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Executive Summary

In this data mining report, we have used WEKA as our main software to identify the question we faced. Data mining on WEKA is an effective method to help us improve our findings.

It is believed that student graduates have been a factor in the future income. Multiple factors and variables that are provided are the data gained on the student income 2 years after the graduation. Moreover, the covid-19 pandemic caused uncertainties. Using WEKA and its multiple algorithms will eventually remove unnecessary variables and gain some knowledge from the data provided.

In a glance, the class of the data is the income_group variable, and some of the variables are not set accordingly. The variables seem to be having missing values and outliers on the numerical data. We used transformation to change the datatype accordingly, remove the unwanted attribute, and replace missing values before discretizing and SMOTE.

As to train the datasets, we used ZeroR as the benchmark, followed by other 4 models are J48, NaiveBayes, IBk, and SimpleLogistic. The train results showed that IBk has the best training model but overfitted the models. Therefore our second best model is tuned J48 which has the best result in evaluating the model.

In the analysis part of the writing process, we will visualise the data and compare the income group in each category. We realised that graduates with a Bachelor degree in Multidisciplinary, health degree holders, graduates who completed the four-year program will likely get a higher pay. As most of the data has illustrated that they will fall in "above average" or "high" income groups.

Besides that, we also found out a bachelor degree holder is more likely to be paid a higher salary than a graduate who only obtains a certificate degree after graduation. Companies will probably be willing to pay higher salaries to graduates from well-known "private for non-profit" institutions.

In conclusion, J48's accuracy, weighted F-measure, and also the weighted ROC have been increased significantly. It is clearly shown that the algorithm is suitable for us as our final model. For the recommendation, we think that it is better to have more time to complete it as the exceedingly huge amount of data and its features makes it more complicated to straightway understand some insights, and it is time-consuming to bring out the best optimal model.

TeamC5 - Group Reflective Video: <u>https://youtu.be/tvcazateshk</u>

Introduction and Methodology

In order to determine the factors behind a graduate's future income, we are going to discuss the options and education level of a student along with other variables that are given in the datasets. What are the advantages of continuing your education? Students wonder if their academic achievements will be worthwhile in the long run. They choose to pursue higher education for a variety of reasons. The expectancy of future salary based on educational achievement is one of the most motivating.

We believe that most students have chosen their universities and academic programs based on the desired incomes in their future goals. Therefore, people are asking the question which option they made will provide the most income in their future life. So, we would like to find out what attributes are important and meaningful for the students to get a higher pay after their graduation.

The datasets provided include training and testing data, containing information on 13,818 students' income, 2 years after their graduation. The variables in the given datasets are focused on four sectors, namely **academic program** (academics program in different field, percentage of degrees awarded in field, cost of tuition fees, etc), **school related variables** (highest degree awarded at institution, staff salaries, level of institution, state of the institutions, etc), **student characteristics** (gender, part time/full time, marital status, etc), **degree related variables** (such as number of degree-types offered at institution). There are 265 variables in total and income group is the class label of the datasets. The result of the income group has been classified into four groups: **below average, average, above average** and **high**.

In this period of uncertainty, many youths are feeling uncertain about the future especially for high school and university students, the COVID-19 pandemic has brought a huge impact to their lives. Job possibilities are scarce and limited in the coming years, no matter what your degree or educational level is. It is often believed that the better your educational background, the greater your possibilities of being hired for a decent job (Elmi, 2010). The main goal of this report is to come up with an idea of a positive decision guideline for identifying relevant variables for generating the most income for the future of graduate students.

We are going to solve the problem by merging the training and testing data, then giving them a row of new id. There will be 13,818 instances and 265 attributes (train= 1-10,169; test= 10,170-13,818). For our data pre-processing part on WEKA, we filter out the attributes by applying *NumericToNominal*. Then, we will set missing values threshold and correlation threshold, remove those attributes which have more than 5% of missing values while have a correlation lower than 0.1. After the removal, we will use the feature of *ReplaceMissingValues* in the filter for those attributes which are not removed.

Now, we will discretise the remaining attributes. Furthermore, we will remove the attributes with attribute selection of *InfoGainAttributeEval* and *Ranker search method*, we decided to set a threshold at 0.1. As a result, we will have 32 attributes left for our data.

Then, we filter the instances by applying the *RemoveRange* feature for our train and test data. Our instances remain unchanged. Lastly, we resample the training dataset by applying the Synthetic Minority Oversampling TEchnique (SMOTE).

In the modelling part, we will first set a benchmark by using the ZeroR algorithm. Then, we will do the modelling by using different classifiers, namely **NaiveBayes, J48, IBk** and **SimpleLogistic.** For the evaluation of test data, we will apply the same algorithms by selecting

the supplied *test set* to get the result. After getting the result from our modelling, we will focus on the accuracy, F-measure, ROC Area and time-taken. We will choose the model with high accuracy, high F-measure, high ROC Area with least time-taken as our standard.

Moreover, we will analyse our report by focusing on the valuable insights we have generated from the data mining process and we will highlight our visualisations in that stage. In the end of the report, we will select our best model and bring along with our recommendations. We will define the key factors that generate the most income in the future.

Data Preprocessing

The first step of data preprocessing is merging the original train and test datasets provided using MS Excel. This is done to tackle the variable and instance label discrepancy issues that existed in both datasets. The combined dataset has a total of 265 variables including the row ID and 13,818 instances consisting of 10,169 train data instances and 3,649 test data instances. This merged data file is then ready to be transformed in WEKA.

Upon uploading to WEKA, the first variable which is the row ID was removed as it only acts as identifier values for the instances and might affect the overall Classification performance. Thus, only the 263 remaining predictor variables and 1 target variable are used in the next step.

a. Summary Statistics

The data comprises 264 variables for 13,818 students' income, 2 years after their graduation. The data was compiled from a wide range of publicly available government data sources. The attribute, *income_group* is the Class label in this dataset. These 264 predictor variables can be used to evaluate 3,649 students' income group 2 years after their graduation.

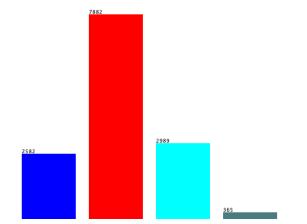


Figure 1: Summary statistics for the class attribute

The class attribute is divided into four income groups: "Below Average," "Average," "Above Average," and "High." There are 2582 instances in the category "Below Average," 7882 instances in the category "Average," 2989 instances in the category "Above Average," and 365 instances in the category "High." Based on the summary statistics presented above, we can conclude that the class attribute has an imbalanced distribution. This is due to the fact that the "High" income class has 21.5 times fewer instances than the "Average" income group. An unbalanced dataset will bias the prediction model towards the more common class. Hence, action is needed to deal with the problem.

