RAMAIAH UNIVERSITY OF APPLIED SCIENCES

ASSIGNMENT

Course Code	CSC402A
Course Name	DATA MINING
Programme	B.Tech
Department	Computer Science
Faculty	FET

Name of the Student	SHUBHAM AGARWAL
Reg. No	17ETCS002175
Semester/Year	7^{th} /4^{th} year
Course Leader/s	Prof. Mohan Kumar

<table>
<tr><th colspan="6"><u>Declaration Sheet</u></th></tr>
<tr><td>Student Name</td><td colspan="5">SHUBHAM AGARWAL</td></tr>
<tr><td>Reg. No</td><td colspan="5">17ETCS002175</td></tr>
<tr><td>Programme</td><td colspan="2">B.Tech</td><td>Semester/Year</td><td colspan="2">$7^{th}/4^{th}$ year</td></tr>
<tr><td>Course Code</td><td colspan="5">CSC402A</td></tr>
<tr><td>Course Title</td><td colspan="5">DATA MINING</td></tr>
<tr><td>Course Date</td><td>****</td><td>to</td><td colspan="3">****</td></tr>
<tr><td>Course Leader</td><td colspan="5">Prof. Mohan Kumar</td></tr>
</table>

Declaration

The assignment submitted herewith is a result of my own investigations and that I have conformed to the guidelines against plagiarism as laid out in the Student Handbook. All sections of the text and results, which have been obtained from other sources, are fully referenced. I understand that cheating and plagiarism constitute a breach of University regulations and will be dealt with accordingly.

<table>
<tr><td>Signature of the Student</td><td></td><td>Date</td><td>05/12/2020
20/01/2021</td></tr>
<tr><td>Submission date stamp
(by Examination & Assessment Section)</td><td colspan="3"></td></tr>
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Signature of the Course Leader and date	Signature of the Reviewer and date

Faculty of Engineering and Technology			
Ramaiah University of Applied Sciences			
Department	**Computer Science and Engineering**	**Programme**	**B. Tech**
Semester/Batch	**7th Sem /2017**		
Course Code	**CSC402A**	**Course Title**	**Data Mining**
Course Leader	**Prof. N D Gangadhar, Prof. Mohan Kumar, Prof. Santoshi Kumari**		

Assignment			
Register No	**17ETCS002175**	Name of Student	**SHUBHAM AGARWAL**

Sections		Marking Scheme	Marks		
			Max Marks	First Examiner Marks	Moderator Marks
Part-A	A 1	Data Cleaning: Redundant and Inconsistent Data	05		
	A 2	Data Cleaning: Missing Values and Outliers	05		
	A 3	Data Normalization	05		
	A 4	Data Transformation	05		
	A 5	Interpretation of Results	05		
		Part-A Max Marks	**25**		
Part -B	B 1.	Supervised Learning	10		
	B 2.	Un-supervised Learning	10		
	B 3	Comparative Analysis	05		
		Part-B Max Marks	**25**		
		Total Assignment Marks	**50**		

Course Marks Tabulation

Component- CET B Assignment	First Examiner	Remarks	Second Examiner	Remarks
A				
B				
Marks (Max 50)				
Marks (out of 25)				

Signature of First Examiner Signature of Second Examiner

1. Part B

Solution to Part B Question No 6:

6. Design and implement any two models each from the following types to classify and categorize the data:

Machine Learning is the field of study that gives computers the capability to learn without being explicitly programmed. As it is evident from the name, it gives the computer that makes it more similar to humans: The ability to learn. Machine learning (ML) is a type of artificial intelligence (AI) that allows software applications to become more accurate at predicting outcomes without being explicitly programmed to do so. Machine learning algorithms use historical data as input to predict new output values.

i. Supervised learning:

Supervised learning, also known as supervised machine learning, is a subcategory of machine learning and artificial intelligence. It is defined by its use of labeled datasets to train algorithms that to classify data or predict outcomes accurately. As input data is fed into the model, it adjusts its weights through a reinforcement learning process, which ensures that the model has been fitted appropriately.

Supervised learning uses a training set to teach models to yield the desired output. This training dataset includes inputs and correct outputs, which allow the model to learn over time. The algorithm measures its accuracy through the loss function, adjusting until the error has been sufficiently minimized.

Here, Supervised learning Algorithms like K- Nearest neighbor and Decision Tree are the models which are used.

K-nearest neighbor:

K-nearest neighbor, also known as the KNN algorithm, is a non-parametric algorithm that classifies data points based on their proximity and association to other available data. This algorithm assumes that similar data points can be found near each other. As a result, it seeks to calculate the distance between data points, usually through Euclidean distance, and then it assigns a category based on the most frequent category or average.

Decision Tree:

Decision Tree algorithm belongs to the family of supervised learning algorithms. Unlike other supervised learning algorithms, the decision tree algorithm can be used for solving regression and classification problems too.

The goal of using a Decision Tree is to create a training model that can use to predict the class or value of the target variable by learning simple decision rules inferred from prior data(training data).

Now lets jump into the implementation of models for the normalized data:

Below are the supervised Models for Min – Max Normalized data:

To build model, the Normalized data frames are used, in the previous section, 3 data copies of cleaned preprocessed data is created and Normalization on each data copy is applied. The updated data copies are used to build different models. {datacopyf1: Min- max Normalization, datacopyf2: Z-score Normalization, datccopyf3: Decimal Scaling}

The implementation part was doing using google Colaboratory. To view the implementation code and for execution: **Click Here** . Or access to the python script by using the below link.

https://colab.research.google.com/drive/1OQ5nDXQGDni2KS5CKxidegnp-0umxrVB?usp=sharing

MIN- MAX Normalization:

Supervised Learing:

```
[80]
    #splitting location into City state and country:
    datacopyf1['city']=city
    datacopyf1['state']=state
    datacopyf1['country']= country

    #converting to non numeric data to category
    datacopyf1.Publisher = pd.Categorical(datacopyf1.Publisher)
    datacopyf1['PublisherCode'] = datacopyf1.Publisher.cat.codes
    datacopyf1.BookAuthor = pd.Categorical(datacopyf1.BookAuthor)
    datacopyf1['BookAuthorCode'] = datacopyf1.BookAuthor.cat.codes
    datacopyf1['Book-Title'] = pd.Categorical(datacopyf1['Book-Title'])
    datacopyf1['BookTitleCode'] = datacopyf1['Book-Title'].cat.codes


    datacopyf1.city = pd.Categorical(datacopyf1.city)
    datacopyf1['citycode'] = datacopyf1.city.cat.codes
    datacopyf1.state = pd.Categorical(datacopyf1.state)
    datacopyf1['statecode'] = datacopyf1.state.cat.codes
    datacopyf1.country = pd.Categorical(datacopyf1.country)
    datacopyf1['countrycode'] = datacopyf1.country.cat.codes
```

In the above piece of code, non-numeric attributes like publisher, author and locations are converted to numerical attributes using categorial functions.

```
for i in range(len(datacopyf1)):
  if datacopyf1['BookRating'][i]>=0.0 and datacopyf1['BookRating'][i]<=2.5:
    datacopyf1['BookRating'].loc[i]= "Low"
  elif datacopyf1['BookRating'][i]>2.5 and datacopyf1['BookRating'][i]<=3.75:
    datacopyf1['BookRating'].loc[i] = "Med"
  else:
    datacopyf1['BookRating'].loc[i] = "High"
```

The target variable is transformed to 3 different classes. These classes are low medium and high.

```
[84] # Identifying the predictor variable(x) and Target Variable
     X = datacopyf1[["Age",'PublisherCode','BookAuthorCode','BookTitleCode','citycode', 'countrycode', 'statecode']]
     y = datacopyf1["BookRating"]
```

```
[85] from sklearn.model_selection import train_test_split
     X_train, X_test, Y_train, Y_test = train_test_split(X,y,test_size=0.25,random_state=42)
```

Here predictor variable and target variable is identified. The Target variable is Book rating column. And all the numerical attributes are selected as predictor variable.

Using the sklearn library train -test split is imported the train: test size is 0.75:0.25 which are selected randomly . X- trains Y_train contains the training data whereas Y-train and Y-test contains testing data.

K- nearest neighbor:

K-Nearest Neighbor (for Min-Max Normalization):

```
[86] from sklearn.neighbors import KNeighborsClassifier
     knn = KNeighborsClassifier(n_neighbors=3)
     knn.fit(X_train,Y_train)
     pred = knn.predict(X_test)
```

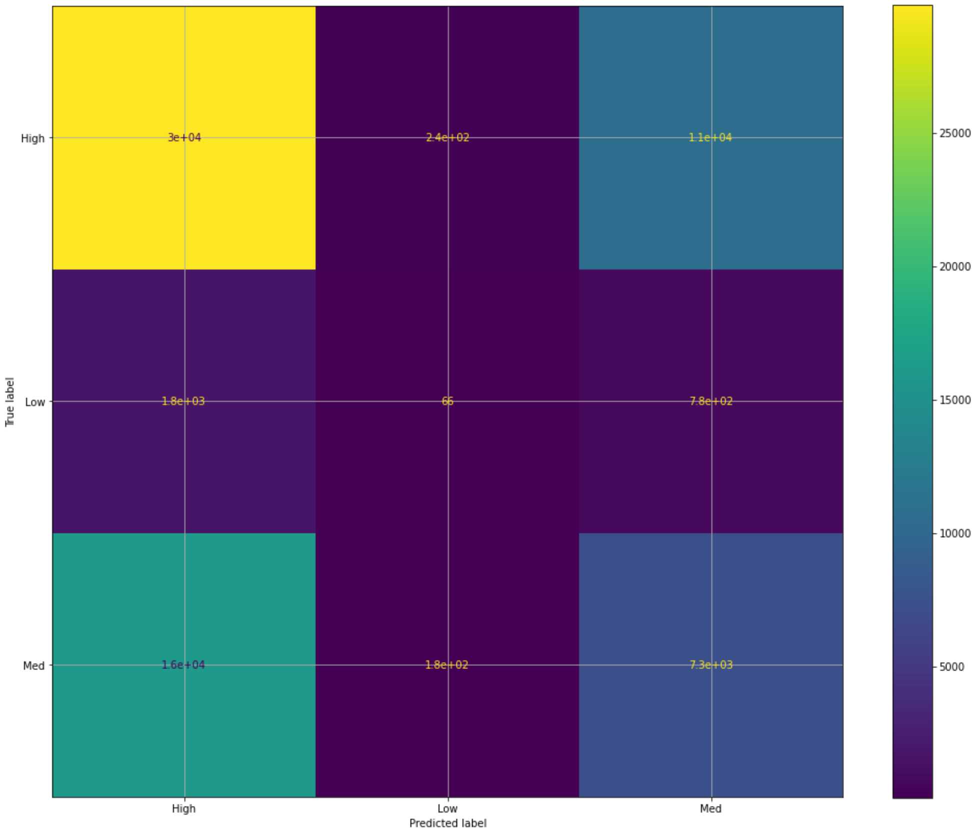
Here the Knn model is used as one of the Supervised model, from Sklearn Library KNeighborclassifier model is imported. The parameter of n- neighbors is set to 3. To this model training data is passed and the model is built using .fit method. After successfully building the model predict method is applied on testing data the predicted output is stored in the pred variable.

```
from sklearn.metrics import classification_report,confusion_matrix,plot_confusion_matrix

print(confusion_matrix(Y_test,pred))
print('\n')
var=classification_report(Y_test,pred)
print(var)

figure, axis = plt.subplots(figsize=(17,14))
plt.grid(b=None)
plot_confusion_matrix(knn, X_test, Y_test, ax=axis)
```

To get the accuracy and precision rate, one can use classification report and confusion matrix. here report is generated, confusion matrix is displayed and plotting confusion_matrix is done.

```
[[29817   240 10847]
 [ 1799    66   778]
 [16132   176  7348]]


              precision    recall  f1-score   support

        High       0.62      0.73      0.67     40904
         Low       0.14      0.02      0.04      2643
         Med       0.39      0.31      0.34     23656

    accuracy                           0.55     67203
   macro avg       0.38      0.35      0.35     67203
weighted avg       0.52      0.55      0.53     67203
```

Above output displays classification report and confusion matrix. the accuracy of Knn model is 0.55 while the f1 score for 3 different classes are 0.67,0.34,0.4 respectively. One can see the precision of the model also which are (High, Low, Med) -> (0.62,0.14,0.39).



The visual graphical display of confusion matrix is displayed above.

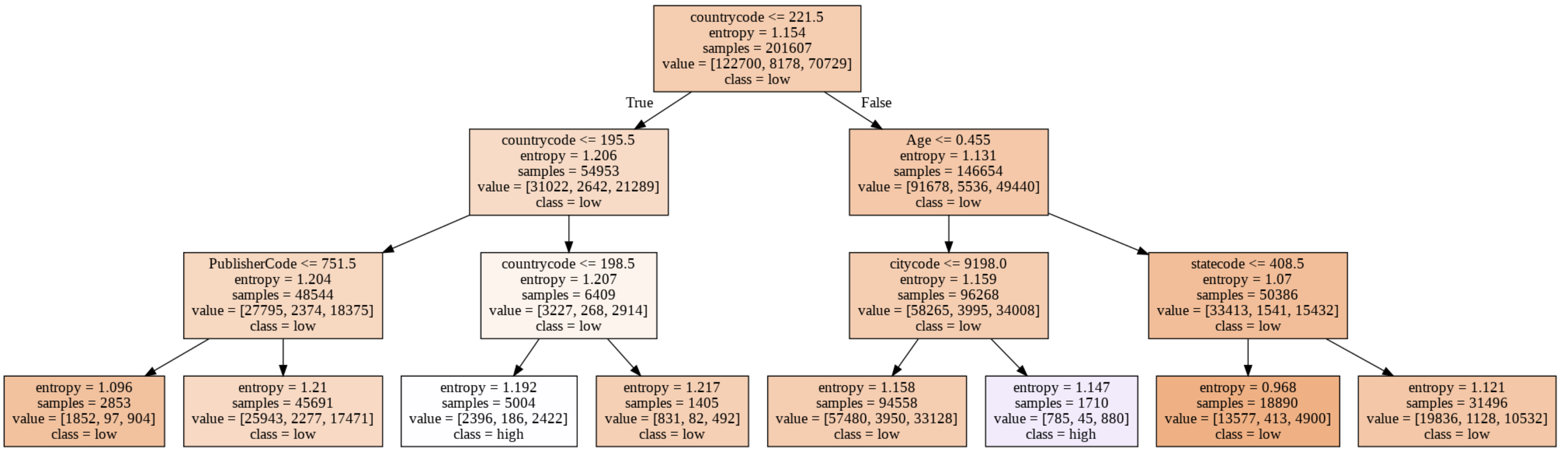
The Second supervised model is Decision Tree:

```
[88] !pip install pydotplus

     Requirement already satisfied: pydotplus in /usr/local/lib/python3.6/dist-packages (2.0.2)
     Requirement already satisfied: pyparsing>=2.0.1 in /usr/local/lib/python3.6/dist-packages (from pydotplus) (2.4.7)

[89] !pip install graphviz

     Requirement already satisfied: graphviz in /usr/local/lib/python3.6/dist-packages (0.10.1)

[90] from sklearn.tree import DecisionTreeClassifier # Import Decision Tree Classifier
     from sklearn import metrics #Import scikit-learn metrics module for accuracy calculation
     import pydotplus
     from IPython.display import Image
     from sklearn import tree
```

For decision tree , one needs to install different packages like pydotplus, graphviz. From Sklearn Library Decision Tree classifier is imported, and other required modules are imported.

```
Dtree = tree.DecisionTreeClassifier(criterion='entropy',max_depth=3)
Dtree = Dtree.fit(X_train, Y_train)
dot_data = tree.export_graphviz(Dtree, feature_names=X.columns, class_names=['low','med','high'], filled=True,out_file=None)
graph = pydotplus.graph_from_dot_data(dot_data)
graph.write_png('decisionTree(MinMax).png')
Image(graph.create_png())
```

In the above piece of code, decision tree classifier is implemented. here criterion{"gini", "entropy"}: The function to measure the quality of a split. Supported criteria are "gini" for the Gini impurity and "entropy" for the information gain, in this case, support criteria is set to entropy with the max depth of 3. The created model is passed to .fit parameter with training dataset as input data. Using the pydotplus graphs decision tree is plotted. Below is the decision tree graph with depth of 3.

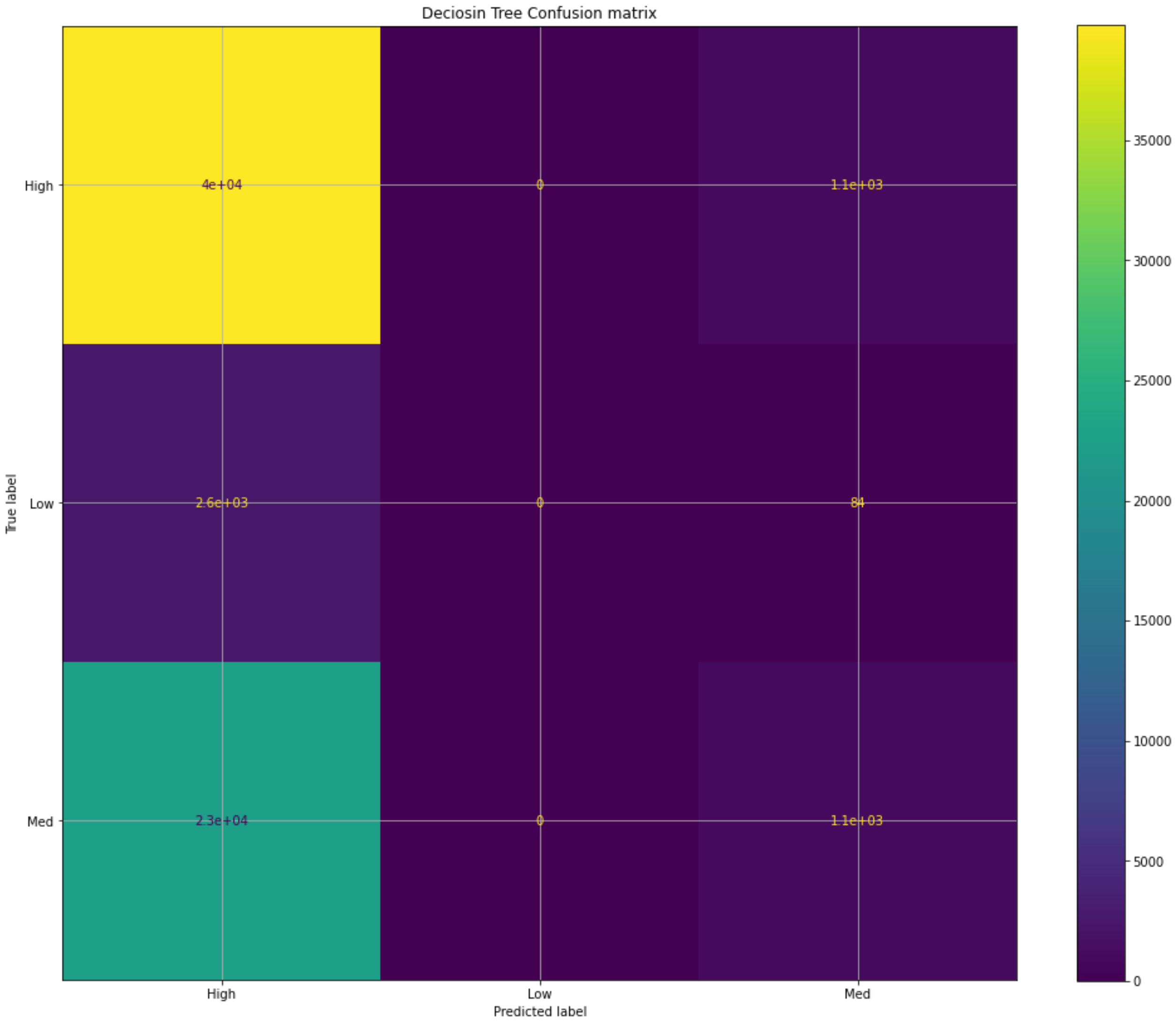



```
DecisionTreepredictedY = Dtree.predict(X_test)
print(confusion_matrix(Y_test,DecisionTreepredictedY))
print('\n')
var=classification_report(Y_test,DecisionTreepredictedY)
print(var)


figure, axis = plt.subplots(figsize=(17,14))
plt.grid(b=None)
plot_confusion_matrix(Dtree, X_test, Y_test, ax=axis)
plt.title("Deciosin Tree Confusion matrix")
```

To get the accuracy and precision rate, one can use classification report and confusion matrix. here report is generated, confusion matrix is displayed and plotting confusion_matrix is done.

```
[[39815     0  1089]
 [ 2559     0    84]
 [22536     0  1120]]

              precision    recall  f1-score   support

        High       0.61      0.97      0.75     40904
         Low       0.00      0.00      0.00      2643
         Med       0.49      0.05      0.09     23656

    accuracy                           0.61     67203
   macro avg       0.37      0.34      0.28     67203
weighted avg       0.55      0.61      0.49     67203
```

Above output displays classification report and confusion matrix. the accuracy of Decision Tree model is 0.61 while the f1 score for 3 different classes are 0.75,0.0,0.09 respectively. One can see the precision of the model also which are (High, Low, Med) -> (0.61,0.01,0.49).



The visual graphical display of confusion matrix is displayed above.

Now lets **Use Z-score normalized data** and try to build the supervised model, again here KNN and Decision Tree will be implemented and corresponding Confusion Matrix is generated.

```
#splitting location into City state and country:
datacopyf2['city']=city
datacopyf2['state']=state
datacopyf2['country']= country

#converting to non numeric data to category
datacopyf2.Publisher = pd.Categorical(datacopyf2.Publisher)
datacopyf2['PublisherCode'] = datacopyf2.Publisher.cat.codes
datacopyf2.BookAuthor = pd.Categorical(datacopyf2.BookAuthor)
datacopyf2['BookAuthorCode'] = datacopyf2.BookAuthor.cat.codes
datacopyf2['Book-Title'] = pd.Categorical(datacopyf2['Book-Title'])
datacopyf2['BookTitleCode'] = datacopyf2['Book-Title'].cat.codes


datacopyf2.city = pd.Categorical(datacopyf2.city)
datacopyf2['citycode'] = datacopyf2.city.cat.codes
datacopyf2.state = pd.Categorical(datacopyf2.state)
datacopyf2['statecode'] = datacopyf2.state.cat.codes
datacopyf2.country = pd.Categorical(datacopyf2.country)
datacopyf2['countrycode'] = datacopyf2.country.cat.codes
```

Here non numerical attributes like Book title, author publisher and location are converted to numeric form, this is done using categorical method from pandas.

```
for i in range(len(datacopyf2)):
  if datacopyf2['BookRating'][i]>=-3.8 and datacopyf2['BookRating'][i]<=-1.50:
    datacopyf2['BookRating'].loc[i]= "Low"
  elif datacopyf2['BookRating'][i]>-1.50 and datacopyf2['BookRating'][i]<=0.08:
    datacopyf2['BookRating'].loc[i] = "Med"
  else:
    datacopyf2['BookRating'].loc[i] = "High"
```

In the above piece of code, Target variable is converted to 3 classes namely low, med and high.

```
# Identifying the predictor variable(x) and Target Variable
X = datacopyf2[["Age",'PublisherCode','BookAuthorCode','BookTitleCode','citycode', 'countrycode', 'statecode']]
y = datacopyf2["BookRating"]
```

In the above piece of code, Predictor variable attributes are stored in independent variable x, where as the target variable book rating is stored in dependent variable y.

```
X_train, X_test, Y_train, Y_test = train_test_split(X,y,test_size=0.25,random_state=42)
```

Using the sklearn Train test split, splitting on predictor and target variable is done with train:test ::0.75:0.25, these splitting are performed in a random format.

KNN model for Z- score Normalization:

```
#Knn model:
kNN = KNeighborsClassifier(n_neighbors=3)
kNN.fit(X_train,Y_train)
pred = kNN.predict(X_test)
```

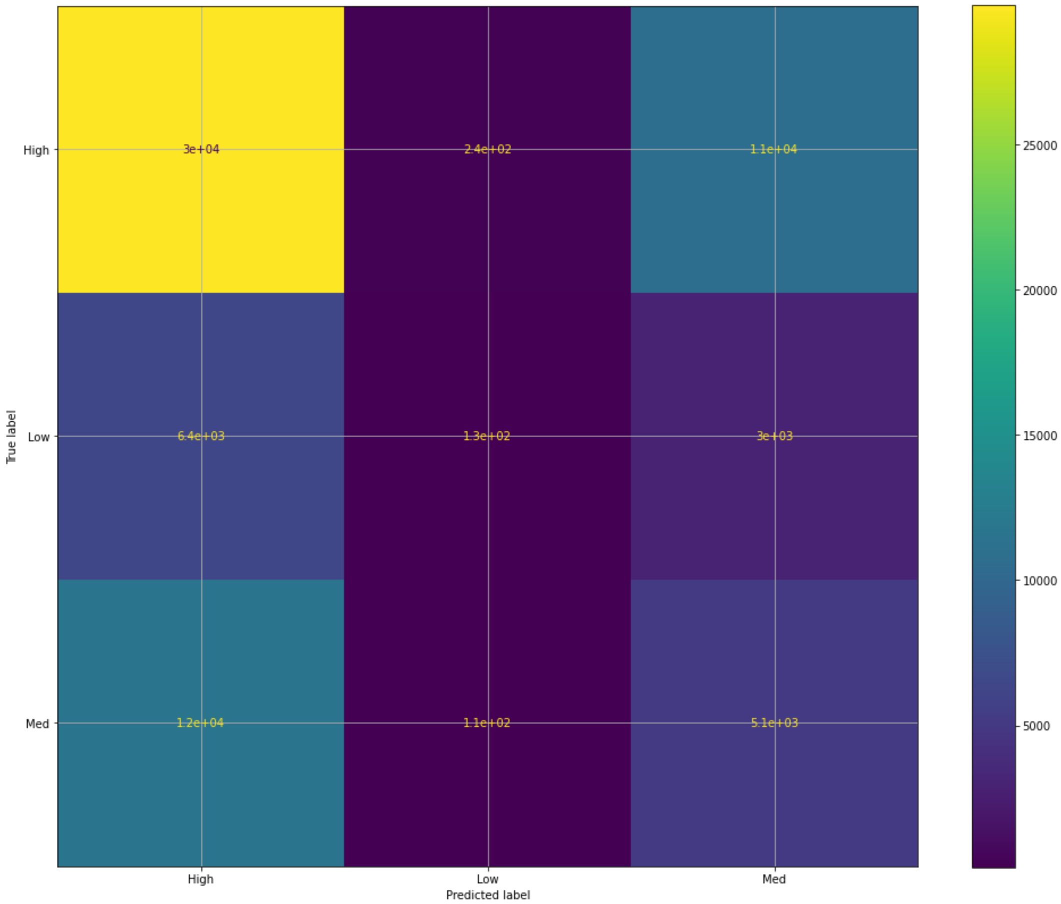
The model is built using Kneighborsclassifier module which is present in the sklearn. This module is passed to the .fit parameter with training inputs. Prediction of testing data is done using . predict method and the corresponding output is stored in the pred variable.

```
#Plotting:
print(confusion_matrix(Y_test,pred))
print('\n')
var=classification_report(Y_test,pred)
print(var)

figure, axis = plt.subplots(figsize=(17,14))
plt.grid(b=None)
plot_confusion_matrix(knn, X_test, Y_test, ax=axis)
```

In the above piece of code, classification report for the Z- score kNN model is generated and corresponding confusion matrix is displayed.

```
[[32753  2181  5970]
 [ 7167   869  1542]
 [12798  1027  2896]]

              precision    recall  f1-score   support

        High       0.62      0.80      0.70     40904
         Low       0.21      0.09      0.13      9578
         Med       0.28      0.17      0.21     16721

    accuracy                           0.54     67203
   macro avg       0.37      0.35      0.35     67203
weighted avg       0.48      0.54      0.50     67203
```

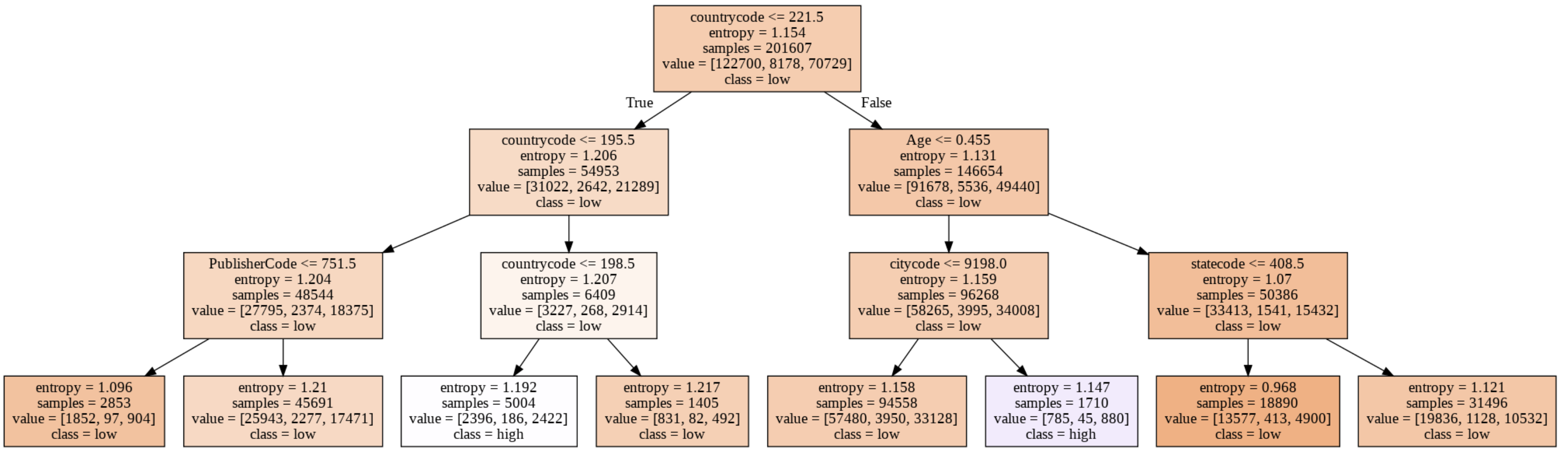
Above output displays classification report and confusion matrix. the accuracy KNN model is 0.64 while the f1 score for 3 different classes are 0.70,0.13,0.21 respectively. One can see the precision of the model also which are (High, Low, Med) -> (0.62,0.21,0.29). The visual graphical display of confusion matrix is displayed below:



Now Lets try Decision Tree on Z-score Normalized data:

```
#Decison Tree model
Dtree = tree.DecisionTreeClassifier(criterion='entropy',max_depth=3)
Dtree = Dtree.fit(X_train, Y_train)
dot_data = tree.export_graphviz(Dtree, feature_names=X.columns, class_names=['low','med','high'], filled=True,out_file=None)
graph = pydotplus.graph_from_dot_data(dot_data)
graph.write_png('decisionTree(z-score).png')
Image(graph.create_png())
```

In the above piece of code, decision tree classifier is implemented. here criterion{“gini”, “entropy”}: The function to measure the quality of a split. Supported criteria are “gini” for the Gini impurity and “entropy” for the information gain, in this case, support criteria is set to entropy with the max depth of 3. The created model is passed to .fit parameter with training dataset as input data. Using the pydotplus graphs decision tree is plotted. Below is the decision tree graph with depth of 3.

