Executive Summary:

The purpose of this report is to examine the tuition fee of US colleges based on number of characteristics. The dataset consists of a sample data collected from 1121 records and includes the following variables (prefixed by their column name in the data file):

- tuition: College tuition ("out-of-state" rate for those with in-state discount).
- pcttop25: Percent of new students from the top 25% of high school class.
- sf_ratio: Student to faculty ratio.
- accrate: Fraction of applicants accepted for admission.
- graduat: Percent of students who graduate.
- pct_phd: Percent of faculty with Ph.D.'s.
- fulltime: Percent of undergraduates who are full time students.
- alumni: Percent of alumni who donate.
- num enrl: Number of new students enrolled.
- public_private: Is the college a public or private institution? public=0, private=1
- fac_comp: Average faculty compensation.

Abstract:

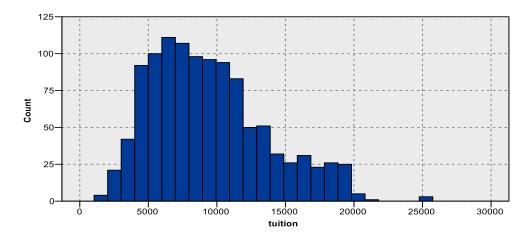
In this project, we will perform data mining processes on a dataset of tuition covering all the other factors of colleges in calculation and prediction. The objective of this project is to create a predictive model of college tuition based on a number of characteristics gathered from higher education institutions.

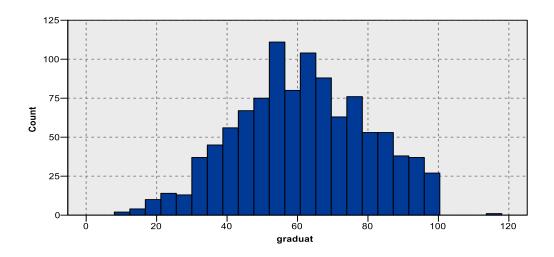
We will perform data mining process addressing the following points:

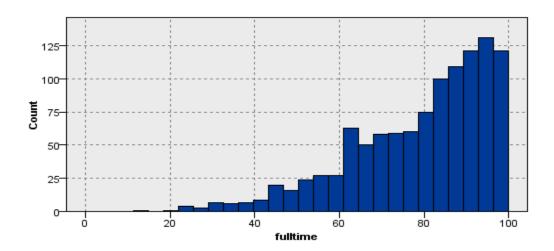
1. Explore the data to get some initial insights, if you think it is useful (your call):

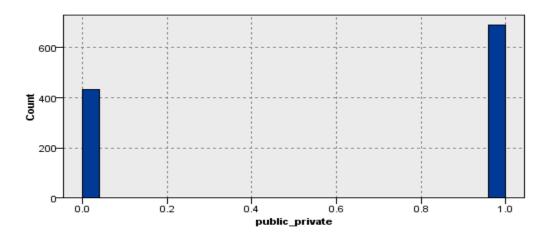
Our first step is to have a visual of some of the data, these will give us a rough idea about now the data is connected to each other, how the data is flowing from one variable to other. In our exploratory data analysis, we explored this phase and the data preparation phase simultaneously in order to utilize the new ideas of how to graphically explore the data every time the new areas of the data are uncovered.

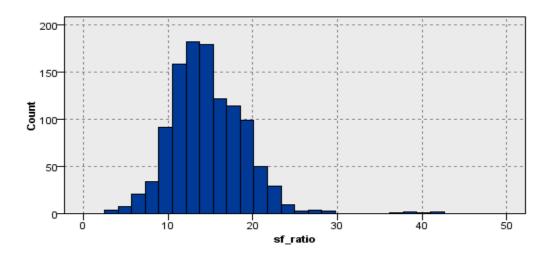
Firstly, we performed a data audit on our provided CVS file. We have found that the data set is not complete has lots of missing values across different fields. We will start by having visuals of some of fields on these data set, below is the attached snapshot of it:





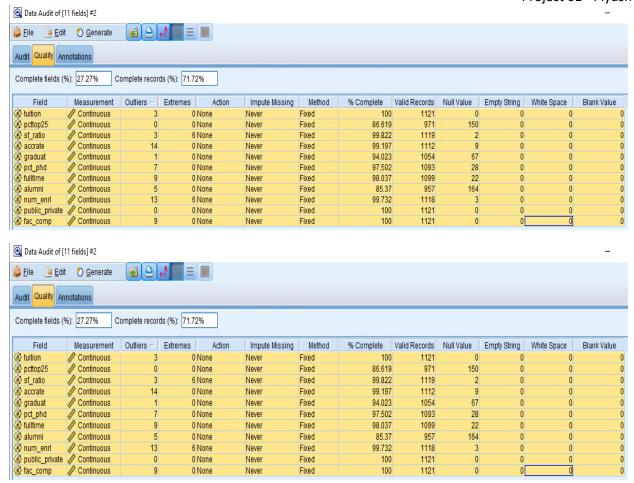






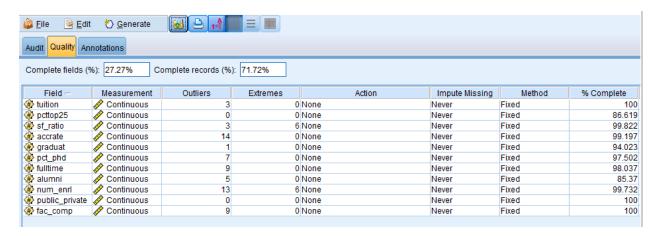
2. Identify outliers and decide what to do with them:

Data Audit node report the outliners, defined here as values between 3 and 5 standard deviations from the mean, in the following fields: tuition, sf_ratio, accrate, graduat, pcr_phd, full time, alumni, num_enrl, fac_comp. There were values exceeding 5 standard deviations from the mean in the fields: Accrate, pct_phd, fulltime, num_enrl and fac_comp.

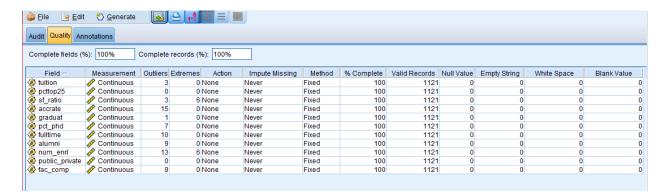


3. Missing data appears to be a problem with this data set. Prepare a copy of the dataset, where the missing values are each replaced with their field means. Report on how this substitution has affected the fields (summary stats, etc.), if at all. What do you think of this method of dealing with missing values?

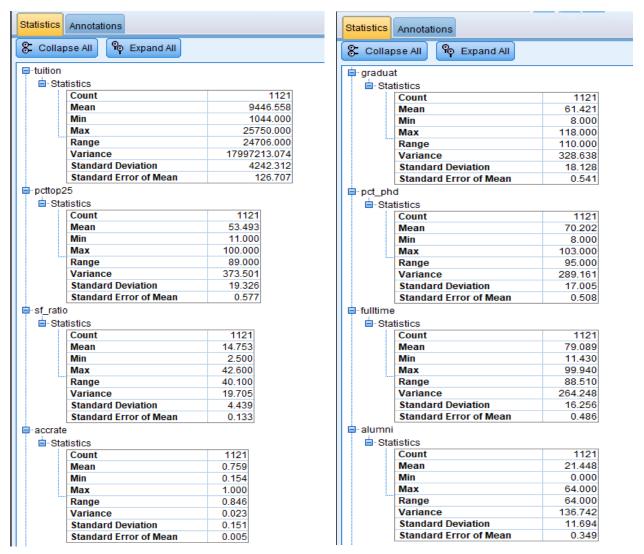
First let's have a visual of missing dataset, the snapshot is attached below:



From the above we can see that the data is not complete, so now we will generate a missing node with addressing all the missing imputes by their mean



Below is complete summary stats of dataset after handling the missing values.

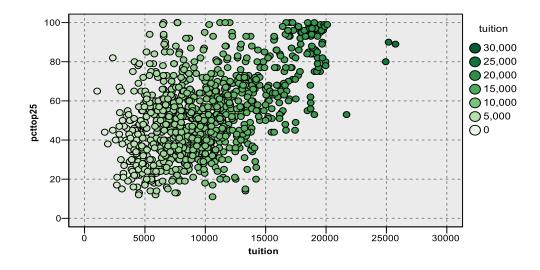


Count	1121		
Mean	833.453		
Min	21.000		
Max	7425.000		
Range	7404.000		
Variance	851431.594		
Standard Deviation	922.731		
Standard Error of Mean	27.560		
public_private			
= Statistics			
Count	1121		
Mean	0.615		
Min	0.000		
Max	1.000		
Range	1.000		
Variance	0.237		
Standard Deviation	0.487		
Standard Error of Mean	0.015		
in fac_comp			
. Statistics			
Count	1121		
Mean	52679.839		
Min	26500.000		
Max	107500.000		
Range			
Variance	147960628.903		
Standard Deviation	12163.907		
Standard Error of Mean	363.304		

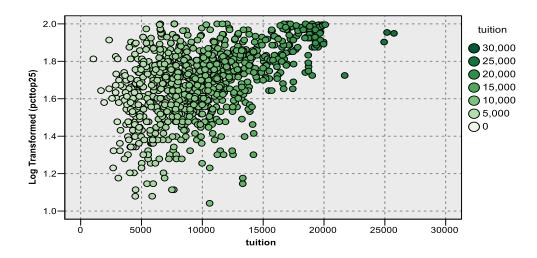
Using the mean of the field seems the best option to complete the missing values, if we have deal with complete data set, but mean field will only give us a projected value for that specific field, for this part of the project mean field seems to the best option.

