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Educational Data Mining: Collection and Analysis of Score Matrices for Outcomes-Based Assessment

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ABSTRACT OF THE DISSERTATION

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In this dissertation we provide an overview of the nascent state of Educational Data Mining (EDM). EDM is poised to leverage an enormous amount of research from the data mining community and apply that research to educational problems in learning, cognition, and assessment. Similar problems have been researched in the educational community for over a century, but the enormous computing power and algorithmic maturity brought to bear by data mining has proven to be more successful at many of these educational statistics problems. The timing of these developments could not be better, given the current rising importance of assessment throughout education, particularly in the United States. After determining the structural commonalities between EDM projects, I detail my own EDM assessment project, covering tools for collecting, strategies for storing and archiving, and new techniques for analyzing matrices of student scores. I also detail issues of real-world deployment and adoption of this assessment system. After examining the state of EDM, both in the abstract and with my own implementation and deployment, I predict near-term trends in EDM and assessment, and conclude with thoughts on the implications of this work, both for pedagogy and for the data mining community as a whole.

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Chapter 1

Introduction: The Importance of Assessment

As we advance into the twenty-first century, educators face new and growing assessment requirements. The pressure for expanded assessment is coming from many directions at once. The highest levels of government are holding public schools to greater accountability (107th Congress of the USA, 2001). Accreditation organizations like ABET (ABET, 2005) are instituting policies that require understanding, acceptance, and compliance by all instructors with new "continuous improvement" processes (Accreditation Policy and Procedure Manual, 2002). In addition to (or possibly instead of) the fulfillment of the relatively straightforward bean-counting requirements, accredited programs must now demonstrate that they have established a "culture of assessment." That is, it is still important that appropriate material is being taught, but it is vital that an accredited program be continuously monitoring the effectiveness of its instruction and demonstrate a willingness and capability to react when problems are detected. Accreditation organizations like ABET are trying to pull education away from "folk pedagogy" stemming from a lack of meaningful quantitative information about the educational process, akin to the shift from Aristotelean to Newtonian mechanics.

Unlike the ISO 9000 (ISO 9000, 2006) standards that have altered manufacturing and business processes over the last ten years, educational outputs are difficult to measure. For over a century, psychologists, cognitive scientists, and statisticians have studied ways of putting a quantitative value on a person's knowledge, but this has never been done reliably without formal assessment and laboriously developed instruments. This is one of the contributing factors behind the current push for standardized testing: without standardized tests developed by professionals and issued to thousands or millions of students simultaneously, how can educators and administrators meet the assessment requirements being so suddenly thrust upon them? If education were merely a manufacturing process, we could measure, weigh, stress test, or run diagnostics on the product at the end of the process and determine if our goals were being met. Without standardized tests, what is the analogue of quality control in the educational domain?

At the same time, administrators and parents look to formal assessment processes as a way of holding instructors accountable for their instruction. Most would argue that if educators take these new requirements as an opportunity to embrace new technologies and formalize educational standards and practices, these developments have the potential to deeply alter the American educational system. Supporters of accreditation argue that if this opportunity is seized, it will have a deeply positive influence on the quality of education at all levels, just as the focus on continuous improvement has boosted performance at ISO 9000 companies (O'Connor, 2005). But even if this potential for improvement is realized, the new focus on assessment requirements represents a significant shift in educational practice, as the tradition has long been that instructors are allowed great flexibility, both in instructional methods and material presented. It is no surprise then, that formal assessment requirements are often looked upon as a burden by many college-level instructors (LeBlanc, 2002): regardless of potential for improvement, these new practices are altering longstanding academic tradition.

In order to balance between the opportunities presented by the drive for assessment and the independence of individual teachers, it is critical to develop assessment methods that are as unintrusive as possible while still providing detailed quantitative assessment. In a society adopting new digital technology at an astonishing rate, it is unsurprising that we look to computing for possible solutions for collecting, storing, and analyzing all the data that can be gathered on student learning.

Recent technological advances have significantly increased our ability to do just that: collect, store, and analyze data. In the late 90s, the field of *data mining* split off from the general artificial intelligence community. Unlike so many buzzwords of that era, data mining followed through on much of its promise. Data mining provides solutions for such problems as anomaly discovery, similarity matching on increasingly complex datatypes, and the extraction of patterns and unseen structures, all while operating on vast volumes of data. In many cases, data mining is solving similar problems to those that have been dealt with for many years: dimensionality reduction and discovery of underlying generative factors are problems that have history dating back to the nineteenth century. In this respect, data mining is well described by the epithet, “Statistics on steroids” (King, 2005). The field has seen impressive growth since its inception, both in terms of volume of top-quality research and the types of problems (Keogh et al., 2002; Kolter and Maloof, 2004) that are becoming tractable by knowledgeable practitioners. Development of data mining libraries like Weka (Witten and Frank, 2005) allow those who are not active researchers in the area to readily make use of this research, and as the field develops it is expected to mature into standardized interfaces much as databases did in the 1970s and 80s. Data mining has already radically altered the way that financial companies operate, playing a key role in detecting credit card fraud or abuse of online services such as PayPal. Mortgage companies increasingly rely on data mining techniques to predict who is a worthy credit risk. Electronic trading houses are making immense profits on the stock and currency markets by applying data mining techniques to identify profit opportunities in real time, effectively creating money from nothing. Given the ever-growing importance of assessment, and our general reliance on technological solutions, it is clear that at least some of those setting out to solve our assessment problems will turn to data mining.

1.1 Educational Data Mining

Poised to meet the growing need for pervasive assessment is the nascent field of Educational Data Mining (EDM). EDM focuses on the collection, archiving, and analysis of data related to student learning and assessment. EDM is a very new and very small academic field. The first publications to mention educational data mining were published in the last two years, and there are likely fewer than thirty people in the world that identify themselves as being a part of it.

As with all new fields, EDM has grown out of existing disciplines and is spreading to overlap with new ones. Many of the researchers who are shaping EDM hail from the Intelligent Tutoring System (ITS) community, where ready access to large quantities of educational data make EDM a logical direction to advance in. EDM research shares some commonalities with the Artificial Intelligence in Education (AIED) community. The analysis performed in EDM research is often related to techniques in psychometrics and educational statistics. EDM is poised to revolutionize, or at the very least enhance and expand, the statistical methods used in education by bringing to bear the results of decades of research in data mining and machine learning. Finally, given the computational backgrounds of most EDM researchers, it is not uncommon to find data pertaining to students learning computer science. As such, it is not surprising to find some overlap between the EDM and Computer Science Education (CSE) fields. This overlap may become stronger in the next few years as CSE naturally progresses toward more quantitative research and EDM broadens away from its original ITS focus.

EDM also borrows much from the machine learning and data mining communities. In truth, the term “Educational Data Mining” is a slight misnomer in that “data mining” is generally associated with enormous datasets and much of the research is focused on developing fast and efficient algorithms for finding meaning in the data. Few EDM projects have data in such quantities. Although there are certainly datasets with thousands or even tens of thousands of records, it is just as common to work with datasets of tens or hundreds of records. It is likely that EDM will more commonly face problems of too little data, rather than the general data mining problem of too much data. General machine learning research, especially unsupervised or semi-supervised learning, has a more direct influence on EDM. It is, however, important to note that EDM does share some usability features with general data mining. Most importantly, well-developed and generalizable EDM techniques should have few parameters and require little or no user intervention.

The structure of most EDM projects can be broken down into three parts: collection, archiving, and analysis. Collection refers to the tools and tutoring systems used to record the relevant information, be it student scores, answers to online quizzes, or events from an Intelligent Tutoring System (ITS). Archiving is the process of storing and browsing the collected data. For score data, this is a relatively minor issue, but for the vast quantities of data generated by some ITSs this can be a significant task. Analysis brings to bear the tools of machine learning and data mining on the collected data in an attempt to gain deeper understanding of student learning, discover the relationships among questions, and possibly develop deeper quantitative understanding of cognitive processes in general. Depending on the EDM project, these three tasks will shift in relative complexity and importance, but all three must be addressed in any EDM project.

1.2 Program Assessment at UC Riverside

Here at the University of California Riverside the Computer Science and Engineering department has undertaken a significant EDM project for program assessment. The project has two main goals related to EDM. First we wish to quantify the amount each student has learned each of the topics covered in our curriculum. These topics are referred to as the *objectives* of the course, and are commonly things of the form, "Students will have knowledge of linked-lists." The objectives for each course are agreed upon by faculty members that teach that course. The second goal of this project is to quantify the level to which our curriculum as a whole is meeting our *program outcomes*. The program outcomes are a set of general abilities we hope our majors have by the time they complete the program. Program outcomes are very general traits like, "An ability to apply knowledge of math and science."

Direct measurement of either the course objectives or program outcomes is impossible. In the absence of professionally developed and validated assessment material like the SAT (SAT Reasoning Test, 2006) or an IQ test (Binet, 1905) there is no absolute scale for measuring knowledge. When working with a specific domain, like computer science (CS), it is necessary to find an assessment tool for that domain. CS is particularly troublesome in this respect, due to the speed with which the field advances. The Computer Science GRE can provide some numeric assessment, but not every student attempts that test, nor do the GRE administrators communicate detailed scores to undergraduate CS departments for assessment purposes.

Rather than utilize standardized testing methods, we have chosen to focus on the assessment that already happens during each academic year. In each course in our curriculum, students are assessed with a variety of methods ranging from homework assignments and programming projects to in-class tests and quizzes. Each homework, quiz, and test is made up of questions that are, of course, individually written and graded by domain experts. Usually the scores from each question are aggregated into an overall score, and the scores from each instrument (assignment, test, or quiz) in a course are further aggregated into an overall course grade. Our assessment method focuses on collecting and analyzing this score data at its finest granularity, recording scores for each student on each question.

The collection of scores for each of the m students on the n questions assigned in a course can be viewed as an $m \times n$ matrix, called a *score matrix*. Each course offering produces a score matrix S, which may have missing entries due to students dropping the course, not completing an assignment, or missing a test or quiz. To simplify analysis, the columns of S are usually scaled to $0..1$. Our analysis challenge is then to develop a method of relating the data in S to the course objectives and program outcomes.

To relate the scores in S to the course objectives, we assume a linear relationship between questions (columns in S) and the t distinct course objectives. This implies an $n \times t$ matrix R, where the i, jth entry of R is the relevance (in the range $0..1$) of question i to objective j. This matrix R is known as the *relevance matrix* for the course.

Given S and R, it is possible to perform several types of course assessment. If we average each of the columns of S we get a $1 \times n$ vector $\overline{S}$, the average score on each question. The average scores for each course objective are given as $\overline{S}R$. If we sum or average the rows of R, we get a measure of the *coverage* of each objective in the course: how many questions were asked that related to that objective? Both the average score per objective and the coverage can be useful in analyzing the effectiveness of a course offering.

A more personalized assessment technique possible with the information in S and R is to determine for each student which topic they have the lowest average score in. This is easily done by finding the minimum entry in each student's row of the $m \times t$ matrix SR. If S and R are kept up-to-date while the course progresses, an assessment system built on this method can easily offer customized study suggestions to every student at any time.

Performing program assessment is largely similar to the techniques used for course assessment. We assume that the course objectives for each course have a linear relationship with our program outcomes. Therefore each course has a *course matrix* C, where the i, jth element of C represents the relation of course objective i to program outcome j. By averaging $\overline{S}R$ for each course and multiplying by C, we are given an estimate of how well our curricula is preparing our students for the outcomes we have set. As with any continuous improvement process, regular monitoring of these values allows us to detect and correct for gaps and shifts in our curriculum, using an entirely data-driven approach.

However, the system as described above is hardly acceptable to instructors. Rather than recording only aggregate scores for each student on each assignment, we are asking instructors to provide us the full score matrix S. Although every question must be graded individually whether or not we request S, the recording of scores is a tedious process at best. Our courses commonly issue between 20 and 200 (n) questions to class sizes ranging from around 10 to over 500 (m). Clearly, manual entry of the data in S is unacceptable. In order for this project to be successful, we must provide methods to facilitate the collection of S while imposing as few absolute restrictions on the faculty as possible.

Although S represents by far the largest input to the system, for many courses R is large enough to be a significant task. Courses have on the order of 5 to 10 course objectives (t), meaning that *R* can have on the order of 100 to 1000 entries. Automating the generation of *R* to the extent possible provides a much more palatable system for faculty members already burdened with countless teaching and research tasks that have more obvious importance.

The final matrix components in our assessment system are the course matrices *C*. Our department has 11 program outcomes, and each course has around 5 to 10 course objectives. Neither the course objectives nor the program outcomes are expected to change regularly, meaning that course matrices are likely to remain relatively stable from year to year. As such, there appears to be little benefit to any attempt at automating the creation of *C* for each course.

Conceptually, the program assessment techniques presented here are simple, requiring no more than rudimentary linear algebra. This could be made more complex using non-linear techniques, but since there is no intrinsic dimensionality or well-known scale for program assessment there is no need for additional complexity. What complexity there is in our EDM project stems entirely from the collection of *S* and attempts to generate *R*. It is these issues that are addressed in this research.

1.3 Dissertation Overview

This dissertation is an effort to serve as an introduction to Educational Data Mining, as well as to advance the current state of the art with respect to collection and analysis of score matrices. The program assessment project detailed above serves as a connective framework for independent pieces of EDM research organized around this theme.

The general organization of this dissertation is as follows. Chapter 2 provides relevant background for EDM, focusing both on topics of education as well as the machine learning techniques that are being used in the EDM community. Chapter 3 surveys the current research and common themes in EDM as of this writing. I will then discuss in detail the work that I have done in this area, detailing the three major phases of a large EDM project. In collection (Chapter 4), this will necessitate a discussion of Agar, my Computer-Aided Assessment system and a cornerstone of my Master's Thesis (Winters, 2004), as well as my Homebrew Optical Mark Recognition (HOMR) system. Agar represents a significant foray into demand-driven software evolution and interface design. HOMR is built on techniques from computer vision and supervised learning for classification, allowing optical mark recognition (OMR) forms to be developed via a word processor, printed on any printer, and scanned by any scanner. Chapter 5 discusses the archiving methods utilized in our project. EDM analysis forms the bulk of the dissertation. in Chapters 6 through 10, I present four contributions to EDM analysis of score matrices and the influence of topic information on that analysis. Finally, I discuss some potential avenues for future work (Chapter 11), both for my own research and for EDM as a whole, and discuss the conclusions that can be drawn from current EDM research with regard to both education and data mining (Chapter 12).

Chapter 2

History & Background

In order to more easily discuss the current state of educational data mining and my own research, it is useful to first look at the history that has brought educational research, as well as data mining and machine learning, to where they are today. As these two fields are immense and such an overview could easily grow into a work of hundreds of pages, this chapter will focus only on those theories and algorithms that are actively cited by recent EDM publications. In this way it is possible to highlight the most important contributions and provide a starting point for readers interested in finding a deeper historical perspective.

2.1 Education & Educational Statistics

The educational community draws on research from a number of different areas, ranging from statistics to cognitive science. Within the EDM community, the most germane fields are those of psychometrics and cognitive psychology.

2.1.1 Psychometrics

At its root, the quantitative branch of education that is most applicable to EDM is *psychometrics*. Psychometrics dates back at least as far as nineteenth century researchers such as Sir Francis Galton, who were the first to focus on measuring latent quantities of knowledge and ability in the human mind (Pearson, 1914). These are difficult values to quantify, as there is no direct way to measure them and no implicit units or dimensionality to such a measurement. Over the past century and more, the field of psychometrics has developed ways of compensating for this, developing implicit scales and methods of comparison that require no absolute measurement.

Within the broad area of psychometrics there are several major theories that have shaped the field over the last century and have influenced current EDM research. The two most influential on EDM are Classical Test Theory (CTT) and Item Response Theory (IRT).

Classical Test Theory

Classical Test Theory is the earlier of the two branches of psychometrics applicable to EDM. CTT is a catch-all term for a collection of statistical techniques developed over the past century. The base foundation of CTT comes from the work of Charles Spearman, whose development of common factor analysis (CFA) in 1904 became the primary area of research in psychometrics for half a century (Spearman, 1904).

Working around the turn of the twentieth century, Spearman was a psychologist and mathematician seeking to support his theories on intelligence. He noted that in many cases student scores on individual test questions were highly correlated, and proposed one of the earliest theories of intelligence, known as g-theory, wherein raw intellect is viewed as a one-dimensional trait g. This theory is still in use in some areas of psychology and education today. Indeed, the most common intelligence test in America today is a univariate estimate of *g*: the IQ test (Binet, 1905) provides scores as a single value encoding the ratio of mental age to physical age.

However, Spearman was not completely satisfied with the single-dimensional *g*-theory. Some data simply did not match the proposed model. Turning to his extensive math background and the then-new techniques for calculating correlations between measured values, Spearman developed common factor analysis, which is still used today to understand large quantities of data by discovering the latent factors giving rise to that data. CFA assumes that a linear model of f factors can describe the underlying behavior of the system, in this case the ability of students to answer items correctly:

$$M_{i,j} = \mu_j + \sum_{k=1}^{f} W_{i,k} H_{k,j} + \varepsilon \tag{2.1}$$

where $M_{i,j}$ is the score for student i on item j, μ_j is a hidden variable related to the difficulty of the item, W is a matrix giving the ability of each student with respect to each factor, H is a matrix relating each factor to each item, and ε is the noise in score measurement.

CFA has remained popular since its inception, but has had its detractors since the beginning. One of the most commonly noted problems with CFA is that the resulting factors are a set of vectors spanning some (possibly proper) vector subspace of the input matrix. The ability for CFA to match the data remains unchanged for any rotation of those vectors within that subspace, and there is no mathematical indication of which rotation best separates the factors into human-understandable results. Additionally, as pointed out by psychologist Raymond Cattell in 1966, there is no built-in method for CFA to determine how many factors to extract from the input matrix. Cattell proposed a visual method, known as the scree test (Cattell, 1966) for identifying the “correct” number of factors to extract.

Whether or not the scree test is utilized to determine the proper number of factors, the criticism of CFA remains. Within current psychometrics there are still only heuristic methods for determining the number of factors; some heuristics are numeric and some are visual.

Algorithmically, CFA uses standard principal-component analysis (PCA) on the correlation matrix of the data. Both CFA and PCA are the standard methods for performing this sort of factoring within the psychometrics community. The primary difference between CFA and PCA being post-processing rotation of the resulting vectors in CFA.

CFA was notable in that it was the first quantitative theory for psychometrics that included the concept of *test error*, the idea that a student's score on a test is not an absolute measurement of knowledge but rather a random draw from their knowledge state. This concept has since spawned a host of statistical estimation methods in psychometrics. It is these CFA and these related methods that are collectively known as classical test theory. For EDM purposes, the important concepts are *reliability, internal consistency,* and validity. Reliability is a measure of how certain the scores produced by an instrument are. A common method for discussing reliability is test-retest reliability: if a student is given a test and her score is recorded, and then all knowledge of the test itself is wiped out (questions are not remembered, nothing is learned by the student on the test), how likely is the same student to get the same score when immediately retaking the test?

Reliability cannot be measured exactly, but a number of approximating techniques work in practice, including issuing alternate forms of the test with slight question variations, or the more common *split-half correlation*. In split-half correlation, only one form of the instrument is given to the entire population. The questions are randomly partitioned into two sets, and the correlation between scores on each half is calculated.

Internal consistency measures the extent to which the questions on a given instrument are measuring the same trait. Internal consistency is highly related to reliability. Split-half correlation, which is primarily viewed as a reliability statistic, is a reduced form of Cronbach's Alpha statistic is the common measure of internal consistency (Cronbach, 1951). Cronbach's Alpha is a mathematical technique to calculate the average split-half correlation across all possible random splits. Having a high internal consistency indicates that everything on an instrument is testing the same concepts, and that those questions have relatively low error rates in measurement.

Validity is a more difficult concept, attempting to provide an estimate of how much scores on the instrument actually measure what they are intended to measure. This often relies on outside comparisons and validation, and is generally harder to quantify.

Among the recognized branches of psychometrics the newest, and in some ways more powerful, branch of psychometrics is Item Response Theory (IRT), the framework behind many computer-adaptive tests such as the new GRE (Baker, 2001; Wim J. Van der Linden, 2000). IRT requires larger student populations than are generally found in a single course, and thus is not directly applicable in our assessment project. However, some of the concepts from IRT are useful for developing a simple method for modeling item difficulty and estimating missing score data, as discussed in Chapter 7. IRT parameterizes a distribution of the probability that a student with a given level of ability, θ, will answer a given item correctly. Usually these *characteristic curves* are represented with a two-parameter logistic function:

$$P(\theta) = 1/(1+e^{\alpha(\theta-\beta)}) \tag{2.2}$$

Here β governs the difficulty of the item and α governs the discrimination of that item. Discrimination is related to how likely it is that a student with ability less than β can answer correctly and how likely a student with ability greater than β may answer incorrectly. These parameters are generally calculated for a set of questions using techniques similar to expectation-maximization (Dempster et al., 1977). This technique requires input sizes of hundreds or thousands of students to function correctly.

IRT is powerful in that it provides a quantitative scale for question difficulty and student ability. However, much like the rotational-symmetry of results from CFA, IRT has an issue of scale. There is no absolute scale onto which abilities or difficulties are projected, and thus, without some initial “known” values for student ability or question difficulty, any scalar multiple or additive constant applied to the difficulties and abilities is equally valid under IRT. This is less problematic than the rotational symmetries of CFA factors, but does add complexity to the application of IRT. In practice this is handled by introducing certain definitions and assumptions, like the known numeric value of a perfect score on the GRE.

Since IRT quantifies difficulty β and ability θ on an absolute scale, it applies regardless of question difficulty. Asking advanced questions to novice students will result in low average scores, but will ideally still trace out a rising portion of the characteristic curve. Asking the same question of advanced students will plot out a higher portion of the curve, but according to IRT the extracted parameters of the curve will be the same in both cases. IRT literature insists this is true, although experimental evidence to support this claim is at best difficult to find.

2.1.2 Theories of Cognition

For as long as there have been studies in psychology, there have been theories about how the mind knows things. The formation and evaluation of these studies is the field of cognitive science. Cognitive scientists study issues of attention, perception, memory, language, and, to a lesser extent, learning.

Psychology itself was wholly the realm of philosophers until the late nineteenth century. The study of the mind had been a philosophical discourse taken up by Plato, Aristotle, and many other philosophers up through René Descartes and John Locke. Psychology as an experimental science is thought to have first appeared in the 1870s, established by Wilhelm Wundt at the University of Leipzig (Rieber and Robinson, 2001). Cognitive science was intimately linked to experimental psychology as a whole until the middle of the twentieth century. In the 1950s, cognitive psychology emerged in a rush as a further specialization. Some of the earliest papers cited as part of the cognitive psychology revolution are also results that are often discussed in academic culture (Miller, 1956).

The aspects of cognitive psychology that are most applicable for EDM are those that overlap with learning and education. These are primarily theories of how the mind organizes and retrieves information. Many of these theories have grown hand-in-hand with research in so-called "strong" artificial intelligence, which attempts to replicate human intelligence in software. Some are even defined in terms of Lisp subroutines and data structures. These are collectively known as *cognitive architectures*. The current EDM interaction with theories of cognition is focused on *symbolic* systems and theories. These ideas correspond most closely with the common approach to AI in the 1970s and 1980s, when it was believed that with a sufficient rule-set and set of symbols it would be possible to create a human-like intelligence based purely on the logical manipulation of discrete symbols. Most modern research focuses on probabilistic reasoning, that allows for a Bayesian "probability of truth" approach,[1] or connectionism, which argues that human-level intelligence cannot be coded directly but must stem from the emergent behavior of many smaller interconnected systems.

The cognitive theory most cited by EDM researchers is ACT$*$, developed at Carnegie Mellon University by John Anderson (Anderson, 1983). In ACT$*$, knowledge is repre-

[1] The canonical example being: after hearing the statement "Tweety is a bird," it is safe to assume with high probability that Tweety can fly, but there must remain a chance that Tweety cannot, for Tweety may in fact be a penguin.

sented in different forms: procedural for skills, declarative for facts and trivia, and a concept similar to registers in computer processors for iconic memory, representing those bits of information currently being held most closely in short-term memory. The ACT$*$ framework was developed in the Lisp programming language to validate the ACT$*$ theory of skill acquisition detailed in (Anderson, 1983) and summarized in (Anderson, 1982). ACT$*$ is an attempt to explain the theoretical differences between declarative factual knowledge (fact lookup) and procedural skill knowledge (skills and abilities).

ACT$*$ primarily functions as a framework for representing the knowledge and its structure, leaving to other cognitive theories the issue of learning. The current incarnation of ACT$*$, ACT-R, has been applied to matters as varied as studies of human-computer interaction (Anderson et al., 1997) and subitizing (Peterson and Simon, 2000), the ability for humans to rapidly identify small quantities without resorting to counting.

The information on learning in the cognitive science literature, especially on the cognitive architectures like ACT$*$, provides a wealth of knowledge that is unknown by most instructors, and even many of those in the CSE and EDM communities. Of particular interest to the CS Education community are the first two sentences of (Anderson, 1982):

> It requires at least 100 hours of learning and practice to acquire any significant cognitive skill to a reasonable degree of proficiency. For instance, after 100 hours a student learning to program a computer has achieved only a very modest facility in the skill.

Even without the quantitative applicability, these sorts of results on learning are critical in the educational process, but remain sadly unknown in the broader educational community.

Soar is another common cognitive architecture (Laird et al., 1987). Soar (once SOAR) is similar to the ACT family of architectures in that it has different methods for representing different types of knowledge. Soar omits the short-term memory modeled by ACT-R but claims to be superior in that the Soar project is the only major cognitive theory that does not need to assume that humans are capable of learning, but instead shows that learning is an emergent property of the architecture. Soar solves problems symbolically, like ACT, but learns new rules using slightly different methods. In many ways the two projects are comparable, although ACT might be described as a cognitive theory that is also a Lisp program, while Soar is an Standard Meta-Language (SML) program that also models cognition. The distinctions are obviously quite subtle, and are grounded in the background training of the developers and the users.

The “Power Law of Learning” or “Power Law of Practice” provides a quantitative relationship governing cognitive tasks:

$$t = X\alpha^n \tag{2.3}$$

In its most common form, this law states that the reaction time on a particular task falls off exponentially with the number of trials taken, meaning that practice improves performance. After many investigations, this has been found to be near universal across test subjects and tasks. Further research into the matter has suggested that it is in fact a result of the (actual) cognitive architectures responsible for human learning. There is evidence to suggest that the error rate on tasks such as applying a skill, recognizing when to apply a skill, or (in a restricted form) retrieval of a particular fact exhibit this same relationship. Practice improves accuracy, and a simple mathematical model can be constructed to quantify this result. This is related to the common phrase, “steep learning curve.” Given the strong quantitative nature of this result, it is clear why this is an enticing approach for EDM researchers.

2.1.3 Q-Matrix

Q-Matrix theory is based on work done in the 1980s and 1990s, primarily by Menucha Birenbaum of Tel Aviv University and Curtis Tatsuoka of George Washington University (Birenbaum et al., 1993). Q-Matrix is another method of capturing the underlying factors and abilities that give rise to a matrix of student scores. In the most simple case, Q-Matrix is applied to a binary $m \times n$ score matrix.

Q-Matrix operates on this matrix along with the assumed number of underlying abilities or factors, t. Each question is assumed to have a binary relationship with each of the t factors. Each student is similarly assumed to have a binary ability in those factors. Thus Q-Matrix is decomposing the input matrix into a binary $m \times t$ matrix of student abilities in each of those factors, as well as a binary $t \times n$ matrix of question relevance. A student is assumed to answer a question correctly if and only if the factors relevant to that question are a subset of their own abilities.

Q-Matrix was originally formulated as a method for identifying a student's "knowledge state" in a restricted domain based on the scores from tests in that domain. Most of the initial research by Birenbaum and Tatsuoka focused on mathematics education. However recent work by Barnes has expanded Q-Matrix into new areas in fault-tolerant teaching, tutoring systems, and EDM (Barnes, 2003).

