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Analyzing Student Enrollment at Ogun State Institute of Technology Igbesa (OGITECH)

Ayannusi A.O[1] Folorunsho S.O[2]
Ogun State Institute of Technology Igbesa[1] Olabisi Onabanjo University[2]

ABSTRACT : *With little support coming from Government authority, Higher Institutions are being compelled to internally produce additional earnings. Boosting enrollment can play a significant contribution in this assignment even to a greater extent when the school fees is the major source of income. Enrolment tasks have the capacity to expend a huge amount of time as well as resources. Analyzing student demographic area (where students comes from) to know the strength and weakness of enrollment process will help improve recruitment strategies which will in turn increase the Internal Generated Revenue of the Institution. Firstly, the paper took extensive research into different Data mining techniques like Decision Trees, Neural Networks, Association Rules, and Naves Bayes etc. Data mining tools like RapidMiner, Weka, Orange and Knime were also conducted, reviewed, compared and evaluated to choose the best solution that would give accurate analysis. Confusion Matrix in Weka platform were used to analyzed the results.*
KEYWORDS. *Weka, Confusion Matrix, Decision Trees, K Nearest Nieghbour.*

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I. INTRODUCTION

As many Universities face the constraints of declining enrollment demographics, pressure from state governments for increased student success, as well as declining revenues, the costs of utilizing anecdotal evidence and intuition based on 'gut' feelings to make time and resource allocation decisions become significant. However, until now, we have not developed analytical tools to address admissions and enrollment. (Bogard, James , Helbig, & Huff, 2012)

Student enrollment data are valuable resources for colleges and universities across the United States as they can be used to identify and measure trends and the growth rate of various programs. Higher education institutions can use this information as well as their own enrollment figures to determine future enrollment goals and objectives. The process of managing enrollment data is the cornerstone of a college's future growth and success. (Hudnett , 2015).

Wilkins, Farshid , & Jeroen, 2012), opined that several studies have shown that influential factors like quality of teaching and research, image and reputation of the institution, image of the country, cost of studies, geographic proximity, friends and family effects and career prospects are considered as the major factors that influence the students' choice of a post-secondary institution. Meanwhile, other scholars have studied the impacts of students' backgrounds (e.g. social class, academic preparedness and ethnicity) on their choice of higher education institution. The literature on student decision-making indicates that a strong relationship exists between a student's choices and the socio-economic status of the student's family. That is, the affordability of the targeted institution is a key element for working class students. (Wilkins, Farshid , & Jeroen, 2012).

According to (Hudnett , 2015)Enrollment data is a key resource for any college that is focused on developing its academic programs through increasing the number of qualified, admitted, and enrolled students. Therefore, the more knowledge that a school can gain about why an admitted student chooses not to enroll can help the school create and implement an effective recruitment plan that takes these specific factors into consideration. A college's existing student recruitment plan is a critical component to every school's enrollment management plan of action. Student recruitment programs initiated by colleges often involve a heavy focus on marketing efforts designed to target potential students; however, there has been a limited amount of research performed on the effectiveness of such programs.

Experience have shown that enrollment trend does not occur in isolation, increases and decreases in enrollment are correlated with multiple influences such as labor markets trends, social and economic factors.

Identifying factors that could influence enrollment in the university system therefore become crucial as this would not only allow governments and institutions to forecast enrollment more effectively, but also permit them to make adjustments to meet current or future labor needs. In order to provide information for decision making and budget planning on higher education, enrollment projection is very important. (Goenner, 2016)

In the light of this, the objective of this paper is to analyze the past trend and existing situation of academic staff and student enrollment in the nation's universities; and make projections for the future that would guide educational planners to effectively calculate the required school indicators as well as stimulate various scenarios for policy alternatives for effective planning. Furthermore, it would serve as a tool for the government to implement effectively policies on university education that could bring about expansion of access, improve enrollment, staffing and funding in the Nigerian university system. (Agboola & Adeyemi, 2015).