• Attribute 229, 230 and 235 (cost_tuition_[in/out]_state, school_faculty_salary)

They are all numerical variables. Their summary statistics are skewed to the left and contain some outlier values. All of them have a high proportion of missing values (>5%) as compared to other attributes that have a lower percentage of missing values. Furthermore, all of the attributes have a high standard deviation, indicating that they are not good variables to be included in the model.

• Attribute 236 (school_ft_faculty_rate)

This is a numerical attribute that illustrates the full-time staff rates. It is demonstrated in percentage form ranging between 0 to 1. It consists of 4866 missing values which account for 35% of the total instances. We can conclude that it is not a good predictor and should not be added into the model.

• Attribute 238, 244 and 258 (school_instuctional_expenditure_pre_fte, school_tuition_revenue_per_fte and student_size) All of them are numerical attributes. They consist of 1% of missing value which is

relatively lesser (<5%) as compared to other attributes who have a higher percentage of missing value. Their summary statistics have shown that the distribution curve is skewed to the left and have outlier values. Both of them also have extremely high standard deviations which are not good to be fitted into our model.

• Attribute 247,252 and 253 (student_demographics_female_share, student_share_25_older and student_share_first_time_full_time)

All of them are numerical variables. They are shown in percentage form ranging between 0 to 1. All of them have a high proportion of missing values (>5%) as compared to other attributes that have a lower percentage of missing values. Their summary statistics have shown that the distribution curve is "abnormal". Hence, they are not a good variable to be included into our model.

Attribute 249 and 250 (student_demographic_married and student_demographics_veteran)

They are all numerical variables that show the proportion of married and veteran students. Both of them are demonstrated in percentage form ranging between 0 to 1. Their summary statistics are skewed to the left and contain some outlier values. All of them have a high proportion of missing values (>5%) as compared to other attributes that have a lower percentage of missing values. Thus, they are not good predictor variables.

• Attribute 255 and 256 (student_share_firstgeneration_parents_highschool and student_share_firstgeneration_parents_somecollege)

All of them are numerical variables. They are shown in percentage form ranging between 0 to 1. All of them have a high proportion of missing values (>5%) as compared to other attributes that have a lower percentage of missing values. Their summary statistics have shown that the curves are distributed normally.

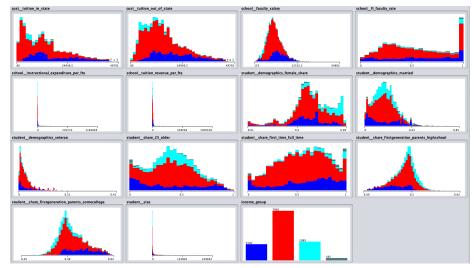


Figure 2: summary statistics for all highlighted attributes

b. Transformation

As mentioned in the above part, the *income_group* is the class attribute in this dataset. Since this variable has categorical values, it is suitable for us to use the Classification Predictive method in our modelling process. Thus, the numerical predictive attributes are required to be transformed into their nominal counterparts.

Firstly, the NumericToNominal filter is put on to the wrongly identified numerical variables which variables supposedly measured categorical values. These are as include academics__program_[name]_[field] 1st-190th variables represented by school degrees awarded predominant recoded 234th represented by variable and *degrees_highearning* represented by 263rd variable.

ter	
Choose NumericToNominal -R 1-190,234,263	Apply Stop

Secondly, the dataset needs to be cleaned by removing or replacing the visible missing values. Based on the summary statistics provided in WEKA, the existing missing values proportion varies between 0% and 48%. Nevertheless, the consensus threshold is set at 5% as most of the portions are below this value. The removal of attributes was done to variables with missing values of more than 5% and correlation value of less than 0.1 with *income_group* (*Appendix 1*).

Using the default settings of *CorrelationAttributeEval* and *Ranker* as shown above, attributes *school__ft_faculty_rate* (236), *school__online_only* (240), *student__demographics_married* (249), *student__demographics_veteran* (250), *student__share_25_older* (252) and *student__share_first_time_full_time*(253) are removed from the datasets. Whereas, the remaining variables with missing values are fixed using *ReplaceMissingValues* filter.

Iter Choose Remove -R 236,240,249-250,252-253	Apply Stop
lter	

Thirdly, the remaining numerical variables are transformed into categorical counterparts by binning it using the default settings of the Discretization filter in WEKA. Moreover, using Discretization is more appropriate in this dataset as it would resolve the outlier and extreme values problems without actually removing it with the usual InterquartileRangefilter. One of the reasons is that most of the independent variables consist of several extreme values which might be useful in predicting the High category in *income_group* class attribute. The variables that were discretized include academics__program_percentage_[field] (191 - 228),cost__tuition_[in/out]_state (229–230), school___faculty_salary(235), school__instructional_expenditure_per_fte (237), school__tuition_revenue_per_fte (242) and several student and degrees related variables (243-256).

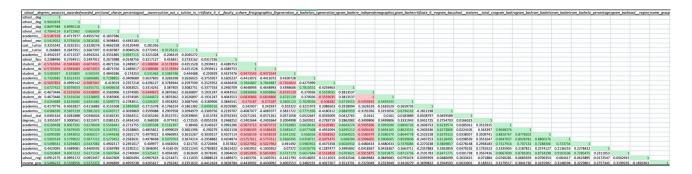
Filter		
Choos	Discretize -B 10 -M -1.0 -R 191-230,235,237,242-256 -precision 6	Apply Stop

c. Attribute Selection

The 257 predictors are further processed with a feature selection method where the irrelevant and redundant attributes are removed to have a better estimation performance. After doing several iterations in the Select Attributes panel with different parameter settings of Attribute Evaluator and Search Method, the *InfoGainAttributeEval* and *Ranker* is proven to project the most accurate rank selection of the variables. Based on the attribute selection output and some trial & errors, the removal is done to a total of 226 attributes that have values below the determined threshold which is 0.1. The remaining 31 significant predictors and 1 target variable are ready to be used in further modelling process.

