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An Intelligent System for Visualization of Intelligence of Learners

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Abstract—**This paper deals with the development of an intelligent system, which can be used to guide learners to visualize and predict their academic excellence and knowledge in future education. For that purpose, the system uses psychological correlates, in order to gain insight into the mind-set of the learners – their approach to challenges and their mutual strengths and weaknesses, thereby optimizing the scope for further performance in education. First, a candidate supplies his/her socio-demographic details and academic performance required by the expert system. Next, the AMS (Achievement Motivation Scale) test is administered. An expert system then analyses and produces the academic, social, vocational and skill achievement scores. Finally, Artificial Intelligence techniques are used to predict and extract academic excellence, social, vocational and skill achievements of the learners in the future. In addition, the factors that encourage or discourage the students, their satisfactions and disappointments and their expectations from life are also inferred.**

Index Terms—**Achievement Motivation, Artificial Intelligence, Inductive Inference, Intelligent System, Knowledge Visualization, Motivation, Psychological Correlates**

I. Introduction

Intelligent systems are usually designed to act as an expert in a particular field of knowledge or area of expertise and to solve complicated problems. To do this, the system simulates the human reasoning process by applying specific knowledge and inferences. It is customary to discuss the psychology of individual behavior under two major headings: Motivation and learning [1]. Motivation is the desire to perform well and attain success. It clearly plays an important role in individual and societal accomplishments [2]. In today's world of active competition, multimedia exposure and distractions, the student is constantly under pressure, as parental expectations and his own personal desires have to be fulfilled [3]. The desire to succeed and excel is called achievement need. Achievement motivation is basic to a good life. Achievers, as a whole, enjoy life and feel in control; being motivated, gives us self-respect as we become achievers [4]. Where and how achievement needs are learned are complex, intriguing and important questions. How motivated we are depends on the strength of fairly consistent motives or needs inside of us. Our expectation of what outcomes certain actions will produce, and, How badly at a particular time we want a certain pay off over all the other wants we have and over the risks we face.

The needs, expectations, and incentives are mostly learned; together these motivation factors largely determine what we do and how far we get in life. Artificial intelligence techniques have been used to infer the futuristic academic motivation and academic performance of learners.

This paper divided into two parts. The first part concerns data collection and the second, data processing and analysis. Data processing and analysis in turn involves two phases. The first phase concerns statistical inference and the second, artificial intelligence inference. This system is designed to overcome the difficulties of assessment of knowledge and the future academic performance of students in the subsequent years of their study. First, a candidate completes his/her socio-demographic details and academic performance required by the expert system and then administers the AMS (Achievement Motivation Scale) test. An expert system then analyses the candidate's answers using an inductive inference algorithm to generate futuristic academic performance, social, vocational and skill motivation. Finally, the scores inferred through statistics and AI techniques, were analyzed with the academic performance of the subsequent years of the candidates. Ultimately, the complete personalized educational model is produced.

2. ACHIEVEMENT MOTIVATION SCALE (AMS)

The Achievement Motivation Scale was constructed and standardized in 1996 by Dr. Shah Beena and published by the Agra Psychological Research Cell, Agra, based on the forced-choice technique [5]. The following four factors of need are essential for AMS:
Need for Academic Success
Need for Vocational Achievement
Need for Social Achievement and
Need for Skill Achievement

The AMS scale is a three-point scale. Each statement is followed by three alternative responses. The alternatives are arranged in the order of one's inclination towards achievement in the areas, namely academic, vocational, social context and skills. Weightage 1, 2 and 3 are respectively awarded for alternatives (a), (b), and (c) of any statement [5]. The AMS test – re-test reliability co-efficient varied between 0.77 and 0.87, which reveals that the test is highly reliable. The validity of the scale was ascertained in a three-fold fashion – content validity, item validity and congruent validity.

3. THE UNIVERSE AND SAMPLING

The Post-graduate and Under-graduate students of Arts and Science Colleges, Kalai Kauvery College of Fine Arts and K.A.P. Viswanatham Medical College, India, form the population and universe of the study.