4. Provide a table describing the relationship of each explanatory variable with tuition (hint: use scatter plots). If the relationship is not linear, you can1 make it so by transforming the predictor variable.

In order to describe the relationship of each variable we first start by having the visual of the data, below is the scatter plot of **tuition vs Pcttop25.** For this part of the project we have used the original data set with missing values to the graphical representation.



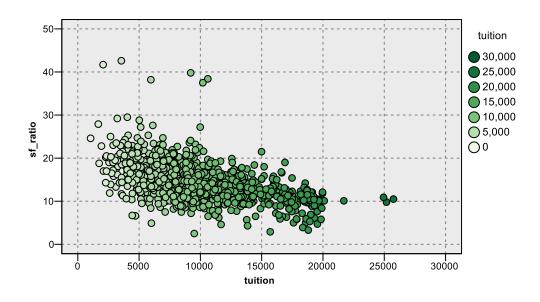
The above data for percent of new student from top 25% of high school class on the y axis and tuition on the x axis seems a bit skewed, but can have out idea that higher percentage of new students from top 25% of high school class has higher tuition fee. Let's have a log transformed y axis (percentage of new students from top 25% of high school class).



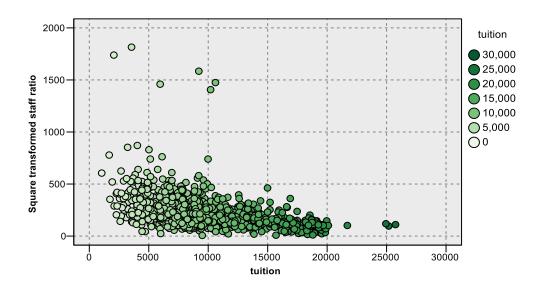
The above graph gives us a idea that with increase in percentage of new students from top 25% of high school class we have a increase in tuition fee.

Looking into the tuition vs staff ratio:

We first have a simple visual of data in graph.

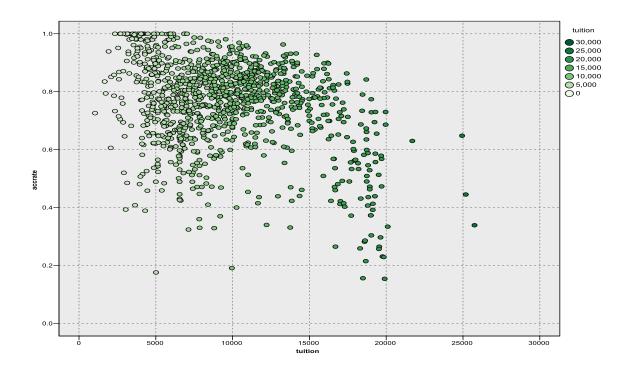


The above data set is seeming inversely proportional with staff ratio to tuition, let's try to transform the staff ratio axis if that makes the graph more logical and understandable.

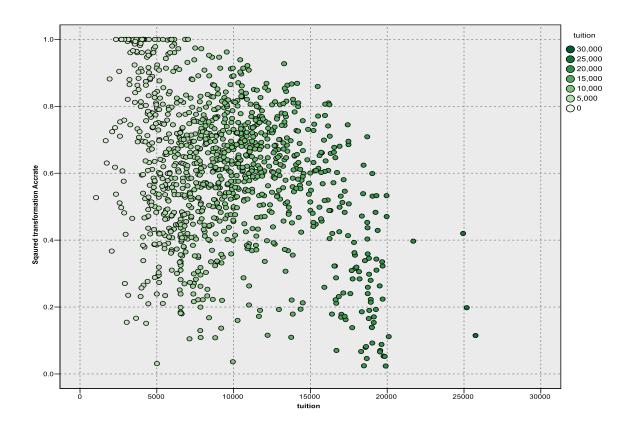


In the above graph, we have used the square transformation for staff ratio, the graph is still bit skewed but have a visual understanding that with the increase in tuition fee we have decrease in staff ratio.

looking into tuition vs accurate:



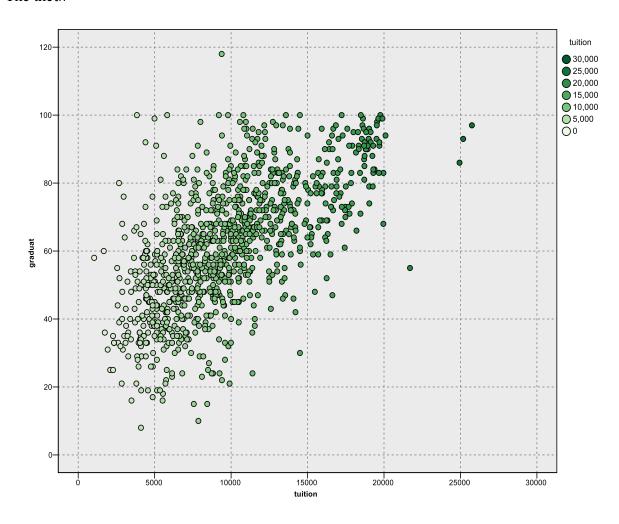
The above graph is skewed is hard to say anything with the visuals. Let's try with different transformation representation of the graph.



After different hit and trial, squared transformation for fraction of applicants accepted for admission vs the tuition fee for US universities, we can say the graph is mostly skewed, but we have some density where we can say the fraction of applications accepted are with tuition fee around 5000 to 10000.

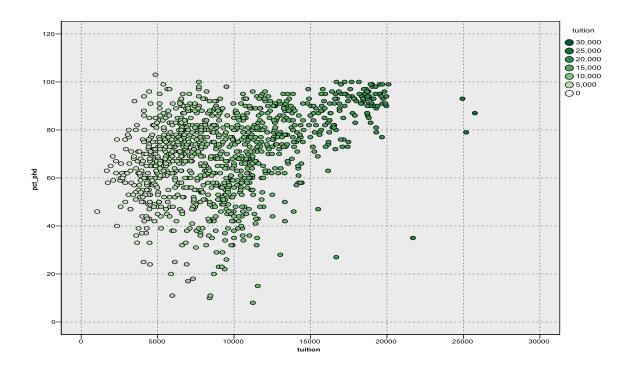
Tuition vs Graduation:

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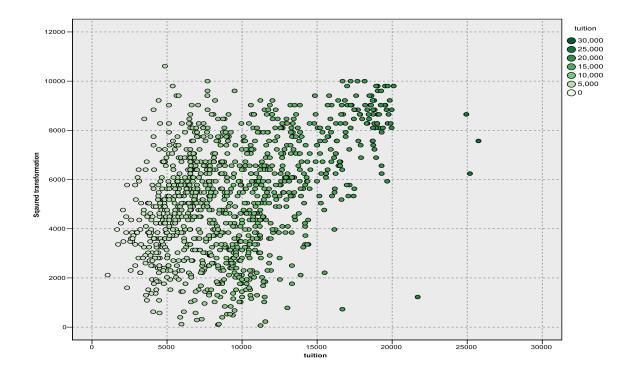


From the above graph we can say that the percentage of students who graduated increases with the increase in tuition fee.

Tuition vs PHD:

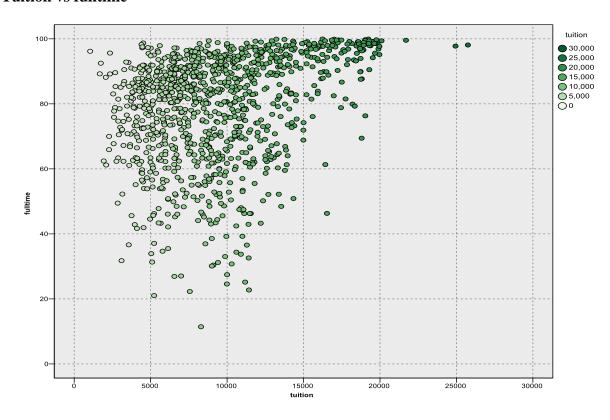


From the above graph we can say that with increase in tuition fee we have an increase in percentage of faculty who have a Ph.D.'s. Let's have transformed y axis if we have more clear visual.