Filter Choose Attribute	•Selection -E "weka.attributeSelection.InfoGainAttributeEval " -S "weka.attributeSelection.Ranker -T -1.79769313	48623157E308 -N -1" Apply Stop
Attributes:	32 schooldegrees_awarded_highest schooldegrees_awarded_predominant schooldegrees_awarded_predominant_recoded schoolinstitutional_characteristics_level academicsprogram_percentage_personal_culinary schoolownership costtuition_out_of_state costtuition_in_state academics_program_certificate_lt_2_yr_personal_culinary schoolfaculty_salary studentshare_firstgeneration studentdemographics_first_generation studentshare_firstgeneration_parents_somecollege academics_program_bachelors_business_marketing studentshare_firstgeneration_parents_highschool	<pre>academics_program_bachelors_computer studentshare_independent_students studentdemographics_dependent academics_program_bachelors_psychology academics_program_bachelors_health schoolstate degrees_total_count academics_program_bachelors_english academics_program_bachelors_history academics_program_bachelors_social_science academics_program_bachelors_mathematics academics_program_bachelors_multidiscipline academics_program_bachelors_multidiscipline academics_program_bachelors_biological school_region_id income_group</pre>

The relationship of these attributes can be seen in the MS Excel Correlation Matrix as well as the WEKA Visualization panel (*Appendix 2*).



According to the graphs above, it is shown that there are more strong positive correlations between the variables compared to the negative correlations. These attributes are the final variables to be included in the modelling process. However, it is not suitable to use 100% of the data since it might cause overfitting issues. Thus, the data was required to be split back into 2 dataset i.e., train data and test data in accordance with the ordering of the original dataset provided. This step is done by using the *RemoveRange* filter. Firstly, to obtain the 10169 train data set, the *instancesIndices* is set at 10170-13818. After the training dataset is saved, the step is reverted by clicking the 'Undo' button. Then, the remaining would be the 3649 test data instances which can be obtained using the same parameter but with *invertSelection* as 'True'.

Filter Choose RemoveRange -R 10170-13818	Apply St
Filter	
Choose RemoveRange -V -R 10170-13818	Apply Sta

Upon opening the training dataset in WEKA, the target attribute is shown to be unbalanced which might affect the overall modelling performance. Thus, income_group variable was rebalanced using SMOTE to the 4th indices in class value and it is set to add 500% instances. This final training dataset consists of 10774 instances which are then ready to be used for modelling purposes.

Filter	
Choose SMOTE -C 4 -K 5 -P 500.0 -S 1	Apply Stop

Modelling

a) Setting Benchmark with ZeroR

ZeroR algorithm is chosen to be the benchmark since it is the simplest algorithm that heavily relies on the target rather than the variables.

	Scheme	weka.classifiers.rules.ZeroR						
		College_Income	e_Train_Test_No	Comma-				
		weka.filters.uns	supervised.attrib	ute.Remove-R1-				
		weka.filters.uns	supervised.attrib	ute.NumericToN	Nominal-R1-190,	234,263-		
		weka.filters.uns	supervised.attrib	ute.Remove-R23	36,240,249-250,2	252-253-		
		weka.filters.uns	supervised.attrib	ute.ReplaceMis	singValues-			
	Relation	weka.filters.unsupervised.attribute.Discretize-B10-M-1.0-R191-230,235,237,242-256-precision6-						
		weka.filters.supervised.attribute.AttributeSelection-Eweka.attributeSelection.InfoGainAttributeEval-S						
Model #1 (Base)		weka.attributeSelection.Ranker -T -1.7976931348623157E308 -N -1-						
		weka.filters.unsupervised.attribute.Remove-R32-257-						
		weka.filters.unsupervised.instance.RemoveRange-R10170-13818-						
		weka.filters.supervised.instance.SMOTE-C4-K5-P500.0-S1						
	Attributes	32 attributes						
	Accuracy	54.2324%		Time Taken	0.00 seconds			
	F-Measure	Below Avg	Avg	Above Avg	High	Weighted		
	r-weasure	?	0.703	?	?	?		
	ROC Curve	Below Avg	Avg	Above Avg	High	Weighted		
	NOC Curve	0.499	0.500	0.499	0.498		0.499	

b) Train Datasets

In the training processes, we selected another 4 algorithm that are :

- <u>NaiveBayes</u> is an algorithm create an assumptions on the datas (both presence or absence) that is unrelated towards each other
- <u>J48</u> is the algorithm to create a pruned or unpruned decision tree, and it is commonly used to examine the data categorically and continuously in the data mining process. In this modelling process, the J48 was originally set at 0.25 *confidenceFactor*. However, the tuned version with 0.5 *confidenceFactor* provides a better performance than the output of default parameter setting.
- <u>IBk</u> is an algorithm to classify each class with the similarity between the instances "neighbours". It uses the K-Nearest Neighbour where the gap between each instance in training data is classified based on the distances between instances similarity.
- <u>Simple Logistic</u> regression is an algorithm that looking and taking assumption on the relationship and it produces discrete output

IBk Training Result

No tuning required as the base model has the best output. The accuracy decreases as the changes made on the K- Value. Therefore, it is concluded that we will test using the standard settings. Moreover, IBk has the best performing model among the other 4 models.

	Scheme	weka.classifie	ers.lazy.IBk -K	1 -W 0 -A "we	ka.core.neigh	boursearch.LinearNNSearch -A \"weka.core.			
Model	Relation	weka.filters.unsupervised.attribute.RemoveR1- weka.filters.unsupervised.attribute.NumericToNominal-R1-190,234,263- weka.filters.unsupervised.attribute.RemoveR236,240,249-250,252-253- weka.filters.unsupervised.attribute.ReplaceMissingValues- weka.filters.unsupervised.attribute.BitoH-1.0-R191-230,235,237,242-256-precision6- weka.filters.unsupervised.attribute.BitoH-2810-M-1.0-R191-230,235,237,242-256-precision6- weka.filters.unsupervised.attribute.BitoH-2810-M-1.0-R191-230,235,237,242-256-precision6- weka.filters.unsupervised.attribute.BitoH-2810-M-1- weka.filters.unsupervised.attribute.RemoveR32-257- weka.filters.unsupervised.instance.RemoveR32-257- weka.filters.unsupervised.instance.RemoveRage-R10170-13818- weka.filters.unsupervised.instance.RemoveRage-R10170-13818-							
	Attributes	32 Attributes							
	Accuracy	82.5042%		Time Taker	0.03s				
	F-Measure	Below Avg	Avg	Above Avg	High	Weighted			
	r-weasure	0.796	0.854	0.757	0.934	0.825			
	ROC	Below Avg	Avg	Above Avg	High	Weighted			
	NOC	0.925	0.884	0.912	0.985	0.904			