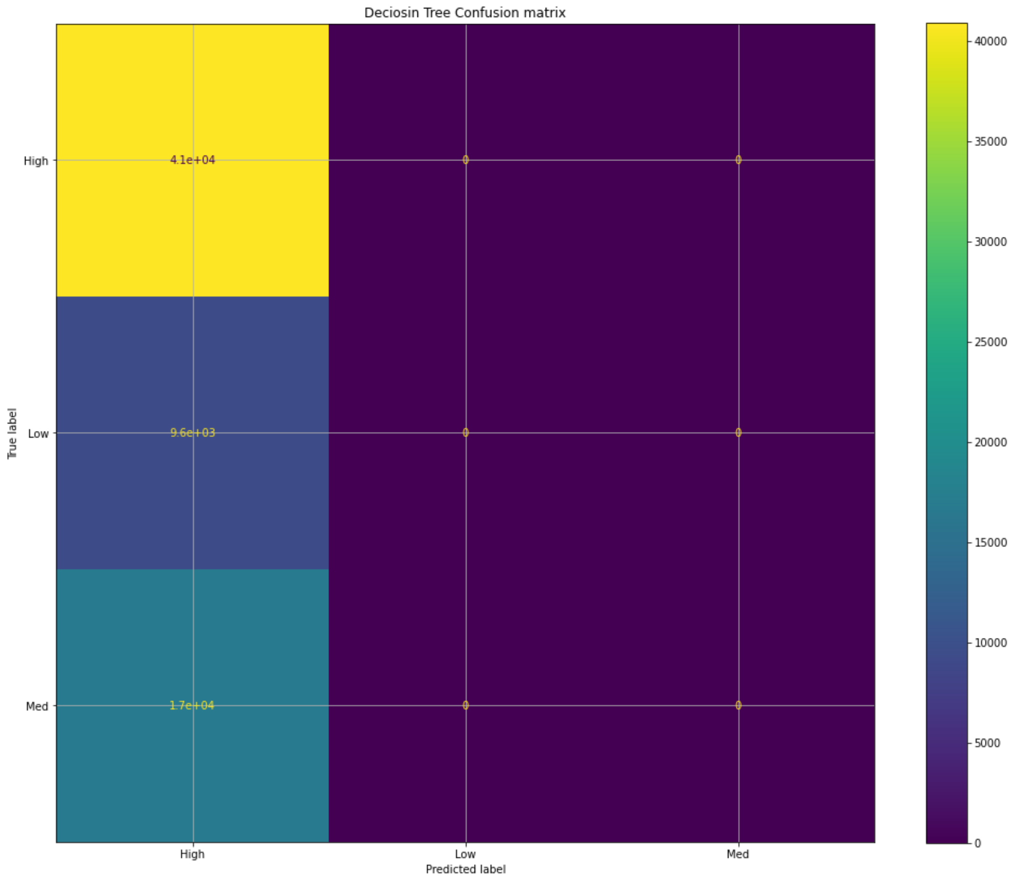


To get the accuracy and precision rate, one can use classification report and confusion matrix. here report is generated, confusion matrix is displayed and plotting confusion_matrix is done.

```
#plotting:
DecisionTreepredictedY = Dtree.predict(X_test)
print(confusion_matrix(Y_test,DecisionTreepredictedY))
print('\n')
var=classification_report(Y_test,DecisionTreepredictedY)
print(var)

figure, axis = plt.subplots(figsize=(17,14))
plt.grid(b=None)
plot_confusion_matrix(Dtree, X_test, Y_test, ax=axis)
plt.title("Deciosin Tree Confusion matrix")
```

```
[[40904     0     0]
 [ 9578     0     0]
 [16721     0     0]]

              precision    recall  f1-score   support

        High       0.61      1.00      0.76     40904
         Low       0.00      0.00      0.00      9578
         Med       0.00      0.00      0.00     16721

    accuracy                           0.61     67203
   macro avg       0.20      0.33      0.25     67203
weighted avg       0.37      0.61      0.46     67203
```

Above output displays classification report and confusion matrix. the accuracy of Decision Tree model is 0.61 while the f1 score for 3 different classes are 0.76,0.0,0.01 respectively. One can see the precision of the model also which are (High, Low, Med) -> (0.61,0.00,0.0). The visual graphical display of confusion matrix is displayed below:



Decimal Scaling Normalization was also performed, so one can even try building Supervised models for Decimal scaling Normalized data. Again, here KNN and Decision Tree will be implemented and corresponding Confusion Matrix is generated.

```
#splitting location into City state and country:
datacopyf3['city']=city
datacopyf3['state']=state
datacopyf3['country']= country

#converting to non numeric data to category
datacopyf3.Publisher = pd.Categorical(datacopyf3.Publisher)
datacopyf3['PublisherCode'] = datacopyf3.Publisher.cat.codes
datacopyf3.BookAuthor = pd.Categorical(datacopyf3.BookAuthor)
datacopyf3['BookAuthorCode'] = datacopyf3.BookAuthor.cat.codes
datacopyf3['Book-Title'] = pd.Categorical(datacopyf3['Book-Title'])
datacopyf3['BookTitleCode'] = datacopyf3['Book-Title'].cat.codes


datacopyf3.city = pd.Categorical(datacopyf3.city)
datacopyf3['citycode'] = datacopyf3.city.cat.codes
datacopyf3.state = pd.Categorical(datacopyf3.state)
datacopyf3['statecode'] = datacopyf3.state.cat.codes
datacopyf3.country = pd.Categorical(datacopyf3.country)
datacopyf3['countrycode'] = datacopyf3.country.cat.codes
```

Here non numerical attributes like Book title, author publisher and location are converted to numeric form, this is done using categorical method from pandas.

```
for i in range(len(datacopyf2)):
  if datacopyf3['BookRating'][i]>=0.00 and datacopyf3['BookRating'][i]<=0.05:
    datacopyf3['BookRating'].loc[i]= "Low"
  elif datacopyf3['BookRating'][i]>0.05 and datacopyf3['BookRating'][i]<=0.75:
    datacopyf3['BookRating'].loc[i] = "Med"
  else:
    datacopyf3['BookRating'].loc[i] = "High"
```

In the above piece of code, Target variable is converted to 3 classes namely low, med and high.

```
# Identifying the predictor variable(x) and Target Variable
X = datacopyf2[["Age",'PublisherCode','BookAuthorCode','BookTitleCode','citycode', 'countrycode', 'statecode']]
y = datacopyf2["BookRating"]
```

In the above piece of code, Predictor variable attributes are stored in independent variable x, where as the target variable book rating is stored in dependent variable y.

```
X_train, X_test, Y_train, Y_test = train_test_split(X,y,test_size=0.25,random_state=42)
```

Using the sklearn Train test split, splitting on predictor and target variable is done with train:test ::0.75:0.25, these splitting are performed in a random format.

KNN model for Decimal Scaling:

```
#Knn model:
kNN = KNeighborsClassifier(n_neighbors=3)
kNN.fit(X_train,Y_train)
pred = kNN.predict(X_test)
```

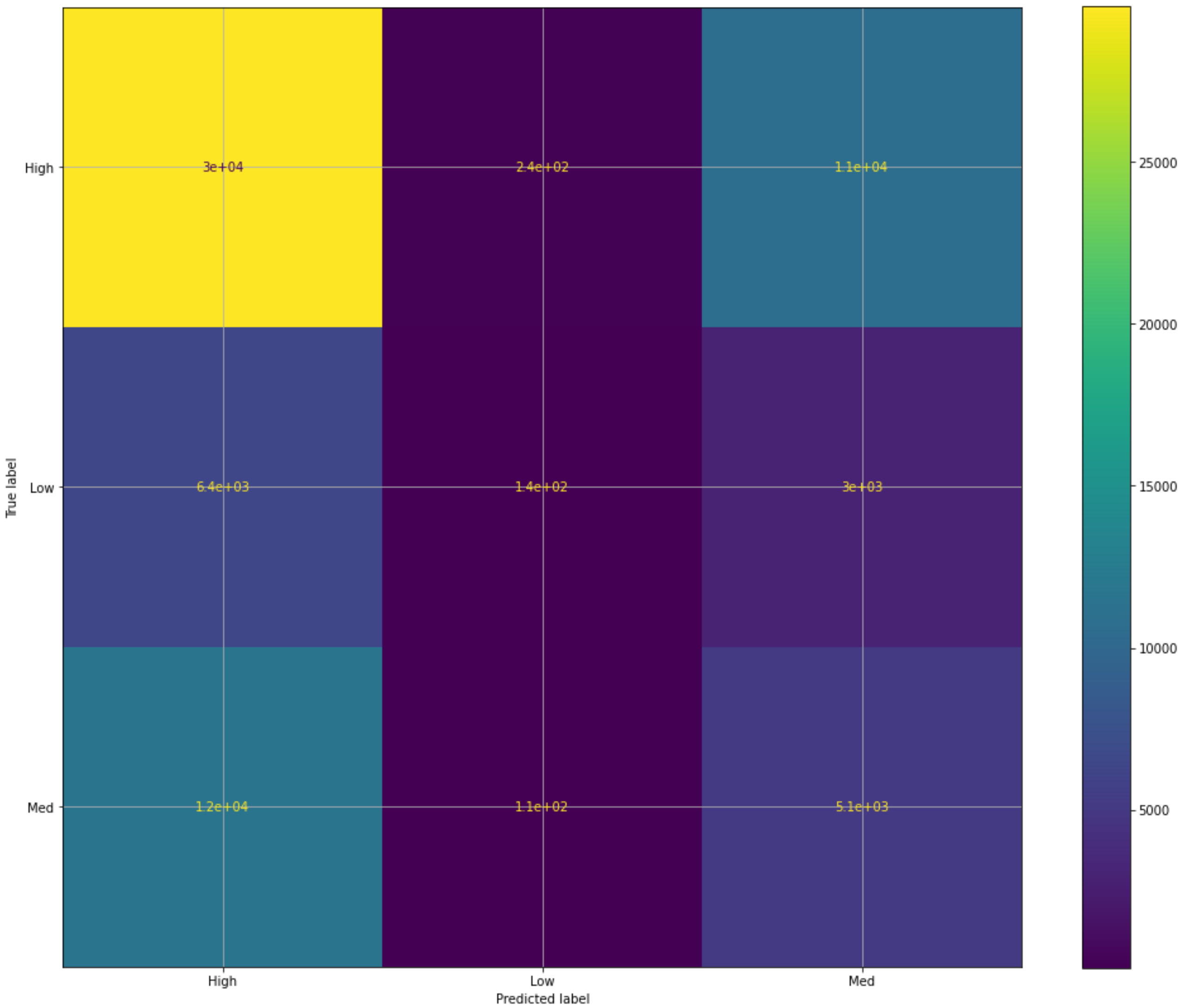
The model is built using Kneighborsclassifier module which is present in the sklearn. This module is passed to the .fit parameter with training inputs. Prediction of testing data is done using . predict method and the corresponding output is stored in the pred variable.

```
] #Plotting:
print(confusion_matrix(Y_test,pred))
print('\n')
var=classification_report(Y_test,pred)
print(var)

figure, axis = plt.subplots(figsize=(17,14))
plt.grid(b=None)
plot_confusion_matrix(knn, X_test, Y_test, ax=axis)
```

```
              precision    recall  f1-score   support

        High       0.62      0.80      0.70     40904
         Low       0.21      0.09      0.13      9578
         Med       0.28      0.17      0.21     16721

    accuracy                           0.54     67203
   macro avg       0.37      0.35      0.35     67203
weighted avg       0.48      0.54      0.50     67203
```

In the above piece of code, classification report for the Z- score kNN model is generated and corresponding confusion matrix is displayed.

Above output displays classification report and confusion matrix. the accuracy KNN model is 0.54 while the f1 score for 3 different classes are 0.70,0.13,0.21 respectively. One can see the precision of the model also which are (High, Low, Med) -> (0.62,0.21,0.28). The visual graphical display of confusion matrix is displayed below:

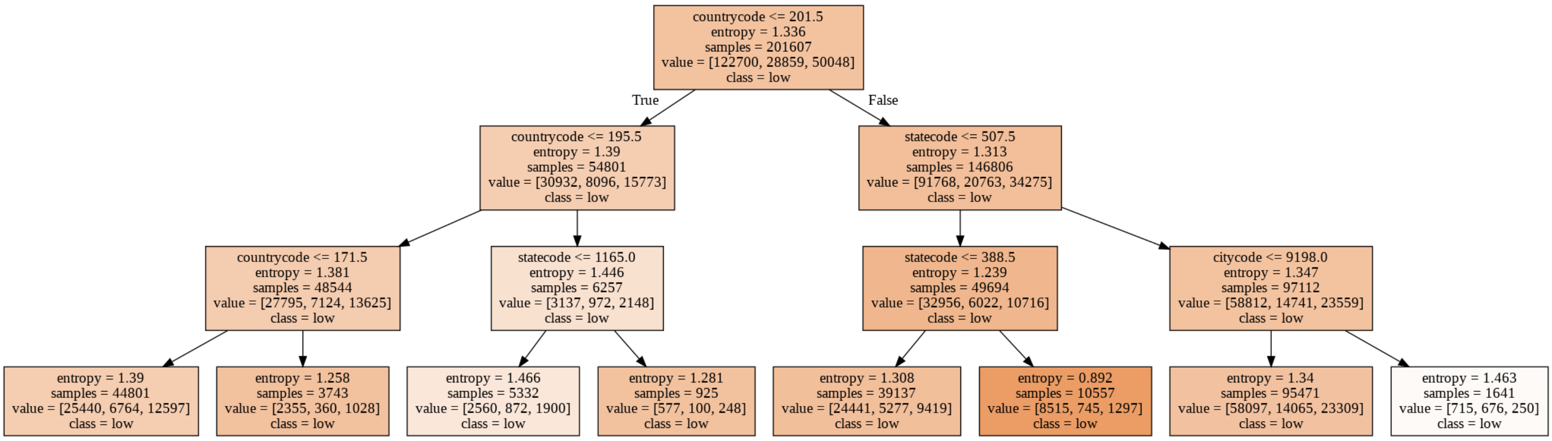


Now Lets try Decision Tree on Decimal Scaled data:

```
#Decison Tree model
Dtree = tree.DecisionTreeClassifier(criterion='entropy',max_depth=3)
Dtree = Dtree.fit(X_train, Y_train)
dot_data = tree.export_graphviz(Dtree, feature_names=X.columns, class_names=['low','med','high'], filled=True,out_file=None)
graph = pydotplus.graph_from_dot_data(dot_data)
graph.write_png('decisionTree(Decimal Scaling).png')
Image(graph.create_png())
```

In the above piece of code, decision tree classifier is implemented. here criterion{"gini", "entropy"}:

The function to measure the quality of a split. Supported criteria are "gini" for the Gini impurity and "entropy" for the information gain, in this case, support criteria is set to entropy with the max depth of 3. The created model is passed to .fit parameter with training dataset as input data. Using the pydotplus graphs decision tree is plotted. Below is the decision tree graph with depth of 3.

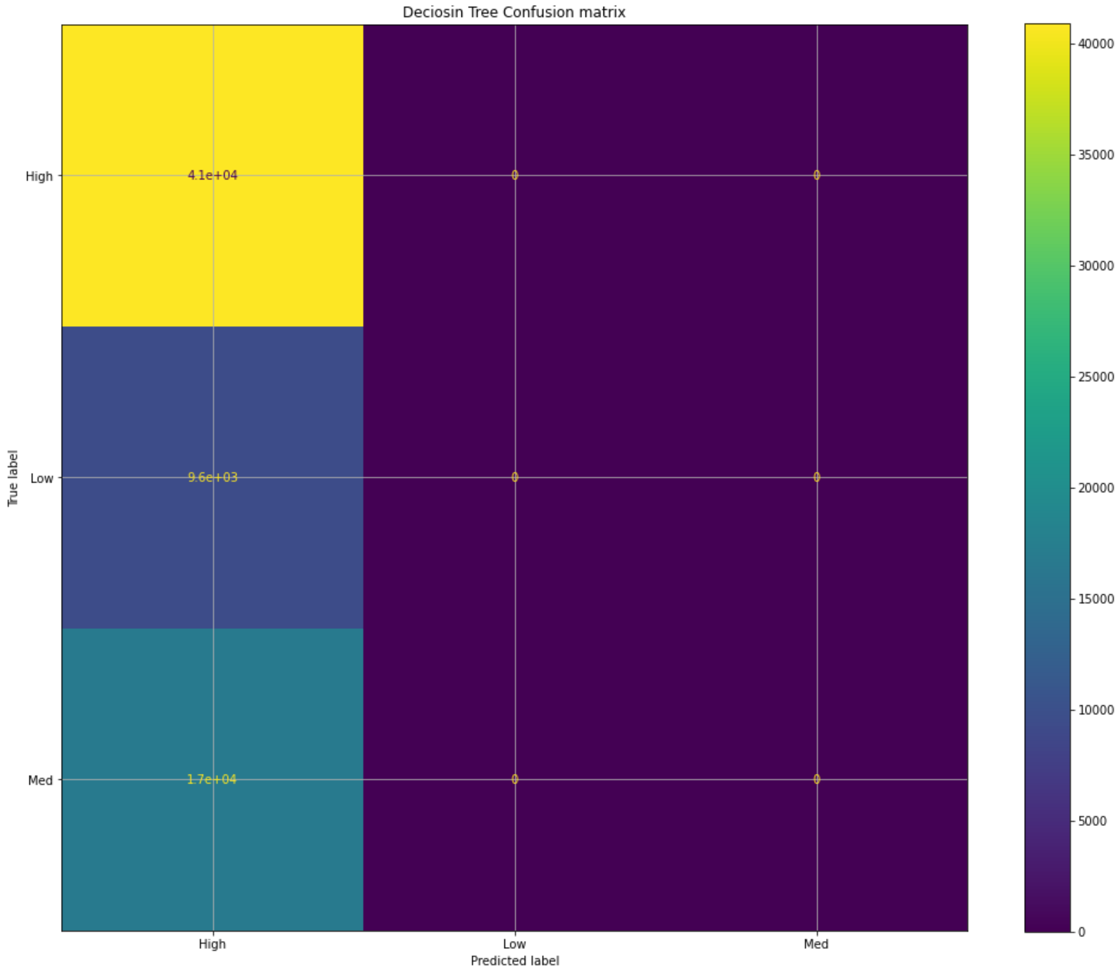


To get the accuracy and precision rate, one can use classification report and confusion matrix. here report is generated, confusion matrix is displayed and plotting confusion_matrix is done.

```
#plotting:
DecisionTreepredictedY = Dtree.predict(X_test)
print(confusion_matrix(Y_test,DecisionTreepredictedY))
print('\n')
var=classification_report(Y_test,DecisionTreepredictedY)
print(var)

figure, axis = plt.subplots(figsize=(17,14))
plt.grid(b=None)
plot_confusion_matrix(Dtree, X_test, Y_test, ax=axis)
plt.title("Deciosin Tree Confusion matrix")
```

```
[[40904     0     0]
 [ 9578     0     0]
 [16721     0     0]]


              precision    recall  f1-score   support

        High       0.61      1.00      0.76     40904
         Low       0.00      0.00      0.00      9578
         Med       0.00      0.00      0.00     16721

    accuracy                           0.61     67203
   macro avg       0.20      0.33      0.25     67203
weighted avg       0.37      0.61      0.46     67203
```

Above output displays classification report and confusion matrix. the accuracy of Decision Tree model is 0.61 while the f1 score for 3 different classes are 0.76,0.00,0.01 respectively. One can see the precision of the model also which are (High, Low, Med) -> (0.61,0.009,0.006). The visual graphical display of confusion matrix is displayed below:



This completes Building Model for Supervised learning with 3 different Normalized Datasets. Now lets jump to Unsupervised Learning model:

ii. Un-supervised learning:

Unsupervised Learning is a machine learning technique in which the users do not need to supervise the model. Instead, it allows the model to work on its own to discover patterns and information that was previously undetected. It mainly deals with the un-labelled data. Unsupervised learning algorithms include clustering, anomaly detection, neural networks, etc.

Here, Unsupervised learning Algorithms like K- means and K- medoids are the models which are used.

K-means:

K means it is an iterative clustering algorithm which helps one to find the highest value for every iteration. Initially, the desired number of clusters are selected. In this clustering method, one need to cluster the data points into k groups. A larger k means smaller groups with more granularity in the same way. A lower k means larger groups with less granularity.

The output of the algorithm is a group of "labels." It assigns data point to one of the k groups. In k-means clustering, each group is defined by creating a centroid for each group. The centroids are like the heart of the cluster, which captures the points closest to them and adds them to the cluster.

Hierarchical Clustering:

Hierarchical clustering, also known as hierarchical cluster analysis, is an algorithm that groups similar objects into groups called clusters. The endpoint is a set of clusters, where each cluster is distinct from each other cluster, and the objects within each cluster are broadly similar to each other.

Hierarchical clustering starts by treating each observation as a separate cluster. Then, it repeatedly executes the following two steps: (1) identify the two clusters that are closest together, and (2) merge the two most similar clusters. This iterative process continues until all the clusters are merged together. Euclidean distance is the most common metric used to calculate the distances

The main output of Hierarchical Clustering is a dendrogram. Diagram of a Dendrogram; reading the chart "bottom-up" demonstrates agglomerative clustering while "top-down" is indicative of divisive clustering. The dendrogram illustrates how each cluster is composed by drawing a U-shaped link between a non-singleton cluster and its children. The top of the U-link indicates a cluster merge. The two legs of the U-link indicate which clusters were merged. The length of the two legs of the U-link represents the distance between the child clusters. It is also the cophenetic distance between original observations in the two children clusters.

Now lets jump into the implementation of models for the normalized data:

Below are the Unsupervised Models for Min – Max Normalized data:

```
datacopyf1['BookRating'] = pd.Categorical(datacopyf1['BookRating'])
datacopyf1['BookRatingCode'] = datacopyf1['BookRating'].cat.codes
```

To Perform so , target variable needs to be in Numeric form, hence by executing the above code, 3 bookrating classes are converted to numerical class say 0, 1 2

```
y_encoded= datacopyf1['BookRatingCode']
X_train, X_test, y_train, y_test = train_test_split(X,y_encoded,test_size=0.25,random_state=42)
```

In the above piece of code, Predictor variable attributes are stored in independent variable x, where as the target variable book rating is stored in dependent variable y_encoded.

Using the sklearn Train test split, splitting on predictor and target variable is done with train:test ::0.75:0.25, these splitting are performed in a random format.

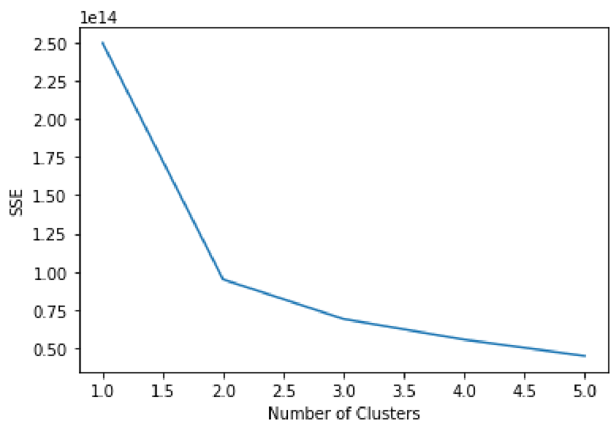
To Perform K-Means clustering:

Cluster model from Sklearn is selected and used. Below model implementation of unsupervised Kmeans:

```
import pandas as pd
from sklearn import cluster
import numpy as np
import matplotlib.pyplot as plt

k_means = cluster.KMeans(n_clusters=3, max_iter=50, random_state=1).fit(X_train)
labels = k_means.labels_

numClusters = [1,2,3,4,5]
SSE = []
for k in numClusters:
    k_means = cluster.KMeans(n_clusters=k)
    k_means.fit(X_train)
    SSE.append(k_means.inertia_)
#Sum of squared distances of samples to their closest cluster center.

plt.plot(numClusters, SSE)
plt.xlabel('Number of Clusters')
plt.ylabel('SSE')
plt.show()


Kmeanspredicted = k_means.predict(X_test)
Kmeanspredicted.reshape(-1,1)

var=classification_report(y_test,Kmeanspredicted)
print(var)
```

Kmeans is imported from cluster module, 3 different cluster are created, the maximum iteration is set to 50 while the random state is set to 1, and all parameter are automatically set to their default values.

To get the accuracy and precision rate, one can use classification report and confusion matrix. here report is generated, confusion matrix is displayed.




```
              precision    recall  f1-score   support

           0       0.60      0.17      0.26     40904
           1       0.04      0.21      0.07      2643
           2       0.35      0.26      0.30     23656
           3       0.00      0.00      0.00         0
           4       0.00      0.00      0.00         0

    accuracy                           0.20     67203
   macro avg       0.20      0.13      0.13     67203
weighted avg       0.49      0.20      0.27     67203
```

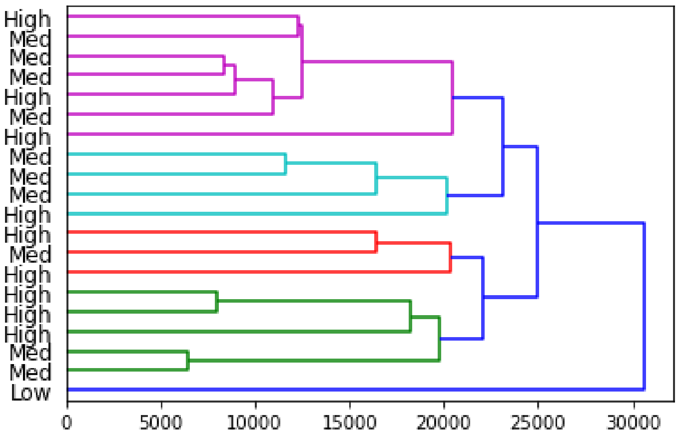
Above output displays classification report and confusion matrix. the accuracy of Kmeans model is 0.20 while the f1 score for 3 different classes are 0.26,0.07,0.30 respectively. One can see the precision of the model also which are (0, 1, 2) -> (0.60,0.04,0.35).