II. RESEARCH QUESTIONS

Based on three years of data registration, in which areas is OGITECH productive in recruiting students. Can socio-economic indices from the Nigerian Community Survey help identify the attributes of these higher enrollment areas? What are the statistically significant variables that help predict enrollment. Can this correlation be successfully represented via unsupervised learning machine technique? Finally can we target areas that currently have lower enrollment but based on the model have the capability of producing more students

III. MOTIVATION

Since the Polytechnic has never had access to GIS mapping, a secondary objective to this project is to produce additional maps for the institution that characterize census demographic information

The motivation is to analyze current student demographics with freely available data and utilizes this information to improve recruitment strategies as well as to identify other areas similar in composition. Which will in turn increase the Internal Generated Revenue of the Institution

IV. PURPOSE OF STUDY

This paper will seek to identify geographic areas that Ogun State Institute of Technology Igbesa can target based on historical data of its students. To identify the characteristics of past and current students by investigating student records gained from Institutional Research. This would give me the opportunity to determine target areas (hotspots) for recruitment activities. The purpose of this research is also to consider the relevance, strengths, and limitations of the geodemographic idea for public and private sector.

V. AIM

The aim of the research is to study and analyze students' enrollment information based on geodemographic in determining the recruitment process so as to generate more revenue at Ogun State Institute of Technology Igbesa.

The specific objectives are:

1. To analyze the geodemographic characteristics of students to better understand the Polytechnic's primary market.
2. To identify the characteristics of past and current students by investigating student records gained from the Institute.
3. To determine the relevance, strengths and limitations of the geodemographic idea for public and private sector use

VI. RELATED WORK

Education in Nigeria is majorly a shared responsibility of the Federal, State and Local governments. The Federal government is more directly involved with tertiary education than it is with pre-tertiary school education that is largely the responsibility of State (secondary) and Local (primary) governments. Education in Nigeria has evolved over a long period of time, and with series of policy changes Nigerian Education sector is facing multiple issues related to administrative, social and infrastructural domains, few of the issues are, limited carrying capacity, quota system, inadequate fund, poor economic background of students, and absence of technology. Lack of funding is also the major reason of reducing the access of many students to the universities. (Mahabub, 2014)

Education is an important tool in the society which helps in the development of an individual and the nation as a whole. For a quality education to be achieved through the enrolment of students there must be adequate educational facilities such as good and well equipped library, good conducive classroom environment and a well-structured building.

Investigations into the factors that affect management of educational facilities on students 'enrolment have attracted the interest and concern of researchers, universities administrators and planners as well as stakeholders in educational sectors in Nigeria. Different factors are capable of influencing the enrolment of students in the Nigerian Universities (Ileuma, 2015)

The essence of education is to inculcate in the learners the knowledge, skills, attitudes and values that would empower them to solve the problems of their country. This would lead to sustainable livelihood. For the citizens to attain the goals of education, they need to have access to education. Access to education means the opportunities in institutions of learning, created for the citizens to gain knowledge, skills, attitudes and values that will empower them to live a sustainable life. It simply means the right to education. (Offorma & Obiefuna, 2105).

(Agboola & Adeyemi, 2015) States that making projection in education has been regarded as the centerpiece of quantitative aspect of educational planning. As such, educational planners are to be grounded in the techniques of making projection. In the same vein they went further to say that projection informs the educational planner of a future pattern and trend of education parameters, especially the resource requirements in the educational system. These include enrollment, staffing, facilities, funding, etc. Projection also acquaints the institutional managers with the number of students and staff that would be expected in the system at a future period, assuming no change occurs in the educational system.