Evaluation results using test data

ZeroR

	Scheme	weka.classifie	rs.rules.ZeroR				
Model #1 (Base)	Relation	weka.filters.uns weka.filters.uns weka.filters.uns weka.filters.uns weka.filters.uns weka.filters.uns weka.attributeS weka.attributeS	upervised.attrib upervised.attrib upervised.attrib upervised.attrib vervised.attribut ielection.Ranker upervised.attrib	oute.Remove-R1- oute.NumericTol oute.Remove-R2: oute.ReplaceMis oute.Discretize-E e.AttributeSelec -T -1.79769313- oute.Remove-R3:	lominal-R1-190, 36,240,249-250,2 singValues- 10-M-1.0-R191- tion-Eweka.attrii 48623157E308 -I	252-253- 230,235,237,242-256-precision6- buteSelection.InfoGainAttributeEval-S N -1-	
	Attributes	32 attributes					
	Accuracy	55.8783%		Time Taken	0.05 seconds		
	F-Measure	Below Avg	Avg	Above Avg	High	Weighted	
		2	0.717	2	2	2	
		r	0.717				_
	ROC Curve	r Below Avg		Above Avg	High	Weighted	

Tuned J48

	Scheme	weka.classifie	ers.trees.J48 -	C 0.25 -M 2						
		College_Income	e_Train_Test_No	oComma-						
		weka.filters.unsupervised.attribute.Remove-R1-								
		weka.filters.uns	upervised.attrib	ute.NumericTol	Nominal-R1-190,	234,263-				
		weka.filters.uns	upervised.attrib	ute.Remove-R2	36,240,249-250,	,252-253-				
		weka.filters.uns	upervised.attrib	ute.ReplaceMis	singValues-					
	Relation	weka.filters.uns	upervised.attrib	ute.Discretize-B	10-M-1.0-R191	-230,235,237,242-256-precision6-				
		weka.filters.supervised.attribute.AttributeSelection-Eweka.attributeSelection.InfoGainAttributeEval-S								
Model #3		weka.attributeSelection.Ranker -T -1.7976931348623157E308 -N -1-								
(J48)		weka.filters.unsupervised.attribute.Remove-R32-257-								
(340)		weka.filters.unsupervised.instance.RemoveRange-R10170-13818-								
		weka.filters.supervised.instance.SMOTE-C4-K5-P500.0-S1								
	Attributes	32 attributes								
	Accuracy	82.7076%		Time Taken	0.08 seconds					
	F-Measure	Below Avg	Avg	Above Avg	High	Weighted				
	F-IVIEdSULE	0.793	0.834	0.704	0.911	0.807				
	ROC Area	Below Avg	Avg	Above Avg	High	Weighted				
	NOC Alea	0.927	0.858	0.895	0.973	0.887				

Comparison on training and test modelling

Model	Accu	Accuracy		Time Taken (in seconds)		Weighted /g	ROC Area	
	Training	Test	Training	Test	Training	Test	Training	Test
ZeroR	54.2324%	55.8783%	0	0.05	?	?	0.499	?
Naive Bayes	59.5576%	55.6317%	0.664	0.06	0.809	0.555	0.809	0.794
Tuned J48	80.7964%	82.7076%	0.07	0.08	0.807	0.807	0.887	0.887
IBk	82.5042%	91.5419%	0.03	4.4s	0.825	0.914	0.904	0.961
Simple Logistic	79.0236%	75.5549%	52.96	53.99	0.788	0.751	0.917	0.9

Training Dataset

From the result shown above, The algorithm that has improved its accuracy during the test data is ZeroR, Tuned J48, and IBk, most of the model has a longer processing time during evaluation using the test data except for Naive Bayes. Moreover, the F-measure which the accuracy on the test indicators improved on the IBk, stayed the same for Tuned J48 and decreased for Naive Bayes and Simple Logistic algorithm. Lastly, Naive Bayes, Tuned J48 and IBk improved it's ROC area which also a measurement of the algorithm performance but slightly decreased on the Simple Logistic algorithm.

In general, all of the algorithms have passed the benchmark which has been set by the simplest algorithm, ZeroR with a score of 54.2324%.

Based on the output as shown above, the Naive Bayes algorithm has the least percentage of correctly classified instances, weighted F-measure and also the weighted receiver operating characteristic (ROC) as compared to other algorithms. Meanwhile, the IBk algorithm has the highest proportion of correctly classified instances, as well as the highest score for both weighted F-measure and weighted ROC scores.

Furthermore, after tuning the confidence factor of the J48 algorithm from 0.25 to 0.5, we discovered that the percentage of correctly classified instances improved by 1.6707 percent. As a result, we opted to use the tuned version to evaluate our test dataset as it has the higher capability in estimating data.

To summarise, IBk has the highest level of understanding of how the given input variables are associated with the class attribute.

Testing Dataset

On the test data evaluation, J48, IBk and SimpleLogistic have passed the benchmark which has been set by the simplest algorithm, ZeroR with a score of 55.8783%, while NaiveBayes has a lower percentage of correctly classified instances than ZeroR. Hence, we will omit NaiveBayes in our following comparison analysis.

Based on the output as shown above, the SimpleLogistic algorithm has the lowest percentage of correctly classified instances, weighted F-measure and also the weighted receiver operating characteristic (ROC) as compared to other algorithms. Meanwhile, the IBk algorithm has the highest percentage of correctly classified instances, weighted F-measure and also the weighted ROC.

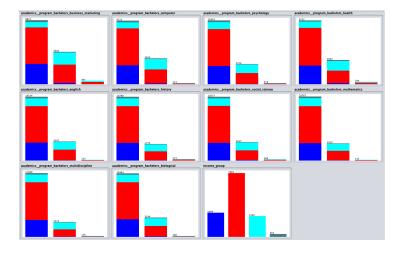
Although the IBk algorithm has the highest accuracy in predicting the model, it is inadequate to be chosen as the best classifier as it has an incredibly high percentage of correctly classified instances with a score of 91.5419%. This is due to the fact that when the score of correctly classified instances exceeds 85% and above, the model becomes overfitting. Overfitting occurs when a model learns the detail and noise in the data to the extent that it negatively impacts the performance of the model on new data. This implies that the algorithm picks up on noise or random fluctuations in the input and learns it as a concept.