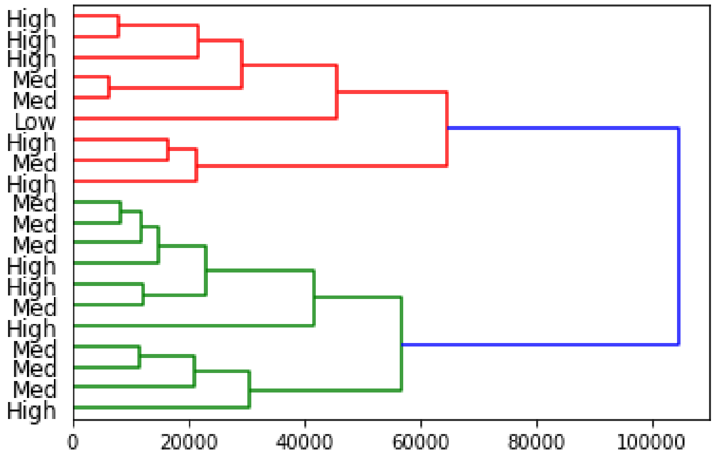
The Second unsupervised model is hierarchical clustering:

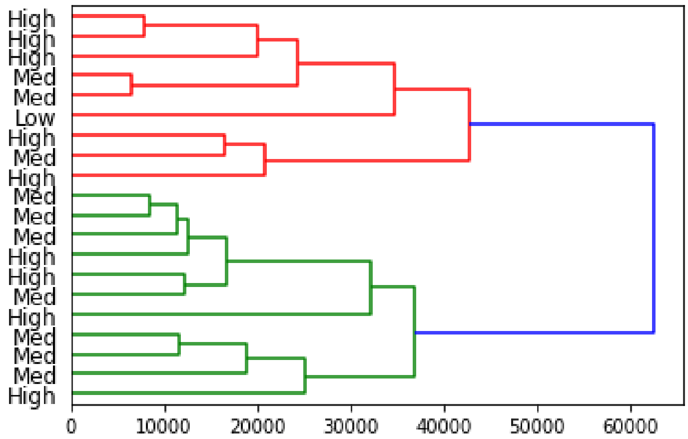
To perform hierarchy clustering, one need to import hierarchy module from scipy cluster. The space complexity of this unsupervised model is too big hence a part of train- test data is considered and the model is built. Below code helps in creating cluster model and plotting Dendrograms.

```
import pandas as pd
from scipy.cluster import hierarchy
import matplotlib.pyplot as plt
X_refined = X_train[:20]
names = datacopyf1['BookRating']
Z = hierarchy.linkage(X_refined, 'single')
dend = hierarchy.dendrogram(Z,labels=names.tolist(),orientation='right')
plt.show()
Z = hierarchy.linkage(X_refined, 'complete')
dend = hierarchy.dendrogram(Z,labels=names.tolist(),orientation='right')
plt.show()
Z = hierarchy.linkage(X_refined, 'average')
dend = hierarchy.dendrogram(Z,labels=names.tolist(),orientation='right')
plt.show()
```

A Dendrogram is a type of tree diagram showing hierarchical relationships between different sets of data. As already said a Dendrogram contains the memory of hierarchical clustering algorithm, so just by looking at the Dendrogram one can tell how the cluster is formed. From the above code, 3 different Dendrograms are created with 3 different method namely single, complete, average.







Now let's Use **Z-score normalized data** and try to build the unsupervised model, again here KMeans and **is** hierarchical clustering will be implemented and corresponding Confusion Matrix is generated.

```
# Identifying the Traget Variable:
datacopyf2['BookRating'] = pd.Categorical(datacopyf2['BookRating'])
datacopyf2['BookRatingCode'] = datacopyf2['BookRating'].cat.codes
y_encoded= datacopyf2['BookRatingCode']
X_train, X_test, y_train, y_test = train_test_split(X,y_encoded,test_size=0.25,random_state=42)
```

To Perform so , target variable needs to be in Numeric form, hence by executing the above code, 3 bookrating classes are converted to numerical class say 0, 1 2.

In the above piece of code, Predictor variable attributes are stored in independent variable x, where as the target variable book rating is stored in dependent variable y_encoded.

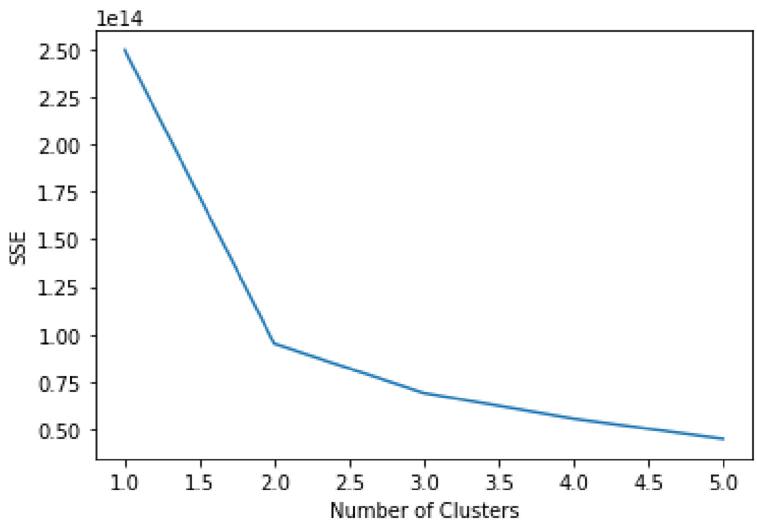
Using the sklearn Train test split, splitting on predictor and target variable is done with train:test ::0.75:0.25, these splitting are performed in a random format.

To Perform K-Means clustering:

Cluster model from Sklearn is selected and used. Below model implementation of unsupervised Kmeans:

```
# Kmeans model:
k_means = cluster.KMeans(n_clusters=3, max_iter=50, random_state=1).fit(X_train)
labels = k_means.labels_

numClusters = [1,2,3,4,5]
SSE = []
for k in numClusters:
    k_means = cluster.KMeans(n_clusters=k)
    k_means.fit(X_train)
    SSE.append(k_means.inertia_)
#Sum of squared distances of samples to their closest cluster center.
#plotting:
plt.plot(numClusters, SSE)
plt.xlabel('Number of Clusters')
plt.ylabel('SSE')
plt.show()


Kmeanspredicted = k_means.predict(X_test)
Kmeanspredicted.reshape(-1,1)

var=classification_report(y_test,Kmeanspredicted)
print(var)
```

The above clustering is performed only on Z-score normalized data, 3 different clusters are found. To get the accuracy and precision rate, one can use classification report and confusion matrix. here report is generated, confusion matrix is displayed.



Here one can see that cluster after 3 are almost zero and only 3 clusters are identified.


```
              precision    recall  f1-score   support

           0       0.61      0.20      0.30     40904
           1       0.15      0.18      0.16      9578
           2       0.25      0.26      0.25     16721
           3       0.00      0.00      0.00         0
           4       0.00      0.00      0.00         0

    accuracy                           0.21     67203
   macro avg       0.20      0.13      0.14     67203
weighted avg       0.45      0.21      0.27     67203
```

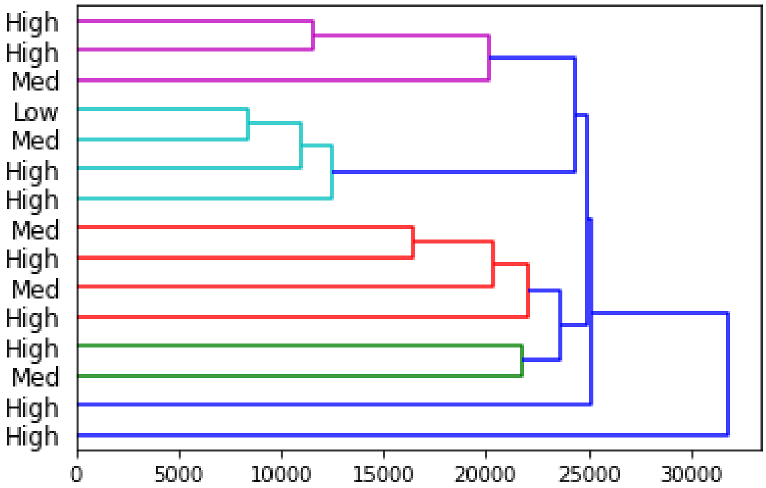
Above output displays classification report and confusion matrix. the accuracy of Kmeans model is 0.21 while the f1 score for 3 different classes are 0.30,0.16,0.25 respectively. One can see the precision of the model also which are (0, 1, 2) -> (0.61,0.15,0.25).

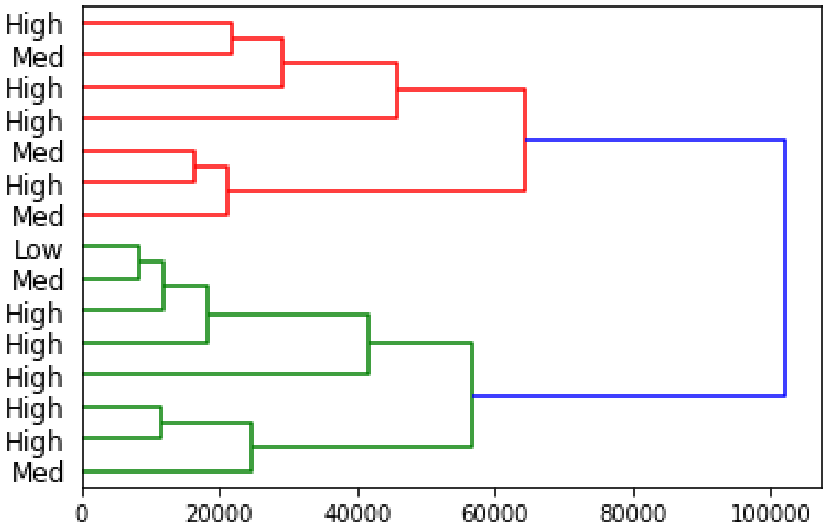
Now lets try to apply Hierarchical Clustering on Z- score normalized data:

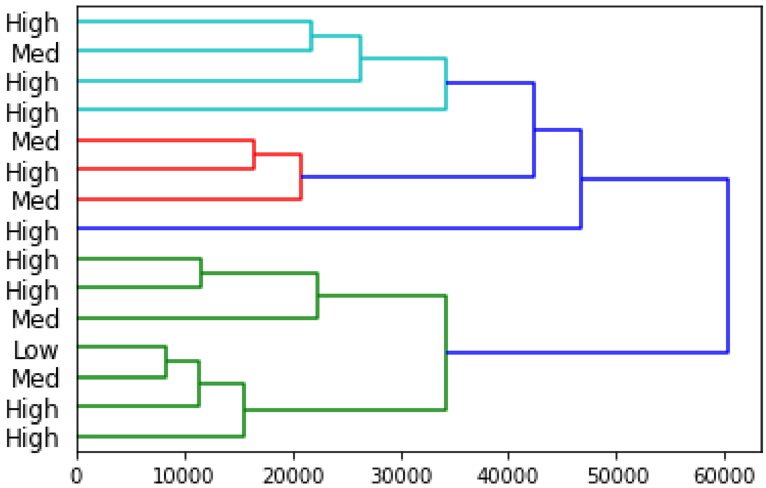
To perform hierarchy clustering, hierarchy module from scipy cluster must be imported. The space complexity is usually $O(n^3)$ hence a part of train- test data is considered and the model is built. Below code helps in creating cluster model and plotting Dendrograms. Here only 15 rows from the dataframe are considered, slicing is performed:

```
# Slicing Predictor variable:
x_reduced= X_train[:15]
names = datacopyf2['BookRating']
#Hierarchy Model:
Z = hierarchy.linkage(x_reduced, 'single')
dend = hierarchy.dendrogram(Z,labels=names.tolist(),orientation='right')
plt.show()
Z = hierarchy.linkage(x_reduced, 'complete')
dend = hierarchy.dendrogram(Z,labels=names.tolist(),orientation='right')
plt.show()
Z = hierarchy.linkage(x_reduced, 'average')
dend = hierarchy.dendrogram(Z,labels=names.tolist(),orientation='right')
plt.show()
```

A dendrogram is a diagram that shows the hierarchical relationship between objects. It is most commonly created as an output from hierarchical clustering. Hierarchy.dendograms are used and the parameters given are orientation and labels along with hierarchy linkage. 3 different linkages are created and 3 different dendrogram are used. Below are the 3 different Dendrogram:


High
High
Med
Low
Med
High
High
Med
High
Med
High
High
Med
High
High
0
5000
10000
15000
20000
25000
30000


High
Med
High
High
Med
High
Med
Low
Med
High
High
High
High
High
Med
0
20000
40000
60000
80000
100000


High
Med
High
High
Med
High
Med
High
High
High
Med
Low
Med
High
High
0
10000
20000
30000
40000
50000
60000

Decimal Scaling Normalization was also performed, so one can even try building Unsupervised models for Decimal scaling Normalized data. Again, here Kmeans and Hierarchical Clustering will be implemented and corresponding Confusion Matrix is generated.

```
# Identifying the Traget Variable:
datacopyf3['BookRating'] = pd.Categorical(datacopyf3['BookRating'])
datacopyf3['BookRatingCode'] = datacopyf3['BookRating'].cat.codes
y_encoded= datacopyf3['BookRatingCode']
X_train, X_test, y_train, y_test = train_test_split(X,y_encoded,test_size=0.25,random_state=42)
```

To Perform so , target variable needs to be in Numeric form, hence by executing the above code, 3 bookrating classes are converted to numerical class say 0, 1 2.

In the above piece of code, Predictor variable attributes are stored in independent variable x, where as the target variable book rating is stored in dependent variable y_encoded.

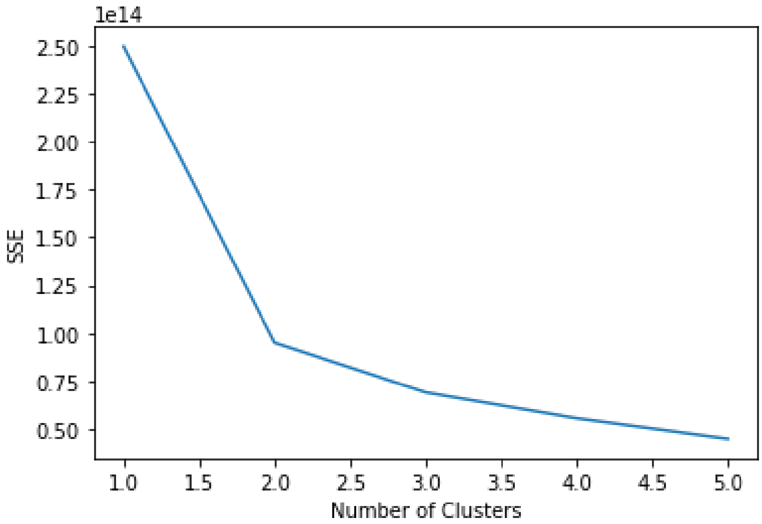
Using the sklearn Train test split, splitting on predictor and target variable is done with train:test ::0.75:0.25, these splitting are performed in a random format.

To Perform K-Means clustering:

Cluster model from Sklearn is selected and used. Below model implementation of unsupervised Kmeans:

```
# Kmeans model:
k_means = cluster.KMeans(n_clusters=3, max_iter=50, random_state=1).fit(X_train)
labels = k_means.labels_

numClusters = [1,2,3,4,5]
SSE = []
for k in numClusters:
    k_means = cluster.KMeans(n_clusters=k)
    k_means.fit(X_train)
    SSE.append(k_means.inertia_)
#Sum of squared distances of samples to their closest cluster center.
#plotting:
plt.plot(numClusters, SSE)
plt.xlabel('Number of Clusters')
plt.ylabel('SSE')
plt.show()


Kmeanspredicted = k_means.predict(X_test)
Kmeanspredicted.reshape(-1,1)

var=classification_report(y_test,Kmeanspredicted)
print(var)
```

The above clustering is performed only on Decimal scaled normalized data, 3 different clusters are found. To get the accuracy and precision rate, one can use classification report and confusion matrix. here report is generated, confusion matrix is displayed.



Here one can see that cluster after 3 are almost zero and only 3 clusters are identified.

Number of Clusters

	precision	recall	f1-score	support
0	0.61	0.17	0.26	40904
1	0.14	0.20	0.17	9578
2	0.25	0.26	0.25	16721
3	0.00	0.00	0.00	0
4	0.00	0.00	0.00	0
accuracy			0.20	67203
macro avg	0.20	0.13	0.14	67203
weighted avg	0.45	0.20	0.25	67203

Above output displays classification report and confusion matrix. the accuracy of Kmeans model is 0.18 while the f1 score for 3 different classes are 0.17,0.28,0.01 respectively. One can see the precision of the model also which are (0, 1, 2) -> (0.14,0.86,0.01).

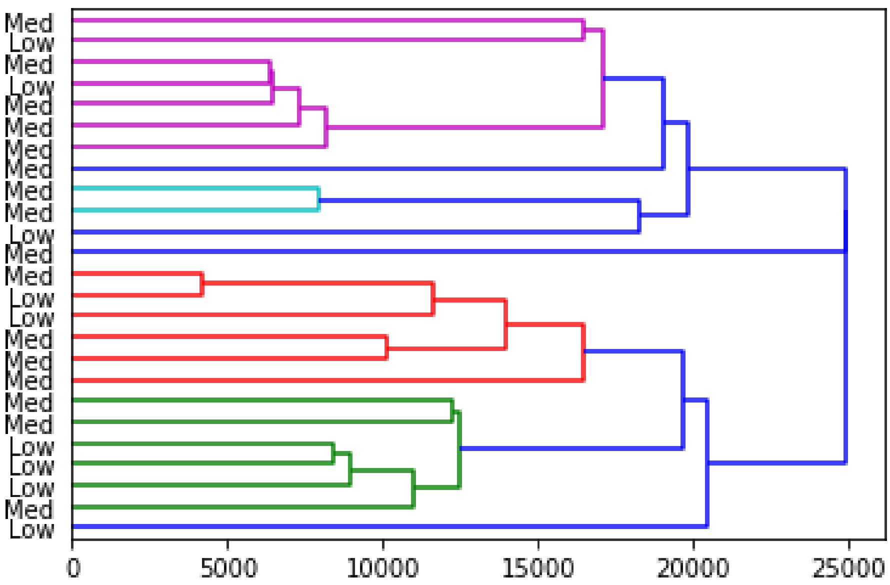
Now lets try to apply Hierarchical Clustering on Decimal Scaling normalized data:

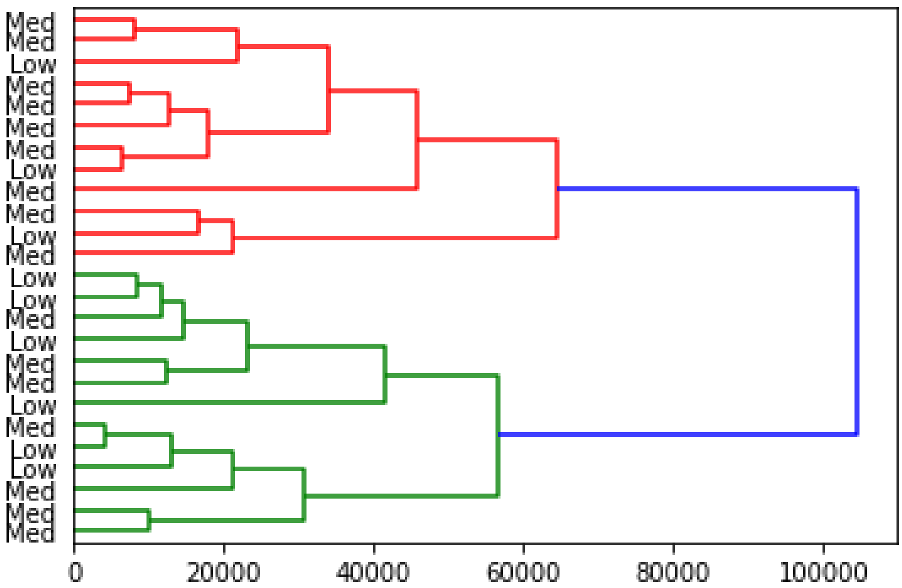
A Hierarchical clustering method works via grouping data into a tree of clusters. Hierarchical clustering begins by treating every data points as a separate cluster.

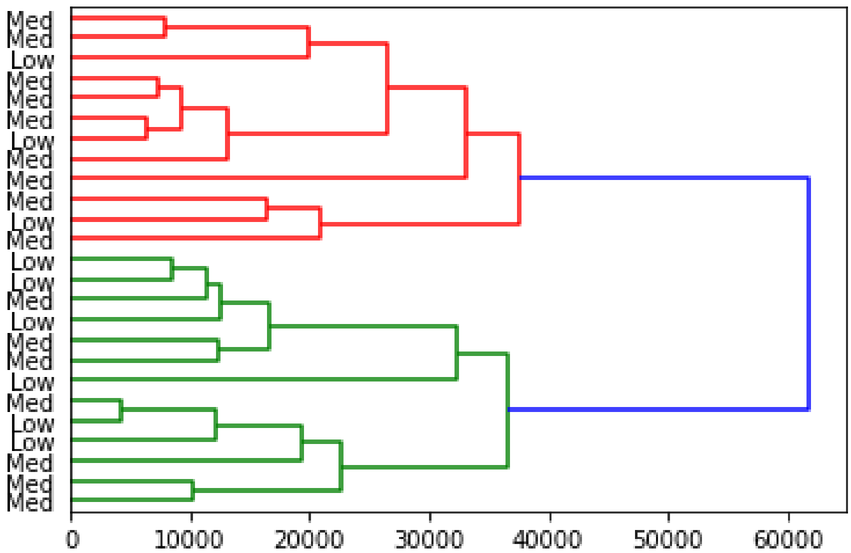
To perform hierarchy clustering, one need to import hierarchy module from scipy cluster. The space complexity is of cubic order, hence a part of train- test data is considered and the model is built. Below code helps in creating cluster model and plotting Dendrograms.

```
# Slicing Predictor variable:
X_reduced = X_train[:25]
names = datacopyf3['BookRating']
#Hierarchy Model:
Z = hierarchy.linkage(X_reduced, 'single')
dend = hierarchy.dendrogram(Z,labels=names.tolist(),orientation='right')
plt.show()
Z = hierarchy.linkage(X_reduced, 'complete')
dend = hierarchy.dendrogram(Z,labels=names.tolist(),orientation='right')
plt.show()
Z = hierarchy.linkage(X_reduced, 'average')
dend = hierarchy.dendrogram(Z,labels=names.tolist(),orientation='right')
plt.show()
```

The horizontal axis of the dendrogram represents the distance or dissimilarity between clusters. The vertical axis represents the objects and clusters. The dendrogram is fairly simple to interpret. Each joining (fusion) of two clusters is represented on the graph by the splitting of a horizontal line into two horizontal lines. The horizontal position of the split, shown by the short vertical bar, gives the distance (dissimilarity) between the two clusters







This completes Building Model for Unsupervised learning with 3 different Normalized Datasets.

Solution to Part B Question No 7:

7. Analyse the outcome various models obtained in Question 6 and discuss which data model and data transformation combination best suits the context. Justify.

In the previous section, Different Machine learning models were implemented, the fitting of these model were done on Normalized data. Different Supervised models like K-nearest Neighbor, Decision Tree and Unsupervised model like K-means, Hierarchy Clustering was built, Accuracy of different models over different Normalized data was calculated using confusion matrix method. Below is the accuracy of different models:

	Supervised Model		Unsupervised Model	
Normalized data	KNN	**Decision Tree**	K-Means	Hierarchy Clustering
Min Max Normalization	53%	**61%**	20%	-
Z- score Normalization	**55%**	**61%**	**21%**	**-**
Decimal Scaling	54%	**61%**	19%	-

The predictor variable consisting of column: "Age", 'PublisherCode', 'BookAuthorCode', 'BookTitleCode', 'citycode', 'countrycode', 'statecode' and target variable consisting of Book rating was used. In the implementation of different model predictor and target variables where kept exactly same, this was mainly due to compare the accuracy of each model on the different dataset. In General, one can clearly say that accuracy of supervised model is high when compared to unsupervised models. One can also say that Decision Tree gives the best results for all 3 different Normalized data while the KNN gives ideal results with 3 nearest neighbor. On the other hand Z- score normalized data can be considered as the best data for all the models. But in case of unsupervised learning, accuracy results are very low.

From the above table, highest accuracy of 61% was achieved, this was obtained using Decision Tree model on Z-score Normalized data, while the lowest accuracy of 19% was seen in K-Means model on the Decimal scaled data. For Hierarchy clustering, The accuracy is empty as the model has no fit method.

Hence Decision Tree model is best along with Z- scored Normalized Data.

Decision Tree is easy to use and understand. Decision tree Can handle both categorical and numerical data. Usually Decision Tree are resistant to outliers, hence require little data preprocessing. While it can be prone to overfitting and Can create biased learned trees if some classes dominate.

2. Bibliography

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- https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.StandardScaler.html
- https://medium.com/@atanudan/kurtosis-skew-function-in-pandas-aa63d72e20de
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- https://medium.com/vickdata/four-feature-types-and-how-to-transform-them-for-machine-learning-8693e1c24e80
- https://scikit-learn.org/stable/data_transforms.html
- https://scikit-learn.org/stable/modules/tree.html
- https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.KNeighborsClassifier.html
- https://scikit-learn.org/stable/modules/generated/sklearn.cluster.KMeans.html
- https://docs.scipy.org/doc/scipy/reference/generated/scipy.cluster.hierarchy.dendrogram.html

3. Appendix

The implementation part was doing using google Colaboratory.

To view the implementation code and for execution: Click Here

Or access to the python script by using the below link.

https://colab.research.google.com/drive/1OQ5nDXQGDni2KS5CKxidegnp-0umxrVB?usp=sharing

Mounting the Drive to the colab for accessing the files and other revalent data.