The Probability Sampling technique (Simple Random Sampling Method) is more appropriate in this study, because every item of the universe has an equal chance of being included as a sample. In this case, 104 students, 26 from each of the disciplines of Computer Science, Social Work, Fine Arts, and Medicine were taken. Among the 104 samples, 52 were male students and 52 female students.

4. PROCESS DESCRIPTION

For the development of an academic excellence prediction system, we have adopted a knowledge-base system development environment. It integrates knowledge engineering concepts from Artificial Intelligence with a database system. Objects allow encapsulation of data and operations for representation of knowledge of spatial data at various levels of abstraction. Actions and conclusions are inferred from facts, rules and heuristics contained in the knowledge base by an inference engine.

The following processes are involved and analyzed to predict the candidate's academic excellence:

First, the Achievement Motivation Scale (AMS) test was administered among 104 randomly selected post-graduate and under-graduate students, in order to assess their motivation level in terms of academic, social, vocational and skill excellence. This test was performed at the time of entry into the course – the clinical approach. Next, with the results of Achievement Motivation score and average percentage of marks, the second test on AMS was administered for the same sample after six months – the clinical approach. Next, a spatial knowledge base was created with the above results. Finally, inference was done with the spatial knowledge, using inductive inference, in order to predict academic excellence in the future and factors that encourage or discourage the students, their satisfactions and disappointments, their expectations from life etc., and thus, a symbolic knowledge base was developed.

This empirical research has been carried out among post-graduate and under-graduate students, in order to analyze whether the independent dimensions like sex, age, educational qualification and occupation of both the parents, religion, type of family, domicile status, extra curricular activities, class, college studied, and average percentage of marks of the respondents influence the levels of their Achievement Motivation. Another question this paper aims to address is, if these variables do influence the dependent variables, and if so in what weightage?

The study focuses on the factors that motivate or de-motivate the young adults to achieve or not achieve what they desire. By being able to study the factors that increase or decrease the students' level of motivation, the researcher is able to gain proper insight into the commonly found but neglected aspects of one's daily life that influence one's thought, and decision-making process.

A rule-based system is used in this step to complete the model representing a candidate's inventory of knowledge and experience. Such a system includes:

A set of production rules, One or more knowledge bases with complete appropriate information, A short-term memory buffer, and The interpreter, which determines the task to done next or the production rule to be fired next [6].

Two approaches are employed here: a forward chaining system [7] is used to establish how much educational credit is due when the candidate provides information about the completed material in each question on motivation, and a backward chaining system when the candidate wants to find out how much more he / she has to add to achieve a certain educational goal in the future.

Normally many achievements are valid to a varying extent towards several educational goals. This system uses the inductive inference method to determine the relative scores. In the final step, the system produces the following for the learners:

AMS test 1 score
AMS test 2 score
Academic performance at the time of entry
Inferred academic performance
Actual academic performance in the subsequent year
Recommendations on further performance

The candidate can reject the recommendations and request a new partial or complete reassessment.

5. KNOWLEDGE INFERENCE

As the main aim of this problem is to infer knowledge from data, it is important to make a distinction between inductive inference and deductive inference. Deductive inference is used whenever enough information is at hand, inductive inference when some necessary information is missing. In real life and in this problem also, inductive inference is mostly used. In this case, the interest lies mainly in the processing of incomplete information [8]. Therefore, inductive inference has been considered. Inductive inference is the process of reaching a general conclusion from specific examples.

The general conclusion should apply to unseen examples. The inductive learning hypothesis is any hypothesis found to approximate the target function well over a sufficiently large set of training examples, which will also approximate the target function well over the other unobserved examples. Inductive bias is an explicit or implicit assumption about what kind of model is wanted.

TABLE 1 SAMPLE SPATIAL KNOWLEDGE BASE

No	Age	Sex	Caste	Religion	Nop	Class	College
1	20	Female	FC	Hindu	Urban	PG	KKCFA
2	31	Female	SC/ST	Christian	Urban	UG	KKCFA
3	28	Female	MBC	Hindu	Urban	PG	KKCFA
4	22	Female	MBC	Christian	Urban	PG	KKCFA

TABLE 1. SAMPLE SPATIAL KNOWLEDGE BASE CONTD.