As a result, the J48 (tuned) algorithm will be our most optimal model. Throughout the iteration processes, the accuracy, weighted F-measure, and also the weighted ROC of the J48 model have been increased significantly. Thus, it is suitable for us to use the **J48** as our final model.

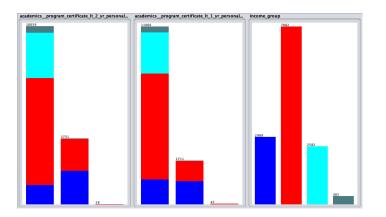
Analysis

The "academics_program_bachelor_history" illustrates that graduates with a Bachelor degree in Multidisciplinary have the lowest probability of getting "below average" income as compared to other degree holders. From the summary of this attribute, we can visually see that it has the least "below average" income group (dark blue) for the "offered" category.

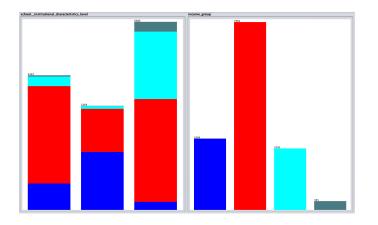
Moreover, the "acedemics_program_bachelor_health" attribute shows us that graduates with a Bachelor degree in Health have the highest probability of having a "high" income as compared to other degree holders. As we know, "health" professions normally have higher salaries. It shows that it has the highest proportion of "high" income groups under the "offered" category.



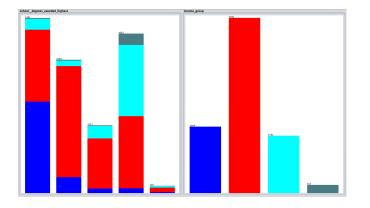
The "academics_program_cerificate_lt_2_yr_personal_culinary" attribute indicates that graduates with a Certificate Degree for 2 years in Personal culinary are more likely to earn "below average" income than graduates with a Certificate Degree for 1 year in Personal culinary. It shows that it has the highest percentage of "below average" income groups under the "offered" category.



The "school_institutional_characteristics_level" attribute shows that graduates from institutions who have studied a program which is less than 2 years have the highest percentage of getting "below average" income. On the contrary, graduates from institutions who have studied a program for 4 years have the highest probability of getting a "high" or "above average" income. As a result, we can conclude that graduates who completed the four-year program have a better chance of earning a higher salary.



When we compare the two types of academic programs, Bachelor Degree and Certificate Degree, we can see that a Bachelor Degree holder is more likely to be paid a higher salary than a graduate who only obtains a certificate Degree. Based on our common knowledge, we know that people who graduate with a Bachelor Degree tend to have a higher salary as compared to those who graduated with a Certificate Degree. This indicates that it is better to obtain a Bachelor Degree rather than taking a Certificate Degree regardless of the programs taken. This is proven by the attribute "school_degree_awarded_highest" as we can see Certificate Degree holders have the highest probability of getting "below average" income as compared to other degree programs.



Based on the analysis above, we would recommend that students should take at least a Bachelor Degree program so that they will have a higher income when starting to work. Furthermore, Certificate Degree holders should further their studies to get a higher income. Graduates seeking a higher income job are advised to obtain a "Graduate Degree," regardless of the programs they are pursuing at the institution, as obtaining a "Graduate Degree" will increase their chances of obtaining an "above average" or "high" income profession.

Moreover, it is important for students to take into consideration what type of institution they graduate from. Students who graduated from a "private for non-profit" institution tend to have the highest probability of getting an "above average" or maybe a "high" income. This may be due to the fact that "private for non-profit" institutions are mainly private prestigious universities that usually have higher tuition fees. Companies will almost certainly be willing to pay higher salaries to graduates from well-known institutions.

Conclusion and Recommendations

The most appropriate technique to handle this dataset is Classification Analysis as our objective is to see what are the factors that increase income in the future (categorical variable). In the data preparation, the training dataset is pre-processed using several filters such as NumericToNominal, ReplaceMissingValues, Discretize, and SMOTE. The cleaned and preprocessed dataset consists of a total 31 significant predictors to estimate the target classification.

As mentioned in the introduction part, the 5 modelling algorithms used in this report are *ZeroR*, *NaiveBayes*, *J48*, *IBk*, and Simple Logistic Regression. After running iterations on the algorithms and its corresponding parameter settings, the J48 (tuned) algorithm will be our most optimal model using the method Cross Validation (k=10). This is because the J48 algorithm has performed consistently throughout the training and testing dataset and it has an optimum percentage of correctly classified instances after eliminating all of the irrelevant attributes by using "InfoGainAttributeEval" and "Ranker".

Furthermore, as opposed to other algorithms, J48's confusion matrix has the optimal number of wrongly classified instances. Although the IBk algorithm's confusion matrix has the least number of wrongly classified instances, it seems to be overfitting. This is due to the fact that it has an incredibly high percentage of accuracy for all of its performance indicators.

<u> J48 (6</u>	31 wr	rongly	/ class	sified instances)	IBk (309 wrongly classified instances)									
=== Cc	onfusi	on Ma	trix =	==	=== Co	onfusi	on Ma	trix :						
а	b	С	d	< classified as	а	b	С	d	< classified as					
579	150	2	0	a = Below Average	717	14	0	0	a = Below Average					
109	1812	112	6	b = Average	108	1862	65	4	b = Average					
1	110	515	9	c = Above Average	1	11	622	1	c = Above Average					
4	34	94	112	d = High	3	22	80	139	d = High					

Throughout the iteration processes, the accuracy, weighted F-measure, and also the weighted ROC of the J48 model have been increased significantly. Thus, it is suitable for us to use the **J48** as our final model.

We apply the principles of CRISP-DM using each of the methods described in order to provide clear and workable business intelligence models based on the dataset given. We use advanced data modeling and machine learning methods to create new meaning to help students to choose what to study but a recurring concern is future income.

There are some recommendations to obtain a better understanding and estimation of predicting the future income of higher education students. A better way of visualizing can be developed if more time is given. The exceedingly large amount of data and its features makes it difficult to immediately grasp some insights, and it is time-consuming to create the most optimal model. Our group might also have some unsupervised approaches such as trying to combine some of the similar features together and identifying the association between the variables. Thereby, we could obtain some possible alternative techniques in determining what factors affect future earnings of university students.