In [ ]:

```
from google.colab import drive
drive.mount("/content/drive")
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount
("/content/drive", force_remount=True).
```

Import libraries

In [ ]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from random import randint
from statistics import stdev
from statistics import variance
import warnings
import seaborn as sns
warnings.filterwarnings("ignore")
%matplotlib inline
```

Reading the Given CSV files using Pandas

In [ ]:

```
Bookuser= pd.read_csv("/content/drive/MyDrive/Data_mining/BX-Users.csv",error_bad_lines=F
alse, delimiter=';', encoding = 'ISO-8859-1')
Bookrating= pd.read_csv('/content/drive/MyDrive/Data_mining/BX-Book-Ratings.csv',error_ba
d_lines=False, delimiter=';', encoding = 'ISO-8859-1')
Bookdata= pd.read_csv('/content/drive/MyDrive/Data_mining/BX-Books.csv',error_bad_lines=F
alse, delimiter=';', encoding = 'ISO-8859-1')
```

```
b'Skipping line 6452: expected 8 fields, saw 9\nSkipping line 43667: expected 8 fields, s
aw 10\nSkipping line 51751: expected 8 fields, saw 9\n'
b'Skipping line 92038: expected 8 fields, saw 9\nSkipping line 104319: expected 8 fields,
saw 9\nSkipping line 121768: expected 8 fields, saw 9\n'
b'Skipping line 144058: expected 8 fields, saw 9\nSkipping line 150789: expected 8 fields
, saw 9\nSkipping line 157128: expected 8 fields, saw 9\nSkipping line 180189: expected 8
fields, saw 9\nSkipping line 185738: expected 8 fields, saw 9\n'
b'Skipping line 209388: expected 8 fields, saw 9\nSkipping line 220626: expected 8 fields
, saw 9\nSkipping line 227933: expected 8 fields, saw 11\nSkipping line 228957: expected
8 fields, saw 10\nSkipping line 245933: expected 8 fields, saw 9\nSkipping line 251296: e
xpected 8 fields, saw 9\nSkipping line 259941: expected 8 fields, saw 9\nSkipping line 26
1529: expected 8 fields, saw 9\n'
```

Merging Dataframes to single Dataframe using pandas merge

The different dataframes are merged using inner merge on ISBN and UserID

In [ ]:

```
data = pd.merge(Bookrating, Bookuser, on='User-ID', how='inner').merge(Bookdata,on= "ISB
N",how='inner')
```

In [ ]:

```
print("The shape of the merged dataframe is:",data.shape)
print("The size of the merged dataframe is:", data.size)
print("The columns of the merged dataframes are:\n",data.columns)
data.info()
```

```
The shape of the merged dataframe is: (1031136, 12)
The size of the merged dataframe is: 12373632
The columns of the merged dataframes are:
 Index(['User-ID', 'ISBN', 'Book-Rating', 'Location', 'Age', 'Book-Title',
       'Book-Author', 'Year-Of-Publication', 'Publisher', 'Image-URL-S',
       'Image-URL-M', 'Image-URL-L'],
      dtype='object')
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1031136 entries, 0 to 1031135
Data columns (total 12 columns):
 #   Column               Non-Null Count    Dtype  
---  ------               --------------    -----  
 0   User-ID              1031136 non-null  int64  
 1   ISBN                 1031136 non-null  object 
 2   Book-Rating          1031136 non-null  int64  
 3   Location             1031136 non-null  object 
 4   Age                  753301 non-null   float64
 5   Book-Title           1031136 non-null  object 
 6   Book-Author          1031135 non-null  object 
 7   Year-Of-Publication  1031136 non-null  object 
 8   Publisher            1031134 non-null  object 
 9   Image-URL-S          1031136 non-null  object 
 10  Image-URL-M          1031136 non-null  object 
 11  Image-URL-L          1031132 non-null  object 
dtypes: float64(1), int64(2), object(9)
memory usage: 102.3+ MB
```

Data Selection

considering the merged dataset, one can see that image URLs columns do not seem to be required for analysis, and hence these can be dropped off from the dataframes.

Merged dataframe contains Book-Rating and User-ID as arrtibutes, renaming these attributes with BookRating and UserID, BookAuthor, YearOfPublication.

In [ ]:

```
to_drop = ['Image-URL-S', 'Image-URL-M', 'Image-URL-L']
data = data.drop(to_drop, axis=1, inplace=False)

data.rename(columns={'Book-Rating':'BookRating', 'User-ID':'UserID','Book-Author':'BookA
uthor','Year-Of-Publication':'YearOfPublication'},inplace=True)
pd.set_option('display.max_colwidth',None)
```

Display the head of the merged dataframe:

In [ ]:

```
data.head()
```

Out[ ]:

	UserID	ISBN	BookRating	Location	Age	Book-Title	BookAuthor	YearOfPublication	Publisher
0	276725	034545104X	0	tyler, texas, usa	NaN	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books
1	2313	034545104X	5	cincinnati, ohio, usa	23.0	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books
2	6543	034545104X	0	strafford, missouri, usa	34.0	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books

	UserID	ISBN	BookRating	Location	Age	Book-Title	BookAuthor	YearOfPublication	Publisher
3	8680	034545104X	5	st. charles county, missouri, usa	2.0	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books
4	10314	034545104X	9	beaverton, oregon, usa	NaN	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books

Data Cleaning

We now check the data types for each of the columns, and correct the missing & discrepant entries. I am also adjusting the column width to display full text of columns.

1.Year of Publication:

In [ ]:

```
data.YearOfPublication.unique()
```

Out[ ]:

```
array([2002, '2001', 1996, '1999', 1998, 2001, 1994, 1995, 2003, 1997,
       '1995', 1999, '1998', '2024', 1992, '1983', '2002', '1996', '2000',
       0, '1989', '2003', '1991', 1993, '1994', 1976, '1993', 1991, '0',
       2000, 1983, 1990, 1982, 1988, 1981, '1988', 1989, 1986, '1987',
       '1992', 1987, '1980', '1990', '1997', 2004, 1984, '1982', '1985',
       1985, 1979, '2004', '1984', 1974, '1979', 1977, 1965, 1972, '1978',
       '1986', '1981', 1962, '1977', 1957, 1958, 1960, 1963, 1969, '1974',
       1978, 1970, '1972', 1980, '1975', 1959, '1960', 1968, '1976',
       '1970', '1971', 1975, 1973, '1950', '1969', '1962', 1971, 1964,
       1955, 1953, 1966, '1965', '1963', '1973', 1930, '1964', 1961,
       '1952', 1940, '1968', 1954, '1967', '1911', 1952, 1946, 1941, 1920,
       1967, 1956, 1942, 1951, 1948, '1959', 1950, 2005, 1943, 1937, 1923,
       1945, 1947, 1936, 1925, '1966', '1958', 1927, 2030, 2011, 2020,
       1939, 1926, 1938, '1961', 1911, 1904, 1949, 1932, 1929, '1953',
       '1955', '1944', '1920', '1956', '1957', '1942', '1933', '1922',
       '1897', '1954', '1941', '1949', '1939', 2050, '1947', 1902, 1924,
       1921, 1900, '1945', '2005', 2038, 2010, 1928, '1932', '2006',
       '1948', '1923', '1943', 1901, 2026, '1900', 2021, '1951', 1931,
       '1940', '1378', '2030', '1946', 1908, '1938', 'DK Publishing Inc',
       'Gallimard', '1909', '1924', '2012', '2008', '1936', 1935, '1376',
       '1926', '2037', '1931', '1927', 1906, 1806, 1933, 1944, 1917,
       '2020', '1930', '2011', '1919', 1914, 1934, 1910], dtype=object)
```

From the above cell output one can find incorrect entries for yearofPublication.'DK Publishing Inc' and 'Gallimard' are incorrect entries which are found in Yearofpublication. Also some Numeric values are in string format. Necessary correction for these rows will be done and data-type for yearOfPublication will be given as int.

In [ ]:

```
data.loc[data.YearOfPublication == 'DK Publishing Inc',:]
```

Out[ ]:

	UserID	ISBN	BookRating	Location	Age	Book-Title	BookAuthor	YearOfPublication	
911154	130571	0789466953	0	summerville, south carolina, usa	NaN	DK Readers: Creating the X-Men, How Comic Books Come to Life (Level 4: Proficient Readers)\";James Buckley"	2000	DK Publishing Inc	http://image
949657	169663	078946697X	0	towson, maryland,	NaN	DK Readers: Creating the X-Men, How It All Began (Level 4:	2000	DK Publishing Inc	http://image

	UserID	ISBN	BookRating	Location	Age	Book-Title	BookAuthor	YearOfPublication	
				usa		Proficient Readers)\";Michael Teitelbaum"			
949658	227771	078946697X	7	savion, n/a, israel	19.0	DK Readers: Creating the X-Men, How It All Began (Level 4: Proficient Readers)\";Michael Teitelbaum"	2000	DK Publishing Inc	http://image

In [ ]:

```
data.loc[data.ISBN =='0789466953' ,'YearOfPublication']=2000
data.loc[data.ISBN =='0789466953' ,'BookAuthor']="James Buckley"
data.loc[data.ISBN =='0789466953' ,'Publisher']="DK Publishing Inc"
data.loc[data.ISBN =='0789466953' ,'Book-Title']="DK Readers: Creating the X-Men, How Com
ic Books Come to Life (Level 4: Proficient Readers)"

data.loc[data.ISBN =='078946697X' ,'YearOfPublication']=2000
data.loc[data.ISBN =='078946697X' ,'BookAuthor']="Michael Teitelbaum"
data.loc[data.ISBN =='078946697X' ,'Publisher']="DK Publishing Inc"
data.loc[data.ISBN =='078946697X' ,'Book-Title']="DK Readers: Creating the X-Men, How It
All Began (Level 4: Proficient Readers)"
```

In [ ]:

```
data.loc[data.YearOfPublication == 'Gallimard',:]
```

Out[ ]:

	UserID	ISBN	BookRating	Location	Age	Book-Title	BookAuthor	YearOfPublication	
918145	137190	2070426769	0	rennes, bretagne, france	31.0	Peuple du ciel, suivi de 'Les Bergers\";Jean-Marie Gustave Le ClÃ?Â©zio"	2003	Gallimard	http://images.amaz

In [ ]:

```
data.loc[data.ISBN =='2070426769' ,'YearOfPublication']=2003
data.loc[data.ISBN =='2070426769' ,'BookAuthor']="Jean-Marie Gustave Le ClÃ?Â©zio"
data.loc[data.ISBN =='2070426769' ,'Publisher']="Gallimard"
data.loc[data.ISBN =='2070426769' ,'Book-Title']="Peuple du ciel, suivi de 'Les Bergers"
```

In [ ]:

```
data.YearOfPublication= pd.to_numeric(data.YearOfPublication,errors= 'coerce')
```

In [ ]:

```
print (sorted(data['YearOfPublication'].unique()))
```

```
[0, 1376, 1378, 1806, 1897, 1900, 1901, 1902, 1904, 1906, 1908, 1909, 1910, 1911, 1914, 1
917, 1919, 1920, 1921, 1922, 1923, 1924, 1925, 1926, 1927, 1928, 1929, 1930, 1931, 1932,
1933, 1934, 1935, 1936, 1937, 1938, 1939, 1940, 1941, 1942, 1943, 1944, 1945, 1946, 1947,
1948, 1949, 1950, 1951, 1952, 1953, 1954, 1955, 1956, 1957, 1958, 1959, 1960, 1961, 1962,
1963, 1964, 1965, 1966, 1967, 1968, 1969, 1970, 1971, 1972, 1973, 1974, 1975, 1976, 1977,
1978, 1979, 1980, 1981, 1982, 1983, 1984, 1985, 1986, 1987, 1988, 1989, 1990, 1991, 1992,
1993, 1994, 1995, 1996, 1997, 1998, 1999, 2000, 2001, 2002, 2003, 2004, 2005, 2006, 2008,
2010, 2011, 2012, 2020, 2021, 2024, 2026, 2030, 2037, 2038, 2050]
```

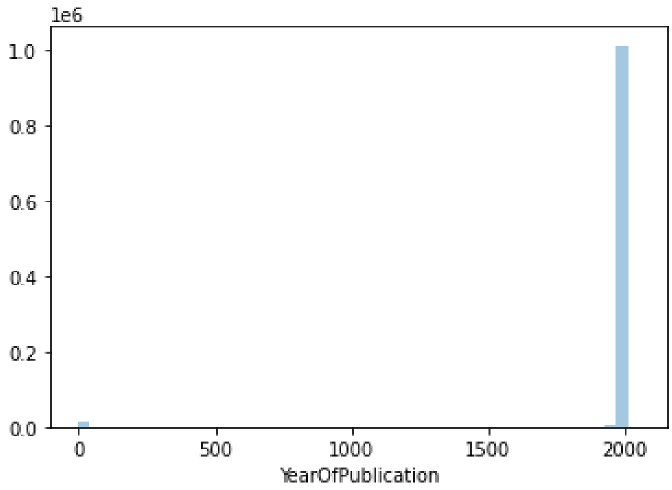
In [ ]:

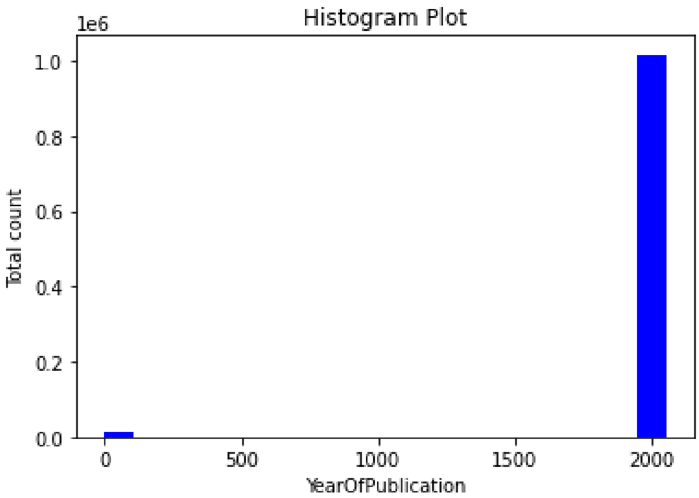
```
#plotting:
def plothist(df,cname,titlename):
  df.hist(column=cname,bins=20,histtype ='bar',facecolor='b')
```

```
    plt.xlabel(cname)
    plt.ylabel('Total count')
    plt.title(titlename)
    plt.grid(False)
```

In [ ]:

```
sns.distplot(data['YearOfPublication'].dropna(), kde=False);
plothist(data,'YearOfPublication','Histogram Plot')
```





It can now be seen that yearOfPublication is of type int and it has values ranging from 0–2050. Since considering the datasete to be fresh hence all year after 2015 are invalid. For all the invalid entries (including 0) will converted to NaNs, and then replace them with random integer values of remaining years.

In [ ]:

```
data.loc[(data.YearOfPublication >2015)| (data.YearOfPublication ==0) |(data.YearOfPubli
cation <1800),'YearOfPublication']=np.NAN
data.YearOfPublication.fillna(randint(1800,2010),inplace=True)
data.YearOfPublication=data.YearOfPublication.astype(np.int32)
```

2.Publisher

In [ ]:

```
data.loc[data.Publisher.isnull(),:]
```

Out[ ]:

	UserID	ISBN	BookRating	Location	Age	Book-Title	BookAuthor	YearOfPublication	Publisher
862973	98391	193169656X	9	morrow, georgia, usa	52.0	Tyrant Moon	Elaine Corvidae	2002	NaN
[illegible]	[illegible]	[illegible]	[illegible]	morrow, georgia,	[illegible]	Finders	Linnea	[illegible]	[illegible]

	UserID	ISBN	BookRating	Location	Age	Book-Title	BookAuthor	YearOfPublication	Publisher
862984	98391	1931696993	9	usa	52.0	Keepers	Sinclair	2001	NaN

In [ ]:

```
data.Publisher.fillna('Not Given',inplace=True)
```

3.UserID

In [ ]:

```
data.UserID.unique()
```

Out[ ]:

```
array([276725,   2313,   6543, ..., 276618, 276647, 276660])
```

4.Age

Attribute named *Age* has NaN values and some very high values. Ages below 7 and above 85 do not make much sense, and hence, these are being replaced with NaNs. All the NaNs are then replaced with mean value of Age, and its data type is set as int.

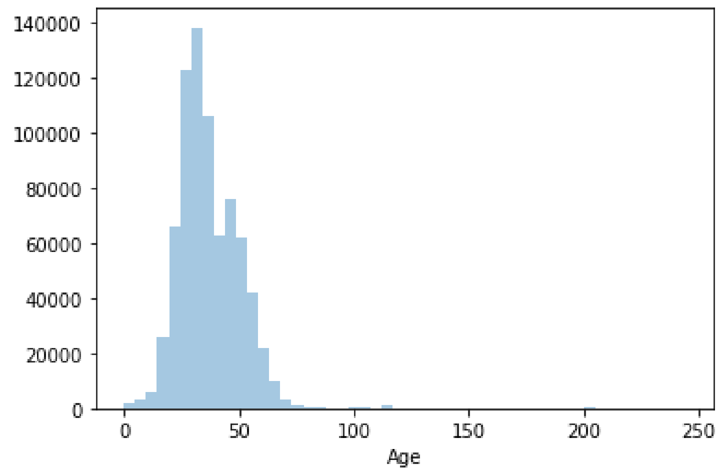
In [ ]:

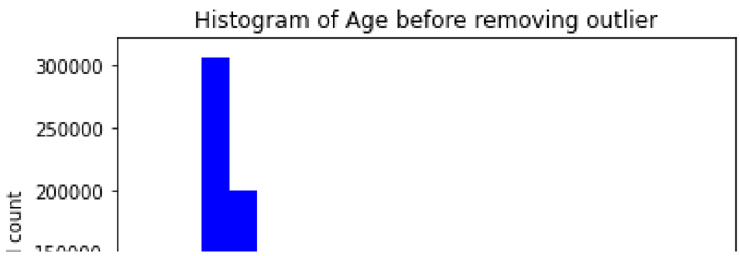
```
print(sorted(data.Age.unique()))
```

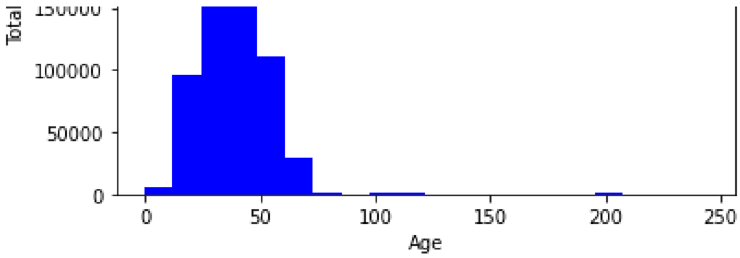
```
[nan, 0.0, 1.0, 2.0, 3.0, 4.0, 5.0, 6.0, 7.0, 8.0, 9.0, 10.0, 11.0, 12.0, 13.0, 14.0, 15.
0, 16.0, 17.0, 18.0, 19.0, 20.0, 21.0, 22.0, 23.0, 24.0, 25.0, 26.0, 27.0, 28.0, 29.0, 30
.0, 31.0, 32.0, 33.0, 34.0, 35.0, 36.0, 37.0, 38.0, 39.0, 40.0, 41.0, 42.0, 43.0, 44.0, 4
5.0, 46.0, 47.0, 48.0, 49.0, 50.0, 51.0, 52.0, 53.0, 54.0, 55.0, 56.0, 57.0, 58.0, 59.0,
60.0, 61.0, 62.0, 63.0, 64.0, 65.0, 66.0, 67.0, 68.0, 69.0, 70.0, 71.0, 72.0, 73.0, 74.0,
75.0, 76.0, 77.0, 78.0, 79.0, 80.0, 81.0, 82.0, 83.0, 84.0, 85.0, 86.0, 89.0, 90.0, 92.0,
93.0, 94.0, 95.0, 96.0, 97.0, 98.0, 99.0, 100.0, 101.0, 103.0, 104.0, 105.0, 107.0, 108.0
, 109.0, 114.0, 116.0, 118.0, 123.0, 124.0, 127.0, 128.0, 132.0, 133.0, 136.0, 138.0, 14
0.0, 141.0, 146.0, 147.0, 148.0, 151.0, 152.0, 156.0, 157.0, 168.0, 199.0, 200.0, 201.0,
204.0, 209.0, 212.0, 219.0, 220.0, 223.0, 226.0, 228.0, 229.0, 237.0, 239.0, 244.0]
```

In [ ]:

```
#plotting the age histogram
sns.distplot(data['Age'].dropna(), kde=False);
plothist(data,'Age','Histogram of Age before removing outlier')
```





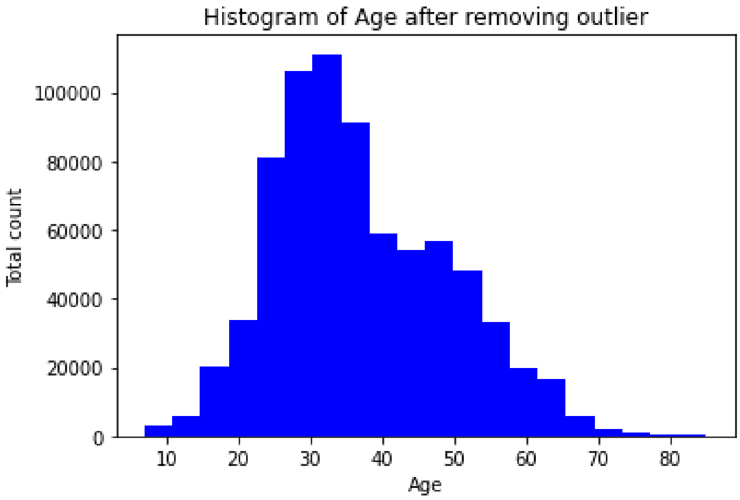


In [ ]:

```
data= data[data['Age']<100]
data.loc[(data.Age >85)| (data.Age <7),'Age']=np.NAN
data.Age.fillna(round(data.Age.mean()),inplace=True)
data.Age=data.Age.astype(np.int32)
```

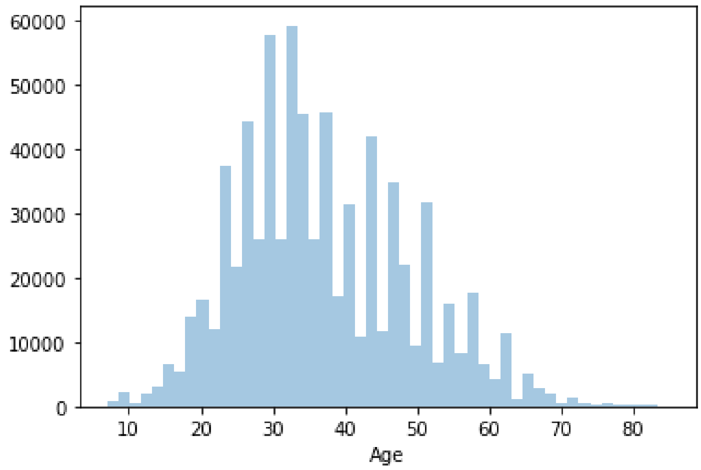
In [ ]:

```
#plotting histogram
plothist(data,'Age','Histogram of Age after removing outlier')
```



In [ ]:

```
sns.distplot(data['Age'].dropna(), kde=False);
```



5.Book Rating:

Book rating ranges between 1-10 but the dataframes has some rating are 0 and does not make sense hence dropping the rows with zero rating and converting all other rating to integer value.

In [ ]:

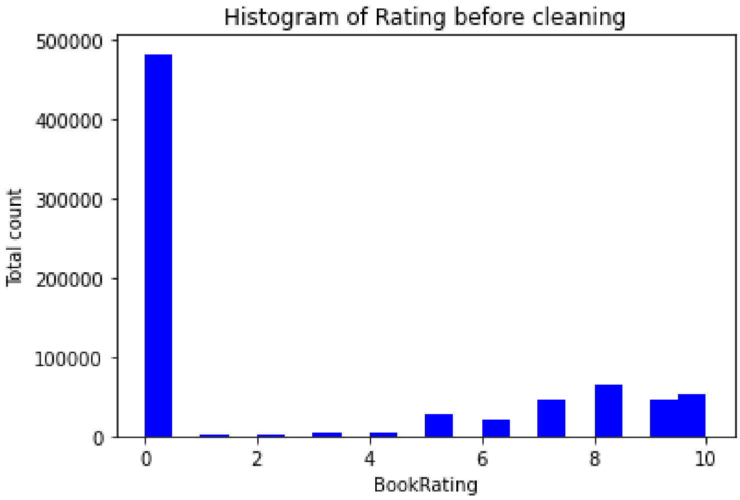
```
data.BookRating.unique()
```

Out[ ]:

```
array([ 5,  0,  8,  9,  6,  7,  4,  3, 10,  1,  2])
```

In [ ]:

```
plothist(data,'BookRating','Histogram of Rating before cleaning')
```



In [ ]:

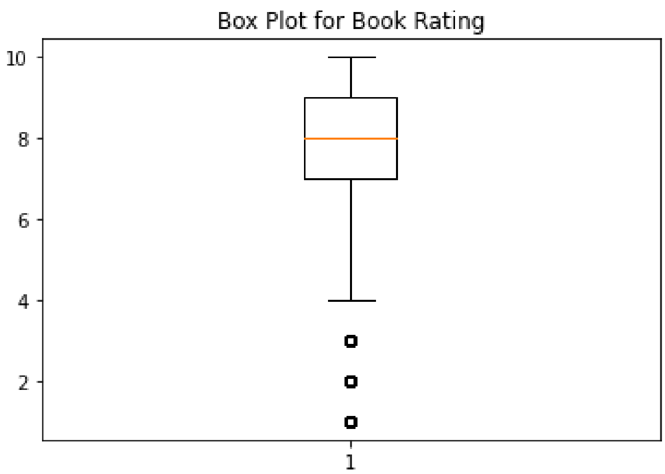
```
data= data[data['BookRating']>0]
data.BookRating=data.BookRating.astype(np.int32)
```

In [ ]:

```
data.reset_index(inplace=True)
data.drop(['index'],axis=1,inplace=True)
```

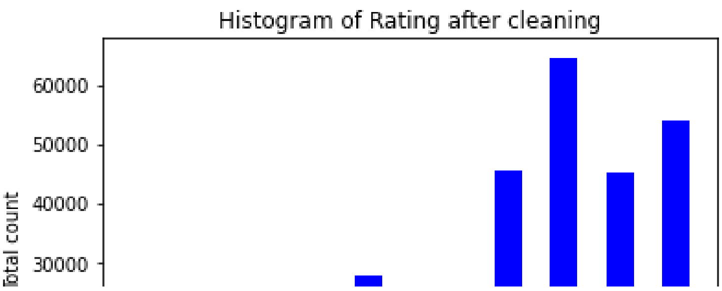
In [ ]:

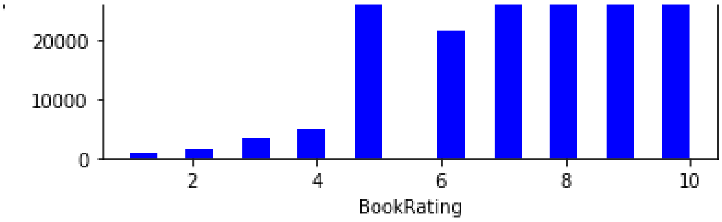
```
#box- plot:
import seaborn as sns
fig1, ax1 = plt.subplots()
ax1.set_title('Box Plot for Book Rating')
ax1.boxplot(data['BookRating']);
```



In [ ]:

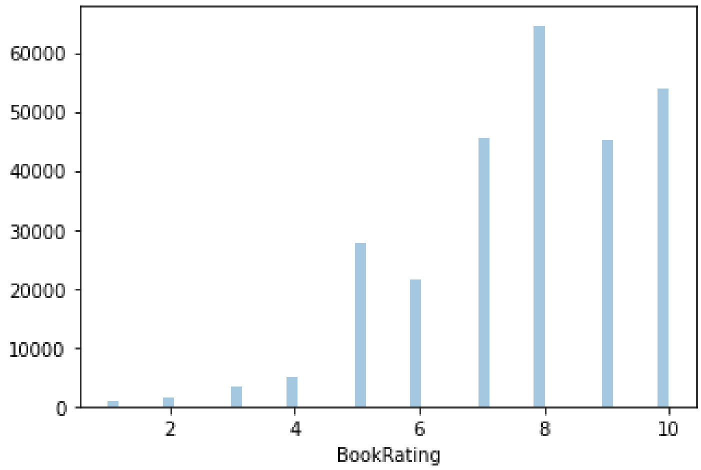
```
plothist(data,'BookRating','Histogram of Rating after cleaning')
```





In [ ]:

```
sns.distplot(data['BookRating'].dropna(), kde=False);
```



Normalization and Transformation:

MIN-MAX Normalization

Here the rating will be normalized to 1-5

In [ ]:

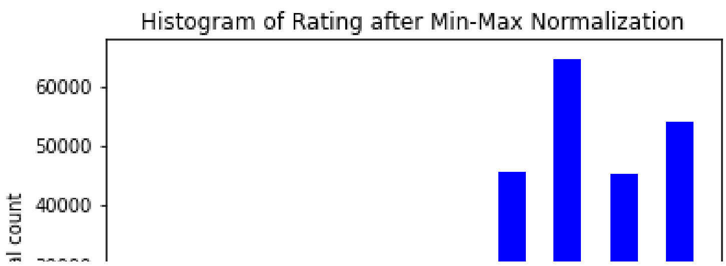
```
import copy
import sklearn
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
import pylab
from scipy import stats
```

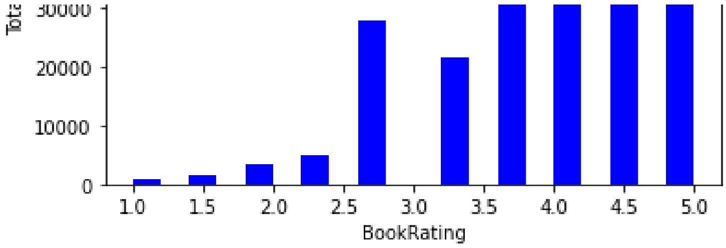
In [ ]:

```
datacopyf1= copy.deepcopy(data)
datacopyf2= copy.deepcopy(data)
datacopyf3= copy.deepcopy(data)
datacopyf4 = copy.deepcopy(data)
```

In [ ]:

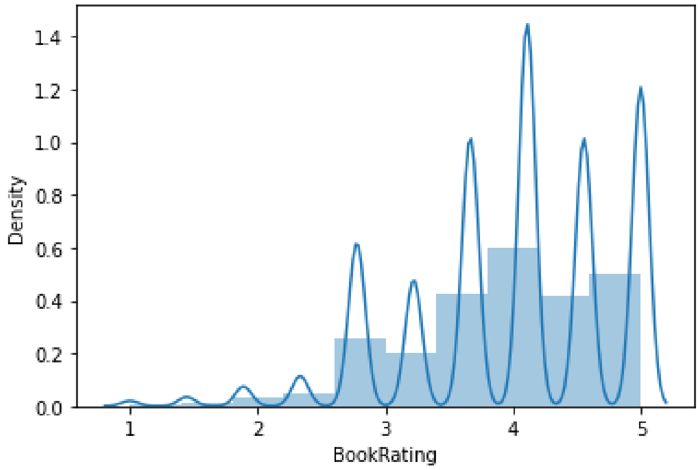
```
#Min-Max Normalization:
scaler = MinMaxScaler(feature_range=(1, 5), copy=False)
scaler.fit(datacopyf1['BookRating'].values.reshape(-1,1))
datacopyf1['BookRating'] = scaler.transform(datacopyf1['BookRating'].values.reshape(-1,1
))
plothist(datacopyf1,'BookRating','Histogram of Rating after Min-Max Normalization')
```





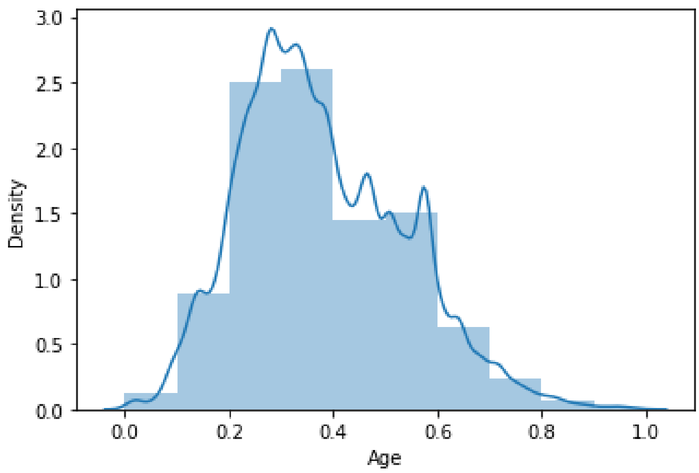
In [ ]:

```
sns.distplot(datacopyf1['BookRating'],bins=10);
```



In [ ]:

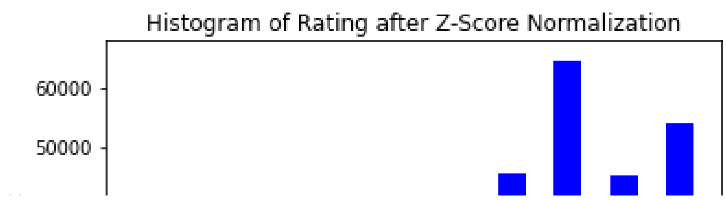
```
#Min-Max Normalization: Age
scaler = MinMaxScaler()
scaler.fit(datacopyf1['Age'].values.reshape(-1,1))
datacopyf1['Age'] = scaler.transform(datacopyf1['Age'].values.reshape(-1,1))
sns.distplot(datacopyf1['Age'],bins=10);
```

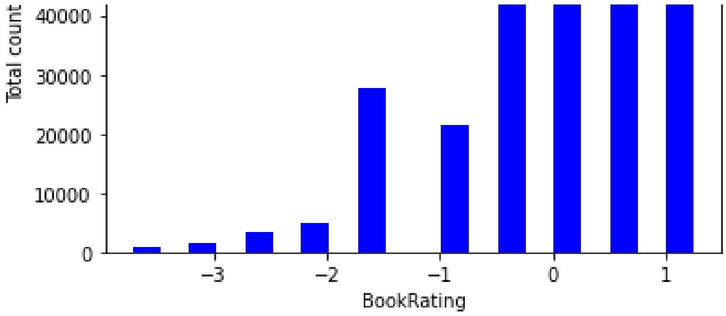


Z- score Normalization

In [ ]:

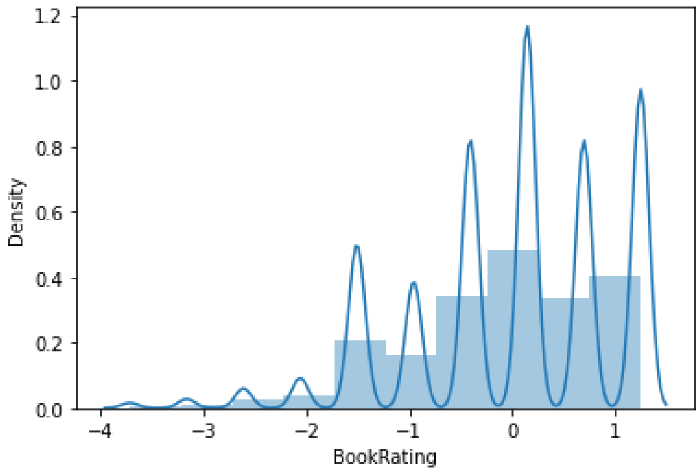
```
scaler = StandardScaler()
scaler.fit(datacopyf2['BookRating'].values.reshape(-1,1))
datacopyf2['BookRating'] = scaler.transform(datacopyf2['BookRating'].values.reshape(-1,1
))
plothist(datacopyf2,'BookRating','Histogram of Rating after Z-Score Normalization')
```





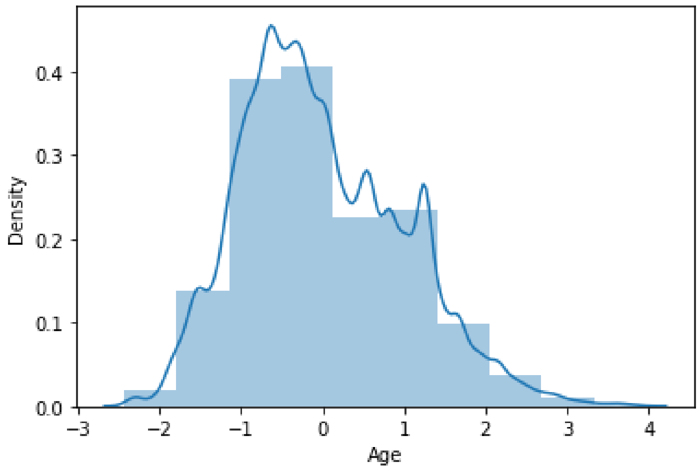
In [ ]:

```
sns.distplot(datacopyf2['BookRating'],bins=10);
```



In [ ]:

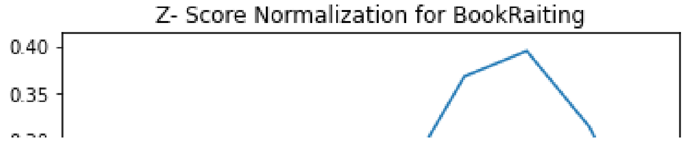
```
# Z-score: AGE
scaler = StandardScaler()
scaler.fit(datacopyf2['Age'].values.reshape(-1,1))
datacopyf2['Age'] = scaler.transform(datacopyf2['Age'].values.reshape(-1,1))
sns.distplot(datacopyf2['Age'],bins=10);
```

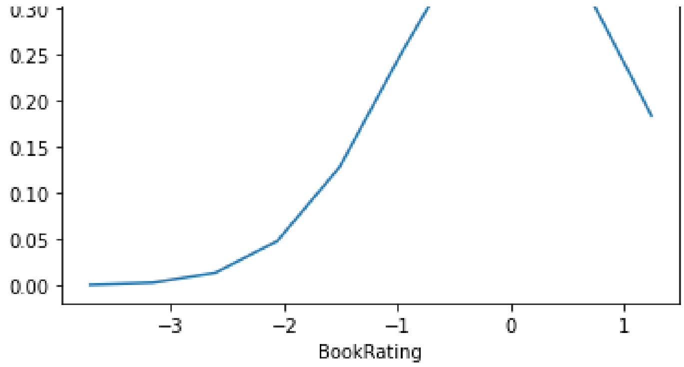


In [ ]:

```
#bell shape plot:
pylab.rcParams['figure.figsize'] = (6.0, 4.0)
ax = plt.subplot(111)
x= np.sort(datacopyf2['BookRating'])
ax.plot(x,stats.norm.pdf(x))
plt.xlabel('BookRating')
plt.title('Z- Score Normalization for BookRaiting')
plt.show()
```

Z- Score Normalization for BookRaiting





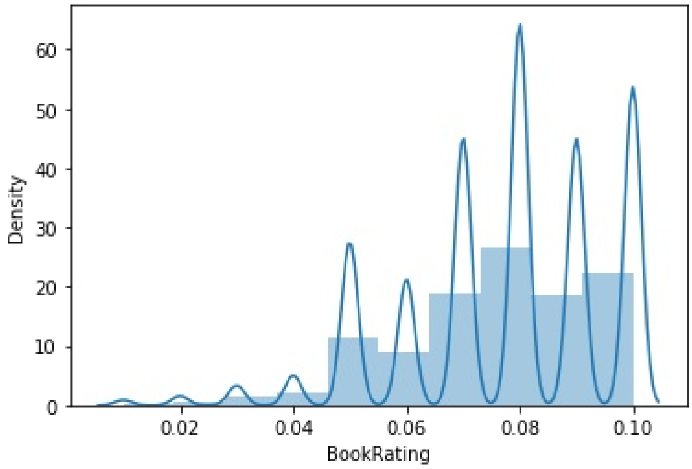
Decimal Scaling:

In [ ]:

```
p = datacopyf3.BookRating.max()
q = len(str(abs(p)))
for i in range(len(datacopyf3['BookRating'])):
  datacopyf3['BookRating'].iloc[i] = datacopyf3['BookRating'].iloc[i]/(10**q)
```

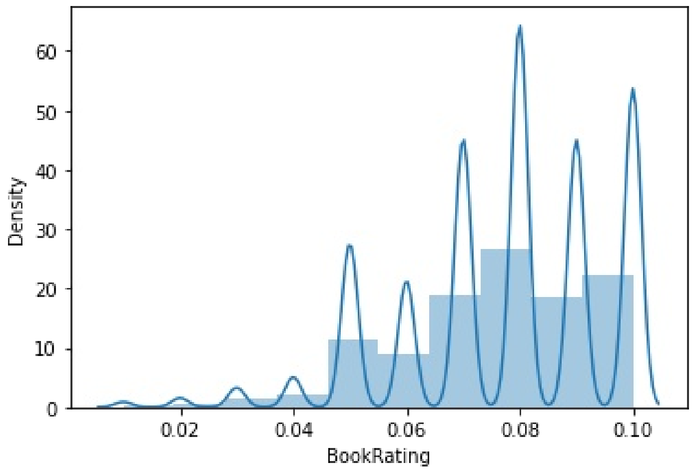
In [ ]:

```
sns.distplot(datacopyf3['BookRating'],bins=10);
```



In [ ]:

```
p = datacopyf3.Age.max()
q = len(str(abs(p)))
for i in range(len(datacopyf3['Age'])):
  datacopyf3['Age'].iloc[i] = datacopyf3['Age'].iloc[i]/(10**q)

sns.distplot(datacopyf3['BookRating'],bins=10);
```



Transformation:

Transformation:

Actual Data:

In [ ]:

```
data['BookRating'].agg(['skew', 'kurtosis']).transpose()
```

Out[ ]:

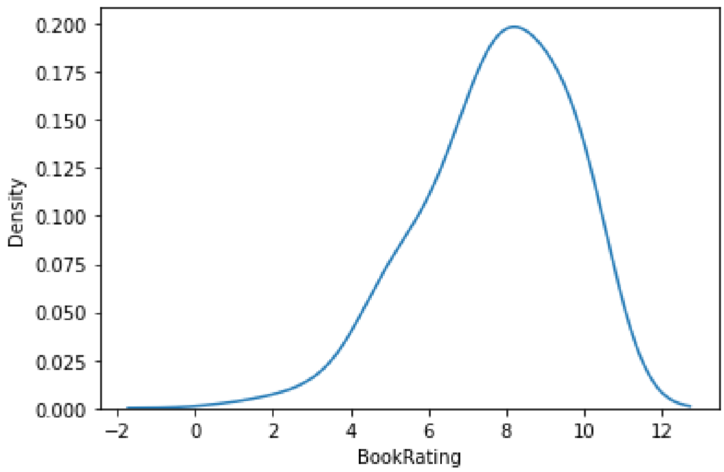
```
skew        -0.723955
kurtosis     0.243986
Name: BookRating, dtype: float64
```

In [ ]:

```
sns.kdeplot(data['BookRating'],bw_method=0.5)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd777ae16a0>
```



In [ ]:

```
data['Age'].agg(['skew', 'kurtosis']).transpose()
```

Out[ ]:

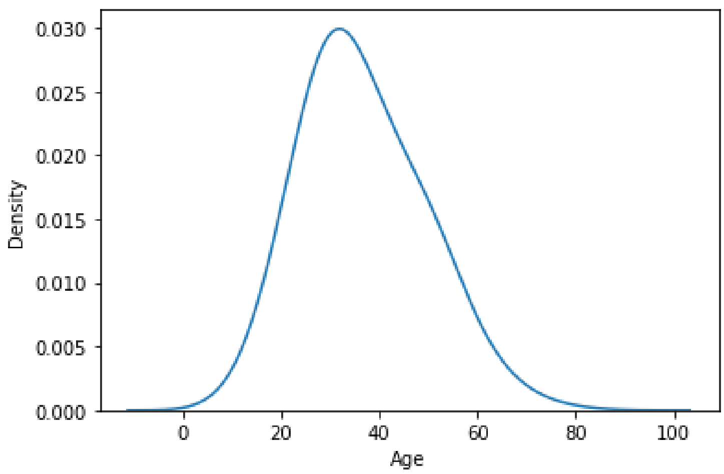
```
skew         0.496685
kurtosis    -0.068720
Name: Age, dtype: float64
```

In [ ]:

```
sns.kdeplot(data['Age'],bw_method=0.5)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd7778ce438>
```



Square Root Transformation:

In [ ]:

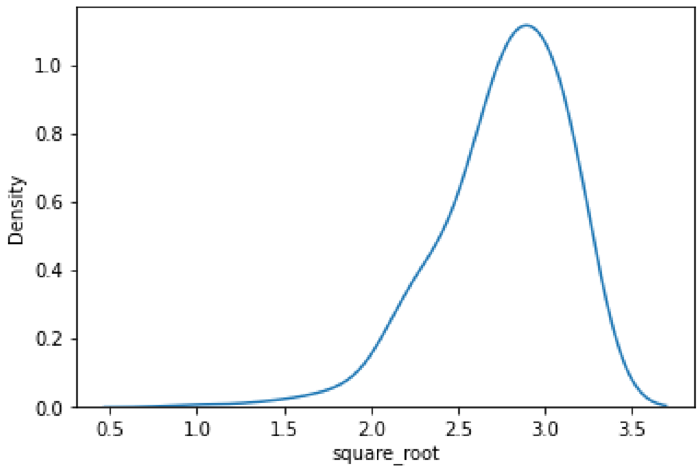
```
datacopyf4.insert(len(datacopyf4.columns), 'square_root',
          np.sqrt(datacopyf4.iloc[:,2]))
```

In [ ]:

```
sns.kdeplot(datacopyf4['square_root'],bw_method=0.5)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd7779bf9b0>
```



In [ ]:

```
datacopyf4.head()
```

Out[ ]:

	UserID	ISBN	BookRating	Location	Age	Book-Title	BookAuthor	YearOfPublication	Publisher	square_root
0	2313	034545104X	5	cincinnati, ohio, usa	23	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books	2.236068
1	8680	034545104X	5	st. charles county, missouri, usa	37	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books	2.236068
2	77480	034545104X	8	gig harbor, washington, usa	51	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books	2.828427
3	94362	034545104X	5	northridge, california, usa	39	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books	2.236068
4	98391	034545104X	9	morrow, georgia, usa	52	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books	3.000000

In [ ]:

```
datacopyf4['square_root'].agg(['skew', 'kurtosis']).transpose()
```

Out[ ]:

```
skew        -1.236429
kurtosis     2.337581
Name: square_root, dtype: float64
```

In [ ]:

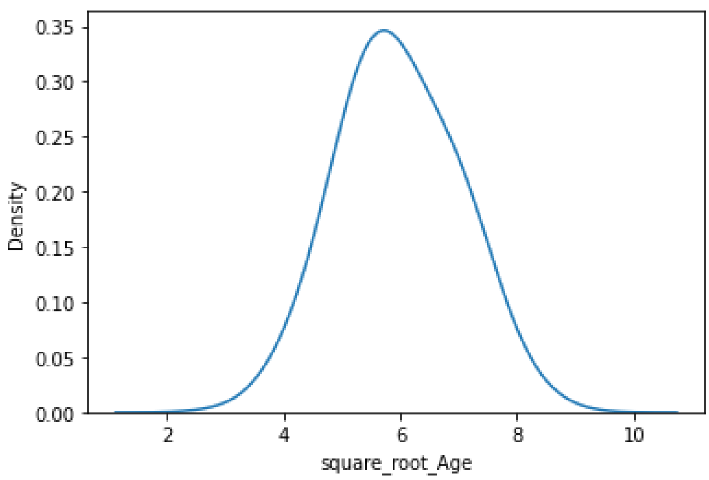
```
datacopyf4.insert(len(datacopyf4.columns), 'square_root_Age',
         np.sqrt(datacopyf4.iloc[:,4]))
```

In [ ]:

```
sns.kdeplot(datacopyf4['square_root_Age'],bw_method=0.5)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd778b24748>
```



In [ ]:

```
datacopyf4['square_root_Age'].agg(['skew', 'kurtosis']).transpose()
```

Out[ ]:

```
skew         0.073462
kurtosis    -0.274513
Name: square_root_Age, dtype: float64
```

Natural Logarithmic Transformation

In [ ]:

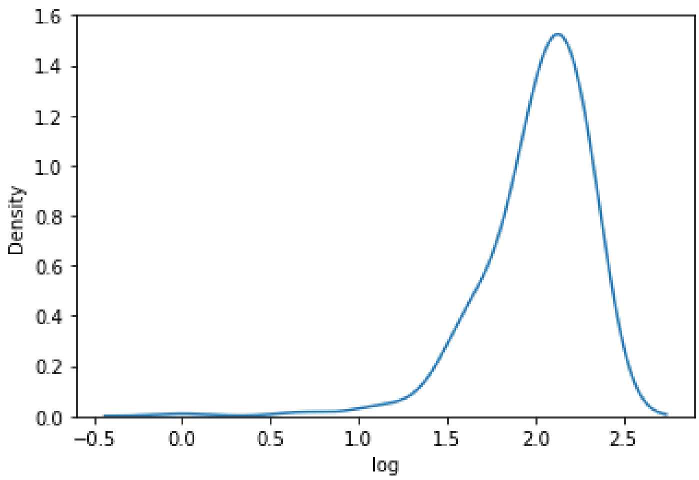
```
datacopyf4.insert(len(datacopyf4.columns), 'log',
         np.log(datacopyf4.iloc[:,2]))
```

In [ ]:

```
sns.kdeplot(datacopyf4['log'],bw_method=0.5)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd76d9c5128>
```



In [ ]:

```
datacopyf4['log'].agg(['skew', 'kurtosis']).transpose()
```

Out[ ]:

```
skew       -2.181383
kurtosis    8.722445
Name: log, dtype: float64
```

In [ ]:

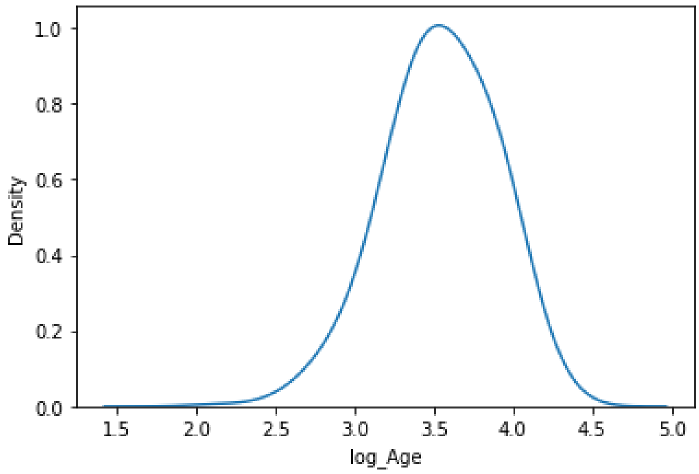
```
datacopyf4.insert(len(datacopyf4.columns), 'log_Age',
         np.log(datacopyf4.iloc[:,4]))
```

In [ ]:

```
sns.kdeplot(datacopyf4['log_Age'],bw_method=0.5)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd776289b00>
```



In [ ]:

```
datacopyf4['log_Age'].agg(['skew', 'kurtosis']).transpose()
```

Out[ ]:

```
skew       -0.423916
kurtosis    0.321697
Name: log_Age, dtype: float64
```

Exploratory Data Analysis:

Analysing UserID Attribute:

In [ ]:

```
print("The length of USer ID is:", len(data['UserID']))
print("Total Number of Unique user are:",len(data['UserID'].unique()))
```

```
The length of USer ID is: 268810
Total Number of Unique user are: 40447
```

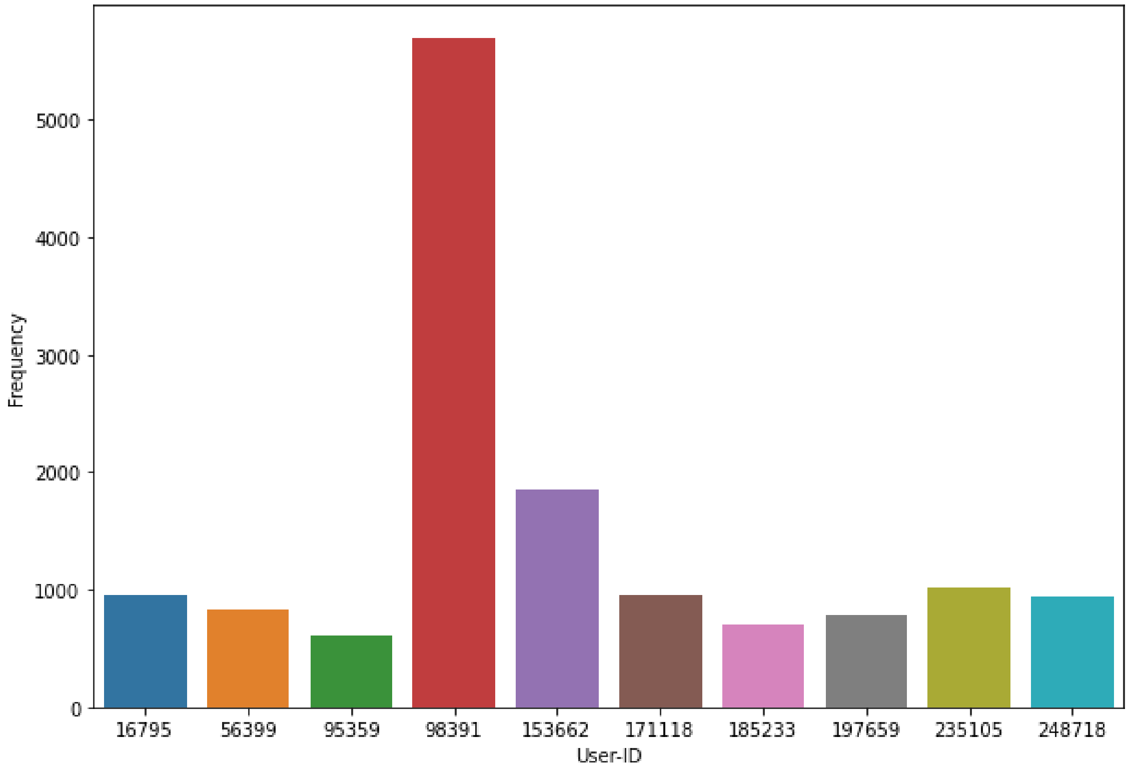
In [ ]:

```
from matplotlib import pyplot
fig, ax = pyplot.subplots(figsize=(10,7))
sns.barplot(x=data['UserID'].value_counts()[:10].index, y=data['UserID'].value_counts()[
:10])
ax.set(xlabel='User-ID', ylabel='Frequency')
```

Out[ ]:

```
[Text(0, 0.5, 'Frequency'), Text(0.5, 0, 'User-ID')]
```

```
[Text(0, 0.5, 'Frequency'), Text(0.5, 0, 'User-ID')]
```



In [ ]:

```
print(data['UserID'].value_counts().mean())
print("One can check for outliers in UserID as the mean is around 6, which states that ea
ch user has rated around 6 books")
```

```
6.645981160531066
One can check for outliers in UserID as the mean is around 6, which states that each user
has rated around 6 books
```

Analysing Book Rating"

In [ ]:

```
print("counting the total books against each rating:\nRating \t count\n",data['BookRating
'].value_counts())
```

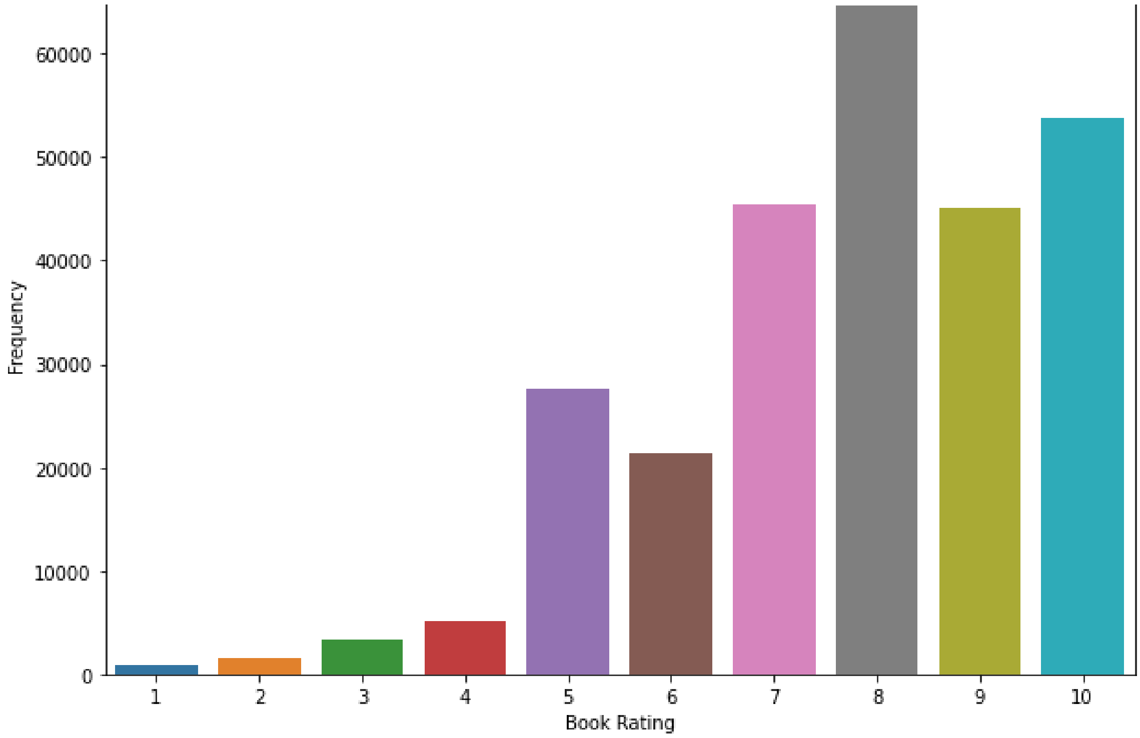
```
counting the total books against each rating:
Rating   count
 8      64625
10     53830
7      45395
9      45149
5      27616
6      21374
4       5073
3       3313
2       1557
1        878
Name: BookRating, dtype: int64
```

In [ ]:

```
fig, ax = pyplot.subplots(figsize=(10,7))
sns.barplot(x=data['BookRating'].value_counts().index, y=data['BookRating'].value_counts
())
ax.set(xlabel='Book Rating', ylabel='Frequency')
```

Out[ ]:

```
[Text(0, 0.5, 'Frequency'), Text(0.5, 0, 'Book Rating')]
```



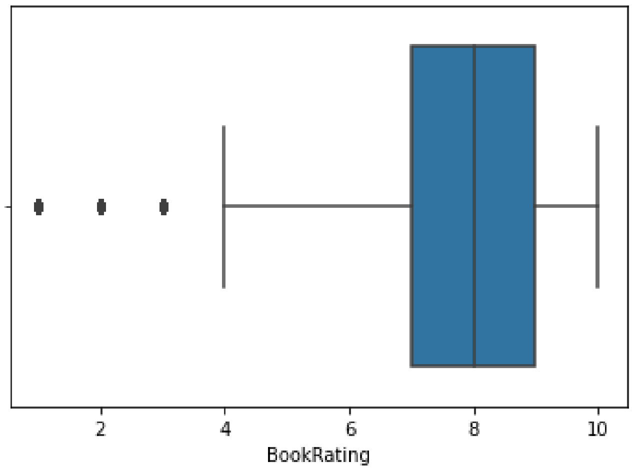
From the above plot, most of the books are rated above 6, very litte books are rated bwteen 1-4.

In [ ]:

```
sns.boxplot(data['BookRating'])
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd778a61f98>
```



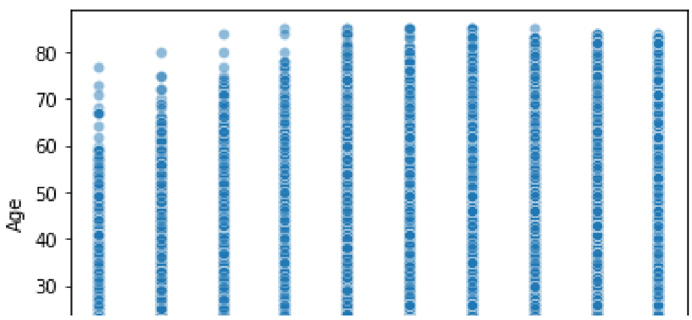
From the above boxplot, most of the book rating lies in between 7-9.

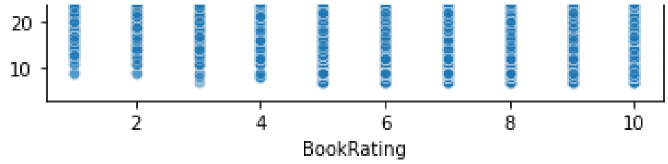
In [ ]:

```
sns.scatterplot(y='Age',x='BookRating',data=data,alpha=0.5)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd777b1dc18>
```





Analysing User Location:

In [ ]:

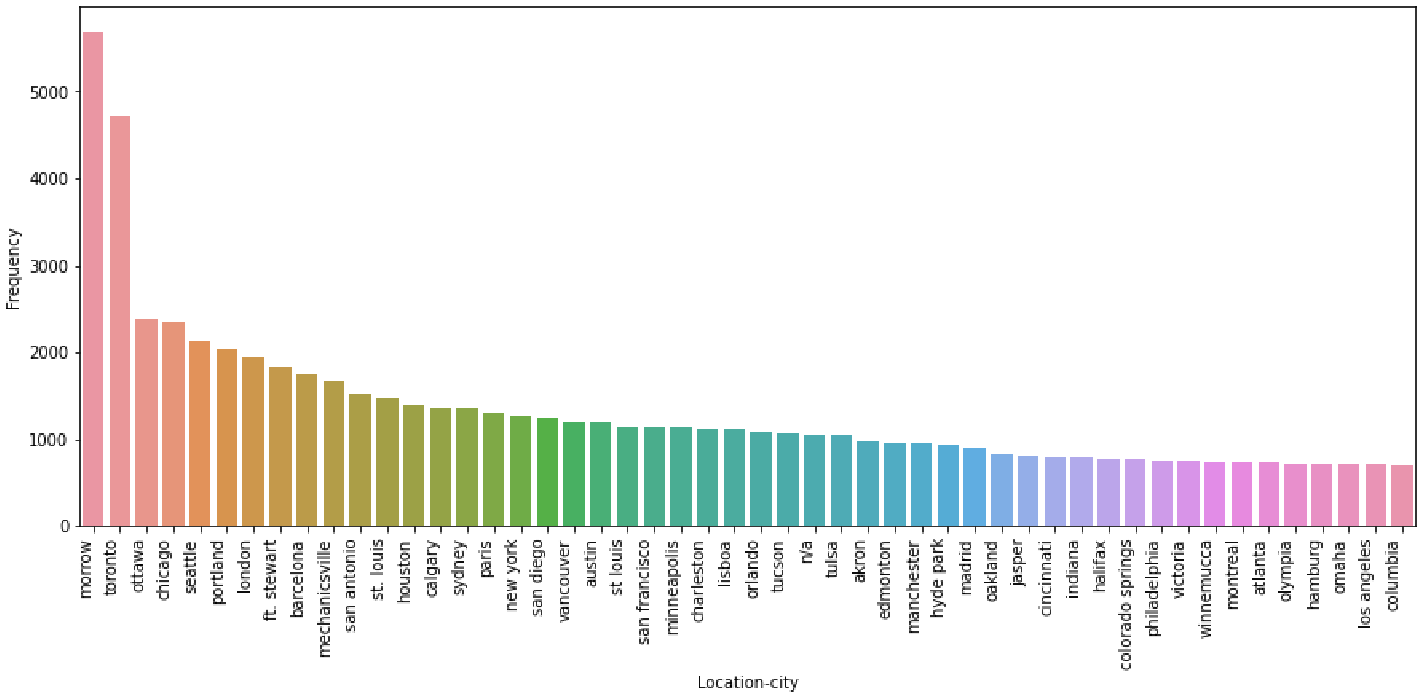
```
city =list()
state= list()
country = list()
for i in range(len(data)):
  splitLoc= data['Location'].iloc[i].split(',')
  city.append(splitLoc[0])
  state.append(splitLoc[1])
  country.append(splitLoc[2])

data['city']=city
data['state']=state
data['country']= country
```

In [ ]:

```
#plotting bar plot for userlocation: city
fig, ax = plt.subplots(figsize = (15,6))
fig = sns.barplot(x = data['city'].value_counts().index[:50], y = data['city'].value_cou
nts()[:50], ci = None, ax=ax)
ax.set_xticklabels(labels=data['city'].value_counts().index, rotation=90, ha='right');
ax.set(xlabel='Location-city', ylabel='Frequency')
```

Out[ ]:

```
[Text(0, 0.5, 'Frequency'), Text(0.5, 0, 'Location-city')]
```

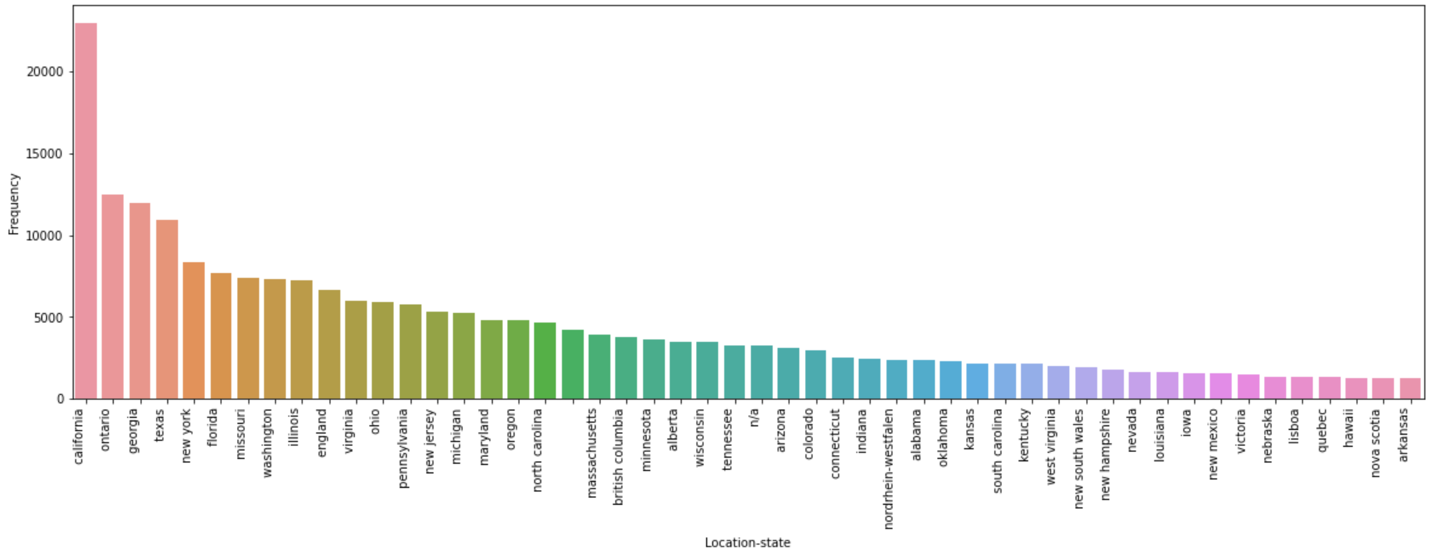


In [ ]:

```
#plotting bar plot for userlocation: state
fig, ax = plt.subplots(figsize = (20,6))
fig = sns.barplot(x = data['state'].value_counts().index[:50], y = data['state'].value_c
ounts()[:50], ci = None, ax=ax)
ax.set_xticklabels(labels=data['state'].value_counts().index, rotation=90, ha='right');
ax.set(xlabel='Location-state', ylabel='Frequency')
```

Out[ ]:

```
[Text(0, 0.5, 'Frequency'), Text(0.5, 0, 'Location-state')]
```

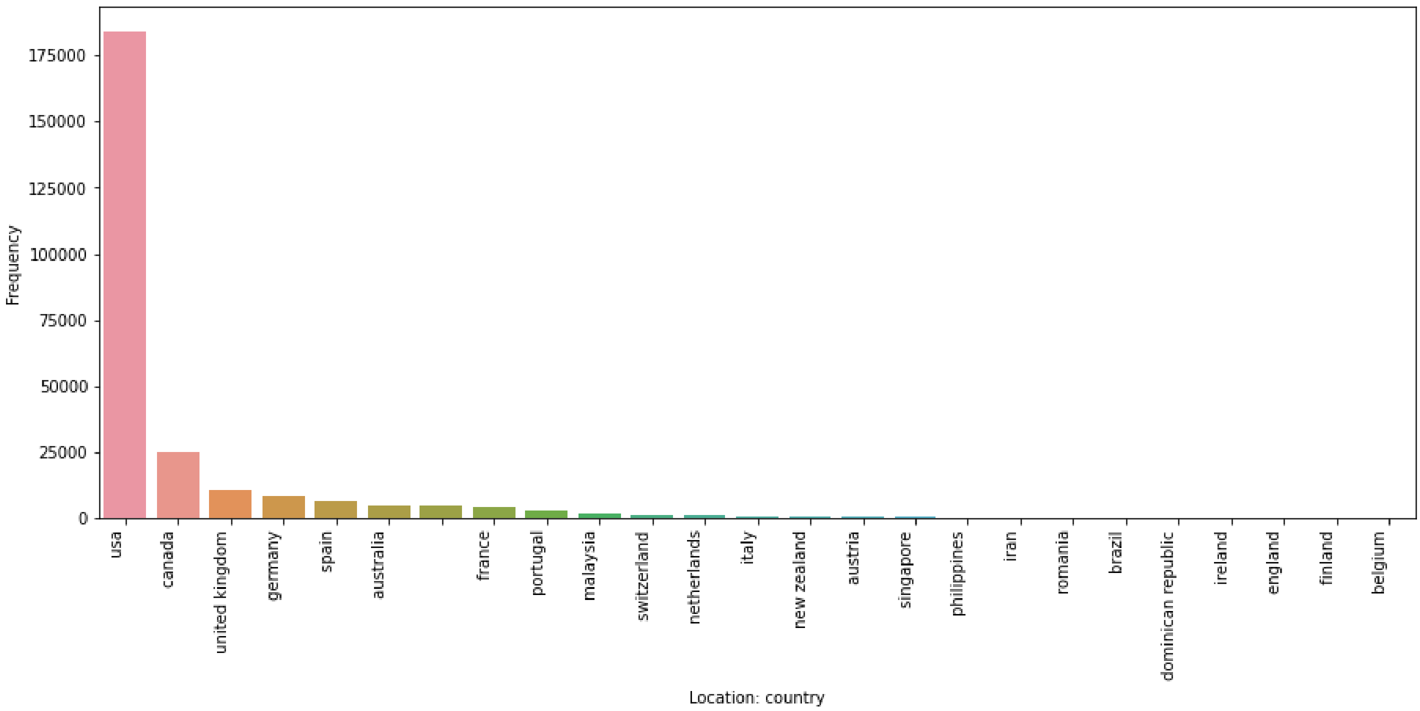


In [ ]:

```
#plotting bar plot for userlocation: country
fig, ax = plt.subplots(figsize = (15,6))
fig = sns.barplot(x = data['country'].value_counts().index[:25], y = data['country'].val
ue_counts()[:25], ci = None, ax=ax)
ax.set_xticklabels(labels=data['country'].value_counts().index, rotation=90, ha='right')
;
ax.set(xlabel='Location: country', ylabel='Frequency')
```

Out[ ]:

```
[Text(0, 0.5, 'Frequency'), Text(0.5, 0, 'Location: country')]
```



Analysisng Book Author:

In [ ]:

```
print("counting the books written by each author:\nAuthor\t\tCount\n ")
data["BookAuthor"].value_counts().sort_values(ascending=False).head()
```

```
counting the books written by each author:
Author	Count
```

Out[ ]:

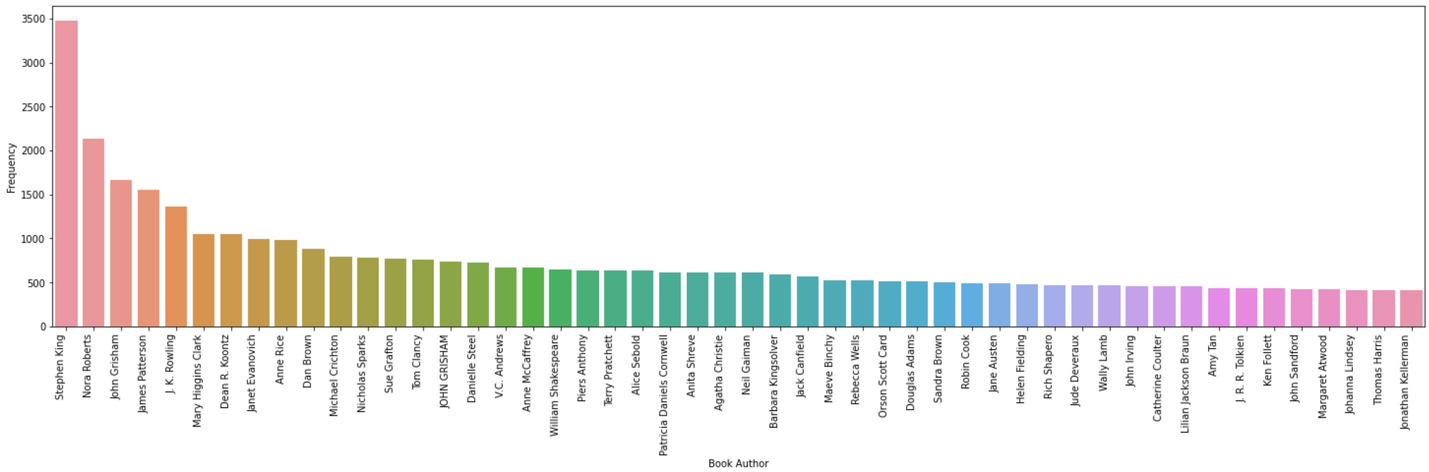
```
Stephen King       3473
Nora Roberts       2131
John Grisham       1665
James Patterson    1555
J. K. Rowling      1366
Name: BookAuthor, dtype: int64
```

In [ ]:

```
#plotting top 50 Writers:
fig, ax = plt.subplots(figsize = (25,6))
fig = sns.barplot(x = data['BookAuthor'].value_counts().index[:50], y = data['BookAuthor'].value_counts()[:50], ci = None, ax=ax)
ax.set_xticklabels(labels=data['BookAuthor'].value_counts().index, rotation=90, ha='right');
ax.set(xlabel='Book Author', ylabel='Frequency')
```

Out[ ]:

```
[Text(0, 0.5, 'Frequency'), Text(0.5, 0, 'Book Author')]
```



Analysis Year of Publication:

In [ ]:

```
print("counting the total books published against each year \n Year \t Count\n")
data['YearOfPublication'].value_counts()
```

```
counting the total books published against each year
 Year   Count
```

Out[ ]:

```
2002    25952
2003    22860
2001    22026
1999    19816
2000    19267
        ...
1928        1
1934        1
1902        1
2006        1
1900        1
Name: YearOfPublication, Length: 89, dtype: int64
```

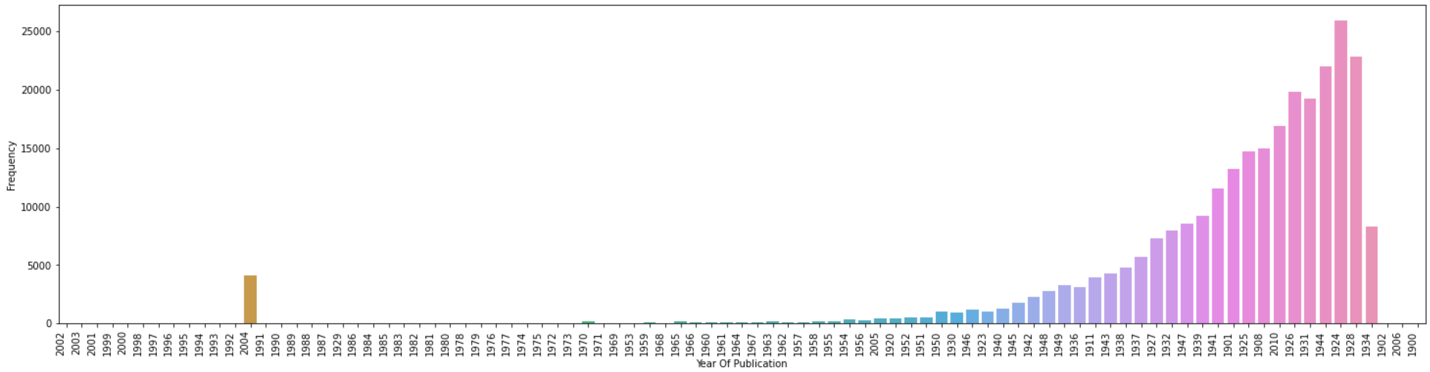
In [ ]:

```
fig, ax = plt.subplots(figsize = (25,6))
fig = sns.barplot(x = data['YearOfPublication'].value_counts().index, y = data['YearOfPublication'].value_counts(), ci = None, ax=ax)
ax.set_xticklabels(labels=data['YearOfPublication'].value_counts().index, rotation=90, ha='right');
```

```
ax.set(xlabel='Year Of Publication', ylabel='Frequency')
```

Out[ ]:

```
[Text(0, 0.5, 'Frequency'), Text(0.5, 0, 'Year Of Publication')]
```

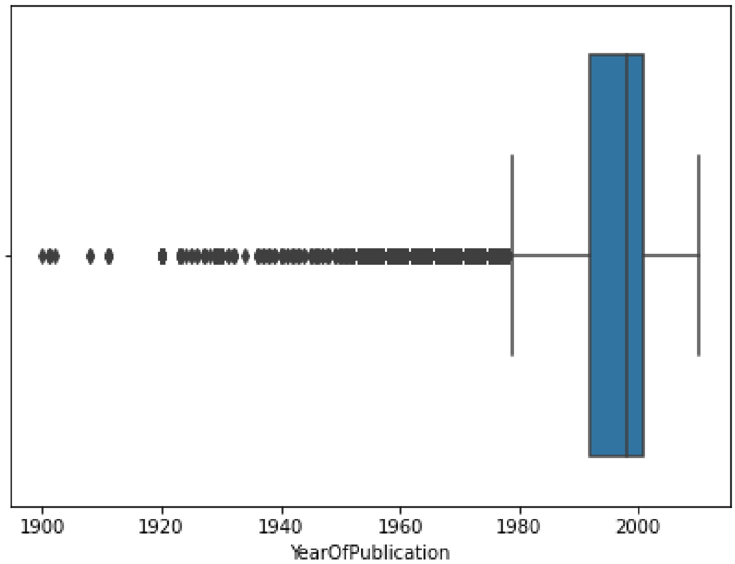


In [ ]:

```
fig, ax = pyplot.subplots(figsize=(7,5))
sns.boxplot(data['YearOfPublication'])
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd76ab7f198>
```



from the above plot, one can see that most of the books are published between 1990-2010.

Analysis Book Publisher:

In [ ]:

```
print("counting the total books published by each publisher \n Publisher \t Count\n")
data['Publisher'].value_counts().head()
```

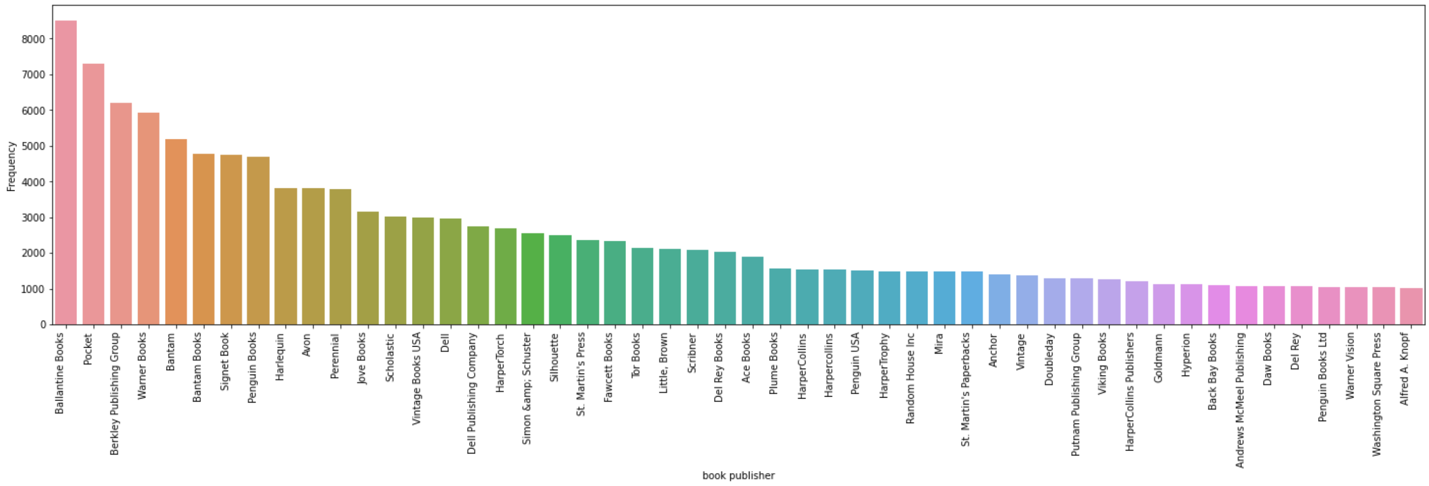
```
counting the total books published by each publisher
 Publisher    Count
```

Out[ ]:

```
Ballantine Books            8519
Pocket                      7287
Berkley Publishing Group    6207
Warner Books                5930
Bantam                      5198
Name: Publisher, dtype: int64
```

In [ ]:

```
#plotting top 50 Publishers:
fig, ax = plt.subplots(figsize = (25,6))
fig = sns.barplot(x = data['Publisher'].value_counts().index[:50], y = data['Publisher']
.value_counts()[:50], ci = None, ax=ax)
ax.set(xlabel='book publisher', ylabel='Frequency')
ax.set_xticklabels(labels=data['Publisher'].value_counts().index, rotation=90, ha='right
');
```



MODELS:

MIN- MAX Normalization:

Supervised Learing:

In [ ]:

```
#splitting location into City state and country:
datacopyf1['city']=city
datacopyf1['state']=state
datacopyf1['country']= country

#converting to non numeric data to category
datacopyf1.Publisher = pd.Categorical(datacopyf1.Publisher)
datacopyf1['PublisherCode'] = datacopyf1.Publisher.cat.codes
datacopyf1.BookAuthor = pd.Categorical(datacopyf1.BookAuthor)
datacopyf1['BookAuthorCode'] = datacopyf1.BookAuthor.cat.codes
datacopyf1['Book-Title'] = pd.Categorical(datacopyf1['Book-Title'])
datacopyf1['BookTitleCode'] = datacopyf1['Book-Title'].cat.codes


datacopyf1.city = pd.Categorical(datacopyf1.city)
datacopyf1['citycode'] = datacopyf1.city.cat.codes
datacopyf1.state = pd.Categorical(datacopyf1.state)
datacopyf1['statecode'] = datacopyf1.state.cat.codes
datacopyf1.country = pd.Categorical(datacopyf1.country)
datacopyf1['countrycode'] = datacopyf1.country.cat.codes
```

In [ ]:

```
for i in range(len(datacopyf1)):
  if datacopyf1['BookRating'][i]>=0.0 and datacopyf1['BookRating'][i]<=2.5:
    datacopyf1['BookRating'].loc[i]= "Low"
  elif datacopyf1['BookRating'][i]>2.5 and datacopyf1['BookRating'][i]<=3.75:
    datacopyf1['BookRating'].loc[i] = "Med"
  else:
    datacopyf1['BookRating'].loc[i] = "High"
```

In [ ]:

```
# Identifying the predictor variable(x) and Target Variable
```

```
# identifying the predictor variable(x) and Target variable
X = datacopyf1[["Age",'PublisherCode','BookAuthorCode','BookTitleCode','citycode', 'coun
trycode', 'statecode']]
y = datacopyf1["BookRating"]
```

In [ ]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X,y,test_size=0.25,random_state=42)
```

K-Nearest Neighbor (for Min-Max Normalization):

In [ ]:

```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(X_train,Y_train)
pred = knn.predict(X_test)
```

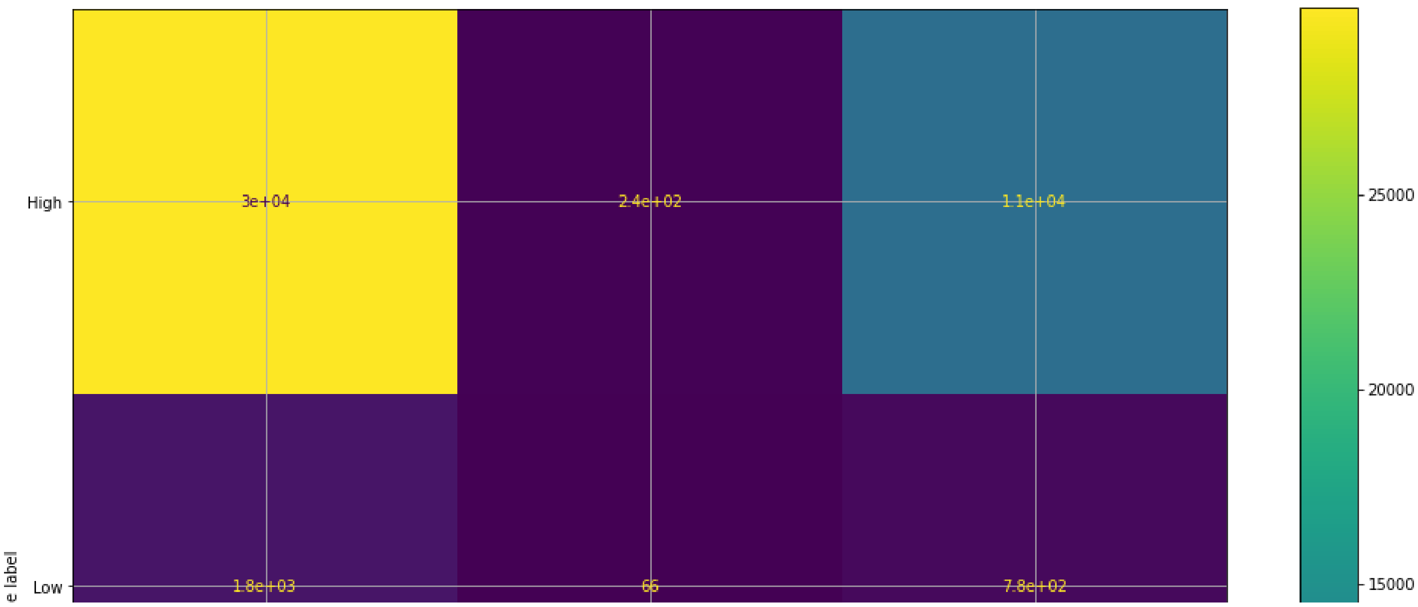
In [ ]:

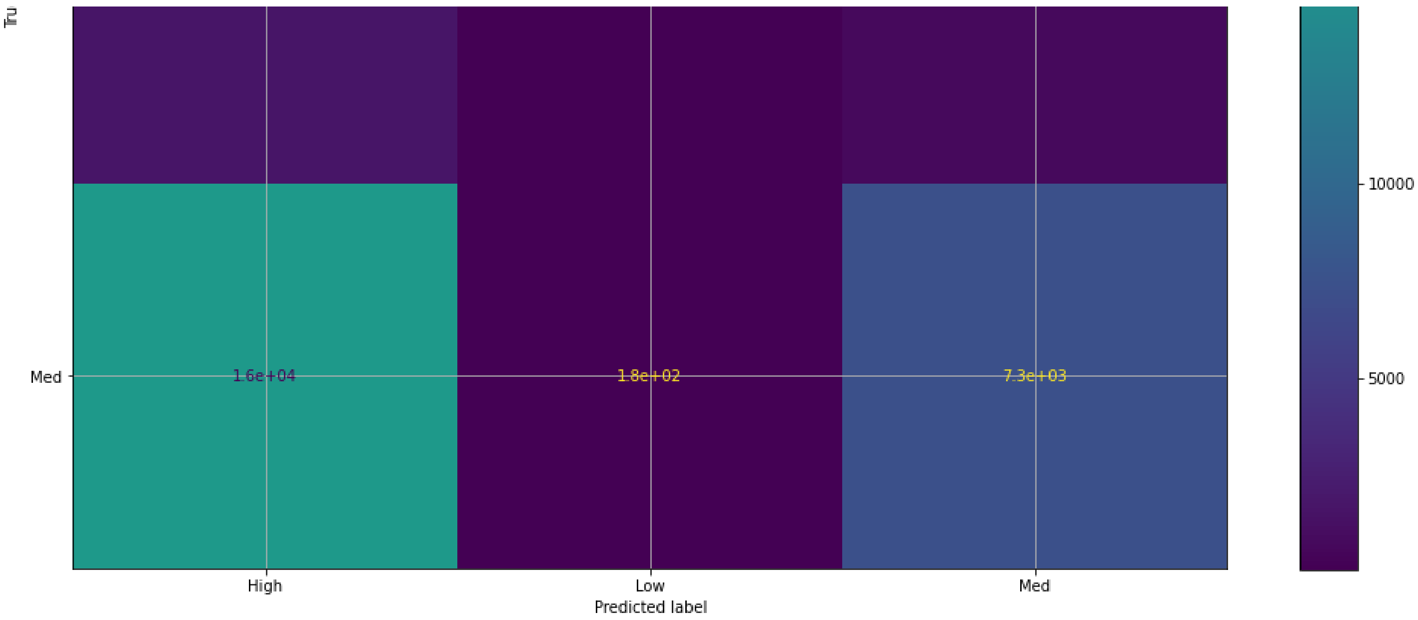
```
from sklearn.metrics import classification_report,confusion_matrix,plot_confusion_matrix

print(confusion_matrix(Y_test,pred))
print('\n')
var=classification_report(Y_test,pred)
print(var)

figure, axis = plt.subplots(figsize=(17,14))
plt.grid(b=None)
plot_confusion_matrix(knn, X_test, Y_test, ax=axis)
```

```
[[29817   240 10847]
 [ 1799    66   778]
 [16132   176  7348]]


              precision    recall  f1-score   support

        High       0.62      0.73      0.67     40904
         Low       0.14      0.02      0.04      2643
         Med       0.39      0.31      0.34     23656

    accuracy                           0.55     67203
   macro avg       0.38      0.35      0.35     67203
weighted avg       0.52      0.55      0.53     67203
```

