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The Relationship between Students' Personality Types and Their Success

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Abstract

Teachers often classify students using simple stereotypes such as," low", "average", and "high" achieving students, and prepare their courses based on this classification. Because students have different personality types and differences in their acquisition of skills, they require differentiated attention from their teachers. This paper tries to determine the relationships between personality type and the student's ability to solve a problem. We reached a number of conclusions and recommendations that basically highlighted the importance of learning more about students' personality types in order to understand their strengths and weaknesses, improve their interpersonal relationships, and gain a better self-knowledge that will help them define and achieve goals.

Keywords: Personality Type, Bayesian Network, Conditional Probability Distribution, MBTI.

Introduction

No two students are alike. Students differ in their personal values, they receive and process information differently, their personality types are different and so is their understanding of a specific mathematical problem. Personality types, as determined by the Myers-Briggs Type Indicator (MBTI) (Myers, McCaulley, & Alto, 1985), are a manifestation of the theory of psychological types proposed by Carl G. Jung (1921/1971). Jung, (Eysenck, 1967), believed that when our minds are active, we are involved in one of two mental functions:

1. Receiving (perceiving) information, or
2. Organizing the information so that we can reach a conclusion (judging).

Myers and McCaulley (Myers, McCaulley, & Alto, 1985) refined the MBTI to make Jung's psychological typology more meaningful and practical in everyday life. The MBTI consists of four separate indices that, when viewed individually, illustrate one of four preferred choices for describing how people perceive and react in a given situation.

Brief Description of the MBTI Factors

Extraversion-Introversion (EI)

The EI index describes whether a person is oriented towards the outer world (Extravert) (E), by focusing on people and objects, or towards the inner world (Introvert), by focusing on concepts and ideas.

Sensing-Intuition (SN)

The SN index describes a person's choice in perceiving new information. A person may prefer to gather information by observing facts or experiences through one of the five senses (S) or by gathering information through meanings, relationships, and/or possibilities. That preference is labeled Intuition (N).

Thinking-Feeling (TF)

The TF index describes how a person draws conclusions or makes decisions. If a person relies on logic to make decisions, the Thinking (T) preference is most prevalent. When personal, subjective, and/or social values are the basis for decision-making, a person is relying on the Feeling (F) preference

Judgment-Perception (JP)

The JP index describes the process one uses to confront the outer world. That is, one who prefers Judgment (J) has a preference for using either Thinking or Feeling in dealing with the outer world. One who chooses Perception (P) has a preference for using Sensing or Intuition in dealing with the outer world.

These four items are the result of combining eight possible personality factors. When combined in totality, these eight factors result in 16 distinct personality types: ISTJ, ESTJ, ISFJ, ESFJ, ISTP, ESTP, ESFP, ISFP, ENTJ, INTJ, ENTP, INTP, ENFJ, INFJ, ENFP, and INFP.

This does not mean that all (or even most) individuals will fall strictly into one category or another. If we learn by applying the tool that we are primarily extraverted, that does not mean that we do not also perform introverted activities. We all function in all of these realms. As we grow and learn, most of us develop the ability to function well in realms which are not native to our basic personalities.

Learning about our personality type helps us to understand why certain areas in life come easily to us, and others are more of a struggle. Learning about other people's personality types helps us understand the most effective way to communicate with them, and how they function best. Research shows the resultant behavior is orderly and consistent over time and is correlated with a person's reactions, interests, values, motivations, and skills (Myers, McCaulley, & Alto, 1985), (Berens & Nardi, 1999).

If students perceive information, draw conclusions, and react differently then they may learn differently, a deeper understanding of their personality types may improve teaching effectiveness. Teachers can gain from advanced understanding of personality types and awareness of how to adapt to each student, or how to group students into clusters which require specific kinds of instructions.

Previous Work

Previous research has demonstrated a relationship between the four-factor model of personality and academic achievement (Costa & McCrae, 1992). This relationship between personality type and course success has been well documented in the studies of Fagan and Squitiers Fagan & Squitiera, 2002), Eysenck (Eysenck, 1967) and Kline (Kline, 1977). McKenzie (McKenzie, 1989) found extraversion to be negatively correlated with success in higher education but found no clear-cut relationship between neuroticism (an enduring tendency to experience negative emotional states) and students' academic achievement. In a study of the relationship between personality and academic achievement, Masgrave- Marquart, Bromley, and Dalley (Marquart, Broomley, & Dalley, 1997) found significant positive correlations between GPA (grade point average) and conscientiousness (the trait of being painstaking and careful, or the quality of acting according to the dictates of one's conscience), openness, and neuroticism. Finally, DeRaad and Schouwenburg (De Raad & Schouwenburg, 1996) found that extraversion, conscientiousness, and openness to experience are educationally relevant.

Similarly, Vomela (Vomela, 1994) studied junior and senior construction engineering students to ascertain the relationship between preferred teaching methods, personality types, and final course grades.

However, there is a lack of research addressing the relationships between personality types and successes in solving math/statistical problems. In this paper we present a model using the Bayesian network that represents the dependencies among several variables and examine the impact of personality types and other factors on the performance of students.

Bayesian Networks

Bayesian networks are diagrams that organize data in any given area by mapping out cause-and-effect relationships among key variables and encoding them with numbers that represent the extent to which one variable is likely to affect another.

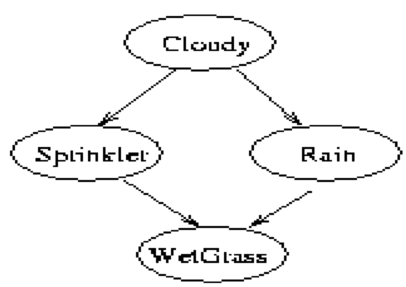
The name if derived from Thomas Bayes who wrote the well-known mathematical formula for calculating probabilities among several variables that are causally related but for which the relationships can't easily be derived by experimentation (Cowell, Dawid, Lauritzen, & Spiegelhalter, 1999).

Formally, a Bayesian network is defined by a set of variables (nodes) and a directed cyclic graph (Jensen, 1996), (Naïm, Wuillemin, Leray, Pourret, & Becker, 2004), (Neapolitan, 2004), defining the mode of conditional dependencies among the variables.

In addition to the graph structure, it is necessary to specify the parameters of the model; a Conditional Probability Distribution (CPD) at each node is specified. If the variables are discrete, this can be represented as Conditional Probability Table (CPT), which lists the probability that the child node takes on each of its different values for each combination of values of its parents. Consider the following example (Jensen, 1996), in which all nodes are binary, i.e., they have two possible values, which will be denoted by T (true) and F (false):

P(C=F)	P(C=T)
0.5	0.5

C	P(S=F)	P(S=T)
F	0.5	0.5
T	0.9	0.1



C	P(R=F)	P(R=T)
F	0.8	0.2
T	0.2	0.8

S	R	P(W=F)	P(W=T)
F	F	1.0	0.0
T	F	0.1	0.9
F	T	0.1	0.9
T	T	0.01	0.99

Figure 1: A Bayesian Network model for the wet grass example. Rain (R), Sprinkler (S), Wet Grass (W), Cloudy(C)

We see that the event, "grass is wet" (W=true) has two possible causes: either the water sprinkler is on (S=true) or it is raining (R=true). The strength of this relationship is shown in the table. For example, we see that P(W=true | S=true, R=false) = 0.9 (second row), and hence, P(W=false | S=true, R=false) = 1 - 0.9 = 0.1, since each row must sum to one. Since the C node has no parents, its CPT specifies the prior probability that it is cloudy (in this case, 0.5). (We can think of C as representing the season: if it is a cloudy season, it is less likely that the sprinkler is on and more likely that the rain is on.)

The simplest conditional independence relationship encoded in a Bayesian network can be stated as follows: a node is independent of its ancestors given its parents, where the ancestor/parent relationship is with respect to some fixed topological ordering of the nodes (Smail, 2004). .

By the chain rule of probability, the joint probability of all the nodes in the graph above is

$P(C, S, R, W) = P(C) * P(S|C) * P(R|C, S) * P(W|C, S, R)$.

By using conditional independence relationships, we can rewrite this as:

$P(C, S, R, W) = P(C) * P(S|C) * P(R|C) * P(W|S, R)$.

Where, we were allowed to simplify the third term because R is independent of S given its parent C, and the last term because W is independent of C given its parents S and R.

Purpose and Objectives

The purpose of the study was to determine if there are relationships amongst the personality types for students taken an introductory management course, the score they obtained for answering a problem, and other factors related to the problem such as the perceived difficulty of the problem, requests for help, and the fact that the necessary mathematical formulas were given to the students.

Procedures

Sample

The accessible population was 42 students enrolled in a quantitative methods class (Quant 301) during the spring 2007 semester at the School of Management at New York Institute of Technology, Amman, Jordan.

The course is taken by students to satisfy the university requirement for credit in Mathematics. The class met twice a week (two hours each time) for a period of ten weeks.

Of these students, 28 were males and 14 females.

Measures

The experiment was done in two steps:

The first step was to determine the personality types using the Myers-Briggs Type Indicator (MBTI). Participating students agreed to have their personality profiles assessed using MBTI. They were given as much time as needed to complete the MBTI which was administered to all students enrolled in this course during the fifth week of this semester.

The second step was a statistical problem attempted by the students during the last 15 minutes of class. The necessary formulas were provided and all data was collected prior to class dismissal.

In addition to attempting a statistical problem, each student answered a few questions related to the problem:

1. What is your impression of this question? Easy Average Difficult
2. Have you done similar questions before? Yes No
3. Did you use the formulas provided for you? Yes No

In addition, whether or not each student asked for help during the test was also recorded.

After the test, a score was given for each problem. The score consisted of a number of points from 4 to 10. Note: (2 points for each part of the solution)

Each student was identified by a five-digit ID number for confidentiality.

At the end of the experiment, the data was arranged in 42 rows, one per student, and 6 columns for the following 6 variables:

1. Personality Types: a discrete categorical variable that indicates the personality type for each student using the MBTI.
2. Perceived Difficulty of the question: a discrete categorical variable for the three values: Easy, Average, or Difficult.
3. Similar Questions Done Before: a discrete categorical variable: Yes or No.
4. Using the Provided Formulas: a discrete categorical variable: Yes or No.
5. Request for Help: a discrete categorical variable: Yes or No.
6. Score: a numerical discrete variable: 4, 6, 8, or 10.

Results and Conclusions

The Descriptive Statistics of the Different Variables

Table 1: The descriptive statistics of the different variables

VARIABLE	VALUES	FREQUENCY	PERCENT
Requests for help	Yes	23	54.76%
	No	19	45.24%
The use of the formulas	Yes	34	80.95%
	No	8	19.05%
Personality Types	ESTP	5	11.90%
	INTJ	3	7.14%
	ESTJ	5	11.90%
	INFP	3	7.14%
	ISFJ	5	11.90%
	ENTJ	2	4.76%
	ESFJ	2	4.76%
	ISTP	3	7.14%
	ISTJ	4	9.52%
	INFJ	2	4.76%
	ISFP	2	4.76%
	ESFP	3	7.14%
	ENFP	2	4.76%
	ENFJ	1	2.38%
The score	4	10	27.94%
	6	13	31.68%
	8	3	5.81%
	10	16	34.57%

Summary of the Results

Data showed that the typical class student was more Extraverted, Sensing, and Thinking.

71.43% of the students were Sensing.

66.67% of Intuitive students asked for help.

ESTJ and ESTP students were the main types who asked for help.

30.94% of Judging and Thinking students asked for help.

In contrast, ENFJ and ENFP students did not ask for help at all.

We found that the ISFP personality type scored higher than did the other types.

J and F students had the highest score.

35.7% of Thinking students scored less than the average.

38.08% of Judging students scored less than the average.

Structure Learning

For structure learning (relationships among variables) we used an algorithm called the PC algorithm described by Spirtes, Glymour, and Scheines (Spirtes, Glymour, & Scheines, 1993). The PC algorithm belongs to the class of constraint-based learning algorithms. The basic idea of these algorithms is to derive a set of conditional independence and dependence statements by statistical tests.

The algorithm performs the following steps:

- Statistical tests for conditional independence are performed for all pairs of variables.
- An undirected link is added between each pair of variables for which no conditional independences was found. The resulting undirected graph is referred to as the *skeleton* of the learned structure.
- V-structures are then identified, ensuring that no directed cycles occur. (A *V-structure* is a pair of links directed such that they meet in a node.) For example, if we find that A and B are dependent, B and C are dependent, but A and C are conditionally independent given S, not containing B, then this can be represented by the structure (Neapolitan 2004)

  A -----> B <----- C.
- Next, directions are enforced for those links whose direction can be derived from the conditional independences found and the V-structures identified.
- Finally, the remaining undirected links are directed randomly, ensuring that no directed cycles occur.

Using the PC algorithm with our data of 42 rows we discovered a relationship among the three variables: Score, Difficulty of the question, and Requests for Help.

The tests found that the two variables, Perceived Difficulty of the question, and Similar questions done before are independent, and the variable, Score, depends on both variables, which is a V-structure.

Statistical tests didn't find any other relationships among the other variables due to the small size of the sample. (The level of significance used for our statistical tests was 0.05).

The final structure obtained is shown in the following figure:

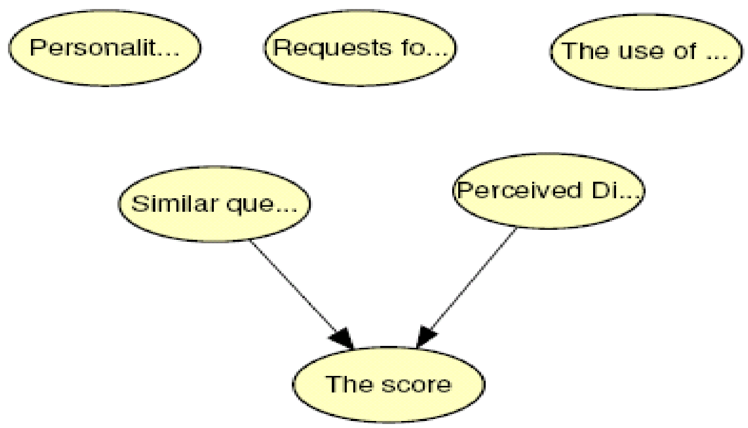


Figure 2: Bayesian Network representing the 42-row data.

In addition to the relationships, the Bayesian network gave us all the marginal probability distributions for all variables (the same percents presented earlier) and also the table of conditional probability for the variable, Score, given the different values for the two parent variables: Similar Questions Done Before and Perceived Difficulty of the question.

Table 2: conditional probability for the variable Score given the different values for the two parent variables: Similar questions done before and Perceived Difficulty of the question

NO			YES			SIMILAR QUSTIONS DONE BEFORE
Difficult	Easy	Average	Difficult	Easy	Average	Perceived Diff. of the question
1	1	0.5	1	0.047619	0.285714	Score = 4
0	0	0	0	0.238095	0.571429	Score = 6
0	0	0.25	0	0.09523	0	Score = 8
0	0	0.25	0	0.619048	0.142857	Score = 10

Due to the overall weak results, we decided to look for a more complex structure using a bigger database. For this purpose, we doubled our database and again used the PC algorithm trying to find dependencies among the different variables.

In this case, we used the obtained structure as a starting point and again the PC algorithm of structured learning using a new database of 84 rows.

The Bayesian network obtained in this case has a more complex structure (more relationships among the different variables):

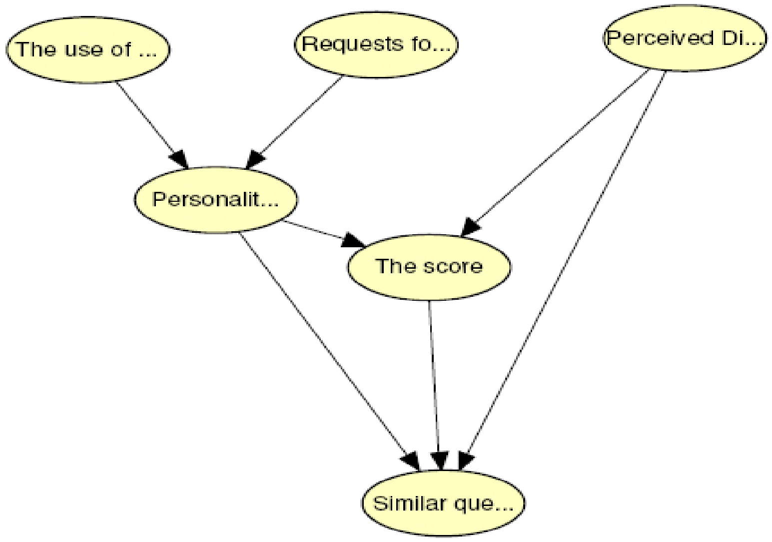


Figure 3: Bayesian Network representing the 84-row data.

Using the concept of cause and effect we obtain a more complex Bayesian network, but equivalent to the previous one. This can be done by a function called "Reverse Link" which is an application of Bayes' theorem (Jensen, 1996).

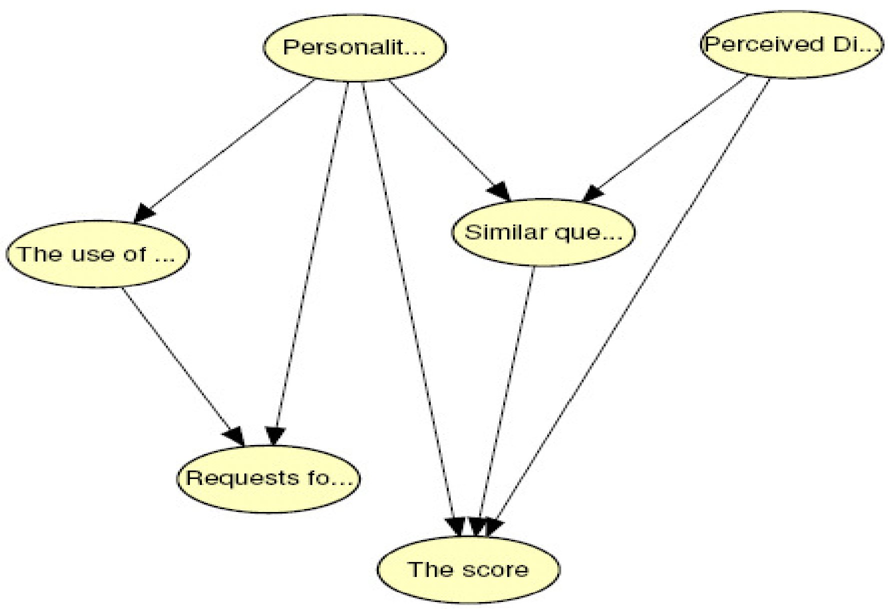


Figure 4: Bayesian Network equivalent to the Bayesian network in figure 3.

The same relationships were demonstrated as earlier, but different organization, for example, in this case, we can read that:

Personality type and Perceived Difficulty of the question are independent (which is an evidence).

Score and Request for Help are independent given the Personality Type.

Score and Using the Provided Formulas are independent given the Personality Type.

The variable Score had three parents in this case and its conditional probability distribution given the values of its parents is given.

The joint probability distribution for all variables, Personality Types (T), Perceived Difficulty of the Question (D), the Use of the Provided Formulas (F), Similar Questions Done Before (Q), Requests for Help (H), and Score (S) can be written as:

P(T, D, F, Q, H, S) = P(T) * P(D) * P(F|T) * P(Q|T, D) P(S/T, D, Q).

Using this Bayesian network all the possible joint and conditional probabilities can be computed by simply using Bayes' theorem.

As an example, if we need to know which personality type scores 100%, in other words, the probability of each personality type given the information that the students scored 10.

To do this Hugin is used, which is one of the most frequently used software in Bayesian networks (an evaluation version of Hugin can be downloaded from http://www.hugin.com), with the following results:
First, given the score = 10 the following results are demonstrated:

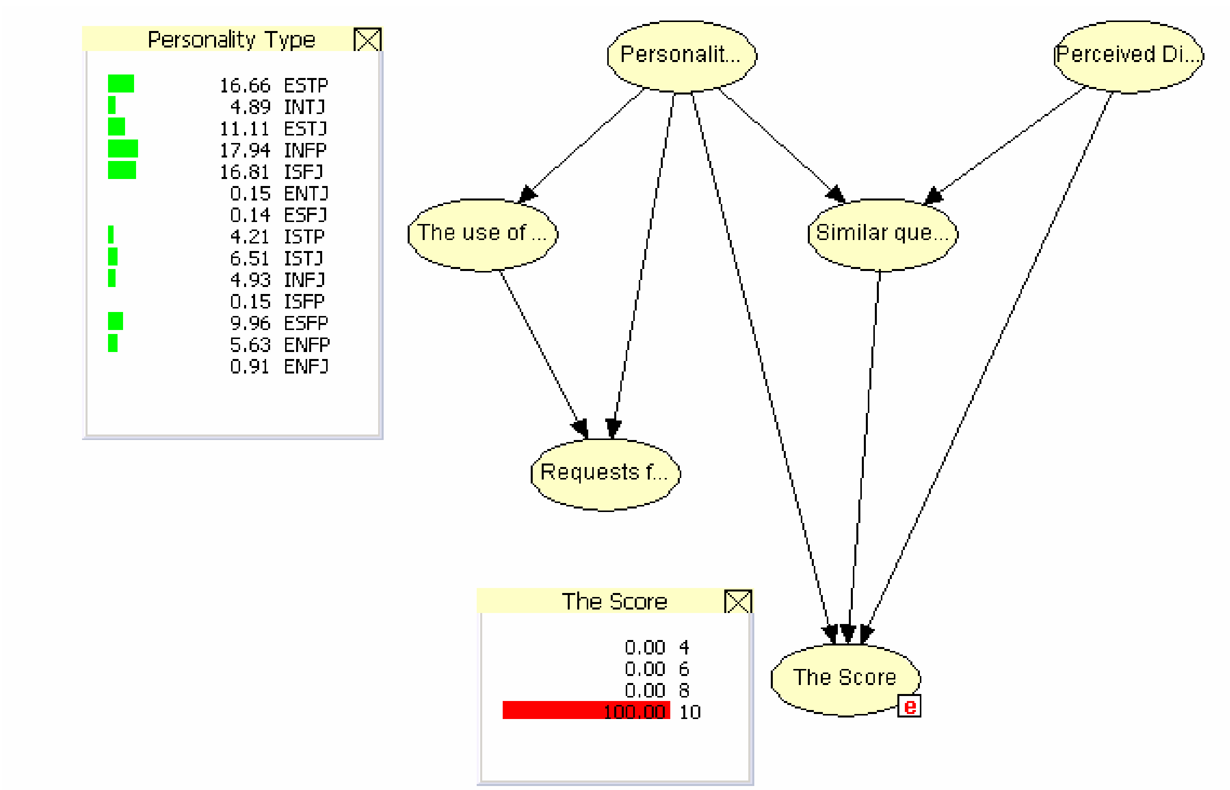


Figure 5: The probability distribution of the Variable Personality Types conditionally to Score=10.

Second, given that the score = 8 results are as follows:

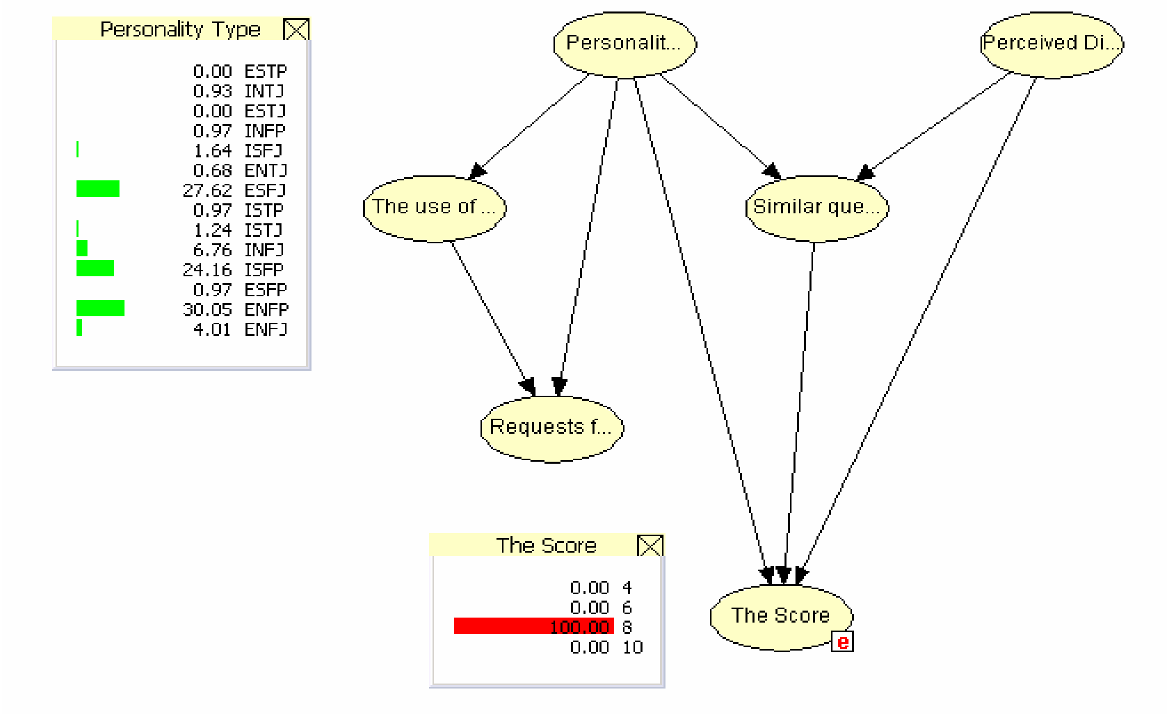


Figure 6: The probability distribution of the Variable Personality Types conditionally to Score=8.

Third, given that the score = 6 the following results are presented:

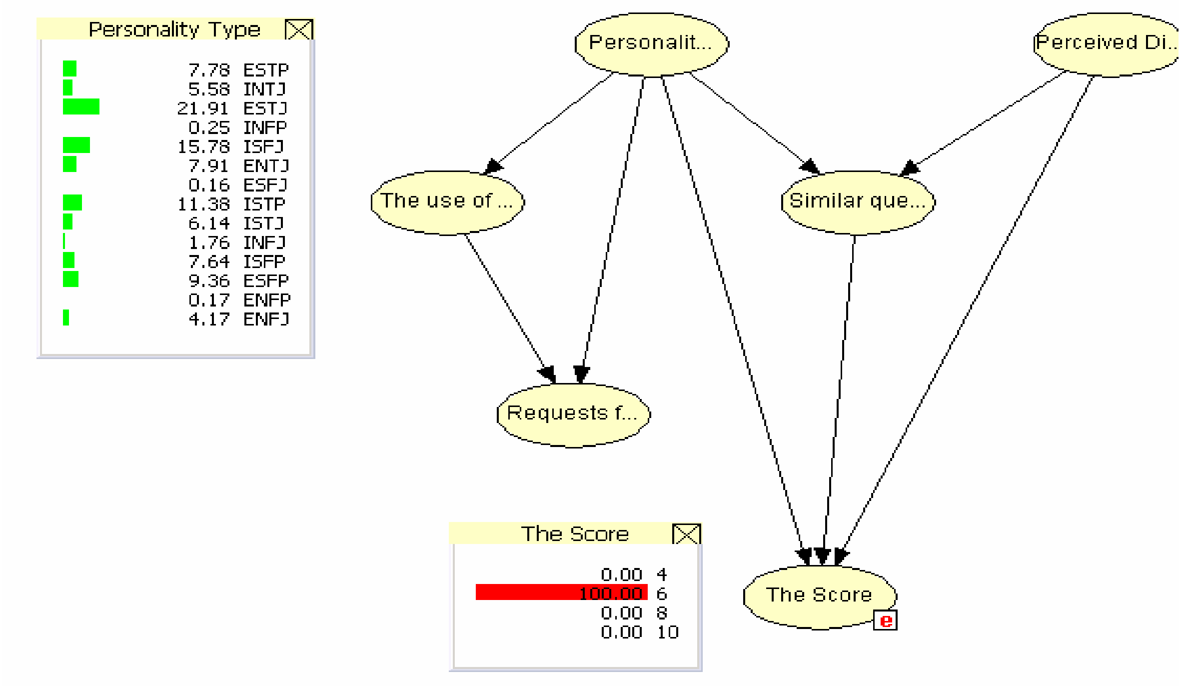


Figure 7: The probability distribution of the Variable Personality Types conditionally to Score=6.

Fourth, given that the score = 4 the following results are presented:

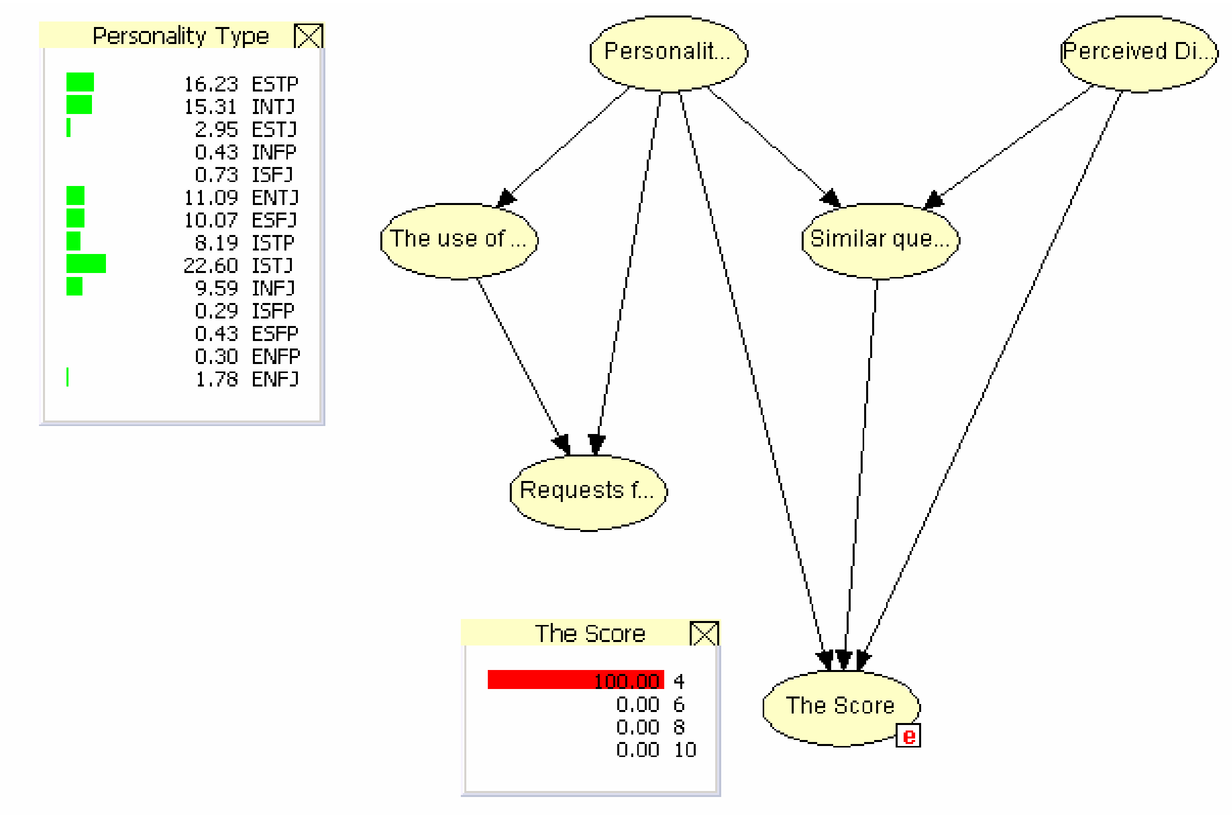


Figure 8: The probability distribution of the Variable Personality Types conditionally to Score=4.

Implications/Recommendations

When teachers are aware of students' differences they can adopt methods that address the needs and concerns of all students, regardless of preferences, through curricula orientation and classroom activities.

During their academic careers, students may be exposed to a variety of teaching styles, assignments, projects, and exams, and may experience a variety of instructors' personality types as well. The interaction effects of these variables could be beneficial for some students, yet severely hamper the learning environments for others.

By learning more about Students' Personality Types we can come to a better understanding of students' strengths and weaknesses, improve their interpersonal relationships, and gain a better self-knowledge that will help them define and achieve goals.

A question not addressed in the present study is whether the personality type preferences of students are similar or dissimilar to the preferences held by teachers.

A need exists to determine if there are any relationships between teachers' personality types and students' personality types.

Another need is to study students according to their personality type, gender, and participation in student organizations.

We are conducting another study of students enrolled in the College of Arts and Sciences. The purpose of this study is to describe characteristics of students and faculty members.

References

Berens, Linda V., Nardi, Dario. (1999). The 16 Personality Types, Descriptions for Self-Discovery, *Telos Publications.*

Chowdhury, Mohammed. (2006). Students' Personality Traits and Academic Performance: A five-Factor Model Perspective. *College Quarterly.* Volume 9 Number 3

Costa, P.T., & McCrae, R.R. (1992). NEO PI-R. Professional manual. Odessa, FL: *Psychological Assessment Resources, Inc.*

Cowell, Robert G., Dawid, A.Philip, Lauritzen, Steffen L., & Spiegelhalter, David J. (1999). Probabilistic Networks and Expert Systems. Series: Information Science and Statistics. *Springer*

De Raad, B. & Schouwenburg, C. (1996). Personality in learning and education: a review. *European Journal of Personality*, 10, 303-336.

Eysenck, H.J. (1967). The Biological basis of personality. New York: *Springfield.*

Fagan, Ron, & Squitiera, Paula. (2002). The Relationship between Personality Characteristics and Academic Success in Law school. *Evaluation and Research in Education*. Vol. 16, No. 2.

Jensen, F.V. (1996). An Introduction to Bayesian Networks. *Springer Verlag*, New York.

Kline, P. (1977). Personality and learning. *In Howe, M. (Ed.), Adult Learning*. Chichester: Wiley.

Marquart, D., Broomley, S. P., & Dalley, M.B. (1997). Personality, academic attribution and substance use as predictors of academic achievement in college students. Musgrave. *Journal of Social Behavior and Personality,* 12, 501-511.

McKenzie. (1989). Neuroticism and academic achievement: The Fureaux factor*. Personality and Individual Differences*, 10, 509-515.

Myers, I., McCaulley, M., Alto, Palo. (1985). Manual: A guide to the development and use of the Myers-Briggs Type Indicator. CA: *Consulting Psychologists Press.*

Naïm, Patrick, Wuillemin, Pierre-Henri, Leray, Philippe, Pourret, Olivier, & Becker, Anna. (2004). Réseaux Bayésiens, *Eyrolles*

Neapolitan, Richard E. (2004). Learning Bayesian Networks. *Prentice Hall*

Smail, Linda. (2004). Algorithmic for Bayesian Networks and Their Extensions, PhD Thesis, Applied Mathematic Laboratory, *Marne-La-Vallée University*. France

Spirtes, P., Glymour, C., & Scheines, R. (1993). Causation, Prediction, and Search, New York, N.Y. Springer-Verlag. 2nd Edition, *MIT Press* (2001)

Spirtes, P., Glymour, C., & Scheines, R. (1993). Inferring Causal Structures in Mixed Populations, In Artificial Intelligence in Statistics: AI and statistics III, D. Hand, ed., *Chapman and Hall,* 141-155.

Vomela, R. (1994). Students in a baccalaureate construction program: Correlations of personality type and teaching method preference. (Doctoral dissertation, University of Minnesota, 1994). *Dissertation Abstracts International,* 55-06A, 1541.

Wicklein, Robert C., & Rojewski, Jay W. (1995). The relationship between Psychological Type and Professional Orientation among Technology Education Teachers. *Journal of Technology Education* Volume 7, Number 1.

Wingenbach, Gary J. (2000). Personality Types and Final Grades in Group Organization and Leadership Development. *Proceedings of the 27th Annual National Agricultural Education Research Conference*