References

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Appendices

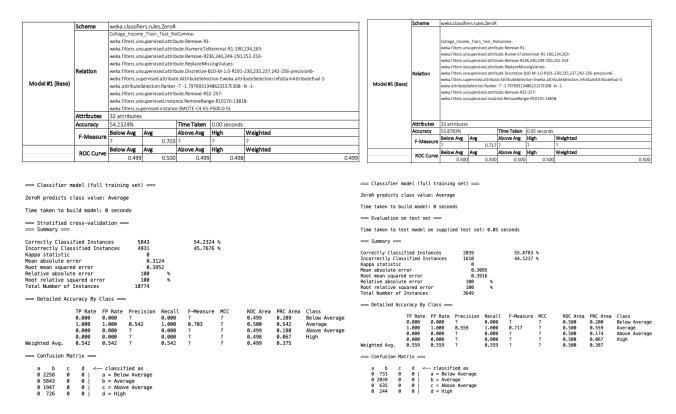
Appendix 1. CorrelationAttributeEval - Remove variables that have more than 5% missing values and are not highlighted.

=== Kun 1nto	ormation ===	0.16299	00 contraint annual contribute 1t 1 an huminess annuation
		0.16299	<pre>80 academics_program_certificate_lt_1_yr_business_marketing</pre>
Evaluator: Search:	<pre>weka.attributeSelection.CorrelationAttributeEval weka.attributeSelection.Ranker -T -1.7976931348623157E308 -N -1</pre>	0.16214	91 academics_program_certificate_lt_1_yr_health
Relation:	College Income Train Test NoComma-weka.filters.unsupervised.attribute.Remove-		<pre>128 academics_program_certificate_lt_2_yr_family_consumer_science</pre>
Relation:	<pre>college_income_irain_lest_wocomma-weka.tilters.unsupervised.attribute.kemove-</pre>	0.1579	93 academics_program_certificate_lt_1_yr_humanities
Instances:	13818	0.15569	48 academicsprogram_bachelors_engineering
Attributes:	264	0.15492	84 academics_program_certificate_lt_1_yr_construction
Acti Ibuces.	[list of attributes omitted]	0.15377	247 studentdemographics_female_share
Evaluation m		0.15316	<pre>90 academics_program_certificate_lt_1_yr_family_consumer_science</pre>
		0.15221	62 academicsprogram_bachelors_multidiscipline
		0.15051	<pre>8 academicsprogram_assoc_construction</pre>
		0.14972	53 academics_program_bachelors_health
=== Attribut	te Selection on all input data ===	0.14928	<pre>122 academics_program_certificate_lt_2_yr_construction</pre>
		0.14871	133 academicsprogram_certificate_lt_2_yr_legal
Search Metho		0.14848	<pre>83 academicsprogram_certificate_lt_1_yr_computer</pre>
Attr	ibute ranking.	0.1462	9 academics_program_assoc_education
	valuator (supervised, Class (nominal): 264 income group):	0.14601	<pre>6 academics_program_assoc_communications_technology</pre>
	elation Ranking Filter	0.14504	<pre>114 academics_program_certificate_lt_1_yr_visual_performing</pre>
Ranked attri		0.14415	45 academicsprogram_bachelors_computer
	216 academics program percentage personal culinary	0.14281	<pre>51 academicsprogram_bachelors_ethnic_cultural_gender</pre>
	232 school degrees awarded highest	0.1412	76 academicsprogram_bachelors_visual_performing
0.21246	4 academics program assoc business marketing	0.13797	68 academics_program_bachelors_psychology
0.21223	34 academics program assoc security law enforcement	0.13395	200 academicsprogram_percentage_engineering
0.21181	7 academics_program_assoc_computer	0.13369	73 academics_program_bachelors_social_science
	233 schooldegrees_awarded_predominant	0.13243	42 academics_program_bachelors_business_marketing
	<pre>118 academics_program_certificate_lt_2_yr_business_marketing</pre>	0.13119	<pre>41 academics_program_bachelors_biological</pre>
	259 degrees_total_count	0.13013	95 academics_program_certificate_lt_1_yr_legal
0.20601	<pre>11 academics_program_assoc_engineering_technology</pre>	0.1289	<pre>120 academics_program_certificate_lt_2_yr_communications_technology</pre>
	260 degreesassoc_count	0.12788	225 academics_program_percentage_social_science
	129 academics_program_certificate_lt_2_yr_health	0.12786	1 academics_program_assoc_agriculture
	140 academics_program_certificate_lt_2_yr_personal_culinary 148 academics_program_certificate_lt_2_yr_security_law_enforcement	0.12723	251 student_part_time_share
0.19937	143 academics_program_certificate_lt_2_yr_security_law_enforcement 143 academics_program_certificate_lt_2_yr_precision_production	0.12683	66 academics_program_bachelors_physical_science
0.19852	241 school ownership	0.12571	59 academics_program_bachelors_mathematics
0,19834	256 student share firstgeneration parents somecollege	0.12531	65 academics_program_bachelors_philosophy_religious
0.19661	38 academics program assoc visual performing	0.1246	<pre>123 academics_program_certificate_lt_2_yr_education</pre>
0.19603	15 academics_program_assoc_health	0.12266	55 academicsprogram_bachelors_humanities
	<pre>136 academics_program_certificate_lt_2_yr_mechanic_repair_technology</pre>	0.1216	50 academicsprogram_bachelors_english
	235 schoolfaculty_salary	0.12095	194 academics_program_percentage_business_marketing
	237 schoolinstitutional_characteristics_level	0.11806	<pre>178 academics_program_certificate_lt_4_yr_personal_culinary</pre>
	230 cost_tuition_out_of_state	0.11786	54 academicsprogram_bachelors_history
0.1915 0.19149	262 degrees_certificate_count 207 academics program percentage humanities	0.11725	<pre>47 academicsprogram_bachelors_education</pre>
0.19149	<pre>287 academics_program_percentage_numarities 98 academics_program_certificate_lt_1_yr_mechanic_repair_technology</pre>	0.11686	56 academicsprogram_bachelors_language
0.18892	22 academics_program_cercificate_it_iyr_mechanic_repair_technology	0.11617	69 academicsprogram_bachelors_public_administration_social_service
	248 student demographics first generation	0.11582	224 academics_program_percentage_security_law_enforcement
	254 student share firstgeneration	0.11114	70 academicsprogram_bachelors_resources
0.1877	125 academics program certificate lt 2 vr engineering technology	0.11054	43 academics_program_bachelors_communication
0.18647	131 academics program certificate lt 2 vr humanities	0.11013	<pre>85 academics_program_certificate_lt_1_yr_education</pre>
0.18477	255 student share firstgeneration parents highschool	0.1087	<pre>151 academics_program_certificate_lt_2_yr_transportation</pre>
0.1842	19 academics_program_assoc_legal	0.10756	246 student_demographics_dependent
0.18279	29 academics_program_assoc_precision_production	0.10756	257 student_share_independent_students
	<pre>105 academics_program_certificate_lt_1_yr_precision_production</pre>	0.10642	<pre>115 academics_program_certificate_lt_2_yr_agriculture</pre>
	234 schooldegrees_awarded_predominant_recoded	0.10611	193 academicsprogram_percentage_biological
0.17907 0.17843	87 academics_program_certificate_lt_1_yr_engineering_technology 26 academics_program_assoc_personal_culinary	0.10492	40 academics_program_bachelors_architecture
0.17843	26 academics_program_assoc_personal_culinary 17 academics program assoc humanities	0.10404	<pre>113 academics_program_certificate_lt_1_yr_transportation</pre>
	17 academics_program_assoc_numanities 102 academics_program_certificate_lt_1_yr_personal_culinary	0.10384	174 academics_program_certificate_lt_4_yr_mechanic_repair_technology
	162 academics_program_certificate_it_iyr_personal_culinary 152 academics_program_certificate_it_2 vr visual_performing	0.1038	82 academics_program_certificate_lt_1_yr_communications_technology
	110 academics_program_certificate_lt_2_yr_visual_performing	0.10376	77 academics_program_certificate_lt_1_yr_agriculture
	263 degrees_high_earning	0.10278	63 academics_program_bachelors_parks_recreation_fitness
	229 cost_tuition in state	0.1011	<pre>25 academics_program_assoc_parks_recreation_fitness</pre>
0.1656	14 academics program assoc family consumer science	0.101	<pre>124 academics_program_certificate_lt_2_yr_engineering</pre>
	121 academics program certificate lt 2 yr computer	0.10029	206 academics program percentage history