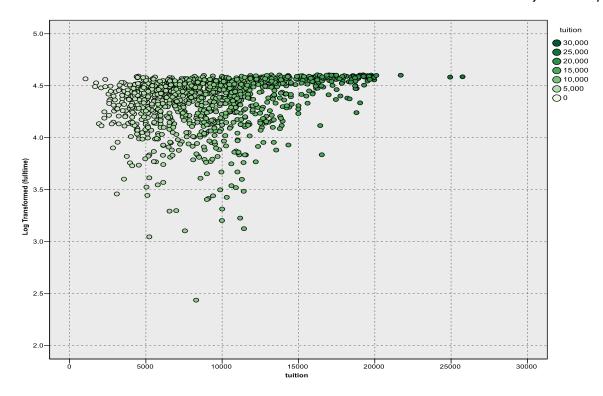


The above graph is still skewed but we can say that with the increase in tuition fee we have more percentage of faculties with PHD degrees from the given data set.

Tuition vs fulltime

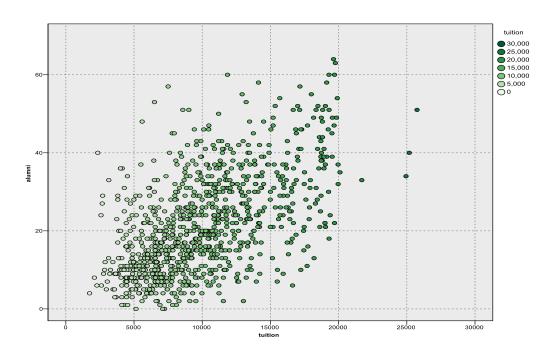


The above graph is skewed but get have visual that with the increase in tuition we have a higher percentage of undergrads who are full time students.

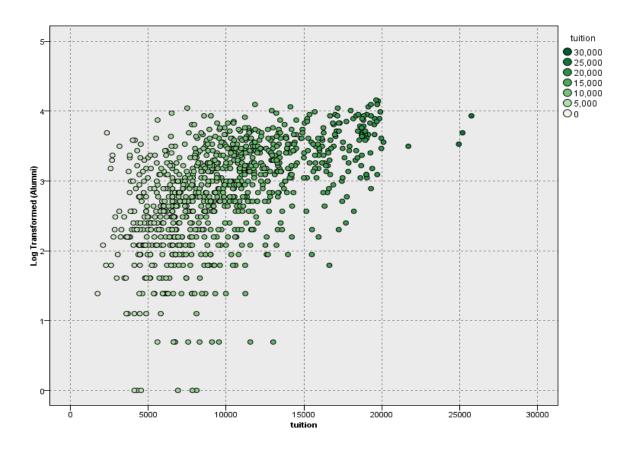


From the we can see that we still have skewed graph but we from the visuals we can say that with the increase in tuition fee we have slightly more percentage of undergrads who are full time students.

Tuition vs Alumni

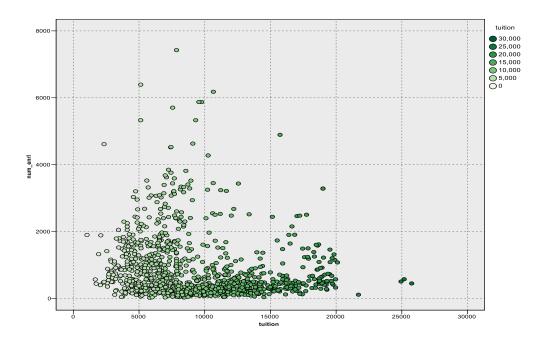


The above is the normal graph between tuition on the x axis and alumni – percentage of alumni who donate. We can say that with the increase in percentage of donation we have increase in tuition fee as well. Let's try a log transformation of y axis we have clearer visual.

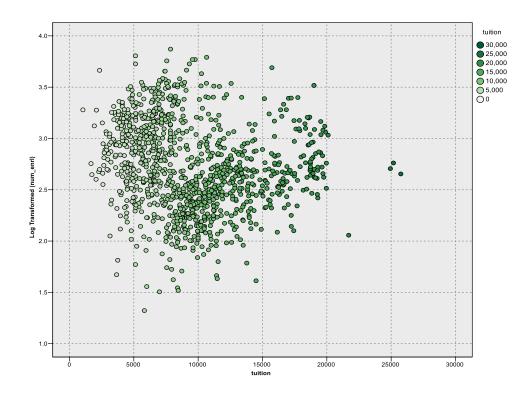


From the above graph we can say that we the increase in percentage of donation we have increase in tuition fee as well.

Tuition vs number of new students enrolled:

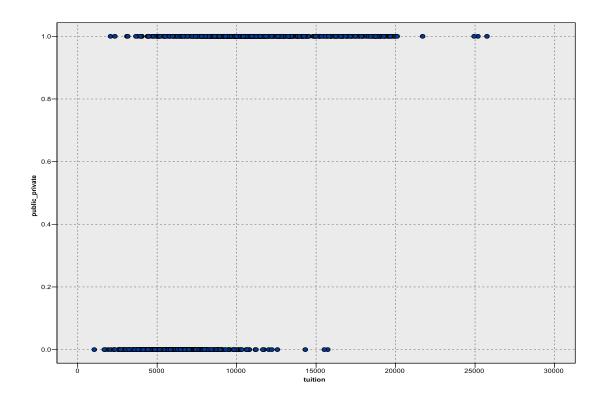


The above graph is very skewed is not possible to say anything from the visual, let try some transformations.



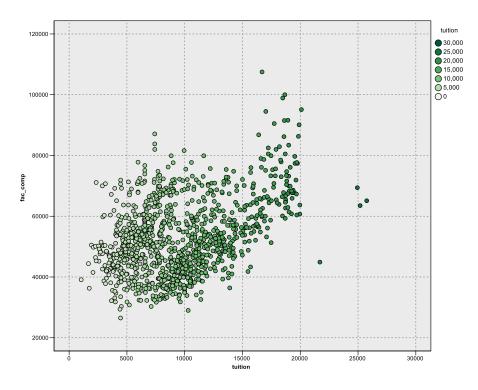
With the log transformation of number of new students enrolled we can say that we have a greater number of new students enrolled with tuition fee increasing mostly between 8000 - 15000.

Tuition vs Public Private:

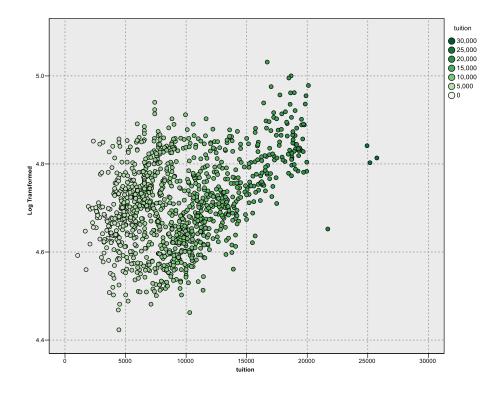


As we have a binary data for tuition vs public = 0 and private = 1, we can say that private schools have more higher tuition fee as compared to the public schools.

Tuition vs average faculty Compensation:



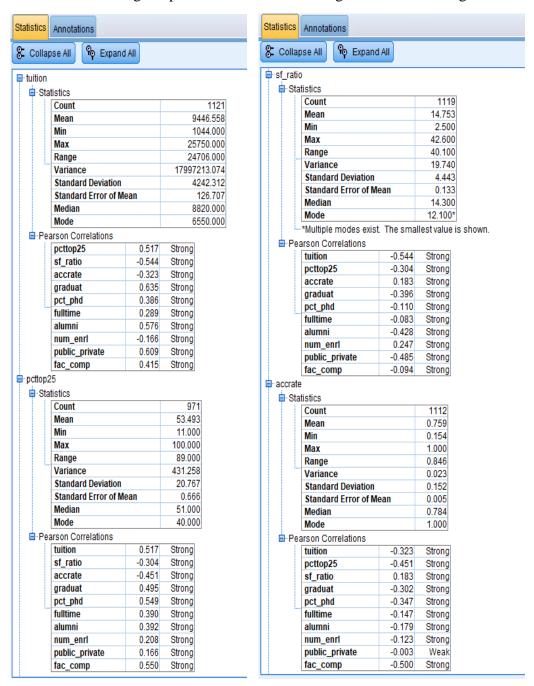
From the above we can say that with the increase in tuition fee we have a increase in average faculty compensation, lets try some transformation if we can get more clear visuals.