Most or all Q-Matrix solvers utilize gradient descent on the reconstruction error of the matrix in order to find the optimal model to fit the data. Given an initial random configuration, the algorithm finds the single best entry to toggle in the student matrix or the question matrix in order to best reproduce the input matrix. As a discrete optimization problem with a search space growing as $O(2^{t*(m+n)})$, this is a computationally intensive solution. A linear programming formulation may reduce the running time and increase the solution quality, but it does not appear anyone has developed such a solution.

2.2 Machine Learning and Data Mining Techniques

Working from the above background in education and cognitive science, EDM focuses on the application of modern AI methods to student data. The following is a brief overview of the methods that EDM has used to date.

2.2.1 Clustering

Clustering focuses on organizing objects into groups that are similar in some way. The nature of that similarity depends on the clustering algorithm that is used, which in turn reflects the presumed underlying model. Clustering is an unsupervised learning application: no training data is required to calibrate the algorithms to your problem. Raw, unlabeled data is fed into the clustering algorithm and clusters are reported.

Clustering is intrinsically a complex topic: there is no absolute measure of correctness. If a collection of people are given a scatterplot and asked to cluster the data points, there is no certainty of agreement. Given a set of points with known labels, we can survey the accuracy of a collection of clustering algorithms on that dataset, but the best algorithm on one dataset may be the worst on another. There is not a single "clustering problem," but rather a unique clustering problem for every dataset, or at least every data source.

Further, as shown by Kleinberg in (Kleinberg, 2002), it is impossible to develop a clustering algorithm that satisfies certain basic properties desirable in clustering. Kleinberg proves that it is impossible to achieve *scale-invariance*, *richness*, and *consistency* in the same clustering algorithm. Here scale-invariance is simply a lack of implicit scale: data points measured in inches should yield the same clusters as those same data points measured in meters. Richness is the requirement that all possible partitions of the data are possible outputs for the clustering algorithm. Consistency is the requirement that moving points in the same cluster closer together while moving clusters further apart should provide the same output when re-clustered. These restrictions map out the trade-offs necessary in all clustering algorithms.

k-means

The *k*-means algorithm (MacQueen, 1967) is the simplest common clustering algorithm, performing reasonably well on a variety of problem types. In *k*-means, it is assumed that there are *k cluster centers*, points which are not necessarily part of the input that define the canonical example of a point in each of the *k* clusters. If the cluster centers were known, clustering is simple: each point in the input data is assigned to the nearest center under some metric. This metric is generally Euclidean distance, although for high-dimensional data some other metric may be used.

In order to determine the location of the cluster centers from the data, *k*-means simply iterates to stability: randomly pick *k* points from the input as cluster centers. Then assign each point in the input to the nearest cluster, and calculate new cluster centers by finding the mean of each cluster. This process continues until no points change assignment, or until the centers are moving only a negligible amount each round. This is not necessarily a globally optimal set of cluster centers, so random restarts are commonly used.

The *k*-means algorithm has a number of shortcomings. The most commonly cited among them is the issue of determining *k*, for which there must usually be some prior knowledge of the data. By specifying *k*, this algorithm drops the *richness* condition: partitions with any number of clusters other than *k* are not possible. Other problems include dimensional scaling: the clusters produced if one dimension is unfairly scaled relative to the other dimensions will not generally be the same as an unscaled clustering. For problems where there is no pre-determined scale for each dimension, this amounts to an extra parameter for each dimension, reducing the general applicability and out-of-the-box usefulness of the algorithm.

Spectral Clustering

Spectral clustering (Fischer and Poland, 2005) is often implemented using linear algebra techniques, but can be explained as a relatively simple graph-partitioning problem. Given input data $X_1, X_2, \ldots X_n$, form the complete, weighted, and fully-connected graph where the edge between points i and j is given weight equal to the *similarity* of those points. A spectral clustering into k clusters is done by finding the minimum weight cuts in the graph that disconnect it into k cliques. Again, as k is known, the *richness* condition is not satisfied.

In practice this is often done by generating the $n \times n$ similarity matrix S, where $S_{i,j}$ is the similarity of X_i to X_j under some similarity measure, often Euclidean distance. The k eigenvectors with largest associated eigenvalues are extracted from this matrix, and another clustering technique, often k-means is applied to the resulting $k \times n$ matrix.

Hierarchical Clustering

To overcome the need for a parameter representing the number of clusters and allow for the *richness* condition, some algorithms produce *hierarchical clusters*. In such a scheme, the output from the clustering algorithm is not an assignment of data points to clusters, but rather a *dendrogram* representing the relative similarity of every input to every other input. This encodes every number of clusters, ranging from each item individually clustered to all items clustered together. By searching down the dendrogram to the level where the desired number of clusters is the same as the number of subtrees in the graph, it is easy to discover these clusters given the dendrogram. A sample dendrogram representing the similarity of the clustering algorithms presented in this section is shown in Figure 2.1.

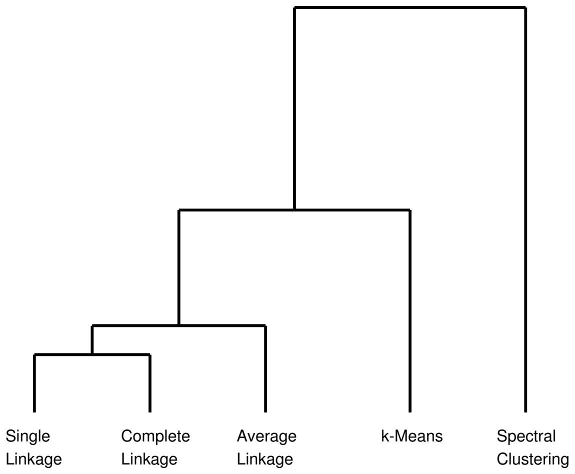


Figure 2.1: Dendrogram depicting the similarities of clustering algorithms

Hierarchical clustering algorithms are generally *agglomerative*, which is to say they start with all items assigned to their own cluster, and then nearby clusters are merged according to some distance metric. Three common techniques in hierarchical or agglomerative clustering are single-linkage, average-linkage, and complete-linkage.

In single-linkage clustering (Sibson, 1973), all items are initially assigned to their own clusters. At each step, the two clusters with the smallest minimum distance between two different-cluster items are identified and linked. That is, single-linkage finds the two points that are not already in the same cluster that have the smallest distance between them, and merges the clusters for those two points. When building a dendrogram for single-linkage clustering, the dissimilarity is simply the distance between these two points, which causes nearby (strongly-clustered) points to show high similarity, and distant (weakly-clustered) points to show low similarity.

Complete-linkage clustering (Defays, 1977) takes the opposite approach to single-linkage. Complete-linkage clustering merges the two clusters that have the smallest maximum point-wise distance. That is, every pair of points in the two clusters must be close together in order to be linked. This creates more tightly-grouped clusters than single-linkage, which often creates clusters shaped like long chains of points.

Average-linkage (Sokal and Michener, 1958) uses the Euclidean mean of the clustered points and finds the smallest distance between cluster centers.

The clustering property that is not held by these algorithms depends on the interpretation of the dendrogram that is used to determine the clusters. If merging stops when k clusters remain, the algorithms again fail in *richness*. If clustering stops when no clusters are within some constant distance, these algorithms fail in *scale invariance.* If that distance threshold is taken as a function of the maximum distance between two points in the input, then *consistency* can be violated.

2.2.2 Dimensionality Reduction

Another class of algorithms that have found use within current EDM research are numeric algorithms for dimensionality reduction. These can be viewed in a number of ways, from applicability to lossy compression, to explaining the variance in input data, to finding the base factors generating the data. The algorithms presented here assume that the input matrix X is based on a linear combination of those factors: $X = UH$.

Singular Value Decomposition

Singular value decomposition (Nash, 1990) is the method that best approximates the input data in the reduced dimensionality, under the standard assumptions about least-squared error. The resulting factors are an orthogonal basis that spans a subspace of the input vector space. The factors are identified in order of importance by finding the direction of highest variance of the input data until the desired number of factors has been extracted. The elements of U and H theoretically range $-\infty..\infty$.

SVD is generally considered to be the best tool to use for dimensionality reduction when nothing is known about the underlying generative model of the data.

Independent Component Analysis

Independent Component Analysis (Hyvärinen, 1999a) is similar to SVD in that it identifies a set of vectors that span a subspace of the input vector space. However, ICA is not restricted to identifying orthogonal vectors. ICA is particularly suited to situations where the data is a linear combination of non-orthogonal inputs.

This non-orthogonality has some important implication in the educational domain. If the underlying factors are interpreted as "topics", then an ICA factoring of X into U and H means U is the student ability in each topic, and H is question relevance to each topic. By not requiring topics to be orthogonal, topics can be discovered that have some overlap. For example, we wouldn't assume that ability with linked-lists is completely orthogonal to ability with binary search trees. Both are recursive discrete structures, and they may share some features in implementation. SVD would attempt to identify factors with no overlap in this case, while conceptually ICA would better capture the relationship between topics.

Non-Negative Matrix Factorization

Another approach to dimensionality reduction is Non-Negative Matrix Factorization (Lee and Seung, 2001). Rather than restricting the geometric properties of the resulting decomposition, NNMF restricts the numeric properties. In NNMF, the entries of U and H are restricted to being non-negative. This has the effect of ensuring that each factor can only contribute positively to the final results. This is particularly intuitive in the educational domain, where questions do not have negative relevance to topic, and students do not have negative ability in particular areas. Like Q-Matrix, NNMF is solved via gradient decent with random restarts. However, as it is a continuous optimization problem, the optimum direction to update *every* entry in U and H can be computed at once, requiring far fewer updates to reach a minima, and generally fewer restarts to reach a good fit.

2.2.3 Association Rules and Apriori

An area of data mining that has found great application in the business world is discovery of association rules. Also known as *Market Basket Analysis*, association rule discovery is best understood through the ubiquitous supermarket example.

Imagine that every register receipt from a supermarket is stored in a central database. The information stored in that database lists of all items purchased together (hence "market basket"). Given a large database of these transaction logs, the question becomes, "Which items are sold together?" Knowledge of the non-obvious item pairings that are most commonly seen appearing together in a transaction allows store owners to reorganize items on the shelves to maximize the impulse buying behavior of their shoppers. The canonical example is beer and diapers: in a hypothetical transaction database it is found that beer and diapers have a tendency to be purchased together. It then makes marketing sense to capitalize on this by placing a beer display near the diapers in an attempt to increase impulse buying of beer for those shoppers in the diaper aisle.

The Apriori algorithm (Agrawal et al., 1993) is the standard method for discovering association rules from transaction databases. Apriori provides rules of the items that are most commonly seen together, as well as a measure of the *lift* of items, the increase in likelihood that item Y will be seen when the items $X_1 \dots X_n$ have been seen, when compared to the overall odds of seeing Y in the database.

Apriori has some relation to Q-Matrix in that both are discovering the most common binary relationships in the data. However, Q-Matrix has an explicit generative model, while

Apriori is simply looking at the data and noting which features most commonly go together, as well as which features “imply” which other features. Apriori is only identifying common patterns, not performing discrete optimization of the reconstruction error. As such, although they have some similarity, Apriori is often significantly faster than Q-Matrix, and may be suitable for use on some similar datasets.

Chapter 3

Educational Data Mining, Spring 2006

As of early 2006, Educational Data Mining is still such a young field that investigating and describing its current state can be done by focusing on fewer than twenty papers published in two workshops. Research that could be classified as EDM is also suitable in areas like the International Journal of AI in Education (IJAIED) and the biennial Conference on AI in Education (AIED). Most EDM research could also find some audience in the areas it imperfectly overlaps with. In machine learning EDM is research can be viewed as a specific and challenging application area. In education, EDM can function as a replacement for less accurate but more established psychometric techniques. Currently, much EDM research can also find an audience in the Intelligent Tutoring System (ITS) community, as a majority of EDM researchers are focused on ITS data.

This chapter summarizes the state of EDM as of Spring 2006, focusing on the types of research, general themes, and the leaders of the community.

3.1 ICITS04

The first of these formative workshops was held at the Seventh International Conference on Intelligent Tutoring Systems in Maceió, Brazil. The workshop, entitled "Analyzing Student-Tutor Interaction Logs to Improve Educational Outcomes", was organized by Beck of Carnegie Mellon University, and focused exclusively on the application of data mining techniques to log data from ITSs.

3.1.1 EDM in 2004

At this workshop, Mostow presented an overview of EDM, although it is not yet called such in his paper (Mostow, 2004). The paper details numerous ways in which additional data-logging capabilities for ITSs can lead to improved knowledge of the system. Mostow points out that such instrumentation and the type of collected data depends greatly on the desired usage of the additional data.

> Faculty may need simple summaries of student usage and progress; administrators need evidence of ITS effectiveness; technical support staff need problem alerts; content authors need usability indicators; developers need accurate bug reports; researchers need detailed examples and informative analyses; and the ITS needs parameters it can use, rules it can interpret, or knowledge it can be modified to exploit. ... Such informational goals are typically not clear at the outset, instead emerging from and in turn guiding successively refined instrumentation and analyses.

Mostow goes on to enumerate a number of factors that make ITS data-minable, and presents statistical values to be calculated or hypotheses to be investigated from canonical

ITS data. This enumeration presents a rough vision of many of the papers presented the following year at the second EDM workshop.

3.1.2 Collection

Researchers from the HCI Institute at Carnegie Mellon and the Collide Research Group of the University of Duisburg-Essen (Duisburg, Germany) presented an intriguing line of research at the ICITS workshop (McLaren et al., 2004). Most ITSs are developed in what is jokingly referred to as the “traditional” way, i.e., by putting together AI researchers and programmers with domain experts for the ITS topic. The authors presented the idea of taking logs from an environment in which students can experiment with the topic, and from those logs building a skeletal ITS. The hope here is that in doing so they can predict many of the errors that novices will make which domain experts are incapable of predicting, reduce the time to creation, and provide additional insight for the experts when the system is refined into a full-fledged ITS. This approach is referred to as “Bootstrapping Novice Data” or BND.

A paper by Heiner, Beck, and Mostow points out the advantages to instrumentation of ITSs to record data even with no anticipation of later analysis (Heiner et al., 2004). The authors present multiple examples of data becoming useful only after it has been collected with no anticipated use. The paper also discusses the difficulties inherent in collecting and archiving the volume of data that can be recorded by a well-instrumented ITS, such as Project LISTEN (Project LISTEN, 2006), the ITS project that much of the current EDM community is involved with. The authors also address the general issues of data collection and analysis that appear in most EDM projects. The paper goes on to discuss general difficulties in working with large amounts of data, such as querying, processing, and presenting the data in understandable ways.

3.1.3 Analysis

An EDM analysis paper by Koedinger and Mathan focuses on a variant of the Power Law of Practice (Koedinger and Mathan, 2004):

$$E = X\alpha^n \tag{3.1}$$

where E gives the error rate, X describes initial performance, n is integer valued and represents the number of opportunities to practice a skill that the student has had, and α gives the learning rate for that skill. This formula comes from research done by Anderson, Conrad and Corbett, showing that learning and mastery of atomic skills (skills that cannot be further subdivided) is governed by this sort of power-law relationship (Anderson et al., 1989). This assumes that α is constant for all students attempting the given learning task.

Koedinger and Mathan explore the possibility that α may take on a number of discrete values representing qualitatively different modes of learning, focusing specifically on the idea of the "intelligent novice" as a student with no prior experience but a general aptitude for related topics. They present some initial findings, but do not go into great detail or expand on the ideas presented. There appears to be quite a bit of work in this vein that could be expanded on, and the authors' CVs do not indicate that this work has been undertaken. This might be considered a fertile field of future work for people entering EDM.

One final paper of note from the ICITS04 workshop came from researchers at Worcester Polytechnic Institute (Freyberger et al., 2004). In this paper, Freyberger et al. present a use for the Apriori association rule algorithm (Agrawal et al., 1993) to efficiently find *transfer rules* that can be viewed as a generative model for student responses in ITS data. These transfer rules govern the interaction between skills. For instance, given the skills: "Calculate the area of a circle given its radius" and "Calculate the radius of a circle given its area," it is likely that practicing one of these may affect a student's skill in the other. Determining which of the atomic skills modelled by an ITS have such a skill transfer can be a computationally expensive task. The researchers provide a method that finds an optimal set of transfer rules, on their single dataset, with a factor of sixty speedup over a brute force approach on that dataset.

3.1.4 ICITS Workshop Summary

Taking the papers presented at this workshop as a whole, a number of common themes and connections to other areas emerge. Although the term "Educational Data Mining" doesn't appear anywhere in the proceedings, it is clear that there is a focus on issues of data mining that transcend the ITS forum in which the workshop was held. Most of the papers focused primarily on ITSs as a data source, but in many cases the algorithms being presented were equally applicable to educational data acquired in another setting, such as a classroom test or quiz. Authors like Freyberger, Koedinger, and Mathan apply modern machine learning techniques to ITS data to make claims about educational issues of cognition and pedagogy.

Another clear theme in the ICITS04 papers is that of the multiple phases of EDM projects. Both the Mostow and Heiner papers discuss issues of data gathering (and to a lesser extent storage) for EDM tasks. McLaren's bootstrapping technique (McLaren et al., 2004) can be viewed as both gathering and analysis, by presenting a tool used to gather the data that will be analyzed and synthesized into a new ITS. The majority of the research presented is EDM analysis. Somewhere in the discussion that took place during the meeting of these researchers it must have been noted that the research being discussed had a stronger flavor of applied machine learning and data mining than much of the research at ICITS, which has some machine learning but often focuses primarily on educational and development issues surrounding ITSs. Within a few months of this workshop, a call for papers for a second workshop was issued, now for the first time bearing the heading of "Educational Data Mining."

3.2 AAAI05

The workshop held in Pittsburgh as part of the American Association for Artificial Intelligence (AAAI) conference in 2005 was also headed by Joe Beck, and attended by many of the same people. Being a part of an AI conference rather than ICITS, much of the research presented had a stronger flavor of machine learning than the work presented the previous year. The separation from ICITS also gave the workshop the chance to attract people working on related projects that might not have a strong educational-technology background, or might be focusing their efforts on data coming from non-ITS sources. According to Beck, this was unanticipated: for many of the participants in the ICITS workshop, ITS data was the material most suitable for analysis. ITS questions are already tagged with known topics and are generally of high quality, the ITS is capable of providing skill estimates for students, and the question text is available if needed. EDM on ITSs seemed so ideal that the idea of people doing EDM on non-ITS data was "startling." Yet, for the workshop, which attracted ten accepted papers, there were data sources as disparate as standardized tests (Hunt and Madhyastha, 2005), online quizzes (Barnes, 2005), and unmodified classroom settings (Winters et al., 2005).

The papers presented at the workshop again present research at each level of EDM design and development. None of the papers directly address data collection, but it is referenced in (Mostow et al., 2005), (Barnes, 2005) and (Winters et al., 2005). Two papers presented here refer to issues of common data formats and collaboration, focusing on both collection and archiving. The majority of the papers, unsurprisingly, focus on analysis.

3.2.1 EDM in 2005

In a discussion of archiving, Mostow and a host of collaborators present an argument for the importance of timestamps on ITS event data (Mostow et al., 2005). Within the surrounding discussion of EDM is the following insightful summary of EDM research:

> Educational data mining is an iterative cycle of hypothesis formation, testing, and refinement that alternates between two complementary types of activities. One type of activity involves aggregate quantitative analysis of many tutorial events. For example, knowledge tracing analyzes growth curves by aggregating over successive opportunities to apply a skill ...
>
> In contrast, qualitative analysis focuses in depth on understanding individual tutorial events. The research question it addresses is descriptive: "What happened when ...?" Such case analysis can serve any of several purposes.

3.2.2 Storage

Aside from that summary, the research presented in (Mostow et al., 2005) focuses on a browsing engine for tutorial events. If events are logged to an SQL database with certain basic requirements on the log table (start time, end time, student, computer), the browser is ITS independent. Other log fields are handled dynamically by the system. Written in Java for portability, it allows fast SQL queries on the events in an attempt to help researchers understand the information being produced by the ITS. It focuses strongly on the temporal aspect of the data, providing varying granularity by building the virtual hierarchy of events implied by the collection of start time/end time pairs on tutorial events being generated by each ITS session. The tool was primarily built to work with Project LISTEN's Reading Tutorial (Project LISTEN, 2006), which in 2004 was listed as containing 54,000 sessions, 162,000 story readings, 1,634,000 sentences, 3,555,000 utterances, and 10,575,000 words. Providing an interface to allow researchers to form hypotheses, examine average behaviors, and investigate logged events is valuable regardless of data size, but critical when dealing with such a volume of data.

3.2.3 Analysis

As expected, the majority of the papers presented in the AAAI workshop show a significant machine learning background, with algorithms ranging from Expectation-Maximization (Jonsson et al., 2005) and gradient ascent algorithms (Barnes, 2005) to dimensionality reduction (Winters et al., 2005) and A$*$ Search (Cen et al., 2005).

The most advanced AI leveraged for an EDM task in this workshop was presented in (Jonsson et al., 2005). This paper is an investigation into learning the parameters for Bayesian networks used to estimate student knowledge states in an ITS. It functions on logs of ITS systems, inferring transition parameters for effectiveness of hints, initial skill estimates, and learning rates. One feature the authors said was particularly important to include was hidden nodes to encode skill mastery. As student skill mastery is truly a latent trait, the addition of hidden nodes does make the model more intuitive than in other Bayesian approaches to ITS modelling e.g. (Mayo and Mitrovic, 2001). The added complexity of the resulting model is difficult to work with, especially with the goal of no hand-coding of the various parameters. In order to learn the network parameters, the authors use the Expectation-Maximization (EM) algorithm (Dempster et al., 1977) to match the model to the input data. However, in order to validate that the correct parameters are being learned, the input data had to be synthesized, and was synthesized *according to this model.* There is no strong evidence that such a model accurately captures the cognitive processes of students interacting with an ITS. Given that the synthetic input data precisely matches the model, it is unsurprising to learn that the Bayesian network parameters can be recovered easily. Given the data source evaluated against, is it not particularly insightful to learn that in such a system, problem difficulty does not have an effect on quality of model estimation. There are a number of very interesting ideas presented in this work, but the experimental design is unconvincing.

A paper by Hao Cen applies A$*$ Search to a collection of expert-tagged features on various questions in an effort to match student performance on those questions to the accepted ACT$*$ learning model for an atomic skill (Cen et al., 2005). This model is detailed extensively in (Nichols et al., 1995), and for skill-based questions (as opposed to fact-retrieval questions) it is related to the aforementioned Power Law of Learning. The idea presented is to use informed search to find the proper granularity of skills to be considered atomic in the context of the given ITS, in much the same way that the Apriori algorithm was used to discover skill-transfer rules in (Freyberger et al., 2004). The technique is evaluated on real ITS log data, although with only a single dataset for the evaluation. Given the extensive history and development of the ACT family of learning models (ACT-R, 2006), and the results presented here, there seems to be much promise to this line of research. Continued work in the area needs to reproduce this effort on multiple datasets and perhaps show comparisons with other methods of determining the base skill set.

Progressing into more educational research, (Hunt and Madhyastha, 2005) focuses on shifting the focus of psychometrics from purely assessing latent traits to identifying misunderstandings and providing specific help to aid in student progress. The authors argue that while assessment is in many ways easier to work with, education is the more important, and more challenging, of the two.

> In the area of diagnostic assessment, where the goal is not merely to place a person along one or more axes of achievement but rather to provide a spe-

> cific educational intervention to help them to progress, it is more important to identify student conceptualizations than to grade them.

This is an analysis project focusing on applying entropy-based clustering of categorical attributes to cluster students into groups with similar knowledge. Based on the most-common (modal) set of answers for those groups, experts can identify the underlying reasoning and identify which groups have minor misconceptions and which need significant remedial instruction. This is high-effort work, requiring hours of expert time to accurately classify the clusters of student misconceptions. However, once those clusters have been identified and labelled, further classification is quick, as it requires very little calculation given the answers for a new student. As such, the intended audience of this research seems to be standardized tests: once developed, a set of questions is distributed to the entire test-taking population, and the expert classifications can be used to suggest specific remedial instruction for each student based on the predicted misconceptions. Conceptually this is very intriguing, and may be a good application of entropy-based clustering. Clustering of students is a difficult problem domain to work with because of the lack of easy validation methods. This paper is also interesting in that it is the first academic EDM publication coming from a corporate entity, rather than an academic institution, the FACET Innovations Corporation of Seattle, Washington.

Researchers from Worcester Polytechnic and CMU presented (Feng et al., 2005), which focused on detecting when students using an ITS might be “gaming” the system. Gaming can take several forms, from quickly guessing answers in sequence to get through a particular question, to abusing the ITS hint system in order to finish as quickly as possible. This research is motivated by a consistent under-estimation of standardized test scores in eighth grade math for users of their “Assistment” ITS. In looking for the sources of error in these predictions, recent research (Baker et al., 2004) has shown that students that engage in gaming behaviors learn about two-thirds as much as students interacting honestly with the system. Using techniques discussed in (Baker et al., 2004), gaming can be detected and accounted for by an ITS that is aware of such behavior. Baker shows that gaming itself is a significant problem by showing incidences of gaming the system to be negatively correlated with student learning. In comparison, other "off-task" behaviors such as sleeping, surfing the web, or talking off-topic with others showed no correlation with learning either positively or negatively. By detecting when students are gaming the system, it is possible for the ITS to determine that they are not honestly attempting the questions and work both to stop the gaming and appropriately modify the predicted score for the actual exam. It is preferable to engage in active detection of these behaviors, rather than modifying the system to prevent them at the outset, since many of the components of gaming are used in honest ways by other students. Altering the system to be less useful or more frustrating for the majority in order to stop some bad behavior of the minority is undesirable.

Along with (Hunt and Madhyastha, 2005), research presented by Barnes focused on non-ITS data, with a strong influence from the educational research community in general (Barnes, 2005). Here, Barnes presented the Q-Matrix method introduced in Chapter 2. In this case the research dates back to the early 1990s (Birenbaum et al., 1993), with Barnes presenting both an algorithm for the automated application of this method to student score data, as well as a black-box approach to using this algorithm to enhance online tutorials. The concept here is that rather than using a full ITS development process, instructors can simply write a basic web tutorial with a series of quiz questions, and the Q-Matrix algorithm will over time determine which questions are testing the same concepts. Once trained, at the end of the quiz the algorithm can suggest questions for each student to go back and practice, based on which skills the student is estimated to be lacking. This targeted recommendation can account for students guessing questions correctly or slight noise in questions, and can thus give more beneficial suggestions than simply choosing from the pool of questions that the student initially answered incorrectly.

An introductory version of some of the analysis presented in this dissertation was also presented at the workshop (Winters et al., 2005). This paper focuses on grouping questions by topic when given per-student scores for those questions. A greatly expanded presentation of this research is presented in Chapter 9.

3.2.4 AAAI Workshop Summary

The themes from the AAAI workshop show great promise, but also some areas of weakness. Perhaps because of the workshop being held at an AI conference rather than ICITS, the level of algorithmic and mathematical sophistication of the papers presented here was, on average, somewhat higher than at the ICITS conference. The range of AI and machine learning techniques applied in the research at this workshop is impressive, given the limited number of papers presented.

However, the presentation of experimental research and results show a general weakness of the work presented at the workshop. In almost all of the papers, experimental validation of the techniques presented was done using a single dataset, if a formal validation method was even discussed. For tool-development papers, demonstrations trumped the ever-difficult usability studies. In at least one paper, the generative model for the data evaluated had no proven relation to the generative model of the data the algorithm will be applied to. Stochastic results were presented without error ranges. Only minimal re-runs of random processes were reported. Even the paper with the most datasets present still presented conclusions based on only three datasets. If EDM is to take hold as a useful and respected cross-disciplinary research area, it will require higher standards of experimental discipline and integrity.

Chapter 4

Data Collection

As with other Educational Data Mining systems, the system constructed here at the University of California Riverside can be broken into collection, archival, and analysis components. Our system focuses on the application of EDM techniques to student score data from unmodified courses. We do not have the luxury of working with ITSs to record our data. This makes the collection phase of our project more difficult. For the adoption of this system it is essential that new collection tools are developed to make it as easy, or easier, to grade using these tools than it would be to grade without them. If the tools themselves are useful enough to foster faculty adoption, then requesting detailed score information is a less onerous request.

