	4.972125	13	1	22.076923	284.657277	0.991837	144	0.501742	83	
1331	1077	2806	542	24	6	0	5.177122	22	3	24.636364	538.988889	0.994444	284	0.523985	155	

1332 rows × 19 columns

In [59]:
```
dataIn = essay.iloc[:, [0, 17]].values # first 18 col for input data
label = essay.iloc[:, 18].values # labelled data
```

3) Use the sklearn.model_selection.train_test_split function to split your data for training and testing.

In [60]:
```
from sklearn.model_selection import train_test_split
dataIn_train, dataIn_test, label_train, label_test = train_test_split(
dataIn, label, test_size = 0.25, random_state = 0)
```

A2. Classification (Training)

1) Explain the difference between binary and multi-class classification.

Binary classification is when a given item is classified into one of two classes, while multi-class classification is used to predict one or more classes for an item.

2) In preparation for classification, your data should be normalised/scaled.

a. Describe what you understand from this need to normalise data (this is in your Week 7 applied session).

b. Choose and use the appropriate normalisation functions available in sklearn.preprocessing and scale the data appropriately.

a. Normalisation of data is needed to ensure that the data features are on a similar scale. This improves the performance and stability of the model, this also prevents certain features from dominating others due to a larger scale.

In [61]:
```
# b. Normalisation of data
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
dataIn_train = sc.fit_transform(dataIn_train)
dataIn_test = sc.transform(dataIn_test)
```

3) Use the Support Vector Machine algorithm to build the model.

a. Describe SVM. Again, this is not in your lecture content, you need to do some self-learning.

b. In SVM, there is something called the kernel. Explain what you understand from it.

c. Write the code to build a predictive SVM model using your training dataset.

(Note: You are allowed to engineer or remove features as you deem appropriate)

a. Support vector machine (SVM) is a type of supervised learning algorithm that can be used on both regression and classification tasks. This method requires an input dataset of already labelled data, and using that data it will plot hyperplanes that separate the data into two categories. SVM finds the hyperplane that best separates the two categories by maximizing the distance between two points in either category. This distance is known as the margin. The points close to the hyperplane are known as support vectors and influence the position of the hyperplane.

b. Kernels are sets of different algorithms used for pattern analysis. Kernels are used in SVMs by Kernel tricks, where the data is transformed to find an optimal boundary for the dataset. There are different types of kernel functions, these include linear, polynomial and many others.

In [62]:
```
# c. SVM model

from sklearn import svm
classify = svm.SVC(kernel='linear')
classify.fit(dataIn_train, label_train)
```

Out[62]:
```
SVC
SVC(kernel='linear')
```

4) Repeat Task A2.3.c by using another classification algorithm such as Decision Tree or Random Forest algorithms instead of SVM.

In [63]:
```
# c. using Decision tree
from sklearn.tree import DecisionTreeClassifier

classifier = DecisionTreeClassifier(
criterion = 'entropy', random_state = 0
)
classifier.fit(dataIn_train, label_train)
```

Out[63]:
```
DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy', random_state=0)
```

A3. Classification (Prediction)

1) Using the testing dataset you created in Task A1.3 above, conduct the prediction for the 'score' (label) using the two models built by SVM and your other classification algorithm in A2.4.

In [64]:
```
# prediction for SVM
pred = classify.predict(dataIn_test)

# prediction for Decision tree
label_pred = classifier.predict(dataIn_test)
```

2) Display the confusion matrices for both models (it should look like a 6x6 matrix). Unlike the lectures, where it is just a 2x2, you are now introduced to a multi-class classification problem setting.

In [65]:
```
# confusion matrix for SVM
from sklearn.metrics import confusion_matrix
cm_svm = confusion_matrix(label_test, pred)
cm_svm
```

Out[65]:
```
array([[  0,   2,   0,   0,   0,   0],
       [  0,  11,  11,   1,   0,   0],
       [  0,   3,  96,  48,   0,   0],
       [  0,   0,  38, 106,   0,   0],
       [  0,   0,   1,  15,   0,   0],
       [  0,   0,   0,   1,   0,   0]], dtype=int64)
```

In [66]:
```
# confusion matrix for decision tree
cm = confusion_matrix(label_test, label_pred)
cm
```

Out[66]:
```
array([[ 0,  2,  0,  0,  0,  0],
       [ 1, 10,  8,  4,  0,  0],
       [ 2,  9, 86, 48,  2,  0],
       [ 0,  2, 48, 86,  7,  1],
       [ 0,  0,  3, 11,  2,  0],
       [ 0,  0,  0,  1,  0,  0]], dtype=int64)
```