Out[ ]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7fd7675a3898>
```





Decision Tree (for Min-Max Normilazation):

In [ ]:

```
!pip install pydotplus
```

```
Requirement already satisfied: pydotplus in /usr/local/lib/python3.6/dist-packages (2.0.2
)
Requirement already satisfied: pyparsing>=2.0.1 in /usr/local/lib/python3.6/dist-packages
(from pydotplus) (2.4.7)
```

In [ ]:

```
!pip install graphviz
```

```
Requirement already satisfied: graphviz in /usr/local/lib/python3.6/dist-packages (0.10.1
)
```

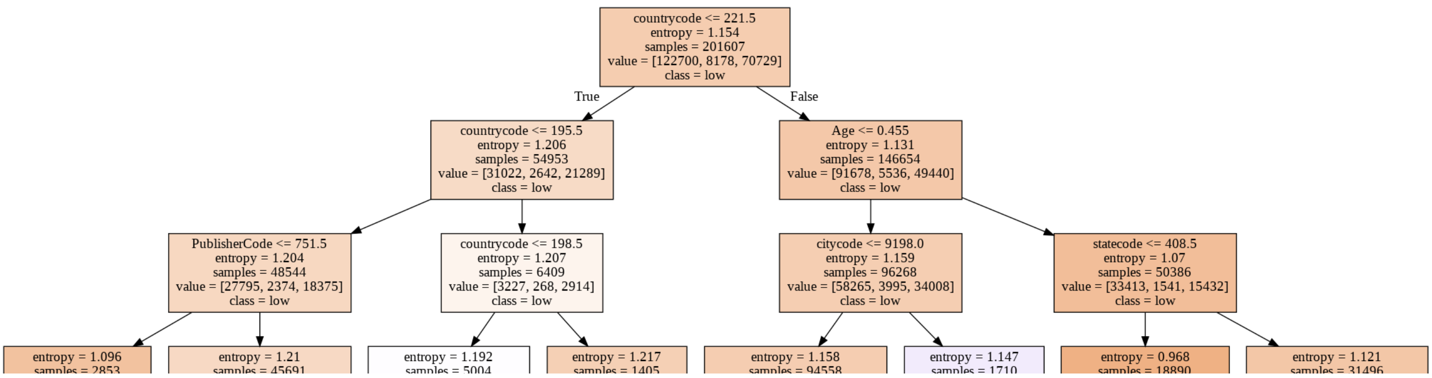
In [ ]:

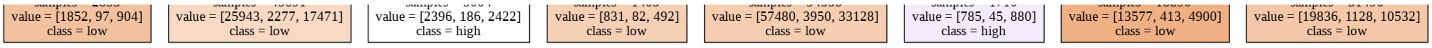
```
from sklearn.tree import DecisionTreeClassifier # Import Decision Tree Classifier
from sklearn import metrics #Import scikit-learn metrics module for accuracy calculation
import pydotplus
from IPython.display import Image
from sklearn import tree
```

In [ ]:

```
Dtree = tree.DecisionTreeClassifier(criterion='entropy',max_depth=3)
Dtree = Dtree.fit(X_train, Y_train)
dot_data = tree.export_graphviz(Dtree, feature_names=X.columns, class_names=['low','med'
,'high'], filled=True,out_file=None)
graph = pydotplus.graph_from_dot_data(dot_data)
graph.write_png('decisionTree(MinMax).png')
Image(graph.create_png())
```

Out[ ]:





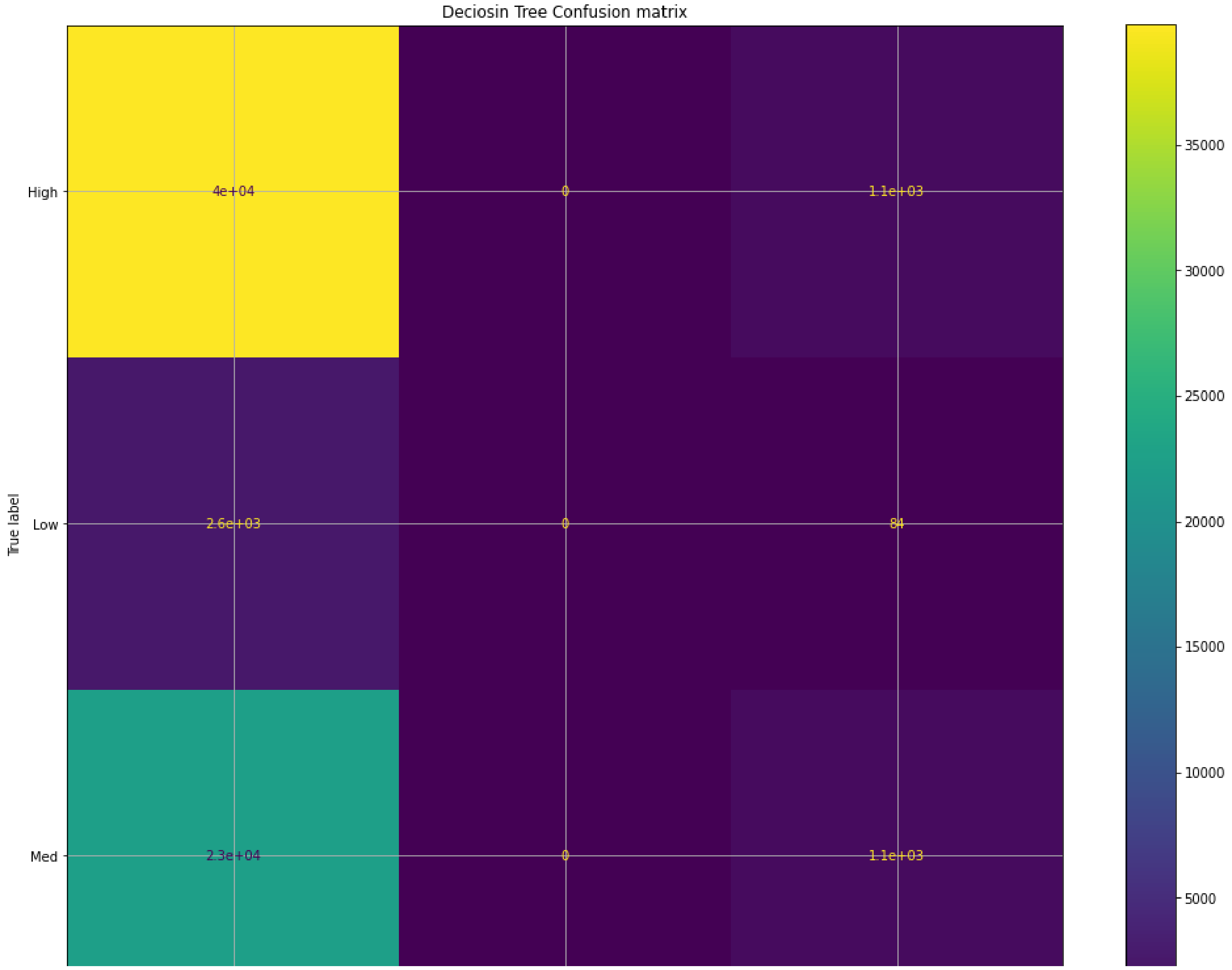
In [ ]:

```
DecisionTreepredictedY = Dtree.predict(X_test)
print(confusion_matrix(Y_test,DecisionTreepredictedY))
print('\n')
var=classification_report(Y_test,DecisionTreepredictedY)
print(var)


figure, axis = plt.subplots(figsize=(17,14))
plt.grid(b=None)
plot_confusion_matrix(Dtree, X_test, Y_test, ax=axis)
plt.title("Deciosin Tree Confusion matrix")
```

```
[[39815     0  1089]
 [ 2559     0    84]
 [22536     0  1120]]


              precision    recall  f1-score   support

        High       0.61      0.97      0.75     40904
         Low       0.00      0.00      0.00      2643
         Med       0.49      0.05      0.09     23656

    accuracy                           0.61     67203
   macro avg       0.37      0.34      0.28     67203
weighted avg       0.55      0.61      0.49     67203
```

Out[ ]:

```
Text(0.5, 1.0, 'Deciosin Tree Confusion matrix')
```



Unsupervised Learning:

k-Means (for Min Max Normalization):

In [ ]:

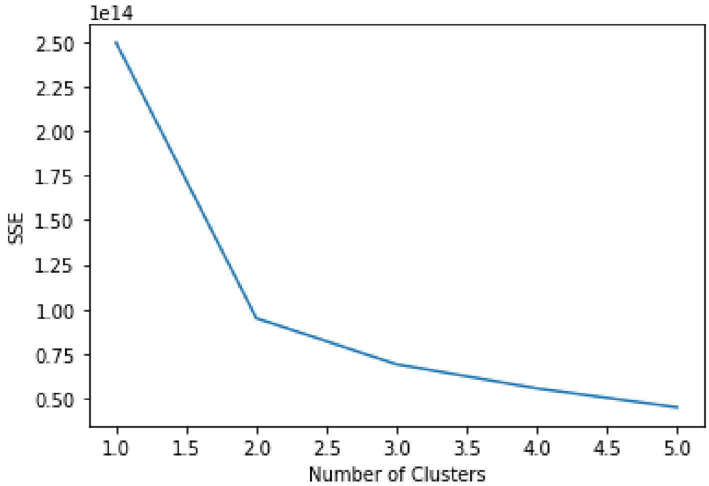
```
datacopyf1['BookRating'] = pd.Categorical(datacopyf1['BookRating'])
datacopyf1['BookRatingCode'] = datacopyf1['BookRating'].cat.codes
```

In [ ]:

```
y_encoded= datacopyf1['BookRatingCode']
#datacol = datacopyf1[["Age",'PublisherCode','BookAuthorCode','BookTitleCode','citycode',
'countrycode', 'statecode','BookRatingCode']]
X_train, X_test, y_train, y_test = train_test_split(X,y_encoded,test_size=0.25,random_st
ate=42)
```

In [ ]:

```
import pandas as pd
from sklearn import cluster
import numpy as np
import matplotlib.pyplot as plt

k_means = cluster.KMeans(n_clusters=3, max_iter=50, random_state=1).fit(X_train)
labels = k_means.labels_

numClusters = [1,2,3,4,5]
SSE = []
for k in numClusters:
    k_means = cluster.KMeans(n_clusters=k)
    k_means.fit(X_train)
    SSE.append(k_means.inertia_)
#Sum of squared distances of samples to their closest cluster center.

plt.plot(numClusters, SSE)
plt.xlabel('Number of Clusters')
plt.ylabel('SSE')
plt.show()


Kmeanspredicted = k_means.predict(X_test)
Kmeanspredicted.reshape(-1,1)

var=classification_report(y_test,Kmeanspredicted)
print(var)
```

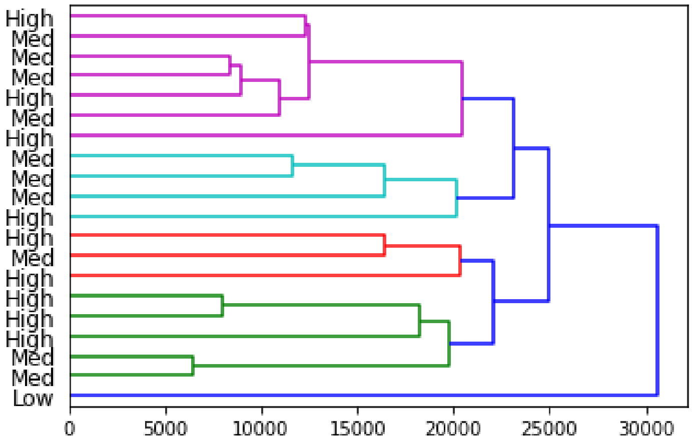


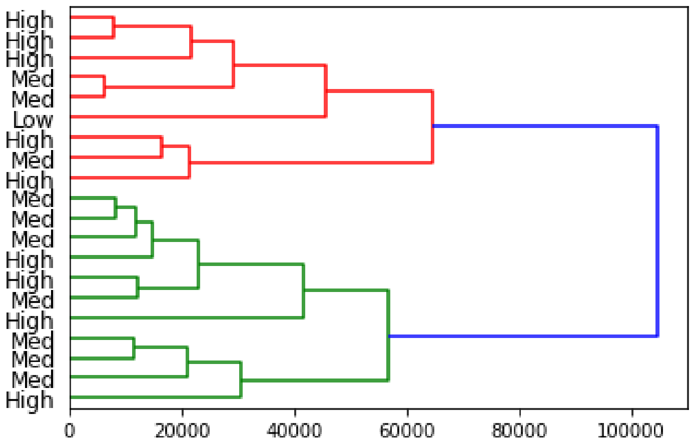
```
              precision    recall  f1-score   support

           0       0.61      0.17      0.27     40904
           1       0.04      0.20      0.07      2643
           2       0.35      0.25      0.29     23656
           3       0.00      0.00      0.00         0
           4       0.00      0.00      0.00         0

    accuracy                           0.20     67203
   macro avg       0.20      0.12      0.13     67203
weighted avg       0.49      0.20      0.27     67203
```

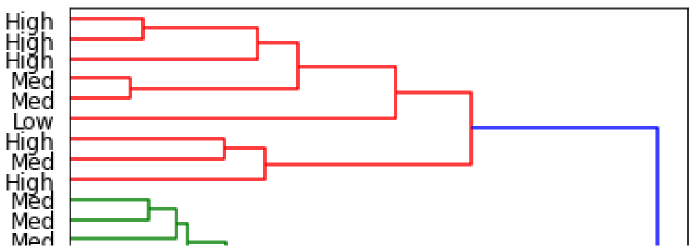
Hierarchy Clustering(Min-Max Normalization):

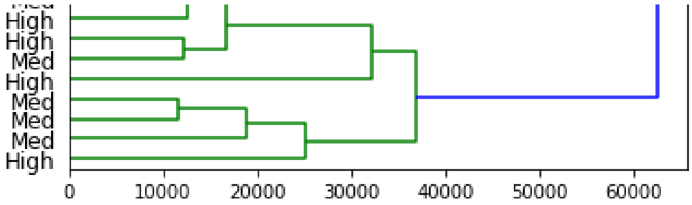
In [ ]:

```
import pandas as pd
from scipy.cluster import hierarchy
import matplotlib.pyplot as plt
X_refined = X_train[:20]
names = datacopyf1['BookRating']
Z = hierarchy.linkage(X_refined, 'single')
dend = hierarchy.dendrogram(Z,labels=names.tolist(),orientation='right')
plt.show()
Z  = hierarchy.linkage(X_refined, 'complete')
dend = hierarchy.dendrogram(Z,labels=names.tolist(),orientation='right')
plt.show()
Z  = hierarchy.linkage(X_refined, 'average')
dend = hierarchy.dendrogram(Z,labels=names.tolist(),orientation='right')
plt.show()
```









Z- score Normalization

Supervised Learning:

K- nearest Neighbor(on Z- score):

In [ ]:

```
#splitting location into City state and country:
datacopyf2['city']=city
datacopyf2['state']=state
datacopyf2['country']= country

#converting to non numeric data to category
datacopyf2.Publisher = pd.Categorical(datacopyf2.Publisher)
datacopyf2['PublisherCode'] = datacopyf2.Publisher.cat.codes
datacopyf2.BookAuthor = pd.Categorical(datacopyf2.BookAuthor)
datacopyf2['BookAuthorCode'] = datacopyf2.BookAuthor.cat.codes
datacopyf2['Book-Title'] = pd.Categorical(datacopyf2['Book-Title'])
datacopyf2['BookTitleCode'] = datacopyf2['Book-Title'].cat.codes


datacopyf2.city = pd.Categorical(datacopyf2.city)
datacopyf2['citycode'] = datacopyf2.city.cat.codes
datacopyf2.state = pd.Categorical(datacopyf2.state)
datacopyf2['statecode'] = datacopyf2.state.cat.codes
datacopyf2.country = pd.Categorical(datacopyf2.country)
datacopyf2['countrycode'] = datacopyf2.country.cat.codes
```

In [ ]:

```
print (sorted(datacopyf2['BookRating'].unique()))
```

```
[-3.714404630550603, -3.1631123754728385, -2.611820120395074, -2.0605278653173094, -1.509
2356102395452, -0.9579433551617808, -0.4066511000840163, 0.14464115499374816, 0.695933410
0715125, 1.247225665149277]
```

In [ ]:

```
for i in range(len(datacopyf2)):
  if datacopyf2['BookRating'][i]>=-3.8 and datacopyf2['BookRating'][i]<=-1.50:
    datacopyf2['BookRating'].loc[i]= "Low"
  elif datacopyf2['BookRating'][i]>-1.50 and datacopyf2['BookRating'][i]<=0.08:
    datacopyf2['BookRating'].loc[i] = "Med"
  else:
    datacopyf2['BookRating'].loc[i] = "High"
```

In [ ]:

```
# Identifying the predictor variable(x) and Target Variable
X = datacopyf2[["Age",'PublisherCode','BookAuthorCode','BookTitleCode','citycode', 'coun
trycode', 'statecode']]
y = datacopyf2["BookRating"]
```

In [ ]:

```
X_train, X_test, Y_train, Y_test = train_test_split(X,y,test_size=0.25,random_state=42)
```

In [ ]:

```
#Knn model:
kNN = KNeighborsClassifier(n_neighbors=3)
kNN.fit(X_train,Y_train)
pred = kNN.predict(X_test)
```

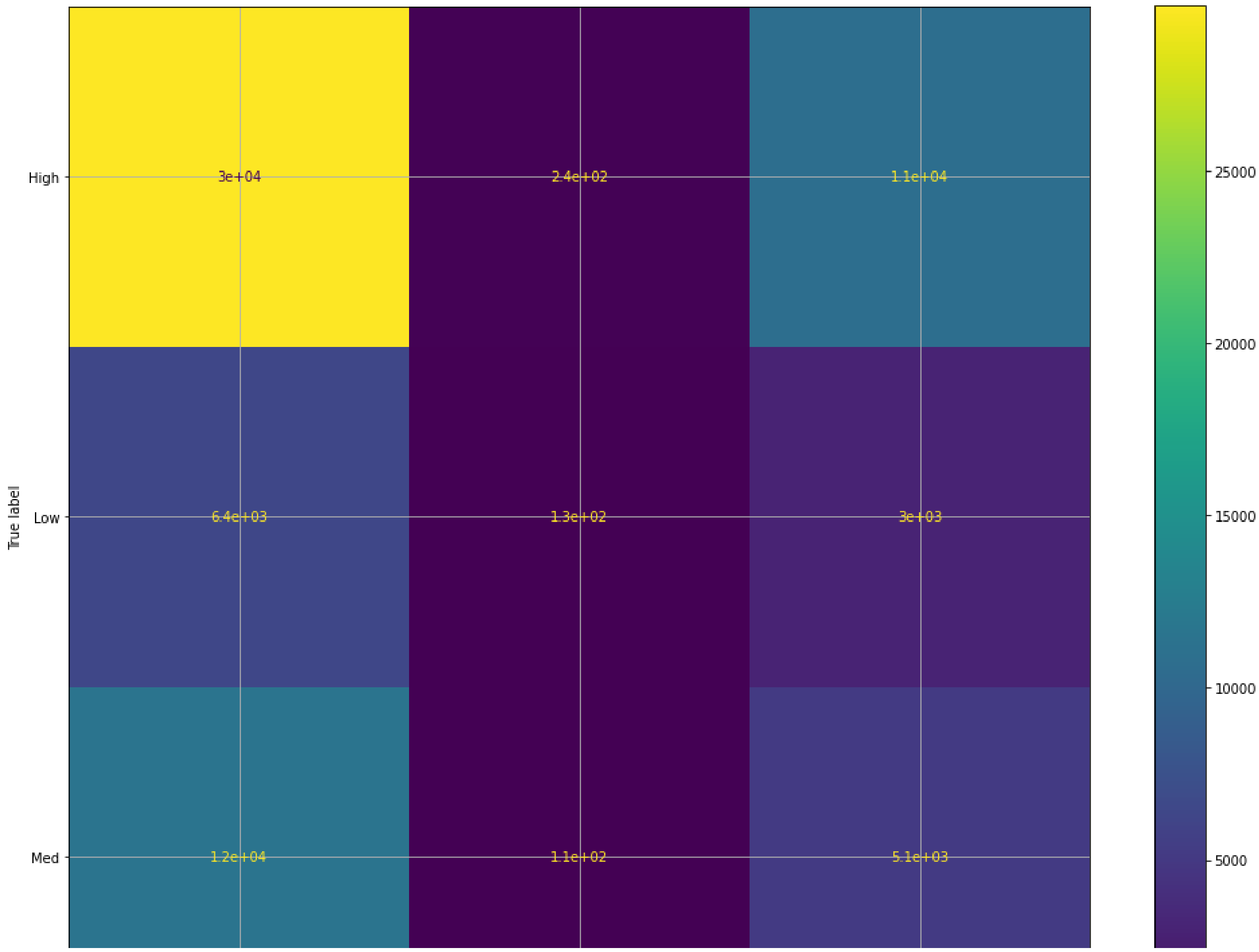
In [ ]:

```
#Plotting:
print(confusion_matrix(Y_test,pred))
print('\n')
var=classification_report(Y_test,pred)
print(var)

figure, axis = plt.subplots(figsize=(17,14))
plt.grid(b=None)
plot_confusion_matrix(knn, X_test, Y_test, ax=axis)
```

```
[[32753  2181  5970]
 [ 7167   869  1542]
 [12798  1027  2896]]


              precision    recall  f1-score   support

        High       0.62      0.80      0.70     40904
         Low       0.21      0.09      0.13      9578
         Med       0.28      0.17      0.21     16721

    accuracy                           0.54     67203
   macro avg       0.37      0.35      0.35     67203
weighted avg       0.48      0.54      0.50     67203
```

Out[ ]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7fd76333dc50>
```

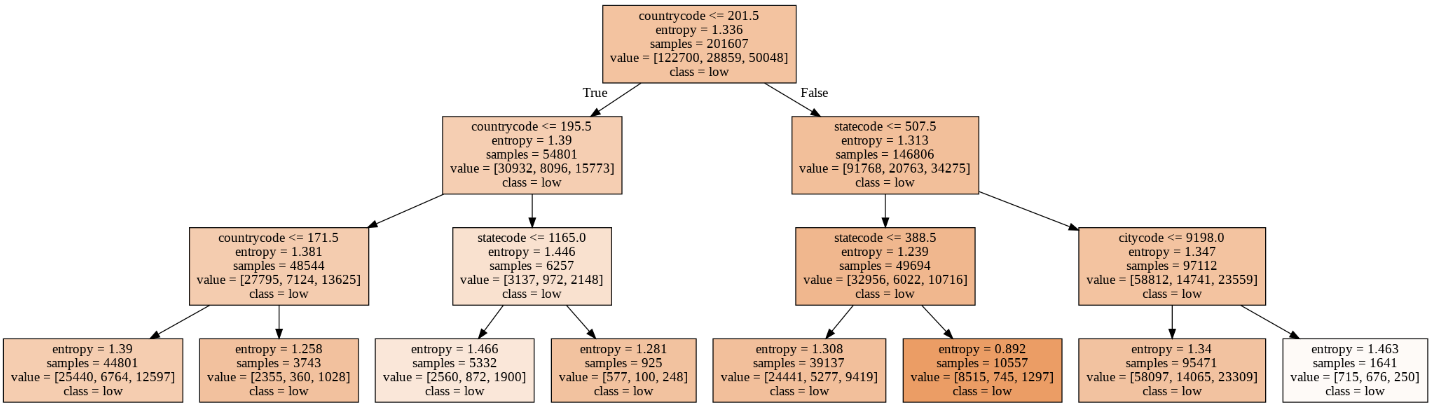


Decison Tree(Z- score Noramlization):

In [ ]:

```
#Decison Tree model
Dtree = tree.DecisionTreeClassifier(criterion='entropy',max_depth=3)
Dtree = Dtree.fit(X_train, Y_train)
dot_data = tree.export_graphviz(Dtree, feature_names=X.columns, class_names=['low','med'
,'high'], filled=True,out_file=None)
graph = pydotplus.graph_from_dot_data(dot_data)
graph.write_png('decisionTree(z-score).png')
Image(graph.create_png())
```

Out[ ]:



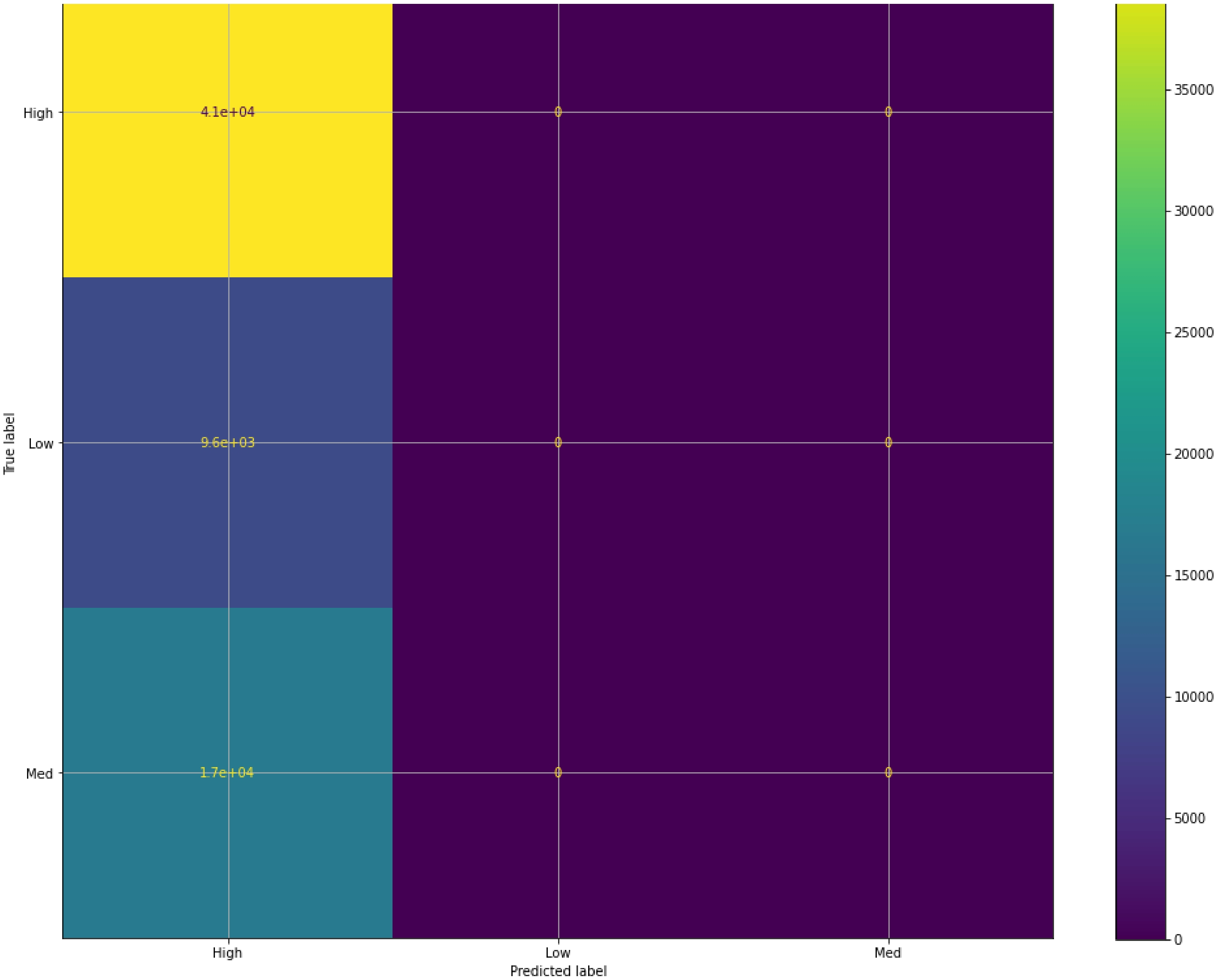
In [ ]:

```
#plotting:
DecisionTreepredictedY = Dtree.predict(X_test)
print(confusion_matrix(Y_test,DecisionTreepredictedY))
print('\n')
var=classification_report(Y_test,DecisionTreepredictedY)
print(var)

figure, axis = plt.subplots(figsize=(17,14))
plt.grid(b=None)
plot_confusion_matrix(Dtree, X_test, Y_test, ax=axis)
plt.title("Deciosin Tree Confusion matrix")
```

```
[[40904     0     0]
 [ 9578     0     0]
 [16721     0     0]]


              precision    recall  f1-score   support

        High       0.61      1.00      0.76     40904
         Low       0.00      0.00      0.00      9578
         Med       0.00      0.00      0.00     16721

    accuracy                           0.61     67203
   macro avg       0.20      0.33      0.25     67203
weighted avg       0.37      0.61      0.46     67203
```