We developed two tools to handle our grading and score recording. The first is Agar, which focuses on automated testing of programs and the grading of subjective work. The second is HOMR, short for Homebrew Optical Mark Recognition, which is a configurable system for optical mark recognition, allowing easy design and scoring of fill-in-the-bubble tests and surveys.

4.1 Agar

Given computer scientists's fondness of automating repetitive tasks, it comes as no surprise that computer-aided assessment (CAA) has been used continuously in various forms for nearly 50 years. Given a set of student submissions, and the repetitive tasks of checking compilation, program correctness, coding style, and documentation, it is hard to imagine a computer science instructor who has not thought of some automation scheme during long and tedious grading sessions.

However, most CAA systems seem to be lacking in two areas, which prevents them from becoming very popular. First, especially in computer science, CAA systems generally focus on automated testing of code and little else. A relatively common example of this is to use JUnit to perform method-level regression testing of Java assignments (Patterson et al., 2003). Programs can also be specified in the now-familiar pattern of ACM Collegiate Programming Contest problems: given a precise input and output specification, test that the student submissions function as a precise transformation on the input, and grade using *diff(1)*. Systems like (von Matt, 1994), (Hext and Winings, 1969), and countless others have relied on this level of precision, and performed strictly functional grading.

A second major hurdle barring widespread adoption of CAA systems is usability. While the academic community undoubtedly has thousands of CAA systems in the literature or active deployment at various institutions, nothing has grabbed the community as a real "killer app." The lack of adoption may be the fault of paradigm mismatch: although there has been a lot of time invested in CAA systems, we collectively have much more experience with the "red-pen" style of grading. In order to be really usable and have a chance of catching on, a CAA system needs to match existing usage paradigms to the extent possible, allow as many real-world usages as possible, and restrict the user as little as possible.

This section introduces Agar, a CAA system that appears to be unique in the literature by overcoming these issues. Agar has a fully featured functionality-testing system for checking compilation, input and output, code unit testing and more. Every test that Agar performs can be overruled by the human grader, and Agar's usefulness extends well beyond objective code testing. Agar has been used on over a hundred completely subjective assignments, quizzes, and exams. Users of the system report at least a factor of two speedup in their grading process.

4.1.1 History of CAA

Computer-aided assessment has a history dating at least as far back as 1959. In that year a computer program was used to test machine-language programming assignments, and was publicized the following year (Hollingsworth, 1960). This paper by Jack Hollingsworth of Rochester Polytechnic Institute captures the very essence of CAA results since then: Given 120 students in a full-semester programming course he claims, "We could not accommodate such numbers without the use of the grader." This is a feeling that has surely been echoed thousands of times as enrollments in CS have surged upward again and again over the past four decades. Surely a sizable number of CAA systems have seen their start because of similar thoughts.

Security is presented as a significant concern for Hollingsworth: the computer systems being utilized did not provide a method for protecting the grader in memory, so malicious or buggy student submissions could alter the grader itself.

The Hollingsworth grader was based on the paradigm of precise functional grading wherein programs are completely specified, and only a complete functional match is considered a correct submission, which stifles many opportunities for student creativity. Hopefully recent work like (Rich et al., 2002) will convince the community that this may be a good paradigm to practice from time to time to ensure students are capable of following directions, but to attract a more diverse population and keep retention high, we must allow for more creativity.

However, this theme of I/O-spec grading continues through most or all of the CAA systems in the literature. In the late 1960s, the breakthrough CAA system was the Basser Automatic Grading Scheme (BAGS) (Hext and Winings, 1969) from the University of Sydney, which represented the first time that a grader could be used without special support from a human operator. The paper describing BAGS makes it quite clear what types of programs are acceptable for grading: precise mathematical operations with zero creativity or margin for error.

More recently, the mid- 1990s saw the development and publication of systems like Kassandra (von Matt, 1994), an automated grading system designed for a scientific computing course to evaluate Maple or Matlab code. Kassandra is a system with a number of very impressive features, like networked operation and a secure client-server paradigm that absolutely prevents students from interacting with the reference solutions. Especially in the face of growing sophistication on the part of the students, Kassandra certainly represents a step in the right direction: who hasn't worried at some point about compiling and running student code, either with the use of a CAA tool or even just by hand? Still, we find that Kassandra focuses exclusively on grading precise functional behavior, and little more.

Based on the published literature it is difficult or impossible to evaluate the usability of the system. A fundamental concept in human-computer interaction is that programs are difficult to use if the system model doesn't match with the user model (Tognazzini, 1996). Since users generally come to a new program with little or no initial concept of the precise workings of the system, user model is often wildly erratic, at least during the initial stages of use. Users experience a great deal of stress when they are suffering from such a model mismatch. A reliable method for reducing the time necessary to correct the user model is to leverage existing, known usage patterns. In essence, the system model should match existing usage patterns as much as possible so that a user doesn't have to deal with expectation violations that cause a program to be "hard to use." Without having actually interacted with these other CAA systems, we cannot judge for certain whether the program matches existing grading styles, but there doesn't appear to be much reason to assume that this sort of usability was of much import to the designers of these systems.

4.1.2 Agar

Agar attempts to be a highly usable tool by focusing on the following design principles:

1. Allow existing grading styles - Both in terms of how an individual grader grades, and how grading tasks are broken up for large classes, Agar attempts to match existing grading styles.

2. Support the subjective - Agar goes beyond most CAA systems by supporting grading of subjective features (style, documentation, written work), rather than just functionality. This means it can be used for tests and quizzes, or programming work with a creative aspect.

3. Eliminate repetition - Whenever possible, Agar eliminates the repetitive tasks in grading. One of the primary ways it does so is by making student feedback instantly reusable. This trait also applies to recording scores in a gradebook, emailing students their scores and feedback, and compiling programming submissions.

Grading with Agar can be broken up into five main phases: identifying submission files, setting up a rubric, running tests and conversions, performing any needed manual grading, and reporting scores.

Identifying Submissions

Our homework-submission system has students turn in an entire directory at once. One effect of this is that there are often extra files that are not strictly necessary to make a programming assignment function: object files, backup source files, sample inputs, etc. Agar includes three main methods of identifying which of the files in a student's submission directory are actually part of their submission and should be included in Agar's list of files for that student. When we first started working on CAA systems, one of our requirements was that students submit files with a precise filename. On average, ten to twenty percent of the students ignored these requirements, regardless of how terrible a penalty was imposed. Eventually we decided it would be far better for our systems to be able to automatically identify which files were pertinent.

The default method of identification uses filemasks to identify which files are important. When starting a new Agar workspace it prompts the user for what kind of grading is to be done. For written grading, this sets the filemask to **.ps, *.pdf, *.txt, *.doc*. Any filename in the submission directory matching *any* of those Unix-style globs will automatically be included in the student's file list. Similarly for C/C++ grading, the filemask is set to **.c, *.cc, *.cpp, *.h, *.hh, Makefile*. This covers the majority of our grading, but an option exists to manually enter an arbitrary filemask as well. Once the filemask is identified, a base directory is selected. It is assumed that this directory contains student submissions in the format generated by our *turnin* system (this can be easily altered for other environments). For each submission directory, the filemask is applied and a collection of matching files are extracted. If no files match the filemask in one or more directories, then the user is prompted to manually identify submission files for those submissions.

Another method of identifying files relies on the student submitting a valid (but simple) Makefile. For each dependency in the Makefile that does *not* have an associated creation

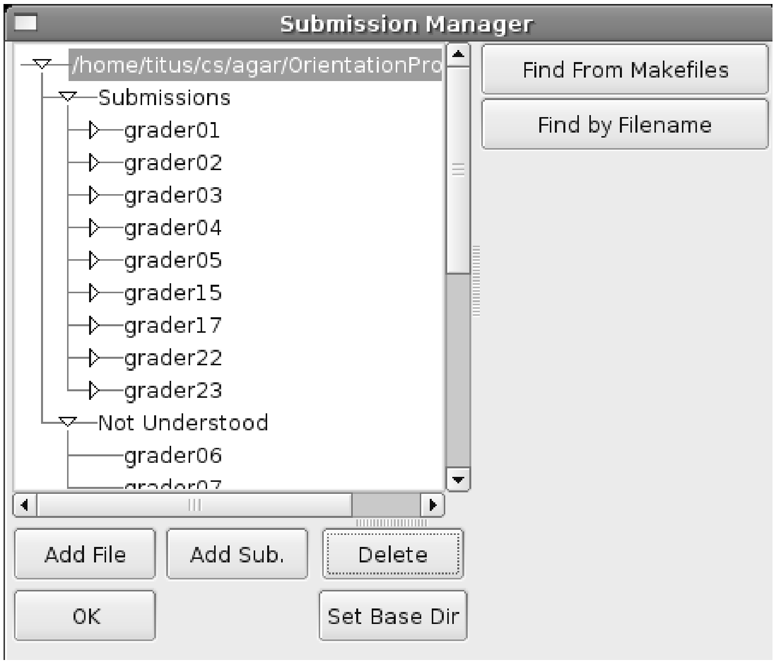


Figure 4.1: Submission Manager

rule, if that file exists in the directory it is added to the file list. The Makefile parser also will do simple variable expansions, although it does not fully emulate *make* and its handling of implicit dependencies and creation rules: all files must be explicitly mentioned to be included.[1]

In general, one of the above two methods will suffice to identify the vast majority of submission files. Once in a while a student will name a file oddly or will have some other problem with a submission, and it is necessary to manually identify the files for that submission. Any possible submissions in the base directory that cannot be understood with one of the above methods can be identified manually by opening a file browser in that directory and adding files to the submission (Figure 4.1).

Usually, identification of submission files is completely automatic, and requires less

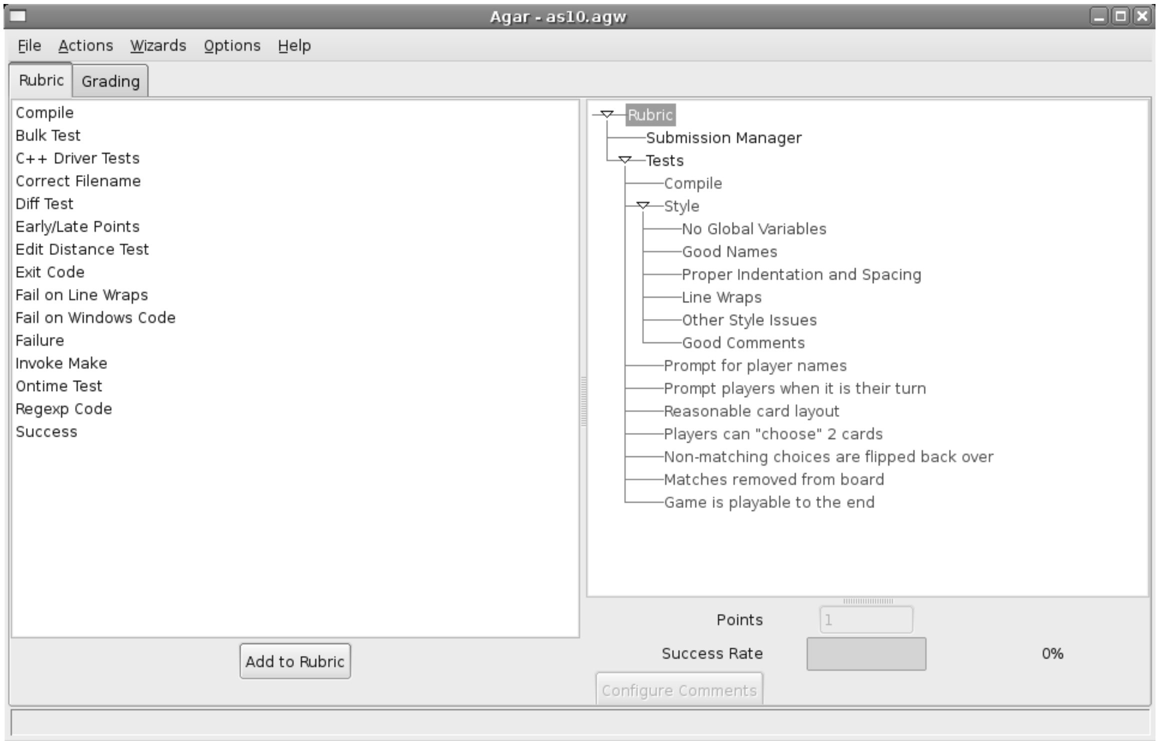
[1] This means that, for example, implicit rules for generating *.o* files will not be picked up by the system.

than five minutes for a class of forty students, even in the presence of submissions whose files were not named correctly or located in the expected locations.

Creating a Rubric

Once submission files are identified, the next step is to create the basic grading rubric. In Agar, a rubric is a tree of tests. The top-level items are the point categories that will be reported for student grades. For programming work these are often one major functional category (“Insert”, “Remove”, “Style”, etc); for written work there is generally a top-level rubric item for each question. Each rubric item is selected from the available set of tests (the left portion of Figure 4.2). If a rubric item fails, any sub-tests of that item will be executed, allowing for conditional execution when necessary. The most common usage of this hierarchical testing thus far is for compilation: in our department we generally require the *g++* flags *-W -Wall -Werror -pedantic* for lower-division programming courses. This helps ensure that the students are writing good code. Often there will be a mandatory penalty for code that fails to compile with these flags: by allocating some rubric points to the default “Compile” (with flags), and then creating a sub-test that re-attempts the compilation without the flags, we can quickly compile all submissions that are compilable as well as identify which students had warnings in their code.

Most of the tests shown in Figure 4.2 are separate executable programs adhering to the Agar tool specification. With very few basic requirements on parameter parsing and exit codes, Agar users can write their own programs and scripts to perform testing tasks in Agar. The tool specification is quite minimal, requiring on the order of tens of lines of code, and eliminates the need for a complex plugin structure, dynamic linking, shared-object generation, or any other complex scheme. Anybody should be able to easily write extensions for Agar, in any language, so long as that language can read command line



Compile
Bulk Test
C++ Driver Tests
Correct Filename
Diff Test
Early/Late Points
Edit Distance Test
Exit Code
Fail on Line Wraps
Fail on Windows Code
Failure
Invoke Make
Ontime Test
Regexp Code
Success

```
Rubric
  Submission Manager
  Tests
    Compile
    Style
      No Global Variables
      Good Names
      Proper Indentation and Spacing
      Line Wraps
      Other Style Issues
      Good Comments
    Prompt for player names
    Prompt players when it is their turn
    Reasonable card layout
    Players can "choose" 2 cards
    Non-matching choices are flipped back over
    Matches removed from board
    Game is playable to the end
```

Points 1

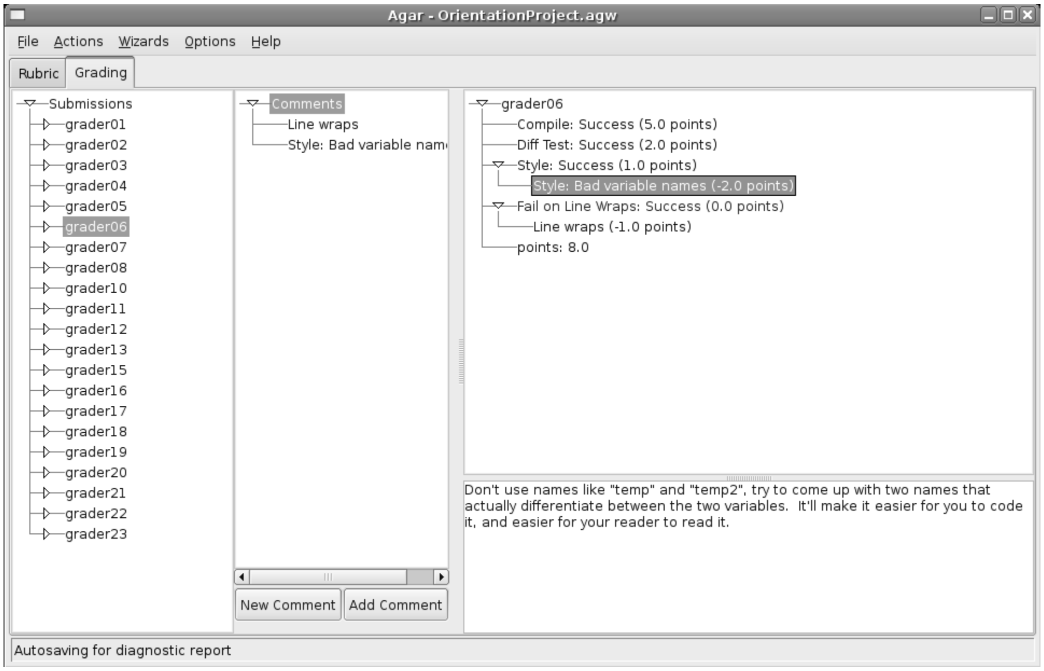
Success Rate 0%

Figure 4.2: Rubric Creation

parameters, run as an executable or script under Unix, and return different error codes when terminating.

In addition to determining which tests make up a rubric, it is also important to identify the point values for each item. Each rubric item has an associated point value, which is changed using the spin control on the lower-right portion of the screen. It is also possible to create *comments* that are automatically assigned to submissions that pass or fail on a particular test. Tests themselves are fairly limited, and are generally intended to be the first-pass: anything that passes is good, anything that doesn't pass or cannot be automatically evaluated will be checked by hand later and scored with comments.

For an average-sized course, creation of a rubric for written work is nearly automatic, and a suitable rubric for programming work takes on the order of ten minutes.



```
Submissions
  grader01
  grader02
  grader03
  grader04
  grader05
  grader06
  grader07
  grader08
  grader10
  grader11
  grader12
  grader13
  grader15
  grader16
  grader17
  grader18
  grader19
  grader20
  grader21
  grader22
  grader23
```

```
Comments
  Line wraps
  Style: Bad variable nam
```

```
grader06
  Compile: Success (5.0 points)
  Diff Test: Success (2.0 points)
  Style: Success (1.0 points)
    Style: Bad variable names (-2.0 points)
  Fail on Line Wraps: Success (0.0 points)
    Line wraps (-1.0 points)
  points: 8.0
```

Don't use names like "temp" and "temp2", try to come up with two names that actually differentiate between the two variables. It'll make it easier for you to code it, and easier for your reader to read it.

Autosaving for diagnostic report

Figure 4.3: Basic Grading Interface

Running Tests

Once the rubric is set up, tests can be run on all submissions. One important feature of Agar is that many of the tests that actually run the student code have built-in safeties to ensure that student code doesn't run too long, use up too much memory, etc. We do not currently resort to sandboxing student programs in a *chroot* jail, since we have never encountered student code malicious enough to warrant such measures, but building such a secure execution environment test is possible within Agar's framework.

After running tests, Agar color-codes rubric items that have a perfect pass or fail rate. Green tests indicate every submission passed, red tests indicate everyone failed. Red tests often indicate that something was improperly configured. After re-configuring the test, individual rubric items can be re-run without re-running all tests. Similarly, if a particular student's submission needs to be altered and re-tested, that submission can be re-tested in isolation from the other submissions without affecting any other test results. These features allow fair and accurate testing without unnecessary re-testing.

It may take as long as ten minutes to run all the tests for an average programming assignment, depending on the computational complexity of the assignment and number of students in the class. As the rubric items for a written assignment require no testing, there is no appreciable computation for written work in this stage.

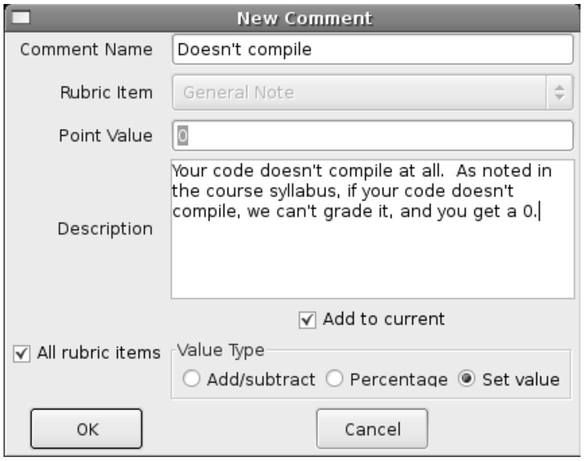
Manual Grading

When testing is complete, the grader can switch to the “Grading” view (Figure 4.3). From there they can switch between submissions, view individual submission files for each submission, launch a terminal in a particular submission directory, and most importantly, assign comments.

Comments are used in Agar just like comments are used when grading with a red pen: identify something worth commenting on, provide the student some feedback, and possibly associate a point value with it. Agar comments can be positive or negative, additive or multiplicative (the difference between bonus points and bonus percentage), or can simply set the value for a particular top-level rubric item. Comments can also be set to apply to all rubric items, like in the example shown in Figure 4.4, which shows a comment that gives the student a zero on the entire assignment.

The general process for grading in this phase is to go through each submission and check anything needing to be manually investigated. For well-specified programming assignments with no Style component to their scores, this could be nothing at all, since Agar does support total automation. For subjective work, this is the bulk of the grading task.

In practice, one of the most useful pieces of functionality in Agar is the “write-once” comment system. Since a large class is almost guaranteed to repeat errors, this commenting



Comment Name: Doesn't compile

Rubric Item: General Note

Point Value: 0

Description: Your code doesn't compile at all. As noted in the course syllabus, if your code doesn't compile, we can't grade it, and you get a 0.

☑ Add to current

☑ All rubric items

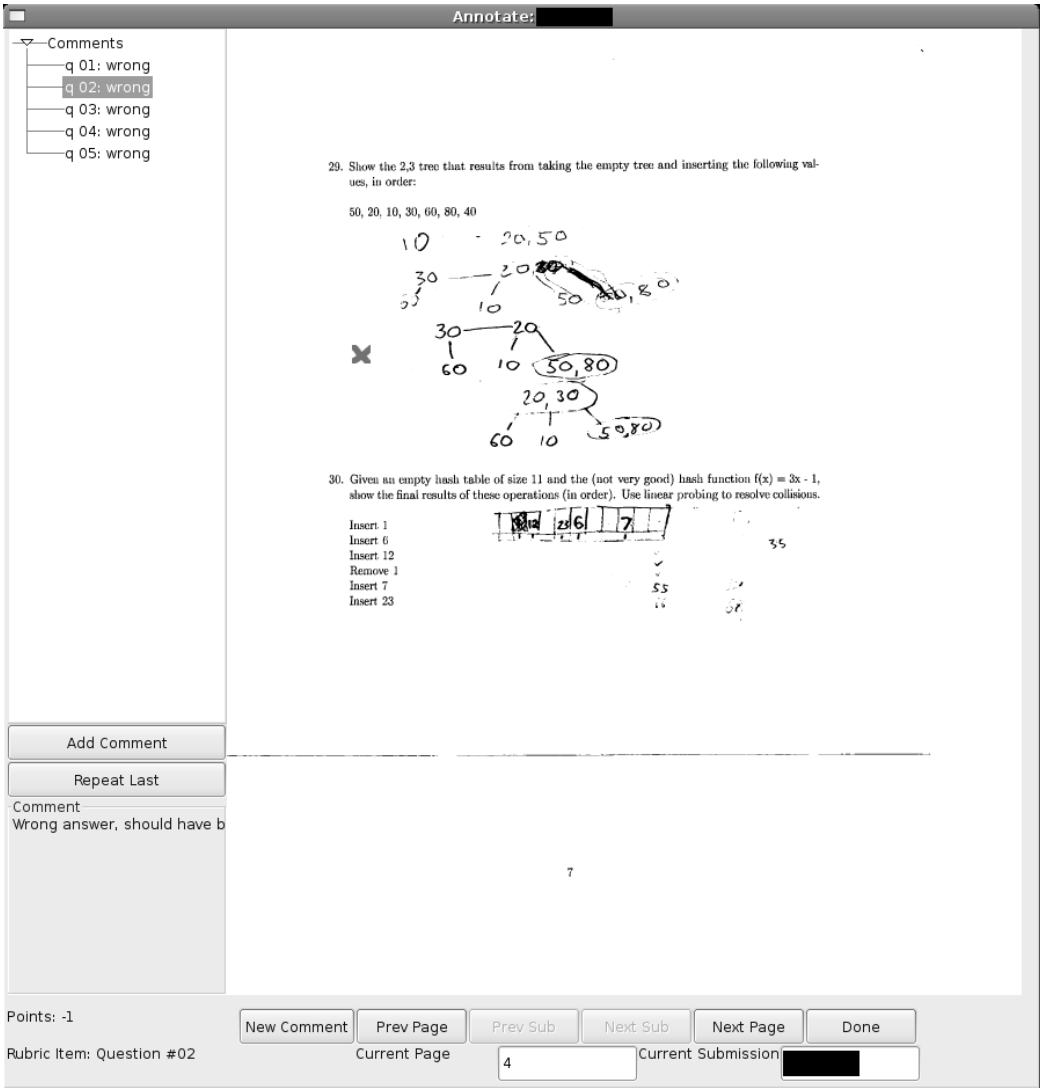
Value Type: ○ Add/subtract ○ Percentage ● Set value

Figure 4.4: Creating or Editing a Comment

system can be a great time saver for a number of reasons. First of all, many people type faster than they write, so typing out feedback is a good step. Secondly, since comments are saved for re-use, when a duplicate error is encountered, the comment can be dragged from the list and dropped on the duplicate error in the new submission, saving even more time. Third, comments are assigned by reference, and thus if they are edited later all instances of that comment are updated. This is useful in cases where penalties need to be adjusted, or feedback requires editing before it is sent back. All of these features greatly reduce the amount of time needed to do a fair job of grading, and increase the overall consistency of the grading itself. Since it is easier to assign an existing comment regarding a problem than to create a new comment, there is a tendency to be more fair in giving the same penalty for similar problems. Students appreciate this consistency.

Annotation

There is also an alternate interface for assigning comments. Especially for written work, tests, or quizzes, it is often best if comments can have some “locality”, like “Notice that



Annotate: [redacted]

29. Show the 2,3 tree that results from taking the empty tree and inserting the following values, in order:

50, 20, 10, 30, 60, 80, 40

30. Given an empty hash table of size 11 and the (not very good) hash function f(x) = 3x - 1, show the final results of these operations (in order). Use linear probing to resolve collisions.

Insert 1
Insert 6
Insert 12
Remove 1
Insert 7
Insert 23

7

Comment
Wrong answer, should have b

Points: -1

Rubric Item: Question #02

Current Page: 4

Current Submission: [redacted]

Figure 4.5: Agar Annotation Interface

this node in your 2-3 Tree has 1 child, which is forbidden in a 2-3 Tree." A comment of this type makes more sense when placed on the page near the offending node of the tree. Agar's annotation interface allows many file types, including PostScript, PDF, DOC, plain text, source code, and many image types, to be displayed on screen and annotated with comments (Figure 4.5).

Using the annotation interface allows graders to grade either submission by submission or question by question (especially useful for scanned tests where all questions are on the same page of the submission). When mailbacks are generated for students, all of the "pages" of their submission are converted to PDF, and the localized comments are added to the PDF as annotations viewable within Adobe Acrobat Reader[2] as colored sticky-notes that expand to hold the comment text.

Reporting Scores

When the manual grading is completed, the remaining tasks are to generate feedback for the students and to record scores in the course gradebook. Generating feedback for the students is easy, assuming the students all have email addresses in the same domain. Agar identifies student submissions by their username, and can be configured with an outgoing SMTP server and the domain of the students. It then generates mailback files containing score summaries, test results, and comment feedback. If the annotation system was used it also converts the submission to PDF and annotates it with the appropriate comments. When the mailbacks have all been generated, it automatically emails them out to the students.

For exporting grades, Agar primarily supports the use of a spreadsheet for storing grades. It prompts for the location of the course gradesheet, which can be in either Microsoft Excel format or the open-source Gnumeric format. It then searches the gradebook for a sheet called "Summary" which has a listing of the student usernames. Based on the row-ordering of those usernames, it creates a new sheet with the scores for the current assignment, with one column for each top-level rubric item and with students ordered into the same row order in the new sheet as they appear on the Summary sheet. It also (optionally) will export a column of indirect-references to the total points column of the Summary sheet

[2] Most other PDF viewers ignore annotation information.

to keep it up to date. Not only does use of Agar obviate hand entry of score data, it also allows scores to be recorded and tracked at a much finer granularity than would otherwise be kept. This detailed data forms the basis of much of our EDM analysis.