3) Compare the performance of SVM and your other classifier and provide your justification of which one performed better

In [67]:
```
# compare performance
from sklearn.metrics import accuracy_score

# performance of SVM
accuracy_score(label_test, pred) *100
```

Out[67]:
```
63.96396396396396
```

In [68]:
```
# performance of decision tree
accuracy_score(label_test, label_pred) *100
```

Out[68]:
```
55.25525525525525
```

Comparing the performance percentages of the two models, the SVM perfromed better than the decision tree model, with a score of 64.96% and 55.26%

A4. Independent evaluation (Competition)

1) Read the 'FIT1043-Essay-Features-Submission.csv' file and use the best model you built earlier to predict the 'score' for the essays in this file.

In [69]:
```
submissions = pd.read_csv("FIT1043-Essay-Features-Submission.csv")
submissions
```

Out[69]:

	essayid	chars	words	commas	apostrophes	punctuations	avg_word_length	sentences	questions	avg_word_sentence	POS	POS/total_words	prompt_words	prompt_words/total_words	synonym_words	synonym_w
0	1623	4332	900	28	13	0	4.813333	39	1	23.076923	893.988852	0.993321	392	0.435556	196	
1	1143	1465	280	11	3	1	5.232143	14	3	20.000000	278.321343	0.994005	131	0.467857	51	
2	660	1696	325	17	2	0	5.218462	19	1	17.105263	321.316770	0.988667	178	0.547692	92	
3	1596	2640	555	20	17	0	4.756757	28	0	19.821429	551.989150	0.994575	228	0.410811	107	
4	846	2844	596	33	4	1	4.771812	24	9	24.833333	593.658810	0.996072	279	0.468121	138	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
194	1226	1208	242	8	8	0	4.991736	13	0	18.615385	237.327684	0.980693	135	0.557851	58	
195	862	4039	817	24	11	1	4.943696	47	2	17.382979	812.656033	0.994683	386	0.472460	210	
196	1562	2448	468	22	7	0	5.230769	22	0	21.272727	465.656652	0.994993	224	0.478632	101	
197	1336	1081	214	14	5	0	5.051402	11	0	19.454545	212.990566	0.995283	114	0.532710	63	
198	1171	2094	433	11	12	0	4.836028	19	0	22.789474	426.651090	0.985337	221	0.510393	121	

199 rows × 18 columns

In [70]:
```
Input = submissions.iloc[:, [0, 17]].values
Input_data = sc.fit_transform(Input)
prediction = classify.predict(Input_data)
```

2) Unlike the previous section in which you have a testing dataset where you know the 'score' and will be able to test for the accuracy, in this part, you don't have a 'score' and you have to predict it and submit the predictions along with other required submission files.

a. Output of your predictions should be submitted in a CSV file format. It should contain 2 columns: 'essayid' and 'score'. It should have a total of 200 lines (1 header, and 199 entries).

In [71]:
```
print(prediction)
```

```
[4 3 3 4 4 4 3 3 3 3 4 3 4 3 4 4 4 4 3 4 3 3 4 4 4 3 4 4 4 3 2 4 3 3 4 3 4
 4 3 3 4 3 3 3 2 3 3 4 4 3 3 4 4 4 3 4 3 3 4 4 2 3 3 4 3 4 3 4 3 3 3 3 4 3
 3 3 3 3 4 4 3 4 4 3 4 2 4 4 2 3 4 3 3 3 4 3 4 4 3 3 3 4 2 4 3 4 3 3 4 4 4
 3 4 4 4 3 2 4 2 3 4 4 4 3 2 3 3 4 3 2 4 4 2 3 4 3 3 4 2 3 4 4 4 3 3 4 4 3
 4 4 4 3 3 3 4 3 3 4 3 4 4 3 2 3 4 4 3 3 2 4 3 4 4 3 4 3 4 3 3 4 4 3 4 4 4
 4 3 3 4 3 3 4 4 4 3 4 4 3 4]
```

In [72]:
```
df =pd.DataFrame(prediction)
df.rename(columns = {0:'score'}, inplace = True)
df.rename_axis("limbs")
df.index.name = 'essayid'
```

In [73]:
```
df.to_csv('predictions.csv')
```

Part B : Selection of Dataset, Clustering and Video Preparation

B1. Selection of a Dataset with missing data, Clustering

1) Select a suitable dataset that contains some missing data and at least two numerical features. Please note you cannot use the same data set used in the applied sessions/lectures in this unit. Please include a link to your dataset in your report. You may wish to:

● provide the direct link to the public dataset from the internet, or

● place the data file in your Monash student - google drive and provide its link in the submission.

link to dataset: https://www.kaggle.com/datasets/dansbecker/melbourne-housing-snapshot

2) Perform wrangling on the dataset to handle the missing data and explain your procedure

In [74]:
```
melb_data = pd.read_csv('melb_data.csv')
melb_data
```

Out[74]:

	Suburb	Address	Rooms	Type	Price	Method	SellerG	Date	Distance	Postcode	...	Bathroom	Car	Landsize	BuildingArea	YearBuilt	CouncilArea	Lattitude	Longtitude	Regionname	Propertycount
0	Abbotsford	85 Turner St	2	h	1480000.0	S	Biggin	3/12/2016	2.5	3067.0	...	1.0	1.0	202.0	NaN	NaN	Yarra	-37.79960	144.99840	Northern Metropolitan	4019.0
1	Abbotsford	25 Bloomburg St	2	h	1035000.0	S	Biggin	4/02/2016	2.5	3067.0	...	1.0	0.0	156.0	79.0	1900.0	Yarra	-37.80790	144.99340	Northern Metropolitan	4019.0
2	Abbotsford	5 Charles St	3	h	1465000.0	SP	Biggin	4/03/2017	2.5	3067.0	...	2.0	0.0	134.0	150.0	1900.0	Yarra	-37.80930	144.99440	Northern Metropolitan	4019.0
3	Abbotsford	40 Federation La	3	h	850000.0	PI	Biggin	4/03/2017	2.5	3067.0	...	2.0	1.0	94.0	NaN	NaN	Yarra	-37.79690	144.99690	Northern Metropolitan	4019.0
4	Abbotsford	55a Park St	4	h	1600000.0	VB	Nelson	4/06/2016	2.5	3067.0	...	1.0	2.0	120.0	142.0	2014.0	Yarra	-37.80720	144.99410	Northern Metropolitan	4019.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
13575	Wheelers Hill	12 Strada Cr	4	h	1245000.0	S	Barry	26/08/2017	16.7	3150.0	...	2.0	2.0	652.0	NaN	1981.0	NaN	-37.90562	145.16761	South-Eastern Metropolitan	7392.0
13576	Williamstown	77 Merrett Dr	3	h	1031000.0	SP	Williams	26/08/2017	6.8	3016.0	...	2.0	2.0	333.0	133.0	1995.0	NaN	-37.85927	144.87904	Western Metropolitan	6380.0
13577	Williamstown	83 Power St	3	h	1170000.0	S	Raine	26/08/2017	6.8	3016.0	...	2.0	4.0	436.0	NaN	1997.0	NaN	-37.85274	144.88738	Western Metropolitan	6380.0
13578	Williamstown	96 Verdon St	4	h	2500000.0	PI	Sweeney	26/08/2017	6.8	3016.0	...	1.0	5.0	866.0	157.0	1920.0	NaN	-37.85908	144.89299	Western Metropolitan	6380.0
13579	Yarraville	6 Agnes St	4	h	1285000.0	SP	Village	26/08/2017	6.3	3013.0	...	1.0	1.0	362.0	112.0	1920.0	NaN	-37.81188	144.88449	Western Metropolitan	6543.0

13580 rows × 21 columns

In [75]:
```
melb_data = melb_data.fillna(method = 'bfill') # fill with next values
```

In [76]:
```
melb_data = melb_data.fillna(method = 'pad') # fill with previous values
melb_data.loc[melb_data['YearBuilt'] < 1200]
melb_data = melb_data.drop(9968)
```