No	F-qua	F-occ	M-qua	M-occ	Family	Ambition	Inference
1	UG	Business	UG	Home making	Nuclear	Low	High
2	UG	Teaching	Oth	Home making	Nuclear	Low	Low
3	UG	Professional	UG	Teaching	Nuclear	High	High
4	UG	Professional	Oth	Home making	Nuclear	Low	High

Table 1 shows the sample spatial knowledge base, which contains the predicted academic excellence and the candidates, whose improved performance in the second year of their studies along with the socio-demographic details of students.

6. INDUCTIVE INFERENCE ALGORITHM AND ANALYSIS

A nonincremental algorithm is developed to infer academic excellence of the respondents. This derives its classes from a fixed set of training instances. If necessary it revises the current concept with a new sample. The classes created are inductive, that is, given a small set of training instances, the specific classes created are designed to work for all future instances. The distribution of the unknowns must be the same as the test cases.

Algorithm 1:

Step 1: Create a root concept for the graph.

Step 2: If all examples are labeled positive (resp. negative) return the single concept graph root with label 'yes' (resp. Label 'no').

Step 3: If attributes is empty, return the single node graph root with label = most common value of target attribute in examples.

Step 4: Otherwise

Let A be the attribute from Attributes that best classifies Examples.

Make A the root of the decision graph.

For each possible value v of A

Let Examples (v) be the subset of Examples for which A= v

Add a new graph branch below root corresponding to the test A = v

If Examples (v) is empty, then add a new leaf with label = most common value of target attribute in examples, else add the sub graph.

{Examples (v), Target -attribute, Attributes- {A})

Step 5: We use the information-theoretic measure of entropy to determine which attribute to split the graph on.

Step 6: Entropy (S) = -p log p – n log n

Where S = set of training examples

p = proportion of positive examples in S

n = proportion of negative examples in S = (1-p)

Step 7: Entropy (S) = expected number of bits needed to encode classification of randomly drawn member of S under the optimal, shortest length code.

Step 8: From information theory, we know that the optimal length code assigns –log2p bits to a message with probability p.

Step 9: Entropy of S is p (-log2 p) + n (-log2 n).

Step 10: If the target attribute can take on c values (c > 2), we can calculate the entropy of the training set S as follows:

$$\text{Entropy (S)} = \sum_{i=1}^{c} -p_i \log p_i$$

Where p is the proportion of S belonging to class i.

Step 11: Gain (S, A) is the expected reduction in entropy due to a split of the examples on attribute A.

$$\text{Gain (S, A)} = \text{Entropy (S)} - \sum_{v \in Values(A)} ((|S_v| / |S|) * \text{Entropy } (S_v))$$

Step 12: Gain (S, A) is the number of bits saved when encoding the target value of an arbitrary member of S by knowing the value of attribute A.

Step 13. Apply the algorithm recursively for all values of c.

Step 14. Compare Gain with Statistical inference.

TABLE 2: SUB TABLE OF AMS

Candidate No.	*AM*	*Prior Academic Performance*	*AMS1 Score*	*Ambition*	*Inference*
C1	academic	low	high	weak	no
C2	academic	low	high	strong	no
C3	skill	low	high	weak	yes
C4	vocational	high	high	weak	yes
C5	vocational	very high	very high	weak	yes
C6	vocational	very high	very high	strong	no
C7	skill	very high	very high	strong	yes
C8	academic	high	high	weak	no
C9	academic	very high	very high	weak	yes
C10	vocational	high	very high	weak	yes
C11	academic	high	very high	strong	yes
C12	skill	high	high	strong	yes
C13	skill	low	very high	weak	yes

A statistical property, called information gain, is used to decide the best attribute. Gain measures how well a given attribute separates training samples into targeted classes. The one with the highest information (useful for classification) is selected. Entropy measures the amount of information in an attribute. The inference process is illustrated through the AMS sub table 2.