4.1.3 Usage Patterns

Two relatively simple features of Agar that have been found to be quite powerful are the ability to save different portions of the workspace into different files, and to merge Agar files together. These abilities allow for usage patterns similar to those that are normally found in courses with large grading loads.

One feature that has been used repeatedly is that of the pre-developed rubric template. The Head TA for a large class generally creates a rubric and a default set of expected comments. The Head TA will then save just the rubric and comments into a “template” file that is given to the other TAs along with a list of which students to grade. Each TA runs Agar on their own set of submissions, grades using that rubric and those comments for even greater consistency, and then sends back an Agar workspace complete with grading information. The Head TA merges all of these Agar workspaces together before sending mailbacks and exporting grades. This is a simple method of splitting the workload student-by-student. After grading, the templates can be updated with the most common problems not covered with the original comments, and saved for use in future course offerings.

When grading exams for large courses, Agar also allows the work to be split question-by-question. Again, a Head TA creates a rubric and possibly some basic comments for each question, and then gives a copy of the full workspace (with all rubric information and student submissions) to each TA, along with instructions for which question to grade. The TAs grade in parallel, just as they would with paper grading, and then send their Agar workspaces back for merging. While the selective saving and merge abilities of Agar are not technically complex, they have proven to be invaluable in the adoption of the system, quickly becoming one of the most-used features.

4.1.4 Conclusions

Agar is, as far as we can tell, a first-of-its-kind entry into the domain of CAA tools. Agar embraces the idea that feedback from a human grader is an essential and invaluable part of the learning process. Rather than strive only for complete automation, Agar works to extend the existing usage patterns of graders by emulating red-pen grading as well as division-of-labor methods for large grading tasks. By automating the tasks of score recording and sending feedback to students, Agar works to eliminate the clerical tasks that can otherwise take up so much time in grading. The "write-once" comment system also makes grading in Agar more consistent, and allows graders to increase the quality of feedback to students. Agar is more than just an automated grading system: it is an actual *aid* for assessment, not a replacement for the feedback and expertise that is so critical in the learning process.

4.2 HOMR

Optical Mark Recognition, fill-in-the-bubble, multiple-choice tests have been a staple of educators for decades. The most common approach to OMR for educational institutions involves specialized reading equipment and preprinted forms, and often lacks important features such as error checking and digital recording of scores. There are number of commercial OMR software packages (Open Directory, 2005) that allow the use of general-purpose sheet scanners and self-printed forms, but they do not seem to have achieved major penetration into the academic market. Our system, affectionately named the Homebrew

Optical Mark Recognition system (HOMR), is an attempt to remedy the lack of a convenient open-source alternative.

HOMR is fully configurable, with certain basic requirements, and allows the authors of tests, quizzes, surveys, or grade reporting forms to design forms to their own specifications and to process the images generated by (increasingly cheap and common) autofeed sheet scanner. HOMR is designed to be highly cross platform, and easily embedded into the high-level language of your choice. During our testing of the system, we have achieved maximum accuracy rates of greater than 99.992%: fewer than 80 errors per million bubbles. For comparison, the OMR system used by the US Census has an estimated accuracy of 99.8% (Bureau, 2004), or 2000 errors per million.

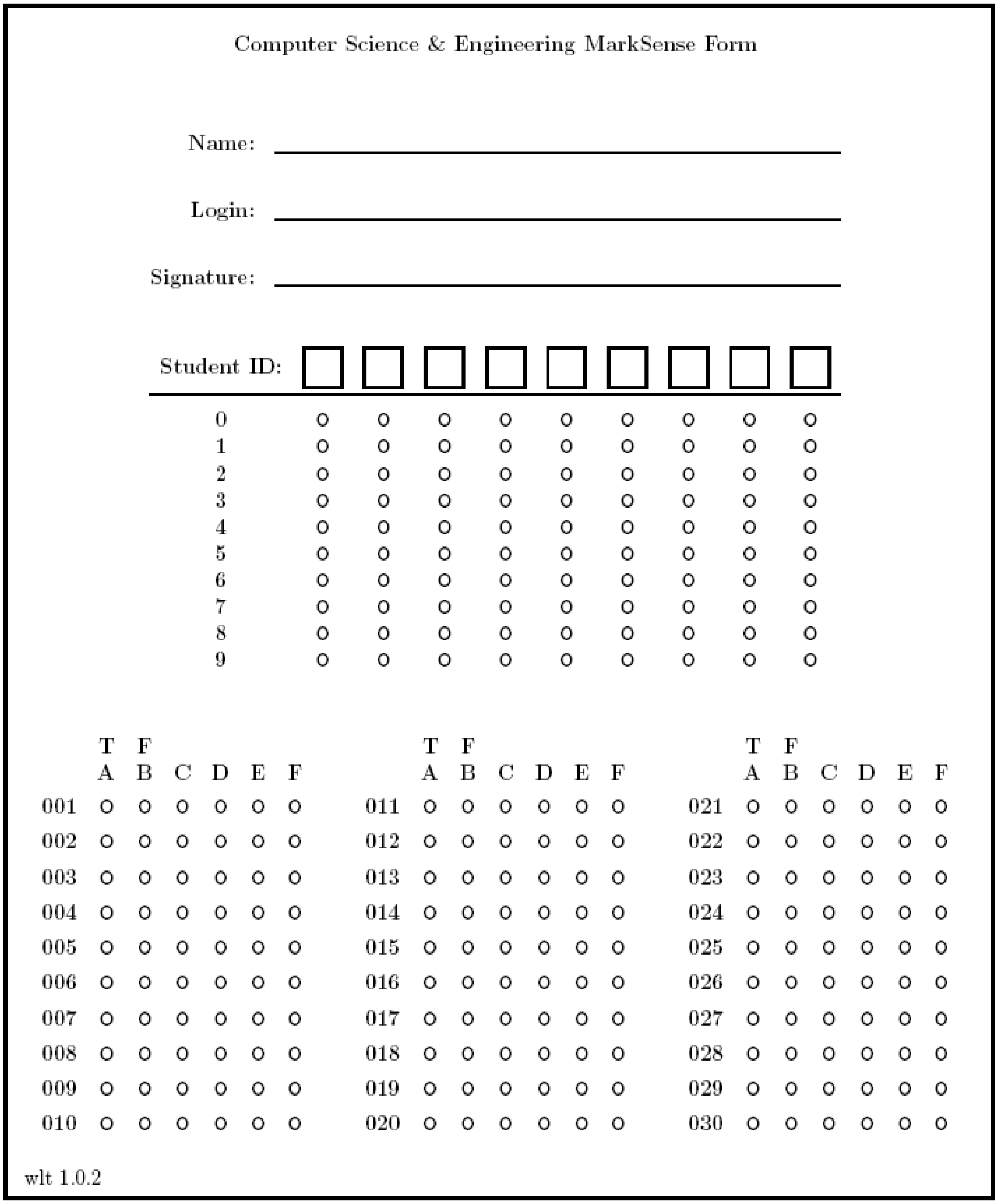
This section describes the requirements for installation and usage of HOMR, the workings of the system itself, and our testing and evaluation methods.

4.2.1 Requirements

HOMR has relatively few requirements. Pages should be bounded with a rectangular border, and bubbles should be arranged in rectangular grids (see Figure 4.2.1). HOMR has been tested on numerous scanners, from single-page flatbed scanners[3] to modern high-volume office scanners. Students have been allowed to print their own answer pages for our mark-recognition system, meaning that hundreds of printers have been used for form generation, and there are thousands of pairwise combinations of printer and scanner that have been tested with this system. As a result, we feel that HOMR is both printer and scanner independent.

To date, the vast majority of testing for HOMR has been done using forms generated in $\LaTeX$, but we have had equivalent success in testing the system on forms generated in

[3] Which are supported, but not recommended for speed reasons.



Computer Science & Engineering MarkSense Form

Name: ______________________________

Login: ______________________________

Signature: ______________________________

Student ID: □ □ □ □ □ □ □ □ □

0	○	○	○	○	○	○	○	○	○
1	○	○	○	○	○	○	○	○	○
2	○	○	○	○	○	○	○	○	○
3	○	○	○	○	○	○	○	○	○
4	○	○	○	○	○	○	○	○	○
5	○	○	○	○	○	○	○	○	○
6	○	○	○	○	○	○	○	○	○
7	○	○	○	○	○	○	○	○	○
8	○	○	○	○	○	○	○	○	○
9	○	○	○	○	○	○	○	○	○

	T	F						T	F						T	F				
	A	B	C	D	E	F		A	B	C	D	E	F		A	B	C	D	E	F
001	○	○	○	○	○	○	011	○	○	○	○	○	○	021	○	○	○	○	○	○
002	○	○	○	○	○	○	012	○	○	○	○	○	○	022	○	○	○	○	○	○
003	○	○	○	○	○	○	013	○	○	○	○	○	○	023	○	○	○	○	○	○
004	○	○	○	○	○	○	014	○	○	○	○	○	○	024	○	○	○	○	○	○
005	○	○	○	○	○	○	015	○	○	○	○	○	○	025	○	○	○	○	○	○
006	○	○	○	○	○	○	016	○	○	○	○	○	○	026	○	○	○	○	○	○
007	○	○	○	○	○	○	017	○	○	○	○	○	○	027	○	○	○	○	○	○
008	○	○	○	○	○	○	018	○	○	○	○	○	○	028	○	○	○	○	○	○
009	○	○	○	○	○	○	019	○	○	○	○	○	○	029	○	○	○	○	○	○
010	○	○	○	○	○	○	020	○	○	○	○	○	○	030	○	○	○	○	○	○

wlt 1.0.2

Figure 4.6: Sample MarkSense Form

WYSIWYG editors like Microsoft Word or OpenOffice Writer, so there are no requirements regarding the method of form preparation. Functionally, the necessity of having a bounding box and the regular grid layout for bubbles are the only two significant requirements, which allows for great flexibility in form creation and layout. For best results, both printer and scanner must produce good quality, high-contrast results.

4.2.2 Internal Design

HOMR is a small program for the amount of usability power and flexibility it provides. It requires a single non-standard library, Magick++ (Magick++, 2006), the C++ bindings to the popular cross-platform open-source graphics library ImageMagick (ImageMagick, 2006). The source for HOMR itself relatively small, comprised of approximately 1200 lines of C++ code. This code performs all of the image normalization, feature detection, sampling, and bubble classification for HOMR.

Image Normalization

The image normalization step for HOMR has become a larger and larger collection of algorithms and tricks to deal with a larger and larger collection of printer and scanner bugs and eccentricities. For example, if a HOMR page is originally stapled to a test and is then ripped off, the corner of the page may be physically disconnected. Many scanners will render this as a black blob in one corner of the image. These blobs can throw off the feature detection in later steps, so HOMR now performs a white flood-fill in each corner to fill in any such blobs, or black triangles from slightly rotated pages.

In order to find the page borders of the image, a copy is made in memory and run through a standard edge enhancement algorithm. The edge enhancer is part of the Magick++ library, but is just convolving the image with an appropriate kernel. The edge enhancement step is necessary for pages that were generated on copiers running low on toner. Such copiers will often leave one or more stripes of lower-intensity black on the image, which may or may not be scanned correctly by the scanner. Edge enhancement boosts the contrast of these lines, allowing the next step to be performed correctly.

On the edge-enhanced copy of the image, we now perform a standard Hough transform (Duda and Hart, 1972) to find the numeric parameters of the lines present in the image. The Hough transform views every filled pixel in the image as a "vote" for every possible line that could pass through that point. By finding all the filled pixels and finding all pairs of r and θ that satisfy $r = x\sin(\theta) + \cos(\theta)$, we can find the lines in the Hough space of r and θ that have sufficient votes to be considered lines in the image[4].

This is a particularly processor intensive step as described. Since the pages being fed to HOMR are expected to have the bounding box lines within a few degrees of vertical and horizontal, significant speedup can be provided by only looking for θs within $\pm 5^\circ$ of 0°, 90°, 180° and 270°. Further, by only sampling every-other pixel (and reducing the vote threshold by half), equivalent lines should be extracted from the image for half the processing time. Both of these techniques are used by HOMR speed up the detection of the bounding box.

In order to determine which set of lines is actually forming the bounding box, HOMR employs a nearest-neighbor search on the "ideal" coordinates in r,θ-space for the bounding box edges. Currently this is an unconnected-search, in that there is no check performed to make sure that the lines do in fact touch at the corners. A possible refinement to the system would be to search for boxes similar to the ideal bounding box in a higher dimensionality space, but the transformation of lines from the r,θ space into boxes in a higher-dimensional space would be computationally complex. The current system performs very well on a

[4] Given only integer values of θ

wide variety of inputs, so such refinements are currently considered unnecessary, and likely would cause a significant speed penalty.

Given the parameterization of the lines for the bounding box, HOMR now returns to the copy of the image without edge detection. Given the bounding box lines, the rotation and skew of the image is calculated. An affine transformation is applied to the image to remove rotation and skew caused by the printing or scanning of the page. The page is cropped on the margins. At this point, the page is straight, deskewed, and the image is made up only of the portion of the scan within the bounding box. A slight Gaussian blur is now applied to the image to reduce noise and spread the color values more evenly, and then the image is quantized down to two colors (roughly black and white) to minimize the effect of varying brightness and contrast scanner settings.

Sampling

At this point the page is prepared for bubble extraction and classification. The configuration file is read to get the description of each of the bubble arrays on the page. The configuration file provides the position of each bubble array *as a percentage of the width and height of the bounding box*, as well as the number of rows and columns present in the array. This avoids the possibility of scaling changes brought about by various printers and scanners. The processing of each bubble array begins by looping through the described area of the page. The *x* and *y* coordinates of each filled pixel are added to an array of *x* values and a separate array of *y* values. In order to determine the precise *x* and *y* values of the rows and columns, these arrays are passed to a one-dimensional *k*-means clustering algorithm, given the number of rows and columns to extract. The clusters returned identify the *x* and *y* values of the rows and columns of bubbles, allowing independent location of each bubble center and sampling of each bubble.

Bubbles are extracted by finding the extent of adjacent filled pixels. Starting at the x,y coordinate given by the grid clustering, the nearest filled pixel in each cardinal direction is identified, and the extent of filled pixels reachable from those points is identified. It is necessary to start from several points to account for the possibility of noise in the center of an unfilled bubble. This is a particularly common condition in the presence of incompletely-erased bubbles. The reachability search is limited in how far from the original x,y coordinate it can search, to prevent sampling too large an area in the case of extra lines through the page (a common problem with some scanners.) Once the extent of the connected area is found, a 10×10 sample is extracted. Several extra features are added to this sample, including the average darkness of the sample, and the width and height ratio. Once all the bubbles are extracted, the most important feature is added to the samples: the relative darkness. Each bubble is ranked on a scale of $0..1$, with 0 being the darkest bubble in the array, and 1 being the lightest bubble in the array.

The sample vectors for each bubble are 106 dimensional. These vectors are made up of 100 dimensions for the 10×10 sample itself, and 6 additional features about the bubble, described below.

- Average pixel intensity in the sample
- Width of the sample as a percentage of page width
- Height of the sample as a percentage of page height
- The product of the width and height values above
- A guess of the correct label (filled or unfilled) based on nearest-neighbor classification against three “ideal” bubbles (one filled, one empty, and one crossed out).

- A value in 0..1 representing how dark this sample is compared to other samples in this array. Thus, the lightest bubble in the array is 0, the darkest is 1, and a bubble only 1% lighter than the darkest is 0.99.

Once the samples are extracted, they may be classified. Classification uses a boosting (Freund and Shapire, 1997) classifier trained on 170 pages of HOMR bubbles (approximately 11000 bubbles) and generated using the Weka framework (Witten and Frank, 2005). The classifier is made up of 25 decision stumps, ranging in weight from 6.77 to 1.2 (meaning that the most important voters in the classifier has as about 3 times the weight of the least-important voter). The classification problem is simple: each bubble is to be reported as either filled or unfilled. In the current classifier, the most important single feature by far is the final feature encoding relative darkness of the sample. This makes good intuitive sense: the darkest samples are most likely to be filled. Even crossed-out samples should be lighter, as the added area of the sample (due to the bars extending out of the bubble) increase the relative amount of unfilled pixels. The width and height product is also used, but has less weight than several individual features in the image sample itself. The twenty-five decision stumps used as the base classifiers utilize a total of thirteen of the available features.

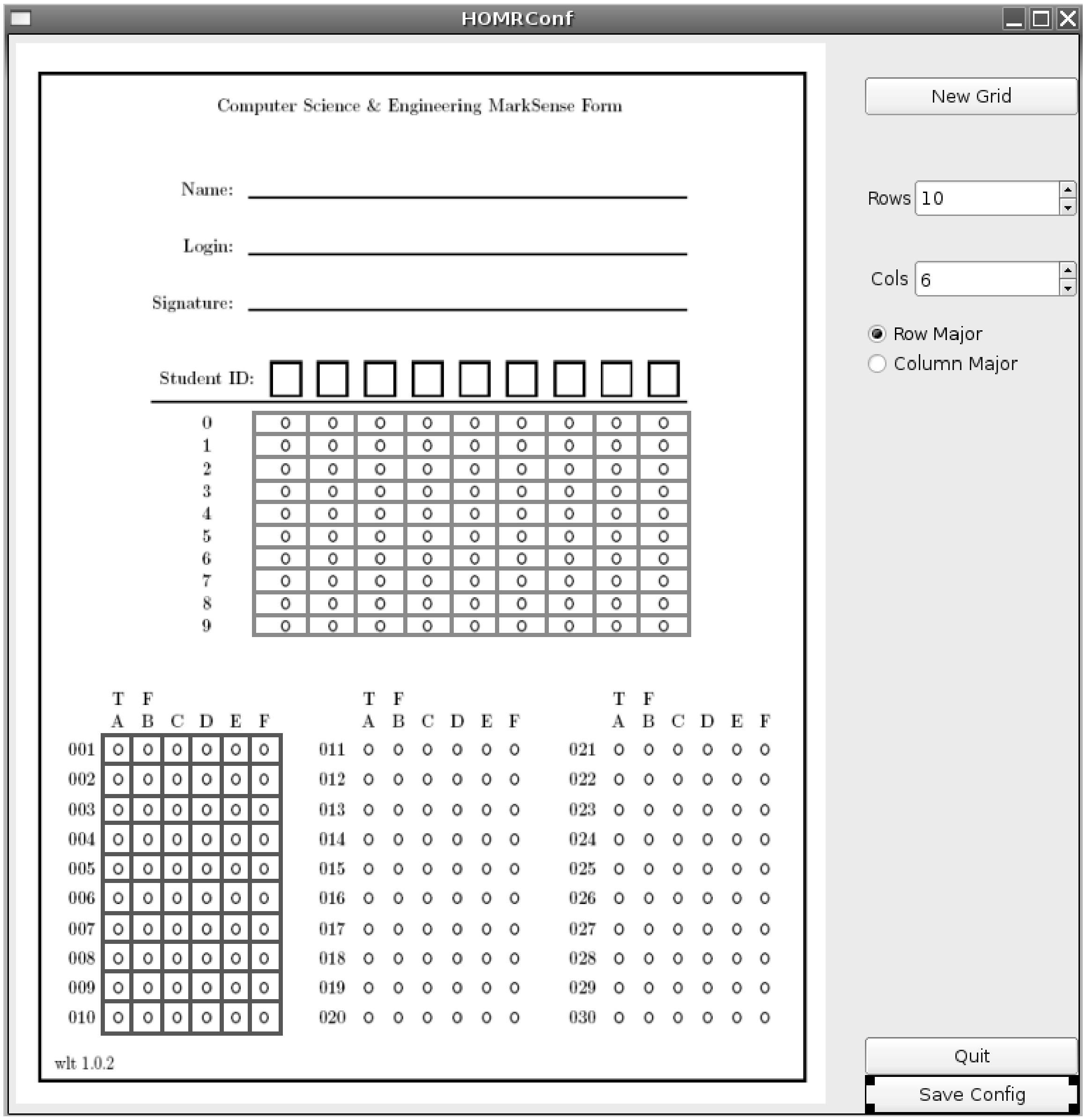
Based on the results from the boosting classifier each sampled bubble is reduced to a 0 or 1, and reported to standard output in that form. There are two options in use for this reporting. The first is a raw best-guess output, wherein each bubble is reported as 0 if it has a negative vote and 1 otherwise. The second utilizes semantic knowledge of the page, in the form of a guarantee: there is exactly one bubble filled in each row (or column, depending on the array configuration). In this form, the bubble with the highest vote in the row or column is output as a 1, and all the other bubbles are output as 0. The best-guess version has bubble classification accuracy greater than 99.9%. The only-one-bubble version has bubble classification accuracy greater than 99.992%. Errors in the only-one-bubble system are exceptional cases, such as spurious horizontal lines drawn through a row, or students scribbling out multiple bubbles in a row and pencilling in the letter of their preferred answer.

4.2.3 Usage

To use HOMR, it is of course first necessary to assemble the form that you will be using. Our recommendation is to use LaTeX, since it allows for easy automation when changing title and course information, but as mentioned earlier that is not necessary. Once a form has been generated according to the page layout requirements, a sample should be printed and scanned. The user will then load the scan into HOMRConf, a simple GUI that helps generate HOMR configuration files (Figure 4.2.3).

HOMRConf is very simple, and cross-platform. It accepts an image-file format, and displays that image in a new window. The user then identifies the bounding box and the bubble grids. For each bubble grid, HOMRConf writes out the location within the bounding box of the upper-left corner, the width and height of the grid, and the number of rows and columns of bubbles. HOMRConf then displays what a grid with those parameters would look like overlayed on the sample page. If this captures the bubbles properly, the user can accept the configuration and (optionally) add the next grid. Additionally, HOMRConf needs to know whether each grid should be read in row-major or column-major order.

For MarkSense, our OMR system built on HOMR, a single-page quiz has four grids: one grid of 9×10 bubbles for the student ID number, and three grids of 6×10 for 30 a-f answers. An optional second page has a separate configuration (since it is a different image layout), and supports an additional 90 bubbles in three columns. Configuration for



Computer Science & Engineering MarkSense Form

Name: ________________________________

Login: ________________________________

Signature: ________________________________

Student ID:	□	□	□	□	□	□	□	□	□
0	○	○	○	○	○	○	○	○	○
1	○	○	○	○	○	○	○	○	○
2	○	○	○	○	○	○	○	○	○
3	○	○	○	○	○	○	○	○	○
4	○	○	○	○	○	○	○	○	○
5	○	○	○	○	○	○	○	○	○
6	○	○	○	○	○	○	○	○	○
7	○	○	○	○	○	○	○	○	○
8	○	○	○	○	○	○	○	○	○
9	○	○	○	○	○	○	○	○	○

	T	F						T	F						T	F				
	A	B	C	D	E	F		A	B	C	D	E	F		A	B	C	D	E	F
001	○	○	○	○	○	○	011	○	○	○	○	○	○	021	○	○	○	○	○	○
002	○	○	○	○	○	○	012	○	○	○	○	○	○	022	○	○	○	○	○	○
003	○	○	○	○	○	○	013	○	○	○	○	○	○	023	○	○	○	○	○	○
004	○	○	○	○	○	○	014	○	○	○	○	○	○	024	○	○	○	○	○	○
005	○	○	○	○	○	○	015	○	○	○	○	○	○	025	○	○	○	○	○	○
006	○	○	○	○	○	○	016	○	○	○	○	○	○	026	○	○	○	○	○	○
007	○	○	○	○	○	○	017	○	○	○	○	○	○	027	○	○	○	○	○	○
008	○	○	○	○	○	○	018	○	○	○	○	○	○	028	○	○	○	○	○	○
009	○	○	○	○	○	○	019	○	○	○	○	○	○	029	○	○	○	○	○	○
010	○	○	○	○	○	○	020	○	○	○	○	○	○	030	○	○	○	○	○	○

wlt 1.0.2

Rows 10

Cols 6

● Row Major
○ Column Major

Figure 4.7: HOMRConf: Generating a configuration for MarkSense

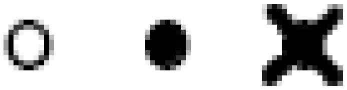


Figure 4.8: HOMR's Three Basic Shapes

a HOMR application like this takes around ten minutes.[5] It is strongly recommended that each HOMR form have a fair amount of blank space around each grid to avoid centering the grid incorrectly.

For those who are programming an application to process HOMR forms, we have decided to avoid the standard dynamically-linked library method in favor of a simpler approach. Dynamic linking would necessitate a significant effort in developing language-bindings for every high-level language used in processing. Instead, HOMR functions as a stand-alone executable. HOMR takes three parameters: the path to a configuration file like those generated by HOMRConf, a number of bubbles to extract, and a source image file. HOMR then processes the image according to the provided configuration, and returns a string of 0s and 1s to standard output. With this system, it is trivial to use HOMR from any language capable of making shell calls. Applications utilizing HOMR can ignore the complexity of computer vision and mark classification, and instead just work on processing the bits returned by HOMR into usable information. Although this is less efficient than a dynamically-linked version, the overhead in process invocation is extremely minor compared to the amount of time spent on image processing in HOMR, and the added simplicity of use is valuable.

For students, usage is much the same as with any other OMR system, with a couple exceptions. Since HOMR is not utilizing the resistivity of lead or graphite to determine filled/unfilled, students may use pencil or pen equivalently. Also, HOMR has been specif-

[5] On the other hand, generating the actual page layout can be arbitrarily complex.

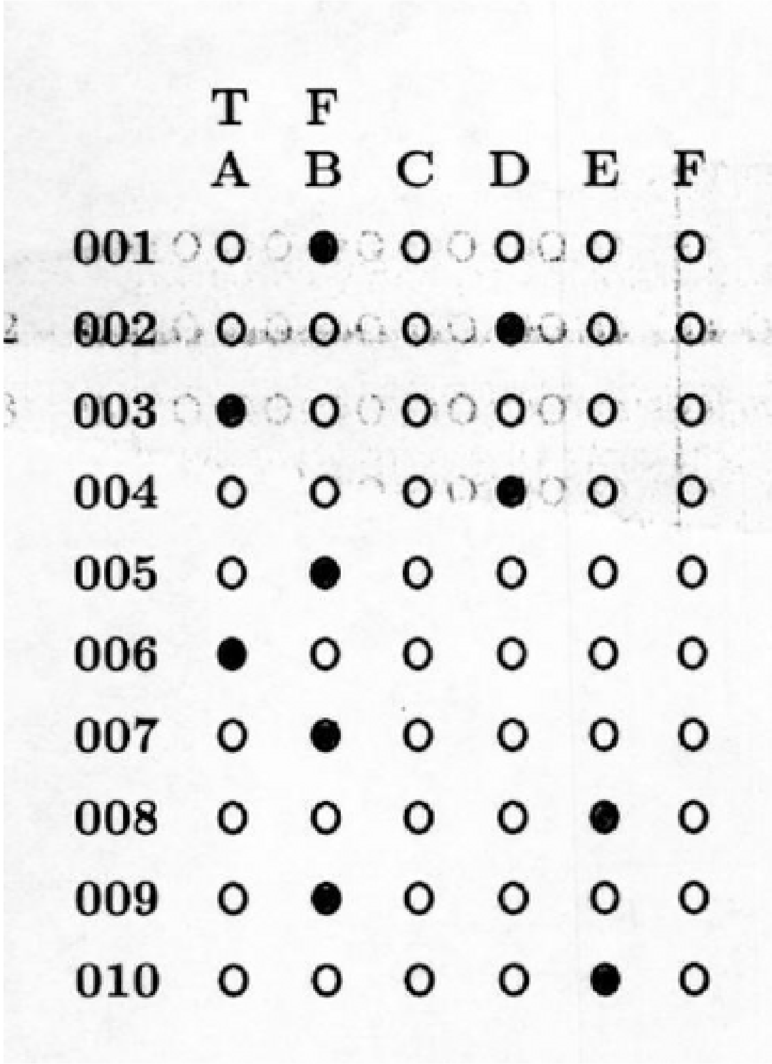
ically trained to identify three primary shapes: empty, filled, and filled-and-crossed-out (See Figure 4.2.3) rather than the common two.[6] Filled-and-crossed-out marks count as empty. Thus, it is generally better for students to cross out an incorrectly filled bubble than to use a messy eraser or white-out. Also, since HOMR allows size independence for the bubbles themselves, if the student changes their mind *again* after crossing a bubble out, they can simply make a larger filled bubble, although this level of complexity is generally not needed.

4.2.4 Testing & Evaluation

HOMR has been utilized on tens of thousands of student submissions, with few user complaints about accuracy. To get more precise accuracy statistics, HOMR was evaluated on hundreds of real-world student submissions. For evaluation purposes, we compared HOMR's results with a human grader's best guess as to the student's intended answer, rather than to whether or not a human would call a given bubble "filled."

We are currently using a testing dataset of 432 exams from three batches. One batch was pre-printed and the instructor spent two or three minutes explaining how to fill in bubbles correctly. Another was the first quiz in a course where students had to bring pre-printed forms. As a result, the printing quality for this quiz is particularly bad, and students ability to follow directions is particularly low. The final evaluation batch is the final quiz from that same course. Many of the same students are present, but now they have some experience using the system and generally make cleaner marks and better printouts. All told, these 432 submissions contain 74160 bubbles. On these three datasets we achieve accuracy of

[6] This was an instance of us "giving in" to student usage, since students inevitably crossed out accidental marks regardless of our threats to the contrary. As it turns out, specifically allowing crossed-out marks is easy to support, and makes everybody happy.



	T	F				
	A	B	C	D	E	F
001	○	●	○	○	○	○
002	○	○	○	●	○	○
003	●	○	○	○	○	○
004	○	○	○	●	○	○
005	○	●	○	○	○	○
006	●	○	○	○	○	○
007	○	●	○	○	○	○
008	○	○	○	○	●	○
009	○	●	○	○	○	○
010	○	○	○	○	●	○

Figure 4.9: A messy bubble grid that is processed perfectly.

.99995, .9996, and .9997. The (weighted) average accuracy is .99973, or about 270 errors per million bubbles. This is significantly more accurate than the U.S. Census, at .998.

However, this level of accuracy is not without a cost. That cost is processing time. On an AMD Athlon XP 2000+, HOMR takes approximately 17 seconds per page to process a full-resolution image. This is the setup for which we are providing accuracy numbers above. For situations in which it is unnecessary to have that much accuracy, or there is insufficient processing power, there is a simple solution. HOMR does not have strict requirements on the resolution of the input images. The images we use for our MarkSense application are 8.5×11 inch scanned pages at approximately 150 dpi, but HOMR is generally able to process the pages at as little as 90 dpi. The processing time is linear in the number of pixels, so dropping from 150 to 90 dpi gives a speedup of nearly a factor of three. Even with such a reduced input resolution, HOMR maintains a minimal accuracy of .999. Below 90 dpi, HOMR has an increasing rate of failure for correctly identifying the bounding box for the page, thus mis-interpreting entire scans. In practice, we do not recommend anything below 100 dpi.

4.2.5 Sample Application: MarkSense

The most obvious application for a system like HOMR is for OMR-based grading of multiple-choice tests. In our department, this application is known as MarkSense. HOMR evolved out of MarkSense as a generalization of shared code.

MarkSense requires two inputs to function: an answer key, and a PDF collection of the scanned pages to grade. Command line parameters allow the system to split on any number of pages per submission and to ignore specified pages.

MarkSense is more powerful than traditional OMR systems in several ways. First, the answer key format is far more expressive. A basic answer key is made up of a single letter a through f per line in a simple text file. However, MarkSense also allows for arbitrary combinations of bubbles for answers, a set of alternate answers, as well as different point scaling for different answers.

Most tests and quizzes in our department follow the normal paradigm of a single correct bubble. However, we do have instructors that prefer more complex systems. The most complicated system we regularly see when grading MarkSense quizzes and tests is as follows: each question is a “mark all that apply,” and for any subset of the correct answer, the student should get points proportional to the percentage of the correct answers they provided. Thus if the correct answer is “abd” and the student bubbled “ab”, the student should receive $2/3$ credit. However, if any incorrect bubble is marked, then the student gets no credit for this question. For a question like this, rather than simply listing “abd” in the answer key for that line, the answer key format is instead:

```
abd,ab=.66,ad=.66,bd=.66,a=.33,b=.33,d=.33
```

This is admittedly somewhat complicated, but this is likely the most complicated system any department is going to encounter. Again, more standard answer keys are just a single character per line.

Beyond the added expressiveness of a MarkSense answer key, MarkSense also supports automated exporting of results to a gradebook. Within our department, the majority of our gradebooks are stored in Gnumeric (Goldberg, 2006) spreadsheets. MarkSense looks in a text file mapping 9-digit student ID numbers (given out by the campus registrar) to student usernames, which can then be found in the course gradebook. Exporting of grades is thus completely automated with MarkSense. Beyond just exporting totals for each test or quiz, MarkSense also allows the creation of a new sheet in the spreadsheet with a single column for each question, and a row for each student. This way we can quickly get per-item student scores for doing more fine-grained processing of score data.

All in all, MarkSense has been a great success in our department. About one in three courses in our program use MarkSense at least once a quarter, with a nearly ubiquitous usage for classes of more than a hundred students. Students like it because it allows them to use pen or pencil, and simply cross out accidental bubbles, to say nothing of avoiding the cost of purchasing preprinted forms from the campus bookstore. Instructors like it for the flexibility and automation. Our administrators like it because it means that all MarkSense-based student quizzes and tests are scanned, and thus readily archived for accreditation.

4.2.6 Conclusions

We have developed a highly-configurable system for Optical Mark Recognition. Using HOMR, an instructor can easily generate surveys, tests, and quizzes utilizing OMR and process returned forms using an automatic scanner and standard PC. HOMR allows for OMR systems with much greater flexibility than traditional OMR systems. For instance, MarkSense, our first HOMR application, allows for much more complex grading rubrics for multiple-choice tests than is generally possible with traditional OMR systems. Additionally, using HOMR allows a completely-digital data path, eliminating the tedious (and error-prone) process of manually entering grades or survey results. Although it is highly configurable, HOMR also maintains an accuracy rate higher than the majority of OMR systems. Most importantly, it is freely available under an Open Source license.

Chapter 5

Data Archiving

Compared to collection or analysis, the archiving phase of an educational data mining project is certainly less critical. If collection is poorly planned or executed, important data may not be recorded. Improperly executed analysis may prevent pattern discovery, or worse, cause incorrect or spurious conclusions to be drawn from the data. Poorly executed archiving should at worst lead to wasted storage space, poor searchability, and inefficient lookup of the data. Given that the common data sizes in the EDM community are many orders of magnitude smaller than readily-available storage capacities or processor speeds, such flaws are hardly fatal. Well archived EDM data can make collection and analysis tasks easier and more efficient, but a poorly designed storage system will rarely lead to a total failure of the project, barring catastrophic data loss.

If we hold to the belief that useful and practical EDM projects must minimize human interaction, the benefits of a well-designed storage system become clear. Just as collection tools must be built to work with the user and minimize the complexity in recording sufficient data to be useful in an EDM project, archiving can make or break the *adoption* of the system, a different problem than the technical completeness of the system.

For most EDM projects, the most obvious method of performing archiving is the now-ubiquitous SQL database. Although not all ITSes are deployed in a networked environment, the proportion of ITS installations that do not have access to the Internet is shrinking as network access becomes ubiquitous in public schools across the country. With off-the-shelf interfaces into a relational database, there is relatively little complexity in the use of a database as the storage system for ITS data.

The Marmoset project from the University of Maryland is another example of EDM storage in a relational database (Spacco et al., 2005). Marmoset archives code snapshots as students develop programs in Java, along with regular results of unit tests applied to those snapshots. Utilizing JUnit (Patterson et al., 2003) allows the unit tests to be applied to individual methods in the assigned Java classes, which allows for very fine-grained testing and evaluation. For easy numeric EDM analysis, these matrices of unit test results are far more interesting than the code snapshots, although this code itself may eventually prove to be a rich data source. According to Spacco, one of the primary researchers on Marmoset, their database has hundreds of thousands of snapshots, along with the pass/fail results for about ten unit tests applied to each of those snapshots. Each programming assignment, and the associated unit tests, generates a different matrix of test results, making these score matrices on the order of hundreds or thousands of snapshots by ten unit tests. A project of this scope obviously requires database support, and gains much from the well-developed query capability and rich user tools associated with modern databases.

Not all EDM data sources can leverage a database. Both the general form of ITS and the Marmoset project collect data as a side effect of the interface provided to the user. The program assessment project presented in this dissertation, on the other hand, specifically must support incremental adoption and instructors who are unwilling to adopt collection tools like Agar or HOMR. In order to support these kinds of users, we rely on a simpler tool that most instructors are already familiar to our users: the spreadsheet. This provides much greater robustness and flexibility.

5.0.7 Gradebook Format

In order to facilitate the reporting of scores, we determined early on that it was critical to make adoption as simple as possible. This is reflected not only in our choice of the spreadsheet as the grade reporting mechanism of choice, but also in our loose requirements for formatting of that data.

The format requirements for a spreadsheet in gradebook format to be correctly parsed by our analysis tools are as follows.

- *Summary sheet* - We require one page of the gradebook to be named “Summary”, and to contain at least the following columns:
  - *ID Column* - One column must be named “sid”, “username”, “login”, or “email” and contain a unique identifier for the students in that row, either their student ID or their username on our departmental systems.
  - *Course Grade* - One column must be named “Course Grade” and contain the letter grades assigned to each student.
  - *Course Score* - One column must be named “Course Score” and contain the numeric score each student earned in the course.
- *Instrument sheets* - At least one sheet must contain per-item data. There may be sheets other than Summary and the Instrument sheets. Instrument sheets are identified by having the following:

  - *ID Column* - One column named “sid”, “username”, “login”, or “email”, which can be mapped to the roster of students on the Summary sheet.
  - *Relevance data* - Instructors *may* provide the relevance matrix *R* for the questions listed on this sheet by adding extra (non-student) rows with “objective1”, “objective2” . . . “objective*N*” in the ID column and relevance entries in the appropriate rows.

Instructors are allowed to provide gradebook spreadsheets in either the standard Microsoft Excel format, or the XML-based format for the open-source Gnumeric spreadsheet package, as well as some lesser-known formats. Script-based extraction and conversion to standard forms is done by converting to Gnumeric with the Gnumeric utility *ssconvert*. The Gnumeric format is merely compressed XML, allowing for rapid development of reusable tools for manipulating spreadsheet data. By providing loose requirements for instructors to record grades, we have greatly expanded the adoption of our system. We have also encouraged the submission of gradebooks by causing our departmentally-approved grade publishing interface to automatically archive the gradebook storing the grades.

5.0.8 GnumeriPy

After gradebooks are submitted and converted into a standard format, it is important to develop software methods to allow for easy programmatic manipulation of the data. With an database interface, this would be SQL. Although the development of an SQL interface for a spreadsheet backend is an interesting possibility, this was thought to be too much effort for too little reward. Instead, the functionality that was developed is a Python class called *GnumeriPy*.

GnumeriPy operates on spreadsheets and provides the a set of common features expected for such a tool: saving and loading, exporting a sheet as a CSV flat-file, and basic data manipulation. GnumeriPy does not parse the full Gnumeric formula syntax, but rather gives users two modes of interacting with each sheet: raw or frozen. In raw mode, formula cells are stored with the full text string for the formula. This may be edited and re-stored, but is essentially just a text string. Altering other cells, inserting or deleting rows and columns, and other spreadsheet operations that could affect the definition of a formula are ignored. While this provides rather limited functionality, the intended purpose of raw mode is to work around the formulas or insert new ones. For all the applications in this dissertation, this has been sufficient functionality. Most collection tools are merely exporting grades into existing gradebooks, and thus utilize raw mode, which is sufficient to know when there are collisions in a cell and prompt for permission to overwrite.

In frozen mode, which can be applied to a single sheet at a time or to the entire spreadsheet, GnumeriPy invokes *ssconvert* to convert sheets to CSV, effectively evaluating all of the formulas and providing their results. This is primarily utilized by analysis tools when converting the gradebook into a suitable format for processing as the score matrix S.

The archiving system developed here, encompassing both our loosely-structured gradebook format and the GnumeriPy class for gradebook manipulation, demonstrates the possibility of developing quality archiving systems for EDM projects, even when use of a database is infeasible.

Chapter 6

EDM Analysis Notation and Data

Given our data in spreadsheet format, we can extract course matrices for each gradebook supplied by participating instructors. These gradebooks can be filled in by HOMR, Agar, or manually, allowing greater flexibility than is found in many academic development projects. Once provided with the score matrices, the question is, "What assessment information can be extracted from the score matrix for this course?" The next four chapters will address EDM analysis techniques developed to answer this question. As these chapters are all experimenting on the same datasets, it is useful to first describe these commonalities.

6.1 Notation

The EDM analysis experiments presented in this dissertation are take as input the *score matrix* S. Recall that S is an $m \times n$ matrix recording the scores of m students on n questions. As part of our program assessment project, we are also concerned with generating R, the *relevance matrix*. R is an $n \times t$ matrix encoding the relevance of the n questions to each of t topics. Each entry in R should be in the range $[0,1]$.

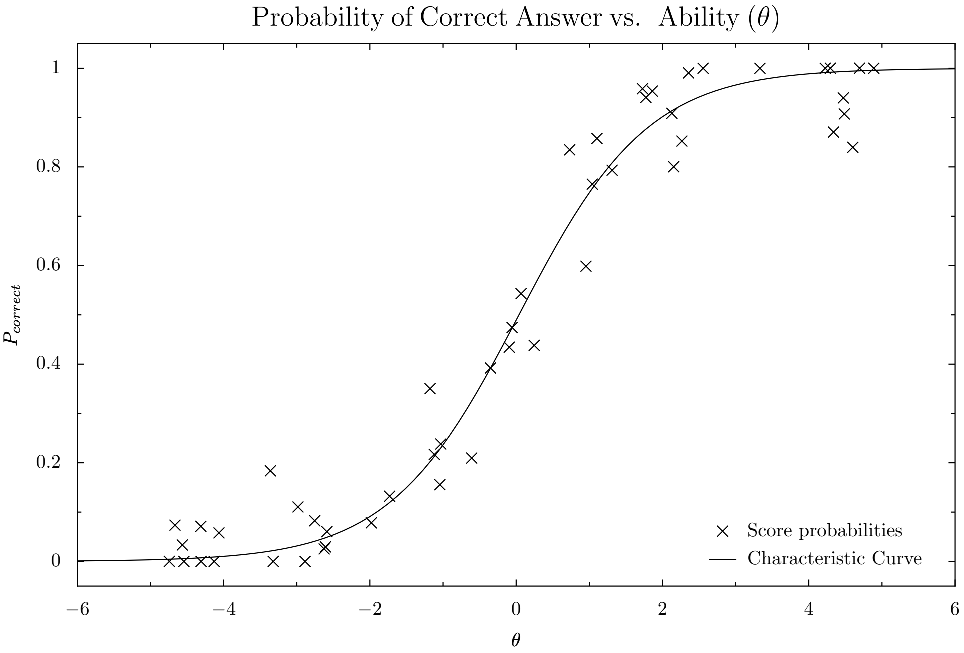


Figure 6.1: Sample IRT Graph

Some of the experiments presented here also involve statistics inspired by Item Response Theory (IRT). In standard IRT the probability of a student with ability θ answering a question correctly is given by

$$P(\theta) = 1/(1 + e^{\alpha(\theta-\beta)}) \tag{6.1}$$

Recall then that β governs the ability level that best splits the students that should answer incorrectly from those that should answer correctly. The parameter α is the *discrimination* parameter, governing the accuracy with which β splits the two groups: a perfect α means that all students with $\beta < \theta$ will answer incorrectly, and vice-versa. A hypothetical sample plot of θ vs. P is shown in Figure 6.1. Points in this plot are estimates of the probability a question will be answered correctly by students with the given ability level θ.

DATA SET	COURSE	m	n	QUESTION TYPES	SCORES
008	INTRO COMPUTING	269	80	MC	BINARY
010	CS 1	190	68	MC	BINARY
141	ALGORITHMS	19	15	FR	PC
153	O. S.	66	34	MC,FR	BINARY,PC
164	NETWORKS	23	72	MC,FR	BINARY,PC

Table 6.1: Descriptions of course datasets. MC indicates multiple choice questions, FR indicates free-response questions subjectively graded, PC indicates partial-credit.

6.2 Data Sets

Each of the datasets evaluated in this dissertation has two components: the score matrix S, and a collection of human-generated sets identifying which of the questions (columns of S) can be viewed as testing the same topic. We currently have two sources for datasets: real course data collected with Agar and HOMR, and an online quiz system.

6.2.1 Course Data

The primary data that we are concerned with are datasets coming from real courses. Over the past several terms we have recorded detailed score information for a number of courses across our curriculum, ranging from large non-major service courses to upper division electives. In total we have five courses represented, detailed in Table 6.1.

For each of these courses, we have asked the instructor of the course, along with any other regular teachers of the course, to provide us with a set of question groups they would considered correctly grouped. To do this they are provided the text of the questions, but not the scores. They were allowed to place each question in as many groups as they choose. This could be none if they felt the question is not connected to any other questions in the course, or more than one group if they felt that a question relates to more than one topic.

DATA SET	SOURCE	m	n	QUESTION TYPES	SCORES
TRIVIA	TRIVIAL PURSUIT	467	40	FR	BINARY
ACADEMIC	SAT SUBJECT TEST	267	40	FR	BINARY

Table 6.2: Descriptions of baseline datasets. FR indicates free-response questions subjectively graded.

For the 141, 153, and 164 datasets we also have a numeric course score for the student over the entire course. This encodes extra information about the student's performance in the course since programming assignments, participation and other non-proctored score information was not included in the score matrix. This course score is viewed as a final scalar estimate of the student's ability in the course. For the other datasets this is simply calculated as an unweighted average of the scores in S.

6.2.2 Online Quiz Data

Several of the analysis experiments in this dissertation rely on the presence of the topic information provided by instructors. However, as it is unknown whether the score matrices for actual courses really contain topic information, we felt it prudent to develop datasets with clear dependence on topic. To this end we built two datasets, one derived from trivia questions from the popular game Trivial Pursuit (Trivial Pursuit, 2006), and one derived from questions from study guides for SAT Subject Tests (SAT Subject Tests, 2006). Both quizzes are forty questions drawn from four topics, with ten questions in each topic.

The trivia quiz draws questions from Sports and Leisure, Science and Nature, Arts and Entertainment, and Literature. These topics were chosen from the six categories in Trivial Pursuit because they were felt to be the most independent from one another. The questions were drawn from the 20th Anniversary edition of Trivial Pursuit, which focuses primarily on the 1980s and 1990s. As our target audience for the quiz was college students, we felt this was more likely to result in correct answers than questions from other editions. Additionally, we chose only questions that had short one or two word answers, as the online quiz system we developed is a free response system and we wanted to minimize issues stemming from poor spelling.

The academic quiz draws questions from published study guides for the SAT Subject Tests. The SAT Subject Tests are taken by students in their final year of high school, and are used to demonstrate to colleges the depth of knowledge that a student has attained in particular areas. There are over twenty test subjects available. Again we chose four subjects that we felt were maximally independent: Math, French, Biology, and World History.

Our assumption was that the trivia quiz could function as a baseline for topic extraction on data with little or no actual correlation within each topic. Examining the trivia questions, it is clear that they are indeed trivia: answering any given question correctly is a matter of isolated fact retrieval, and not a test of any deeper knowledge or skill. As such, even though there is an obvious “correct” answer when grouping these questions, we did not expect to be able to extract that answer with any of our candidate algorithms.

The academic quiz represents the opposite end of the spectrum: the questions that were included come from subjects that are generally studied for at least one academic year in high school, and possibly several more in college. The questions require a fair depth of knowledge, and are more topically connected than the trivia questions. Our expectation was that any algorithm that can succeed in topic clustering will have at least partial success on this dataset.

The quizzes were administered online over the course of about a week. The trivia quiz was completed by 467 different visitors, the academic quiz was completed by 267. Correct answers were immediately reported to the test taker, incorrect answers were reported only as “probably” incorrect. The full text input for any incorrect answers was recorded, allowing for post-testing processing and correction for unexpected formatting or spelling. This allowed us to focus on whether the student knew the answer. The two datasets are summarized in Table 6.2.

Chapter 7

Question Evaluation

This chapter introduces an assessment mechanism suitable for driving low-level feedback loops. This answers the questions, “How difficult was question X?” and, “How much do scores on this question really tell me about what students know?” It can identify questions that are unintentionally misleading or ambiguous. It produces numeric estimates of the difficulty and discrimination of a given question, on a known scale for easy comparison. Most importantly, it is instructor agnostic: this method in no way compares an instructor’s questions against some theoretical perfect question or a perfect instructor. Questions are assessed relative to the instructor’s teaching style. Under certain assumptions, we can also show that these estimates are relatively stable across semesters, allowing more accurate tests to be generated from banks of existing questions.

7.1 Good Questions

Given *S* and the vector of course scores, we can easily evaluate which questions are correlated (in the colloquial sense) with high ability in the course, and estimate the difficulty of each question. We can then begin to learn which types of questions are most meaningful (have a high α) and which are not. This refinement of questions is based entirely on how a course is managed, allowing an instructor to know how good a question is with respect to what the instructor is assessing. Questions that are perfect for one instructor may not be perfect for another, although it is hoped they are strongly correlated.

The other IRT statistic for each question is β, the difficulty. Knowing β for each question can grant some insight into what the students are really understanding. If β seems too high after evaluating a question, it indicates that the topic is not well understood by the students. Generally, one can assume that a question with a high α and a β in the useful range (the range of course scores that would pass the course) is a "good question."

7.1.1 Calculating α and β

To see how calculating difficulty and discrimination parameters can be done easily, let us first assume β is known for each question. It is then possible to find the empirical discrimination α for a question by quantifying how well that β separates students that got the question right from those that got it wrong.

There are a number of ways of calculating α, and in general they give similar results in most cases. We have evaluated complex techniques like entropy-based measures, but in general the simplest technique provides similar results to the more complex techniques. Our preferred estimate of α is the fraction of scores that would be guessed correctly under the assumption that every student with ability under β got the question wrong and every other student got it right. For non-binary questions this won't predict scores correctly, but does provide an estimate of how well this model matches the data (Figure 7.1).

If it really is the case that β is a perfect split point, then α will be 1, a perfect score. If correct and incorrect scores are evenly distributed on both sides of β then α will be .5, and

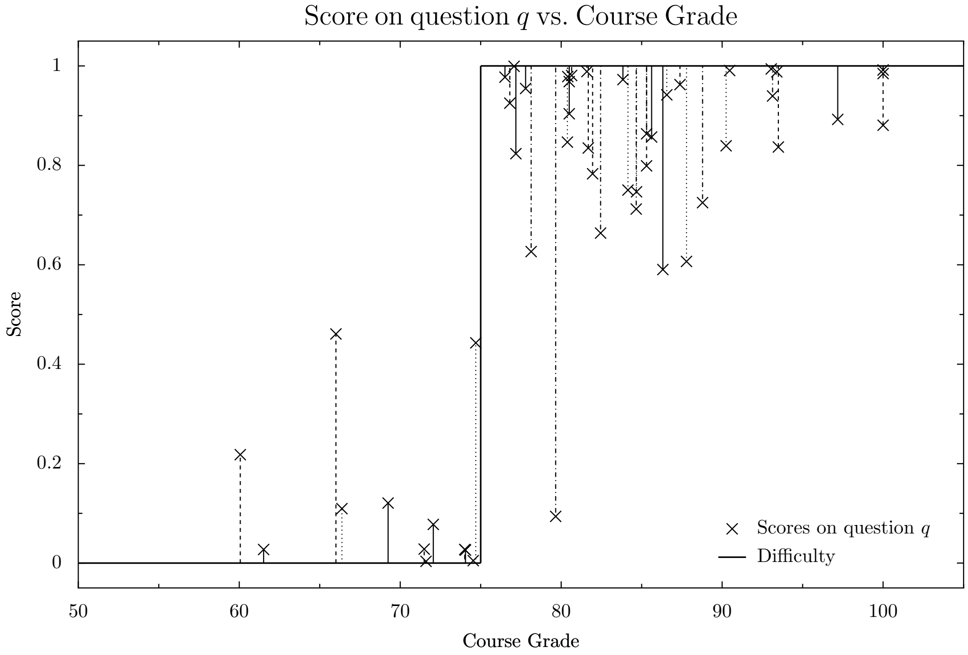


Figure 7.1: Question Evaluation Example

if somehow the question were completely backward (only students with ability less than β answered correctly) this results in a score of 0.

Nearly any similarity measure developed for "decision tree" algorithms from supervised learning can be used or adapted to provide an α value, since the primary requirement is to identify how well a split at β partitions the scores into two homogeneous groups. Interested readers are invited to peruse the decision tree literature to find other techniques for calculating α given a split point β (Quinlan, 1986).

Given an ability to produce α given the question scores, ability scores (course scores), and β, it is now straightforward to find the actual β. The best estimate of β is the value of β that maximizes α. Since α depends only on which scores were guessed correctly, it is sufficient to only loop through each distinct course score and evaluate on those split points, avoiding any gradient optimization methods.

7.1.2 Assumptions

In order for the above method to be usable, several assumptions must be made. First of all, we are assuming that the question is valid, that is, it has some relevance to the general topic of the course. Additionally, since nobody can track the true ability level of the students, the use of course scores is only an estimate. If those scores are highly uncertain (at the beginning of the course) or have nothing to do with the question, then this is not a valid assumption. Using course scores implies that each course is a single proficiency. This is clearly not usually true, but for any course that this is a particularly bad assumption (for example, a course composed of two half-courses on different topics), it is allowable to use the scores from only the appropriate portion of the course. It would be ideal to automatically extract topic information from the score data and track student proficiencies on a fine-grained level (e.g. ability with linked lists, rather than score in the Data Structures course), but this remains an area of future work.

The estimates of both parameters rely heavily on the distribution of the course scores. Student grades fluctuate significantly at the beginning of the course before the law of large numbers begins to stabilize each student's grade toward its final value. Therefore, the values of α and β are going to be most accurate at the end of the course, and a final evaluation of which questions are worth keeping for next semester is best done after the course has completed. It is useful to evaluate questions immediately after grading the instrument, especially to find topics that were tested but not fully understood, but such evaluations should be recognized as less-accurate estimates.

Independence of scores is also a concern. If the estimate of ability (course score) includes the score on the given question, then by definition there is some correlation between the two. To get the best estimates of α and β, it is best to provide ability estimates that do not include the score on that question or instrument. In practice, if each individual question has a very small effect on the total grade, then this effect is negligible and few questions need to be evaluated separately.

Finally, it should be pointed out that the course grade may not take into account the discrimination of each question while the course is in progress. If course scores are adjusted to de-emphasize low-discrimination questions and over-emphasize high-discrimination questions, then this will make it difficult for anyone to change their overall course standing. If scores are re-weighted based on discrimination, then a student that initially performed poorly and studied extra hard would decrease the discrimination on those questions that they answered correctly due to extra study. A similar argument can be made for good students performing poorly at the end of the term. This is a technique for assessing questions, and the intent is for this to be utilized to make instructors more aware of the questions they are asking. If this is used to adjust scores, especially *as the course progresses*, early course grades become more difficult to overcome for students that get off on the wrong foot. As such, this may be used to perform an initial immediate assessment of the difficulty of the questions to test for student understanding, but low-discrimination questions should not be dropped or de-emphasized, and the initial β values are to be considered an estimate. Evaluation between offerings will yield more accurate and meaningful statistics.

7.2 Results

This technique was used extensively during Summer 2004 in Introduction to Data Structures and Algorithms, where it provided very useful feedback to the instructor in question evaluation. Some of the intuitive insights it confirmed included:

- Do not test on specifics from the text: Questions that test not the subject, but merely a particular presentation of the subject have little assessment value if that presentation is not a major component of the lecture. Some instructors may choose to explicitly test this material to encourage students to do the required reading, but that was not this instructor's goal. This was demonstrated by a consistently low α for all questions testing textbook minutiae rather than the more fundamental concepts.

- Do not test things mentioned in passing: While some may feel that mentioning something once or twice during lecture is sufficient for the "good" students, this appears not to be the case. Iterators were discussed as an aside for 10–15 minutes the day before Quiz 1. This was not nearly enough for even the good students to pick up the concept. Although 47% of the class answered this question correctly, it is likely because they narrowed it down to 2 or 3 choices and guessed rather than knowing the answer, since this question had discrimination of 0.59, implying nearly zero correlation with general course performance.

The most useful feedback this technique provided was in finding questions with unexpectedly high difficulties. The most striking example was for the question, "What is the worst-case time to find an element in a binary search tree of *n* nodes?" While there is a mild "trick" in recognizing that a binary search tree is not necessarily balanced, it was surprising to find that the difficulty score for this question was 87% (with a high α), meaning that it did a better job of differentiating A's from B's than anything else. This was certainly not intended to be a question splitting the A's from the B's. The fact that it was found to be quite difficult indicated that this aspect of binary search trees was a topic that needed additional coverage. Since the quiz was graded and evaluated the same day it was issued, the lesson plan for the next day was altered to account for the fact that the class had missed this important concept.

Question	Course	β	α
What is the result of NOT(1000 AND (1100 OR 0101))	CO	67%	.81
How many values can be represented by a 4 byte binary word?	CO	95%	.81
Mergesort cannot be used efficiently in place (T/F)	CS2	76%	.78
What is the representation of -1 in 4 bit 1's complement?	CO	77%	.77
Quicksort has a worst case running time of $O(n \log n)$	CS2	80%	.72
AND and OR are two binary logic operators. How many binary operators can be defined?	CO	85%	.72
The following code will do what?	CS1	93%	.71

Table 7.1: Sample Difficulty and Discrimination Values for Good Questions. (CO = Computer Organization)

This technique can provide immediate feedback in two important ways. First, it allows instructors to determine which questions are good questions and can be used to train instructors not to ask overly vague questions. Second, and more importantly, it can provide concise feedback on what students are actually understanding and what they are only guessing. In this way, topics that were confusingly or incompletely covered can be immediately brought to the instructor's attention and remedied as quickly as possible. Both of these seem to be valuable tools in the effort to increase educational effectiveness.

Table 7.1 provides empirical difficulty and discrimination values for several "good" questions, and Table 7.2 provides the same for some questions that are particularly bad. Note that for the "bad" questions it is often the case that the question was poorly worded or ambiguous in some way, or is a trick question. This matches our intuitive concept of discrimination perfectly: for questions that are subtle or textually confusing, the odds of a good student getting it wrong are much higher than they would be otherwise.

Question	Course	β	α
All return statements must return a value (T/F)	CS1	94%	.54
What is the result of 20.0%8 in C++?	CS1	97%	.55
Thrashing may not occur on a system with a two-level scheduling policy.	OS	100.6%	.58
Which of these may block? (printf, strlen, malloc, free, getpid)	OS	90%	.61
If *Foo* a* and *Bar* b* are pointers to objects allocated in shared-memory space, and process *A* accesses *a* while process *B* accesses *b* without using mutual exclusion, there will be memory corruption (T/F)	OS	77.5%	.67

Table 7.2: Sample Difficulty and Discrimination Values for Bad Questions

7.2.1 Cross-Semester Consistency

This technique also allows databanks of questions to be assembled along with an estimate of the difficulty associated with those questions. There are a few caveats here: the difficulties are likely very dependent on instructor, are obviously dependent on course, and are hopefully dependent on what time during the course the question was asked. For example, if one instructor uses a question on a quiz early in the semester in one semester and on the final exam in the next semester, it is hopefully the case that the students will have solidified the skills necessary to answer that question, so the empirical difficulty will decrease. (This is a deviation from IRT, where question parameters are absolute but student abilities are generally increasing throughout the term.)

To demonstrate the validity of this statement, we have identified 20 questions that were repeated between Fall 2004 and Winter 2005. Of these, nearly half were dramatically too easy, with difficulty levels in the D− range or lower (in this range, without enormous class sizes, the density of student scores is too low for predictions to be precise). After ignoring anything with a difficulty less than 65%, we are left with 12 questions ranging from difficulties of 66% to 95%. On average the difference between difficulties between semesters is 5%, with a standard deviation of 4%, meaning that more than 2/3 of the time, a repeated question will have a difficulty within one letter grade when used under similar circumstances.

7.3 Question Evaluation Conclusions

Every student attempt on every question is fundamentally testing two things: the ability of the student at that point in time, and the quality of the question. In normal teaching, we evaluate students continuously, and with the aid of the techniques presented here we can begin to evaluate the questions as well. Evaluating educational effectiveness is an important concept in current accreditation practices, and we expect that importance to grow in years to come. The techniques presented in this section provide a simple method to close the loop on the lowest level of a course feedback process by reinforcing which questions are most meaningful. Building a catalog of good questions with known difficulties now becomes an easy task for an instructor. Given the ability to estimate with confidence ahead of time how difficult a give question is, it is easier to build tests that more accurately assess the students. Most importantly, a quick analysis of the scores right after administering an exam can yield immediate feedback to the instructor regarding what topics are being misunderstood, allowing for quick alterations to the lesson plan to fix misconceptions before they get out of control. Continuously improving the quality of questions with these techniques is a low-effort, high-reward strategy that can help all of us.

Chapter 8

Predicting Missing Scores

The term Educational Data Mining (EDM) is a bit of a misnomer. In more traditional fields associated with data mining, like the research published at SIGKDD, the volume of data present is of such a volume that the running time of the algorithms in question is of primary concern. Many algorithms presented in the data mining literature are fast approximations to common machine-learning techniques like SVD or ICA, techniques that would be difficult or impossible to apply to the volume of data commonly found in the data mining community. In Educational Data Mining, data volume is generally far lower. EDM researchers are more likely to have too little data, rather than too much. This is especially true in research where the data comes from sources other than intelligent tutoring systems (ITSs), which typically provide data sizes of hundreds or thousands of students on dozens of problems. In contrast, a typical score matrix for a college-level course involves students from an average-size class and fewer than 100 questions.

As these smaller datasets become common in EDM research, it will become increasingly important to have complete data in the score matrix. If the score matrix is being recorded as the scores for each student on each homework or test question across an entire course, then student absences and failure to complete assignments will lead to missing entries in the matrix. Assuming blank entries are zero grossly underestimates student ability, confusing lack of completion with lack of knowledge. Missing entries are therefore problematic. Many, if not most, of the algorithms that are being tested in the EDM community require full data. The options in such cases are few: either discard the scores for every student that has at least one missing score, or develop techniques to fill in the missing entries in the score matrix.

Even in the ITS scenario, score prediction may be a useful practice. Not all students utilizing a given ITS will necessarily attempt each of the possible questions. In general, the score matrices from an ITS are likely to be quite sparse, perhaps too sparse for prediction to be feasible. However, given sufficient density of scores in the score matrix, prediction may usefully fill in the blank spots.

8.1 Prediction Techniques

In this idealized score prediction experiment we are given a score matrix with a single missing entry. From the list of valid scores for this question (which we take to be the set of values seen in this column), we want to predict the missing entry. There are a number of techniques, ranging from obvious to relatively complex, that are suitable for this problem. Below are the prediction techniques that were evaluated in this experiment.

8.1.1 Matrix Average (Avg)

The simplest and most naïve technique for score prediction is to calculate the average of the entire matrix and predict each missing score to be the candidate value closest to that average. For binary score matrices, this will predict all missing entries identically as 0 or

1, depending on the overall average score. This is entirely unsuitable as a real solution for this problem, but is presented as a strawman: this is the level of predictive performance that can be attained with essentially zero effort.

8.1.2 Student Average (RowAvg)

A slightly more meaningful technique is to calculate the average score for the *student* and choose the score that is closest to that average. This assumes that a student's performance is relatively constant across questions, and that the ability of the student is more important than the difficulty of the question.

8.1.3 Question Average (ColAvg)

The converse of the RowAvg technique is to calculate the average score for all students on this question and predict the value closest to that value. This implies that question difficulty is more important than student ability, an implication shared with the model for CFA.

8.1.4 Student & Question Average (RowColAvg)

Assigning preference to either student ability or question difficulty seems fairly arbitrary in the face of exceptional students or exceptional questions. Calculating both the student average and the question average and averaging those values to select a value for prediction provides an easy compromise.

8.1.5 Difficulty & Discrimination (DD)

Utilizing the question evaluation technique from the previous chapter, we can extract the difficulty β for the question using average scores in the matrix as the estimate of overall ability. Note that even for the datasets where an instructor-generated final course score is present, we are using only the average from the scores in S due to the possibility of topic information discussed below. Given θ as the average of this student on the other questions, we predict 0 if the student has $\theta < \beta$ and 0 otherwise.

One significant problem with this approach is that it is only suitable for binary questions, as it is non-obvious how to expand this to pick from the full list of candidate values.

8.1.6 Conditional Probability (CondProb)

Another method for prediction is to examine the conditional probabilities for each outcome score based on the known scores in this row or column. For complexity reasons, we can't do a full conditional probability based on the joint distribution of scores on the other questions. However, by looking at the individual distributions of scores on the unknown question given the scores on each of the other questions independently, we can still make useful predictions based on estimated conditional probabilities.

More formally: let x be the score in question, and Y be the vector $y_1, y_2, \ldots y_n$, this student's scores on the other n questions. Given the number of students that we anticipate, it is not feasible to estimate $P(x|Y)$, since the number of possibilities for Y are an exponential function of n. However, it is reasonable to estimate $P(x|y_i)$ for each i in $1 \ldots n$, and base our prediction on those distributions. Experimentally, the best prediction given the collection of distributions is given by finding the most-often predicted value, which corresponds to the selecting the maximum likelihood outcome from the *sum* of the distributions rather than the more mathematically-grounded product of the distributions. This may be due to the chances of not seeing a particular x, y pairing, and thus incorrectly estimating one probability as 0, causing an otherwise good prediction to be ignored completely. This seems likely given the particularly low performance on smaller datasets. Results for the additive model are presented as CondProb$+$, and results for the more easily justified multiplicative model are presented as CondProb$\times$

8.1.7 Noisy OR (N-OR)

A possible explanation for the odd success of the "additive" probability model in the CondProb algorithm is the "noisy or" model. The N-OR model assumes the probability that a given score will be correct (set to 1) is related to whether *any* conditional probability feature predicts that it will be correct. The formal model for this is:

$$p(x = 1) = 1 - \Pi_i(1 - p(x|y_i)) \tag{8.1}$$

Like the DD algorithm, this only predicts 0 or 1 — specifically it predicts 0 if $p(x = 1) < 0.5$, otherwise it predicts 1.

8.1.8 AdaBoost

We have also evaluated the AdaBoost algorithm of Freund and Schapire (Freund and Shapire, 1997) using a decision stump[1] as the base classifier. AdaBoost works by training a collection of weaker base classifiers on a weighted representation of the training data. In each round, the training examples that are correctly classified are given reduced weight, and the remaining examples are given greater weight. The collection of weak classifiers vote for the correct overall classification, with each classifier given voting weight related to the accuracy of that weak classifier. After summing the weighted votes, the prediction with the highest vote is the predicted output.

[1] A single-question decision tree

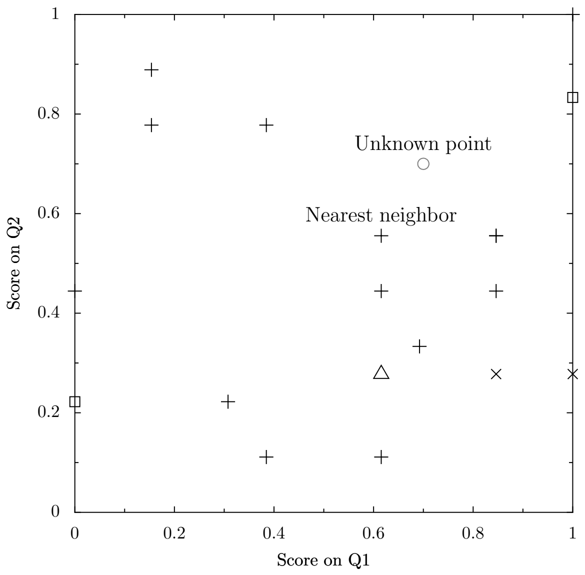


Figure 8.1: Nearest Neighbor Classification Example

8.1.9 Nearest Neighbor (NN)

Nearest neighbor is a quick-and-easy, but respected, technique for classification or prediction. Nearest neighbor stores the data points for which the correct classification is known, and finds the closest known point, under a particular distance metric, to the point to be classified. In this application we use the missing column as the labels, and the rows without missing entries are used as the known classifiers. The non-missing elements of the prediction row are used to calculate the Euclidean distance to each of the classifiers, and the label of the nearest classifier is used as the prediction. Figure 8.1 shows an example from the CS 141 dataset, reduced to only two classification dimensions for simplicity.

8.1.10 Topic Information

A final issue to be evaluated in our experiment is the extent to which "topic" information can boost the predictive ability of the various techniques described above. The questions in these datasets have all been grouped by topic, either by human evaluators in the case of the course data or by virtue of knowing which subjects the questions were drawn from in the case of the online quiz data. In order to evaluate the extent to which the topic information allows better prediction, we have also broken each dataset into a collection of (possibly overlapping) subsets, where every question in a subset is claimed to be testing the same topic. As some questions may test more than one topic, some questions may appear in multiple subsets, and thus results on the ColAvg technique vary slightly because of the overlap, even though ColAvg has no dependence on information in a different row.

Question Type	MC		MC & FR		FR			
Predictor	008	010	153	164	141	SAT	Trivia	AVG
N-OR	77.37	65.14	53.97	68.51	77.35	42.77	21.17	58.04
RowAvg	77.71	66.67	54.28	**74.71**	65.69	62.57	81.03	68.95
Avg	77.37	65.14	55.62	70.75	74.41	59.68	80.93	69.13
NN	74.42	67.67	61.86	68.62	79.71	74.85	79.42	72.36
RowColAvg	78.49	69.58	63.58	70.15	78.05	67.06	81.06	72.57
CondProb×	78.30	70.64	70.04	60.27	69.59	75.68	83.53	72.72
ColAvg	78.25	68.96	**71.87**	74.21	79.97	72.21	82.96	75.49
AdaBoost	77.60	70.74	68.96	72.81	76.74	80.31	84.15	75.90
CondProb+	77.97	69.59	70.52	71.03	**85.54**	75.48	81.33	75.92
DD	**80.25**	**74.19**	70.54	71.84	75.90	**80.01**	**84.91**	**76.81**

Table 8.1: Percentage accuracy in prediction without topic information for the proposed predictors. The maximum entries of each column are presented in **bold**.

We have evaluated each method presented in Section 8.1 against all seven score matrices using leave-one-out cross-validation. This requires hiding each value in the matrix in turn, building the necessary predictive model on the remaining data, and predicting the single missing entry. Each question was scaled to be in 0..1 before processing, so we present L_1 norm (absolute value) error to emphasize the small errors in prediction.[2] Results for

[2] Of course, use of absolute value rather than squared error only matters for questions with non-binary scoring.

Question Type	MC		MC & FR		FR			
Predictor	008	010	153	164	141	SAT	Trivia	AVG
N-OR	78.41	65.19	59.47	69.19	65.93	53.09	55.07	63.76
RowAvg	76.30	62.52	54.28	66.37	74.66	70.81	79.86	69.26
NN	73.71	64.83	64.48	70.48	72.78	73.90	73.90	71.02
Avg	78.41	65.03	61.16	72.66	75.82	65.59	80.93	71.37
RowColAvg	77.00	64.91	63.67	71.73	77.37	71.37	81.22	72.47
CondProb×	79.67	70.46	70.99	67.19	67.66	78.59	83.54	74.01
ColAvg	79.45	69.51	71.63	75.21	77.17	72.21	82.96	75.45
AdaBoost	79.70	71.33	69.77	74.92	72.99	80.57	83.70	76.12
DD	**82.29**	73.34	72.48	75.12	73.34	**82.93**	**84.86**	78.02
CondProb+	80.97	**77.94**	**89.56**	**84.99**	**95.83**	80.77	83.59	**84.81**

Table 8.2: Prediction accuracy with topic information

prediction without topic information are presented in Table 8.1, and results for prediction with topic information are presented in Table 8.2.

In general, two methods stand out in this analysis. For datasets that have not been pre-split into questions related by topic, the IRT-inspired DD method performs well, and outperforms any other method investigated on binary data. For datasets that have been reduced into questions related by topic, our CondProb+ algorithm significantly outperforms any other method, and does particularly well on non-binary data. The performance on partial-credit data makes good intuitive sense, since having a larger number of distinct values on which to condition the distributions should increase the ability of the CondProb+ technique to differentiate ability levels.

However, it is worth noting that on prediction across multiple topics (that is, when the score matrix contains questions drawn from more than one topic), the simple ColAvg predictor performs nearly as well as either the DD method or the conditional classifier. For the datasets evaluated, the average performance of ColAvg is only 1.3% worse than the DD method, and within 0.5% of the performance of the conditional classifier. That is, when scores are representing multiple topics, predicting *without looking at the scores for other questions* is very nearly as accurate as attempting to build a model to take into account the full score matrix. The issue of partitioning questions into topic based on the score matrix is investigated in the next two chapters.

It is also quite interesting that the RowAvg predictor often performs even worse than predicting based on the overall matrix average, and in almost every experimental case RowAvg performs worse than ColAvg. If RowAvg prediction were superior, it would imply that a student's performance on other questions is more important than the scores of other students on a particular question. ColAvg outperforms both RowAvg and RowColAvg indicating that the opposite is true: the effect of student ability is dominated by properties of the question itself. This is in line with previous psychometric models like Common Factor Analysis (CFA), where the underlying model contains terms for features of the question, but not for features of the student.

8.2 Educational Use and Implications

Some teachers may be tempted to apply these results to the classroom. Indeed, there are a few relevant implications that can be drawn. Commonly, when a student misses an assignment or quiz with a valid excuse, instructors face a dilemma: whether to allow the student to make up the work, or simply to make the instrument "not count," often by granting credit equal to the student's current course percentage, equivalent to the RowAvg method. From the results shown in Section 8.1.10, it is clear that granting credit in this nature is the wrong solution: if the missed work was particularly easy or particularly hard, it uniformly affected the grades of the rest of the students, but would not affect the absent student. ColAvg is more likely to be accurate, but is harder to justify to the student, since their score is completely based on the work of others. The more advanced techniques like DD or CondProb+ are feasible, in that they take into account both the student's performance and the difficulty of the individual questions. Whether students will accept a more complex algorithm as the basis for their score is a subtle social issue, outside the scope of this discussion.

However, it must be noted that this work is preliminary and not yet generalized to the level of a deployable tool. A side-effect of the leave-one-out validation utilized in this study is that the predictions can assume that *every other* entry in the score matrix is present. Generalizing these techniques to work in the face of numerous missing entries is not generally difficult, but remains an area of future work. However, there is no obvious reason that the performance of the techniques investigated here would change dramatically given properly adapted algorithms.

8.3 Score Prediction Conclusions

Especially when applying new EDM techniques to score matrices coming from classroom settings, which are most likely producing smaller data sets than do ITS sources, prediction of missing entries is an important task. Within ITS data sources, accurate prediction may be necessary before the application of EDM techniques requiring full data, since not all ITS students will attempt each ITS question. EDM may in fact be more commonly plagued by missing data than are the data-mining or machine-learning communities.

Accurate prediction of missing entries in score matrices is a problem that depends on the type of input being provided. If a score matrix represents scores on questions testing only a single topic, accuracy in prediction rates appear to rise by 5% to 10% over mixed-topic matrices. It is easy to achieve prediction rates near 70% or 75%, using extremely simple methods. Unfortunately, more advanced techniques such as IRT-based question parameterization or conditional prediction provide only incremental improvement in the general case, when evaluated against available data.

The most notable improvement in prediction comes from reducing mixed-topic score matrices into single-topic matrices. This underscores the importance of having score information available for all datasets in EDM research. In many situations, especially with the types of data presented here, topic information may not be readily available. The automatic clustering of questions by topic given the scores of those questions is an important area of further work. This was addressed in last year's EDM workshop at AAAI (Winters et al., 2005; Barnes, 2005), but to date no techniques have been found that can consistently outperform random chance on course datasets. More information can be found on this line of research in the next chapter.

Chapter 9

Topic Clustering

One particularly valuable application of educational data mining is clustering exam or homework questions by topic. If valid topic clusters can be produced from the score matrix S and the number of topics t, building a binary relevance matrix R can be done in t operations by manually identifying the topic underlying each cluster. Such a system reduces the work in developing R from nt operations to only t operations. Relevance matrices generated in this fashion are also less prone to claims of biased interpretation, as the relevance information is algorithmically generated and backed by the score data itself.

This problem, which we call the *topic clustering* problem, can be approached with a number of modern machine learning methods. Obviously clustering is appropriate, as we are primarily looking for groups of related questions. This can also be viewed as a form of collaborative filtering, where each score takes the place of product ratings. The standard collection of dimensionality reduction techniques, which reduce the score matrix S from $m \times n$ to $m \times t$, can be used for this filtering, as the matrix can be assumed to have no missing entries after using the techniques developed in the previous chapter. Additionally, there are algorithms from the educational domain that are directly applicable to topic clustering.

As there is no known generative model for predicting entries in *S*, the underlying distribution of those entries is unknown, and thus we cannot reason from first principles which algorithms will be best suited to matching the human notion of topic. This is an important, and somewhat subtle, point: a correct answer must match the human judgement of topic, rather than simply minimizing reconstruction error between the implied model and the observed data in *S*. Labelling questions based on other factors, such as type of question, time of day, or another non-topic factor has little assessment value, although it may in fact have high value in matrix reconstruction. Thus we must evaluate possible algorithms against known correct answers to find the maximal agreement.

9.1 Evaluation Method

To evaluate the output of our candidate algorithms in topic clustering, we focus on question pairings. Each algorithm produces a set of groups of questions that are being claimed to belong to the same topic. Each dataset has a similar set of groups that are correct or acceptable answers. For the course datasets these were produced by the course instructors, for the quiz datasets these are the topics from which the questions were drawn.

To measure the similarity of the correct answer and the algorithm's results, we create the list of all pairs of questions that were placed in the same group by the algorithm, and the list of all pairs of questions that were grouped together by a human. Given these lists we can evaluate *precision* and *recall* for each algorithm. Precision is the percentage of the pairs reported by the algorithm that are present in the correct answer. Recall is the percentage of pairs in the correct answer that were also reported by the algorithm. Thus precision measures how accurate the answer is, and recall measures how complete the answer is. These are independent: grouping only two questions, and grouping those correctly, produces perfect precision but very low recall. Grouping all questions together into one group provides low precision (equal to random chance), but perfect recall.

Further, all but one of the algorithms can produce a numeric certainty on each question's group membership. This varies by algorithm, and is described below. By varying the cutoff threshold on that certainty, we can adjust the size of the groups reported by each algorithm. If an algorithm's underlying model is accurate, then at least the most-certain questions should be correctly grouped. By evaluating precision and recall across the range of the certainty, we can generate precision-recall curves for each algorithm, demonstrating the accuracy of the algorithm across the certainty range.

9.2 Algorithms

The algorithms considered in this study fall into three main groups: clustering algorithms, dimensionality reduction algorithms, and algorithms from educational statistics. Here we list the algorithms, how they are used to produce the certainty groups underlying the precision-recall curves, and describe those that readers may be unfamiliar with.

9.2.1 Clustering

We are evaluating *k*-means (MacQueen, 1967), spectral clustering (Fischer and Poland, 2005) single-linkage (Sibson, 1973), complete-linkage (Defays, 1977), and average-linkage (Sokal and Michener, 1958) algorithms. All of these can give an ordering on which questions are most certainly grouped by sorting the questions by the distance from the center of the cluster to which it is assigned.

For *k*-means, we order the certainty function in increasing distance from the cluster center. Thus the most certain group-membership assignment is the for question closest to its cluster center, and the last assignment is for the question that falls farthest from its center. The same technique is used for the agglomerative algorithms, where the cluster center is determined by the average of the points that were hierarchically clustered together. For spectral clustering, we have modified the *specclusAS* package (Fischer and Poland, 2005) for R (R Development Core Team, 2005) to return the reduced matrix before performing the final clustering step. The maximal entry in the reduced matrix would determine group membership, we determine the certainty ordering of the questions based on the magnitude of those entries.

9.2.2 Agglomerative Correlation Clustering

Another set of algorithms that we are investigating is the use of single linkage, average linkage, or complete linkage agglomerative clustering on the *correlation matrix* of the questions, rather than working with the raw data itself. In this form, the pair of questions or question clusters to be merged at each step is given by the maximal entry in the correlation matrix. The three agglomeration techniques differ in how they merge the rows and columns for the chosen clusters for the next step.

Let M represent the correlation matrix, initially calculated such that the i, j^{th} entry of M is the correlation of question i with question j across all students. Each step of agglomeration will merge two questions or question clusters, reducing the total number of clusters. In our version of single-linkage clustering, when merging elements i and j, the resulting entry is given by the maximum of the two entries. Thus, when determining the l^{th} entry of the new vector, we use the maximum of $M_{i,l}$ and $M_{j,l}$. Average-linkage takes the average of $M_{i,l}$ and $M_{j,l}$, and complete-linkage takes the minimum of $M_{i,l}$ and $M_{j,l}$.

Agglomeration continues until we have created the appropriate number of groups. Group membership is obvious, as this is a clustering algorithm. The ordering of which questions are most certain is given by the sum of the "correlations" used in merging together the clusters for each individual question. For example, a question that was merged twice, first because of an entry in M of 0.5 and then because of an entry of 0.35, the sum will be 0.85. Questions with a higher sum are considered more certain. This strongly favors questions that were clustered earlier.

This is somewhat analogous to spectral clustering. Here the "similarity" is correlation, the reduced dimensionality is n, and agglomerative clustering is used rather than k-means. A sufficiently general implementation of spectral clustering could directly support these alternate clustering forms.

9.2.3 Dimensionality Reduction

Dimensionality reduction algorithms can also be used to find the underlying structure of the data. For dimensionality reduction, we evaluated Singular Value Decomposition (SVD) (Nash, 1990), Independent Component Analysis (ICA) (Hyvärinen, 1999b), and a non-negative matrix factorization (NNMF) (Lee and Seung, 2001).

We also evaluate slight alterations of SVD and ICA. In the base versions of these algorithms group membership is determined by the maximum absolute value in the output vector corresponding to each question. In the modified versions we are utilizing a k-means clustering on the reduced matrices, setting k to t (the number of factors) and assigning group membership for each question according to the resulting clustering.

These clustered versions of SVD and ICA provide a simple interpretation of the output when creating question clusters. The base versions of SVD and ICA are more complex to interpret, as the reduced vectors theoretically range $-\infty$ to ∞. In our evaluation, we place each question into the group for which it has the largest magnitude entry. The same applies for the NNMF algorithm, which is easier in that entries in the reduced-dimensionality question vectors are limited to range 0..1, so group membership can more intuitively be assigned based on maximal magnitude. In all cases, the certainty ordering of the questions is based on the magnitude of the entry, starting with the largest magnitude.

9.2.4 Educational Statistics

We are also investigating two methods from educational statistics in this study: Common Factor Analysis (Spearman, 1904) and Q-Matrix (Birenbaum et al., 1993). Both of these have been specifically suggested by researchers in education for this problem.

For CFA we used the default settings in the CFA implementation *factanal* in the R statistical package (R Development Core Team, 2005). Preliminary experiments were performed with the CFA implementation *PROC FACTOR* in SAS/STAT (SAS, 2005). Both implementations produced similar results. Lacking a publicly available implementation of Q-Matrix, it was necessary to develop one for this experiment.

As CFA performs a dimensionality-reduction very similar to SVD, group membership here is also given by the maximum-magnitude entry. The certainty ordering is also identical to SVD or ICA. Q-Matrix is somewhat more complex: all entries in the output matrix are binary. There are two obvious methods of interpreting these results. Questions can be placed in any group for which they have a 1 in the entry for that group, which often results in the creation of very large groups. Alternatively, questions may be placed into a group if that group is the *only* non-zero entry for that question. Since we have no other method for differentiating the certainty of each question, these are the only two interpretations for Q-Matrix results, which makes precision-recall plots for Q-Matrix a line segment.

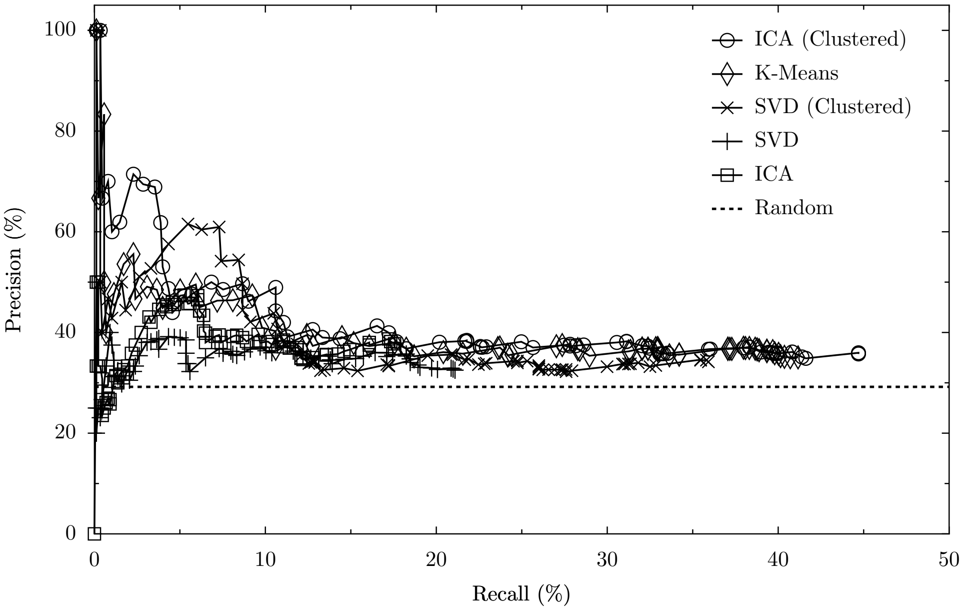


Figure 9.1: Best five algorithms, 008 dataset, six factors

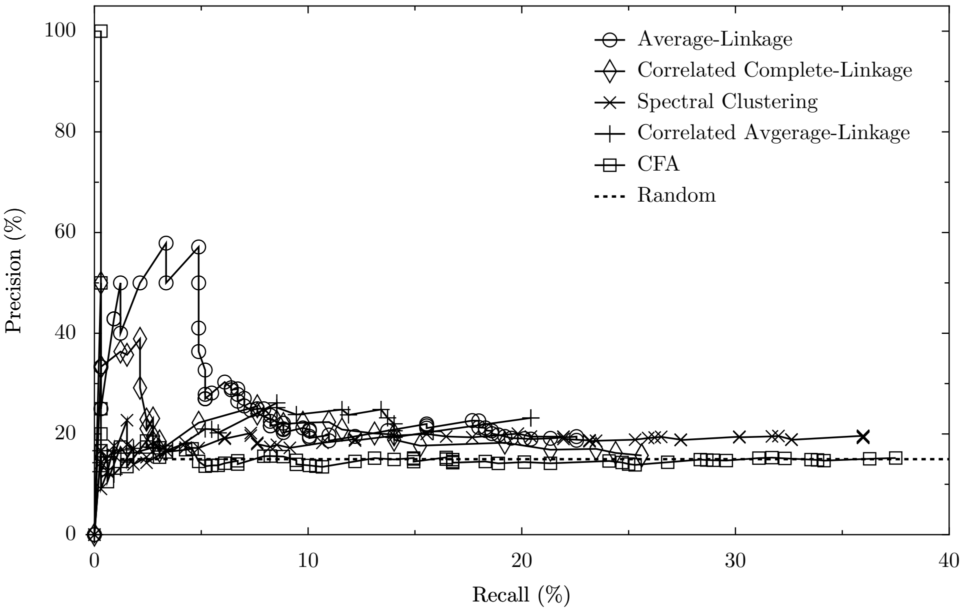


Figure 9.2: Best five algorithms, 010 dataset, six factors

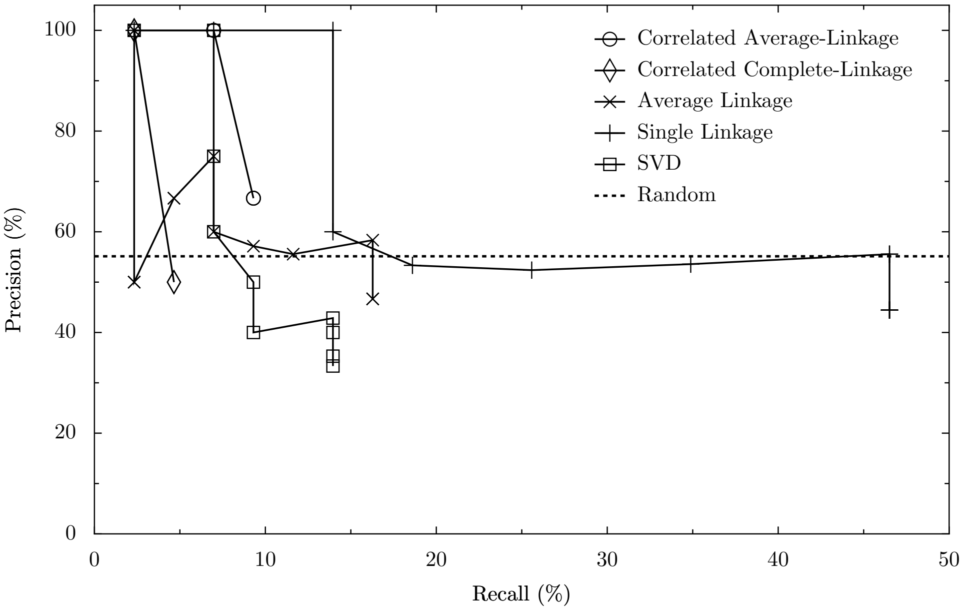


Figure 9.3: Best five algorithms, 141 dataset, six factors

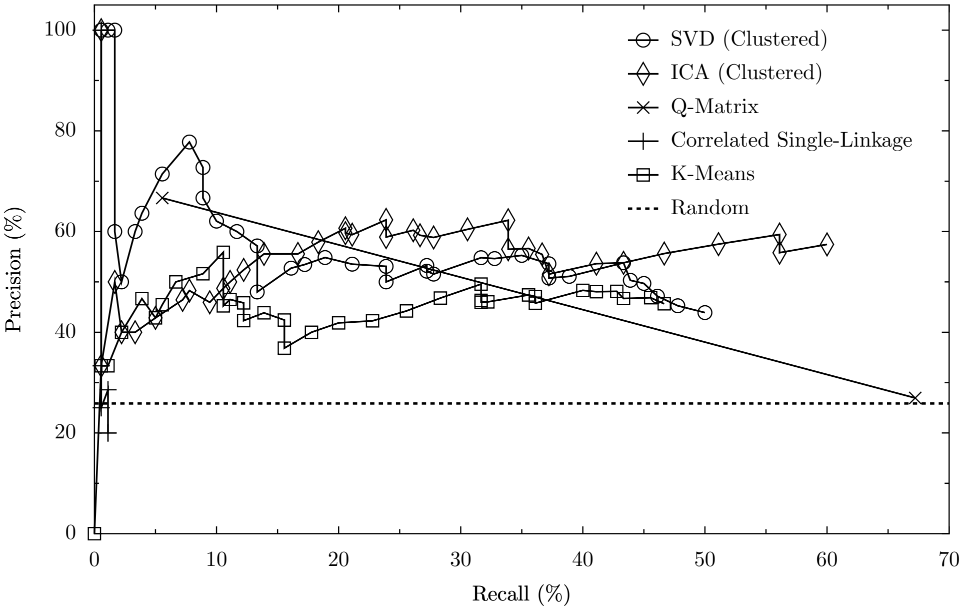


Figure 9.4: Best five algorithms, Academic dataset, four factors

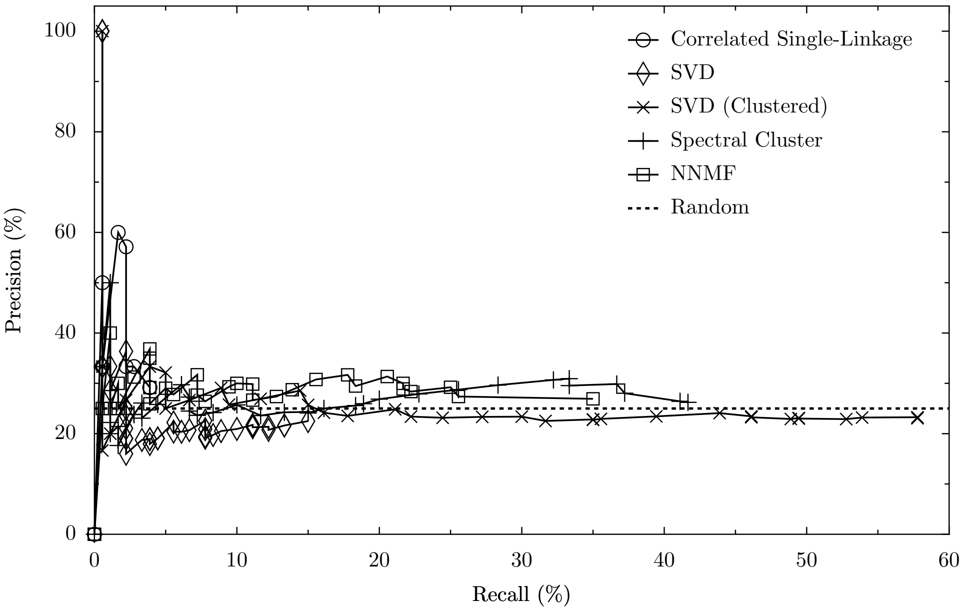


Figure 9.5: Best five algorithms, Trivia dataset, four factors

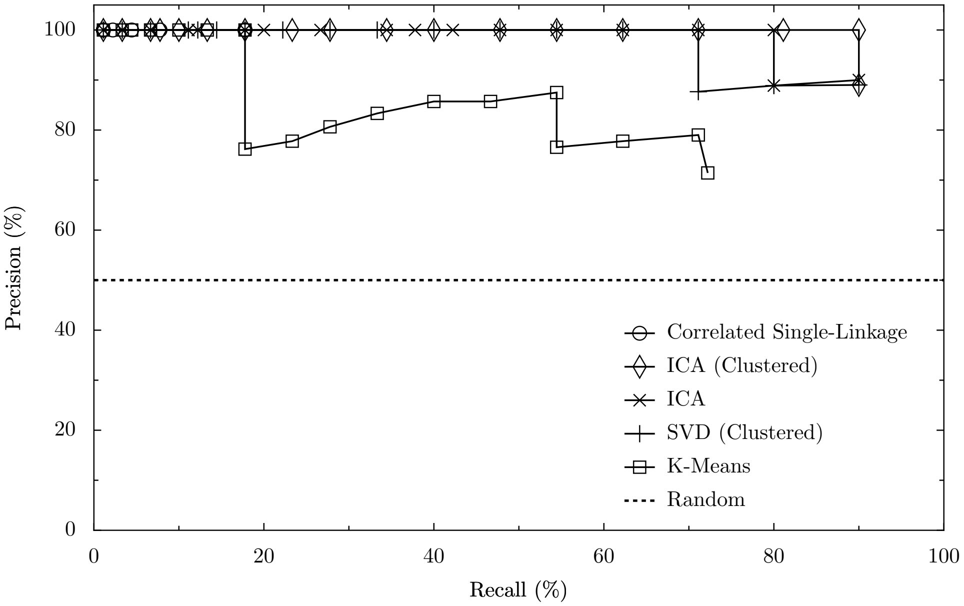


Figure 9.6: Best five algorithms, Academic dataset, Math & French only, two factors

9.3 Results

Comparative results on our candidate algorithms on the topic clustering problem are surprising. In general, the only dataset that is separable at a level better than random chance is our good baseline, the academic dataset (Figure 9.4). However, even within the academic dataset most algorithms only perform at about 50% precision. Examination of the questions that are correctly grouped shows that again and again the candidate algorithms are correctly partitioning the Math and French topics from the academic dataset, but the Biology and World History topics do not appear to be separable. Breaking out only the Math and French topics from this dataset, it is clear that most of our candidate algorithms do well at partitioning these two topics (Figure 9.6). Some do better than others; notably, using ICA to reduce the dataset and then running *k*-means produces an ideal partitioning of the data. SVD with the same clustering does nearly as well, with only a small number of bad groupings. Spectral clustering is the only algorithm that does poorly on the Math and French dataset. In general, dimensionality reduction algorithms outperform clustering algorithms here, but there is not enough data to generalize this result beyond this dataset.

The trivia dataset behaves exactly as predicted: performance on this dataset is effectively random regardless of algorithm (Figure 9.5). Again, the only candidate algorithm that stands out is spectral clustering, although the performance here is still only slightly better than random chance. The performance disparity for spectral clustering on the baseline datasets may hint at the underlying structure for the course data, but we have found no obvious solutions from this observation to date. The course datasets all show effectively the same behaviors as the trivia dataset. Only the 141 dataset (Figure 9.3) has any noticeable structure. As this is the smallest dataset, and the dataset with the highest random chance of correctly pairing questions, this may be completely spurious.

Tables 9.1 and 9.2 provide a more complete, although greatly condensed, picture of the performance of the candidate algorithms on the course data. In these tables we have taken each precision-recall line for each algorithm on the course data and broken it into 5 partitions: from 0 to 20% recall, from 20% to 40% recall, on up to 80% to 100% recall. Within each partition, all of the precision values for all of the included settings of t are averaged. For any algorithm that has no entries for a given recall partition, a blank is left in the table. Also presented is the average precision across the entire output of the algorithm. Since some of these partitions are more heavily represented than others (many points in the curves fall in the 0–20% partition, few fall in the 80–100% partition), this is not an average that can be calculated from the other values in the table. Table 9.1 presents these values averaged across number of extracted factors, which decreases precision by forcing multiple topics into a small number of extracted factors at for small t. Table 9.2 presents the same analysis, restricted to only extracting eight factors.[1]

9.3.1 Varying The Number of Factors

In order to fairly compare the baseline data and the course data, we must account for not knowing the true number of topics in the course datasets. To account for this we have varied the number of topics for each of the course datasets from as few as two to as many as nine, with the expectation that for *some* number of topics there might be a good result. Graphs for top-performing algorithms are shown in Figures 9.7 through 9.9, and demonstrate that the number of factors extracted from the data does not seem to have any significant effect. As factors are increased, precision goes up slightly in some cases, recall goes down significantly in most, but in no case is there one line in the factor graphs that conclusively shows the number of topics present in the data. A similar graph for the clustered ICA algorithm

[1] Some of the algorithms have trouble on the smaller datasets when extracting nine or more factors.

Algorithm	0 to 20	20 to 40	40 to 60	60 to 80	80 to 100	AVG
rand	**30.2**	30.2	30.2	30.2	30.2	**30.2**
icacluster	28.8	**32.3**	31.2	29.3	35.7	29.7
nnmf	28.8	32.0	32.4	**59.9**		29.4
ica	29.0	26.2	29.4			28.8
kmeans	28.9	26.9	**33.2**	36.9		28.7
svdcluster	26.2	31.3	31.6	37.0	**40.7**	27.7
completeLink	26.0	29.2	31.8	35.4		27.2
corrclink	27.7	18.0	17.0			26.6
corrmlink	26.7	24.1	23.1			26.5
avgLink	26.5	24.7	25.3	21.2		26.2
corrslink	25.7					25.7
speccluster	26.0	22.3	23.0	21.7	27.3	25.6
qmat	24.0	30.6	20.8	30.2		25.6
singleLink	24.5	24.3	23.9	24.7	21.9	24.3
cfa	25.0	22.3	21.4			24.1
svd	23.8	23.8	25.2			23.8

Table 9.1: Average Precision within given Recall Ranges on Course Datasets, 2–9 factors

Algorithm	0 to 20	20 to 40	40 to 60	60 to 80	80 to 100	AVG
nnmf	**33.9**	**41.2**				**33.9**
corrclink	33.8	17.5				33.1
rand	30.2	30.2	30.2	30.2	**30.2**	30.2
completeLink	28.8	36.1	**37.4**			29.8
icacluster	28.0	38.0				29.5
svdcluster	27.0	37.7				28.9
ica	28.4					28.4
corrmlink	28.3					28.3
speccluster	28.1	23.4		26.0	27.2	27.6
kmeans	26.4	30.0				27.3
avgLink	26.8					26.8
cfa	27.6	20.8				25.9
singleLink	24.4	26.4	22.6	23.1	22.0	24.4
corrslink	24.3					24.3
svd	23.4					23.4
qmat	19.1	21.4		**31.8**		22.4

Table 9.2: Average Precision within given Recall Ranges on Course Datasets, 8 factors

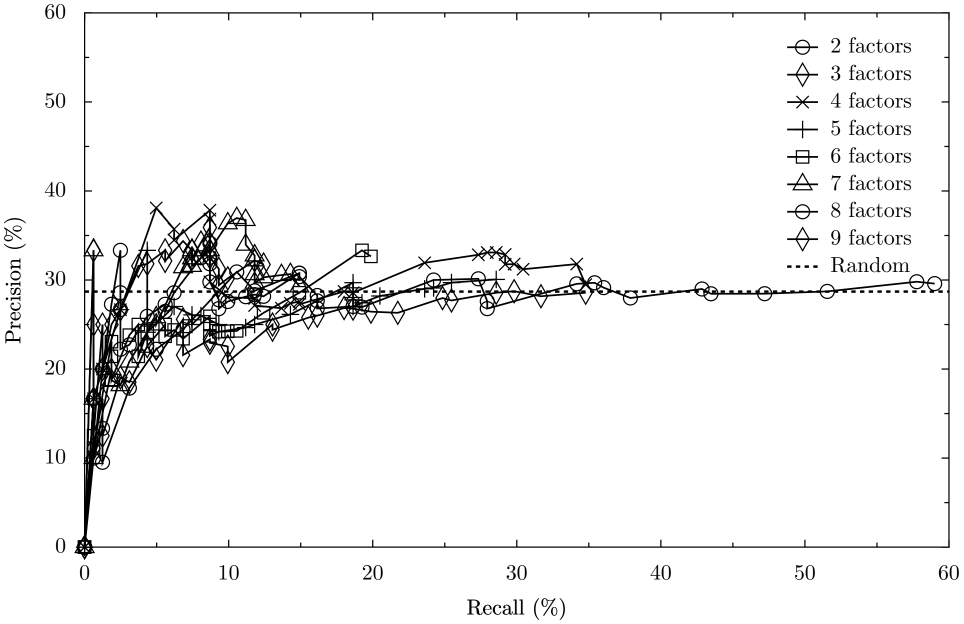


Figure 9.7: Precision-recall curves for ICA (Clustered), the highest performing algorithms on the 153 dataset, varying number of factors

on the Math and French data shows similar behavior: no change in precision, but declining recall, as the number of factors is increased (Figure 9.9).

9.3.2 Independence of Input Size

In order to fairly compare the performance between the academic dataset and the various course datasets, it is important to investigate the relation between student population and performance. Figures 9.10 to 9.11 show that on good data like that found in the Math and French topics, performance is not significantly degraded until the input size drops below about 20 students, well within the size of the majority of our courses. Although we do not have enough data like the Math and French to generalize strongly, the evidence available indicates that the difficulty with the class data is not due to small student populations.

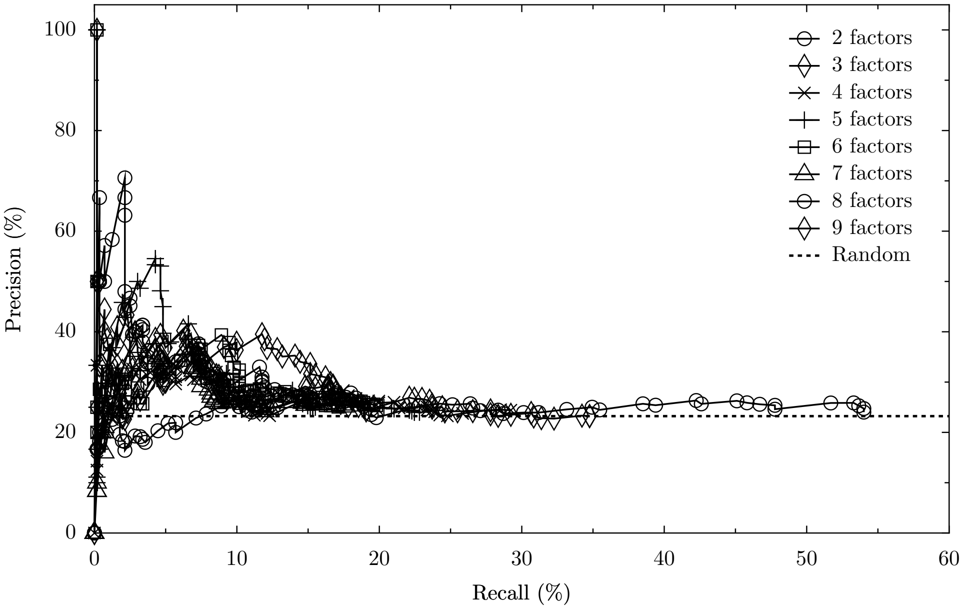


Figure 9.8: Precision-recall curves for ICA (Clustered), the highest performing algorithms on the 164 dataset, varying number of factors

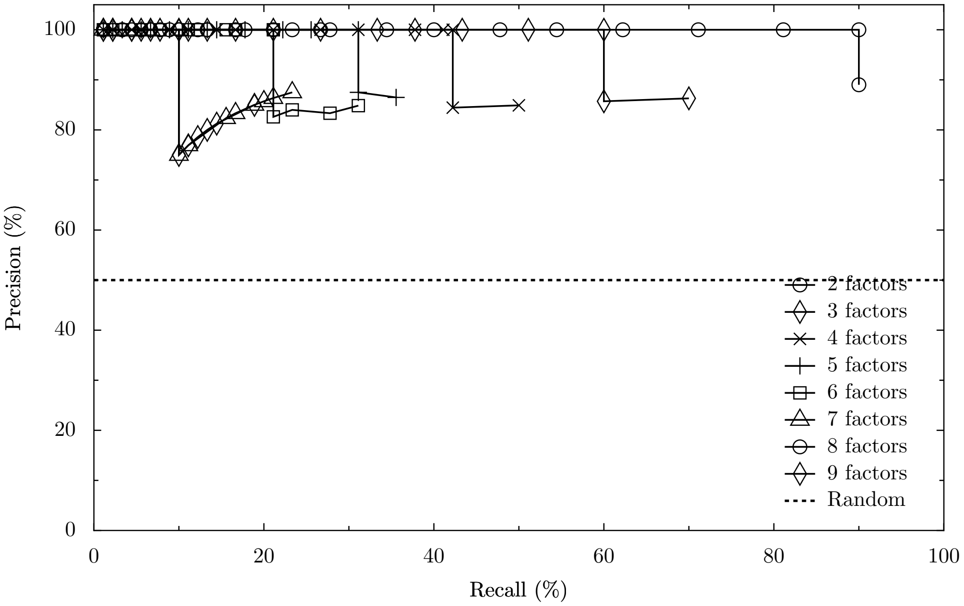


Figure 9.9: Precision-recall curves for ICA (Clustered), the highest performing algorithms on the Academic dataset, Math & French only, varying number of factors

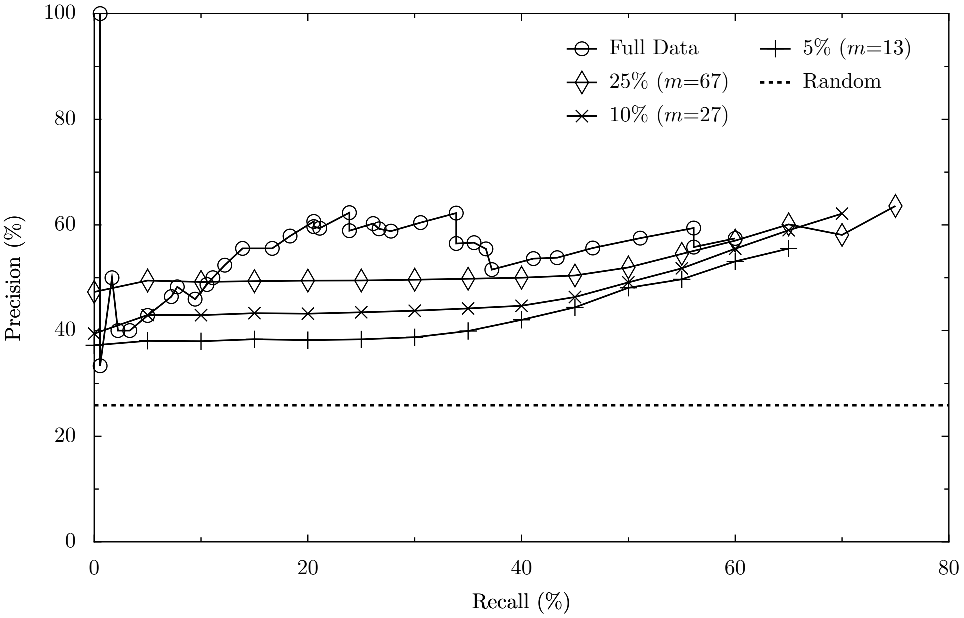


Figure 9.10: Varying population size on Academic dataset, ICA (Clustered), 4 factors

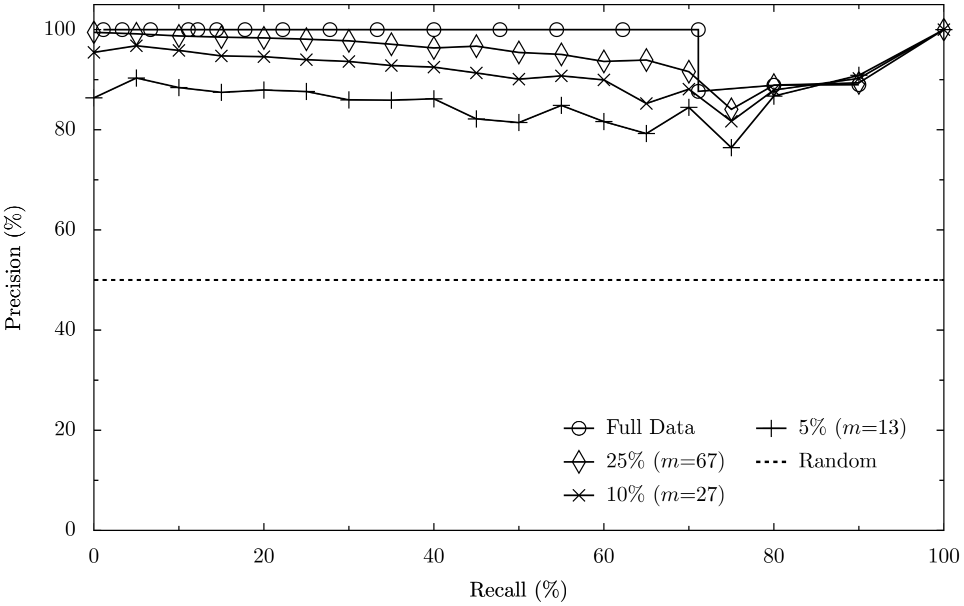


Figure 9.11: Varying population size on Academic dataset, Math & French only, 2 factors

9.3.3 Free-Response vs. Multiple-Choice

Given that our 141 dataset is the only course dataset that is a good candidate for containing topic information, and that the 141 dataset is the only one generated purely from free-response questions, it is worth investigating the hypothesis that multiple-choice questions confound topic extraction. This is also supported by the academic and trivial quiz baseline quizzes, which were presented as short answer free-response questions.

Of the five available datasets, three are homogeneous question types: the 008 and 010 datasets are all multiple choice, the 141 is all free-response. The 153 dataset is mixed, but contains only seven free-response questions. Looking at the human-generated groupings that are made up of only free-response questions, there are only four pairs of questions that are labelled “acceptable.” This is too small to provide significant results. The fifth course dataset (164) is mixed, and contains 42 free-response questions and 30 multiple-choice. Regrettably, this is the only dataset available for us to evaluate the this hypothesis.