Appendix 2. Correlation Visualization the final 32 attributes

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Appendix 3. ZeroR - Training and Testing Output



Appendix 4. NaiveBayes - Training and Testing Output



=== Stratified cross-validation === === Summary ===

Weighted Avg.

Correctly Classified Instances Incorrectly Classified Instances Kappa statistic Mean absolute error Relative absolute error Relative absolute error 6309 4465 0.417 0.2078 0.4401 66.5138 % 111.3571 % 10774 58.5576 % 41.4424 % Root relative squared error Total Number of Instances === Detailed Accuracy By Class ===
 TP Rate
 FP Rate
 Precision
 Recall

 0.851
 0.232
 0.493
 0.851

 0.433
 0.669
 0.130
 0.798
 0.433

 0.669
 0.182
 0.448
 0.669

 0.762
 0.825
 0.690
 0.762

 0.586
 0.153
 0.664
 0.586
 MCC 0.525 0.332 0.422 0.704 0.414
 ROC Area
 PRC Area
 Class

 0.901
 0.757
 Below Average

 0.742
 0.780
 Average

 0.837
 0.479
 Above Average

 0.978
 0.778
 High

 0.809
 0.778
 High
 F-Measu 0.625 0.562 0.537 0.724 0.581

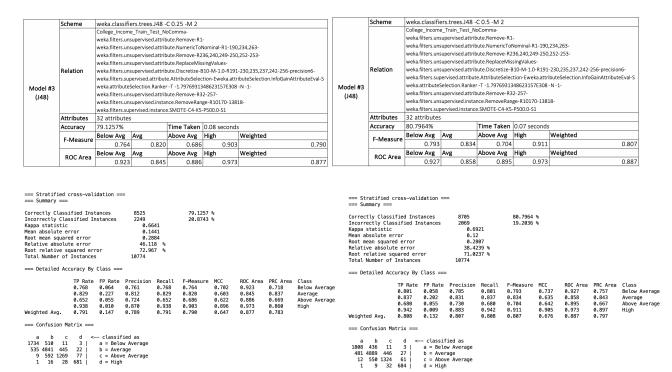
Correctly Class	ified Inst	ances	2030		55.6317	%			
Incorrectly Cla	ssified In	stances	1619		44.3683	%			
Kappa statistic			0.37	73					
Mean absolute e	rror		0.22	17					
Root mean squar			0.45	58					
Relative absolu	te error		71.60	81 %					
Root relative s	quared err	or	116.40	53 %					
Root relative s Total Number of	Instances		3649	53 %					
	Instances		3649	53 % Recall 0.845 0.421 0.660 0.549	F-Measure 0.602 0.556 0.503 0.550	MCC 0.503 0.330 0.384 0.518	ROC Area 0.892 0.734 0.820 0.935	PRC Area 0.749 0.780 0.433 0.595	Class Below Average Average Above Average High

=== Confusion Matrix === a b c d <--- classified as 1922 275 55 6 | a = Below Average 1736 2532 1475 100 | b = Average 206 296 1302 143 | c = Above Average 31 69 73 553 | d = High

a b c d <--- classified as 618 80 31 2 | a = Below Average 611 859 524 45 | b = Average 71 83 419 62 | c = Above Average 21 31 58 134 | d = High

Time taken to test model on supplied test set: 0.06 seconds

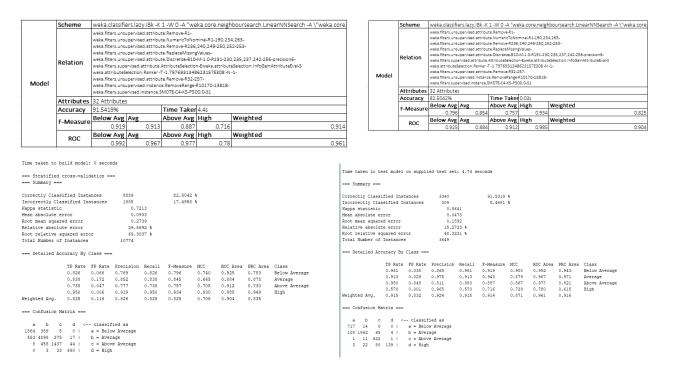
Appendix 5. J48 - Training Before and After Tuning