Out[ ]:

```
Text(0.5, 1.0, 'Deciosin Tree Confusion matrix')
```



Unsupervised Learning:

K-Means:(Z-Score Normalization):

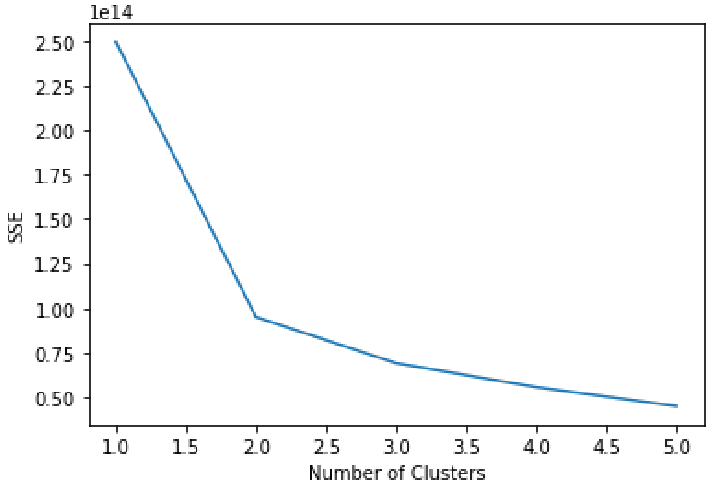
In [ ]:

```
# Identifying the Traget Variable:
datacopyf2['BookRating'] = pd.Categorical(datacopyf2['BookRating'])
datacopyf2['BookRatingCode'] = datacopyf2['BookRating'].cat.codes
y_encoded= datacopyf2['BookRatingCode']
X_train, X_test, y_train, y_test = train_test_split(X,y_encoded,test_size=0.25,random_st
ate=42)
```

In [ ]:

```
# Kmeans model:
k_means = cluster.KMeans(n_clusters=3, max_iter=50, random_state=1).fit(X_train)
labels = k_means.labels_

numClusters = [1,2,3,4,5]
SSE = []
for k in numClusters:
    k_means = cluster.KMeans(n_clusters=k)
    k_means.fit(X_train)
    SSE.append(k_means.inertia_)
#Sum of squared distances of samples to their closest cluster center.
#plotting:
plt.plot(numClusters, SSE)
plt.xlabel('Number of Clusters')
plt.ylabel('SSE')
```

```
plt.show()


Kmeanspredicted = k_means.predict(X_test)
Kmeanspredicted.reshape(-1,1)

var=classification_report(y_test,Kmeanspredicted)
print(var)
```

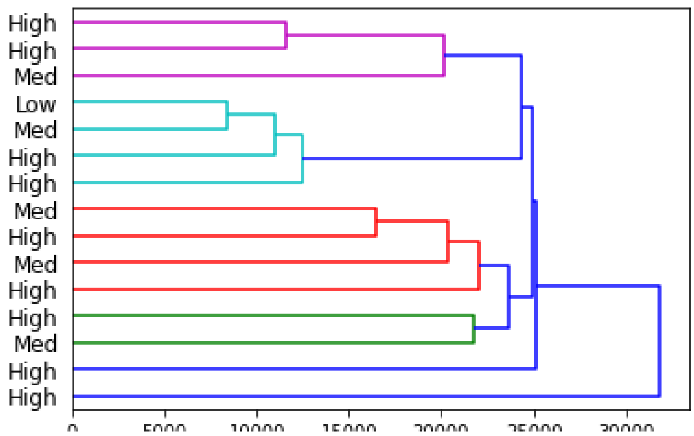


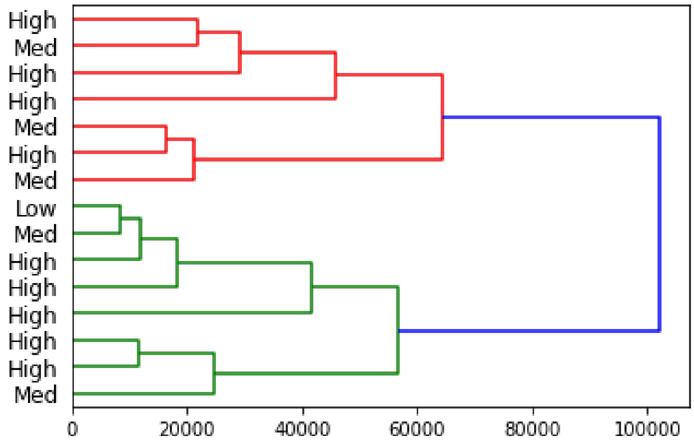

```
              precision    recall  f1-score   support

           0       0.61      0.20      0.30     40904
           1       0.14      0.25      0.18      9578
           2       0.24      0.19      0.22     16721
           3       0.00      0.00      0.00         0
           4       0.00      0.00      0.00         0

    accuracy                           0.21     67203
   macro avg       0.20      0.13      0.14     67203
weighted avg       0.45      0.21      0.27     67203
```

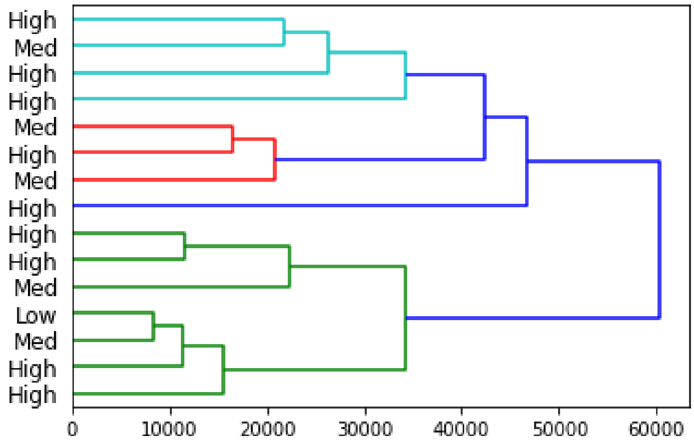
Hierarchy Clustering(Z-ScoreNormalization):

In [ ]:

```
# Slicing Predictor variable:
x_reduced= X_train[:15]
names = datacopyf2['BookRating']
#Hierarchy Model:
Z = hierarchy.linkage(x_reduced, 'single')
dend = hierarchy.dendrogram(Z,labels=names.tolist(),orientation='right')
plt.show()
Z = hierarchy.linkage(x_reduced, 'complete')
dend = hierarchy.dendrogram(Z,labels=names.tolist(),orientation='right')
plt.show()
Z = hierarchy.linkage(x_reduced, 'average')
dend = hierarchy.dendrogram(Z,labels=names.tolist(),orientation='right')
plt.show()
```







Decimal Scaling:

Supervised Learning

K-nearest Neighbor(for Decimal Scaling)

In [ ]:

```
#splitting location into City state and country:
datacopyf3['city']=city
datacopyf3['state']=state
datacopyf3['country']= country

#converting to non numeric data to category
datacopyf3.Publisher = pd.Categorical(datacopyf3.Publisher)
datacopyf3['PublisherCode'] = datacopyf3.Publisher.cat.codes
datacopyf3.BookAuthor = pd.Categorical(datacopyf3.BookAuthor)
datacopyf3['BookAuthorCode'] = datacopyf3.BookAuthor.cat.codes
datacopyf3['Book-Title'] = pd.Categorical(datacopyf3['Book-Title'])
datacopyf3['BookTitleCode'] = datacopyf3['Book-Title'].cat.codes


datacopyf3.city = pd.Categorical(datacopyf3.city)
datacopyf3['citycode'] = datacopyf3.city.cat.codes
datacopyf3.state = pd.Categorical(datacopyf3.state)
datacopyf3['statecode'] = datacopyf3.state.cat.codes
datacopyf3.country = pd.Categorical(datacopyf3.country)
datacopyf3['countrycode'] = datacopyf3.country.cat.codes
```

In [ ]:

```
print (sorted(datacopyf3['BookRating'].unique()))
```

```
[0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1]
```

In [ ]:

```
for i in range(len(datacopyf3)):
  if datacopyf3['BookRating'][i]>=0.00 and datacopyf3['BookRating'][i]<=0.05:
    datacopyf3['BookRating'].loc[i]= "Low"
  elif datacopyf3['BookRating'][i]>0.05 and datacopyf3['BookRating'][i]<=0.075:
    datacopyf3['BookRating'].loc[i] = "Med"
  else:
    datacopyf3['BookRating'].loc[i] = "High"
```

In [ ]:

```
# Identifying the predictor variable(x) and Target Variable
X = datacopyf3[["Age",'PublisherCode','BookAuthorCode','BookTitleCode','citycode', 'coun
trycode', 'statecode']]
y = datacopyf3["BookRating"]
```

In [ ]:

```
X_train, X_test, Y_train, Y_test = train_test_split(X,y,test_size=0.25,random_state=42)
```

In [ ]:

```
#Knn model:
kNN = KNeighborsClassifier(n_neighbors=3)
kNN.fit(X_train,Y_train)
pred = kNN.predict(X_test)
```

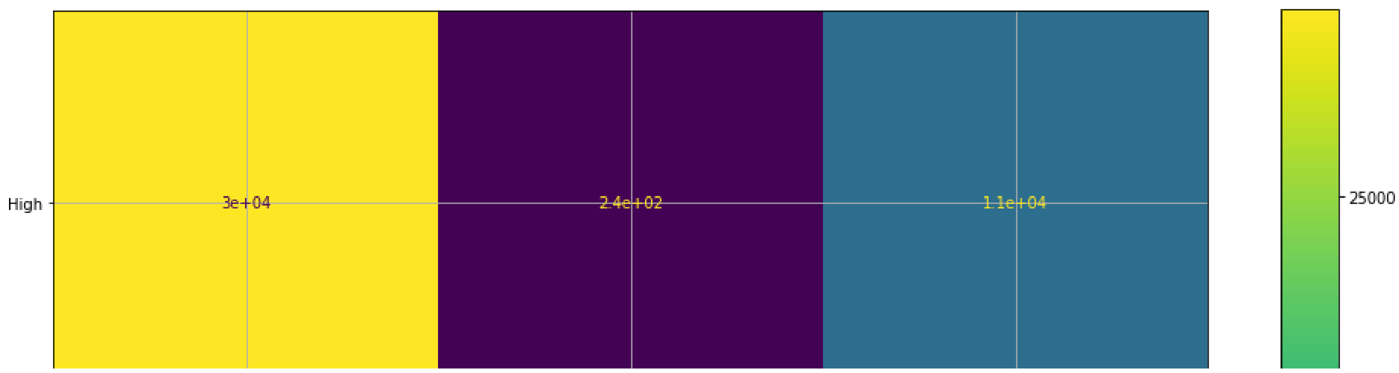
In [ ]:

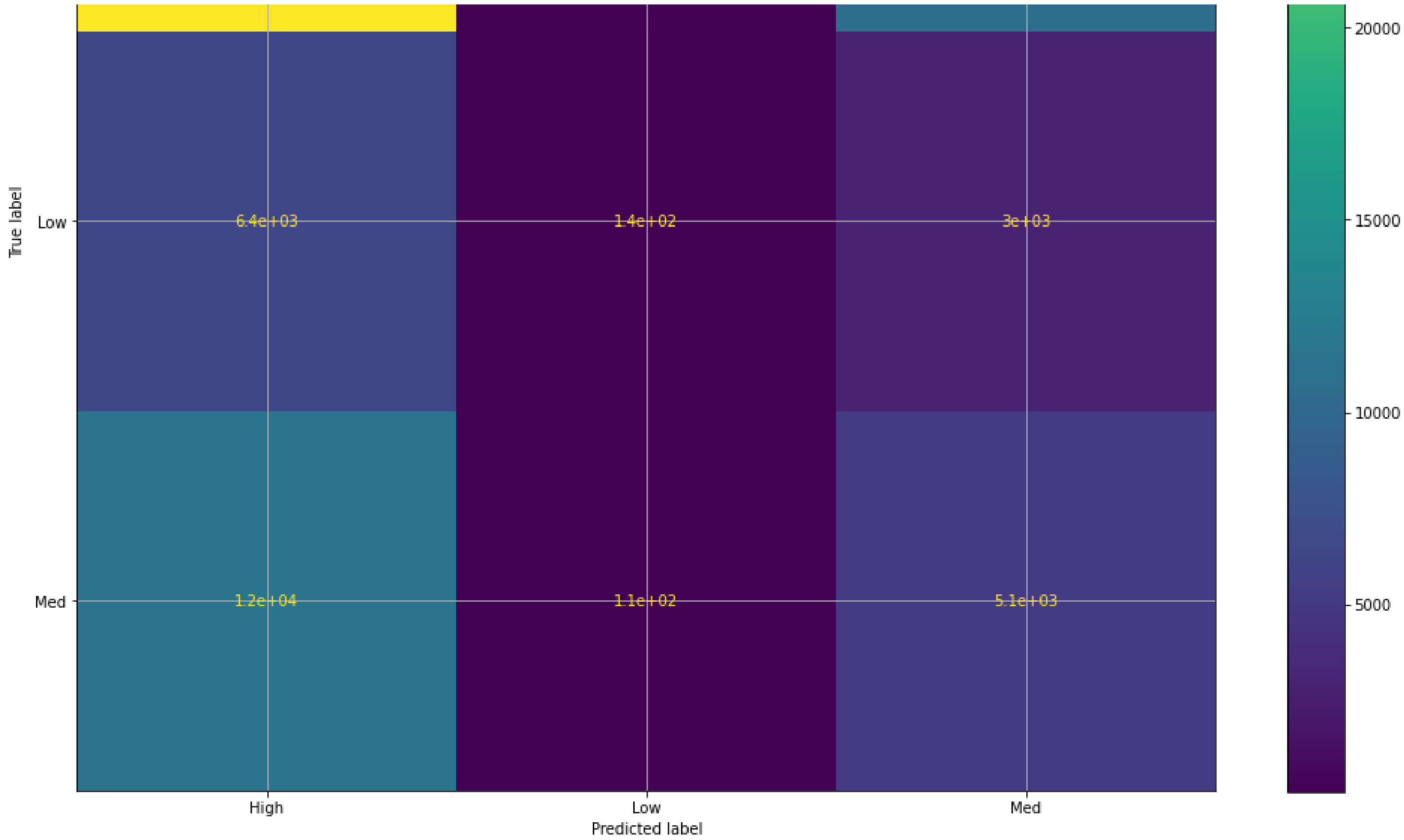
```
#Plotting:
print(confusion_matrix(Y_test,pred))
print('\n')
var=classification_report(Y_test,pred)
print(var)

figure, axis = plt.subplots(figsize=(17,14))
plt.grid(b=None)
plot_confusion_matrix(knn, X_test, Y_test, ax=axis)
```

```
[[32753  2181  5970]
 [ 7167   869  1542]
 [12797  1027  2897]]


              precision    recall  f1-score   support

        High       0.62      0.80      0.70     40904
         Low       0.21      0.09      0.13      9578
         Med       0.28      0.17      0.21     16721

    accuracy                           0.54     67203
   macro avg       0.37      0.35      0.35     67203
weighted avg       0.48      0.54      0.50     67203
```

Out[ ]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7fd762efdc18>
```



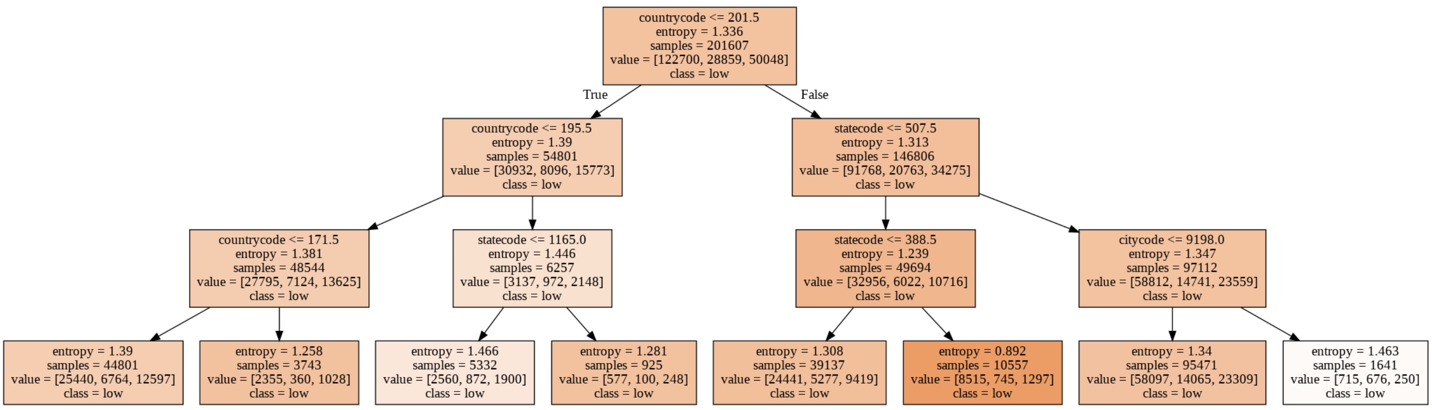


Decison Tree(Decimal Scaling):

In [ ]:

```python
#Decison Tree model
Dtree = tree.DecisionTreeClassifier(criterion='entropy',max_depth=3)
Dtree = Dtree.fit(X_train, Y_train)
dot_data = tree.export_graphviz(Dtree, feature_names=X.columns, class_names=['low','med'
,'high'], filled=True,out_file=None)
graph = pydotplus.graph_from_dot_data(dot_data)
graph.write_png('decisionTree(Decimal Scaling).png')
Image(graph.create_png())
```

Out[ ]:



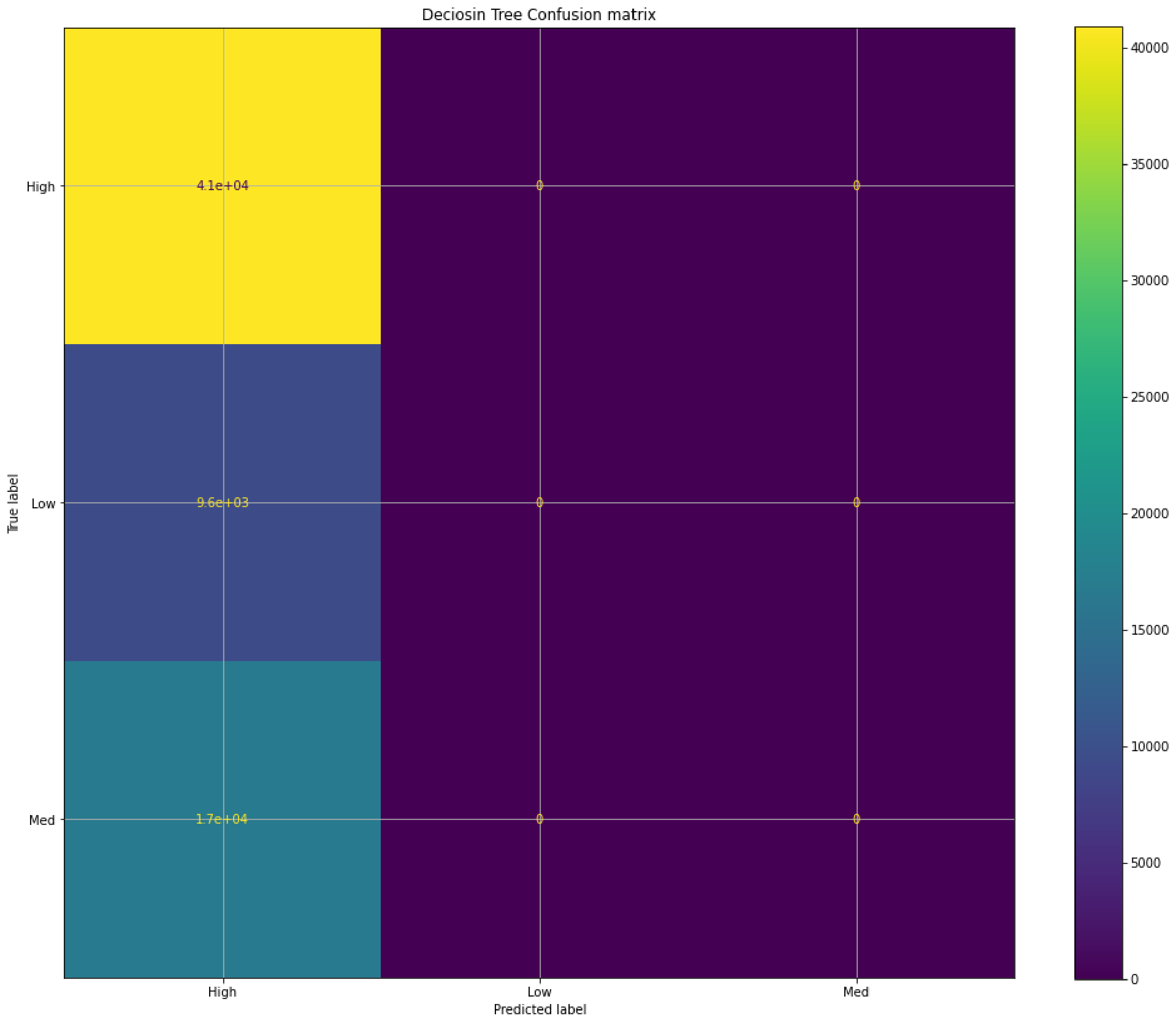
In [ ]:

```python
#plotting:
DecisionTreepredictedY = Dtree.predict(X_test)
print(confusion_matrix(Y_test,DecisionTreepredictedY))
print('\n')
var=classification_report(Y_test,DecisionTreepredictedY)
print(var)

figure, axis = plt.subplots(figsize=(17,14))
plt.grid(b=None)
plot_confusion_matrix(Dtree, X_test, Y_test, ax=axis)
plt.title("Deciosin Tree Confusion matrix")
```

```
[[40904     0     0]
 [ 9578     0     0]
 [16721     0     0]]

              precision    recall  f1-score   support

        High       0.61      1.00      0.76     40904
         Low       0.00      0.00      0.00      9578
         Med       0.00      0.00      0.00     16721

    accuracy                           0.61     67203
   macro avg       0.20      0.33      0.25     67203
weighted avg       0.37      0.61      0.46     67203
```

Out[ ]:

```
Text(0.5, 1.0, 'Deciosin Tree Confusion matrix')
```



Unsupervised Learning:

K-Means:(Decimal-Scaling Normalization):

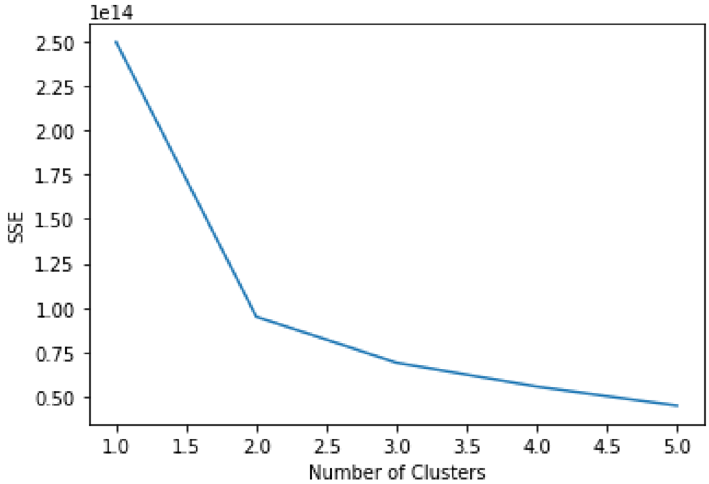
In [ ]:

```
# Identifying the Traget Variable:
datacopyf3['BookRating'] = pd.Categorical(datacopyf3['BookRating'])
```

```
datacopyf3['BookRatingCode'] = datacopyf3['BookRating'].cat.codes
y_encoded= datacopyf3['BookRatingCode']
X_train, X_test, y_train, y_test = train_test_split(X,y_encoded,test_size=0.25,random_st
ate=42)
```

In [ ]:

```
# Kmeans model:
k_means = cluster.KMeans(n_clusters=3, max_iter=50, random_state=1).fit(X_train)
labels = k_means.labels_

numClusters = [1,2,3,4,5]
SSE = []
for k in numClusters:
    k_means = cluster.KMeans(n_clusters=k)
    k_means.fit(X_train)
    SSE.append(k_means.inertia_)
#Sum of squared distances of samples to their closest cluster center.
#plotting:
plt.plot(numClusters, SSE)
plt.xlabel('Number of Clusters')
plt.ylabel('SSE')
plt.show()


Kmeanspredicted = k_means.predict(X_test)
Kmeanspredicted.reshape(-1,1)

var=classification_report(y_test,Kmeanspredicted)
print(var)
```



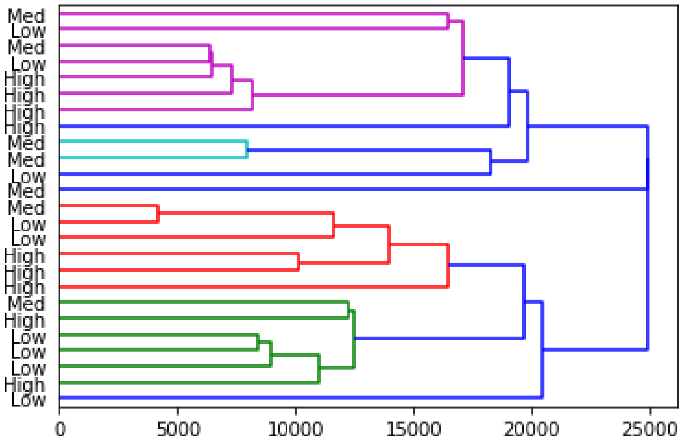

```
              precision    recall  f1-score   support

           0       0.61      0.17      0.26     40904
           1       0.14      0.20      0.17      9578
           2       0.25      0.26      0.25     16721
           3       0.00      0.00      0.00         0
           4       0.00      0.00      0.00         0

    accuracy                           0.20     67203
   macro avg       0.20      0.13      0.14     67203
weighted avg       0.45      0.20      0.25     67203
```

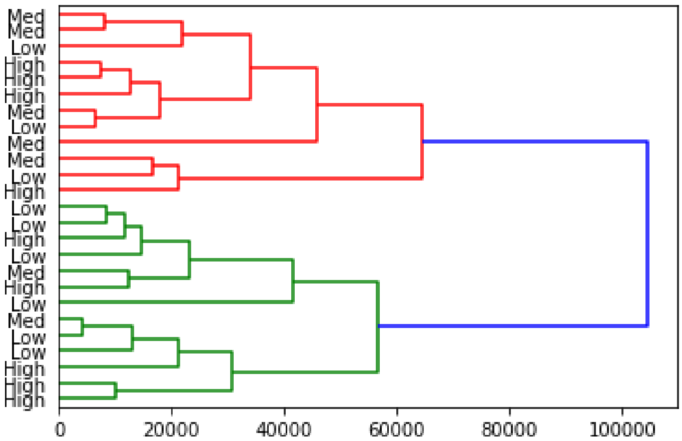
Hierarchy Clustering(Decimal Scaling):

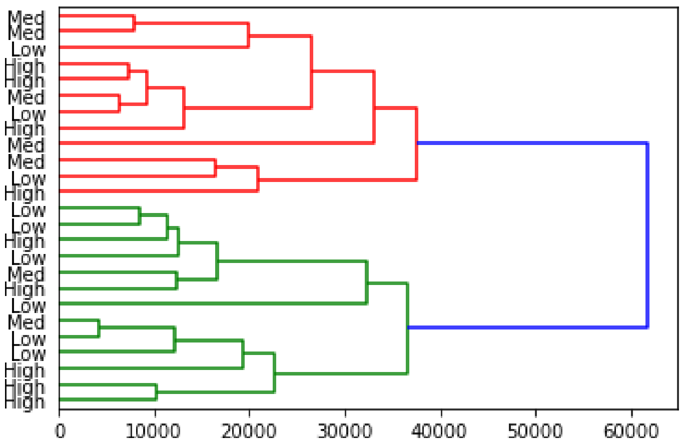
In [ ]:

```
# Slicing Predictor variable:
X_reduced = X_train[:25]
names = datacopyf3['BookRating']
#Hierarchy Model:
Z = hierarchy.linkage(X_reduced, 'single')
```

```
dend = hierarchy.dendrogram(Z,labels=names.tolist(),orientation='right')
plt.show()
Z = hierarchy.linkage(X_reduced, 'complete')
dend = hierarchy.dendrogram(Z,labels=names.tolist(),orientation='right')
plt.show()
Z = hierarchy.linkage(X_reduced, 'average')
dend = hierarchy.dendrogram(Z,labels=names.tolist(),orientation='right')
plt.show()
```







In [ ]:

```
print('-X-'*100)
print(' '*50 + "The End" + ''*10)
```

```
-X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X-
-X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X-
-X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X--X-
-X--X--X--X--X--X--X--X--X--X--X--X--X-
                                                  The End
```