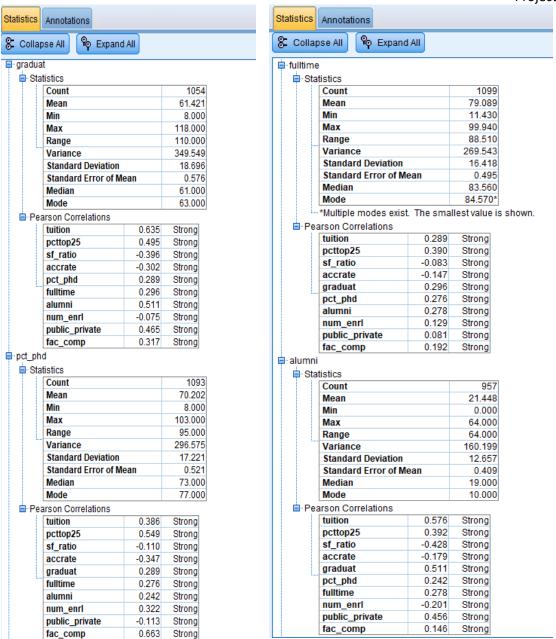


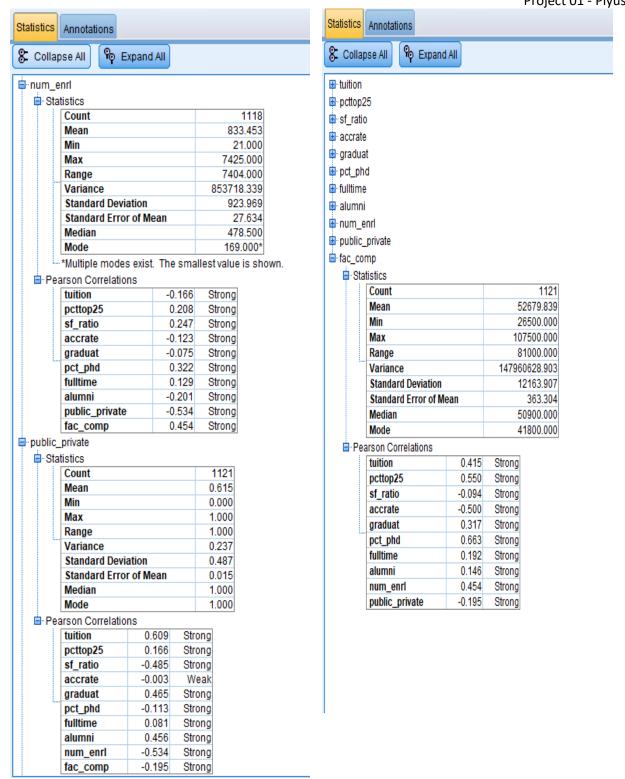
The above graph is still bit skewed but we can say that with the increase in tuition fee we have increase in average compensation of faculty.

5. Investigate the correlation among the predictor variables. Suggest a creative course of action (rather than simply omitting a variable) for dealing with any medium or strong correlations encountered (e.g. textbook, section 9.7; avoid any method linked to principal component analysis, as we have not covered it yet).

The correlation among the predictor can be seen using statics node with given data set.





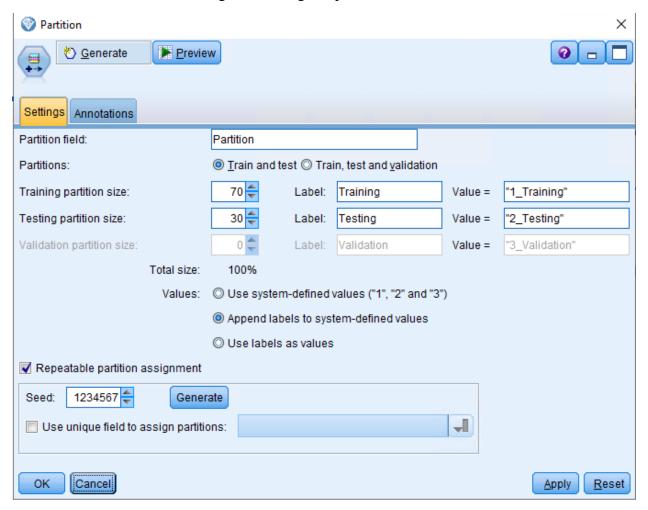


The above we have noticed that we have strong correlation in the fields for College tuition, percentage of new students from the top 25% of high school class, percentage of alumni who

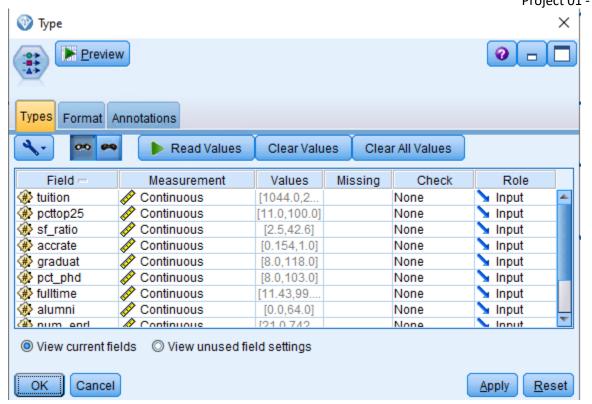
donate and in public and private college fields.

6. Use SPSS Modeler linear regression tool to investigate whether a linear relationship exists between tuition and the other variables. Investigate the differences in the models, if any, among these methods: enter, stepwise, backwards. Construct a table showing method, variables included, statistical tests on regression coefficients, goodness of fit metric(s), predictive accuracy metric on training and test data. Discuss. Which model do you prefer and why?

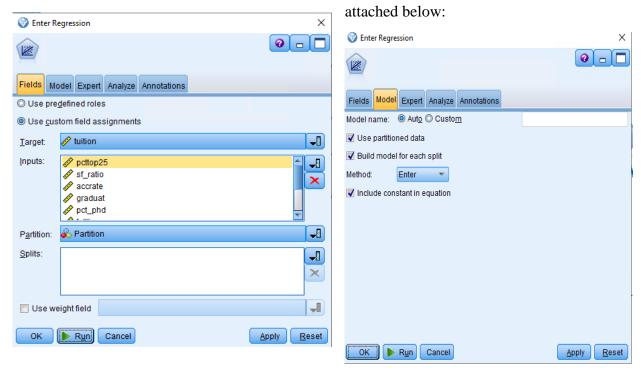
For this part of the question before modeling the data, we have first divided the given data set into 70: 30 ratios for Training and Testing, snapshot has been attached below:

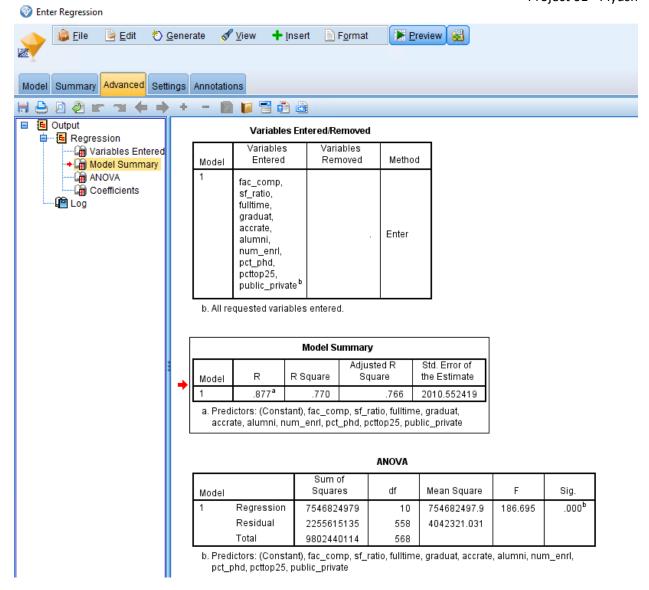


Then we have used the type node to read values of dataset, below is the attached snapshot:



The next step is to perform the Regression from SPSS, we have first have started with Enter Regression the choices for implementing the Enter regression is

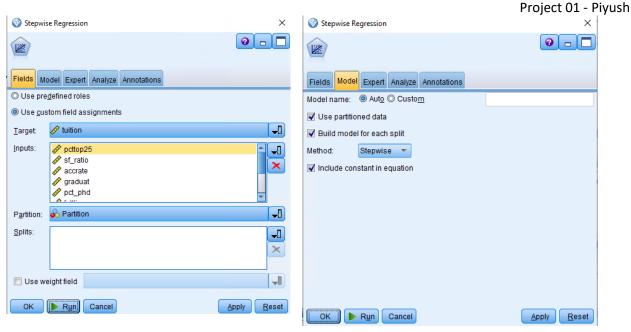


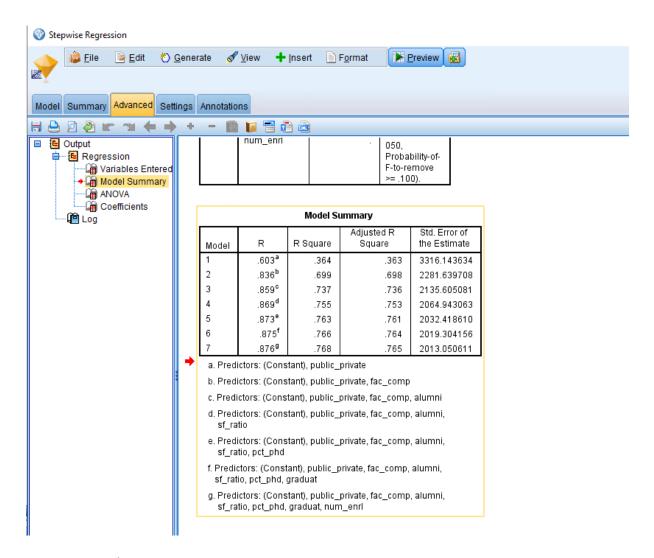


From the above model we have R value = 87.7, R squared value = 76.6 and F value is 186.695. From the above regression we can also say that the both of the regression coefficients are statically significant. We know that because the significant value obtain from the above regression is 0.000 which indicates that p < 0.001.