The following are the academic excellence trainer attributes and their values:

Achievement Motivation (AM) = {academic, skill, vocational, social}

Prior Academic Performance = {low, high, very high}

AMS 1 Score = {high, veryhigh}

Ambition = {weak, strong}.

Given a collection S of c outcomes

Entropy (S) = ∑ - p (I) log2 p (I)

Where p (I) is the proportion of S belonging to class I. ∑ is over c. S refers to the entire sample set.

Entropy (S) = – (9/13) log2 (9/13) – (4/13) log2 (4/13) = 0.8905.

Gain (S, AM) = Entropy (S) – (5/13) * Entropy (S academic) – (4/13) * Entropy (S skill) - (4/13) * Entropy (S vocational).

Entropy (S academic) = - (2/5) log2 (2/5) - (3/5) log2 (3/5) = 0.9651.

Entropy (S skill) = - (4/4) * log2 (4/4) = 0.

Entropy (S vocational) = - (3/4) * log 2 (3/4) – (1/4) log2 (1/4) = 0.8113.

Gain (S, AM) = 0.8905 – (5/13) * 0.9651 – (4/3) * 0 – (4/13) * 0.8113 = 0.2697.

Gain (S, Prior Academic Performance) = Entropy (S) – (4/13) * Entropy (S low) - (5/13) * Entropy (S high) - (4/13) * Entropy (S veryhigh)

Entropy (S low) = - (2/4) log 2 (2/4) - (2/4) log 2 (2/4) = 1.000

Entropy (S high) = - (4/5) * log 2 (4/5) – (1/5) log 2 (1/5) = 0.7219.

Entropy (S veryhigh) = - (3/4) log 2 (3/4) – (1/4) log 2 (1/4) = 0.8113.

Gain (S, Prior Academic Performance) = 0.8905 – (4/13) * 1.000 – (5/13) * 0.7219 - (4/13) * 0.8113 = 0.0556.

Gain (S low) = - (2/4) log2 (2/4) – (2/4) log2 (2/4) = 1.000.

Gain (S high) = - (4/5) * log2 (4/5) – (1/5) log2 (1/5) = 0.7219.

Gain (S veryhigh) = - (3/4) log2 (3/4) – (1/4) log2 (1/4) = 0.8113.

Gain (S, Prior Academic Performance) = 0.8905 – (4/13) * 1.000 – (5/13) * 0.7219-(4/13) * 0.8113 = 0.0556.

Gain (S, AMS 1 Score) = Entropy (S) – (6/13) * Entropy (S high) - (7/13) * Entropy (S veryhigh).

Entropy (S high) = - (3/6) log2 (3/6) – (3/6) log2 (3/6) = 1.000.

Entropy (S veryhigh) = - (6/7) log2 (6/7) – (1/7) log2 (1/7) = 0.5917.

Gain (S, AMS 1 Score) = 0.8905 – (6/13) * 1.000 – (7/13) * 0.5917) = 0.1104.

Gain (S, Ambition) = Entropy (S) – (8/13) * Entropy (S weak) - (5/13) * Entropy (S strong).

Entropy (S weak) = – (6/8) log2 (6/8) – (2/8) log2 (2/8) = 0.811

Entropy (S strong) = – (3/5) log2 (3/5) – (2/5) log2 (2/5) = 0.9710

Gain (S, Ambition) = 0.8905 – (8/13) * 0.811 – (5/13) * 0.9710 = 0.0179.

Gain (S, AMS) = 0.2697.

Gain (S, Prior Academic Performance) = 0.0556.Gain (S, AMS 1 Score) = 0.1104.

Gain (S, Ambition) = 0.0179.

Achievement motivation attribute has the highest gain; therefore it is used as the decision attribute in the root node. Since achievement motivation has three possible values, the root node has three branches (academic, skill, vocational). The next question is “what attribute should be tested at the academic branch node?”. Since achievement motivation is at the root, the trainer should consider the three attributes prior academic performance, total AM.

Sacademic = {C1, C2, C8, C9, C11} = 5 examples from table 1 with achievement motivation = academic.

Prior academic performance has the highest gain; therefore, it is used as the decision node. This process goes on until all data is classified perfectly or the trainer run out of attributes.