Appendix 6. J48 - Testing Output

=== Evaluation o	n test set ===													
Time taken to te	st model on sup	plied test se	: 0.05 se	econds										
=== Summary ===														
Correctly Classi Incorrectly Clas Kappa statistic Mean absolute er Rotot mean square Relative absolut Root relative sq Total Number of === Detailed Acc	sified Instance ror d error e error uared error Instances	0.7 0.1 0.2 36.9 65.8 3649	145	82.7076 17.2924										
Weighted Avg.	TP Rate FP Ra 0.792 0.039 0.889 0.183 0.811 0.069 0.459 0.004 0.827 0.122	te Precision 0.835 0.860 0.712 0.882	Recall 0.792 0.889 0.811 0.459 0.827	F-Measure 0.813 0.874 0.758 0.604 0.824	MCC 0.768 0.710 0.706 0.620 0.715	ROC Area 0.967 0.924 0.954 0.830 0.931	PRC Area 0.856 0.938 0.763 0.637 0.871	Class Below Average Average Above Average High						
=== Confusion Ma a b c		sified as												
a b c d $<$ classified as 579 150 2 0 a Below Average 109 1812 112 6 b = Average 1 110 515 9 c = Above Average 4 34 94 112 d = High														

Appendix 7. IBk - Training Before and Testing Output



Appendix 8. SimpleLogistic - Training and Testing Output

	Scheme	weka.classifiers.	functions.	SimpleLogistic	c -I 0 -M 500 -I	1 50 -W 0.0			Scheme	weka.classifi	ers.functions	.SimpleLogist	ic -I 0 -M 500	-H 50 -W 0.0			
Model #5 SimpleLogistic)	Relation		ervised.attril ervised.attril ervised.attril ervised.attril ervised.attril ised.attribu ction.Ranke ervised.attril ervised.insta	bute.Remove-R1 bute.NumericTo bute.ReplaceMis bute.Discretize-E te.AttributeSelec r -T -1.79769313 bute.Remove-R3 nce.RemoveRa	Nominal-R1-190, 136,240,249-250, 190-M-1,0-R191- 190-M-1,0-R191- 1948623157E308 192-257- 198-R10170-1381	252-253- 230,235,237,242-256-precision6- buteSelection.InfoGainAttributeEval-S N -1-		Model #5 (SimpleLogistic)	Relation	College_Income_Train_Test_NoComma- weka.filters.unsupervised.attribute.Remove-R1- weka.filters.unsupervised.attribute.Remove-R2632,240,249-250,252-253- weka.filters.unsupervised.attribute.Remove.R263,240,249-250,252.253- weka.filters.unsupervised.attribute.Remove.R263,240,249-250,252,237,242.256-precision6- weka.filters.unsupervised.attribute.Berchive.FolkM-10.R191-230,255,237,242.256-precision6- weka.filters.unsupervised.attribute.Berchive.FolkM-2012,012,02,257,242.256-precision6- weka.filters.unsupervised.attribute.Remove.R32-257- weka.filters.unsupervised.instance.Remove.R32-257- weka.filters.unsupervised.instance.RemoveRange-R10170-13818- weka.filters.unsupervised.instance.SMOTE-C4-K3-P500.0-S1							
	Attributes	32 attributes							Attributes	32 attributes							
	Accuracy	79.0236%		Time Taken	52.96 second	s			Accuracy	75.5549%		Time Taken 53.99 se		ds			
		Below Avg Av	′g	Above Avg	High	Weighted			F-Measure	Below Avg	Avg	Above Avg	High	Weighted			
	F-Measure	0.772	0.827	0.667	0.853		0.788		r-ivieasure	0.710	0.82	0.62	4 0.63	4	0.751		
	ROC Area	Below Avg Av	′g	Above Avg	High	Weighted			ROC Area	Below Avg		Above Avg	High	Weighted			
	RUC Area	0.953	0.891	0.928	0.992		0.917		NOC Area	0.939	0.87	8 0.90	3 0.95	3	0.900		
fime taken t	o build mod	el: 52.96 secono	ls					luation on te: ken to test mo		lied test set	t: 0.2 secor	ıds					
Stratifi Summary		lidation					=== Sum	mary ===									

	Kappa statistic			0.65	94						Kappa statistic			0.58	53					
	Mean absolute er	ror		0.14	99						Mean absolute er	ror		0.16	25					
	Root mean square	d error		0.27	19						Root mean squared error			0.29	12					
Relative absolute error			47.9674 %							Relative absolute error			52.51	1 %						
Root relative squared error		or	68.80	15 %						Root relative squared error			74.35	74 %						
Total Number of Instances										Total Number of	Instances		3649							
	Detailed Accuracy By Class											uracy By	Class ===							
		TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class		TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
		0.763	0.056	0.782	0.763	0.772	0.713	0.953	0.846	Below Average		0.658	0.049	0.771	0.658	0.710	0.647	0.939	0.806	Below Average
		0.846	0.239	0.808	0.846	0.827	0.611	0.891	0.906	Average		0.862	0.304	0.782	0.862	0.820	0.569	0.878	0.899	Average
		0.622	0.054	0.718	0.622	0.667	0.602	0.928	0.735	Above Average		0.611	0.073	0.637	0.611	0.624	0.547	0.908	0.655	Above Average
		0.873	0.013	0.834	0.873	0.853	0.843	0.992	0.910	High		0.537	0.011	0.775	0.537	0.634	0.625	0.953	0.701	High
	Weighted Avg.	0.790	0.152	0.788	0.790	0.788	0.646	0.917	0.863		Weighted Avg.	0.756	0.193	0.754	0.756	0.751	0.585	0.900	0.824	
	=== Confusion Mat	trix ===									Confusion Ma	trix								
	a b c	d <-	- classif	ied as							a b c	d <-	- classif	ied as						
	1723 525 9	1	a = Belo	w Average							481 240 9 1 a = Below Average									
	468 4946 390	39	b = Aver	age							139 1757 128 15 b = Average									
	12 638 1211	86	c = Abov	e Average							4 221 388	22	c = Abov	e Average						
0 16 76 634 d = High									0 29 84 131 d = High											