Analyzing Students' Performance Using Frequent Item Set Mining, Clustering & Classification

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ABSTRACT

Educational data mining (EDM) is defined as the area of scientific inquiry centered around the development of methods for making discoveries within the unique kinds of data that come from educational settings , and using those methods to better understand students and the settings which they learn in.
Data mining enables organizations to use their current reporting capabilities to uncover and understand hidden patterns in vast databases. As a result of this insight, institutions are able to allocate resources and staff more effectively.
In this paper, we present a real-world experiment conducted in Shree Rayeshwar Institute of Engineering and Information Technology (SRIEIT) in Goa, India. Here we found the relevant subjects in an undergraduate syllabus and the strength of their relationship. We have also focused on classification of students into different categories such as good, average, poor depending on their marks scored by them by obtaining a decision tree which will predict the performance of the students and accordingly help the weaker section of students to improve in their academics.
We have also found clusters of students for helping in analyzing student's performance and also improvising the subject teaching in that particular subject.

Keywords *Data Mining, Education Domain, India, Association Rule Mining, Pearson Correlation Coefficient.*

1. INTRODUCTION

The advent of information technology in various fields has lead the large volumes of data storage in various formats like records, files, documents, images, sound, videos, scientific data and many new data formats. The data collected from different applications require proper method of extracting knowledge from large repositories for better decision making. Knowledge discovery in databases (KDD), often called data mining, aims at the discovery of useful information from large collections of data [1]. The main functions of data mining are applying various methods and algorithms in order to discover and extract patterns of stored data. There are increasing research interests in using data mining in education. This new emerging field, called Data Mining on Educational Domain, concerns with developing methods that discover knowledge from data originating from educational environments. Educational Data Mining uses many techniques such as Decision Trees, Neural Networks, Naïve Bayes, K- Nearest neighbor, and many others.
Using these techniques many kinds of knowledge can be discovered such as association rules, classifications and clustering. The discovered knowledge can be used for prediction regarding the overall performance of the student. The main objective of this paper is to use data mining methodologies to study student's performance in their academics.

2. **METHODOLOGY**

2.1 Background

SRIEIT's undergraduate degree programme - B.E. - consists of three fields of specialization (i.e. Information Technology, Electronics and Telecommunication, and Computer Engineering). Each field of specialization offers students many subjects during eight different semesters within a period of four years. A student belongs to a batch and the batch is offered a number of subjects.

The performance of students in the different courses offered provides a measure of the students' ability to meet lecturer/institution's expectations. The overall marks obtained by students in the different subjects are utilized in our experiment in finding related subjects. The main objective is to determine the relationships that exist between different courses offered as this is required for optimizing the organization of courses in the syllabi. This problem is solved in two steps:

I. Identify the possible related subjects.
II. Determine the strength of their relationships and determine strongly related subjects.

In the first step, we utilized association rule mining [1] to identify possibly related two subject combinations in the syllabi which also reduces our search space. In the second step, we applied Pearson Correlation Coefficient [2] to determine the strength of the relationships of subject combinations identified in the first step.

For this experiment, we selected students of batches from 2009-2010 in semesters 3-6 and 60 student in the three fields of specialization. The first step, finding possible related subjects, requires considering 2-subject combinations.

To do this we applied Association Rules Mining [1].Association Rule Mining and its application are discussed in sections B and C.

2.2 Association Rule Mining

Firstly, 2-subject combinations were obtained using Apriori algorithm by using database of the form Table 2. Then Association rules were applied to the output of Apriori algorithm.

Association rules are an important class of regularities that exists in databases. The classic application of association rules is the market basket analysis [1]. It analyzes how items purchased by customers are associated.

Formally, the association rule-mining model can be stated as follows. Let $I = \{i_l, i_2,...,i_m\}$ be a set of items. Let D be a set of transactions (the database), where each transaction d is a set of items such that $d \subset I$. An association rule is an implication of the form, X->Y, where $X \subset I$, $Y \subset I$, and $X \cap Y = 0$. The rule X -> Y holds in the transaction set D with confidence c if c% of transactions which contain X in D also contains Y.The rule has support s in D if s% of the transactions in D contains $X \cup Y$.

Given a set of transactions D (the database), the problem of mining association rules is to discover all association rules that have support and confidence greater than or equal to the user specified minimum support (called *minsup*) and minimum confidence (called *minconf*).

2.3 Application of Association Rule Mining

At SRIEIT, a student earns either a "pass" grade (that is, a student meets the minimum requirements for successful completion of the subject) or "failure" grade (that is, a student fails to meet the minimum requirements for successful completion of the subject) for every subject the student followed. A transaction table is considered consisting of students with their passed subjects (see TABLE II).

Our goal is to find the relationship between two subjects (i.e. $subject_i$ and $subject_j$ where $i \neq j$) using association rule mining. That is, find association rules with the following format meeting a certain selection criteria.

$$subject_i \rightarrow subject_j, \text{ where } i \neq j$$

Table 1. Database instance of student

Student	Student Passed Subjects
S1	$subject_1$, $subject_2$, $subject_3$
S2	$subject_1$, $subject_2$, $subject_4$
S3	$subject_1$, $subject_5$

In creating the database, we considered only passed subjects due to the fact that no subject had a 100% failure. To identify all possible related subjects (not necessarily subjects with high pass rates), we ignored the support and considered only confidence measure. The confidence was sufficient to determine the possible related subjects (for instance, in the above rule, confidence provides us with the percentage of students that had passed $subject_i$ also passed $subject_j$).

We considered the average pass rate as the minimum confidence:

$$minconf = \frac{\sum(pass\_rate\_for\_each\_subject)}{number\_of\_subjects}$$

2.4 Pearson Correlation Coefficient

The Pearson Correlation Coefficient (r) measures the strength of the linear relationship between two continuous variables. We computed r and selected a threshold value (i.e. γ) to determine strong relationships.

The Pearson Correlation Coefficient (r) is computed as follows:

$$r = \frac{\sum_{i=1}^{n}(Xi - \bar{X})\ (Yi - \bar{Y})}{(n-1)SxSy}$$

where:

- X, Y are two continuous variables,
- Sx and Sy are the standard deviations of X and Y, and
- $\bar{X}$ and $\bar{Y}$ are the mean values of X and Y.

The value of r is such that -1 < r < +1. The + and – signs are used for positive linear correlations and negative linear correlations, respectively. If there is no linear correlation or a weak linear correlation, r is close to 0. A correlation greater than 0.5 is generally described as strong, whereas a correlation less than 0.5 is generally described as weak.

2.5 Application of Pearson Correlation Coefficient

After experimentation we selected 0.5 for the threshold value (i.e. $\gamma = 0.5$) as a suitable estimate for determining a strong relationship. A subject combination (say $subject_i$ and $subject_j$ where $i \neq j$) may contain a strong relationship (that is $r \geq 0.5$ for $subject_i$, $subject_j$ permutation).

2.6 Classification Algorithm

Here we make use of decision tree to classify the data and the tree is obtained by making use of ID3 algorithm. A decision tree is a tree in which each branch node represents a choice between a number of alternatives, and each leaf node represents a decision. Decision tree starts with a root node on which it is for users to take actions. From this node, users split each node recursively according to decision tree learning algorithm. The final result is a decision tree in which each branch represents a possible scenario of decision and its outcome. We provide the collected data to the algorithm to create a model called as classifier. Once the classifier is built we can make use of it and can easily classify any student and can predict its performance.

ID3 is a simple decision tree learning algorithm. The basic idea of ID3 algorithm is to construct the decision tree by employing a top-down, greedy search through the given sets to test each attribute at every tree node. In order to select the attribute that is most useful for classifying a given sets, we introduce a metric - information gain. To find an optimal way to classify a learning set we need some function which provides the most balanced splitting. The information gain metric is such a function. Given a data table that contains attributes and class of the attributes, we can measure homogeneity (or heterogeneity) of the table based on the classes. The index used to measure degree of impurity is Entropy.

The Entropy is calculated as follows:

$$E(S) = \sum_j - p_j \log_2 p_j$$

Splitting criteria used for splitting of nodes of the tree is Information gain. To determine the best attribute for a particular node in the tree we use the measure called Information Gain. The information gain, Gain (S, A) of an attribute A, relative to a collection of examples S, is defined as

$$Gain(S,A) = E(S) - \sum_v \frac{|S_v|}{|S|} E(S_v)$$

The ID3 algorithm is as follows:
- Create a root node for the tree
- If all examples are positive, Return the single-node tree Root, with label = +.
- If all examples are negative, Return the single-node tree Root, with label = -.
- If number of predicting attributes is empty, then Return the single node tree Root, with label = most common value of the target attribute in the examples.
- Otherwise Begin
- A = The Attribute that best classifies examples.
  - Decision Tree attribute for Root = A.
  - For each possible value, vi, of A,
  - Add a new tree branch below Root, corresponding to the test A = vi.
  - Let Examples (vi) be the subset of examples that have the value vi for A
  - If Examples (vi) is empty
  - Then below this new branch add a leaf node with label = most common target value in the examples
  - Else below this new branch add the subtree ID3 (Examples (vi), Target_ Attribute, Attributes – {A})
- End
-Return Root

Here we used attendance and marks of 60 students from 3 branches each. (See TABLE IV).

2.7 Clustering Algorithm

DBSCAN is a density-based spatial clustering algorithm. By density-based we mean that clusters are defined as connected regions where data points are dense. If density falls below a given threshold, data are regarded as noise.

DBSCAN requires three inputs:

a) The data source.
b) A parameter, Minpts- which is the minimum number of points to define a cluster.
c) A distance parameter, Eps- a distance parameter- if there are atleast Minpts within Eps of a point is a core point in a cluster.

Core Object: Object with at least MinPts objects within a radius 'Eps-neighborhood'
Border Object: Object that on the border of a cluster
NEps(p): {q belongs to D | dist(p,q) <= Eps}
Directly Density-Reachable: A point p is directly density-reachable from a point q w.r.t Eps, MinPts if p belongs to NEps(q)
|NEps (q)| >= MinPts
Density-Reachable: A point p is density-reachable from a point q w.r.t Eps, MinPts if there is a chain of points p1, …, pn, p1 = q, pn = p such that pi+1 is directly density-reachable from pi
Density-Connected: A point p is density-connected to a point q w.r.t Eps, MinPts if there is a point o such that both, p and q are density-reachable from o w.r.t Eps and MinPts.

It starts with an arbitrary starting point that has not been visited. This point's ε-neighborhood is retrieved, and if it contains sufficiently many points, a cluster is started. Otherwise, the point is labeled as noise. Note that this point might later be found in a sufficiently sized ε-environment of a different point and hence be made part of a cluster.

If a point is found to be part of a cluster, its ε-neighborhood is also part of that cluster. Hence, all points that are found within the ε-neighborhood are added, as is their own ε-neighborhood. This process continues until the cluster is completely found. Then, a new unvisited point is retrieved and processed, leading to the discovery of a further cluster or noise.

Here too we used attendance and marks of 60 students from 3 branches each. (See TABLE III).

3. RESULT

3.1 Observations

The output of association rule mining and later Pearson coefficient correlation provided us with the possibly related 2-subject combination and the strength of their relationship.

The subjects reviewed and the strongly related subjects are mentioned in the appendix.

The results obtained through clustering gained important knowledge and insights that can be used for improving the performance of students. The yield was different clusters that is, cluster1: students attending the classes regularly scored high marks and cluster2: students attending regularly scored less marks. This result helps to predict whether scoring marks in a subject actually depends on attendance or not. It even helps to find out weak students in a particular subject. This will help the teachers to improve the performance of the students who are weak in those particular subjects. (see Appendix F).

Table 2. Instance of a database for clustering

Stud_id	attendance	marks
1	93	20
2	100	41
3	100	41
4	100	25
5	87	46
. .	. .	. .

The result obtained from classification is a classifier in the form of decision tree which classifies the unseen student in order to predict the performance of the student. Prediction will help the teachers to pay attention to poor and average students in order to enhance their capabilities in their academics.

The result of Clustering and Classification is mentioned in the appendix

Table 4. Instance of a database for classification

Stud_id	Dept	Attendance	Marks	Performance
1	ETC	Y	310	AVERAGE
2	IT	N	450	GOOD
3	COMP	Y	500	GOOD
4	IT	Y	230	POOR
. .	. .	. .	. .	. .

After applying classification algorithm we get a decision tree which is dependent on the "gain" (see Appendix).

3.2 Significance of Results

The results obtained through our experiment gained important knowledge and insights that can be used for improving the quality of the educational programmes. Some of these insights are outlined below:

- Preconceived notion of a relationship between Mathematics subjects and programming subjects:

There existed a general notion that mathematics subjects and programming subjects are correlated. However, our experiments illustrated that there does not exists a strong relationship between these subjects. That is, passing or failing a mathematics subject does not determine the ability to pass/fail a programming subject and vice-versa.

- Assist in determining pre-requisite subjects:

When determining prerequisites it is advantageous to know that the existence of the strong relationship between subjects. A student may fail a particular subject (say subjectA) and proceed to taking further subjects (say subjects, subjectB, subjectC). However, the student may not have acquired the necessary knowledge and skills required (i.e. pre-requisite knowledge) for passing subjectB and subjectC. Hence, the student may fail with a high probability and waste student's and institution's resources. If there a large percentage of students who fail a pre-requisite subject (i.e. subjectA) also fail the subject (i.e. subjectB), then these subjects are strongly related (subjectA is strongly related to subjectB) and is captured in our experimental results.

- Project Course:

At the end of the 6th semester, RIEIT focuses on students completing a project as a team. The main objective of the course is to apply knowledge gained from other subjects to solve a real-world problem. So our experiment will be beneficial for the students to select project ideas which are based on present subject and related to past subject.

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APPENDIX

List of subject id and their titles

id	Subject
IT31	Applied Mathematics III
IT32	Numerical Methods
IT33	Analog And Digital Communication
IT34	Computer Organization And Architecture
IT35	Data Structures Using C
IT36	System Analysis And Design
IT41	Discrete Mathematical Structures
IT42	Signals And Systems
IT43	Computer Hardware And Troubleshooting
IT44	Microprocessors And Interfaces
IT45	Design And Analysis Of Algorithms
IT46	Object Oriented Programming System
IT51	Introduction To Data Communication
IT52	Digital Signal Processing
IT53	Software Engineering
IT54	Intelligent Agents
IT55	Operating Systems
IT56	Database Management System
IT51	Entrepreneurship Development
IT52	Theory Of Computation
IT53	Computer Networks
IT54	Computer Graphics

IT55	Web Technology
IT56	Software Testing And Quality Assurance
ETC31	Applied Mathematics III
ETC32	Digital System Design
ETC33	Network Analysis And Synthesis
ETC34	Electronic Devices And Circuits
ETC35	Managerial Economics
ETC36	Computer Oriented Numerical Techniques
ETC41	Applied Mathematics IV
ETC42	Signals And Systems
ETC43	Electrical Technology
ETC44	Electromagnetic Field And Waves
ETC45	Linear Integrated Circuits
ETC46	Data Structures Using C++
ETC51	Probability Theory And Random Processes
ETC52	Control System Engineering
ETC53	Communication Engineering 1
ETC54	Microprocessors
ETC55	Digital Signal Processing
ETC56	Transmission Lines And Waveguides
ETC61	Communication Engineering 2
ETC62	Peripheral Devices And Interfacing
ETC63	Power Electronics
ETC64	Antenna And Wave Propagation
ETC65	Electronic Instrumentation
ETC66	VLSI Technologies And Design
COMP31	Applied Mathematics III
COMP32	Basics Of C++
COMP33	Principles Of Programming Languages
COMP34	Computer Oriented Numerical Techniques
COMP35	Logic Design
COMP36	Integrated Electronics
COMP41	Discrete Mathematical Structures
COMP42	Data Structures
COMP43	Computer Organization
COMP44	Electronic Measurements
COMP45	System Analysis And Design
COMP46	Object Oriented Programming & Design Using C++
COMP51	Organizational Behavior And Cyber Law
COMP52	Automata Language And Computation
COMP53	Microprocessors And Microcontrollers
COMP54	Computer Hardware Design
COMP55	Database Management System
COMP56	Operating System
COMP61	Modern Algorithm Design Foundation
COMP62	Object Oriented Software Engineering

COMP63	Artificial Intelligence
COMP64	Computer Graphics
COMP65	Device Interface And Pc Maintenance
COMP66	Data Communications

Subjects offered in the IT stream for semesters 3-6

3rd Semester	4th Semester	5th Semester	6th Semester
IT31	IT41	IT51	IT61
IT32	IT42	IT52	IT62
IT33	IT43	IT53	IT63
IT34	IT44	IT54	IT64
IT35	IT45	IT55	IT65
IT36	IT46	IT56	IT66

Subjects offered in the ETC stream for semesters 3-6

3rd Semester	4th Semester	5th Semester	6th Semester
ETC31	ETC41	ETC51	ETC61
ETC32	ETC42	ETC52	ETC62
ETC33	ETC43	ETC53	ETC63
ETC34	ETC44	ETC54	ETC64
ETC35	ETC45	ETC55	ETC65
ETC36	ETC46	ETC56	ETC66

Subjects offered in the COMP stream for semesters 3-6

3rd Semester	4th Semester	5th Semester	6th Semester
COMP31	COMP41	COMP51	COMP61
COMP32	COMP42	COMP52	COMP62
COMP33	COMP43	COMP53	COMP63
COMP34	COMP44	COMP54	COMP64
COMP35	COMP45	COMP55	COMP65
COMP36	COMP46	COMP56	COMP66

Strongly Related subjects in the respective streams with $\gamma > 0.5$

IT Stream

ENTREPRENEURSHIP DEVELOPMENT	SOFTWARE TESTING AND QUALITY ASSURANCE
COMPUTER GRAPHICS	SOFTWARE TESTING AND QUALITY ASSURANCE
ENTREPRENEURSHIP DEVELOPMENT	COMPUTER GRAPHICS
DATA STRUCTURES USING C	DISCRETE MATHEMATICAL STRUCTURES
SOFTWARE ENGINEERING	SOFTWARE TESTING AND QUALITY ASSURANCE
DATA STRUCTURES USING C	DESIGN AND ANALYSIS OF ALGORITHMS
COMPUTER HARDWARE AND TROUBLESHOOTING	SOFTWARE TESTING AND QUALITY ASSURANCE
COMPUTER HARDWARE AND TROUBLESHOOTING	ENTREPRENEURSHIP DEVELOPMENT
SOFTWARE ENGINEERING	ENTREPRENEURSHIP DEVELOPMENT
SOFTWARE ENGINEERING	COMPUTER GRAPHICS
DISCRETE MATHEMATICAL STRUCTURES	ENTREPRENEURSHIP DEVELOPMENT
COMPUTER HARDWARE AND TROUBLESHOOTING	COMPUTER GRAPHICS
DESIGN AND ANALYSIS OF ALGORITHMS	ENTREPRENEURSHIP DEVELOPMENT
COMPUTER HARDWARE AND TROUBLESHOOTING	DESIGN AND ANALYSIS OF ALGORITHMS
DATA STRUCTURES USING C	SOFTWARE TESTING AND QUALITY ASSURANCE
INTRODUCTION TO DATA COMMUNICATION	COMPUTER GRAPHICS
DATA STRUCTURES USING C	ENTREPRENEURSHIP DEVELOPMENT
DISCRETE MATHEMATICAL STRUCTURES	DESIGN AND ANALYSIS OF ALGORITHMS

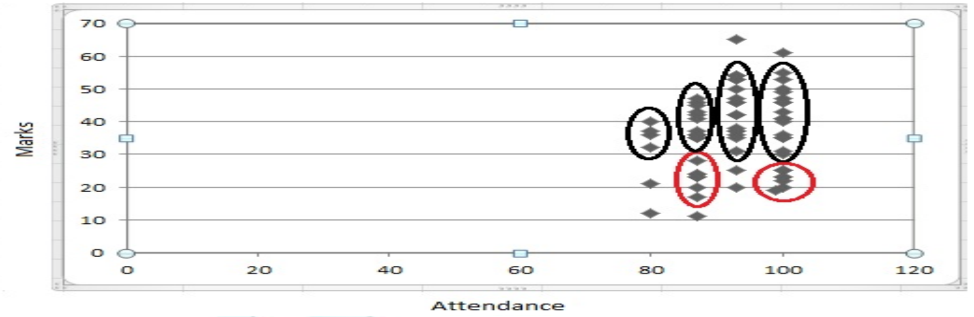
COMP Stream

DEVICE INTERFACE AND PC MAINTENANCE	DATA COMMUNICATIONS
OPERATING SYSTEM	DEVICE INTERFACE AND PC MAINTENANCE
BASICS OF C++	DATA STRUCTURES
BASICS OF C++	DEVICE INTERFACE AND PC MAINTENANCE
ORGANISATIONAL BEHAVIOUR AND CYBER LAW	DEVICE INTERFACE AND PC MAINTENANCE
COMPUTER ORGANISATION	DEVICE INTERFACE AND PC MAINTENANCE
SYSTEM ANALYSIS AND DESIGN	DEVICE INTERFACE AND PC MAINTENANCE
ORGANISATIONAL BEHAVIOUR AND CYBER LAW	DATA COMMUNICATIONS
DATA STRUCTURES	DATA COMMUNICATIONS
COMPUTER ORGANISATION	DATA COMMUNICATIONS
OBJECT ORIENTED PROGRAMMING AND DESIGN USING C++	DEVICE INTERFACE AND PC MAINTENANCE
BASICS OF C++	COMPUTER ORGANISATION
ELECTRONIC MEASUREMENTS	DEVICE INTERFACE AND PC MAINTENANCE
COMPUTER ORGANISATION	ELECTRONIC MEASUREMENTS
OBJECT ORIENTED SOFTWARE ENGINEERING	COMPUTER GRAPHICS
COMPUTER GRAPHICS	DATA COMMUNICATIONS
BASICS OF C++	DATA COMMUNICATIONS
BASICS OF C++	SYSTEM ANALYSIS AND DESIGN

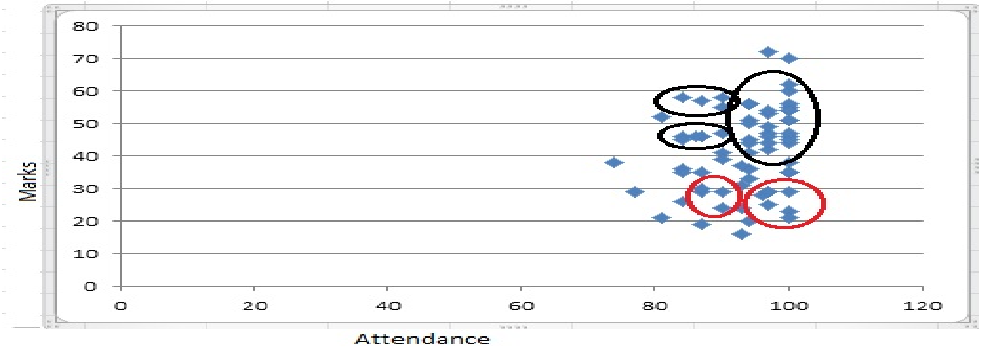
ETC Stream

ELECTRONIC INSTRUMENTATION	VLSI TECHNOLOGIES AND DESIGN
NETWORK ANALYSIS AND SYNTHESIS	SIGNALS AND SYSTEMS
ELECTRONIC DEVICES AND CIRCUITS	SIGNALS AND SYSTEMS
NETWORK ANALYSIS AND SYNTHESIS	COMPUTER ORIENTED NUMERICAL TECHNIQUES
ELECTRONIC DEVICES AND CIRCUITS	ELECTROMAGNETIC FIELD AND WAVES
ELECTRONIC DEVICES AND CIRCUITS	MANAGERIAL ECONOMICS
MANAGERIAL ECONOMICS	COMPUTER ORIENTED NUMERICAL TECHNIQUES
ELECTROMAGNETIC FIELD AND WAVES	LINEAR INTEGRATED CIRCUITS
DIGITAL SIGNAL PROCESSING	VLSI TECHNOLOGIES AND DESIGN
ELECTRONIC DEVICES AND CIRCUITS	APPLIED MATHEMATICS IV
ELECTRONIC DEVICES AND CIRCUITS	DATA STRUCTURES USING C++
COMPUTER ORIENTED NUMERICAL TECHNIQUES	SIGNALS AND SYSTEMS
MANAGERIAL ECONOMICS	SIGNALS AND SYSTEMS
NETWORK ANALYSIS AND SYNTHESIS	ELECTRONIC DEVICES AND CIRCUITS
ELECTRONIC DEVICES AND CIRCUITS	ELECTRICAL TECHNOLOGY
SIGNALS AND SYSTEMS	ELECTRICAL TECHNOLOGY
SIGNALS AND SYSTEMS	ELECTROMAGNETIC FIELD AND WAVES
NETWORK ANALYSIS AND SYNTHESIS	DATA STRUCTURES USING C++

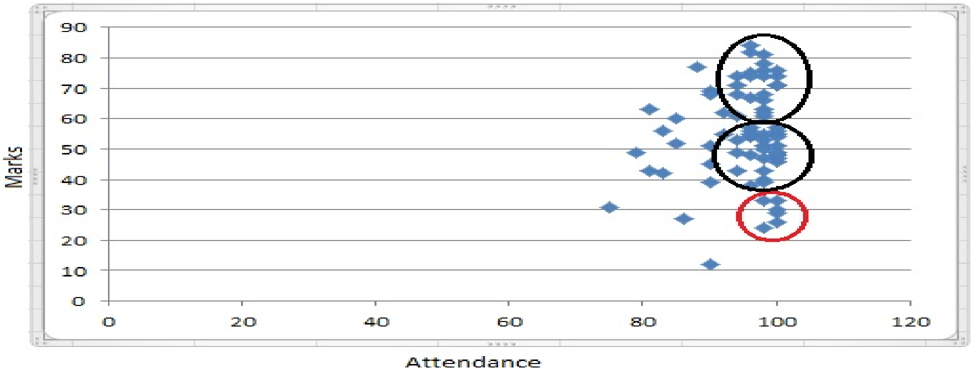
Clusters obtained in the respective streams



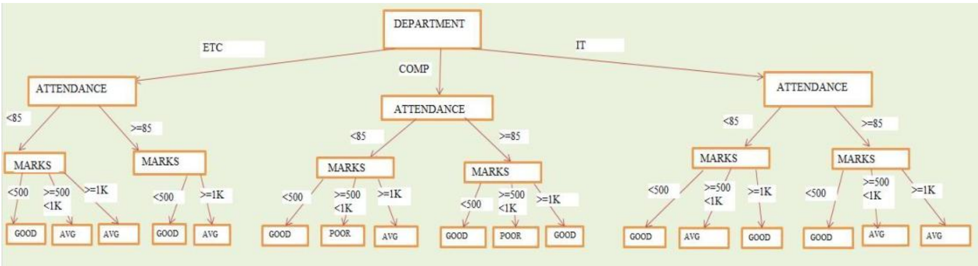
IT Stream



Computer Engg. Stream



ETC Stream



Decision Tree obtained as a result of classification