Geodemographic variables such as distance, gender, ethnicity, and test scores all factor into where a student decides to go to school and how successful they are there. If properly harnessed in a geographic or spatial context, student information has the potential to provide great insight for institutions. Specifically, geodemographic analysis in a university setting has applications in a number of areas, including improving recruitment methods, aiding admissions decisions, focusing development, and enhancing the overall student living and learning experience. (Huff, 2015)

(Belanger, 2013) In her publication "Birds of a Feather," defines the term geodemographics as the "analysis of people by where they live." The importance of studying geodemographics stems from the idea that where you come from says something about who you are. If we accept this notion as true, it is fair to say that, to a certain extent, people who come from the same place are similar, especially regarding characteristics like socioeconomic status, race, and interests or hobbies. As such, the age-old mantra "birds of a feather flock together" is an important concept in the study of geodemographics as it applies to Higher Institutions enrollment (Huff, 2015).

Location has a natural influence on people's attitudes and inclinations about a higher Institutions. For instance, awareness of an institution tends to be higher amongst people in its immediate vicinity and lower amongst people farther away. Perceptions also differ from region to region, even if the level of awareness is the same. Furthermore, spatial relationships between the student and university change on an individual basis. Referred to as the "golden circle" principle, the geographic area from which 80 percent of a college's primary student market resides can be a useful analytical tool in the field of enrollment management. Furthermore, the study concluded that "most students are more likely to select a school based on its geographic distance from their home" as well as initial interest. (Huff, 2015)

The basic tenet of geodemography is that people with similar cultural backgrounds, means, and perspectives naturally gravitate toward one another or form relatively homogeneous communities; in other words, birds of a feather flock together. When they are living in a community, people emulate their neighbors, adopt similar social values, tastes, and expectations, and—most importantly for consumer marketers—share similar patterns of consumer behavior toward products, services, media, and promotions. (Belanger, 2013)

Educational institutions—universities, colleges, schools, libraries, and other centers of learning—are physical entities. Typically when we picture these places, we see people—the learners themselves and the persons who support that learning. Possibly a bit more invisible to our eyes is the actual geography these people inhabit, experience, and navigate—the physical environment of buildings, campuses, and districts (Dailey & Stockton , 2012).

The chances of entry into tertiary education are in most cases a function of how healthy the educational system is and consequently the general behavioral patterns of students. This cannot be studied in isolation from the circumstances surrounding the prospective candidate within social context that affect both economic and societal status. (Ademola, Ogundipe, & Babatunde, 2014)

The behavioral patterns of college enrolment are becoming complex in that administrators are just developing programs that are of mix nature of both micro and macro market levels. The administrators respond to market interests promptly due to the awareness of the increasingly competitive nature of the students' enrolment pattern in Africa where there is scarce enrolment opportunities owing to various reasons. The picture of quantum enrolment of students in Nigerian universities has become highly imperative. (Ademola, Ogundipe, & Babatunde, 2014).

VII. DATA MINING

Data mining is the main important step to reach the knowledge discovery. Normally for data preprocessing it goes through various process such as data cleaning, data integration, data selection and data transformation and after these it is prepared for mining task. Its main contribution is in the fields of traditional sciences as astronomy, biology, high engineering physics, medicine and investigations. Various algorithms and tools can be used according to the application in unsupervised learning, there is no target attribute known in advance and there may be some time no comparison and correction in building groups. (Gera & Goel 2015)

Supervised learning is applied to make predictions about future cases where current available instances are given with known labels (the corresponding correct outputs) .Supervised machine learning involves trying to find out the algorithms that learn from externally supplied instances in order to produce general hypotheses. (Sharareh , Niakan , & Xiao-Jun , 2014)

The main goal of supervised learning is model development reasoned from the distribution of class labels in terms of predictor features selected by feature analysis. Then, the resulting classifier is applied to allocate class labels to the testing instances where the values of the predictor features are identified, but the value of the class label is unknown.