Now let's perform the Stepwise regression using the same parameter, we have the below Model summary:

Due Date: October 21, 2020
Data Mining and Predictive Analytics

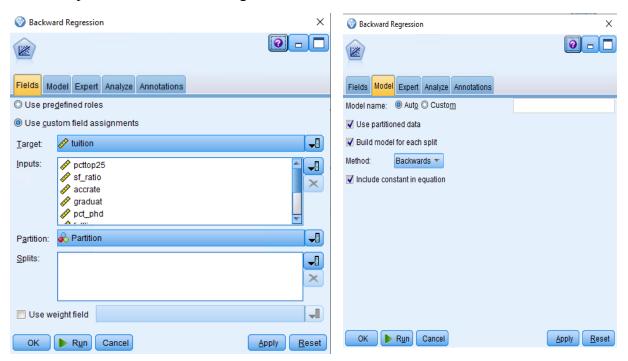


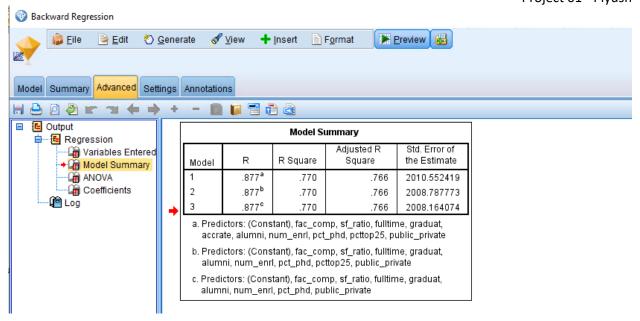


From the above model we have R value = 87.6, R squared value = 76.8 and F value is 186.695. From the above regression we can also say that the both of the regression coefficients are statically significant. We know that because the significant value obtain from the above regression is 0.000 which indicates that p < 0.001.

Now let's perform the backward regression using the same parameter, we have the below Model summary:

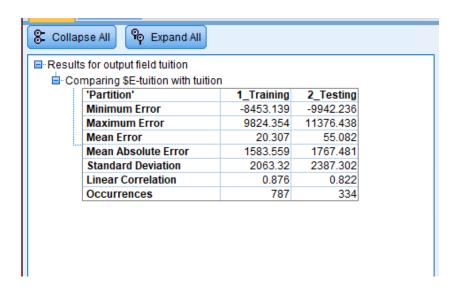
Now let's perform the backward Regression:



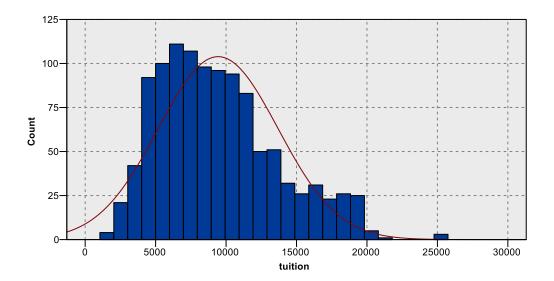


From the above model we have R value = 87.7, R squared value = 77 and F value is 185.95. From the above regression we can also say that the both of the regression coefficients are statically significant. We know that because the significant value obtain from the above regression is 0.000 which indicates that p < 0.001.

From the above three models we have similar values for R, R squared value, F and P values. If we have to choose a model we would move forward or select stepwise model, just because of its model processing, as step wise model is estimated on every step and we would select the stepwise model from the above 3 models. Below are the complete details stats for stepwise model.



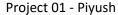
We will discuss more in details about the above stats and graph is below question number 9.

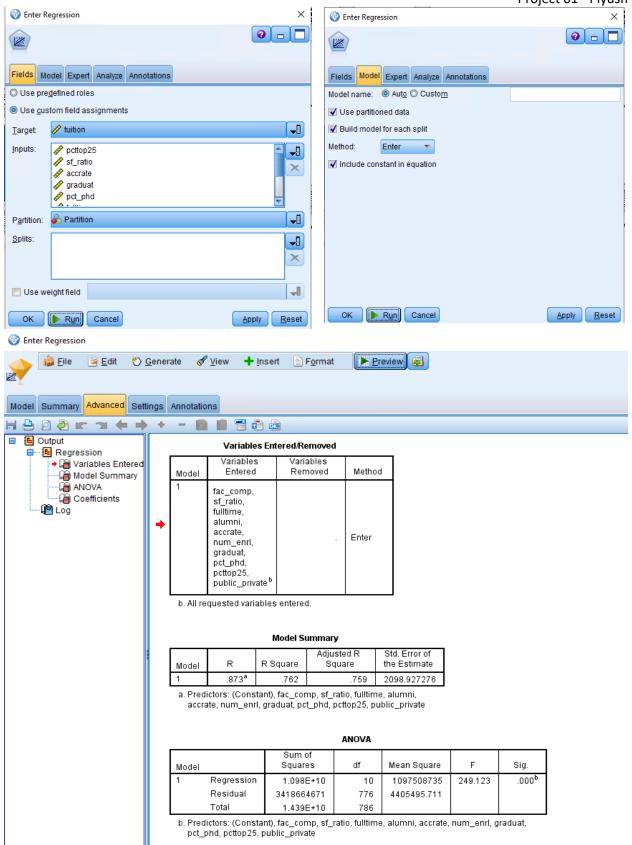


7. Use SPSS Modeler linear regression tool on the data set where the missing values are each replaced with their field means. Investigate the differences in the models, if any, among these methods: enter, stepwise, backwards. Construct a table showing method, variables included, statistical tests on regression coefficients, goodness off its metric(s), predictive accuracy metric on training and test data. Discuss. Which model do you prefer and why?

For this part of the question before modeling the data, we have first divided the given data set into 70: 30 ratios for Training and Testing, then will perform the enter, stepwise and backward regressions on our data set after handling the missing data. Below is the snapshot for each regression models.

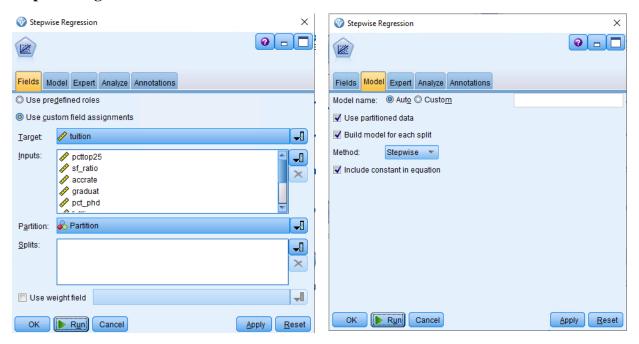
Starting with Enter Regression:

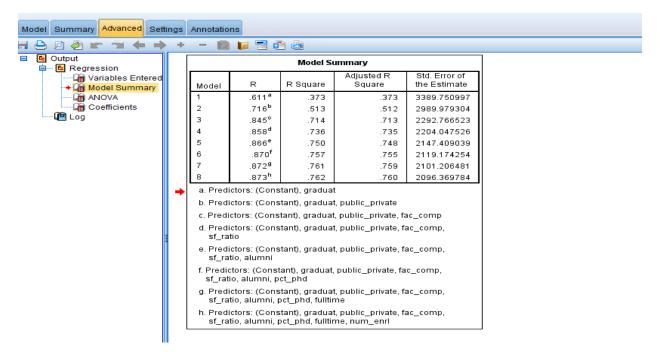


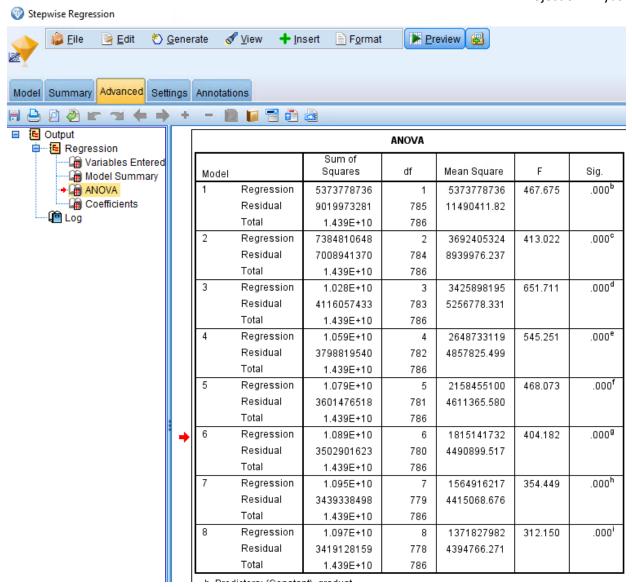


From the above model we have R value = 87.3, R squared value = 75.9 and F value is 249.123. From the above regression we can also say that the both of the regression coefficients are statically significant. We know that because the significant value obtain from the above regression is 0.000 which indicates that p < 0.001.

Stepwise Regression:

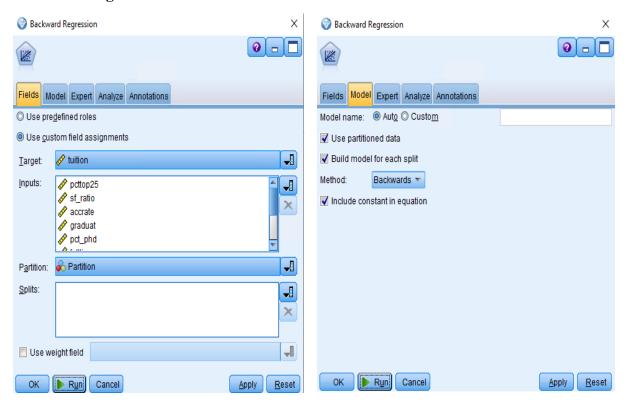


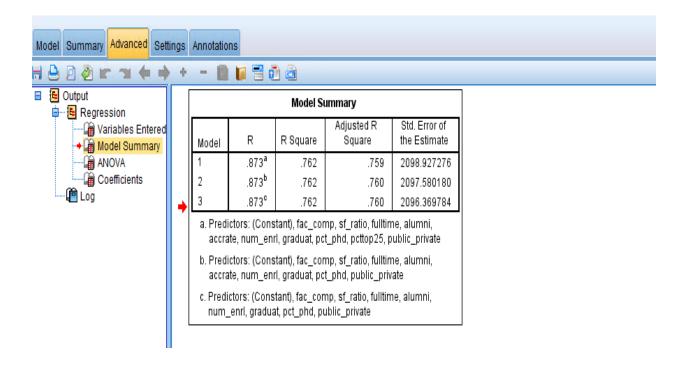


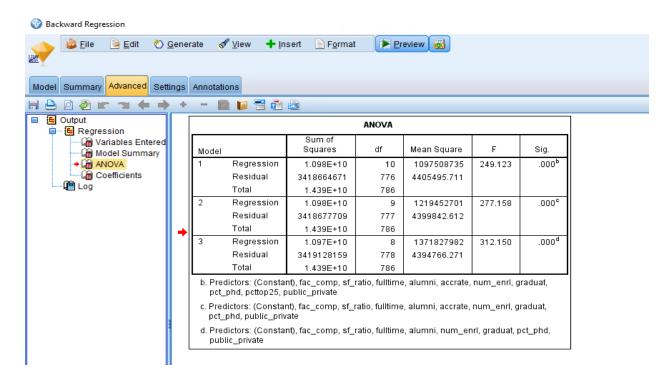


From the above Stepwise Regression model, we have R value = 87.3, R squared value = 76.2 and F value is 312.150. From the above regression we can also say that the both of the regression coefficients are statically significant. We know that because the significant value obtain from the above regression is 0.000 which indicates that p < 0.001

Backward Regression:



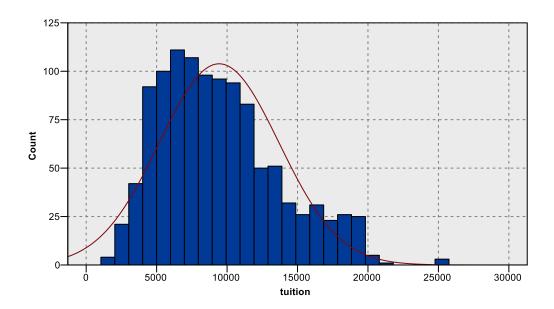




From the above backward Regression model, we have R value = 87.7, R squared value = 76.2 and F value is 312.150. From the above regression we can also say that the both of the regression coefficients are statically significant. We know that because the significant value obtain from the above regression is 0.000 which indicates that p < 0.001.

From the above three models we have similar values for R, R squared value, F and P values. If we have to choose a model we would move forward or select stepwise model, just because of its model processing, as step wise model is estimated on every step and we would select the stepwise model from the above 3 models. Below are the complete details stats for stepwise model.

Comparing \$E-tuition with tuition 'Partition'	1 Training	2 Testing
Minimum Error	-9124.261	-10284.888
Maximum Error	10129.296	10969.061
Mean Error	-0.0	7.388
Mean Absolute Error	1591.721	1746.892
Standard Deviation	2085.674	2307.435
Linear Correlation	0.873	0.831
Occurrences	787	334



8. Compare the best model in 6 and the best model in 7. Which model do you prefer and why?

After comparing two models which are stepwise model with missing values and stepwise regression model without missing values, if we have the choose a model we would choose the model with missing values just because taking a mean for the important features for predicting a model, and we had approximately 76 % complete data set, rest of them are with missing values. If the missing values feature we less than 5% then we might would have choose Regression model

with after handling the missing data. But for the given conditions and data set, we would go with the Stepwise Regression model with missing values as it would be best the best model for predicting.

9. For the final (chosen) model:

a) Write out the estimated regression equation and explain the meaning of the coefficients

```
Tuition = (-3774.1) +

sf_ratio * -154.5 +

Graduate* 18.4 +

Pct_phd * 25.46 +

Fulltime * 19.94 +

Alumni * 36.9 +

Num_enrl * - 0.2562 +

Public_private * 4416.5 +

Fac_comp * 0.1464 +
```

- An intercept of -3774.1 has no interpretation as it would be the tuition fee of university based on different factors included in the data set.
- A slope of -154.5 in sf-ratio means that with each increase in tuition fee the ratio of student to faculty reduces by 154.5.
- A slope of 18.4 in graduate means that with increase in tuition fee the percentage of students who graduated increases by 18.4%.
- A slope of 25.46 in pct_phd means that with increase in tuition fee the percentage of faculty with PHD's increases by 25.46%.
- A slope of 19.94 in fulltime means that with increase in tuition fee the percentage of undergraduates who are full time students increases by 19.94%.
- A slope of 36.9 in alumni means that with increase in tuition fee the percentage of alumni who donate increases by 36.9%.

- A slope of (-0.2562) in num_enrl means that with increase in tuition fee the number of new students who enrolled decreases by 0.2562.
- A slope of (4416.5) in public_private has no interpretation as it would be the tuition fee of university based on public = 0 and private = 1, from the graphical representation in question 3, we have seen that private universities have more tuition fee as compared with to public universities.
- A slope of 36.9 in alumni means that with increase in tuition fee the percentage of alumni who donate increases by 36.9%.
- A slope of 0.146 in fac_comp means that with the increase in tuition fee the average compensation of faculty increases by 0.146.
 - b) Provide a full report of the chosen regression model and report its metrics (goodness of fit, predictive performance) and statistics on training and test data Make sure you tweak your models to get the best performance. Use 70/30 partition in all cases

Below is the complete metrics report of the chosen model

Model Summary

	model Cultimary					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate		
1	.611 ^a	.373	.373	3389.750997		
2	.716 ^b	.513	.512	2989.979304		
3	.845 ^c	.714	.713	2292.766523		
4	.858 ^d	.736	.735	2204.047526		
5	.866 ^e	.750	.748	2147.409039		
6	.870 ^f	.757	.755	2119.174254		
7	.872 ^g	.761	.759	2101.206481		
8	.873 ^h	.762	.760	2096.369784		

- a. Predictors: (Constant), graduat
- b. Predictors: (Constant), graduat, public_private
- c. Predictors: (Constant), graduat, public_private, fac_comp
- d. Predictors: (Constant), graduat, public_private, fac_comp, sf_ratio
- e. Predictors: (Constant), graduat, public_private, fac_comp, sf_ratio, alumni
- f. Predictors: (Constant), graduat, public_private, fac_comp, sf_ratio, alumni, pct_phd
- g. Predictors: (Constant), graduat, public_private, fac_comp, sf_ratio, alumni, pct_phd, fulltime
- h. Predictors: (Constant), graduat, public_private, fac_comp, sf_ratio, alumni, pct_phd, fulltime, num_enrl

