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**الجامعة الإسلامية – غزة  
شؤون البحث العلمي والدراسات العليا  
كلية تكنولوجيا المعلومات  
ماجستير تكنولوجيا المعلومات**

## **Predicting Lecturer's Performance Using Datamining Techniques Based on Lecturer's Characteristics and Historical Student Evaluation of Lecturer**

(Islamic University-Gaza case study)

**توقع أداء المحاضر باستخدام تقنيات تنقيب البيانات استناداً إلى  
خصائص المحاضر وتقييمات الطلبة السابقة للمحاضر  
(الجامعة الإسلامية بغزة كحالة دراسية)**

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إقرار

أنا الموقع أدناه مقدم الرسالة التي تحمل العنوان:

**Predicting Lecturer's Performance Using Datamining  
Techniques Based on Lecturer's Characteristics and Historical  
Student Evaluation of Lecturer**

**(Islamic University-Gaza case study)**

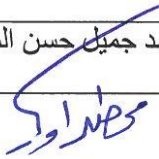
توقع أداء المحاضر باستخدام تقنيات تنقيب البيانات استناداً إلى خصائص  
المحاضر وتقييمات الطلبة السابقة للمحاضر  
(الجامعة الإسلامية بغزة كحالة دراسية)

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## نتيجة الحكم على أطروحة ماجستير

بناءً على موافقة شئون البحث العلمي والدراسات العليا بالجامعة الإسلامية بغزة على تشكيل لجنة الحكم على أطروحة الباحث/ محمد جميل حسن الطهراوي لنيل درجة الماجستير في كلية تكنولوجيا المعلومات برنامج تكنولوجيا المعلومات وموضوعها:

توقع أداء المحاضر باستخدام تقنيات تنقيب البيانات استناداً إلى خصائص المحاضر وتقييمات الطلبة السابقة للمحاضر - الجامعة الإسلامية بغزة كحالة دراسية

**Predicting Lecturer's Performance Using Datamining Techniques Based on Lecturer's Characteristics and Historical Student Evaluation of Lecturer Islamic University-Gaza case study**

وبعد المناقشة العلنية التي تمت اليوم الاثنين 12 ذو القعدة 1437هـ، الموافق 2016/08/15م الساعة الواحدة ظهراً في قاعة المؤتمرات بمبنى القدس، اجتمعت لجنة الحكم على الأطروحة والمكونة من:

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واللجنة إذ تمنحه هذه الدرجة فإنها توصيه بتقوى الله و لزوم طاعته وأن يسخر علمه في خدمة دينه ووطنه.

والله ولي التوفيق ،،،

نائب الرئيس لشئون البحث العلمي والدراسات العليا

أ.د. عبدالرؤوف علي المناعمة

## **Abstract**

**One of the most expensive resources in the higher educational process is lecturers, so most of the educational institutes spend a lot of effort and consume the HR resources to allocate the best lecturer to their students. Which will maximize the learning potential of the students according to the lecturer's qualifications, skills and abilities. Therefore, the challenge is how to predict lecturer's performance based on lecturer characteristics and historical student assessments of previous lecturers.**

**Our approach uses data mining techniques to analyze existing data composed of lecturer academic and non-academic characteristics and predict prospective lecturer's performance in order to support the decision-making in lecturer selection. We use four data mining techniques: Decision tree, K-Nearest Neighbor, Multinomial Logistic Regression and Naïve Bayesian. The models are trained and evaluated on a subset of the data. The model with the highest prediction outcome is selected.**

**We used data belonging to the academic staff of Islamic University – Gaza (IUG) that taught in 11 semesters (from second semester 2011/2012 to summer semester 2014/2015). The dataset contains an attribute for the overall evaluation result from the end-of-semester questionnaires routinely filled by students, and 28 attributes of lecturer characteristics. The overall student questionnaire result is aggregated over all sections of a course that is taught by the lecturer in one semester.**

**Based on training and evaluation of the four techniques mentioned above, and if we suppose that the closest prediction of the true evaluation is true, we can say that the models is predicting the evaluation truly or far from true in one step as next: Multinomial Logistic Regression gave the highest accuracy of 86.5%. Decision tree, K-Nearest Neighbor, and Naïve Bayesian gave accuracies of 85.0%, 86.4%, and 80.9%, respectively.**

**Key words: Prediction, Lecturer Performance, Data mining, Lecturer's Characteristics, Lecturers Evaluation**

## Abstract in Arabic

### المخلص

يعتبر المدرسون أحد أعلى المصادر في عملية التعليم العالي. تنفق معظم المؤسسات التعليمية الكثير من الجهد وتستهلك الموارد البشرية لتوفير أفضل المحاضرين لطلابهم مما يزيد من قدرة الطلاب على التعلم من الطلاب وفقا لمؤهلات المحاضر، والمهارات والقدرات التي يتمتع بها. و يكمن التحدي هنا في كيفية توقع أداء المدرسين بناء على خصائص المدرس والتقييم السابق للطلاب لمدرسيهم السابقين.

تقوم طريقتنا على استخدام تقنيات تنقيب البيانات من أجل تحليل البيانات المتوفرة حول الخصائص الأكاديمية وغير الأكاديمية للمحاضر الجامعي، والتنبؤ بأداء المحاضرين المحتمل عند توظيفهم و هذا بهدف تعزيز عملية اتخاذ القرار حين اختيار المحاضرين.

و استخدمنا لهذا الغرض أربع تقنيات لتنقيب البيانات و هي: شبكة القرارات، تقنية الجار الأقرب K، الانحدار متعدد الحدود اللوجستية، تصنيف نايف بايز. ويتم تدريب النماذج وتقييمها على مجموعة فرعية من البيانات و يتم اختيار النموذج وفقا لأعلى نتائج التنبؤ.

و قد استخدمنا البيانات الخاصة بالمدرسين الأكاديميين في الجامعة الإسلامية بغزة الذين درسوا لمدة 11 فصلا دراسيا (من الفصل الثاني للعام الجامعي 2011/2012 و حتى الفصل الصيفي للعام الجامعي 2014/2015). و اشتملت مجموعة البيانات على نتائج التقييم الكلي التي تم الحصول عليها من استبيانات يقوم الطلاب بتعبئتها و اشتملت كذلك على 28 خاصية للمحاضر. يتم تجميع النتيجة الإجمالية لاستبيان الطالب على جميع أجزاء المساق الذي يدرسه المحاضر خلال فصل دراسي واحد.

وبناء على تقييم التقنيات الأربعة المذكورة أعلاه، وعلى اعتبار أن القيمة المتنبئة المجاورة للقيمة الصحيحة صحيحة أعطى الانحدار متعدد الحدود اللوجستية أعلى دقة و مقدارها 86.5%. و أعطت شبكة القرارات، و الجار الأقرب K، تصنيف نايف بايز دقة مقدارها 85.0%، 86.4%، 80.9% على التوالي.

كلمات مفتاحية: التنبؤ، أداء المدرسين، تنقيب البيانات، خصائص المدرسين، تقييم المدرسين.

بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

﴿فَصَبْرٌ جَمِيلٌ﴾

[يوسف: 18]

﴿فَغَفَرْنَا لَهُ ذَلِكَ وَإِنَّ لَهُ عِنْدَنَا لَزُلْفَىٰ وَحُسْنَ مَآبٍ﴾

[ص: 25]

## Dedication

To my beloved mother *Samia*

To my beloved father *Dr. Jamel*

To my dear and supporter wife *Zolfa*

To my eye on the future, my lovely son *Jamel*

To my *sisters* and *brothers*

To my *in-Laws*

To my *relatives*

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## List of Abbreviations

|            |                                 |
|------------|---------------------------------|
| <b>DM</b>  | Data mining                     |
| <b>DT</b>  | Decision Tree                   |
| <b>EDT</b> | Eduactional Data Mining         |
| <b>IUG</b> | Islamic University of Gaza      |
| <b>KNN</b> | K-Neareast Nighbour             |
| <b>MLR</b> | Multinomial Logestic Regression |
| <b>NB</b>  | Naïve Bayeasian                 |
| <b>HR</b>  | Human Resources                 |

# **Chapter 1**

## **Introduction**

# Chapter 1

## Introduction

Through the year, the educational institutes undertake the process of allocating its resources to their right position or field, and some of these resources are allocated in a manual way, which adds more effort and consume the HR resources in this process because of the huge number of students and teachers of these institutes. The educational institutes consider students and lecturers their main assets and they look forward to improve their key process indicators by effective and efficient use of their assets (Naik, Sarma, Manjula, & Ramesh, 2011). But unfortunately, little attention has been paid to rethinking the use of existing institutional resources -such as teachers- the most important and expensive resource in the academic institutes (Miles, Darling-Hammond, & Linda, 1998).

One of the main goals of lecturer allocating process is to maximize the learning potential of the students by allocating the best teachers to the right classes according to the teacher's qualifications, skills and abilities. To achieve the previous goal, the academic institutes should be able to manage the resources such as teachers, lectures times tables, students, classes and subjects. This ability depends –in some way- on how to use the existing data about these resources in an efficient way. The existing data in the academic and educational domain offers a fertile ground for many interesting and challenging data mining applications. These applications can help administrators and academics in the academic universities and schools to improve the quality of the education and learning process (Ma, Liu, Wong, Yu, & Lee, 2000).

Data mining is the application of specific algorithms for extracting patterns from data (Fayyad, Piatetsky-Shapiro, & Smyth, 1996), another definition of data mining is the process that involves the use of sophisticated data analysis tools to discover previously unknown, valid patterns and relationships in large data set (Phyu, 2009). With the continues growing of educational data, and with the so much need to support taking right decision, the data mining embedding in educational systems will be in great demand on the next years.

The data mining offers a lot of methods and techniques to be benefited from the huge amount of existing data in the academic institutes and schools. Using data mining on

analyzing academic related data and extract knowledge from it to support the decision making is called Educational Data mining (EDM). The Educational Data Mining community website, [www.educationaldata mining.org](http://www.educationaldata mining.org), defines educational data mining as follows: “Educational Data Mining is an emerging discipline, concerned with developing methods for exploring the unique types of data that come from educational settings, and using those methods to better students understanding, and the settings which they learn in.”

EDM can play an important role in solving the lecturer recommendation in the academic institutes and schools. This can be done using the different data mining methods and techniques such as association rule, classification and prediction depending on the history data available at the Management Information Systems (MIS) as a source, the output of applying data mining on this data can be used as a guide or heuristic base on the academic decision making process.

In this thesis, we get a data set from Islamic university of Gaza that contains some attributes about lecturers characteristics and students assessment of lecturer performance in some courses, we will analyze the patterns and roles that affect students assessment of lecturer, and using these roles to predict the performance of new teacher when he begins to teach in a new semester. This chapter contains six sections. We will display problem statement, objective, scope and limitation, Significance of the project, Research Methodology and research format respectively.

## **1.1 Statement of the problem**

How to predict students ratings of lecturers based on characteristics of the lecturers.

## **1.2 Objectives**

This research has a main objective that can be achieved by achieving numbers of specific, or sub, objectives.

### **1.2.1 Main objective**

The main objective of the research is developing a data mining method to predict student’s ratings of lecturers based on the characterestics of the lecturers.



### **1.2.2 Specific objectives**

- 1- Obtaining a rich dataset of historical data (student evaluation of previous lecturers).
- 2- Obtaining data sets of related to lecturer characteristics.
- 3- Choosing a suitable data mining technique (through training and testing on historical data)
- 4- Evaluating the performance of the selected model (through testing on actual present cases).

### **1.3 Scope and limitations**

- 1- The research will focus on higher education and use Islamic University as cast study.
- 2- The data set, which will be used, corresponds to a specific semesters.
- 3- The proposed solution not is related to lecturer scheduling, only used to recommend teacher by predicting student's ratings of lecturers.

**Note:** This research will take into consideration the ethical and privacy issues, and the privacy related attributes in the data set will be extracted and excluding from the research implementation.

### **1.4 Significance**

- 1- Enhancing lecturers' recommmendation by predicting student's ratings of lecturers.
- 2- The research focus on solving teacher/lecturer related problem which did not receive adequate attention in the research.
- 3- The used method can be generalized and applied to other domains.
- 4- The proposed solution could be integrated easily with the used academic information systems.

### **1.5 Research Methodology**

Our methodology in this research consists of a number of steps each leading into one or more of the objectives presented in [section 1.2](#) above. Table 1.1 describes the steps of our methodology and brief description of each step.

Table 1.1 Research methodology

| Step | Description  | Objective   |
|------|--|---|
| 1.   | <b>Literature review:</b> In this step, we will review and study the previous researches conducted in fields of using data mining in educational purposes and using data mining in prediction. Also a deep reading, understanding and analysis will be conducted in the data mining topics in general.                                     | Expanding our knowledge in the problem domain (related works and related techniques used in data mining)  |
| 2.   | <b>Collecting and preprocessing data:</b> in this step we will work to find a suitable data set that contains information about university teachers and their evaluations and qualifications. Then we will apply the data mining preprocessing techniques such as cleaning, discretization, sampling, feature selection and normalization. | Increase data quality and perform data preprocessing to increase the accuracy of the mining.<br>To do serious, effective, real-world data mining. |
| 3.   | <b>Apply and evaluate data mining models:</b> after we had processed the data set, we will apply the data mining classification techniques such as Decision Tree, Naïve Baysan, KNN and multinomial logistic regression.   | Using the most usefulness and most techniques task to be considered the main used techniques.   |
| 4.   | <b>Select and evaluate performance of the best model</b> through testing on actual present cases.  | Evaluating the performance of the selected model.   |

## 1.6 Research Format

The research is organized in six chapters. Chapter one is an introduction, research problem, objectives, scope and significant. Chapter two is a background and state of the art. Chapter three is a related work. Chapter four is a proposed method and implementation. Chapter five is results and discussion. Chapter six presents conclusions and future work.

**Chapter 2**

**Background and state  
of the art**

## **Chapter 2**

### **Background and state of the art**

Based on the field of this research, this chapter is divided into two main sections: 1) performance evaluation, and 2) data mining. The first section explains the concept of performance evaluation, and focuses on lecturer's performance evaluation. The second section defines data mining, and explains how it is used in performance evaluation. The section also covers data preprocessing techniques, tasks of data mining, classification methods, and performance metrics for predictive modeling.

#### **2.1 Performance evaluation**

By investigated many papers we found that there were many terms used interchangeably with the term performance evaluation (Sok-Foon, Sze-Yin, & Yin-Fah, 2012) (Ahmadi & Abadi, 2013) (Wang, Dziuban, Cook, & Moskal, 2009) like performance assessment (Gupta & Suma, 2014) (Mardikyan & Badure, 2011), performance appraisal (Pal & Pal, 2013) (Peleyeju & Ojebiyi, 2013) or performance measurement (Molefe, 2010). We adopted the term performance evaluation in our thesis.

##### **2.1.1 Definition**

(Millmore, Lewis, Saunders, Thornhill, & Morrow, 2007) defined performance evaluation as a process of assessing the performance against pre-determined measures of performance, that is based on key success factors (KSF) which may include measures of deviation from the norm, tracking past achievements and measures of output and input.

(Gül, 2010) Add that performance evaluation is a process of management. It has become compulsory in human relations information system in the management of organizations.

It is clear that performance measurement monitors and reports how well someone or something is doing. In theory, it is a broad term applicable to people, things, situations, activities and organizations whilst performance management is a process that helps organizations to formulate, implement and change their strategy in order to satisfy their shareholders' needs (Millmore et al., 2007) .

## 2.1.2 Lecturer's performance

When we talk about evaluation performance in higher education, the first thing comes to our minds is employee performance, especially the lecturer's performance, because the lecturer is the most important and expensive resource in the academic institutes (Miles et al., 1998). This, translates into pressure on managers in the higher education environment to ensure that their staff (particularly academic staff) is working more productively and their institutions are responsive to the changing demands placed upon them by stakeholders.

To better understand the lecturer's performance evaluation; in this section, we discussed its dimensions and importance. We also presented how lecturer's performance has changed in light of the Web 2.0 technologies.

### 2.1.2.1 Dimensions

Performance dimensions for a university lecturer's job an approach adopted internationally in line with competency based thinking suggests that the following are some of the competencies that may be associated with lecturers' positions (Molefe, 2010):

Table 2.1 Some of the competencies that may be associated with lecturers' positions (Molefe, 2010)

|  |                                     |                            |
|--|-------------------------------------|----------------------------|
| communication                                | student and stakeholder orientation | learner assessment         |
| interpersonal skills                         | innovation and creativity           | organizational skills      |
| leadership                                   | decision-making                     | listening skills           |
| self-development                             | judgement                           | project management         |
| development of others                        | research                            | change management          |
| change management                            | subject mastery                     | originality                |
| commitment to quality                        | professional relations              | critical analytical skills |
| the ability to challenge conventional views. |                                     |                            |

Besides, performance evaluation is supposed to be subjective as it is measured indirectly. Performance evaluation is on the effectiveness of what personnel carry out and the understanding of their performance levels. It can be understood by performance evaluation to what extend an employee carries out the work. At the end of the evaluation, it can be understood not only the evaluation of performance but also the failure (Gül, 2010).

### **2.1.2.2 Importance**

(Samian & Noor, 2012) emphasized the purpose of Lecturer's Performance Assessment by students is to provide teaching staff with information to make informed decisions about improving lecturers teaching. It is a positive process and should be used for the enhancement of staff development and student learning.

(Gül, 2010) show the importance of lecturer's performance in next points:

- Higher education institutions are willing to learn more about the performances of lecturers.
- What is important in evaluation of lecturers are students' perceptions.
- It is essential for higher education institutions to know students' opinions about the lecturers.
- Provides an opportunity to define students' needs and their plans.
- Improves duty and responsibility feelings of students and prevents the probable problems in the communication between students and lecturers.
- Helps the management to be ready for the unknown and unpredictable external factors in order to take necessary precautions in advance.
- Gives clues to the lecturers in terms of their development potential.

(Mardikyan & Badure, 2011) point out that student evaluations of teaching (SET) results are utilized for other purposes by providing information to different parties in educational institutions.

- Administrators use ratings in:
  - Hiring new instructors.
  - Promotion and tenure decisions.
  - Selecting faculty and graduate students for teaching awards.
  - Assigning teachers to courses.
- Instructors use SET results to:
  - Improve their teaching effectiveness.
  - Monitoring the performance of their graduate student assistants.
- Students use the ratings in selecting courses and selecting teachers.

### **2.1.3 Lecturer's Performance in the World of Web 2.0**

(Wang et al., 2009) point out to important issue that makes using of data mining techniques very important to develop rule based models that best predict what students can evaluate Lecturer.

They said that during the recent decade, the emerging Internet and in particular the concept of Web 2.0 impacted students' evaluations of their instructors. This phenomenon is interacting with a generation of young people on campus who have been alternatively termed millennials, the net generation, the digital generation, and generation Y, among others. Their learning and technology characteristics are described as operating at twitch speed (miniscule response time), using parallel processing for information intake, preferring information in graphic rather than textual form, using their digital, personal, and mobile technologies to stay continually connected, preferring active rather than passive learning scenarios, incorporating play into their working lifestyles, embracing learning through virtual environments, and seeing technology as fun rather than a challenge. For them, the Web 2.0 with its sharing, communicating, blogging, text messaging, social networking, group writing through wikis, and interactive social opportunities is a seamless and continuous communication medium. These developments present a learning model far different from one-directional, teacher-to-student techniques that served as the prototype for most student evaluation of instruction research of the past decades. Today's students experience education through online and blended courses (partly face-to-face and partly online) and extending devices, such as podcasts, chat rooms, and worldwide virtual collaborative groups. These trends have implications for students and their instructors. One example of emerging issues is the Web site <http://www.ratemyprofessors.com> where students formed a worldwide community to share their perceptions about their instructors' teaching abilities. Further, they share their impressions on social networking tools, such as Facebook and MySpace, or post videos of their instructors in the act of teaching on YouTube. On many campuses students rate their professors online rather than using the paper and pencil scansheets of old. Students respond, not only to their face-to-face courses, but evaluate any number of technology mediated classes in which they might be involved. These emerging trends make it even more important to explore elements that underpin effective teaching in the eyes of students.

## **2.2 Data Mining**

In this section, we will present some explanations about some related data mining topics as data mining definitions, data mining process, data mining classification techniques and performance metrics for predictive modeling.

### **2.2.1 Data mining definitions**

(Han & Kamber, 2011) simply stated, data mining refers to extracting or “mining” knowledge from large amounts of data. They added that mining is a vivid term characterizing the process that finds a small set of precious nuggets from a great deal of raw material. Thus, such a misnomer that carries both “data” and “mining” became a popular choice. Many other terms carry a similar or slightly different meaning to data mining, such as knowledge mining from data, knowledge extraction, data/pattern analysis, data archaeology, and data dredging. Many people treat data mining as a synonym for another popularly used term, Knowledge Discovery from Data, or KDD. Alternatively, others view data mining as simply an essential step in the process of knowledge discovery. Knowledge discovery as a process is depicted in Figure 2.1 and consists of an iterative sequence steps.

(Larose, 2005) defined data mining as “the process of discovering meaningful new correlations, patterns and trends by sifting through large amounts of data stored in repositories, using pattern recognition technologies as well as statistical and mathematical techniques.”

(Hand, Mannila, & Smyth, 2001) Data mining is the analysis of (often large) observational data sets to find unsuspected relationships and to summarize the data in novel ways that are both understandable and useful to the data owner. The relationships and summaries derived through a data mining exercise are often referred to as models or patterns.



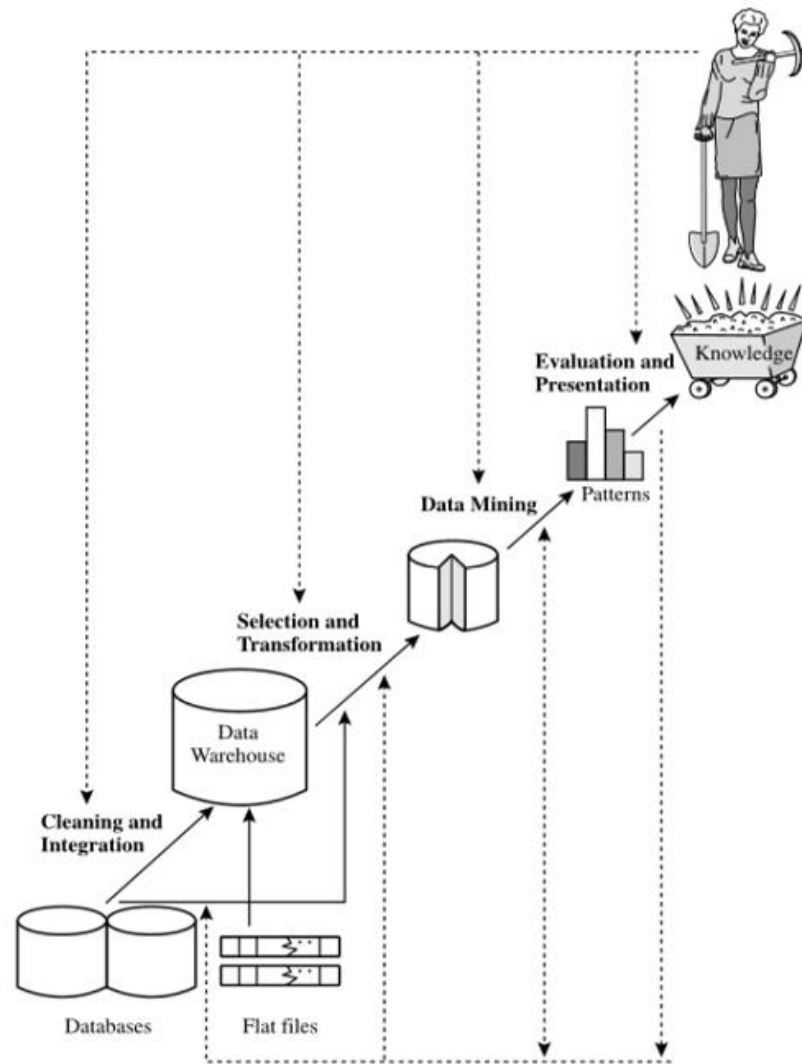


Figure 2.1 Data mining as a step in the process of knowledge discovery (Han & Kamber, 2011)

### 2.2.2 Data mining process

(Giudici, 2003) divided the data mining process into a series of activities from defining objectives to evaluating results. The seven activities or phases are:

- 1- Definition of the objectives for analysis
- 2- Selection, organization and pretreatment of the data
- 3- Exploratory analysis of the data and subsequent transformation
- 4- Specification of the statistical methods to be used in the analysis phase
- 5- Analysis of the data based on the chosen methods

- 6- Evaluation and comparison of the methods used and the choice of the final model for analysis
- 7- Interpretation of the chosen model and its subsequent use in decision processes.

We will describe the seven steps briefly in next subsections.

#### **2.2.2.1 Definition of the objectives**

Definition of the objectives involves defining the aims of the analysis. It is not always easy to define the phenomenon we want to analyze. In fact, the organization's objectives that we are aiming for, are usually clear, but the underlying problems can be difficult to translate into detailed objectives that need to be analyzed. A clear statement of the problem and the objectives to be achieved are the prerequisites for setting up the analysis correctly. This is certainly one of the most difficult parts of the process since what is established at this stage determines how the subsequent method is organized. Therefore, the objectives must be cleared and there must be no room for doubts or uncertainties.

#### **2.2.2.2 Organization of the data**

Once, the objectives of the analysis have been identified, it is necessary to select the data for the analysis. First, it is necessary to identify the data sources. Usually data is taken from internal sources that are cheaper and more reliable. This data also has the advantage of being the result of experiences and procedures of the organization itself. The ideal data source is the company data warehouse, a storeroom of historical data that is no longer subject to changes and from which it is easy to extract topic databases, or data marts, of interest. Once, a data matrix is available it is often necessary to carry out a preliminary cleaning of the data. In other words, a quality control is carried out on the available data, known as data cleaning. We will explain it in details in subsection 2.2.3 data preprocessing.

#### **2.2.2.3 Exploratory analysis of the data**

Exploratory analysis of the data involves a preliminary exploratory analysis of the data. An initial evaluation of the data's importance can lead to a transformation of the original variables to better understand the phenomenon or it can lead to statistical methods based on satisfying specific initial hypotheses. Exploratory analysis can

highlight any anomalous data-items that are different from the rest. These items data will not necessarily be eliminated because they might contain information that is important to achieve the objectives of the analysis. The author think that an exploratory analysis of the data is essential because it allows the analyst to predict which data mining methods might be most appropriate in the next phase of the analysis. The exploratory analysis might also suggest the need for new extraction of data because the data collection is considered insufficient to achieve the set aims.

#### **2.2.2.4 Specification of DM methods**

There are various data mining methods that can be used and there are also many algorithms, so it is important to have a classification of the existing methods. The choice of method depends on the problem being studied or the type of data available. The data mining process is guided by the applications. For this reason, the methods used can be classified according to the aim of the analysis. Then we can distinguish three main classes:

- Descriptive methods.
- Predictive methods.
- Local methods.

We will explain each of them in next subsections.

##### **2.2.2.4.1 Descriptive methods**

Methods that are aiming to describe groups of data more briefly; they are also called symmetrical, unsupervised or indirect methods. Observations may be classified into groups not known beforehand (cluster analysis, Kohonen maps); variables may be connected among themselves according to links unknown beforehand (association methods, log-linear models, graphical models). In this way all the variables available are treated at the same level and there are no hypotheses of causality.

##### **2.2.2.4.2 Predictive methods**

Methods that are aiming to describe one or more of the variables in relation to all the others; they are also called asymmetrical, supervised or direct methods. This is done by looking for rules of classification or prediction based on the data. These rules help us to predict or classify the results of future of one or more response or target variables

in relation to what happens to the explanatory or input variables. The main methods of this type are those developed in the field of machine learning such as the neural and decision trees but also classic statistical models such as linear and logistic regression models. We will explain some of these techniques in subsection 2.2.4 data mining classification techniques.

#### **2.2.2.4.3 Local methods**

Methods that are aiming to identify particular characteristics related to subset interests of the database; descriptive methods and predictive methods are global rather than local. Examples of local methods are association rules for analyzing transactional data.

#### **2.2.2.5 Data analysis**

Once, the data mining methods have been specified, they must be translated into appropriate algorithms for computing calculations that help us synthesize the results we need from the available database. The wide range of specialized and non-specialized software for data mining means that for most standard applications it is not necessary to develop adhoc algorithms; the algorithms that come with the software should be sufficient. Nevertheless, those managing the data mining process should have a sound knowledge of the different methods as well as the software solutions, so they can adapt the process to the specific needs of the company and interpret the results correctly when taking decisions.

#### **2.2.2.6 Evaluation of statistical methods**

To produce a final decision it is necessary to choose the best model of data analysis from the statistical methods available. Therefore, the choice of the model and the final decision rule are based on a comparison of the results obtained with the different methods. This is an important diagnostic check on the validity of the specific statistical methods that are then applied to the available data. In data mining it is rarely a good idea to use just one data mining method to analyze the data. Different methods have the potential to highlight different aspects, aspects which might otherwise have been ignored. To choose the best final model it is necessary to apply and compare various techniques quickly and simply, to compare the results that is produced and then give a business an evaluation of the different rules that is created.

In section 2.2.5 we will explain some methods to evaluate the techniques specially the prediction techniques.

#### **2.2.2.7 Implementation of the methods**

Data mining is not just an analysis of the data, it is also the integration of the results into the decision process of the company. Business knowledge, the extraction of rules and their participation in the decision process allow us to move from the analytical phase to the production of a decision engine. Once, the model has been chosen and tested with a data set, the classification rule can be applied to the whole reference population.

#### **2.2.3 Data preprocessing**

Real world data tend to be dirty, incomplete, and inconsistent. Data preprocessing techniques can improve the quality of the data, thereby helping to improve the accuracy and efficiency of the subsequent mining process. Data preprocessing is an important step in the knowledge discovery process, because the quality of decisions must be based on quality data. Detecting data anomalies, rectifying them early, and reducing the data to be analyzed can lead to huge payoffs for decision making (Han & Kamber, 2011).

In the following subsections, we introduce the most important steps in data preprocessing as seen in Figure 2.2:

##### **2.2.3.1 Data understanding**

This step can include initial data collection, data description, data exploration, and the verification of data quality. Data exploration such as viewing summary statistics (which includes the visual display of categorical variables) can occur at the end of this phase. Models such as cluster analysis can also be applied during this phase, with the intent of identifying patterns in the data (Olson & Delen, 2008)

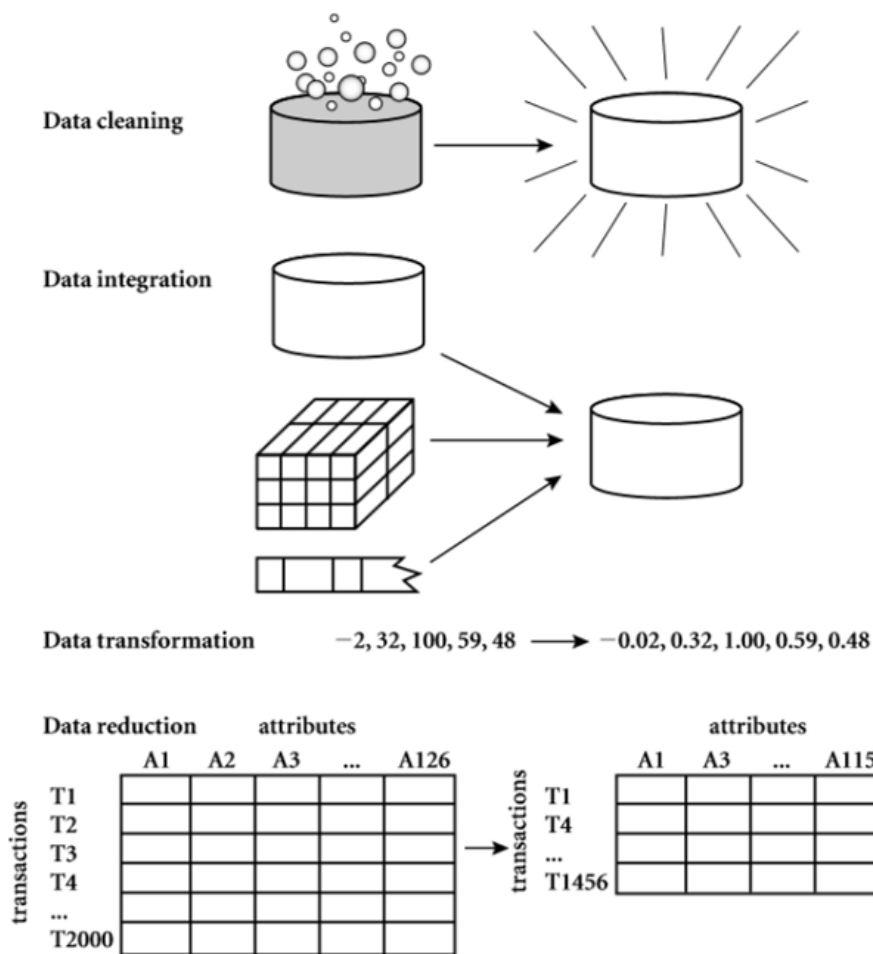


Figure 2.2 Forms of data preprocessing (Han & Kamber, 2011)

### 2.2.3.2 Data cleaning

(Han & Kamber, 2011) determined some basic methods for data cleaning. They are in the following subsections, missing values, noisy data and inconsistent data

#### 2.2.3.2.1 Missing values

You can go about filling in the missing values for attribute by one of the following methods:

1. Ignore the record: This is usually done when the class label is missing.
2. Fill in the missing value manually: In general, this approach is time-consuming.
3. Use a global constant to fill in the missing value: Replace all missing attribute values by the same constant, such as a label like “Unknown” or  $-\infty$ .

4. Use the attribute mean to fill in the missing value: For example, suppose that the average of one attribute is X. Use this value to replace the missing value in this attribute.
5. Use the attribute mean for all samples belonging to the same classes that given tuple.
6. Use the most probable value to fill in the missing value: This may be determined with regression, inference-based tools using a Bayesian formalism, or decision tree induction.

#### **2.2.3.2.2 Noisy data**

Noise is a random error or variance in a measured variable. We can smooth out the data to remove the noise by the following data smoothing techniques:

1. Binning: Binning methods smooth a sorted data value by consulting its “neighborhood,” that is the values around it. The sorted values are distributed into a number of “buckets,” or bins. Because binning methods consult the neighborhood of values, they perform local smoothing, you can use the following binning methods:
  - a. Partition into (equal-frequency) bins.
  - b. Smoothing by bin means.
  - c. Smoothing by bin boundaries.
2. Regression: Data can be smoothed by fitting the data to a function, such as with regression. Linear regression involves finding the “best” line to fit two attributes (or variables), so that one attribute can be used to predict the other.
3. Clustering: Outliers may be detected by clustering, where similar values are organized into groups, or “clusters.” Intuitively, values that fall outside of these clusters may be considered outliers.

#### **2.2.3.2.3 Inconsistent data**

The data analyst should be looked out for the inconsistent data representations such as: “2004/12/25” and “25/12/2004” for date. Field overloading is another source of errors that typically results when developers squeeze new attribute definitions into

unused (bit) portions of already defined attributes (e.g., using an unused bit of an attribute whose value range uses only, say, 31 out of 32 bits).

### **2.2.3.3 Data integration**

It is the process of taking operational data from one or more sources and mapping it, field by field, onto a new data structure in the data warehouse. The common identifier problem is one of the most difficult integration issues in building a data warehouse. Essentially, this situation occurs when there are multiple system sources for the same entities and there is no clear way to identify those entities as the same. This is a challenging problem, and in many cases, it cannot be solved in an automated fashion. It frequently requires sophisticated algorithms to pair up probable matches. Another complex data-integration scenario occurs when there are multiple sources for the same data element. In reality, it is a common that some of these values are contradictory, and resolving a conflict is not a straightforward process. Just as difficult as having conflicting values is having no value for a data element in a warehouse. All these problems and corresponding automatic or semiautomatic solutions are always domain-dependent (Kantardzic, 2003 ).

### **2.2.3.4 Data transformation**

In data transformation, the data are transformed or consolidated into forms appropriate for mining. Data transformation can involve the following (Han & Kamber, 2011):

- Smoothing, which works to remove noise from the data. Such techniques include binning, regression, and clustering.
- Aggregation, where summary or aggregation operations are applied to the data. For example, the daily sales data may be aggregated so as to compute monthly and annual total amounts.
- Generalization of the data, where low-level or “primitive” (raw) data are replaced by higher-level concepts through the use of concept hierarchies. For example, categorical attributes, like street, can be generalized to higher-level concepts, like city or country. Similarly, values for numerical attributes, like age, may be mapped to higher-level concepts, like youth, middle-aged, and senior.



- Normalization, where the attribute data are scaled so as to fall in a small specified range, such as -1.0 to 1.0, or 0.0 to 1.0.
- Attribute construction (or feature construction), where the new attributes are constructed and added from the given set of attributes to help the mining process.

### **2.2.3.5 Data reduction**

Data reduction techniques can be applied to obtain a reduced representation of the data set that is much smaller in volume, yet closely maintains the integrity of the original data. That is, mining on the reduced data set should be more efficient yet produce the same (or almost the same) analytical results (Han & Kamber, 2011).

(Kantardzic, 2003 ) describe the three basic operations in a data reduction process, delete a column, delete a row, and reduce the number of values in a column. These operations attempt to preserve the character of the original data by deleting data that are nonessential.

#### **2.2.3.5.1 Feature selection (Delete a column)**

The operations that may mentioned here are highly application-dependent, so we can mention briefly on one approach. Like the replacement of a set of initial features with a new composite feature. For example, if samples in a data set have two features, person-height and person-weight, it is possible for some applications in the medical domain to replace these two features with only one, body-mass-index, which is proportional to the quotient of the initial two features. Final reduction of data does not reduce the quality of results; in some applications, the results of data mining are even improved. Two standard tasks are associated with producing a reduced set of features, and they are classified as:

- Feature selection: Based on the knowledge of the application domain and the goals of the mining effort, the human analyst may select a subset of the features found in the initial data set. The process of feature selection can be used as a manual or supported by some automated procedures.
- Feature composition: There are transformations of data that can have a surprisingly strong impact on the results of data-mining methods. In this sense,

the composition of features is a greater determining factor in the quality of data-mining results than the specific mining technique. In most instances, feature composition is depending on knowledge of the application, and an interdisciplinary approach to feature the composition tasks to produces significant improvements in the preparation of data.

#### **2.2.3.5.2 Sampling (delete a row)**

The largest and the most critical dimension in the initial data set is the number of cases or samples or, in other words, the number of rows in the tabular representation of data. Case reduction is the most complex task in data reduction. Already, in the preprocessing phase, we have elements of case reduction through the elimination of outliers and, sometimes, samples with missing values. But the main reduction process is still ahead. If the number of samples in the prepared data set can be managed by the selected data mining techniques, then there is no technical or theoretical reason for case reduction. In real-world data-mining applications, however, with millions of samples available, that is not the case. Practical sampling possesses one or more of the following advantages: reduced cost, greater speed, greater scope, and sometimes even higher accuracy.

#### **2.2.3.5.3 Discretization (reduce the number of values in a column)**

The task of feature-discretization techniques is to discretize the values of continuous features into a small number of intervals, where each interval is mapped to a discrete symbol. The benefits of these techniques are simplified data description and easy-to-understand data and final data-mining results. Also, more data mining techniques are applicable with discrete feature values. An "old fashioned" discretization is made manually, based on our a priori knowledge about the feature. For example, using common sense or consensus, a person's age is given at the beginning of a data-mining process as a continuous value (between 0 and 150 years) may be classified into categorical segments: child, adolescent, adult, middle age, and elderly.

#### **2.2.4 Data mining classification techniques**

(Larose, 2005) investigating the classification as a task of data mining techniques, he explains that the classification is a target categorical variable, such as income bracket. For example, could be partitioned into three classes or categories: high income, middle

income, and low income. The data mining model examines a large set of records, each record is containing information on the target variable as well as a set of input or predictor variables. For example, consider the excerpt from a data set is shown in Table 2.2. Suppose that the researcher would like to be able to classify the income brackets of persons not currently in the database, based on other characteristics associated with that person, such as age, gender, and occupation. This task is a classification task, very nicely suited to data mining methods and techniques. The algorithm would proceed roughly as follows. First, examine the data set containing both the predictor variables and the (already classified) target variable, income bracket. In this way, the algorithm (software) “learns about” which combinations of variables are associated with income brackets. For example, older females may be associated with the high-income bracket. This data set is called the training set. Then the algorithm would look at new records, for no information about income bracket is available. Based on the classifications in the training set, the algorithm would assign classifications to the new records. For example, a 63-year-old female professor might be classified in the high-income bracket.

Table 2.2 Excerpt from Data Set for Classifying Income (Larose, 2005)

| Subject | Age | Gender | Occupation           | Income Bracket |
|---------|-----|--------|----------------------|----------------|
| 1       | 47  | F      | Software engineer    | High           |
| 2       | 28  | M      | Marketing consultant | Middle         |
| 3       | 35  | M      | Unemployed           | Low            |

In the following subsections, we will investigate the most common data mining classification techniques that we used in this thesis.

#### 2.2.4.1 Decision tree

Decision tree induction is the learning of decision trees from class –labeled training tuples. A decision tree is a flow chart- like tree structure, where each internal node (non leaf node ) denotes test on an attribute, each branch represents an outcome of the test, and each leaf node (or terminal node) holds a class label. The topmost node in a tree is the root node. (Han & Kamber, 2011)

Figure 2.3:A decision tree for the concept buys computer, indicating whether a customer is likely to purchase a computer. Each internal (non leaf) node represents a

test on an attribute. Each leaf node represents a class (either buys computer = yes or buys comput (Han & Kamber, 2011)

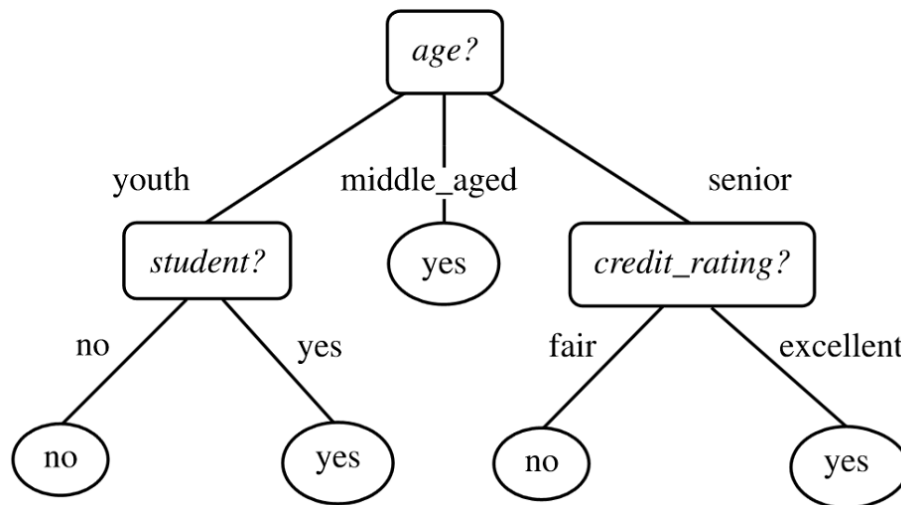


Figure 2.3 an example of decision tree for the concept buys computer

A typical decision tree is shown in Figure 2.3. It represents the concept buys computer, that it predicts whether a customer at some companies are likely to purchase a computer. Internal nodes are denoted by rectangles, and leaf nodes are denoted by ovals. Some decisions tree algorithms produce only binary trees (where each internal node branches to exactly two other nodes), whereas others can produce non binary trees. (Han & Kamber, 2011)

Decision tree classifiers are considered on of the most popular classifiers, because the construction of decision tree classifiers does not require any domain knowledge or parameter setting, and therefore is appropriate for exploratory knowledge discovery. Decision trees can handle high dimensional data. Their representation of acquired knowledge in tree form is intuitive and generally easy to assimilate by humans. The learning and classification steps of decision tree induction are simple and fast. In general, decision tree classifiers have good accuracy. Figure 2.4 summary of the basic decision tree algorithm. (Han & Kamber, 2011)

```

(1) create a node  $N$ ;
(2) if tuples in  $D$  are all of the same class,  $C$  then
(3)   return  $N$  as a leaf node labeled with the class  $C$ ;
(4) if  $attribute\_list$  is empty then
(5)   return  $N$  as a leaf node labeled with the majority class in  $D$ ; // majority voting
(6) apply  $Attribute\_selection\_method(D, attribute\_list)$  to find the “best”  $splitting\_criterion$ ;
(7) label node  $N$  with  $splitting\_criterion$ ;
(8) if  $splitting\_attribute$  is discrete-valued and
      multiway splits allowed then // not restricted to binary trees
(9)    $attribute\_list \leftarrow attribute\_list - splitting\_attribute$ ; // remove  $splitting\_attribute$ 
(10) for each outcome  $j$  of  $splitting\_criterion$ 
      // partition the tuples and grow subtrees for each partition
(11)   let  $D_j$  be the set of data tuples in  $D$  satisfying outcome  $j$ ; // a partition
(12)   if  $D_j$  is empty then
(13)     attach a leaf labeled with the majority class in  $D$  to node  $N$ ;
(14)   else attach the node returned by  $Generate\_decision\_tree(D_j, attribute\_list)$  to node  $N$ ;
      endfor
(15) return  $N$ ;

```

Figure 2.4 Basic algorithm for inducing a decision tree from training tuples (Han & Kamber, 2011)

#### 2.2.4.2 K-Nearest Neighbor KNN

(Han & Kamber, 2011) The k nearest neighbor method was first described in the early 1950s. The method is intensive when is given large training sets, and did not gain popularity until the 1960s when increased computing power became available. It has since been widely used in the area of pattern recognition. Nearest-neighbor classifiers are based on learning by analogy, that is by comparing a given test tuple with training tuples that are similar to it. The training tuples are described by  $n$  attributes. Each tuple represents a point in an  $n$ -dimensional space. In this way, all of the training tuples are stored in an  $n$ -dimensional pattern space. When it gives an unknown tuple, a  $k$ -nearest-neighbor classifier searches the pattern space for the  $k$  training tuples that are closest to the unknown tuple. These  $k$  training tuples are the  $k$  “nearest neighbors” of the unknown tuple. “Closeness” is defined in terms of a distance metric, such as Euclidean distance. The Euclidean distance between two points or tuples, say,  $X_1 = (x_{11}, x_{12}, \dots, x_{1n})$  and  $X_2 = (x_{21}, x_{22}, \dots, x_{2n})$ , is

$$dist(X_1, X_2) = \sqrt{\sum_{i=1}^n (x_{1i} - x_{2i})^2}$$

Equation 1: The Euclidean distance

In other words, for each numeric attribute, we take the difference between the corresponding values of that attribute in tuple X1 and in tuple X2, square this difference, and accumulate it. The square root is taken of the total accumulated distance count. Typically, we normalize the values of each attribute before using Equation 1. This helps to prevent attributes with initially large ranges from outweighing attributes with initially smaller ranges. Min-max normalization, for example, can be used to transform a value  $v$  of a numeric attribute A to  $v'$  in the range [0,1] by computing

$$v' = \frac{v - \min_A}{\max_A - \min_A}$$

Equation 2 Min-max normalization

Where  $\min_A$  and  $\max_A$  are the minimum and maximum values of attribute A. For k-nearest-neighbor classification, the unknown tuple is assigned the most common class among its k nearest neighbors. When  $k = 1$ , the unknown tuple is assigned the class of the training tuple that is closest to it in pattern space. Nearest neighbor classifiers can also be used for prediction, that is to return a real-valued prediction for the given unknown tuple. In this case, the classifier returns the average value of the real-valued labels associated with the k nearest neighbors of the unknown tuple.

### 2.2.4.3 Naïve Bayesian

Bayesian classifiers are statistical classifiers. They can predict class membership probabilities, such as the probability that the given tuple belongs to a particular class. It has also exhibited high accuracy and speed when it is applied to large databases.

Naïve Bayesian classifiers assume that the effect of an attribute value on a given class is independent of the values of the other attributes. This assumption is called class conditional independence. It is made to simplify the computations involved and, in this sense, is considered “naïve”. Bayesian belief networks are graphical models, which

unlike naïve Bayesian classifiers, allow the representation of dependencies among sub sets of attributes. Bayesian belief networks can also be used for classification.

The naïve Bayesian classifier, or simple Bayesian classifier, works as follows (Han & Kamber, 2011):

Let  $D$  be a training set of tuples and their associated class labels. As usual, each tuple is represented by an  $n$ -dimensional attribute vector,  $X = (x_1, x_2, \dots, x_n)$ , depicting  $n$  measurements made of the tuple from  $n$  attributes, respectively,  $A_1, A_2, \dots, A_n$ .

Suppose that there are  $m$  classes,  $C_1, C_2, \dots, C_m$ . Given a tuple,  $X$ , the classifier will predict that  $X$  belongs to the class having the highest posterior probability, conditioned on  $X$ . That is, the naïve Bayesian classifier predicts that tuple  $X$  belongs to the class  $C_i$  if and only if  $P(C_i|X) > P(C_j|X)$  for  $1 \leq j \leq m, j \neq i$ . Thus we maximize  $P(C_i|X)$ . The class  $C_i$  for which  $P(C_i|X)$  is maximized is called the maximum posteriori hypothesis. By Bayes' theorem

$$P(C_i|X) = \frac{P(X|C_i)P(C_i)}{P(X)}$$

As  $P(X)$  is constant for all classes, only  $P(X|C_i)P(C_i)$  needed to be maximized. If the class prior probabilities are not known, then it is commonly assumed that the classes are equally likely, that is,  $P(C_1) = P(C_2) = \dots = P(C_m)$ , and we would therefore maximize  $P(X|C_i)$ . Otherwise, we maximize  $P(X|C_i) P(C_i)$ . Note that the class prior probabilities may be estimated by  $P(C_i) = |C_i, D| / |D|$ , where  $|C_i, D|$  is the number of training tuples of class  $C_i$  in  $D$ .

Given data sets with many attributes, it would be extremely computationally expensive to compute  $P(X|C_i)$ . In order to reduce computation in evaluating  $P(X|C_i)$ , the naive assumption of class conditional independence is made. This presumes that the values of the attributes are conditionally independent of one another, given the class label of the tuple (i.e., that there are no dependence relationships among the attributes). Thus,

$$P(X|C_i) = \prod_{k=1}^n P(x_k|C_i)$$

$$= P(x_1|C_i) \times P(x_2|C_i) \times \dots \times P(x_n|C_i).$$

We can easily estimate the probabilities  $P(x_1|C_i), P(x_2|C_i), \dots, P(x_n|C_i)$  from the training tuples. Recall that here  $x_k$  refers to the value of attribute  $A_k$  for tuple  $X$ .

In order to predict the class label of  $X$ ,  $P(X|C_i)P(C_i)$  is evaluated for each class  $C_i$ . The classifier predicts that the class label of tuple  $X$  is the class  $C_i$  if and only if

$$P(X|C_i)P(C_i) > P(X|C_j)P(C_j) \text{ for } 1 \leq j \leq m, j \neq i.$$

In other words, the predicted class label is the class  $C_i$  for which  $P(X|C_i)P(C_i)$  is the maximum.

#### **2.2.4.4 Multinomial Logistic regression**

(Han & Kamber, 2011) Logistic regression models the probability of some events are occurring as a linear function of a set of predictor variables.

(Starkweather & Moske, 2011) Multinomial logistic regression is used to predict categorical placement in or the probability of category membership on a dependent variable based on multiple independent variables. The independent variables can be either dichotomous (i.e., binary) or continuous (i.e., interval or ratio in scale). Multinomial logistic regression is a simple extension of binary logistic regression that allows to more than two categories of the dependent or outcome variable. Like binary logistic regression, multinomial logistic regression uses maximum likelihood estimation to evaluate the probability of categorical membership. Multinomial logistic regression does necessitate careful consideration of the sample size and examination for outlying cases. Like other data analysis procedures, initial data analysis should be thorough and include careful univariate, bivariate, and multivariate assessment. Specifically, multicollinearity should be evaluated with simple correlations among the independent variables. Also, multivariate diagnostics (i.e. standard multiple regression) can be used to assess for multivariate outliers and for the exclusion of outliers or influential cases. Sample size guidelines for multinomial logistic regression indicate a minimum of 10 cases per independent variable (Schwab, 2002). Multinomial logistic regression is often considered an attractive analysis because; it does not



assume normality, linearity, or homoscedasticity. A more powerful alternative to multinomial logistic regression is discriminant function analysis which requires these assumptions are met. Indeed, multinomial logistic regression is used more frequently than discriminant function analysis because the analysis does not have such assumptions. Multinomial logistic regression have assumptions, such as the assumption of independence among the dependent variable choices. This assumption states that the choice of or membership in one category is not related to the choice or membership of another category (i.e., the dependent variable). The assumption of independence can be tested with the Hausman-McFadden test. Furthermore, multinomial logistic regression also assumes non-perfect separation. If the groups of the outcome variable are perfectly separated by the predictor(s), then unrealistic coefficients will be estimated and effect sizes will be greatly exaggerated. There are different parameter estimation techniques based on the inferential goals of multinomial logistic regression analysis. One might think of these as ways of applying multinomial logistic regression when strata or clusters are apparent in the data. Unconditional logistic regression (Breslow & Day, 1980) refers to the modeling of strata with the use of dummy variables (to express the strata) in a traditional logistic model. Here, one model is applied to all the cases and the strata are included in the model in the form of separate dummy variables, each reflecting the membership of cases to a particular strata. Conditional logistic regression (Breslow & Day, 1980; Vittinghoff, Shiboski, Glidden, & McCulloch, 2005) refers to applying the logistic model to each of the strata individually. The coefficients of the predictors (of the logistic model) are conditionally modeled based on the membership of cases to a particular strata. Marginal logistic modeling (Vittinghoff, Shiboski, Glidden, & McCulloch, 2005) refers to an aggregation of the strata so that the coefficients reflect the population values averaged across the strata. As a rudimentary example, consider averaging each of the conditional logistic coefficients, from the previous paragraph, to arrive at set marginal coefficients for all members of the population – regardless of strata membership. Variable selection or model specification methods for multinomial logistic regression are similar to those used with standard multiple regression; for example, sequential or nested logistic regression analysis. These methods are used when one dependent variable is used as criteria for placement or choice on subsequent dependent variables (i.e., a decision or

flow-chart). For example, many studies indicate the decision to use drugs follows a sequential pattern, with alcohol at an initial stage followed by the use of marijuana, cocaine, and other illicit drugs.

### 2.2.5 Performance Metrics for Predictive Modeling

(Olson & Delen, 2008) explains that the primary source of performance measurements in classification problems is a coincidence matrix. Figure 2.5 shows a coincidence matrix for a two-class classification problem. The equations of most commonly used metrics that can be calculated from the coincidence matrix is also given below.

|                 |          | True Class                |                           |
|-----------------|----------|---------------------------|---------------------------|
|                 |          | Positive                  | Negative                  |
| Predicted Class | Positive | True Positive Count (TP)  | False Positive Count (FP) |
|                 | Negative | False Negative Count (FN) | True Negative Count (TN)  |

Figure 2.5 a simple coincidence matrix (Olson & Delen, 2008).

The numbers along the diagonal from upper-left to lower-right represent the correct decisions made, and the numbers outside this diagonal represent the errors. The true positive rate (also called hit rate or recall) of a classifier is estimated by dividing the correctly classified positives (the true positive count) by the total positive count. The false positive rate (also called false alarm rate) of the classifier is estimated by dividing the incorrectly classified negatives (the false negative count) by the total negatives. The overall accuracy of a classifier is estimated by dividing the total correctly classified positives and negatives by the total number of samples. Other performance measures, such as recall (sensitivity), specificity and F-measure are also used for calculating other aggregated performance measures.

$$\text{True Positive Rate} = \frac{TP}{TP + FN}$$

$$\text{True Negative Rate} = \frac{TN}{TN + FP}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$F - \text{measure} = \frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}}$$

When the classification problem is not binary, the coincidence matrix gets a little more complicated (see Figure 2.6). In this case the terminology of the performance metrics becomes limited to “per class accuracy rates” and the “overall classifier accuracy”. These formulas are given below.

|                      |                | Actual Classification of Classes in the Dataset |                |                |      |
|----------------------|----------------|---|----------------|----------------|------|
|                      |                | <i>Class 1</i>                                  | <i>Class 2</i> | <i>Class 3</i> |      |
| Model Classification | <i>Class 1</i> | 22  | 7              | 2              |      |
|                      | <i>Class 2</i> | 5   | 18             | 7              |      |
|                      | <i>Class 3</i> | 3   | 5              | 21             |      |
| Sum                  |                | 30  | 30             | 30             |      |
| Probability          |                | 0.33  | 0.33           | 0.33           |      |
| Accuracy             |                | 0.73  | 0.60           | 0.70           | 0.68 |

Figure 2.6 A sample coincidence matrix for a three class classifier (Olson & Delen, 2008).

$$(\text{True Classification Rate})_i = \frac{(\text{True Classification})_i}{\sum_{i=1}^n (\text{False Classification})_i}$$

$$(\text{Overall Classifier Accuracy})_i = \frac{\sum_{i=1}^n (\text{True Classification})_i}{\text{Total number of Cases}}$$

Where  $i$  is the class number,  $n$  is the total number of classes.

Estimating the accuracy of a classifier induced by some supervised learning algorithms is important for the following reasons:

- 1- It can be used to estimate its future prediction accuracy which could imply the level of confidence one should have in the classifier's output in the prediction system.
- 2- It can be used for choosing a classifier from a given set (selecting the "best" model from two or more qualification models).
- 3- It can be used to assign confidence levels to multiple classifiers so that the outcome of a combining classifier can be optimized. Combined classifiers are increasingly becoming more popular due to the empirical results that suggest them producing more robust and more accurate predictions as they are compared to the individual predictors.

For estimating the final accuracy of a classifier one would like an estimation method with low bias and low variance. In some application domains, to choose a classifier or to combine classifiers the absolute accuracies may be less important and one might be willing to trade off bias for low variance.

# **Chapter 3**

## **Related Works**

## **Chapter 3**

### **Related Works**

In this chapter, different related works are studied and investigated. The chapter is divided into three sections. In section 3.1, we will give some related works about using data mining techniques in human performance prediction *in general*. In section 3.2, we will present some related works about *lecturer's* performance using data mining techniques. Finally, in section 3.3 we will give some conclusions about this chapter.

#### **3.1 Performance prediction using DM techniques**

In this section, we present some related works that use data mining techniques in predicting performance of people in general. We try to focus on performance in the field of education to be more close to our thesis problem.

(Hajizadeh & Ahmadzadeh, 2014) have used two applicable data mining techniques that known as “Classification” and “Association rule discovery” to explore effective factors on non re taking a course by students. They use evaluation tools as a step toward identifying and extracting factors affecting educational failure in students. They use data set contains a total 5820 evaluation scores and 33 attributes that provided by students from Gazi University in Ankara (Turkey). The attributes are nb.repeat, attendance, difficulty and 28 attributes that taken from the questionnaire: 12 attributes are related to course that taken by students and 16 attributes are related to features of the course instructor. According to their purpose, it was necessary nb.repeat field had to be chosen as the “class” attribute and the numerical values had to be replaced. By using data mining tool WEKA (Waikato Environment for Knowledge Analysis), three types of evaluation have been performed on the data. The first analysis the goal is to investigate the role of providing a specific course by an instructor on not taking that course again by students. The second analysis the goal is to investigate the features of provided course on not taking that course again by students. To evaluate this analysis attributes attendance, difficulty and Q1 to Q12 have been selected. Among classification algorithms that is applied to the selected data, the best result provided by REPTree algorithm with the following features and decision tree: Correctly Classified Instances 84.24% Avg. F-Measure 0.774. The third analysis The goal is to investigate the features of an instructor on not taking more than once the course provided by that

instructor. To evaluate this analysis attributes Q1 to Q12 have been selected. Among classification algorithms that is applied to the selected data, the best result provided by REPTree algorithm with the following features and decision tree: Correctly Classified Instances 84.26% Avg. F-Measure 0.772.

The work is related to our thesis because the problem is in the field of educational data mining, and it is a classification problem. Some differentiations between this study and our thesis, 1- our thesis goal is predicting the performance of new instructor not to determine exist instructor to be tech the course again or not. 2- this study was focused on student side by predicting student performance in a course if he will fail or pass, but our thesis focused on the lecturer side.

(Gupta & Suma, 2014) predicted the performance of software project member on the basis of previous database or training set. They have focused on the human aspect of software engineering to achieve good quality of software by building a classification model for predicting employees' performance based on certain attributes. Data mining techniques could identify those attributes required in a project member which will contribute to good performance and thereby enhance software quality and success. Classification techniques like ID3, CART and C4.5 showed similar results. Performance was earlier assumed to be best for candidates having a good college aggregate. The study showed that other talent attributes like programming skills and reasoning skills have proved to be more important, although software companies emphasize upon aggregate percentile and followed the same trend for many years. Due to lack of analytical method in human aspects, software companies were not selecting the right people who could perform well in the software process and thereby failed to achieve the desired quality in the time and cost constraints. They use data mining techniques that give a very interesting patterns and helped in earlier identification of project members who will perform well. The study enables the managers to refocus on human capability criteria and thereby enhance the development process of software project. Just like all process within generic framework of software development is given importance, human aspect also needs a deeper investigation for effective software development. Without the right people even the best process analysis and development are bound to fail. Further scope of this study is to investigate on several

projects of different domains and take into account more attributes of project personnel and correlate it with software quality and success.

This paper describes the importance of using data mining in analysis and predicting performance of human resources in organizations, they help software companies to select the right people that will perform well in the software process. This study have the same goals of our thesis with different field, our thesis goal is to help universities to select the best lecturer to teach courses by predicting his performance when he requests to teach based on his characteristics using data mining techniques.

(Bhardwaj & Pal, 2011) gathered data of 300 students from different degree colleges and institutions in Awadh University, Faizabad, India. These data are analyzed using classification method to predict the student's performance. The researchers used the attributes: Students Sex, Students category, Medium of Teaching, Students food habit, Students other habit, Living Location, Student live in hostel or not, student's family size, Students family status, Family annual income status, Students grade in Senior, Secondary education, Students College Type, Fathers qualification, Mother's Qualification, Father's Occupation, Mother's Occupation, Grade obtained in BCA. They use Bayesian classification method on student database to predict the students division on the basis of previous year database. The study help the students and the teachers to improve the division of the student. and work to identify those students which needed special attention to reduce failing ration and taking appropriate action at right time. The study shows that academic performances of the students are not always depending on their own effort. It shows that other factors have got significant influence over students' performance. The variables whose probability values were greater than 0.50 were given due considerations and the highly influencing variables with high probability values have been shown in Table 3.1. These features were used for prediction model construction. For both variable selection and prediction model construction, they have used MatLab.



Table 3.1 High Potential Variables (Bhardwaj & Pal, 2012)

| Variable | Description                                  | Probability |
|----------|--|-------------|
| GSS      | Students grade in Senior Secondary education | 0.8642      |
| LLoc     | Living Location                              | 0.7862      |
| Med      | Medium of Teaching                           | 0.7225      |
| MQual    | Mother's Qualification                       | 0.6788      |
| SOH      | Students other habit                         | 0.6653      |
| FAIn     | Family annual income status                  | 0.5672      |
| FStat    | Students family status                       | 0.5225      |

The researchers focused on student side in educational data mining. Our opinion of this work that he uses a good series of procedures to predict the student performance, that we will use in our thesis, but with differences because we will focus on lecturer performance side, and the amount of data that we will use. Here the researchers used a sample consist of 300 students only, it makes the results less reliable. We will use about 5000 records.

In section 3.1 we try to found some related work that investigated the performance predicting in general, the term performance predicting is a wide term that use in most things: variant organizations, factories, human, machines, etc. we can benefited from the methodologies that used to predict performance, so we try to explore works that closed to our work field, Educational data mining.

### 3.2 Lecturer's performance using DM techniques

This section presents some works that studied the evaluation of performance of university lecturers using DM techniques.

(Pal & Pal, 2013) proposed to evaluate teacher's performance on the basis of different factors, using data mining techniques. They collected data from post graduate studies at department in the college of engineering over a three-year period of the same students. Their proposed model consider the various aspects of performance measures of teachers, like Students' Feedback (voice modulation, speed of delivery, content arrangement, presentation, communication, overall impression, content delivery, explanation power, overall teaching and regularity, Results, Students attendance, that

have deep influence on the teachers' performance in university. All the predictor and response variables, which were derived from the database, are given in Table 3.2.

Table 3.2 Student related variables (Pal & Pal, 2013)

| Variables | Description                                 | Possible Values                |
|-----------|---|--------------------------------|
| Name      | Teacher Name                                | Text                           |
| SD        | Speed of delivery                           | (1,2,3,4,5)                    |
| CA        | Content arrangement                         | (1,2,3,4,5)                    |
| PR        | Presentation                                | (1,2,3,4,5)                    |
| CO        | Communication                               | (1,2,3,4,5)                    |
| OI        | Knowledge                                   | (1,2,3,4,5)                    |
| CD        | Content delivery                            | (1,2,3,4,5)                    |
| EP        | Explanation power                           | (1,2,3,4,5)                    |
| DC        | Doubts Clearing                             | (1,2,3,4,5)                    |
| DP        | Discussion of Problems                      | (1,2,3,4,5)                    |
| OCR       | Overall completion of course and regularity | (1,2,3,4,5)                    |
| SA        | Students attendenc                          | 1- Below, 2 – average, 3- high |
| RE        | Result                                      | 1- Pass, 2- fail, 3- promoted  |
| PT        | Performance of Teacher                      | (1,2,3,4,5)                    |

They use Weka, which is an open source software that implements a large collection of machine leaning algorithms and is widely used in data mining applications. Tests were conducted using three tests for the assessment of input variables: Chi-square test, Info Gain test and Gain Ratio test. Different algorithms were provide different results, i.e. each of them accounts the relevance of variables in a different way, therefore the average value of all the algorithms is taken in the final result of variables ranking, instead of selecting one algorithm and evaluating it.

Then they have carried out some experiments in order to evaluate the performance and usefulness of different classification algorithms for predicting students' placement. The algorithm used for classification is Naive Bayes, ID3, CART and LAD. The results of the experiments are shown in Table 3.3

Table 3.3 Performance of the classifiers in (Pal & Pal, 2013)

| Evaluation Criteria              | Classifiers |        |        |        |
|----------------------------------|-------------|--------|--------|--------|
|                                  | LAD         | CART   | ID3    | NB     |
| Timing to build model (in Sec)   | 0.08        | 0.11   | 0      | 0      |
| Correctly classified instances   | 84          | 81     | 73     | 90     |
| Incorrectly classified instances | 28          | 31     | 34     | 22     |
| Accuracy (%)                     | 75.00%      | 72.32% | 65.17% | 80.35% |

It is clear that the highest accuracy is 80.35% and the lowest is 65.17%. In fact, the highest accuracy belongs to the Naïve Bayes Classifier followed by LAD tree with a percentage of 75.00% and subsequently CART. After tested many attributes, some of them are found effective on the performance prediction. The content arrangement was the strongest attribute, and then the result plays an important role in the performance of teachers. The speed of delivery attribute did not show any clear effect while the overall completion of course and regularity attribute has shown some effect in some of the experiments for predicting the performance. Other attributes had a degree of effect on predicting the performance.

It is clear that the attributes that use by the research belong to students like student attendance and student result, in our thesis, all the attributed belong to lecturer expect the class label (evaluation) that is related to lecturers but it is determined by students.

(Mardikyan & Badure, 2011) conduct a research that aimed at identifying the factors associated with the teaching performance of instructors of the Management Information Systems (MIS) Department of Bogazici University in Turkey. they include in their study variables related to instructor and course characteristics. Student course evaluations are conducted during the last two weeks of each semester by the registration office in Bogazici University. The data set used in this study includes all reported MIS graduate and undergraduate course sections offered from Fall 2004 to Summer Term 2009 except project, seminar, and graduate foundation courses. After this exclusion, the final data set contains totally 259 course sections offered by both full time and part-time instructors of MIS department.

The data include two basic categories of variables. The first group consists of the data obtained from evaluation questionnaires where students response anonymously 13 questions about course (Q1–Q6) and instructor (Q7–Q13) characteristics. In addition

to some of the data used concerns us two attributes: whether or not the instructor is a part time and giving the course for the first time. The average of Q12 and Q13 (named as AVERQ1213) is used as the dependent variable, since among all the variables; these are the only two variables that measure the overall teaching performance of the instructor. To reduce the number of independent variables and to understand the patterns of relationship among them the factor analysis was applied. In this study, two well-known data mining techniques; stepwise regression and decision tree techniques are applied to the data. The results show that, a factor summarizing the instructor related questions in the evaluation form, the employment status of the instructor, the work load of the course, the attendance of the students, and the percentage of the students filling the form are significant dimensions of instructor's teaching performance. The evaluation form in use distinguishes two groups of questions: related to the course and related to the instructor. According to these results, the most important factor to explain the instructors' teaching performance is the instructor attitudes that are primarily measured by the evaluation process. This result is not peculiar to the MIS education since the same evaluation form is used in all departments of Bogazici University. The courses offered by part time instructors tend to receive higher ratings in MIS education. According to the results of stepwise regression and decision tree analyses the instructors' teaching performance is explained with mostly instructor related questions summarized by the variable COMP1. Instructors, who have well prepared course outlines, use satisfactory materials, help the students outside the lectures, grade exams fairly and on time receive higher evaluations. An additional instructor characteristics; the employment status of the instructor that is not included in the questionnaire is found to be significant. Giving the course for the first time is not found to be a significant factor in explaining the teaching performance.

The study present prediction of lecturer performance based on course characteristics and lecturer characteristics from students view, it use only two attributes about personal characteristics: whether or not the instructor is a part time and giving the course for the first time. The first attribute will be one of our data set; we will compare its significant in this study to its significant in our thesis. The second attribute is not available in our data set because it is not in IUG database. In our thesis all the attributes we use is related only to lecturer characteristics.

(Wang et al., 2009) sought to determine which of a number of independent variables (demographic and rating response) would predict student response to an overall rating item for their instructor. The University of Central Florida (UCF) administers an end-of-course student evaluation instrument. The Student Perception of Instruction (SPI) form is a 16-item, Likert-type device that students use to rate their instructors (e.g., excellent, very good, good, fair, poor). Respondents have the opportunity to provide written comments about the instructor, and considerable demographic information (course level, college, department, and instructor) can be obtained from the instrument because the class and date are recorded on the form. After classes end, instructors receive the original forms with student comments and a summary of course-rating responses. Presently, many students have an online response option as well.

The investigators assembled a dataset containing all student ratings of instructors for the 5 academic years beginning 1996/97 through 2000/01. The file contained 588,575 student records with responses to the 16 items (Table 3.4) and corresponding demographic information. The investigators reformatted the file so that it comprised only the responses to the 16 items (five levels) and indicators of course level (lower undergraduate, upper undergraduate, graduate), college (Arts and Sciences, Business Administration, Education, Engineering and Computer Science, Health and Public Affairs), and the academic year. No further identifying information was available in the analysis file. Throughout the study, the investigators preserved department and instructor anonymity. Therefore, this study investigated the independent measures, college, course levels, academic year, and items 1 through 15 on the Student Perception of Instruction instrument for their ability to predict overall rating of the instructor (item 16).

Table 3.4 Student perception of instruction items for the University of Central Florida (Wang et al., 2009)

| Source           | Questions   |
|------------------|---|
| Administration   | 1. Feedback concerning your performance in this course was:               |
|                  | 2. The instructor's interest in your learning was:                        |
|                  | 3. Use of class time was:   |
|                  | 4. The instructor's overall organization of the course was:               |
|                  | 5. Continuity from one class meeting to the next was:                     |
|                  | 6. The pace of the course was:  |
|                  | 7. The instructor's assessment of your progress in the course was:        |
|                  | 8. The texts and supplemental learning materials used in the course were: |
| Board of regents | 9. Description of course objectives and assignments:                      |
|                  | 10. Communication of ideas and information:                               |
|                  | 11. Expression of expectations for performance:                           |
|                  | 12. Availability to assist students in or outside of class:               |
|                  | 13. Respect and concern for students:                                     |
|                  | 14. Stimulation of interest in the course:                                |
|                  | 15. Facilitation of learning:   |
|                  | 16. Overall assessment of instructor:                                     |

In order to explore these data, the authors incorporated decision trees that developed three rules that predicted a high probability that an instructor would receive an overall rating of excellent (Table 3.5) while three other rules led to a poor rating (Table 3.6)

Table 3.5 Decision rules that lead to an overall instructor rating of "excellent"

| Question                                 | Rating |    |   |   |   | Excellent (p) |
|--|--------|----|---|---|---|---------------|
|  | E      | VG | G | F | P |               |
| Rule 1 (n = 46,805)                      |        |    |   |   |   |               |
| - Facilitation of learning               | ●      |    |   |   |   | 0.96          |
| - Communication of ideas and information | ●      |    |   |   |   |               |
| Rule 2 (n = 3,462)                       |        |    |   |   |   |               |
| - Facilitation of learning               | ●      |    |   |   |   |               |
| - Communication of ideas and information |        | ●  |   |   |   | 0.85          |
| - Organization of the course             | ●      |    |   |   |   |               |
| - Assessment of student progress         | ●      | ●  |   |   |   |               |
| Rule 3 (n = 6,215)                       |        |    |   |   |   |               |
| - Facilitation of learning               |        |    |   | ● |   | 0.78          |
| - Communication of ideas and learning    | ●      | ●  |   |   |   |               |
| - Organization of the course             | ●      |    |   |   |   |               |
| -Instructor interest in your learning    | ●      |    |   |   |   |               |

Table 3.6 Decision rules that lead to an overall instructor rating of “poor”

| Question                                 | Rating |    |   |   |   | Excellent (p) |
|--|--------|----|---|---|---|---------------|
|  | E      | VG | G | F | P |               |
| Rule 4 (n = 1,821)                       |        |    |   |   |   |               |
| - Facilitation of learning               |        |    |   | • | • |               |
| - Communication of ideas and information |        |    |   |   | • | 0.83          |
| - Instructor interest in your learning   |        |    |   |   | • |               |
| Rule 5 (n = 1,135)                       |        |    |   |   |   |               |
| - Facilitation of learning               |        |    |   | • | • |               |
| - Communication of ideas and information |        |    |   |   | • | 0.58          |
| - Organization of the course             |        |    |   |   | • |               |
| Rule 6 (n = 532)                         |        |    |   |   |   |               |
| - Facilitation of learning               |        |    |   | • | • |               |
| - Communication of ideas and learning    |        |    | • | • |   | 0.54          |
| - Assessment of student progress         |        |    |   |   | • |               |
| - Assessment of student progress         |        |    |   |   | • |               |

Table 3.7 presents the results of the analyses for the items contributing to an overall excellent rating of the instructor. All items selected by the decision tree contributed to the equation with the Wald chi-square probabilities rounded to 0.00. The model predicted with 97.6% accuracy producing a Somer’s D of 0.945.

Table 3.7 Logistic regression for “excellent” rule items (Wang et al., 2009)

| Items   | df | Coefficient | Wald $x^2$ | p      |
|---|----|-------------|------------|--------|
| Intercept   | 1  | 0.895       | 23,385.10  | 0.0001 |
| Interest  | 1  | 0.796       | 23,157.20  | 0.0001 |
| Organization  | 1  | 0.798       | 23,903.10  | 0.0001 |
| Assessment  | 1  | 0.847       | 12,454.40  | 0.0001 |
| Communication   | 1  | 0.847       | 25,162.30  | 0.0001 |
| Facilitation  | 1  | 1.092       | 33,328.60  | 0.0001 |
| A Percent correctly predicted = 97.6, Somer’s D = .963. |    |             |            |        |

Table 3.8 Logistic regression for “poor” rule items (Wang et al., 2009)

| Items   | df | Coefficient | Wald $x^2$ | p      |
|---|----|-------------|------------|--------|
| Intercept   | 1  | 0.171       | 349.9      | 0.0001 |
| Interest  | 1  | -0.691      | 6,472.9    | 0.0001 |
| Organization  | 1  | -0.919      | 12,650.7   | 0.0001 |
| Assessment  | 1  | -0.667      | 7,062.0    | 0.0001 |
| Communication   | 1  | 0.924       | 13,598.8   | 0.0001 |
| Facilitation  | 1  | -0.961      | 14,867.4   | 0.0001 |
| A Percent correctly predicted = 97.6, Somer's D = .963. |    |             |            |        |

This research predicting the overall evaluation based on the internal answers of end semester evaluation questionnaire. Our opinion that this is can called analysis not prediction, because it depend on the answers of evolution questions, so the overall prediction is exist by simple calculation for the answers, and there is no need for prediction. Our theses is depend on attributes of lecturer characteristics, the lecturer may come to teach for the first time, so all data needed is available when the lecturer request to teach.

(Ahmadi & Abadi, 2013) are collected information and results of a survey about 104 teachers in Sanandaj Daughter Vocational Faculty on teacher's behaviors in classroom then with data mining algorithms such Association Rule and decision trees (j48), it is proceeded to analyze and predict acceptance of a teacher for continuing the teaching in faculty. There are new rules and relations between selected parameters such as Evaluation's score, Teacher's degree, Degree's Type, Teaching experience, Acceptation to next semesters on teacher's evaluation that is interested for education managers. They use the acceptance attributes as class label that take tow values Yes or No. It is done a web base survey from 830 students then it is prepared results of this survey for 104 teachers.

They indicated that evaluation's score of students is very important factor that many universities gather this information on performance of teachers. By using data mining and J48 tree as a decision tree new rules are results that education managers could use these rules in future decisions to submit new teachers and continue with elected old teachers. They generate rules for example in Figure 3.1.



- 1- IF( Evaluation\_score=GOOD)THEN (Acceptation is Yes, means next semester will continue his/her teaching)
- 2- IF( Evaluation\_score=Excellent)AND (Teaching\_experience=FALSE means is low)THEN(Acceptation is Yes means next semester will continue his/her teaching)

Figure 3.1 Discovered rules (Ahmadi & Abadi, 2013)

The study limited on four variables related to lecturer, without determining the accuracy of this model, and not exploited the historical data for mining. However, in our study we use many attributes related to lecturer characteristics, with high accuracy model relatively.

(Sok-Foon et al., 2012) try to identify the factors and predictors of lecturer performance among undergraduates in a private university in Malaysia using the existing questionnaire. They use a total of 223 respondents were recruited using multistage sampling. In the first stage, a faculty was randomly chosen. In the second stage, the School of Management was randomly chosen out of two schools. In the third stage, two subjects were randomly chosen from subjects in year 1 of the undergraduate program. A similar selection was undertaken for two subjects from years 2 and 3. A total of six subjects from years 1 to 3 were chosen. A total of 32 items was used to gather the responses to measure: lecturer and tutor characteristics (13 items), subject characteristics (6 items), the studentship (7 items) and learning resources and facilities (4 items). They also added two questions to the existing questionnaire on overall performance (2 items). The authors use Statistical Package for Social Science for Windows (SPSS for Windows Version 13.0) to analyze the collected data. They use Multiple linear regressions and the stepwise method to identify the significant determinants of overall lecturer performance.

The results of the final model showed that lecturer and tutor characteristics, subject characteristics, and learning resources and facilities explained 61.9% of the variance in overall lecturer performance among students. They point out that even though lecturer or tutor characteristics are the main predictors of overall performance and lead to student satisfaction. The results of this study showed that: lecturer and tutor

characteristics ( $r = 0.722$ ,  $p < 0.01$ ), subject characteristics ( $r = 0.699$ ,  $p < 0.01$ ), the studentship ( $r = 0.472$ ,  $p < 0.01$ ) and learning resources and facilities ( $r = 0.650$ ,  $p < 0.01$ ) were positively correlated with overall lecturer performance. The side that related to our study that lecturer and tutor characteristics were not statistically different in terms of gender.

This study depends on statistical methods not data mining methods, it deal with samples not with historical data, it can benefited for us that the study results show that the lecturers characteristics are the main predictors of overall performance.

(Agaoglu, 2016) was collected data from one of the randomly selected departments of Marmara University, Istanbul, Turkey. A total of 2850 evaluation scores are obtained. He use 70% of the data for training the classifier models and the remaining 30% for testing. Student evaluation data has 26 variables all except one, which is class label, are responses, measured on an interval scale, to questions in course and instructor performance evaluation forms. Response values of these questions are of the form (1,2,3,4,5) where 1,2,3,4,5 represents the answers “Never”, “Rarely”, “Sometimes”, “Often”, “Always” respectively for Q1 to Q4; and 1,2,3,4,5 represents “Strongly disagree”, “Disagree”, “Neutral”, “Agree”, and “Strongly agree” respectively for Q5 to Q25. The last variable is dichotomous variable measured on a nominal scale in the form of (1,2) where 1 stands for “Not satisfactory” and 2 for “Satisfactory”.

The researcher use seven classification models: two using decision tree algorithms (C5.0, and CART), one using SVM, three using ANNs, and one using DA. The performances of these models are evaluated on the test data in terms of accuracy, precision, recall, and specificity.

He compare all the applied classifiers using evaluation measures. As seen in Figure 3.2, classifiers give similar results on the test dataset.

| <b>Model</b> | <b>Accuracy</b> | <b>Precision</b> | <b>Recall</b> | <b>Specificity</b> |
|--------------|-----------------|------------------|---------------|--------------------|
| C5.0         | <b>92.3 %</b>   | <b>94.4 %</b>    | 92.1 %        | <b>92.5 %</b>      |
| CART         | 89.9 %          | 89.9 %           | 93.1 %        | 85.5 %             |
| SVM          | 91.3%           | 92.2%            | 92.9%         | 89.1%              |
| ANN-Q2H      | 91.2 %          | 94.1 %           | 90.5 %        | 92.2 %             |
| ANN-Q3H      | 90.8 %          | 89.7 %           | <b>95.0 %</b> | 85.0 %             |
| ANN-M        | 90.5 %          | 92.1 %           | 91.5 %        | 89.1 %             |
| DA           | 90.5 %          | 94.1 %           | 90.6 %        | 90.4 %             |

Figure 3.2 Performances of classifiers (Agaoglu, 2016)

Accuracy values, which assess the effectiveness of the models, are all at least approximately 90%. C5.0 classifier is the best in performance according to accuracy followed by SVM, and CART is the worst

This research is similar to (Wang et al., 2009), both of them try to identify the factors that affect the lecturer performance by studying the relation between student satisfaction and the internal points of questionnaire that applied on student at the last two weeks of semester. In our research we deal with the average of the questionair and try to predict the student ratings of lecturer based on lecturers characteristics.

In this section, we reviewed some previous studies that related to our thesis, these studies about prediction of lecturer performance using data mining techniques. Some of these studies shared us in proposed logical methodology like (Hajizadeh & Ahmadzadeh, 2014) (Gupta & Suma, 2014) and (Bhardwaj & Pal, 2011). Most of these studies focused on course characteristics and student characteristics to predict lecturer performance, a few studies involved lecturers characteristics poorly like (Pal & Pal, 2013), (Mardikyan & Badure, 2011) and (Ahmadi & Abadi, 2013).

### **3.3 Conclusion**

In chapter 3 we talk about studies that related to our thesis, we divided these studies into two categories. Section 3.1 contain studies that investigated in the field of performance prediction using data mining techniques, we try to be closed to educational data mining field. In section 3.2, we present studies about prediction of lecturer performance using data mining techniques.

We notice that most studies built its prediction on course characteristics, student characteristics, or lecturer's characteristics poorly. The studies that involved lecturer's characteristics are involved as secondary predictors. In our thesis, we will predict the lecturer's performance depending mainly on lecturers characteristics. We get dataset contain 30 attribute about lecturers characteristics in Islamic University of Gaza. We will describe these attributes in section [4.1.1](#).

# **Chapter 4**

## **Proposed Method and Implementation**

## Chapter 4

### Proposed method and implementation

In this chapter, we are going to explain our proposed method of predicting lecturer's performance based on lecturer's characteristics using data mining techniques. This chapter is divided into three sections: Section one describes our methodology to achieve the research problem. Section two explains the steps that is followed to apply the selected techniques, and the implementation environment that has been done. Section three summarizes the proposed method and the implementation steps.

#### 4.1 Methodology

To achieve the research goals, we are going to follow some steps, we are going to describe these steps briefly and we will explain it in details in next subsections.

- Data collection: collecting data sets from various IUG departments.
- Data integration: integrate the data sets to be one data set.
- Data preprocessing: dealing with missing values and noisy data and increasing data quality to give good results.
- Apply data mining techniques: we have chosen four data mining techniques:
  - Decision tree
  - KNN
  - Multinomial Logistic Regression
  - Naïve Bayesian

We will apply these techniques on our data set.

- Compare results: by comparing the accuracy of each model.
- Choose the proved model: that gives a higher accuracy and depends on it.

The next Figure 4.1 explains the steps of our methodology.

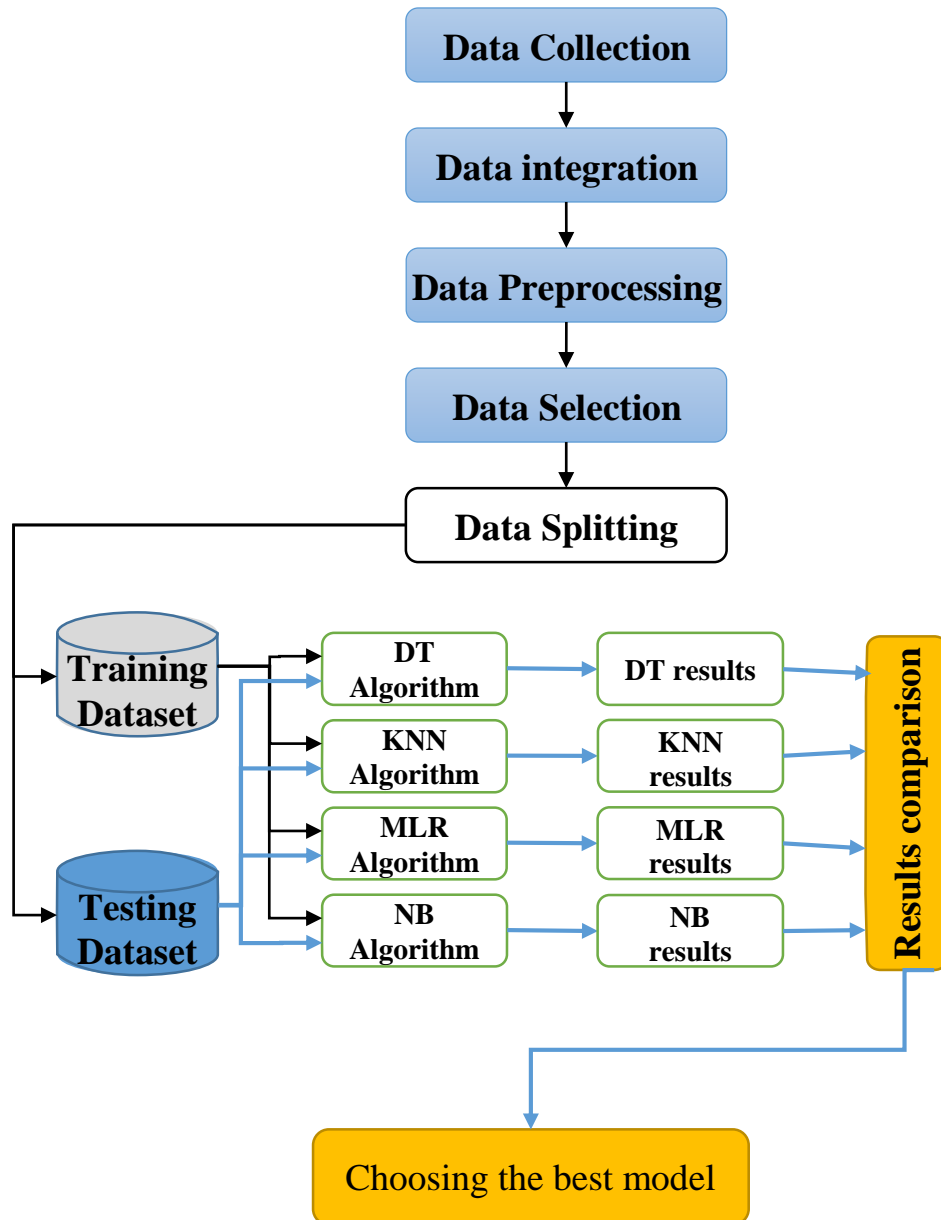


Figure 4.1 Thesis methodology

#### 4.1.1 Data collection

The used data is belonging to the academic staff of Islamic university – Gaza (IUG) that was taught in last 11 semesters (from second semester 2011/2012 to summer semester 2014/2015), we chose these semesters because the evaluation model was stable in this period. Previously IUG used many models of evaluation and there were many editions, so the specialist in IT department cannot extract the overall evaluation for the lecturer per course in this period.

IUG applies the evaluation model at the last two weeks of the semester, the model consists of 20 Likert-type questions. Students use this model to rate their lecturers by choice (كبيرة جدا، كبيرة، متوسطة، قليلة، قليلة جدا). Students can also provide written comments about their lecturers. The result of student's answers, calculated to be one percentage value per course. This value considers the overall lecturer's evaluation of the students in all classes in one course at the semester.

The used questionnaire in IUG is attached in Appendix A.

In this research, we get the evaluation (one percentage value) of all lecturers that taught in IUG in the last 11 semesters, this data is available in Academic affairs at the university and it is contains 4 attributes and 5170 records. It is for 664 courses that is taught by 551 lecturer. Every lecturer taught one or more courses and the lecturer has one evaluation value per course, without any consideration to the count of the students that ratings and their sex. And we may found repetition to the lecturer and course with different semesters. Table 4.1 describes the attributes and possible values.

Table 4.1 Academic Affairs data

| attribute name | attribute description  | values                     |
|----------------|--|----------------------------|
| EMP_NO         | Employee ID  | 551 IDs of lecturers       |
| SEMESTER_NO    | Semester number  | 11 semesters               |
| SUBJECT_NO     | Course Code  | 664 course                 |
| EVALUATION     | Overall evaluation of the lecturer in this course on this semester | numeric value (29.2 - 100) |

After we had got these data, we contact with department of employee affairs at IUG to provide us the data that is available at the department about the 551 academic staff, they provide us the data which contains 30 attribute and 544 records, the attributes are explained in Table 4.2.



Table 4.2 Employee affairs data

| no. | attribute name              | attribute description                | values   |
|-----|-----------------------------|--------------------------------------|--|
| 1   | EMP_NO                      | Employee ID                          | serial number  |
| 2   | JOB_NAME                    | Job Title                            | أستاذ مساعد، أستاذ، أستاذ مشارك، مدرس، معيد، محاضر   |
| 3   | DEPARTMENT_A_NAME           | the college of lecturer              | 12 colleges in IUG   |
| 4   | Section_A_Name              | the department of lecturer           | 41 academic department in IUG  |
| 5   | Gender                      | Lecturer Gender                      | ذكر، أنثى  |
| 6   | Birth_Date                  | date of birth                        | numeric value (1945 - 1992)  |
| 7   | MARITAL_STATUS              | material status                      | متزوج، أعزب، مطلق  |
| 8   | Governorate_Name            | Place of residence                   | شمال غزة، غزة، الوسطى، خانينونس، رفح   |
| 9   | Education_Name              | Qualification                        | دكتوراه، ماجستير، بكالوريوس، دبلوم عالي  |
| 10  | Contract Name               | contract Type                        | دائم، إشراف عملي، خاص، العاملون بالساعة، وكالة بالساعة، راتب مقطوع، تجريبي                                       |
| 11  | Status_Name                 | managerial status                    | منتظم، متجدد، إنتهاء عقد، إجازة علمية، ابتعاث، متقاعد، استقالة، إجازة بدون مرتب، متوفي على رأس عمله، انتهاء خدمة |
| 12  | Professional_Experience     | number of experience years           | numeric value (0 - 22)   |
| 13  | Specialist_A_Name_Bc        | specialist in BSc.                   | 38 defferint specialist  |
| 14  | Specialist_Detail_A_Name_Bc | accurate specialist in Bachelor      | 177 defferint accurate specialist  |
| 15  | University_Name_Bc          | university that graduate in Bachelor | 81 different university  |
| 16  | Country_Bc                  | Country that graduate in Bachelor    | 29 different country   |
| 17  | End_Date_Bc                 | date of graduate in Bachelor         | numeric value (1966 - 2014)  |
| 18  | Emp_Level_Bc                | grade of Bachelor                    | مقبول، جيد جداً، ممتاز، جيد  |
| 19  | Specialist_A_Name_M         | specialist in master                 | 47 different specialist  |
| 20  | Specialist_Detail_A_Name_M  | accurate specialist in master        | 224 defferint accurate specialist  |
| 21  | University_Name_M           | university that graduate in master   | 122 different university   |
| 22  | Country_M                   | Country that graduate in master      | 30 different country   |
| 23  | End_Date_M                  | date of graduate in master           | numeric value (1977 - 2014)  |
| 24  | Emp_Level_M                 | grade of master                      | جيد جداً، ممتاز، جيد   |
| 25  | Specialist_A_Name_Dr        | specialist in Ph.D.                  | 45 defferint specialist  |
| 26  | Specialist_Detail_A_Name_Dr | accurate specialist in Ph.D.         | 226 defferint accurate specialist  |
| 27  | University_Name_Dr          | university that graduate in Ph.D.    | 138 different university   |
| 28  | Country_Dr                  | Country that graduate in Ph.D.       | 35 different country   |
| 29  | End_Date_Dr                 | date of graduate in Ph.D.            | numeric value (1983 - 2014)  |
| 30  | Emp_Level_Dr                | grade of Ph.D.                       | جيد جداً، ممتاز، جيد   |

## 4.1.2 Data preprocessing

After data collection, we proceed with activities in order to get familiar with the data, to identify data quality problems, to discover first insights into the data and to increase the accuracy of the mining. We use Microsoft Excel 2013 to perform the following data preprocessing.

### 4.1.2.1 Data integration

We merge the two datasets through the common attribute EMP\_NO to result 34 attributes and 5122 records.

### 4.1.2.2 Missing values:

- Delete the attribute Professional\_Experience because the missing value is 91%.
- Delete the records (7 records) of the lecturer who is emp\_no is 99568 because most of the values are missing.
- Fill some missing value manually based on other attributes.
  - End\_Date\_Bc based on Birth\_Date by adding 22 years.
  - End\_Date\_M based on End\_Date\_Bc and End\_Date\_Dr by average.
  - Emp\_Level\_Bc based on the mean for all samples belonging to the same classe.
  - Specialist\_A\_Name\_Bc, Specialist\_A\_Name\_M and Specialist\_A\_Name\_Dr based on each other.
- Fill the 12 columns that related to master degree and PhD degree to who is education level is "بكالوريوس" with the value "has\_B\_Only".
- Fill the 6 columns that related to PhD degree to who is education level is "ماجستير" with the value "has\_M\_Only"
- Fill the remains of missing values in the columns that are related to qualifications data with the values "un\_Known\_columnName", for example the missing values in the column Country\_Dr we fill it with the value "un\_Known\_Country\_Dr"

#### 4.1.2.3 Inconsistent data:

We edit some values in some attributes manually because there is inconsistency between values, for example the attribute Specialist\_Detail\_A\_Name\_Dr, it contains three values with printing errors for the same Specialist (" تفسير وعلوم القرآن", " تفسير وعلوم قرآن", "القرآن"), we consolidate these values in one value " التفسير وعلوم القرآن "

In attribute Specialist\_Detail\_A\_Name\_Dr we edit 44 values as illustrated in Table 4.3.

Table 4.3 Inconsistent values in Specialist\_Detail\_A\_Name\_Dr attribute

| The original values             | Modified values                 |
|---------------------------------|---------------------------------|
| الاختصاص الجنائي العالمي        | الاختصاص الجنائي العالمي        |
| إحصاء                           | الإحصاء                         |
| الأسلوبية (المسرحية الإنجليزية) | الأسلوبية (المسرحية الإنجليزية) |
| البورء الفلستينى+البورء الأورء  | البورء الفلستينى+البورء الأورءى |
| تارىخ                           | التارىخ                         |
| تارىخ إسلمى                     | التارىخ الإسلامى                |
| تحاليل طبىة                     | التحاليل الطبىة                 |
| تربىة انجلىزى                   | التربىة/اللغة الإنجلىزىة        |
| التعلیم الإلكتروني باستخدام ال  | التعلیم الإلكتروني              |
| تفسیر                           | التفسیر                         |
| تفسیر وعلوم القرآن              | التفسیر وعلوم القرآن            |
| تفسیر وعلوم قرآن                | التفسیر وعلوم القرآن            |
| الحديث الشريف وعلومه            | الحديث وعلومه                   |
| حقوق                            | الحقوق                          |
| خدمة إجتماعىة                   | الخدمة الإجتماعىة               |
| صحة نفسىة                       | الصحة النفسىة                   |
| عقيدة                           | العقيدة                         |
| العقيدة                         | العقيدة الإسلامىة               |
| فقه مقارن                       | الفقه المقارن                   |
| فقه مقارن                       | الفقه المقارن                   |
| فقه وأصول فقه                   | الفقه وأصوله                    |
| فقه وأصوله                      | الفقه وأصوله                    |
| فلسفة-مناهج وطرق تدريس          | الفلسفة فى التربىة(مناهج وطرق)  |
| فىزىاء                          | الفىزىاء                        |
| كىمىاء                          | الكىمىاء                        |
| لغة عربىة                       | اللغة العربىة                   |
| اللغة العربىة- النحو والصرف     | اللغة العربىة - نحو وصرف        |
| المحاسبىة (كلىة الأقتصاد)       | المحاسبىة                       |
| محاسبىة                         | المحاسبىة                       |
| مناهج وطرق التدريس              | المناهج وطرق التدريس            |

| The original values            | Modified values                  |
|--------------------------------|----------------------------------|
| مناهج وطرق تدريس               | المناهج وطرق التدريس             |
| نحو وصرف                       | النحو والصرف                     |
| الهندسة الكهربائية والإلكتروني | الهندسة الكهربائية والإلكترونية  |
| هندسة كهربائية وإلكترونية      | الهندسة الكهربائية والإلكترونية  |
| هندسة مدنية                    | الهندسة المدنية                  |
| هندسة ميكانيكية                | الهندسة الميكانيكية              |
| إدارة أعمال                    | إدارة أعمال                      |
| أحياء دقيقة                    | أحياء دقيقة                      |
| دكتوراة الفلسفة في اللغة العرب | دكتوراة الفلسفة في اللغة العربية |
| دكتوراه الفلسفة في اللغة العرب | دكتوراة الفلسفة في اللغة العربية |
| علوم حاسوب                     | علم الحاسوب                      |
| علم نفس                        | علم النفس                        |
| علوم التمريض/ تمريض باطني جراح | علوم التمريض                     |
| كهرمغناطيسية                   | كهرومغناطيسية                    |

This procedure is applied on most attributes, Table 4.4 illustrate these attributes, numbers of values that is edited and numbers of records that is affected by the editing.

Table 4.4 Values and records that are influenced by inconsistent data editing

| Attribute name              | Altered values | Altered records |
|-----------------------------|----------------|-----------------|
| Specialist_Detail_A_Name_Bc | 49             | 1946            |
| Specialist_Detail_A_Name_M  | 37             | 1441            |
| Specialist_Detail_A_Name_Dr | 44             | 907             |
| University_Name_Bc          | 2              | 188             |
| University_Name_M           | 1              | 6               |

#### 4.1.2.4 Data reduction:

##### a. Delete redundant and irrelevant attributes:

- Delete the attributes that is called emp\_no that duplicated after merging the two datasets because they are irrelevant attributes.
- Delete the attributes Course\_NO and Semester\_NO that is not related to lecturer characteristics.

##### b. Binning by frequency for the attributes Evaluation, we divided the values into 4 categories based on Quartiles as seen in Table 4.5.

Table 4.5 Evaluation column binning

| Class | from        | to          | Number of records |
|-------|-------------|-------------|-------------------|
| 1     | $\geq 29.2$ | $\leq 75.5$ | 1297              |
| 2     | $\geq 75.6$ | $\leq 80.0$ | 1261              |
| 3     | $\geq 80.1$ | $\leq 85.6$ | 1282              |
| 4     | $\geq 85.7$ | $\leq 100$  | 1275              |

**c. Generalization:**

We found that the attribute Education\_Name contain only one value "دبلوم عالي", for one employee, we generalize it to be "بكالوريوس".

The final data consists of 29 attributes and 5115 records, Table 4.6 explains these attributes and the final values for each attribute.

Table 4.6 Final data after preprocessing

| No. | attribute name              | attribute description                | values   |
|-----|-----------------------------|--------------------------------------|--|
| 1   | JOB_NAME                    | Job Title                            | أستاذ مساعد، أستاذ، أستاذ مشارك، مدرس، معيد، محاضر   |
| 2   | DEPARTMENT_A_NAME           | the college of lecturer              | 12 colleges in IUG   |
| 3   | Section_A_Name              | the department of lecturer           | 41 academic department in IUG  |
| 4   | Gender                      | Lecturer Gender                      | ذكر، أنثى  |
| 5   | Birth_Date                  | date of birth                        | 47 values (from 1945 to 1992)  |
| 6   | MARITAL_STATUS              | material status                      | متزوج، أعزب، مطلق  |
| 7   | Governorate_Name            | Place of residence                   | شمال غزة، غزة، الوسطى، خانيونس، رفح  |
| 8   | Education_Name              | Qualification                        | دكتوراه، ماجستير، بكالوريوس  |
| 9   | Contract Name               | contract Type                        | دائم، إشراف عملي، خاص، العاملون بالساعة، وكالة بالساعة، راتب مقطوع، تجريبي                                       |
| 10  | Status_Name                 | managerial status                    | منتظم، متجدد، إنتهاء عقد، إجازة علمية، ابتعاث، متقاعد، استقالة، إجازة بدون مرتب، متوفي على رأس عمله، انتهاء خدمة |
| 11  | Specialist_A_Name_Bc        | specialist in Bc.                    | 38 different specialist  |
| 12  | Specialist_Detail_A_Name_Bc | accurate specialist in Bachelor      | 177 different accurate specialist  |
| 13  | University_Name_Bc          | university that graduate in Bachelor | 81 different university  |
| 14  | Country_Bc                  | Country that graduate in Bachelor    | 29 different country   |
| 15  | End_Date_Bc                 | date of graduate in Bachelor         | 45 values (from 1966 to 2014)  |
| 16  | Emp_Level_Bc                | grade of Bachelor                    | مقبول، جيد جداً، ممتاز، جيد  |
| 17  | Specialist_A_Name_M         | specialist in master                 | 47 different specialist  |
| 18  | Specialist_Detail_A_Name_M  | accurate specialist in master        | 224 defferint accurate specialist  |
| 19  | University_Name_M           | university that graduate in master   | 122 different university   |
| 20  | Country_M                   | Country that graduate in master      | 30 different country   |
| 21  | End_Date_M                  | date of graduate in master           | 37 values (from 1977 to 2014)  |
| 22  | Emp_Level_M                 | grade of master                      | جيد جداً، ممتاز، جيد   |
| 23  | Specialist_A_Name_Dr        | specialist in Ph.D.                  | 45 different specialist  |
| 24  | Specialist_Detail_A_Name_Dr | accurate specialist in Ph.D.         | 226 different accurate specialist  |
| 25  | University_Name_Dr          | university that graduate in Ph.D.    | 138 different university   |
| 26  | Country_Dr                  | Country that graduate in Ph.D.       | 35 different country   |
| 27  | End_Date_Dr                 | date of graduate in Ph.D.            | 33 values (from 1983 to 2015)  |
| 28  | Emp_Level_Dr                | grade of Ph.D.                       | جيد جداً، ممتاز، جيد   |
| 29  | EVALUATION                  | The overall evaluation               | [29.2 – 75.5]<br>[75.6 – 80.0]<br>[80.1 – 85.6]<br>[85.7 – 100]  |

### **4.1.3 Selected models**

We used in our research four models: 1- Decision tree, 2- K nearest neighbor, 3- Multinomial Logistic Regression and 4- Naïve Bayesian. The models were described in details in section [2.2.4](#).

As we found on a lot of researchs and books that stated on chapter two like (Giudici, 2003), (Han & Kamber, 2011), (Witten & Frank), that the prediction models we used consider the most common predictive models in prediction problems, so we chose these models for their common and no specific advantage of anyone of them on the others with respect to our applicati

## **4.2 Implementation**

### **4.2.1 Implementation environment**

By implementation environment, we mean that the hardware and software tools used to run the training and testing experiments. We performed our prediction and data preprocessing on PC machine with the following specification:

- 1- Operating System: Windows 8.1 Pro 64-Bit
- 2- Processor: Intel® Core™ i53230M CPU @2.60GHz (4 CPUs)
- 3- RAM: 6144 MB RAM

We used two software tools:

- 1- Microsoft Excel:

A spreadsheet was developed by Microsoft for Windows, Mac OS X, and iOS. And its features calculation, graphing tools, pivot tables, and a macro programming language that is called Visual Basic for Applications. Microsoft Excel has the basic features of all spreadsheets, using a grid of cells arranged in numbered rows and letter named columns to organize data manipulations like arithmetic operations. It has a battery of supplied functions to answer statistical, engineering and financial needs. In addition, it can display data as line graphs, histograms and charts, and with a very limited three-dimensional graphical display. It allows sectioning of data to view its dependencies on various factors for different perspectives (using pivot tables and the scenario manager). (Wikipedia, 2016a)

We use version Microsoft excel 2013 in data preprocessing and summarizing our dataset. For its common, many researchers using excel in preparation of data (Bratt & Moodley, 2015) (Natek & Zwilling, 2013) ,some of them beyond that to use excel in more advanced way and perform some data mining models like (Tang, 2008).

2- IBM® SPSS® Modeler:

IBM SPSS Modeler is a data mining and text analytics software application has been built by IBM. It is used to build predictive models and conduct other analytic tasks. It has a visual interface which allows users to leverage statistical and data mining algorithms without programming.

IBM SPSS Modeler was originally named Clementine by its creators, Integral Solutions Limited. This name continued for a while after SPSS's acquisition of the product. SPSS later changed the name to SPSS Clementine, and then later to PASW Modeler. Following IBM's 2009 acquisition of SPSS, the product was renamed IBM SPSS Modeler, its current name.(Wikipedia, 2016b)

We use SPSS Modeler to accomplish our training and testing models of prediction, the software provide wide range of data mining models.

We use the virgin IBM® SPSS® Modeler 14.2.

#### **4.2.2 Applying the models**

In this section we describe how each of the classification models (Decision tree, KNN, Multinomial Logistic regression, Naïve Bayesian) where applied on our data, and the specific settings required for each model.

In the four models, we divided our data set into two partitions: 1- Training data set and 2- Testing data set, with ratio 80% training and 20% testing. The following Table 4.7 shows the number of records for each partition.



Table 4.7 Data set partitions details

| partition title | No. of records | Ratio |
|-----------------|----------------|-------|
| Training        | 4089           | 80%   |
| Testing         | 1026           | 20%   |
| sum             | 5115           | 100%  |

The experiment workflow illustrated in Figure 4.2, in applying decision tree classifier. The other three models are replacing the decision tree classifier and follows the exactly same workflow.

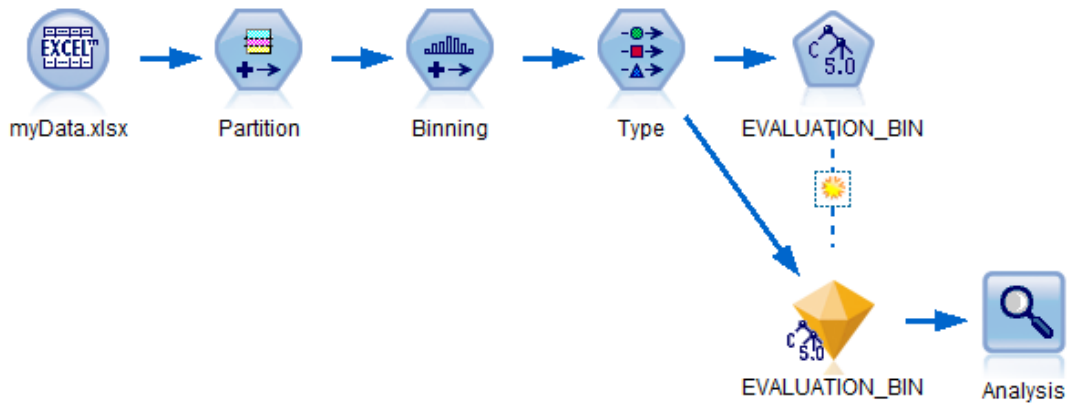


Figure 4.2 Experiment Workflow

### 4.2.3 Decision tree:

We used the Decision tree model with the following settings that was described in next table:

Table 4.8 Decision tree model settings

|   |   |
|---|---|
| Use partitioned data: true                  | Alpha for Merging: 0.05                     |
| Partition: Partition                        | Epsilon For Convergence: 0.0                |
| Calculate predictor importance: true        | Maximum iterations for convergence: 100     |
| Calculate raw propensity scores: false      | Use Bonferroni adjustment: true             |
| Calculate adjusted propensity scores: false | Allow splitting of merged categories: false |
| Continue training existing model: false     | Chi-Square method: Likelihood ratio         |
| Use frequency: false                        | Stopping criteria: Use absolute value       |
| Use weight: false                           | Minimum records in parent branch: 30        |
| Levels below root: 5                        | Minimum records in child branch: 5          |
| Alpha for Splitting: 0.05                   | Use misclassification costs: false          |

The next figures: Figure 4.3, Figure 4.4, Figure 4.5 and Figure 4.6 show some settings based on the interface of SPSS Modeler:

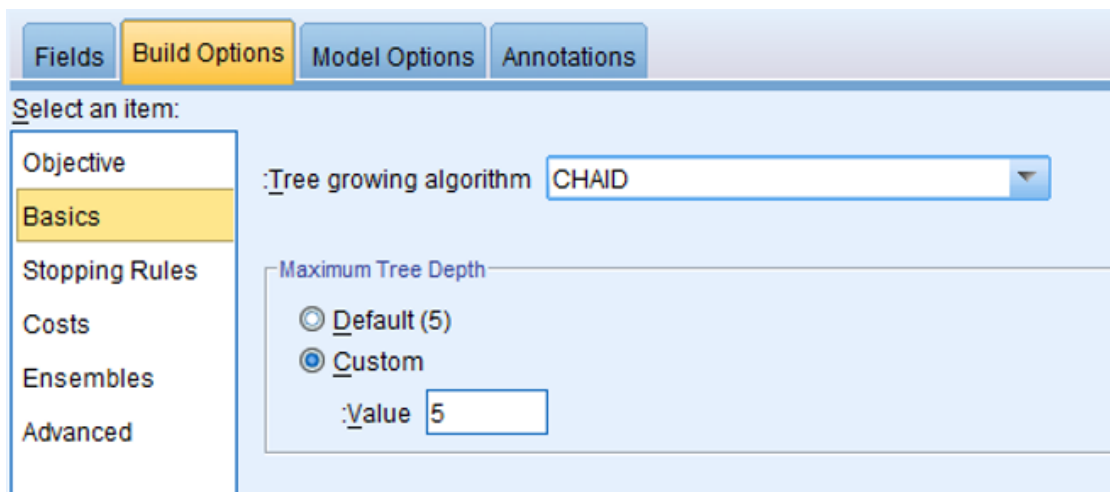


Figure 4.3 Basic Settings for Decision tree

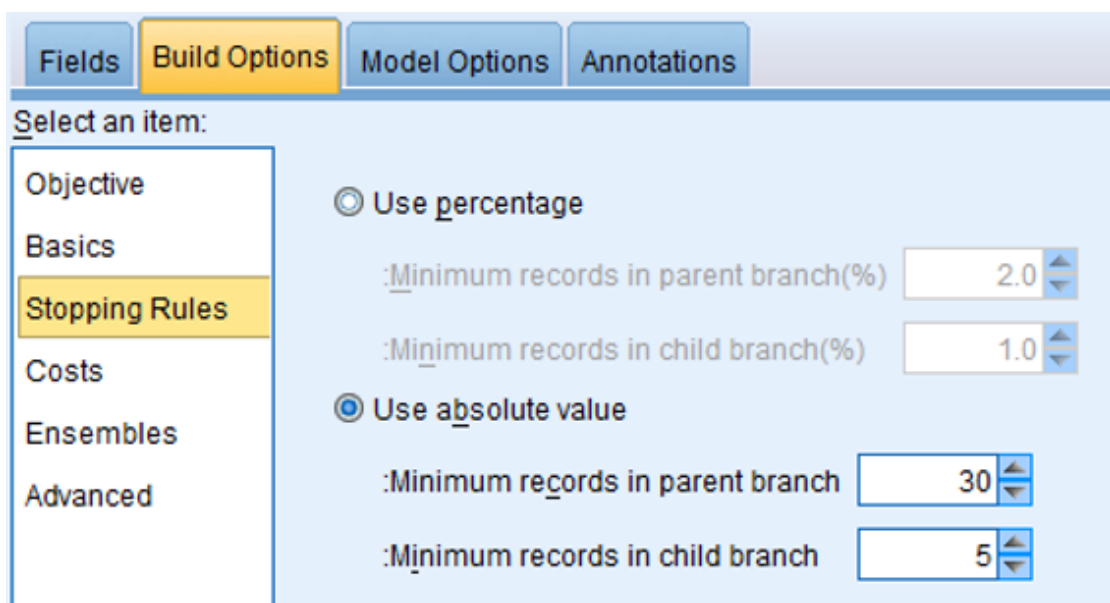


Figure 4.4 Stopping Rules Settings for Decision tree

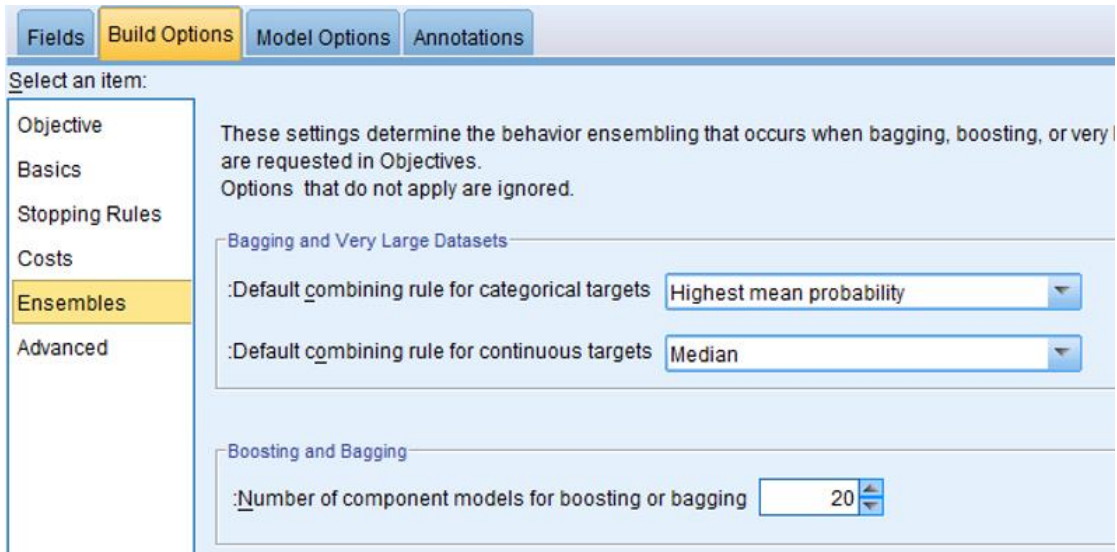


Figure 4.5 Ensembles Settings for Decision tree

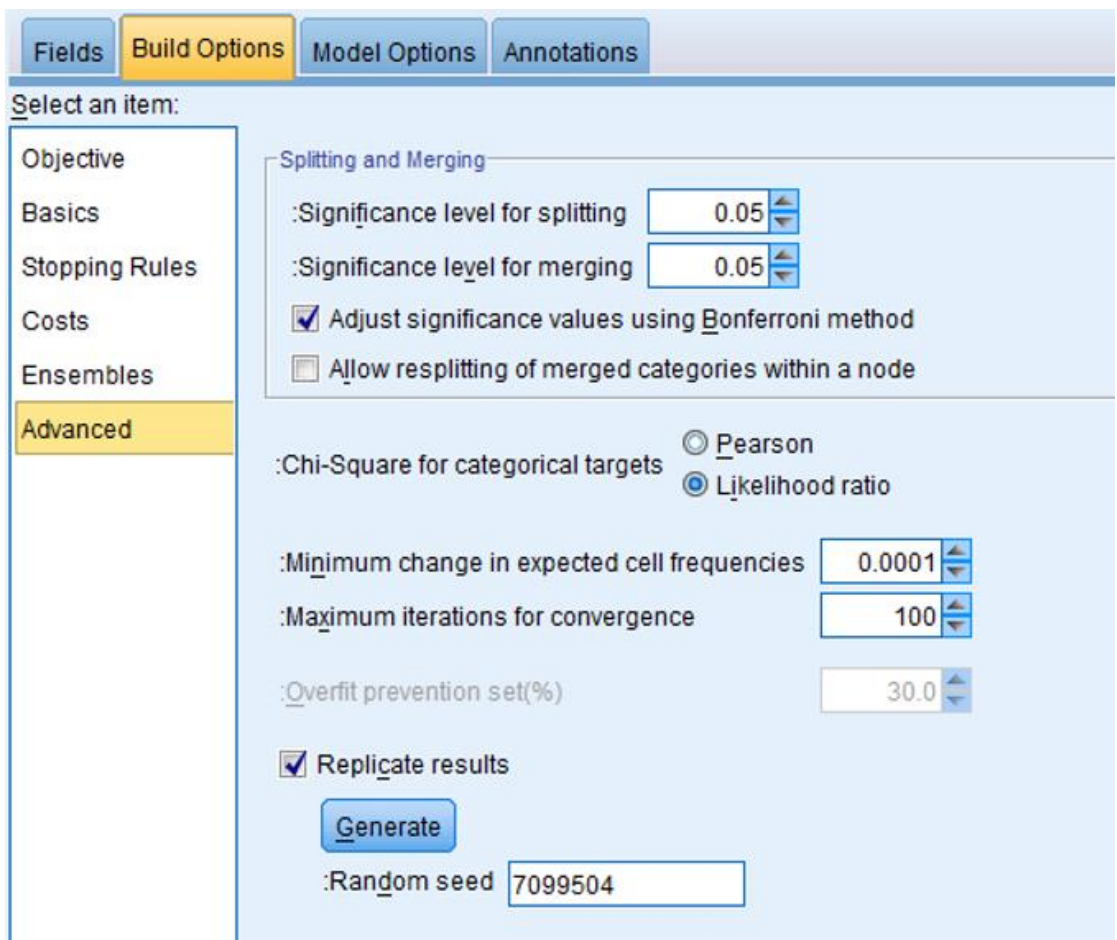


Figure 4.6 Advanced Settings for Decision tree

#### 4.2.4 K-Nearest Neighbour:

KNN model was applied with the following settings that was illustrated in Table 4.9, it is also appeared in Figure 4.7 and Figure 4.8 based on the interface of SPSS Modeler.

Table 4.9 KNN model settings

|  |  |
|--|--|
| Use partitioned data: true   | K: 3   |
| Partition: Partition   | Minimum: 3   |
| Calculate raw propensity scores: false                                 | Maximum: 7   |
| Calculate adjusted propensity scores: false                            | Perform feature selection: false   |
| What type kof analysis do you want to perform?: Predict a target field | Forced entry: [ ]  |
| What is your objective?: Custom analysis                               | Stop when the change in the absolute error ratio is less than or equal to the minimum: false |
| Use case labels: true  | Number to select: 10   |
| Case Label variable: Governorate_Name                                  | Minimum change: 0.01   |
| Identify focal record: false   | Use field to assign cases: false   |
| Focal Case Value: 0  | Folds variable: Partition  |
| Normalize range inputs: true   | Number of folds: 10  |
| Distance Computation: Euclidean metric                                 | Set random seed: false   |
| Predictions for Range Target: Mean of nearest neighbor values          | Seed: 12,345   |
| Weight features by importance when computing distances: true           | Append all probabilities: false  |
| Automatically select k: false  | Save distances between cases and k nearest neighbors: false                                  |

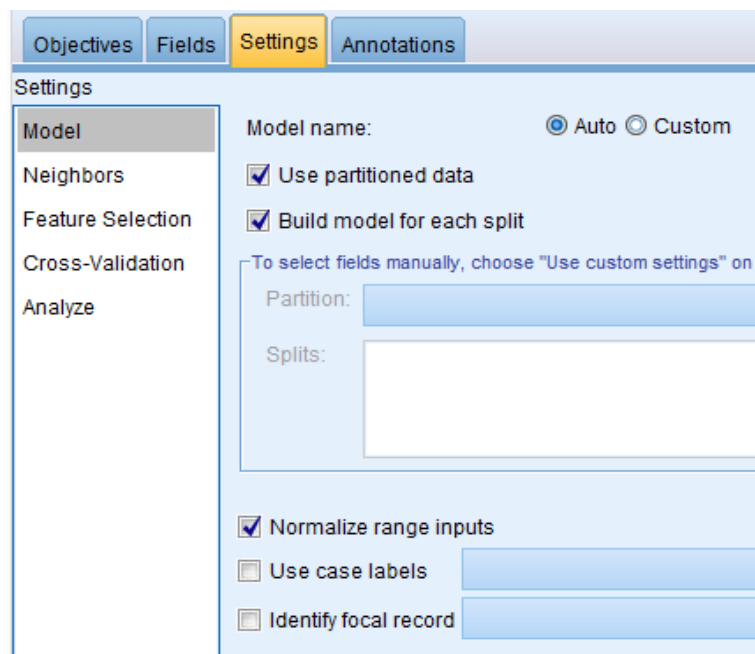


Figure 4.7 Model settings for KNN model

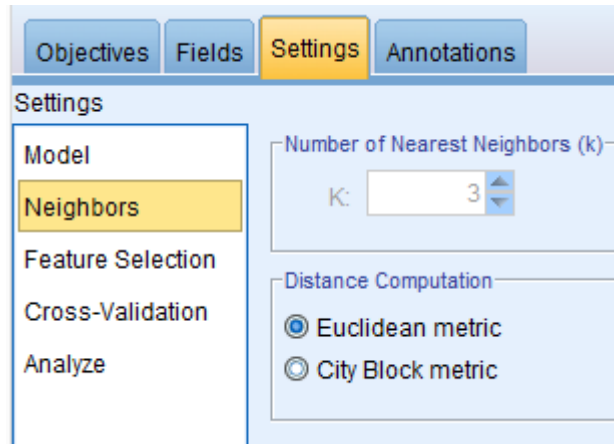


Figure 4.8 Neighbors settings for KNN model

#### 4.2.5 Multinomial Logistic regression:

Figure 4.9 shows the settings that are applied on Multinomial Logistic regression model.

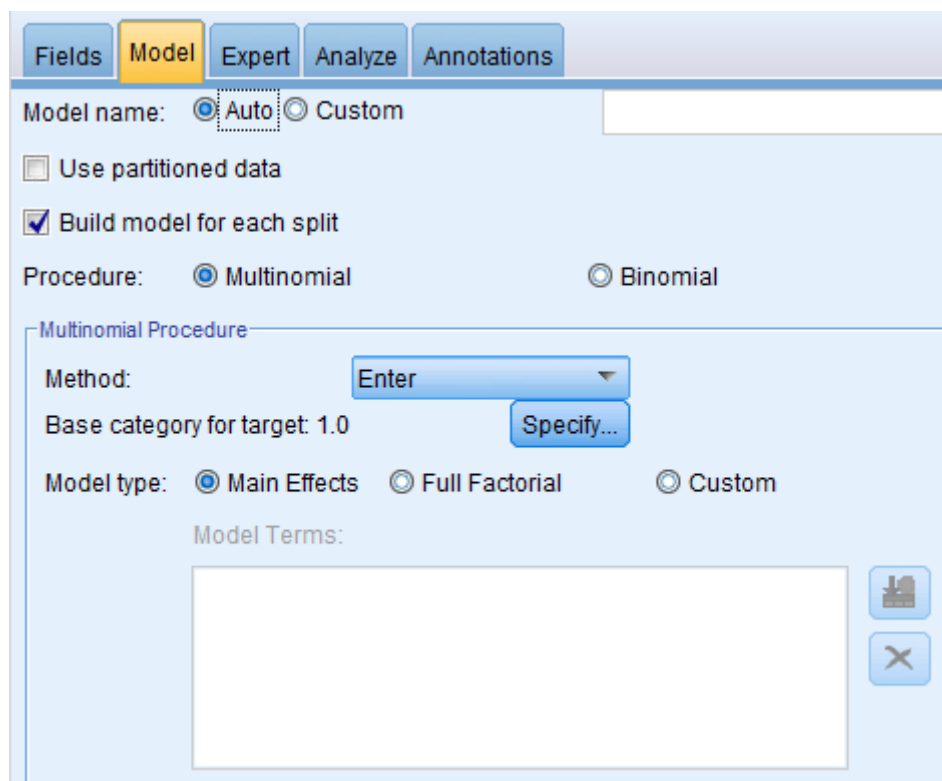


Figure 4.9 Multinomial Logistic Regression model settings

## 4.2.6 Naïve Bayesian:

Figure 4.10 show the settings that applied on Naïve Bayesian model.

The screenshot shows the 'Mode' tab of a software interface for configuring a Naïve Bayesian model. The settings are as follows:

- Model name:** Auto (selected), Custom (unselected)
- Use partitioned data
- Build model for each split
- To select fields manually, choose "Use custom settings" on the Fields tab
- Partition:** (empty dropdown menu)
- Splits:** (empty list box)
- Continue training existing model
- Structure type:** TAN (selected), Markov Blanket (unselected)
- Include feature selection preprocessing step
- Parameter learning method:** Maximum likelihood (selected), Bayes adjustment for small cell counts (unselected)

Figure 4.10 Naïve Bayesian model settings

Table 4.10 NB model settings

|   |   |
|---|---|
| Use partitioned data: true                          | Parameter learning method: Maximum likelihood |
| Partition: Partition                                | Mode: Simple                                  |
| Calculate predictor importance: true                | Use only complete records: true               |
| Calculate raw propensity scores: false              | Append all probabilities: false               |
| Calculate adjusted propensity scores: false         | Independence test: Likelihood ratio           |
| Use frequency field: false                          | Significance level: 0.01                      |
| Continue training existing model: false             | Maximal conditioning set size: 5              |
| Structure type: TAN                                 | Inputs always selected: []                    |
| Include feature selection preprocessing step: false | Maximum number of inputs: 10                  |

### **4.3 Summary**

In this chapter, we explained our proposed method, and showed the training and testing steps that were performed on the data. Section 4.1, Proposed Method, talked about data collection, description, integration and preprocessing in details. Section 4.2, Implementation, explained the implementation environment, settings, and steps to apply the proposed method. The next chapter presents and discusses the results of our research.

# **Chapter 5**

## **Results and discussion**



## Chapter 5

### Results and discussion

The testing and training experiments were described in the previous chapter were repeated in a sequence of experimental attempts. In each attempt, some aspects were altered from the previous attempts with the aim of achieving a better accuracy. In each attempt, some of the four models processed the data. Otherwise we set the accuracy by the value “n/a” that means that the model is not applicable here. The following table lists and describes each of the experimental attempts we had performed.

Table 5.1 Not acceptable experimental attempts results

| No. | Title and Description   | Accuracy |       |       |       |
|-----|---|----------|-------|-------|-------|
|     |   | DT       | KNN   | MLR   | NB    |
| 1   | Group data set by EMO_NO column:<br>By calculate the average of evaluation column for each lecturer.  | 60%      | 55.6% | n/a   | n/a   |
| 2   | Generalize the next attributes to point to the continent instead of the country:<br>Contry_Bc<br>Country_M<br>Country_Dr<br>Delete the attributes :<br>Specialist_Detail_A_Name_BC<br>Specialist_Detail_A_Name_M<br>Specialist_Detail_A_Name_Dr<br>group the next attributes to reduce the values by divided the period to 4 sub periods:<br>Birth_Date<br>End_Date_Bc<br>End_Date_M<br>End_Date_Dr | 23.5%    | 20.1% | 14.2% | n/a   |
| 3   | Delete the 18 attributes that describe bachelore, master and doctora characteristics and change them by 6 attributes describe the last qualification.<br>To avoid messing values existence.   | 67.8%    | 65.1% | 60.9% | 58.7% |
| 4   | Dispensing of qualifications columns and put it in rows, for example, Lecturer X has 10 column for personal data and 18 column for qualifications and 1 column for evaluation, we divided the 18 column for 3 records (6 attribute for each record) and repeated the other 11 column with each record of 3 records. Then we delete the column that is has empty data.                               | 42.0%    | n/a   | n/a   | n/a   |
| 5   | Split the evaluation attribute to 8 periods as next<br>>=90<br>>=80 and <90   | 31%      | 27.3% | n/a   | n/a   |

| No. | Title and Description | Accuracy |     |     |    |
|-----|-----------------------|----------|-----|-----|----|
|     |                       | DT       | KNN | MLR | NB |
|     | >=70 and <80          |          |     |     |    |
|     | >=60 and <70          |          |     |     |    |
|     | >=50 and <60          |          |     |     |    |
|     | >=40 and <50          |          |     |     |    |
|     | >=30 and <40          |          |     |     |    |
|     | <30                   |          |     |     |    |

In this chapter, we present results of applying data mining models that was presented in previous chapter. We depend on accuracy to evaluate the use models; we did not found any special cases that need to apply the other evaluation methods like precision, recall and F-measure. This chapter is divided into 5 sections: section 1 Decision tree results, section 2 KNN results, section 3 MLR results, section 4 Naïve Bayesian results, section 5 we summarize the previous sections and identify the best model, then compare and discuss the result of best model with other researches.

## 5.1 Decision tree

An important topic in classification is how to focus your modeling efforts on the predictor fields that matter most and consider dropping or ignoring those that matter least. The predictor importance chart helps to do this by indicating the relative importance of each predictor in estimating the model. Predictor importance does not relate to model accuracy. It just relates to the importance of each predictor in making a prediction, not whether or not the prediction is accurate (IBM\_Knowledge\_Center, 2016).

We found that the highest importance on our data set is the attribute Specialist\_Detail\_A\_Name\_Dr, so the tree is splitted firstly depending on this column, Figure 5.1 illustrate the highest predictor importance in our research. In addition, Table 5.2 illustrate the values of predictor importance.

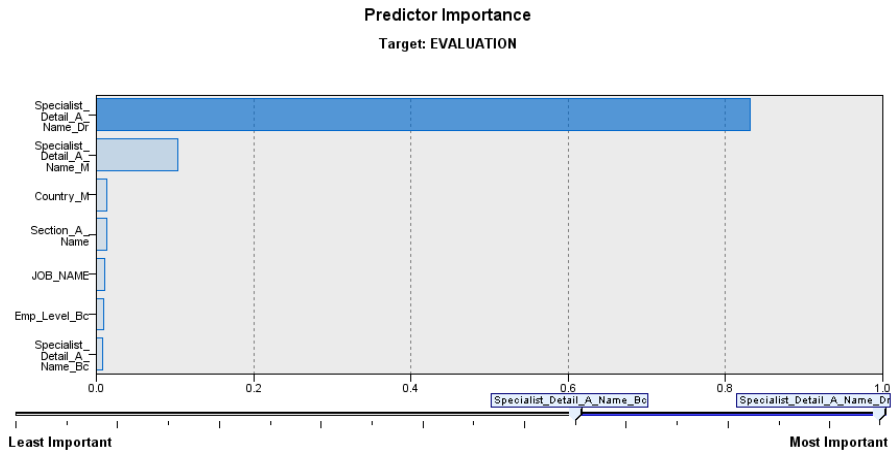


Figure 5.1 Decision Tree Predictor Importance

Table 5.2 Impotrance values for decision tree classification

| Nodes                       | Importance |
|-----------------------------|------------|
| Specialist_Detail_A_Name_Dr | 0.8316     |
| Specialist_Detail_A_Name_M  | 0.1033     |
| Country_M                   | 0.0134     |
| Section_A_Name              | 0.0131     |
| JOB_NAME                    | 0.0099     |
| Emp_Level_Bc                | 0.0089     |
| Specialist_Detail_A_Name_Bc | 0.0073     |
| End_Date_Bc                 | 0.0065     |
| Country_Dr                  | 0.0024     |
| Birth_Date                  | 0.0019     |
| Gender                      | 0.0018     |

After applying the decision tree depending on splitting with the highest importance, the IBM SPSS Modeler generate the tree, Figure 5.2 shows a part of decision tree.



Figure 5.2 Part of Decision tree

One of the rules Rule1 says that **IF** Specialist\_Detail\_A\_Name\_Dr in Set1 **Then** Evaluation = 4.0, that means that lecturer's evaluation is predicted to be greater than or equal 85.7%.

Where Set1 is the set of the items that listed in Table 5.3.

More detailed roles of the decision tree is illustrated in Appendix B

Table 5.3 Set1 in Rule1

|                                   |                                 |                              |                            |
|-----------------------------------|---------------------------------|------------------------------|----------------------------|
| Construction Management           | التنمية الزراعية                | تخطيط معماري                 | ميكانيكا                   |
| اتصالات والكترونيات               | الصحة الإنجابية                 | تخطيط وتصميم المواقع         | نظم المعلومات الجغرافية    |
| الاختصاص الجنائي العالمي          | القانون الدولي                  | جيوفيزياء                    | هندسة الاتصالات الكهربائية |
| الاستزراع المائي                  | الهندسة الكهربائية والإلكترونية | دراسات إعلامية               | هندسة الشواطئ              |
| الإسكان                           | الهندسة المدنية/البيئية         | رياضيات بحتة                 | هندسة صناعية               |
| الأدب والنقد                      | إدارة مشاريع هندسية             | صحة عامة                     | هندسة كهربائية             |
| الأثار/ قديم                      | أدب ونقد                        | طب وجراحة العيون/زراعة عدسات | هندسة معمارية              |
| البلاغة العربية                   | بنوك ومالية                     | فيزياء جوامد                 | هندسة موائع                |
| البيورد الفلسطيني+البيورد الأردني | بيئة                            | كيمياء المبيدات              |                            |
| التحاليل الطبية                   | تاريخ حديث                      | لغة إنجليزية                 |                            |
| التعليم الإلكتروني                | تاريخ عرب حديث                  | مصادر مياه وبيئة             |                            |

After we had applied our testing data set that contains 1026 records, we got the next results that illustrated in Table 5.4.

Table 5.4 Detailed coincidence matrix for Decision tree

| 'Partition' = Testing |   | Predicted values |     |     |     | Sum |
|-----------------------|---|------------------|-----|-----|-----|-----|
|                       |   | 1                | 2   | 3   | 4   |     |
| Actual values         | 1 | 192              | 25  | 31  | 19  | 267 |
|                       | 2 | 36               | 163 | 24  | 27  | 250 |
|                       | 3 | 32               | 55  | 160 | 20  | 267 |
|                       | 4 | 19               | 25  | 37  | 161 | 242 |

The header of column is for predicted values and the header of rows for actual values, which means that 267 records of 1026 records of testing data set have the target 1, and the Decision tree model is predicting these values as 192 for target 1, 25 for target 2, 31 for target 3 and 19 for target 4. That is mean the model predicts the target class truly 192 times. And so with 2, 3 and 4 target class labels.

This leads that the overall truly predicted values is  $(192+163+160+161) = 676$  times with 65.89% this called the accuracy of the model, Table 5.5 illustrates the accuracy of the model.

Table 5.5 General coincidence matrix for Decision tree

| 'Partition' | Testing | Percentage |
|-------------|---------|------------|
| Correct     | 676     | 65.89%     |
| Wrong       | 350     | 34.11%     |
| Total       | 1,026   | 100.00%    |

If we suppose that the closest prediction of the true evaluation is true we can say that the model is predicting the evaluation truly or far from true in one step for 873 times, that means that the model accuracy is 85%

## 5.2 K-Nearest Neighbor

In this research we apply the KNN model with 6 experiments by editing the value K in each time, because the difficulty of determining the k value, Table 5.6 illustrates the accuracy of the model and value of K for each time.

Table 5.6 KNN accuracy with defferent K

| <b>K</b> | <b>Accuracy</b> |
|----------|-----------------|
| 2        | 62.77%          |
| 3        | 65.20%          |
| 4        | 62.48%          |
| 5        | 61.60%          |
| 6        | 60.04%          |
| 7        | 59.94%          |

We found that the model gives the highest accuracy when  $K = 3$ , so we depend the model with  $K=3$ , Table 5.7 shows the coincidence matrix for KNN model when  $k=3$ .

Table 5.7 Detailed coincidence matrix for KNN

| 'Partition' = Testing |   | Predicted values |     |     |     | sum |
|-----------------------|---|------------------|-----|-----|-----|-----|
|                       |   | 1                | 2   | 3   | 4   |     |
| Actual values         | 1 | 194              | 28  | 26  | 13  | 261 |
|                       | 2 | 35               | 149 | 57  | 33  | 274 |
|                       | 3 | 21               | 24  | 170 | 46  | 261 |
|                       | 4 | 25               | 21  | 28  | 156 | 230 |

Table 5.8 General coincidence matrix for KNN

| 'Partition'    | Testing | Percentage |
|----------------|---------|------------|
| <b>Correct</b> | 669     | 65.20%     |
| <b>Wrong</b>   | 357     | 34.80%     |
| <b>Total</b>   | 1,026   | 100.00%    |

If we suppose that the closest prediction of the true evaluation is true we can say that the KNN model is predicting the evaluation truly or far from true in one step for 887 times, that means that the model accuracy is 86.4%

### 5.3 Multinomial Logistic Regression

When implemented Multinomial Logistic Regression, it presented the accuracy 67.64%. Table 5.9 presents the predicted and actual values, and Table 5.10 illustrates the overall correct prediction values.

Table 5.9 Detailed coincidence matrix for Multinomial Logistic Regression

| 'Partition' = Testing |   | Predicted values |     |     |     | sum |
|-----------------------|---|------------------|-----|-----|-----|-----|
|                       |   | 1                | 2   | 3   | 4   |     |
| Actual values         | 1 | 180              | 31  | 34  | 16  | 261 |
|                       | 2 | 28               | 164 | 54  | 28  | 274 |
|                       | 3 | 18               | 23  | 185 | 35  | 261 |
|                       | 4 | 16               | 26  | 23  | 165 | 230 |

Table 5.10 General coincidence matrix for Multinomial Logistic Regression

| 'Partition' | Testing | Percentage |
|-------------|---------|------------|
| Correct     | 694     | 67.64%     |
| Wrong       | 332     | 32.36%     |
| Total       | 1,026   | 100.00%    |

If we suppose that the closest prediction of the true evaluation is true we can say that the model is predicting the evaluation truly or far from true in one step for 888 times, that means that the model accuracy is 86.5%

## 5.4 Naïve Bayesian

Table 5.11 Detailed coincidence matrix for Naïve Bayesian

| 'Partition' = Testing |   | Predicted values |     |     |     | Null | sum |
|-----------------------|---|------------------|-----|-----|-----|------|-----|
|                       |   | 1                | 2   | 3   | 4   |      |     |
| Actual values         | 1 | 166              | 37  | 35  | 21  | 8    | 267 |
|                       | 2 | 31               | 146 | 34  | 29  | 10   | 250 |
|                       | 3 | 26               | 43  | 154 | 32  | 12   | 267 |
|                       | 4 | 14               | 25  | 30  | 158 | 15   | 242 |

Table 5.12 General coincidence matrix for Naive Bayesian

| 'Partition' | Testing | Percentage |
|-------------|---------|------------|
| Correct     | 624     | 60.82%     |
| Wrong       | 402     | 39.18%     |
| Total       | 1,026   | 100.00%    |

If we suppose that the closest prediction of the true evaluation is true we can say that the model is predicting the evaluation truly or far from true in one step for 831 times, that means that the model accuracy is 80.9%

## 5.5 Summary

This chapter described experiments results of predicting lecturer performance based on lecturer characteristics and historical student evaluation of lecturers. We used four data mining techniques: Decision tree, K Nearest Neighbor, Multinomial Logistic Regression and Naïve Bayesian.

The four techniques gives different accuracy values based on data nature, many attempts had done on the data set to give accuracies better than accuracies that were illustrated in previous sections, the final accuracies are listed in Table 5.13 bellow based on considering the predicted values that neighbour the true value is true.



Table 5.13 Used models accuracies based on considering the predicted values that neighbour the true value is true

| Model                           | Accuracy |
|---------------------------------|----------|
| Decision Tree                   | 85.0%    |
| K Nearest Neighbor              | 86.4%    |
| Multinomial Logistic Regression | 86.5%    |
| Naïve Bayesian                  | 80.9%    |

As clear in Table 5.13, three models are relatively closed to one another, Decision Tree, K Nearest Neighbor and Multinomial Logistic Regression, the fourth model Naïve Bayesian gives the least accuracies.

Clearly, Multinomial Logistic Regression achieves highest accuracy, and therefore, it should be adopted as the model for predicting lecturer performance.

The researcher attributes the low accuracies in general to the nature of the data set that was entered in very long period of time, and no clear criteria or template for entering data, that makes the quality of the data low, which reflects on the mining of this data and requires a lot of effort to extract knowledge.

We found that our reseach results are consisted with results of (Sok-Foon et al., 2012) were they showed that lecturer and tutor characteristics, subject characteristics, and learning resources and facilities explained 61.9% of the variance in overall lecturer performance among students.

The study of (Mardikyan & Badure, 2011) presents prediction of lecturer performance based on course characteristics and lecturer characteristics from students view, it uses only two attributes about personal characteristics: whether or not the instructor is a part time and giving the course for the first time. The study found that the courses offered by part time instructors tend to receive higher ratings. Hence, Administration should offer a variety of elective courses given by part time instructors. In our research, we found that this attribute has no significant and does not contribute in decision tree as predictor.

(Ahmadi & Abadi, 2013) were reaching to relations between parameters such as Evaluation's score, Teacher's degree, Degree's Type, Teaching experience, Acceptation to next semesters on teacher's evaluation . They used the acceptance

attributes as class label that take two values Yes or No. The study limited on four variables related to lecturer, and did not exploit the historical data for mining. But in our study we used many attributes related to lecturer characteristics. We found that there is consistency with our research in the common lecturer characteristic that is named Teacher's degree; it has a relation with the evaluation attribute and contribute in prediction in both two researches.

# **Chapter 6**

## **Conclusion and future work**

## Chapter 6

### Conclusion and future work

#### 6.1 Conclusion

As a research of investigating data mining techniques for predicting Lecturer's performance based on lecturer characteristics and historical evaluation of lecturer, we collect the related data from two department at Islamic University of Gaza, academic affairs and employees affairs departments, the data belonging to the academic staff that was taught at the university in 11 semesters start from second semester 2011/2012 and at the end of summer semester 2014/2015. The data set contain the evaluation of the lecturers in the courses that was taught by these lecturers. we preprocessed the data and format it to be in predictable format, then we apply four famous classification techniques, Decision tree, K-Nearest Neighbors, Multinomial Logistic Regression and Naïve Bayesian. If we suppose that the closest prediction of the true evaluation is true the four techniques give closed results as follow, Decision tree 85.0%, K-Nearest Neighbors 86.4%, Multinomial Logistic Regression 86.5%, and Naïve Bayesian 80.9%, the Multinomial Logistic Regression model gives the highest result so we adopted it.

## **6.2 Future work**

In future works, the following issues will be considered, we can improve predicting lecturer's performance by using more attributes that may affect the evaluation of lecturer performance, for example an important attribute was ignored from this research is as an experience years, it is ignored for the large missing values. We can try to apply new data mining techniques that may give results that are more accurate. We may use data from another destination like lecturer's characteristics that is found in the civil registry of the ministry of the interior.

# **Referencies List**

## References List

- Agaoglu, M. (2016). Predicting Instructor Performance Using Data Mining Techniques in Higher Education. 4.
- Ahmadi, F., & Abadi, S. (2013). Data Mining in Teacher Evaluation System using WEKA. *International Journal of Computer Applications*, 63(10), 12-18.
- Bhardwaj, B. K., & Pal, S. (2011). Data Mining: A prediction for performance improvement using classification. (*IJCSIS*) *International Journal of Computer Science and Information Security*, 9.
- Bratt, S., & Moodley, K. (2015). *Promoting Public Library Sustainability through Data Mining: R and Excel*. Retrieved March 5,2016, from:<http://library.ifla.org/1257/1/180-bratt-en.pdf>
- Fayyad, U., Piatetsky-Shapiro, G., & Smyth, P. (1996). From data mining to knowledge discovery in databases. *AI magazine*, 17(3), 37.
- Giudici, P. (2003). *Applied Data Mining, Statistical Methods for Business and Industry* (2nd Ed.). USA: Wiley.
- Gül, H. (2010). Evaluation of Lecturer Performance Depending on Student Perception in Higher Education. *Egitim ve Bilim*, 35(158).
- Gupta, S., & Suma, V. (2014). *Prediction of Human Performance Capability during Software Development Using Classification*. Paper presented at the ICT and Critical Infrastructure: Proceedings of the 48th Annual Convention of Computer Society of India, India.
- Hajizadeh, N., & Ahmadzadeh, M. (2014). Analysis of factors that affect students' academic performance-Data Mining Approach. *International Journal of advanced studies in Computer Science and Engineering IJASCSE*, 3(8).
- Han, J., & Kamber, M. (2011). *Data Mining: Concepts and Techniques* (2nd ed.). USA: Diane Cerra
- Hand, D., Mannila, H., & Smyth, P. (2001). *Principles of Data Mining* Cambridge, Massachusetts London England The MIT Press
- IBM\_Knowledge\_Center. (2016). *Predictor Importance*. Retrieved May 20,2016, from:[https://www.ibm.com/support/knowledgecenter/SS3RA7\\_15.0.0/com.ibm.spss.modeler.help/model\\_nugget\\_variableimportance.htm](https://www.ibm.com/support/knowledgecenter/SS3RA7_15.0.0/com.ibm.spss.modeler.help/model_nugget_variableimportance.htm)
- Kantardzic, M. (2003 ). *Data Mining: Concepts, Models, Methods, and Algorithms*. USA: John Wiley & Sons.
- Larose, D. T. (2005). *Discovering Knowledge in Data An Introduction to Data Mining*: John Wiley & sons.

- Ma, Y., Liu, B., Wong, C. K., Yu, P. S., & Lee, S. M. (2000). *Targeting the right students using data mining*. Paper presented at the Proceedings of the sixth ACM SIGKDD international conference on Knowledge discovery and data mining, National University of Singapore, Singapore.
- Mardikyan, S., & Badure, B. (2011). *Analyzing Teaching Performance of Instructors Using Data Mining Techniques*. Paper presented at the Informatics in Education, Vilnius University, Lithuania.
- Miles, K. H., Darling-Hammond, & Linda. (1998). Rethinking the allocation of teaching resources: Some lessons from high-performing schools. *Educational Evaluation and Policy Analysis*, 20(1), 9-29.
- Millmore, M., Lewis, P., Saunders, M., Thornhill, A., & Morrow, T. (2007). *Strategic Human Resources Management Contemporary Issues*. London: Prentice Hall.
- Molefe, G. N. (2010). Performance measurement dimensions for lecturers at selected universities: An international perspective. *SA Journal of Human Resource Management*, 8(1), 13 pages.
- Naik, R. L., Sarma, S., Manjula, B., & Ramesh, D. (2011). Study of Trends in Higher Education. *International Journal of Computer Trends and Technology*, 6-10.
- Natek, S., & Zwilling, M. (2013). *Data mining for small student data set: Knowledge management system for higher education teachers*. Paper presented at the management, knowledge and learning international conference, Zadar.
- Olson, D. L., & Delen, D. (2008). *Advanced Data Mining Techniques*. USA: Springer-Verlag Berlin Heidelberg
- Pal, A. K., & Pal, S. (2013). Evaluation of Teacher's Performance: A Data Mining Approach. *International Journal of Computer Science and Mobile Computing*, 2(12), 359-369.
- Peleyeju, J. O., & Ojebiyi, O. A. (2013). lecturers' performance appraisal and total quality management of public universities in south-western nigeria. *British Journal of Education*, 1(2), 41-47.
- Phyu, T. N. (2009). *Survey of classification techniques in data mining*. Paper presented at the Proceedings of the International MultiConference of Engineers and Computer Scientists, Hong Kong.
- Samian, Y., & Noor, N. M. (2012). Student's Perception on Good Lecturer based on Lecturer Performance Assessment. *Procedia-Social and Behavioral Sciences*, 56, 783-790.
- Sok-Foon, Y., Sze-Yin, J. H., & Yin-Fah, B. C. (2012). Student evaluation of lecturer performance among private university students. *Canadian Social Science*, 8(4), 238-243.



- Starkweather, J., & Moske, A. K. (2011). *Multinomial logistic regression*. Retrieved March 13, 2016, from: [http://researchsupport.unt.edu/class/Jon/Benchmarks/MLR\\_JDS\\_Aug2011.pdf](http://researchsupport.unt.edu/class/Jon/Benchmarks/MLR_JDS_Aug2011.pdf)
- Tang, H. (2008, 12-14 Oct). *A Simple Approach of Data Mining in Excel*. Paper presented at the Wireless Communications, Networking and Mobile Computing, 4th International Conference, China.
- Wang, M. C., Dziuban, C. D., Cook, I. J., & Moskal, P. D. (2009). Using data-mining techniques to examine student ratings of instruction *Quality research in literacy and science education* (pp. 383-398). University of Central Florida: Springer.
- Wikipedia. (2016a). *Microsoft\_Excel*. Retrieved Mar.19.2016, from: [https://en.wikipedia.org/wiki/Microsoft\\_Excel](https://en.wikipedia.org/wiki/Microsoft_Excel)
- Wikipedia. (2016b). *SPSS\_Modeler*. Retrieved Mar.19.2016, from: [https://en.wikipedia.org/wiki/SPSS\\_Modeler](https://en.wikipedia.org/wiki/SPSS_Modeler)
- Witten, I. H., & Frank, E. *Data Mining, Practical Machine Learning Tools and Techniques* (Second ed.): Diane Cerra

# Appendices

## Appendix A: IUG questionnaire for lecturer's performance

بسم الله الرحمن الرحيم



عمادة الجودة والتطوير

الشؤون الأكاديمية

### استطلاع رأي الطلبة في أداء الأستاذ الجامعي

الفصل الدراسي الأول- العام الجامعي 2016/2015

أخي الطالب ، أختي الطالبة: تهدف هذه الاستمارة إلى استطلاع رأيك فيما يتعلق بتعلمك في هذا المساق من خلال تقييم الأداء التدريسي ، وذلك سعياً للارتقاء بالمستوى الأكاديمي في البرنامج ، وتحقيقاً لأهداف الجامعة في التطوير المستمر ، أملين مراعاة الدقة والموضوعية ، علماً أنه لا توجد إجابات صحيحة وأخرى خاطئة.

|         |  |
|---------|--|
| الكلية: | القسم:                                 |
| المساق: | الشعبة:                                |
| المدرس: | المعدل التراكمي للطالبة/ة: % (اختياري) |

نرجو إبداء الرأي في الجوانب المختلفة بوضع علامة (✓) في الخانة التي تعبر عن رأيك باستخدام المقياس التالي:

المفتاح: (5) =درجة كبيرة جداً ، (4) =درجة كبيرة ، (3) =درجة متوسطة ، (2) =درجة قليلة ، (1) =درجة قليلة جداً

| م  | البند  | 1 | 2 | 3 | 4 | 5 |
|----|--|---|---|---|---|---|
| 1  | يظهر المدرس تمكنًا جيدًا لموضوعات المساق.  |   |   |   |   |   |
| 2  | يقدم محتوى المساق وفصوله بطريقة واضحة ومنظمة.  |   |   |   |   |   |
| 3  | يشرح مفردات المساق بطريقة معمقة ومتنوعة.   |   |   |   |   |   |
| 4  | يوصل المدرس أفكار المساق ومفاهيمه بأسلوب واضح وسلس.  |   |   |   |   |   |
| 5  | ينصف المدرس بالحيوية والنشاط، ويشرح بصوت واضح ومسموع.  |   |   |   |   |   |
| 6  | يستخدم المدرس أساليب تعلم متنوعة من طرق التدريس (المحاضرة، المناقشة.....).   |   |   |   |   |   |
| 7  | يستخدم المدرس وسائل تكنولوجيا التعلم الحديثة (البروينت، برنامج مودل.....).   |   |   |   |   |   |
| 8  | يوضح المدرس المفاهيم والجوانب النظرية للمساق بأمثلة مرتبطة بالواقع إن أمكن.  |   |   |   |   |   |
| 9  | يشجع المدرس الطلبة على المشاركة من خلال طرح أسئلة وتوفير فرصا للمناقشة.  |   |   |   |   |   |
| 10 | يحسن المدرس الاستفادة من وقت المحاضرة بالتدريس الفعلي.   |   |   |   |   |   |
| 11 | يستطيع المدرس ضبط المحاضرة وإدارتها بشكل فاعل.   |   |   |   |   |   |
| 12 | يلتزم المدرس بمواعيد بدء وانتهاء المحاضرة.   |   |   |   |   |   |
| 13 | صفحة المدرس الشخصية على الموقع الإلكتروني للجامعة محدثة وتضم مواد وأبحاث علمية ومواقع داعمة لتعلم الطلبة.                        |   |   |   |   |   |
| 14 | يعامل المدرس الطلبة بود واحترام، ويقدم المساعدة عند الحاجة.  |   |   |   |   |   |
| 15 | يتقبل المدرس اقتراحات الطلبة بسعة صدر.   |   |   |   |   |   |
| 16 | يستخدم المدرس وسائل تقييم متنوعة (مثل: أبحاث، اختبارات قصيرة، نصفية ونهائية، تعيينات وواجبات.....).                              |   |   |   |   |   |
| 17 | يعتبر المدرس موضوعياً ومنصفاً في تقييمه للطلبة.  |   |   |   |   |   |
| 18 | يقدم المدرس تغذية راجعة للأنشطة التقييمية (يحل أسئلة الامتحانات، يوزع أوراق الإجابة، يجيب على أسئلة الطلبة أثناء المحاضرة.....). |   |   |   |   |   |
| 19 | يضع المدرس خطة تدريس المساق على صفحته الشخصية الإلكترونية أو المودل.   |   |   |   |   |   |
| 20 | يلتزم المدرس بالساعات المكتبية المحددة للمساق.   |   |   |   |   |   |

|    |  |
|----|--|
| 21 | <p>1- عدد المحاضرات التي تغيب عنها المدرس: ..... محاضرات</p> <p>2- عدد المحاضرات التي قام المدرس بتعويضها (المحاضرات البديلة): ..... محاضرات</p> |
| 22 | <p>أكثر ثلاث أشياء ساعدت في تعلمي المساق:</p> <p>1- .....</p> <p>2- .....</p> <p>3- .....</p>  |
| 23 | <p>أكثر ثلاث أشياء لم تعجبني في المساق:</p> <p>1- .....</p> <p>2- .....</p> <p>3- .....</p>  |
| 24 | <p>في رأيك كيف يمكن تحسين أو تطوير هذا المساق؟</p> <p>1- .....</p> <p>2- .....</p> <p>3- .....</p>   |

مع الشكر والتقدير،،،

## Appendix B: Rule2 of decision tree result

Rule2 says that **IF** Specialist\_Detail\_A\_Name\_Dr in [ "has\_B\_Only" ], This means that the lecturer's qualification is Bachelor (Education\_Name column = "بكالوريوس"), **Then:**

**IF** University\_Name\_Bc in Set1, **Then** Evaluation = 1.0 , that means that lecturer evaluation is predicted to be less than or equal 75.5%. Where Set1 is the set of the items that listed in Table 8.1.

- **IF** University\_Name\_Bc in [ "الإسكندرية" "عين شمس" "كلية فلسطين للتمريض" ] **Then** Evaluation = 4.0, that means that lecturer's evaluation is predicted to be greater than or equal 85.7%.
- **IF** University\_Name\_Bc in [ "الإسلامية - غزة" ] **Then:**
  - **IF** Specialist\_Detail\_A\_Name\_Bc in Set2 **Then** Evaluation = 1.0, that means that lecturer's evaluation is predicted to be less than or equal 75.5%. Where set2 is the set of items that listed in Table 8.2.
  - **IF** Specialist\_Detail\_A\_Name\_Bc in [ " آداب إنجليزي" "أصول الدين" ] **Then** Evaluation = 1.0, that means that lecturer's evaluation is predicted to be less than or equal 75.5%.
  - **IF** Specialist\_Detail\_A\_Name\_Bc in [ "الأحياء" ] **Then :**
    - **IF** Governorate\_Name in [ "الوسطى" "رفح" ] **Then** Evaluation = 4.0 , that means that lecturer's evaluation is predicted to be greater than or equal 85.7%.
    - **IF** Governorate\_Name in [ "خانيونس" "غزة" ] **Then** Evaluation = 4.0 , that means that lecturer's evaluation is predicted to be greater than or equal 85.7%.
    - **IF** Governorate\_Name in [ "شمال غزة" ] **Then** Evaluation = 1.0, that means that lecturer's evaluation is predicted to be less than or equal 75.5%.
  - **IF** Specialist\_Detail\_A\_Name\_Bc in [ "البصريات الطبية" ] **Then :**
    - **IF** MARITAL\_STATUS = أعزب **Then** Evaluation = 1.0, that means that lecturer's evaluation is predicted to be less than or equal 75.5%.

- **IF** MARITAL\_STATUS = متزوج **Then** Evaluation = 4.0 , that means that lecturer's evaluation is predicted to be greater than or equal 85.7%.
- **IF** MARITAL\_STATUS = مطلق **Then** Evaluation = 4.0 , that means that lecturer's evaluation is predicted to be greater than or equal 85.7%.
- **IF** Specialist\_Detail\_A\_Name\_Bc in [ "البيئة وعلوم الأرض" "الحاسوب" ] **Then** Evaluation = 2.0, that means that lecturer's evaluation is predicted to be between 75.6% and 80%.
- **IF** Specialist\_Detail\_A\_Name\_Bc in [ "التحاليل الطبية" "الرياضيات" "العلوم" ] **Then** Evaluation = 4.0 , that means that lecturer's evaluation is predicted to be greater than or equal 85.7%.
- **IF** Specialist\_Detail\_A\_Name\_Bc in [ "التكنولوجيا الحيوية" ] **Then** :
  - **IF** Governorate\_Name in [ "الوسطى" "خانيونس" "رفح" ] **Then** Evaluation = 3.0, that means that lecturer's evaluation is predicted to be between 80.1% and 85.6%.
  - **IF** Governorate\_Name in [ "شمال غزة" ] **Then** Evaluation = 3.0, that means that lecturer's evaluation is predicted to be between 80.1% and 85.6%.
  - **IF** Governorate\_Name in [ "غزة" ] **Then** :
    - **IF** Emp\_Level\_Bc = جيد **Then** Evaluation = 3.0, that means that lecturer's evaluation is predicted to be between 80.1% and 85.6%.
    - **IF** Emp\_Level\_Bc = جيد جدا **Then** Evaluation = 4.0 , that means that lecturer's evaluation is predicted to be greater than or equal 85.7%.
    - **IF** Emp\_Level\_Bc = مقبول **Then** Evaluation = 2.0, that means that lecturer's evaluation is predicted to be between 75.6% and 80%.

- **IF** Emp\_Level\_Bc = ممتاز **Then** Evaluation = 2.0, that means that lecturer's evaluation is predicted to be between 75.6% and 80%.
- **IF** Specialist\_Detail\_A\_Name\_Bc in [ "الجغرافيا" ] **Then** :
  - **IF** MARITAL\_STATUS = أعزب **Then** Evaluation = 3.0, that means that lecturer's evaluation is predicted to be between 80.1% and 85.6%.
  - **IF** MARITAL\_STATUS = متزوج **Then** Evaluation = 4.0 , that means that lecturer's evaluation is predicted to be greater than or equal 85.7%.
  - **IF** MARITAL\_STATUS = مطلق **Then** Evaluation = 3.0, that means that lecturer's evaluation is predicted to be between 80.1% and 85.6%.
- **IF** Specialist\_Detail\_A\_Name\_Bc in [ "الطب البشري" ] **Then** :
  - **IF** MARITAL\_STATUS = أعزب **Then** Evaluation = 2.0, that means that lecturer's evaluation is predicted to be between 75.6% and 80%.
  - **IF** MARITAL\_STATUS = متزوج **Then** Evaluation = 1.0, that means that lecturer's evaluation is predicted to be less than or equal 75.5%.
  - **IF** MARITAL\_STATUS = مطلق **Then** Evaluation = 1.0, that means that lecturer's evaluation is predicted to be less than or equal 75.5%.
- **IF** Specialist\_Detail\_A\_Name\_Bc in [ "الفيزياء" ] **Then** :
  - **IF** MARITAL\_STATUS = أعزب **Then** :
    - **IF** Governorate\_Name in [ "الوسطى" ] **Then** Evaluation = 2.0, that means that lecturer's evaluation is predicted to be between 75.6% and 80%.
    - **IF** Governorate\_Name in [ "خانيونس" ] **Then** :

- **IF** Specialist\_A\_Name\_Bc in Set3 **Then** Evaluation = 1.0, that means that lecturer's evaluation is predicted to be less than or equal 75.5%. Where Set3 is the set of items that listed in Table 8.3.
- **IF** Specialist\_A\_Name\_Bc in [ "علوم" ] **Then** Evaluation = 3.0, that means that lecturer's evaluation is predicted to be between 80.1% and 85.6%.
- **IF** Specialist\_A\_Name\_Bc in [ "فيزياء" ] **Then** Evaluation = 1.0, that means that lecturer's evaluation is predicted to be less than or equal 75.5%.
- **IF** Governorate\_Name in [ "رِفح" "شمال غزة" ] **Then** Evaluation = 2.0, that means that lecturer's evaluation is predicted to be between 75.6% and 80%.
- **IF** Governorate\_Name in [ "غزة" ] **Then** :

**IF** End\_Date\_Bc in Set4 **Then** Evaluation = 3.0, that means that lecturer's evaluation is predicted to be between 80.1% and 85.6%. Where Set4 is the set of items that listed in

- Table 8.4.
- **IF** End\_Date\_Bc in [ "2011" ] **Then** Evaluation = 2.0, that means that lecturer's evaluation is predicted to be between 75.6% and 80%.
- **IF** End\_Date\_Bc in [ "2014" ] **Then** Evaluation = 3.0, that means that lecturer's evaluation is predicted to be between 80.1% and 85.6%.
- **IF** MARITAL\_STATUS = متزوج **Then** Evaluation = 1.0, that means that lecturer's evaluation is predicted to be less than or equal 75.5%.



- **IF** MARITAL\_STATUS = مطلق **Then** Evaluation = 2.0, that means that lecturer's evaluation is predicted to be between 75.6% and 80%.
- **IF** Specialist\_Detail\_A\_Name\_Bc in [ "اللغة الإنجليزية" ] **Then** :
  - **IF** End\_Date\_Bc in Set5 **Then** Evaluation = 2.0, that means that lecturer's evaluation is predicted to be between 75.6% and 80%. Where Set5 is the set of items that listed in Table 8.5.
  - **IF** End\_Date\_Bc in [ "2013" ] **Then** :
    - **IF** Emp\_Level\_Bc in [ "جيد" ] **Then** Evaluation = 1.0, that means that lecturer's evaluation is predicted to be less than or equal 75.5%.
    - **IF** Emp\_Level\_Bc in [ "جيد جدا" ] **Then** :
      - **IF** MARITAL\_STATUS = أعزب **Then** Evaluation = 3.0, that means that lecturer's evaluation is predicted to be between 80.1% and 85.6%.
      - **IF** MARITAL\_STATUS = متزوج **Then** Evaluation = 2.0, that means that lecturer's evaluation is predicted to be between 75.6% and 80%.
      - **IF** MARITAL\_STATUS = مطلق **Then** Evaluation = 2.0, that means that lecturer's evaluation is predicted to be between 75.6% and 80%.
    - **IF** Emp\_Level\_Bc in [ "مقبول" "ممتاز" ] **Then** Evaluation = 2.0, that means that lecturer's evaluation is predicted to be between 75.6% and 80%.
  - **IF** End\_Date\_Bc in [ "2014" ] **Then** Evaluation = 4.0 , that means that lecturer's evaluation is predicted to be greater than or equal 85.7%.
- **IF** Specialist\_Detail\_A\_Name\_Bc in [ "تطوير البرمجيات" ] **Then** :

- **IF** Emp\_Level\_Bc in [ "جيد" ] **Then** Evaluation = 1.0, that means that lecturer's evaluation is predicted to be less than or equal 75.5%.
- **IF** Emp\_Level\_Bc in [ "جيد جدا" ] **Then** Evaluation = 2.0, that means that lecturer's evaluation is predicted to be between 75.6% and 80%.
- **IF** Emp\_Level\_Bc in [ "مقبول" "ممتاز" ] **Then** Evaluation = 2.0, that means that lecturer's evaluation is predicted to be between 75.6% and 80%.
- **IF** Specialist\_Detail\_A\_Name\_Bc in [ "تكنولوجيا المعلومات" ] **Then** :
  - **IF** Gender = ذكر **Then** :
    - **IF** MARITAL\_STATUS = أعزب **Then** Evaluation = 4.0 , that means that lecturer's evaluation is predicted to be greater than or equal 85.7%.
    - **IF** MARITAL\_STATUS = متزوج **Then** Evaluation = 2.0, that means that lecturer's evaluation is predicted to be between 75.6% and 80%.
    - **IF** MARITAL\_STATUS = مطلق **Then** Evaluation = 4.0 , that means that lecturer's evaluation is predicted to be greater than or equal 85.7%.
  - **IF** Gender = أنثى **Then** Evaluation = 3.0, that means that lecturer's evaluation is predicted to be between 80.1% and 85.6%.
- **IF** Specialist\_Detail\_A\_Name\_Bc in [ "صحافة وإعلام" "كهربائية" ] **Then** Evaluation = 3.0, that means that lecturer's evaluation is predicted to be between 80.1% and 85.6%.
- **IF** Specialist\_Detail\_A\_Name\_Bc in [ "هندسة بيئية" ] **Then** :
  - **IF** Gender = ذكر **Then** Evaluation = 4.0 , that means that lecturer's evaluation is predicted to be greater than or equal 85.7%.
  - **IF** Gender = أنثى **Then** Evaluation = 1.0, that means that lecturer's evaluation is predicted to be less than or equal 75.5%.
- **IF** Specialist\_Detail\_A\_Name\_Bc in [ "هندسة حاسوب" ] **Then** :

- **IF** Gender = ذكر **Then** Evaluation = 1.0, that means that lecturer's evaluation is predicted to be less than or equal 75.5%.
- **IF** Gender = أنثى **Then** Evaluation = 4.0 , that means that lecturer's evaluation is predicted to be greater than or equal 85.7%.
- **IF** Specialist\_Detail\_A\_Name\_Bc in [ "هندسة صناعية" ] **Then** :
  - **IF** Gender = ذكر **Then** Evaluation = 1.0, that means that lecturer's evaluation is predicted to be less than or equal 75.5%.
  - **IF** Gender = أنثى **Then** Evaluation = 3.0, that means that lecturer's evaluation is predicted to be between 80.1% and 85.6%.
- **IF** Specialist\_Detail\_A\_Name\_Bc in [ "هندسة كهربائية" ] **Then** :
  - **IF** Governorate\_Name in [ "الوسطى" "خانيونس" "رفح" ] **Then** Evaluation = 1.0, that means that lecturer's evaluation is predicted to be less than or equal 75.5%.
  - **IF** Governorate\_Name in [ "شمال غزة" ] **Then** Evaluation = 2.0, that means that lecturer's evaluation is predicted to be between 75.6% and 80%.
  - **IF** Governorate\_Name in [ "غزة" ] **Then** :
    - **IF** Birth\_Date in Set6 **Then** Evaluation = 1.0, that means that lecturer's evaluation is predicted to be less than or equal 75.5%. Where Set6 is the set of items that listed in Table 8.6 .
    - **IF** Birth\_Date in [ "1990" ] **Then** Evaluation = 4.0 , that means that lecturer's evaluation is predicted to be greater than or equal 85.7%.
    - **IF** Birth\_Date in [ "1991" ] **Then** :
      - **IF** University\_Name\_Bc in [ "المنصورة" ] **Then** Evaluation = 2.0, that means that lecturer's evaluation is predicted to be between 75.6% and 80%.

- *IF* University\_Name\_Bc in [ "كلية دبي" ] *Then* Evaluation = 1.0, that means that lecturer's evaluation is predicted to be less than or equal 75.5%.

Table 8.1 Set1 in Rule 2

|                          |                        |                  |                      |
|--------------------------|------------------------|------------------|----------------------|
| American                 | Near East              | التحدي           | أسيوط                |
| Andhra                   | New Mexico             | التكنولوجيا      | أم القرى             |
| Aristotle                | Nottingham             | الجزائر          | أم درمان             |
| Arizona                  | Philipps               | الخرطوم          | بغداد                |
| Arkansas                 | Poona                  | الزقازيق         | بيت لحم              |
| Bangalore                | Saint-Petersburg state | الزيتونة         | ببر زيت              |
| Berlin technical         | Santo Tomas            | السابع من إبريل  | بيروت العربية        |
| Colorado                 | Southwestern           | السند            | حلوان                |
| Darlsruhe                | The East               | الشلف            | سبأ                  |
| Darmstadt                | Toledo                 | العلوم التطبيقية | صنعاء                |
| Delhi                    | Venice                 | الفتاح           | طنطا                 |
| Donetsk Poly             | Virginia Polytecl      | القاهرة          | عبد المالك السعدي    |
| Engineering & Technology | الإسراء                | القدس المفتوحة   | عمر المختار البيضاء  |
| Exeter                   | الإسلامية العالمية     | القرآن الكريم    | قاريونس              |
| Far Eastern              | الإمارات العربية       | الكلبات العربية  | قناة السويس          |
| Guangxi                  | الإمام محمد            | الكويت           | كلية التربية(الأقصى) |
| Heritage College         | الأردنية               | الملك عبد العزيز | مالطة                |
| Kazakh                   | الأزهر                 | النجاح الوطنية   | محمد الأول           |
| Middle East              | الأمريكية              | اليرموك          | ناصر                 |

Table 8.2 Set2 in Rule 2

|                           |                                   |                           |                        |
|---------------------------|-----------------------------------|---------------------------|------------------------|
| اتصالات وتحكم             | اللغة العربية والدراسات الإسلامية | تربية ابتدائية            | علوم / تحاليل          |
| الاتصال والعلاقات العامة  | اللغة العربية وآدابها             | تربية إنجليزي             | علوم تربوية            |
| الإدارة المالية والمصرفية | المحاسبة                          | تربية تاريخ               | علوم زراعية            |
| الإرشاد النفسي والتربوي   | المناهج وطرق التدريس              | تربية عربي                | علوم سياسية            |
| الإقتصاد والعلوم السياسية | النحو والصرف                      | تربية علوم                | علوم سياسية ودبلوماسية |
| الأدب والنقد              | النقد والبلاغة                    | تصميم معماري              | علوم فيزياء            |
| البلاغة العربية           | الهندسة المعمارية                 | تعليم التكنولوجيا         | علوم قانونية           |
| التاريخ                   | الهندسة الميكانيكية               | تعليم العلوم والتكنولوجيا | علوم كمبيوتر           |
| التمريض العام             | إحصاء                             | تكنولوجيا التعليم         | فسولوجي                |
| الحقوق                    | إدارة أعمال                       | تكنولوجيا وعلوم تطبيقية   | كمبيوتر                |
| الحيوان والكيمياء         | إقتصاد                            | جيولوجيا                  | كهرباء آلات            |

|                           |                           |                 |                            |
|---------------------------|---------------------------|-----------------|----------------------------|
| الخدمة الاجتماعية         | اقتصاد إسلامي             | جيولوجيا المياه | كيمياء المبيدات            |
| الشريعة                   | أحياء وكيمياء             | رياضيات /تربية  | ليسانس آداب وتربية إنجليزي |
| الشريعة الإسلامية         | أدب إنجليزي               | رياضيات/فيزياء  | محاسبة وتدقيق              |
| الشريعة والقانون          | أنظمة المعلومات الحاسوبية | رياضيات/كمبيوتر | هندسة اتصالات              |
| الطب العام                | آداب - جغرافيا            | صحافة           | هندسة الطرق                |
| الطب والجراحة             | آداب لغة عربية            | صيدلة           | هندسة العوامل البشرية      |
| الطبيعة                   | آداب وتربية               | طب              | هندسة إلكترونية            |
| العلاج الطبيعي            | بيولوجي                   | طب مخبري        | هندسة تخطيط مدن            |
| العلوم الطبيعية، الصيدلة  | تاريخ فرعي وأثار          | علاج طبيعي      | هندسة تكرير بترول          |
| العلوم والتربية – رياضيات | تخطيط حضري                | علم الحيوان     | هندسة كهربائية (اتصالات)   |
| القانون                   | تخطيط عمراني              | علم النفس       | هندسة معمارية              |
| القانون الخاص             | تربية                     | علم إجتماع      |                            |
| الالكترونيات              | تربية / تاريخ             | علوم            |                            |
| اللغة العربية             | تربية /كيمياء             | علوم-طبيعية     |                            |

Table 8.3 Set3 in Rule 2

|                |                   |                  |                 |
|----------------|-------------------|------------------|-----------------|
| إدارة أعمال    | تربية             | طب               | هندسة بيئية     |
| اقتصاد         | تكنولوجيا معلومات | علم نفس          | هندسة حاسوب     |
| أحياء          | تمريض             | قانون            | هندسة صناعية    |
| أصول تربية     | جغرافيا           | كمبيوتر          | هندسة كهربائية  |
| أصول دين       | حقوق              | كيمياء           | هندسة مدنية     |
| بيئة وعلوم أرض | خدمة إجتماعية     | لغة إنجليزية     | هندسة معمارية   |
| تاريخ          | رياضيات           | لغة عربية        | هندسة ميكانيكية |
| تجارة          | شريعة             | محاسبة           |                 |
| تحاليل طبية    | صحافة             | مناهج وطرق تدريس |                 |

Table 8.4 Set4 in Rule 2

|      |      |      |      |
|------|------|------|------|
| 1966 | 1981 | 1992 | 2003 |
| 1968 | 1982 | 1993 | 2004 |
| 1971 | 1983 | 1994 | 2005 |
| 1972 | 1984 | 1995 | 2006 |
| 1973 | 1985 | 1996 | 2007 |
| 1975 | 1986 | 1997 | 2008 |
| 1976 | 1987 | 1998 | 2009 |
| 1977 | 1988 | 1999 | 2010 |
| 1978 | 1989 | 2000 | 2012 |
| 1979 | 1990 | 2001 | 2013 |
| 1980 | 1991 | 2002 |      |

Table 8.5 Set5 in Rule 2

|      |      |      |      |
|------|------|------|------|
| 1966 | 1981 | 1992 | 2003 |
| 1968 | 1982 | 1993 | 2004 |
| 1971 | 1983 | 1994 | 2005 |
| 1972 | 1984 | 1995 | 2006 |
| 1973 | 1985 | 1996 | 2007 |
| 1975 | 1986 | 1997 | 2008 |
| 1976 | 1987 | 1998 | 2009 |
| 1977 | 1988 | 1999 | 2010 |
| 1978 | 1989 | 2000 | 2011 |
| 1979 | 1990 | 2001 | 2012 |
| 1980 | 1991 | 2002 |      |

Table 8.6 Set6 in Rule 2

|      |      |      |      |
|------|------|------|------|
| 1945 | 1958 | 1970 | 1982 |
| 1946 | 1959 | 1971 | 1983 |
| 1948 | 1960 | 1972 | 1984 |
| 1949 | 1961 | 1973 | 1985 |
| 1950 | 1962 | 1974 | 1986 |
| 1951 | 1963 | 1975 | 1987 |
| 1952 | 1964 | 1976 | 1988 |
| 1953 | 1965 | 1977 | 1989 |
| 1954 | 1966 | 1978 | 1992 |
| 1955 | 1967 | 1979 |      |
| 1956 | 1968 | 1980 |      |
| 1957 | 1969 | 1981 |      |