Many supervised classifiers are currently available; they have been categorized in main groups like logic-based methods, perceptron-based techniques, statistical learning algorithm, and support vector machine. Generally, Decision trees (DT), neural networks (NN), support vector machine (SVM), Bayesian network (BN), K-nearest Neighbor

classifier (K-NN), Logistic Regression (LR), and radial Basis function (RBF) are applied classification algorithms for medical datasets. (Sharareh , Niakan , & Xiao-Jun , 2014)

In supervised learning, a model is built prior to the analysis. We then apply the algorithm to the data in order to estimate the parameters of the model. Classification, Decision Tree, Bayesian Classification, Neural Networks, Association Rule

Mining etc. are common examples of supervised learning. (Garg & Arvind , 2013).

In unsupervised or undirected learning, there is a set of training data tuples with no collection of labeled target data available. The aim of unsupervised learning is discovering clusters of close inputs in the data where the algorithm has to find the similar data as a set. In unsupervised learning all variables are treated the same way without the difference between dependent and independent attributions. (Sharareh , Niakan , & Xiao-Jun , 2014).

In unsupervised learning, we do not create a model or hypothesis prior to the analysis. We just apply the algorithm directly to the dataset and observe the results. Then a model can be created on the basis of the obtained results. Clustering is one of the examples of unsupervised learning. Various data mining techniques such as Classification, Decision Tree, Bayesian Classification, Neural Networks, Clustering, Association Rule Mining, Prediction, Time Series Analysis, Sequential Pattern and Genetic Algorithm and Nearest Neighbor have been used for knowledge discovery from large data set (Garg & Arvind , 2013).

Unsupervised classification that is called clustering or sometimes known as exploratory data analysis in which there is no provision of labeled data. The main aim of clustering technique is to separate the unlabeled data set into finite and discrete set of natural and hidden data structures. There is no provision of providing accurate characterization of unobserved samples that are generated from by same probability distribution. (Gera & Goel , 2015). Clustering as the name suggests is the process of grouping data into classes, so that objects within a cluster have high similarity in comparison to one another, but are very dissimilar to objects in other cluster.

Algorithm	Merits	Demerits
Decision Tree	It can handle both continous and disceret data It provides fast result in classifying unknown records. It works well with redundant attribute It provides good result with small size tree. Result do not affect with outliers. It does not require preparation method with normalization It also works well with numeric data	It cannot predict It can"t predict the value of a continous classs atribute It provides error prone results when too man classes are used Irrelevant attribute affect construction of decision tree in a bad manner Small change in data can change the decisio tree completely
Naïve Bayesian	It provides high accuracy and speed on large database It has minimum error rate in comparison to all other classifier It is easy to understand It is mot sensitive to irrelevant features It can handle streaming data well It can also handle real and discrete values	It assumes independence of featuress so it provides less accuracy
Neural Networks	NNs have high tolerance of noisy data They are well suited for continous value They can classify pattern on which they have not tamed	They have poor interpretability They contain long training time
Association Rules	Uses large Itemset propert Easily parallelized Easy to implement	Assumes trasaction database is memory resident Requires many database scans
Regression Analysis	Estimates the relationship that exists, on the average, between the dependent variable and the explanatory. variableDetermine the effect of each of the explanatory variable on th dependent variable, controlling the effects of all other explanatory variables Predict the value of dependent variable for a given value the e explanatory values	No multicollinearity No autocorrelation of the errors No outlier distortion

Table 2.1 Comparism of classification algorithm

VIII. DATA MINING TOOLS

The Data Mining software tools combine fundamentals, theories, methods and algorithms. These applications base their operation in algorithms that look for patterns of knowledge by combining a set of tools for interrogation and exploration of data with tools that allow the visualization of results and reporting. This tools are free and open source and they include KNIME, Orange, RapidMiner and Weka. (Borges, Viriato , & Bernardino, 2103).

Tools	**Average Accuracy**
Weka	84.28%
KNIME	81.40%
Orange	81.19%
RapidMiner	77.67%

Table 2.2 Sources: (Borges, Viriato , & Bernardino, 2103**)**

From the above table we can infer that the best accuracy was obtained by Weka software and the least Accuracy was obtained by RapidMiner.

This Is a Subsubsection Heading. Use of T In conclusion, according to (Jovic, Brkic, & Bogunovic, 2014) there is no single best tool. Each tool has its strong points and weaknesses. Nevertheless, RapidMiner, R, Weka, and KNIME have most of the desired characteristics for a fully-functional DM platform and therefore their use can be recommended for most of the DM tasks.

1X. METHODOLOGY

Data for this analysis came from the management Information Systems (MIS) of the Information and Communication Technology unit (ICT) of Ogun State Institute of Technology Igbesa. The years of the data span the period of academic year 2014 through academic year 2017. The four years of enrollment data and records of students were collected and this was done purposely to allow for long period analysis. The institutions enroll approximately 3,000 new student at both National and Higher Diploma level.

The data samples were restricted to students who were admitted by early January of the year i.e. by the end of the first week in January. The four years of enrollment data and records of students were collected purposely to allow for long period projections. And also to manage it in the temporal sense as the enrollment projection is an annual routine and needs to be done in a particular season of the year which thus makes it theoretically and statistically sound

The framework that we adopted in this paper is in many ways similar to that of (Belanger, 2013) in that we are both analyzing the student enrollment in a Higher Education of Learning. Our paper though, differs in several important aspect like the tools, model and algorithm used.

We used geography and demography data by using student addresses to aid our analysis. From this we are able to get the geographic location of students. The geography location of students help us to know measure students distance to OGITECH, distance to our closest regional competitors, the High School they attended and whether they live in Ogun State where the Institution is situated.

Data preprocessing and preparation are the most time consuming and the most important part of data mining. Knowingly that the data must be converted to acceptable format for the prediction algorithm.

To determine the city and state from the students address a code was run considering the fact the fact that we are dealing with a huge volume of data see (appendix 1.0). Most of the initial data work for this study was done using Microsoft Excel which provides an easy to use structures for data preparation, analysis and modelling. With Excel we were able to change data types, rename columns, CLEAN, TRIM and also save with CSV. File format which was very useful while utilizing the WEKA tools. After the completing the data cleanup, manipulation and exploration process by way of identifying the outliners, cleanse data and ignoring the constant variable. We identified the important fields' tagged (labels) to be used for the prediction of the algorithm. Each year data set was exported from the excel sheet in a CSV format to WEKA tools using the city and state the labels respectively.

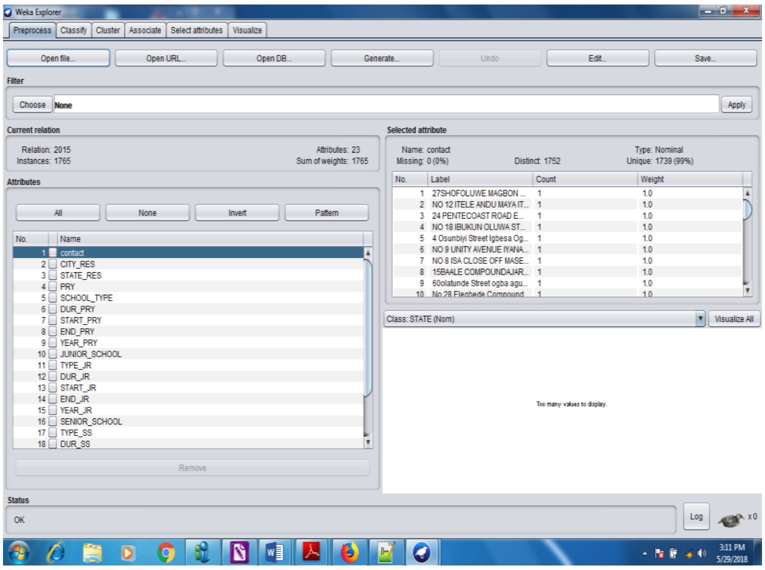

Fig 1 showing the WEKA tool Explorer Environment and the attributes used in the analysis.

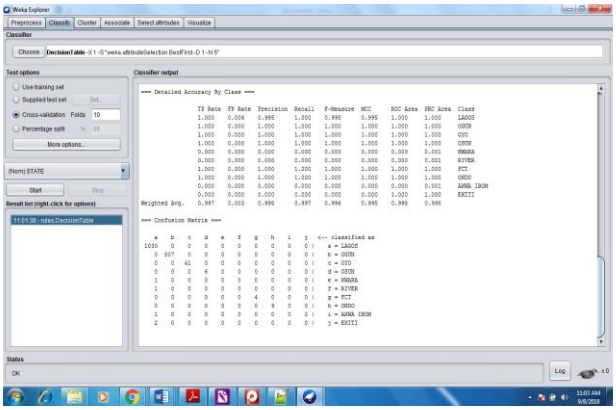

Fig 2 in WEKA tool showing the confusion Matrix and detailed accuracy by Class.

X. RESULTS AND DISCUSSION

The experimental result under the framework of Waikato Environment for knowledge Analysis (WEKA) shows the comparison of various algorithm based on performance. Figure 3.4 shows that Zero R, Decision rule, Tree and Naves Bayes were compared based on performance. We can see that all the algorithm were skillful on the datasets compared to Zero R which is being used as the baseline. We can also see that our baseline for skill is 53.21% accuracy. Looking at the raw classification accuracies, it looks like the Trees (J.48) may have achieved higher accuracy than the other. Further analysis shows that Trees (J48) results are better than other results but not statistically different from Decision rule and Naves Bayes

From fig 3.6 we can also infer that the estimated accuracy of the Tree model is 99.84% with a standard deviation of 1.2%. Though, Decision rule has a higher standard deviation of 1.5% which are more than the standard cut off mark of 0.5%. The standard deviation of the model accuracy can be used to help quantify the expected variability in the estimated accuracy of the data. We can also generally expect that the performance of the Tree algorithm on the data collected will be 99.84% plus or minus (2* 0.12) %.

Based on the aforementioned, Tree (J48), was chosen to predict or analyze the data for student enrolment based on the geodemographic at Ogun State Institute of Technology Igbesa. Apart from the fact that Trees (J48) has the best skill accuracy based on performance compared with other algorithm: The Tree also has the advantage of not only be able to handle continuous and discrete data and work well with redundant attribute. But it also help to provide fast result in classifying unknown records. Though other algorithm like Decision rule and Naves Bayes could also give a fair result based on the performance on the data set.

Necessary parameters such as Precision, True positive, False positive, Accuracy, Recall, ROC were used to analyze the result. It is clear from the screen shots that the values of Recall that the algorithm returned most of the relevant result and the High precision which is more than 0.5% means that the algorithm returned more relevant results than irrelevant.

Another way of evaluating the performance of this algorithm on Ogun State Institute of Technology Igbesa enrolment using state attribute is to use a receiver Operating Characteristics (ROC) curve which is the model of sensitivity versus 1-specificity of the model which is also the false positive rate. A value of 0.5 indicates a model that predicts as well as chance; where as a value of 1 indicates a model with perfect predicting power. In the Tree model the ROC of most of the states returned a value that is greater than 0.5 which is an indication of good performance.

In addition, the cost analysis shown in fig 3.9, 3.10 and 3.11 indicates that Lagos state has the highest number of enrolment and Ogun state is also better than other states in the enrolment exercise. The main aim of this paper was to give Ogun State Institute of Technology Igbesa a better knowledge of student enrolment behavior that is based on geodemographic. I.e. the physical location. It can be deduced from the above discussion that strongest area is Lagos State and the weakest area is plateau state.

XI. CONCLUSION

With a high level of competition in recruiting new students among colleges, Polytechnics and Universities around the country. The enrolment analysis made has implication for the admission planner to simulate, forecast and project the future use of resources with precision, thus avoiding the pitfall of resources and wastage.The research employed in this thesis will expedite Ogun State Institute of Technology Igbesa in the enrolment process by providing guidance for new recruitment and marketing technologies based on demographics

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