In [77]:
```
melb_data.isnull().sum()
```

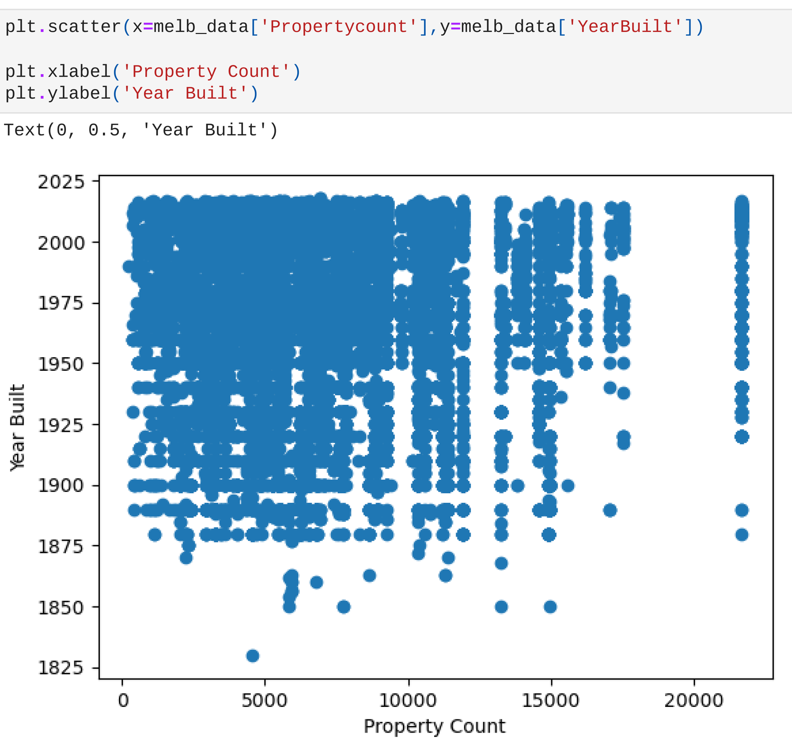
Out[77]:
```
Suburb           0
Address          0
Rooms            0
Type             0
Price            0
Method           0
SellerG          0
Date             0
Distance         0
Postcode         0
Bedroom2         0
Bathroom         0
Car              0
Landsize         0
BuildingArea     0
YearBuilt        0
CouncilArea      0
Lattitude        0
Longtitude       0
Regionname       0
Propertycount    0
dtype: int64
```

3) Perform k-means clustering, choosing two numerical features in your dataset, and apply k-means clustering to your data to create k clusters in Python (k>=2)

In [81]:
```
plt.scatter(x=melb_data['Propertycount'],y=melb_data['YearBuilt'])

plt.xlabel('Property Count')
plt.ylabel('Year Built')
```

Out[81]:
```
Text(0, 0.5, 'Year Built')
```



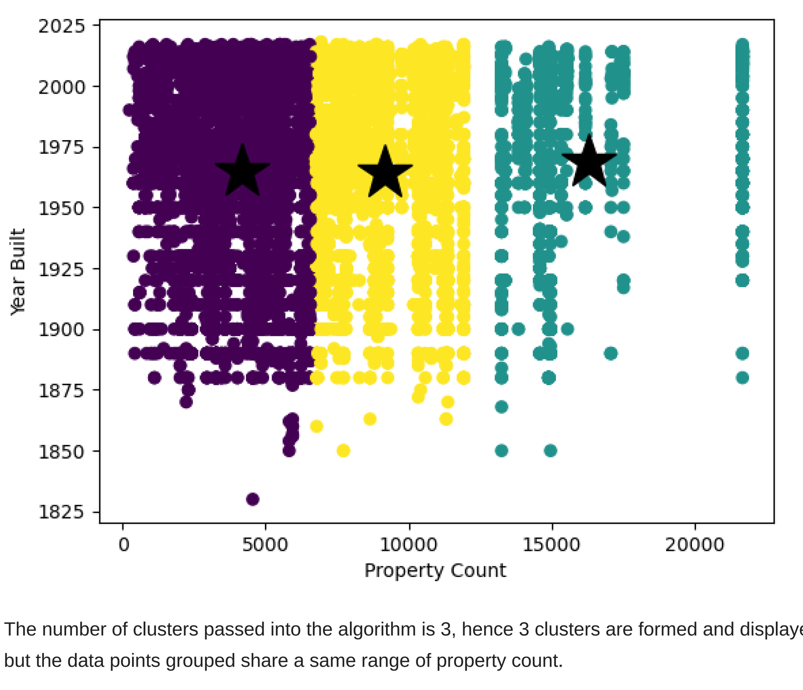
In [82]:
```
from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters=3).fit(
melb_data[['Propertycount','YearBuilt']]
)
```

```
C:\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicit
ly to suppress the warning
  warnings.warn(
```

4) Visualise the data as well as the results of the k-means clustering, and describe your findings about the identified clusters.

In [83]:
```
plt.scatter(
    x=melb_data['Propertycount'],y=melb_data['YearBuilt'],
    c=kmeans.labels_)

plt.plot(
    kmeans.cluster_centers_[:,0],
    kmeans.cluster_centers_[:,1],
    'k*',
    markersize=30
)
plt.xlabel('Property Count')
plt.ylabel('Year Built')
plt.show()
```



The number of clusters passed into the algorithm is 3, hence 3 clusters are formed and displayed. Each cluster grouped is similar to each other, that is the range of the property count. Each of the 3 clusters differ in this range but the data points grouped share a same range of property count.

In [ ]: