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An Expert System Approach to Graduate School Admission Decisions and Academic Performance Prediction

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An operational two-stage expert system is built with rule induction. The first stage examines the admission decision process for applicants to an MBA program, while the second stage focuses on the prognosis for degree completion for those actually admitted. It is this performance prediction capability that is submitted as the major contribution of the system. While given the opportunity to make use of personal demographic variables that would be suggestive of discriminatory academic policies, the system's pattern recognition algorithm established an optimal rule structure based solely upon academic and professional backgrounds. This induced rule structure was found to be consistent with all cases in the training subset; the rules were then validated on an independent hold out sample. © 1998 Elsevier Science Ltd. All rights reserved

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1. INTRODUCTION AND PURPOSE

RECENT DEVELOPMENTS IN computer based information systems (CBIS) have made it possible to store actual knowledge, as well as raw data and information, in a form that enables each to be "on call" and exploitable by decision makers. Machine-learning techniques such as rule induction show great promise in assisting with this process of collection, preservation and distribution of working knowledge.

The purpose of this paper is to build an operational prototype of an expert system to address two related and sequential issues in the area of human capital development. The first is to examine the decision making process regarding the admission of applicants to an MBA program. An expert system is built with rule induction and historical case data. The resulting decision rule structure from this initial phase enables an institutional review of such issues as consistency of policy adherence and detection of the presence of discriminatory practices in the admission process. The second phase of the system examines the academic performance prognosis of graduate students admitted to the MBA program. This phase of the system is also built with rule induction and historical data on the attributes of the students, and seeks to predict individual student success in completion of the degree (Yes/No). From an administrative perspective, the primary contribution of this system is that the resulting rule structure enables identification of key discriminators which may serve as an initial warning for students academically "at-risk" in their pursuit of the masters degree. As an operational tool of an academic counselor, the objective nature of the system's projection provides the awareness and motivation for individuals at-risk to succeed academically in spite of their marginal prognosis. For each of these two phases, the induced rule structure also assists in the detection of the presence of possible discriminatory practices by the institution should demographic variables be found to be more influential predictors than variables reflecting academic preparedness.

2. LITERATURE REVIEW

In a methodological study, Finlay and King [13] examined three approaches to building an expert system using domain expertise; their application was the admission decision into an MBA program. They argue for an approach blending progressive prototyping and systems analysis. While the role of specific machine-learning techniques on issues such as student admission in higher education and subsequent performance in such programs has received only minimal attention in the literature, the application of other management science approaches in these areas has a rich history. Schroeder [26] called for an examination of the appropriateness of Markov analysis in student-flow models. Such a Markov model was used by Bessent and Bessent [1] to determine doctoral student admissions that could be accommodated without overloading current faculty. Moscarola [20] examined the decision to admit candidates for management education as a case of preference modeling with multiple criteria. Davey *et al.* [7] used protocol analysis to investigate the information acquisition process regarding the accept/reject decision for applicants to a Ph.D. program. The evaluation of student profiles for program admission has been investigated by stepwise multiple discriminant analysis [8], multiple regression analysis [28], and ridge regression [29].

A DSS for undergraduate admission policies at Kuwait University was built by Elimam [10]. Edwards and Bader [9] propose the use of an expert system in undergraduate admission decisions and emphasize its potential for improving consistency, since a university admission system and a performance prediction system are essentially classification schemes. The appropriateness of using expert system technologies for classification is discussed by Holroyd *et al.* [15], Pollitzer and Jenkins [22], and O'Keefe *et al.* [21]. Mingers [19] uses a rule induction algorithm to classify students' academic performance in a specific course based upon attributes they possessed when starting the course. His use of the performance model was to extend the use of an induction algorithm from deterministic data sets to stochastic data containing random variations as well as basic relationships between the variables. Hardgrave, Wilson, and Walstrom [14] compared four statistical regression techniques with artificial neural networks in predicting the success of MBA students based upon a quantitative profile of the student characteristics. While none of the techniques distinguished itself from the others, the neural network was found to perform at least as well as the traditional stochastic methods.

A comprehensive bibliography of the use of expert systems in business applications from 1975 through 1989 is compiled by Eom *et al.* [11]. A survey of the use of management science techniques in higher education models at the institutional level can be found in a paper by White [31]. He identifies decision support systems addressing financial planning, resource allocation, budgeting, and scheduling. White notes a trend of moving away from large-scale, generic planning models toward specific issues that can be addressed by special purpose techniques and adapted to a specific institution. The specific results of the analysis of this study may well be institution specific, but the approach may merit consideration by a broad base of institutions seeking to predict the academic performance of those admitted to programs of human capital development as well as to critique their own programs for symptoms of inconsistency or even academic bias.

3. MACHINE-LEARNING METHODOLOGIES

Spreadsheets and data base management systems have greatly facilitated the steps of data gathering, retrieval, and transformation into information. The subsequent processing of this information into useful intelligence was left to the human decision maker by the traditional computer based information system. Moreover, the computer explosion has generated a parallel explosion of data and analysis, yet the computer's role in interpreting and understanding this rich resource is only beginning to be tapped. The incorporation of such basic judgements into a CBIS has, thus far, eluded systems designed to assess and predict academic performance.

Unlike conventional programming languages, a rule based expert system is founded on the concept of non-procedural programming, where the problem domain is depicted as a set of rules rather than a sequence of processing steps. These rules, or heuristics, are sought out and executed by the system's inference engine as they are needed to make a decision, rather than in the sequential order in which they exist within the system. Once the factual data and heuristics involving admission and performance prediction are assimilated in the system's knowledge base, the system will ask the user for the inputs relevant to a new case. The user's responses will be matched with the relevant branch of the rule structure. This will enable the inference engine to simulate the collective expertise and judgement of the contributing experts and effectively accomplish a classification/decision.

Knowledge engineering refers to the process of transferring knowledge from its human form into a form that may be retained and applied by the CBIS. The use of one or more contributing domain experts to build the system's knowledge base requires the knowledge engineer to formally write down the domain expert's procedure(s) to accomplish the decision. The limitations to this ''direct articulation'' form of knowledge acquisition include a continuing dependence upon domain experts to provide information which they are often uncomfortable, if not unprepared, to provide. Schneider and Shiffrin [25] found that an expert's consciousness of his own decision process is compromised as his level of expertise increases, thus creating the perspective that the decision process is automatic and, in turn, creating difficulties for eliciting the expert's actual decision rules by direct articulation methods. Moreover, direct acquisition of the expert's knowledge has become a major bottleneck in the development of expert system applications, [2].

An alternative method of knowledge acquisition is ''machine learning'', which is a data driven approach to extracting expertise from prior decisions. Machine-learning systems use training examples to induce classification heuristics which map sets of input attributes into classification sets. These mappings can be accomplished with expert systems that employ rule induction or through artificial neural networks. Such learning-by-example systems that recognize patterns have been shown to be useful in a growing body of literature regarding business decision situations (stock market behavior: [3]; credit applicant assessment: [5,27]; S and P's 500 index forecasts: [32]; predicting thrift failures: [24]). While Hardgrave *et al.* [14] argue the merits of artificial neural networks relative to various multiple regression techniques, they did not compare their non-parametric approach to expert systems with rule induction. A direct comparison of these two pattern recognition techniques, using the same case data, offers fertile ground for future study. The mechanical nature of the neural net weights provides little operational insight into the underlying decision process. Since this process is a focus of this paper, the relative ease of interpretation and implementation of a resulting heuristic from rule induction supports its employment in this administrative application.

4. RULE INDUCTION

The development of decision rules directly from case examples presumes that future relationships will follow the patterns of past outcomes. The underlying assumption is that knowledge can be inferred from representative examples of prior behaviors, and the system will generate a model of the process that will map sets of attribute values onto possible decisions/outcomes. Thus, rule induction is the process of reasoning from the specific (examples) to the general (rules). A major strength of rule induction relative to direct articulation is that experts often find it easier to provide representative cases from prior decision situations than to actually reconstruct their decision making process. Often they can be more confident and hence more deterministic about the ''what'' than the ''how''.

Other inductive tools include multiple discriminant analysis (MDA), Logit, and Probit models, each of which has severe assumptions on the data which it can legitimately employ, (e.g. multivariate normality for MDA). Even more serious, the use of a mechanical mathematical function to represent the decision process of the domain expert(s) offers very little insight about the decision process itself [6, 30]. Messier and Hansen [17] compared the quality of the results of an induction algorithm with those of MDA and other tools. Using financial bankruptcy cases, they found that the induction model outperformed the competing models. Rule induction more closely represents the synthesis performed by the human brain; the engineering techniques used in training synthetic neural networks follow the learn-by-example approach of rule induction methods. Inductive classification will be applied to the examples of the training subset so as to generate the rule(s) that would be consistent with the cases presented.

Induction methods can be evaluated on: (1) their ability to replicate the true form of the expert's decision process, (i.e. "structure validity"); (2) their ability to infer the relative influence of the predictive attributes on the final decision, (i.e. "diagnostic validity"); and (3) their ability to predict decisions for cases outside the estimation/knowledge acquisition sample, (i.e. "predictive validity" on a holdout sample). Michalski and Chilausky [18] found that rule induction methods performed well in terms of their structural validity. This study seeks to examine, via rule induction, the identification and specific sequencing of the predictive attributes involved in the admission decision and the successful completion of an MBA program, as well as the projection of future performance for out-of-sample cases, (i.e. both the diagnostic and predictive validity issues).

The rule induction routine employed in this study is an optimization procedure based upon Quinlan's iterative dichotomizer, Version 3 (i.e. ID3 algorithm) and computerized by Hunt *et al.* [16]. This data-driven induction method examines a set of prior decisions and seeks to identify the relevant attributes and patterns among them which have led to the recorded findings; the induction algorithm generates the most parsimonious system of production rules which result in the known decisions. Thus, ID3 seeks to minimize the number of attributes in the final decision rule, and consequently, find the most efficient path to the conclusion [23]. Bundy *et al.* [4] compared the major inductive algorithms and found that ID3 was able to learn disjunctive concepts that are more general than those that can be learned by most other algorithms. Braun and Chandler [3] found that the ID3 algorithm performed better than other induction methods in the development of a production system for stock market behavior.

Quinlan's iterative dichotomizer algorithm eliminates redundancies by screening out those factors that are *not* necessary for the minimal decision tree. Thus it operates on the premise that the "ideal" decision rule is one with as few attributes/factors as possible that will successfully distinguish among the different choices in the ultimate decision. Clearly, such a rule would result in the smallest set of questions being asked of a user during a consultation with the final system. A consultation will start at the root of the tree and, by means of questions for the user, establish the value of the associated attribute, take the branch appropriate to that value, and continue in that manner until a final outcome is reached. Once the result is identified for the new case, the system can cite precedent cases that support a given conclusion.

5. THE FRAMEWORK

The admission of students into a graduate program and the assessment of the prognosis for successful degree completion of those admitted involves numerous cognitive skills such as knowledge, comprehensive analysis, synthesis, and evaluation. Such skills are directly supported when human expertise is successfully modeled and preserved in a form that permits ready dissemination to other experts and non-experts alike. The application of machine-learning approaches to situations involving student admission and performance prognosis allows for the integration of the qualitative and quantitative aspects of the outcome while introducing the beneficial dimensions of further objectivity and consistency.

Specifically, the system presented here will seek to assess and capture the influence given to:

(1) admission decision factors used by faculty and administrators, and
(2) attributes of admitted students in their pursuit of the MBA degree.

Thus, of particular interest in this study is the *identification* of the specific factors and their sequencing that constitutes the admission decision and an objective prognosis for those ultimately admitted.

This model proposes that both the admit/reject decision and the subsequent successful/unsuccessful completion outcome *could* be founded on some combination of the broad conceptual issues of academic preparedness, professional background, and personal demographics. Applicants to a university MBA program are asked to provide extensive materials on each of these areas. Data collected across applicants becomes the data base for university administrators and faculty admission committees to select the next incoming class of graduate students. Ideally, such a selection process should be founded on the applicant's qualifications and prognosis for success in the program. The academic and experiential background factors serve as surrogates for the motivational and academic commitment levels that will be projected into the pursuit of the MBA. The legal implications are unsettling, should the personal demographics be found to be highly influential on either the admission decision or the performance of those admitted.

The specific variables that are available to the admission decision makers for this model include the following.

Academic preparedness.

- Undergraduate major, institution, GPA (on a 4.0 scale), and years required to graduate.
- Additional advanced degree major (if any), institution, and GPA.
- GMAT scores for Quant, and Verbal, and Total.
- (The institution providing the data has an internal construct known as an "admission index" which is developed as:
  $\text{INDEX} = 200 \times \text{GPA} + \text{GMAT}_{\text{TOTAL}}$
  which they use as a composite indicator of academic preparedness for graduate work. Consequently, this index will be recognized instead of its two individual components.)

Prior work experience.

- "Professional" or "otherwise".
- Number of years of professional experience.

Personal demographics:

- age at application;
- gender;
- nationality;
- veteran status;
- number of years since last degree.

Admittedly, recommendation letters or applicant essays are not considered by this model. While the former may help an admission committee interpret a GPA anomaly or clarify academic commitment, and the latter may help reveal verbal and organizational skills, the open-ended nature of these inputs did not make them good candidates for use by the expert system. Their information content is assumed to be captured in the existing measures of academic preparedness. Variables hypothesized to be *directly* linked with both admission and successful completion include: GPA, the presence of other advanced degrees, GMAT scores, the presence of professional work experience, and the length of such experience. Those attributes projected to be *inversely* linked with admission and completion include: the number of years required for the undergraduate degree and the number of years since the last degree.

In the second phase of the system, where the prognosis for successful completion of the program is assessed for those admitted, two additional "academic preparedness" variables are tested for applicability. These additional variables are the following.

- Full-time/part-time academic intentions within MBA program, and
- number of courses waived upon admission to MBA program.

The "full-time/part-time" variable is projected to serve as a surrogate for future academic commitment. The "number-of-courses-waived" variable reflects the extent of a "running start" the individual has attained at the time of admission. Both are hypothesized as being directly linked with successful completion of the graduate degree.

Clearly some of the available variables are continuously valued (GPA), binary (gender), counting integers (years), and others are multi-categorical (major, etc.). Unlike traditional statistical classification techniques, one of the strengths of an expert system is its ability to work with such diverse forms of quantitative and qualitative data.

6. THE DATA BASE

The data for the initial admission phase consist of 255 applicants to an AACSB accredited MBA program at a midwestern US university. The anonymous cases were randomly selected from the 1985–1989 period so that those admitted would have completed their time window to finish the program by the date this study was begun and the prototype system made operational. The sample was randomly split into a training subset ($N = 170$) for the development of the expert system, and a holdout sample ($N = 85$) for out-of-sample validation of the resulting rule structure for admissions. The importance of expert system validation is discussed by Finlay *et al.* [12].

In the second phase, only those admitted were used in the design of the system for the prediction of degree completion. Students that were admitted, but who left the program without completing the degree requirements, *while in good academic standing* at the time of their departure, were excluded from the "phase two" sample. These cases were dominated by instances of the student being transferred by their employer; such program termination, being beyond the direct control or influence of the student, could only serve to confound the role of the proposed substantive influences on the outcome. This reduced the effective "phase two" sample to 172 which was subsequently randomly split into training and validation subsets of equal size. Thus, each phase had a holdout sample of comparable size.

The historic cases chosen for the development of the induced knowledge base are crucial to the viability of the decision rules. The training set should be as large and representative as possible; it can adversely affect the accuracy of the system should it fail to provide a comprehensive set of outcomes and the full spectrum of critical attributes. Such an occurrence could lead to the generation of ambiguous rules. Alternatively, if the training set contains too many attributes, it could cause the rule structure to be overly detailed, i.e. "bushy". Fortunately, the rule induction procedure, ID3, discussed in this study can address this potential complication through its optimization approach. Cases, identical in all recorded attributes yet with different outcomes, would be viewed as contradictory and flagged by the system. This would indicate that one or more key discriminating attributes has been omitted. Fortunately, this did not arise with this data set, indicating that the recorded attributes were sufficient to generate an unambiguous outcome for each case.

7. RESULTS

7.1. Phase one: system development of the program admission decision

When given the latitude to establish an efficient pattern among any of the 18 potential variables discussed above, the optimization algorithm was able to build a very simple rule structure for the training subset that involved the exclusive use of academic background variables. The resulting decision tree for "phase one" is shown in Fig. 1.

Such a tree depicts the final outcomes as leaves at the far right, ("Yes" = admit; "No" = reject). The optimization algorithm positions the most discriminating variable at the root of the tree (far left). The sequencing of variables from root to leaf of the tree, involves a progression of attributes relevant only in the context of values established on "parent" branches. Thus, a case consultation with the finished system need not be concerned with all possible variables, but rather only with those along a particular path laid out by values for attributes encountered from left to right. For all numerically valued attributes, the rule induction algorithm determines the thresholds/breakpoints to achieve maximum discriminating capability between/among the outcomes. As shown in Fig. 1, the initial discriminator variable was found to be the internal admission index; if it is in excess of 1002.5, the candidate is granted admission unless *both* the GMAT components are so low as to identify the candidate as a "non-predictor". This qualification on the nationally normed test is an added protection against an inflated GPA in the admission index. If the index is below 991, the admission decision is unfavorable to the applicant. When the index

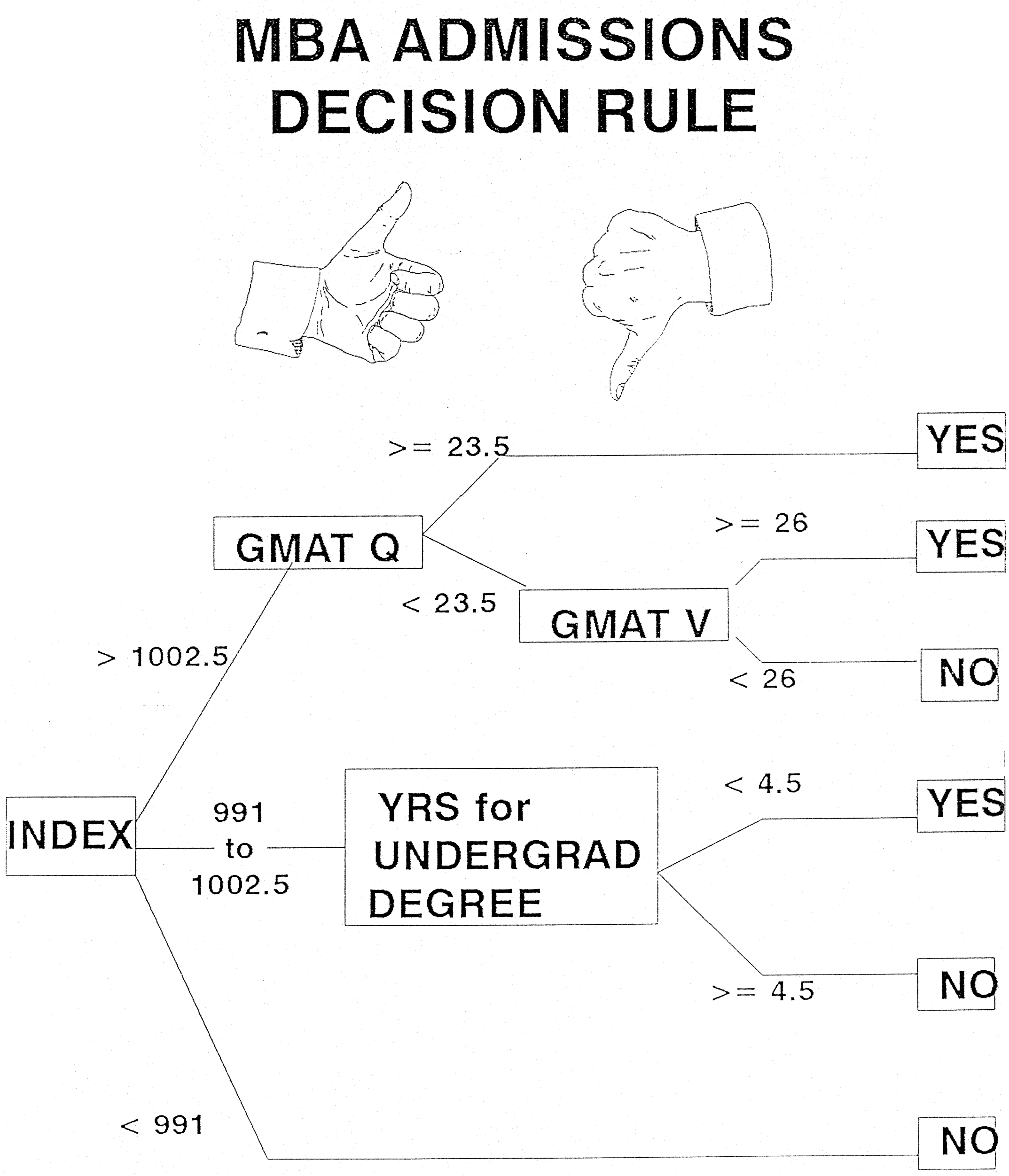

Fig. 1. MBA admissions decision rule

is marginal (991 to 1002.5), the number of years required to obtain the baccalaureate degree is used to make the final decision. Should the candidate have been able to obtain the undergraduate degree in less than 4.5 years, the decision is to admit. If the applicant required 4.5 years or more for this degree, the application is denied. This numeric variable is capturing whether the applicant was a full or part time undergraduate student. This full or part time status is potentially serving as a surrogate for the level of prior academic commitment and its subsequent role as a predictor of future commitment.

During the time period of these cases, the business school's officially stated admission policy involved a minimum index value of 1000 with a minimum total GMAT of 430 and without formal regard to work experience or undergraduate major etc. As a publicly supported institution, this policy affords the opportunity to pursue a graduate business degree to those with above average undergraduate academic performance. The system's independently generated results are in fundamental agreement with the operational threshold of the admission index complemented by some form of protection against grade inflation in the undergraduate GPA (for this the expert system used both GMAT components, while the existing policy used total GMAT). The system permitted a "gray area" for the index, not acknowledged in the operating policy, where a surrogate for academic commitment could turn a marginal index into a favorable decision. The admission committee of the business school's graduate program was quite satisfied with the corroboration found and quite relieved with the "non-role" found for the demographic attributes. The consistency found between the spirit of the policy and the revealed patterns of the operating practice served to reaffirm the objectivity of the committee. The system is currently running in parallel with the committee as an independent check once the committee's decisions are tentatively made. Clearly, its greatest value has been with cases at the margin.

Perhaps as interesting as what parameters *are* consistent with the admission decision, is the *absence* of a role for the personal demographic variables. As hoped, variables that would trigger concerns about discrimination on the basis of sex, age, nationality etc. failed to play any role in the resulting rule structure.

The rule is built by the ID3 algorithm to be the minimal rule possible that is consistent with all the cases in the training subset. When this rule was presented with the out-of-sample cases from the hold out subset, it correctly predicted the accept/reject decision for 82 of 85 cases for a 96.47 percent success rate. All three incorrectly classified cases were for individuals with an admission index in the "gray area" that took more than 4.5 years to complete the undergraduate degree. The system recommended "No" for each individual while the committee chose to admit them. Interestingly, one undergraduate degree was by design a five year program (pharmacy), and the other two applicants changed majors during their upperclass years and needed additional semesters to complete the degree. Each student had been a regular full-time student throughout the undergraduate experience; thus the part-time/full-time proxy of the system failed to capture these specific situations as the training set did not contain similar scenarios. These "misses" point out the need to complement the system with human discretion rather than to view the system as a substitute for it.

As a discrimination test, a "devil's advocate" rule was induced from the same data but the personal demographic variables were forced to guide the rule. In order to accommodate the 170 cases in the training set, the rule involving gender, age, nationality, and veteran status required 105 conditional lines, versus six lines in the result reported above. Moreover, each line of this coerced rule structure could accommodate roughly only 1.6 cases on average; clearly such a demographic model can only induce a non-robust rule.

7.2. Phase two: system development of the prognosis for degree completion

In the second phase, the focus shifts to just those applicants that are admitted and their prognosis for successful completion of the MBA degree. When given the latitude to establish an efficient pattern among any of the 20 potential variables discussed above, the optimization algorithm was able to build another simple rule structure for the training subset that also involved the exclusive use of academic background and professional experience variables. As shown in the decision tree of Fig. 2, the initial discriminator variable is again the internal admission index.

If this index is in excess of 1353, the prognosis for the student's successful completion of the MBA is positive. For those with the weaker admission index, the presence/absence of their professional experience in the workplace is the next discriminator. Applicants without any professional work experience are simply not predicted to succeed. This role for professional experience is interpreted as capturing the influence of a better identity with the topics and concepts of the academic program rather than as a surrogate for "maturity" since the expert system had access to the chronological age of the individual and did

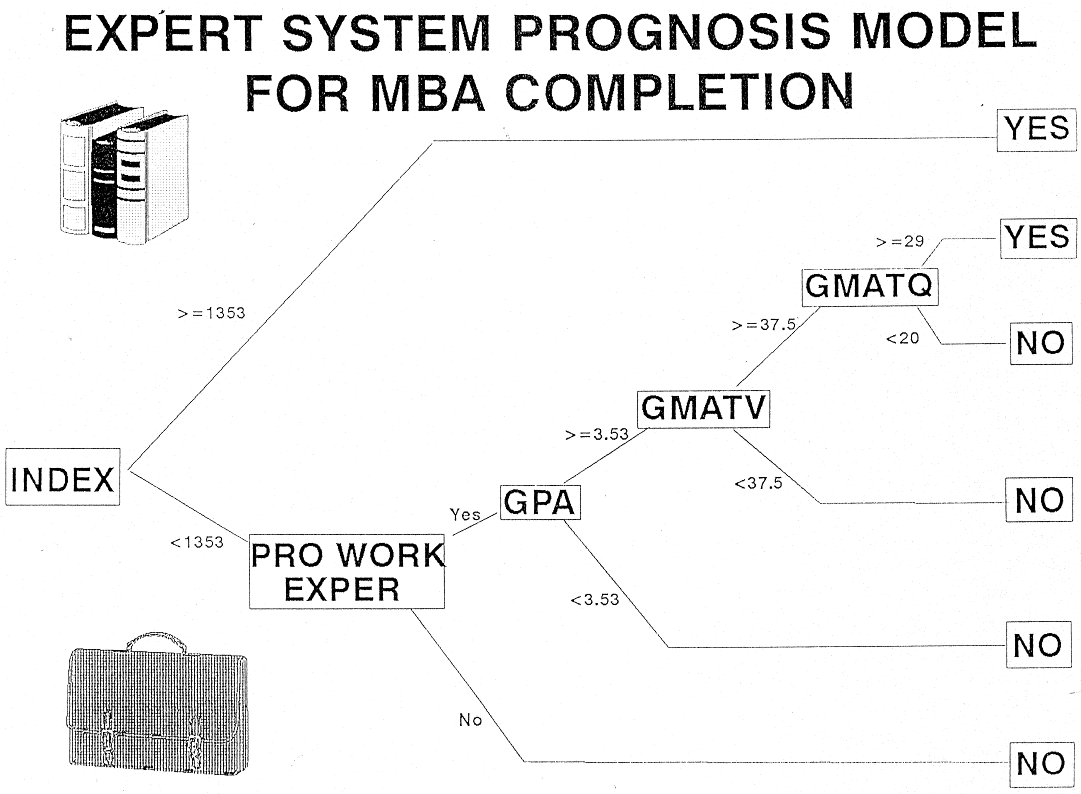

Fig. 2. Expert system prognosis model for MBA completion

not incorporate it into the rule structure. For those with professional work experience to draw upon, their undergraduate grade point average is found to be a critical determinant of graduate school success. Those with less than a "B + " undergraduate GPA (3.53 on a 4.0 scale), are not projected to be successful in the MBA program. Those following the branch of the tree reflecting the lower admission index *and* professional work experience *and* an undergraduate GPA of "B + " or better still need the balance of strength in both GMAT verbal and quantitative scores in order to be projected as future MBA graduates. Either GMAT strength alone is not sufficient. It is interesting to note the formal confirmation of an implicit trade off between professional work experience and prior academic performance in this prediction, as the presence of previous exposure to the professional workplace can still secure the favorable prognosis in the presence of a lesser, yet balanced, academic record.

As was the case in the prior admission phase, perhaps as interesting as what parameters *are* consistent with the successful completion outcome, is the *absence* of a role for the personal demographic variables. As hoped, variables that would trigger concerns about discrimination on the basis of sex, age, nationality etc. failed to play any role in the resulting rule structure for the completion of the graduate degree.

This rule is also built by the ID3 algorithm to be the minimal rule possible that is consistent with *all* the cases in the training subset. When this rule was presented with the out-of-sample cases from the hold out subset, it correctly predicted the completion (Y/N) outcome for 71 of 86 cases for an 82.6 percent success rate. While 3 of the 15 erroneous predictions were for individuals with a high (> = 1353) admission index who did not complete the degree, most of the errors (12 of 15) were for "non-predictor" students who *were able* to successfully finish the MBA program. Thus, this particular system may be quite conservative in its prognosis phase, a reality which academic counselors must keep in mind. The prognosis phase of this model is not optimistic for those admitted with an index <1353 and no professional work experience. Yet to revise the operating policy this dramatically would deny the academic opportunity to many potential students. Rather, the value of this stage is as a counseling/advising tool with regard to a student's awareness of being at-risk. A run-time version of the system is available for use during the advising process.

As was done above with the admission decision of "phase one", an added test was performed on the discrimination issue. A "devil's advocate" rule was induced from the same data but forced the personal demographic variables to guide the rule. In order to accommodate the 86 cases in the training set, the rule involving gender, age, nationality, and veteran status required nearly five times the number of branches in the decision tree as the result reported in Fig. 2. Moreover, each line of this coerced rule structure could accommodate only a very few cases on average; clearly this is again indicative of a non-robust rule. Thus, in each of the two phases of this sequence, variables reflecting academic preparedness and prior work experience are found to be effective predictors of both graduate admission and success within the academic program.

7.3. Phase three: system implementation

This prototype has been operational at the developing institution since mid-year 1996 for applicants to the Fall 1996, January 1997 and Fall 1997 entering classes. The admission component has been run as an independent process parallel to that of the faculty admission committee who retains the final authority to accept or reject each individual applicant. The committee has found that the system adds formal and objective corroboration to the decision on straightforward cases. For "difficult" cases, the system's recommendations have allowed for a "gray area" (middle branch of Fig. 1) that is not acknowledged in the committee's operating policy. In the absence of the system's contribution in this area, most of these applicants would have been rejected by the committee. This identification of marginal cases has enabled the committee to further examine the motivation and academic commitment of such individuals, resulting in additional favorable admission decisions than would otherwise have been the case.

Even more valuable than the system's role in the admission process, has been its role as an advising tool for those actually admitted. When an admitted, yet marginal, student can witness the run-time version of the system work with his own case, and can explore hypothetical permutations of the factors contributing to the prognosis, the student gains an appreciation of the objectiveness of the degree completion forecast. The system's prognosis provides the "tangible evidence" that has been needed to get the attention of those admitted with marginal credentials. Without the system, the academic advisor had very little systematic evidence and, hence, ability to provide newly admitted students with the sense of urgency that their particular marginal situation warranted. In the brief implementation of the system, more than eighty percent of these "at-risk" students have successfully completed the first year of the program and remain in good academic standing. Unfortunately, no comparable pre-system "survival rates" exist for this group of students because the marginal/at-risk students were never formally identified nor tracked over time as a group. While it is certainly possible that other factors (e.g. simply gaining maturity) may have also motivated them to succeed in spite of their prior marginal standing, both the faculty admission committee and school administrators are confident that the system's prognosis component has *consistently* created this awareness for "at-risk" students without relying solely upon chance or maturity to provide the motivational stimulus to succeed academically.

8. CONCLUSIONS AND DIRECTIONS FOR FURTHER RESEARCH

An expert system for the admission and completion prognosis for applicants to an MBA program has been built with rule induction. While given the opportunity to make use of numerous personal demographic variables that would be suggestive of discriminatory academic policies, the system's algorithm found a simple optimal rule structure based solely upon academic and professional background to be consistent with all cases in the training subset. The rule structure was then validated on an independent hold out sample. Finally, implementation issues of the system's use by the faculty admission committee and as a counseling tool for students were discussed.

This paper has sought to demonstrate the appropriateness of expert system technology to situations of human capital development. While the resulting rule structure reported here should not be generalized beyond the institution providing the data, the use of rule induction and institution specific case data in the construction of a parallel system would enable an institution to critique its practices and policies for symptoms of inconsistency and academic bias. Once built, such a system would prove useful to academic admission committees in providing an objective, unbiased, and consistent operational tool for both screening applicants and identifying those admitted students whose prognosis for successful completion of the degree may be compromised. Thus, it could serve as an "early warning device" for at-risk students in pursuit of the MBA degree. Such an awareness on the front–end of their graduate program could provide the motivation and focus needed to improve their prognosis for academic success.

From a methodological perspective, this two-stage expert system, remains to be contrasted with another form of machine learning (the neural network) for a comparative assessment of pattern recognition capabilities in the same application.

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