TABLE 3. INTER-CORRELATION MATRIX BETWEEN PERCEPTION OF DIMENSIONS OF AMS AND SELECTED SOCIO-ECONOMIC CHARACTERISTICS

Variable	Age	Apm1	Apm2	Nas	Skill	Social
Age	1.000					
Apm1	0.096	1.000				
Apm2	0.015	0.903 **	1.000			
Nas	0.072	0.432 **	0.328**	1.000		
Skill	0.088	0.343 **	0.232*	0.551 **	1.000	
Social	0.132	0.225 **	0.173	0.381 **	0.486 **	1.000
Voc	0.058	0.348 **	0.049	0.381 **	0.344 **	0.387 **
Tot 1	0.014	0.259 **	0.239*	0.764 **	0.798 **	0.780 **
Tot 2	0.122	0.010	0.164	0.434 **	0.421 **	0.411 **
Inf	**0.077**	**0.991 ****	**0.909****	**0.382 ****	**0.272 ****	**0.166**
Cla	0.207 *	0.522 **	0.499**	0.056	0.083	0.288 **
F Qu	0.047	0.053	0.136	0.065	0.000	0.080
M Qu	0.117	0.179	0.129	0.100	0.086	0.343 **

The following are the sample rules generated by the algorithms, which form a portion of the symbolic knowledge base:

Rule 1: If AMS is skill then the Inference is Yes.

Rule 2: If AMS is academic and AMS 1 Score is high then the Inference is No.

Rule 3: If AMS is vocational and ambition is Strong then the Inference is No.

Rule 4: If AMS is vocational and Ambition is Weak then the Inference is Yes.

Rule 5: If AMS is academic and AMS Score 1 is Very High then the Inference is Yes.

Table (2) shows the sample spatial knowledge base that includes socio-demographic details of respondents and AMS scores.

TABLE 3. INTER-CORRELATION MATRIX BETWEEN PERCEPTION OF DIMENSIONS OF AMS AND SELECTED SOCIO-ECONOMIC CHARACTERISTICS CONTD

Vari Able	Voc	Tot1	Tot2	Ai Inf	Cla	Fqu	Mqu
Age							
Apm 1							
Apm 2							
Nas							
Skill							
Social							
Voc	1.000						
Tot 1	0.642 **	1.000					
Tot 2	0.367 **	0.545 **	1.000				
Inf	**0.039**	**0.271 ****	**0.224 ***	**1.000**			
Cla	0.047	0.138	0.006	**0.545 ****	1.000		
F Qu	0.065	0.036	0.069	**0.059**	0.072	1.000	
M Qu	0.178	0.248 *	0.174	**0.162**	0.024	0.009	1.000

** 0.01 level significant   * 0.05 level significant

APM1 – Academic Percentage of Marks in the first semester
APM2 – Academic Percentage of Marks in the second semester
NAS – Need for Academic Success
SKILL – Need for Skill Achievement
SOCIAL – Need for Social Achievement
VOC – Need for Vocational Achievement
TOT1 – First Test Total Achievement Score
TOT2 – Second Test Total Achievement Score
AI INF – Inferred Score
CLA – Class
FQU – Father's Qualification
MQU – Mother's Qualification

From table 3 it is inferred that the relationship between the academic percentage of marks of the first semester of the respondents and the academic percentage of marks of the second semester is highly significant. This inference was made after a test on motivation had been performed. The relationship between the total AMS score and AMS inference is also highly significant. This reveals that the results of the inductive inference algorithm are highly significant. Another interesting result with regard to the need for academic success, the need for skill achievement, the need for vocational achievement and the need for social achievement are that they are all almost significant to each other.

7. CONCLUSION

In this paper, we have presented an intelligent system for prediction of academic excellence of learners. Statistical and Artificial Intelligence techniques have been used for prediction of futuristic excellence of learners. It is observed that there is a close agreement between the computed and the inferred scores. Although, the model developed deals with knowledge for the students of computer science, fine arts, social work and medical disciplines, it can also be used for many other related disciplines, and for any number of students.

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