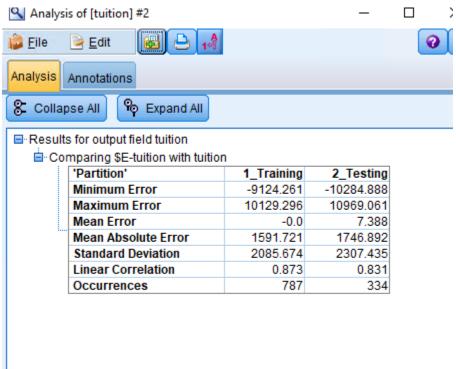
ANOVA

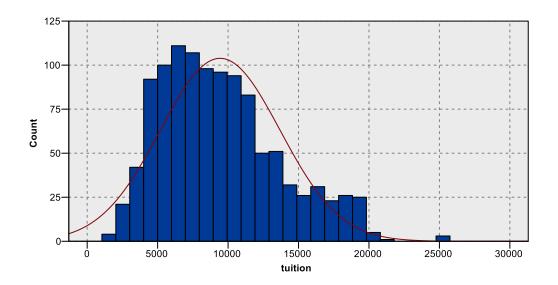
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	Sum of Squares	df	Mean Square	F	Sig.
Regression	5373778736.398	1	5373778736.398	467.675	.000b
Residual	9019973281.414	785	11490411.823		
Total	14393752017.812	786			
Regression	7384810647.687	2	3692405323.844	413.022	.000°
Residual	7008941370.125	784	8939976.237		
Total	14393752017.812	786			
Regression	10277694584.560	3	3425898194.853	651.711	.000 ^d
Residual	4116057433.252	783	5256778.331		
Total	14393752017.812	786			
Regression	10594932477.866	4	2648733119.467	545.251	.000e
Residual	3798819539.946	782	4857825.499		
Total	14393752017.812	786			
Regression	10792275500.092	5	2158455100.018	468.073	.000 ^f
Residual	3601476517.720	781	4611365.580		
Total	14393752017.812	786			
Regression	10890850394.600	6	1815141732.433	404.182	.000 ^g
Residual	3502901623.212	780	4490899.517		
Total	14393752017.812	786			
Regression	10954413519.574	7	1564916217.082	354.449	.000 ^h
Residual	3439338498.238	779	4415068.676		
Total	14393752017.812	786			
Regression	10974623858.588	8	1371827982.324	312.150	.000 ⁱ
Residual					
	Residual Total Regression	Regression 5373778736.398 Residual 9019973281.414 Total 14393752017.812 Regression 7384810647.687 Residual 7008941370.125 Total 14393752017.812 Regression 10277694584.560 Residual 4116057433.252 Total 14393752017.812 Regression 10594932477.866 Residual 3798819539.946 Total 14393752017.812 Regression 10792275500.092 Residual 3601476517.720 Total 14393752017.812 Regression 10890850394.600 Residual 3502901623.212 Total 14393752017.812 Regression 10954413519.574 Residual 3439338498.238 Total 14393752017.812 Regression 10974623858.588 Residual 3419128159.224	Regression 5373778736.398 1 Residual 9019973281.414 785 Total 14393752017.812 786 Regression 7384810647.687 2 Residual 7008941370.125 784 Total 14393752017.812 786 Regression 10277694584.560 3 Residual 4116057433.252 783 Total 14393752017.812 786 Regression 10594932477.866 4 Residual 3798819539.946 782 Total 14393752017.812 786 Regression 10792275500.092 5 Residual 3601476517.720 781 Total 14393752017.812 786 Regression 10890850394.600 6 Residual 3502901623.212 780 Total 14393752017.812 786 Regression 10954413519.574 7 Residual 3439338498.238 779 Total 14393752017.812 786 Regression 10974623858.588 8 <td< td=""><td>Regression 5373778736.398 1 5373778736.398 Residual 9019973281.414 785 11490411.823 Total 14393752017.812 786 Regression 7384810647.687 2 3692405323.844 Residual 7008941370.125 784 8939976.237 Total 14393752017.812 786 8939976.237 Total 14393752017.812 786 3425898194.853 Residual 4116057433.252 783 5256778.331 Total 14393752017.812 786 42648733119.467 Residual 3798819539.946 4 2648733119.467 Residual 3798819539.946 782 4857825.499 Total 14393752017.812 786 4611365.580 Regression 10792275500.092 5 2158455100.018 Residual 3601476517.720 781 4611365.580 Total 14393752017.812 786 4490899.517 Total 14393752017.812 786 4490899.517 Total</td><td>Regression 5373778736.398 1 5373778736.398 467.675 Residual 9019973281.414 785 11490411.823 467.675 Total 14393752017.812 786 2 3692405323.844 413.022 Residual 7008941370.125 784 8939976.237 704 413.022 Residual 14393752017.812 786 786 788 78939976.237 786 Regression 10277694584.560 3 3425898194.853 651.711 651.711 Residual 4116057433.252 783 5256778.331 5256778.331 7041 786 Regression 10594932477.866 4 2648733119.467 545.251 545.251 Residual 3798819539.946 782 4857825.499 7041 468.073 Regression 10792275500.092 5 2158455100.018 468.073 Residual 3601476517.720 781 4611365.580 704.182 Regression 10890850394.600 6 1815141732.433 404.182</td></td<>	Regression 5373778736.398 1 5373778736.398 Residual 9019973281.414 785 11490411.823 Total 14393752017.812 786 Regression 7384810647.687 2 3692405323.844 Residual 7008941370.125 784 8939976.237 Total 14393752017.812 786 8939976.237 Total 14393752017.812 786 3425898194.853 Residual 4116057433.252 783 5256778.331 Total 14393752017.812 786 42648733119.467 Residual 3798819539.946 4 2648733119.467 Residual 3798819539.946 782 4857825.499 Total 14393752017.812 786 4611365.580 Regression 10792275500.092 5 2158455100.018 Residual 3601476517.720 781 4611365.580 Total 14393752017.812 786 4490899.517 Total 14393752017.812 786 4490899.517 Total	Regression 5373778736.398 1 5373778736.398 467.675 Residual 9019973281.414 785 11490411.823 467.675 Total 14393752017.812 786 2 3692405323.844 413.022 Residual 7008941370.125 784 8939976.237 704 413.022 Residual 14393752017.812 786 786 788 78939976.237 786 Regression 10277694584.560 3 3425898194.853 651.711 651.711 Residual 4116057433.252 783 5256778.331 5256778.331 7041 786 Regression 10594932477.866 4 2648733119.467 545.251 545.251 Residual 3798819539.946 782 4857825.499 7041 468.073 Regression 10792275500.092 5 2158455100.018 468.073 Residual 3601476517.720 781 4611365.580 704.182 Regression 10890850394.600 6 1815141732.433 404.182

- b. Predictors: (Constant), graduat
- c. Predictors: (Constant), graduat, public_private
- d. Predictors: (Constant), graduat, public_private, fac_comp
- e. Predictors: (Constant), graduat, public_private, fac_comp, sf_ratio
- f. Predictors: (Constant), graduat, public_private, fac_comp, sf_ratio, alumni
- g. Predictors: (Constant), graduat, public_private, fac_comp, sf_ratio, alumni, pct_phd
- h. Predictors: (Constant), graduat, public_private, fac_comp, sf_ratio, alumni, pct_phd, fulltime
- i. Predictors: (Constant), graduat, public_private, fac_comp, sf_ratio, alumni, pct_phd, fulltime, num_enrl

Statistical tests on Regression Coefficients for Stepwise Method:

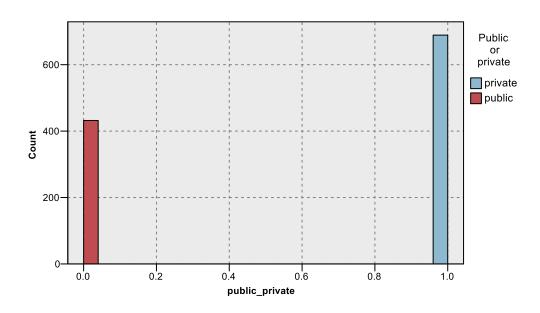
Coefficients						
				Standardized		
		Unstandardized Coefficients		Coefficients		
Model	/	В	Std. Error	Beta	t	Sig.
1	(Constant)	674.471	427.046		1.579	.115
2	graduat	143.565	6.639	.611	21.626	.000
2	(Constant)	1120.596	377.855		2.966	.003
	graduat	98.652	6.577	.420	15.000	.000
2	public_private	3711.486	247.461	.420	14.998	.000
3	(Constant)	-5533.657	405.480		-13.647	.000
	graduat	36.074	5.705	.154	6.323	.000
	public_private	5557.363	205.425	.629	27.053	.000
	fac_comp	.178	.008	.515	23.459	.000
4	(Constant)	-1740.869	610.095		-2.853	.004
	graduat	31.939	5.508	.136	5.798	.000
	public_private	4797.264	218.732	.543	21.932	.000
	fac_comp	.168	.007	.485	22.668	.000
_	sf_ratio	-172.209	21.310	177	-8.081	.000
5	(Constant)	-2218.834	598.890		-3.705	.000
	graduat	22.244	5.568	.095	3.995	.000
	public_private	4531.614	216.945	.513	20.888	.000
	fac_comp	.165	.007	.476	22.802	.000
	sf_ratio	-148.960	21.064	153	-7.072	.000
	alumni	49.137	7.511	.141	6.542	.000
6	(Constant)	-2745.366	601.606		-4.563	.000
	graduat	21.146	5.499	.090	3.845	.000
	public_private	4623.430	214.988	.523	21.506	.000
	fac_comp	.141	.009	.407	16.057	.000
	sf_ratio	-151.408	20.794	156	-7.281	.000
	alumni	42.552	7.545	.122	5.640	.000
	pct_phd	27.968	5.970	.113	4.685	.000
7	(Constant)	-3636.337	641.060		-5.672	.000
	graduat	17.561	5.534	.075	3.173	.002
	public_private	4636.095	213.191	.524	21.746	.000
	fac_comp	.141	.009	.407	16.183	.000
	sf_ratio	-156.528	20.662	161	-7.576	.000
	alumni	39.104	7.536	.112	5.189	.000
	pct_phd	24.776	5.978	.100	4.144	.000
	fulltime	18.722	4.934	.072	3.794	.000
8	(Constant)	-3774.122	642.803		-5.871	.000
	graduat	18.400	5.535	.078	3.324	.001
	public_private	4416.536	236.059	.500	18.709	.000
	fac_comp	.146	.009	.424	16.126	.000
	sf_ratio	-154.500	20.636	159	-7.487	.000
	alumni	36.902	7.588	.106	4.863	.000
	pct_phd	25.459	5.973	.103	4.262	.000
	fulltime	19.941	4.956	.076	4.024	.000
	num_enrl	256	.119	052	-2.144	.032

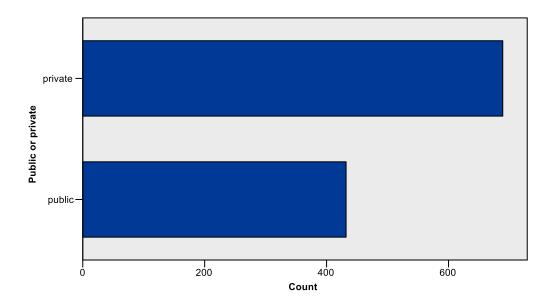




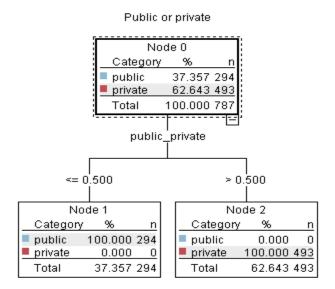
10. Decision tree classification: Using the public_private variable as categorical (flag), or deriving from it a flag variable, model the profile of a typical public and private college with a C5.0 decision tree algorithm, using all other variables as predictors (disregard tuition, given the typical difference in tuition between state and private institutions). Compute the confusion matrix and derive proper performance metrics.

The data set is unbalanced, as there are more private university 61.46 % which is 689 than compared to public university 38.54% which is 432.





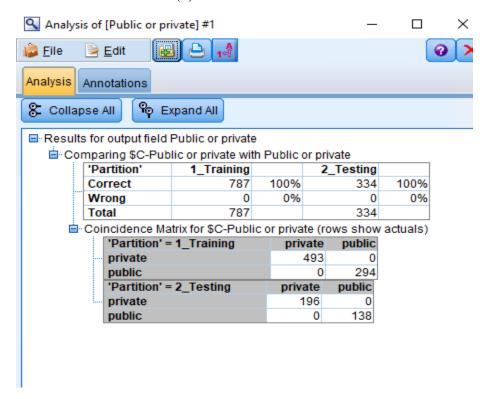
The decision tree can be built as below:



Decision Rules:

If	Consequence	Support	Confidence
If university = public	Public <= 0.500	294/ 787	294/ 787 = 37.357%
If university = private	Private < 500	493/ 787	493/787 = 62.643

Performance Evaluation (1)- Confusion Matrix and Derived Metrics can be given as

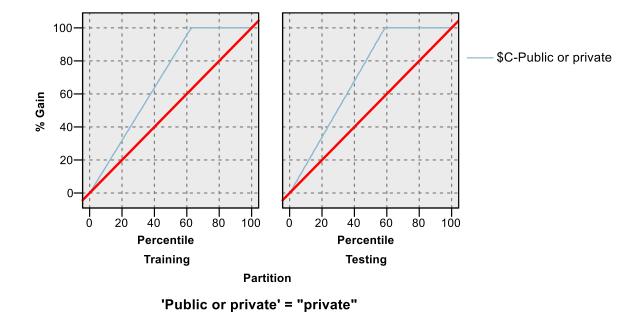


For Testing set:

Since the data set is unbalanced, it is necessary to examine Recall and Precision in addition to the Accuracy:

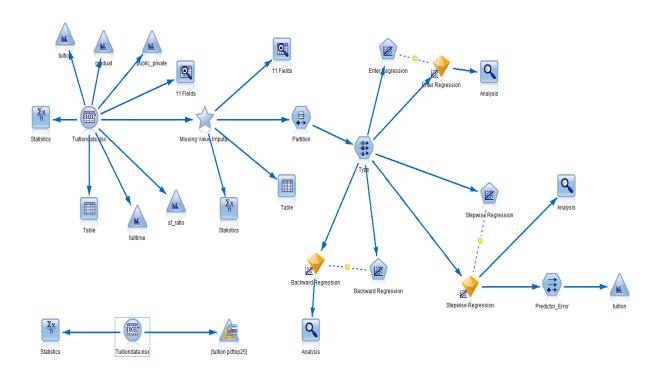
Accuracy	(TP+TN)/(TP+FP+TN+FN) = (196+138)/334	100%
Recall	TP/(TP+FN) = 196/ (196+0)	100%%
Precision	TP/(TP+FP) = 196/ (196+0)	100%
False Positive (1 - Specificity)	1-(TN/(FP+TN)) = 1 - (138/ (0+138))	0%

Performance Evaluation (2) – Gain Chart can be given as:

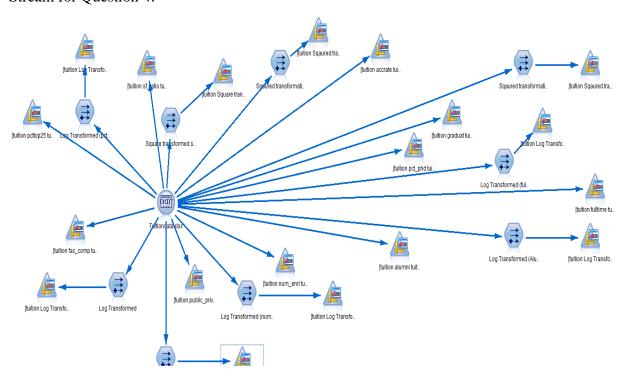


The above is Gain chart.

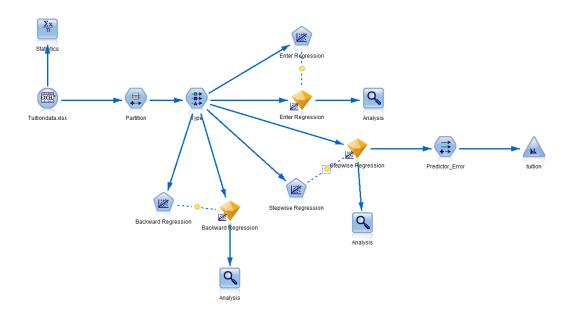
Stream for Q 1,2,3 and 7:



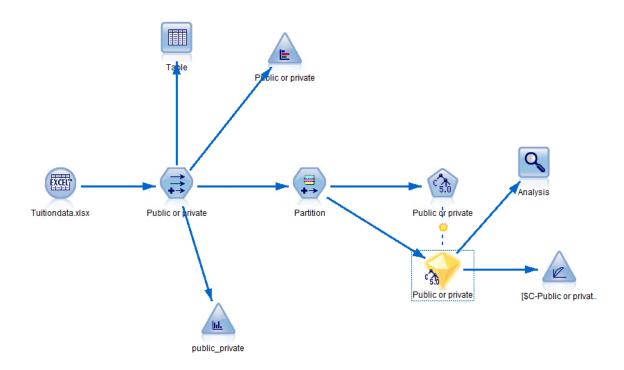
Stream for Question 4:



Stream for Q5 and Q6:



Stream for Question 10:



Project 01 (Piyush) MSIS 645 Due Date: October 21, 2020 Data Mining and Predictive Analytics Project 01 - Piyush