When the free-response and multiple-choice questions are separated from each other in the 164 dataset, we see again that the algorithms that perform well are those that assume linear relationships among the topic factors, but no algorithm stands out as being the correct answer. From a comparison of the free-response plot (Figure 9.12) and the multiple-choice plot (Figure 9.13), there is little difference, but any advantage would seem to favor the multiple choice questions. Question type does not appear to be a strong role in the separability of a score matrix.

9.3.4 Q-Matrix Model Mismatch

Of the entire candidate set, the slowest algorithm is our implementation of Q-Matrix. This may partially be because of inexperience with it, or poor performance choices. However, a

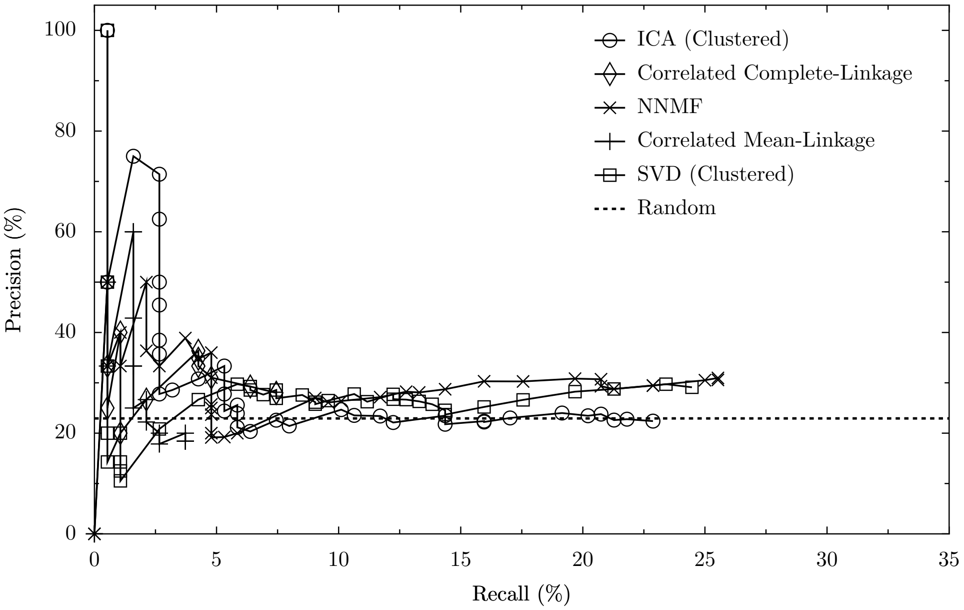


Figure 9.12: Best five algorithms, 164 dataset, free-response only

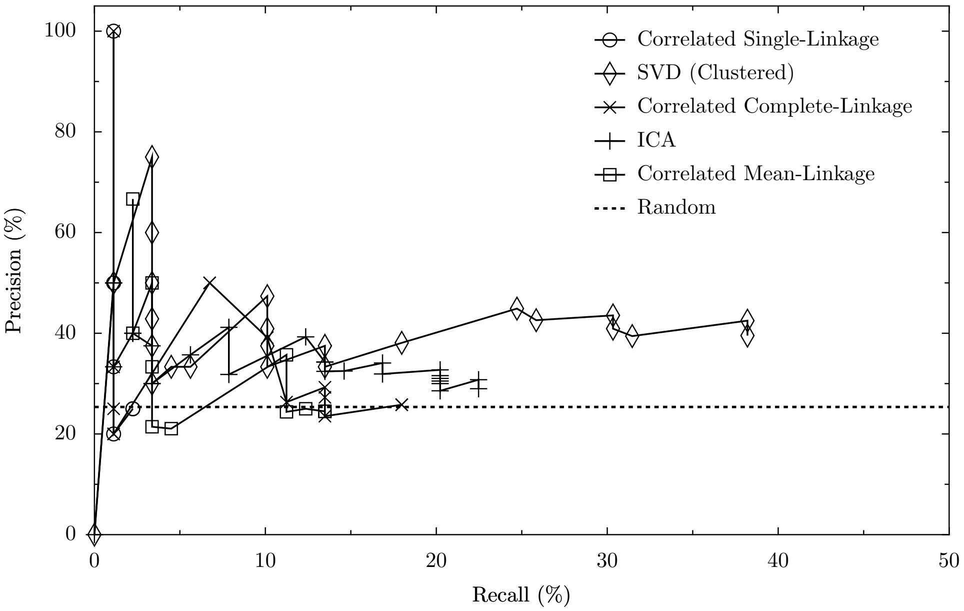


Figure 9.13: Best five algorithms, 164 dataset, multiple-choice only

likely cause is the fundamental difficulty of performing the Q-Matrix optimization: unlike the other algorithms involved here, Q-Matrix is a discrete optimization, and one that has a fast-growing search space. The search space for Q-Matrix grows as $O(2^{t(m+n)}/(t!))$. For the smallest dataset, the CS 141 dataset, this is already on the order of 10^{80}. The results presented here are for 1000 random restarts, each of which performs gradient ascent through an average of $100,000$ states. Clearly, a very limited portion of the search space is being explored. It is important to evaluate whether or not we have given Q-Matrix sufficient computational time, or whether perhaps its poor performance is due to premature termination of the gradient ascent.

To answer this question, we plot the reconstruction accuracy of the discovered model against precision. The plots shown here are generated as follows: in a run of Q-Matrix, the current reconstruction accuracy is evaluated in each round. If this value of reconstruction accuracy has not been seen before, the groups implied by the current model are evaluated for precision. If the underlying model behind Q-Matrix is in agreement with the generative model for the data in S, there should be a strong positive correlation between the reconstruction accuracy and precision: as the model is made more accurate through gradient ascent, the precision of the implied groups should increase.

Example plots are shown in Figure 9.14 through Figure 9.17. For the course datasets, the majority of such plots show *negative* correlations between reconstruction accuracy and precision, indicating that the better Q-Matrix does at reconstructing the original input data, the worse the precision of the predicted groups. Table 9.3 provides the correlations between reconstruction accuracy and precision of the predicted groups for Q-Matrix on binary datasets. This shows that for the course datasets, Q-Matrix is not finding any useful structure. For the Math and French subset of the academic dataset, Q-Matrix does manage correlations of 0.34 for the smallest group-size or 0.64 for the largest.

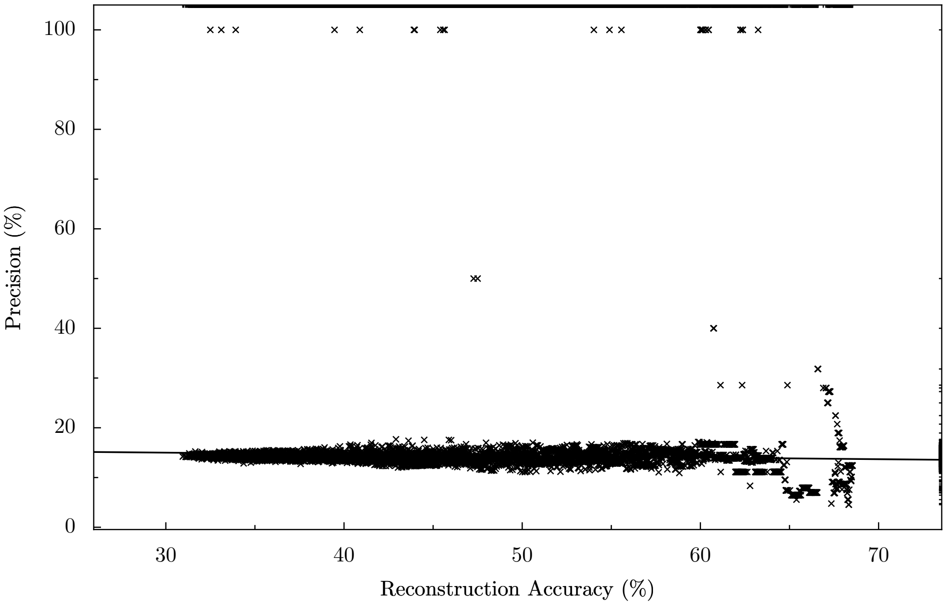


Figure 9.14: Q-Matrix Reconstruction vs. Precision for 010 dataset, 9 factors. Minimal group size.

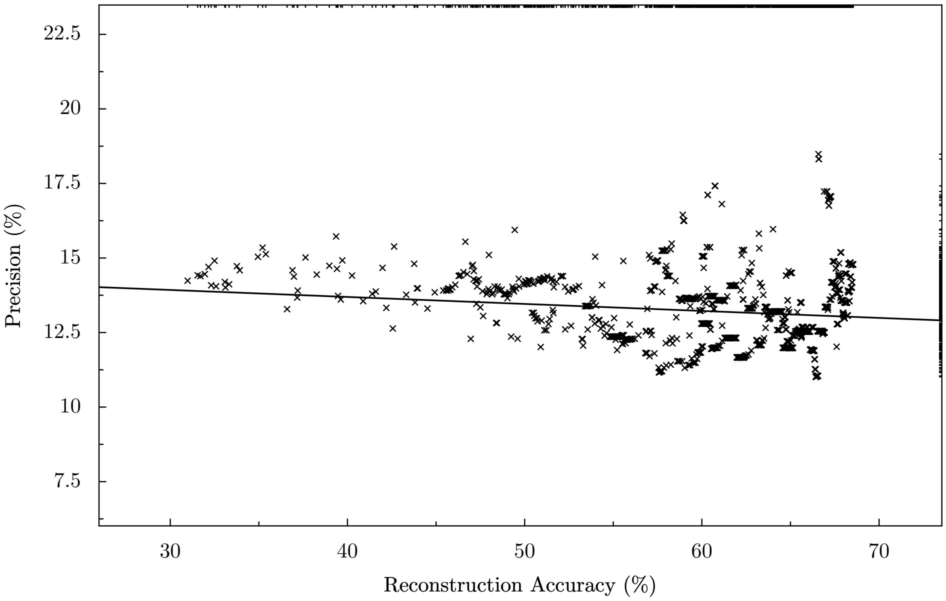


Figure 9.15: Q-Matrix Reconstruction vs. Precision for 010 dataset, 9 factors. Maximal group size.

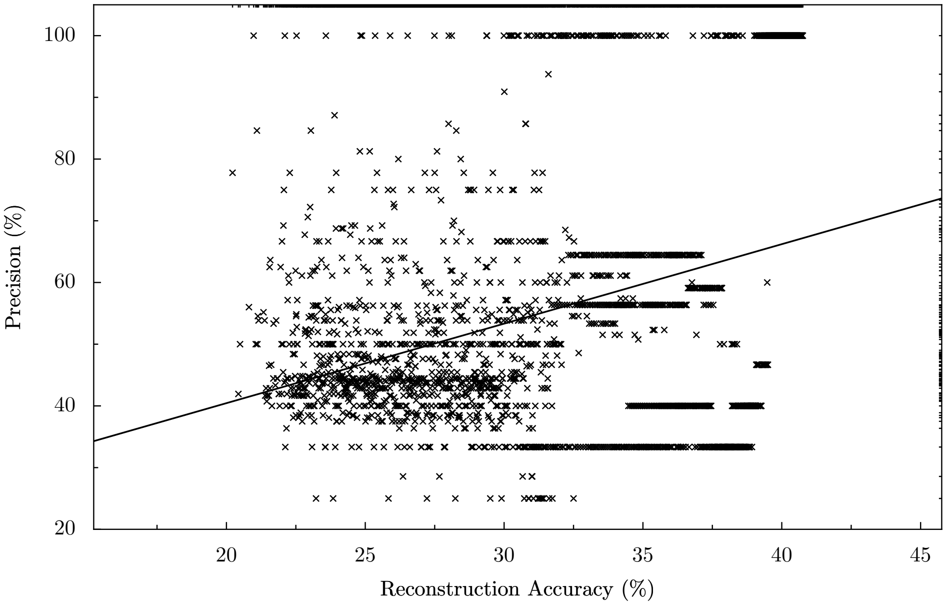


Figure 9.16: Q-Matrix Reconstruction vs. Precision for Math & French dataset, 2 factors. Minimal group size.

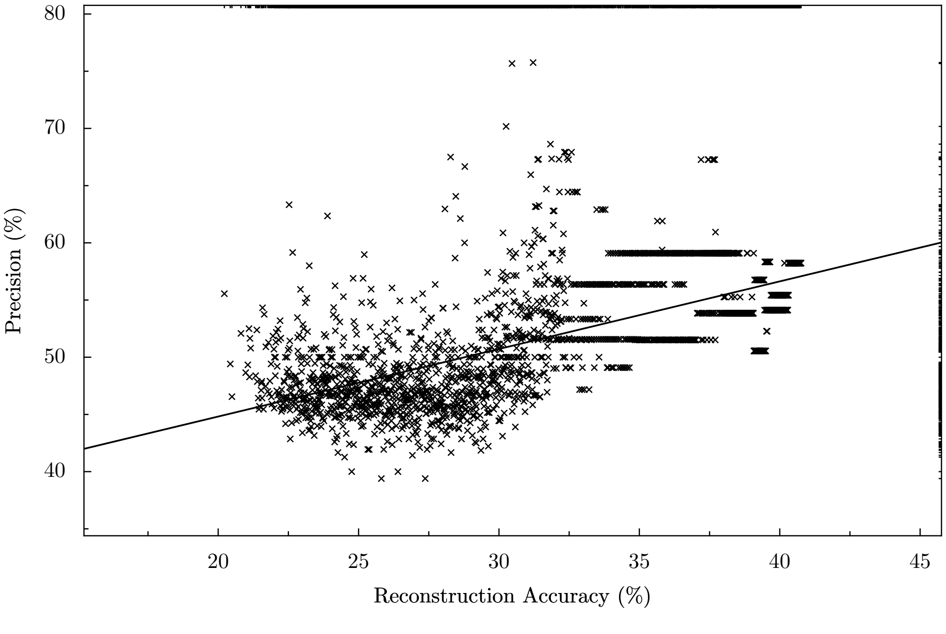


Figure 9.17: Q-Matrix Reconstruction vs. Precision for Math & French dataset, 2 factors. Maximal group size.

	MATH & FRENCH	TRIVIA	008	010
HIGH INCLUSIVENESS	0.64	0.1	-0.85	-0.14
LOW INCLUSIVENESS	0.34	-0.08	-0.03	-0.05

Table 9.3: Correlation of reconstruction accuracy vs. precision on binary datasets

9.3.5 Removing Low-Discrimination Questions

If we assume that much of the difficulty in grouping questions by topic is the fact that student scores are noisy, then an obvious line of investigation is to try to remove questions that are particularly noisy before performing our clustering. Utilizing the technique introduced in Chapter 7, we can discard questions that have a discrimination α below some threshold. While this will reduce the number of questions that get clustered, it does have the benefit of only clustering the questions that we believe are most meaningful. Dropping questions with $\alpha \leq 0.75$, the “bad” questions, reduces the number of questions in the course datasets by an average of 42.5%. Running the full suite of algorithms against these reduced datasets produces the summaries given in Table 9.4 and Table 9.5.

The results here indicate that dropping the low-discrimination questions does indeed lead to slightly better results. When compared to Table 9.1, Table 9.4 has a few notable features. Most importantly, even when averaged over the whole factor range, the high discrimination questions yield three algorithms that are able to beat random chance on this data. Here SVD, k-means, and ICA are all slightly above random chance, although even the best is within 1% of the random chance performance.

A better measure of the precision overall is again to look at the single large-factor table, Table 9.5. By overestimating the number of topics we eliminate the possibility of an algorithm producing correct clusters and being forced by the pigeonhole principle to group two unrelated clusters together. Table 9.5 provides the precision values for $t = 8$

ALGORITHM	0 TO 20	20 TO 40	40 TO 60	60 TO 80	80 TO 100	AVG
SVD	**33.7**	37.7				**33.7**
KMEANS	33.0	35.6	**36.9**			33.4
ICA	33.3	40.7				33.3
RAND	32.8				**32.8**	32.8
ICACLUSTER	32.5	35.9	36.8			32.8
SVDCLUSTER	31.9	36.3	36.3			32.3
SPECCLUSTER	31.2	23.4	36.2			32.1
NNMF	31.0	36.9				31.1
CORRSLINK	31.0					31.0
CORRMLINK	29.5	31.7				29.5
CORRCLINK	28.6	**42.1**				28.9
CFA	28.0	35.4				28.1
SINGLELINK	27.7	26.8	36.4			27.9
AVGLINK	25.4	31.2				25.5
COMPLETELINK	23.4	31.7	35.9			24.5
QMAT	16.6	20.2				16.8

Table 9.4: Average Precision within given Recall Ranges on Course Datasets, 2–9 factors, only questions with $\alpha > 0.75$

on the high-discrimination data. Here we expect the average recall values to be lower, but precision to be higher as there is less forcing of unrelated topics into the same factor. On this table, the best-performing algorithm is the single-linkage agglomerative clustering applied to the correlation matrix, with a 41.1% average recall, which is notably higher than the random probability of 33.4%.

Precision vs. Discrimination

The effectiveness of this technique is definitely a function of the cutoff point for α that is used: at low α, where few are removed, we get performance as shown in Table 9.1: random chance outperforms anything we have investigated. On the opposite extreme, where many questions are dropped, we have likely lost all of the topic information, as the questions that are kept are going to be the questions that have the most in common with the whole set of

ALGORITHM	0 TO 20	20 TO 40	40 TO 60	60 TO 80	80 TO 100	AVG
CORRSLINK	**41.1**					**41.1**
SVD	40.1					40.1
ICACLUSTER	39.7					39.7
SPECCLUSTER	38.4	**40.8**	36.0			37.8
SVDCLUSTER	37.5					37.5
NNMF	35.6					35.6
KMEANS	33.9	40.3				34.4
ICA	34.1					34.1
RAND	33.4				**33.4**	33.4
CORRMLINK	33.0					33.0
CFA	32.7					32.7
CORRCLINK	31.4					31.4
SINGLELINK	29.2	27.3	**36.6**			29.1
AVGLINK	27.9					27.9
COMPLETELINK	22.2	35.6				23.6
QMAT	13.5					13.5

Table 9.5: Average Precision within given Recall Ranges on Course Datasets, 8 factors, only questions with $\alpha > 0.75$

questions. The technique for estimating α and β presented in Chapter 7 is *assuming that the scores are univariate.* It is implicit in the workings of that algorithm that the questions provided are only testing a single topic. If a particular question is a perfect test of whether students know linked lists, in a course composed of many topics other than linked lists, then the estimated discrimination of that question relative to the full range of topics is going to be low. In general, the questions that have high discrimination in this case are going to be the questions, that are best correlated with overall performance. Ideally, a plot of the cutoff α versus precision should be a concave curve, low when α is low (around 0.5) because of the presence of noisy questions, and low when α is high (around 0.9) because all of the questions that test a single question have been dropped.

Given the promising results shown in Tables 9.4 and 9.5, we have investigated the relationship between precision and the cutoff α for the five course datasets. Sample plots

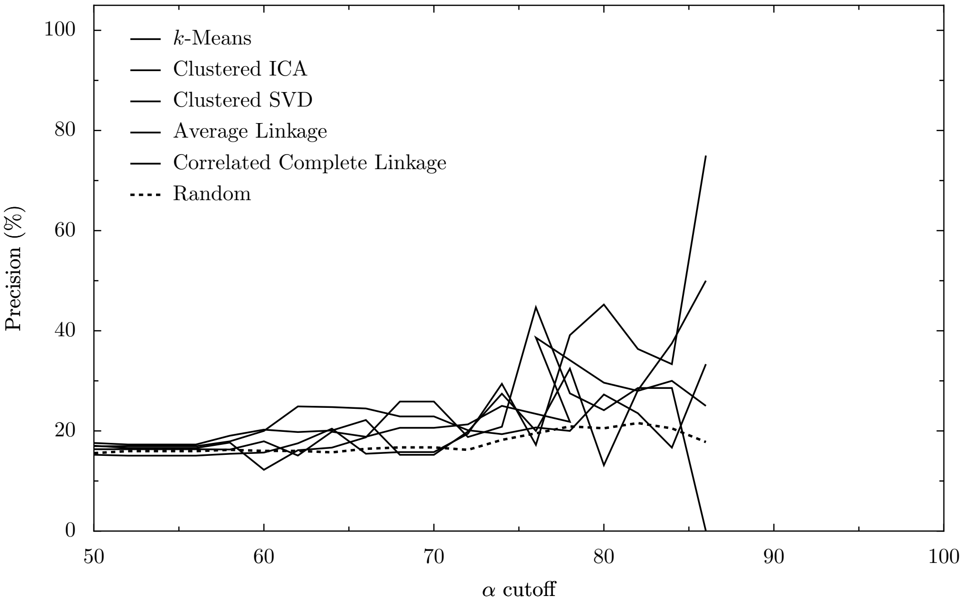


Figure 9.18: Discrimination cutoff α vs. precision, 010 dataset, top 5 algorithms, 8 factors.

for the individual course datasets are shown in Figure 9.18 and 9.19. The plot averaged across all five course datasets is shown in Figure 9.20. The results here are again clear: in practice, the course data is too noisy to see much of the desired effect. Even when averaged across all five course datasets, as in Figure 9.20 it is difficult to discern any concavity, or indeed any significant pattern in the plots. Most algorithm/dataset pairs do have spike in precision somewhere in the range 0.65 – 0.80, but it is narrow, meaning only a small range of α will yield that bump in precision. There is, as of yet, no known method of exploiting this bump, nor any certainty that it is statistically significant.

9.4 Topic Clustering Conclusions

Here we have introduced what appears to be a very difficult problem domain, that of correctly topic clustering questions based on the score matrix S. For a number of pedagogical

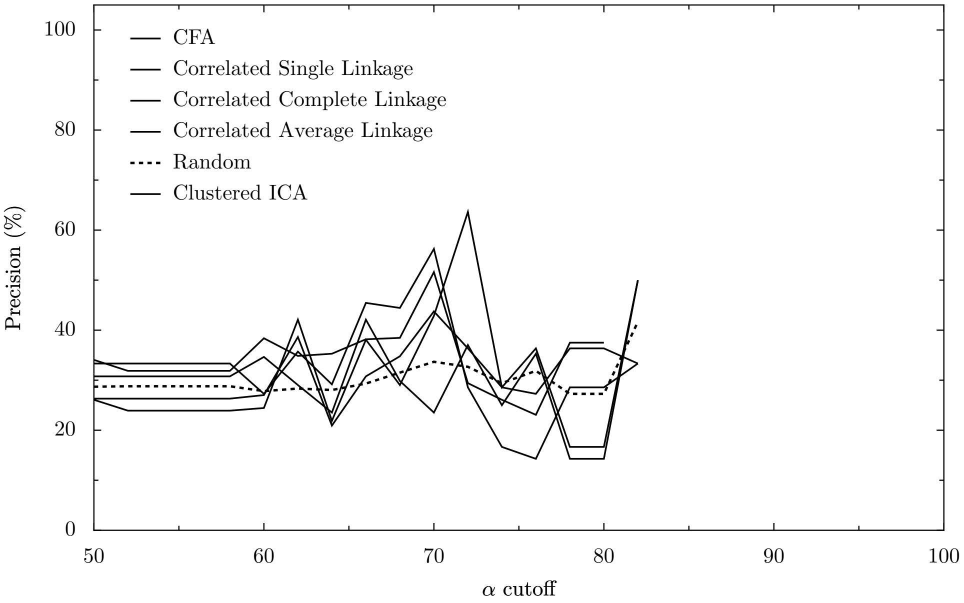


Figure 9.19: Discrimination cutoff α vs. precision, 153 dataset, top 5 algorithms, 8 factors.

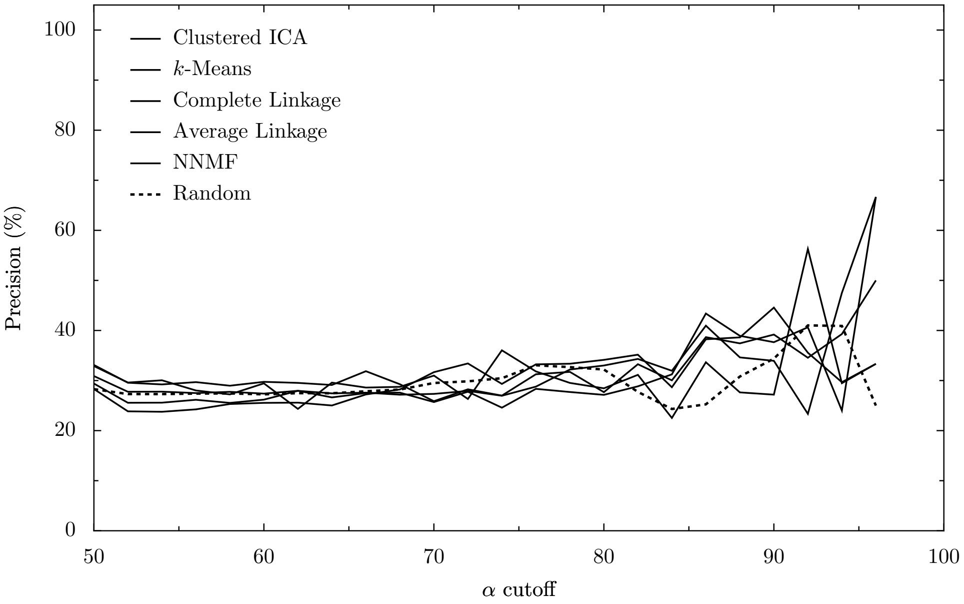


Figure 9.20: Discrimination cutoff α vs. Precision, averaged across all course dataset, top 5 algorithms, 8 factors.

and assessment reasons, this is an important problem. However, at this point it appears that none of the algorithms in this survey have any reliable success on this problem for the targeted datasets. On score data generated by extremely different topics testing deeply learned skills, choice of algorithm makes relatively little difference. The majority of simple algorithms work well on such data. However, on score data from actual courses, all surveyed algorithms perform similarly to random chance, with very few outperforming chance. Those that do outperform generally imply a linear model with high noise underlying the data.

Whether this is a failure of modern machine learning methods, of the experimenters for not finding the right algorithms in this survey, or of the teachers of the various courses, cannot be answered at this time. Regardless of the source of the problem, the results presented here highlight the complexities found in score-based educational data mining: relatively small datasets, high levels of noise, and unknown generative processes.

Chapter 10

Clustering with Partial Topic Information

Although nothing presented in Chapter 9 works well enough to be considered a solution to the topic clustering problem, any automation in the generation of R is beneficial for our assessment project. We have therefore investigated semi-supervised clustering of the questions represented in S. Some algorithms, like SVD or ICA, cannot be easily adapted into a semi-supervised form. Others, like NNMF, Q-Matrix, or any of the agglomerative clustering algorithms, can be adapted quite easily. The primary concern in this section is to determine the usefulness of providing partial information. If it is the case that identifying a single group membership for 25% of the questions is sufficient to provide high-precision results, then we can easily justify asking instructors for partial information and algorithmically determine the remainder[1]. If it requires 75% of the questions to be identified, then it is likely to be more efficient to simply ask the instructors for a full labelling, without resorting to algorithmic methods.

[1] It is also worth noting that in doing so, it may be *less* work for instructors, as the labels on the clusters can be carried over from the partial information, preventing any post-clustering prompt of the instructor.

10.1 Hints Provided

In order to continue this analysis with the datasets used in previous chapters, it is necessary for us to develop a method of providing partial information for the algorithms based on the human groupings, rather than the relevance matrix R directly. Since R could be generated from the human groupings, this means that the partial information is provided in terms of sets of questions that should be clustered, rather than subset of entries from R.

The hint that is provided to each algorithm is determined as follows. Hints are determined based on a hint percentage p and number of topics t, as follows.

- The hint is initialized as a full copy of the correct answer.
- For each question in the dataset, we include information about it in the hint with probability p.
- If a question is not selected, then that all information about that question is removed from the hint.
- The final hint is composed of the k largest sets. We iteratively select each of these sets.
- When a set is selected as part of the final hint, each question in that set is removed from any other hint sets. This ensures each question is only in a single set, to be comparable with the topic clustering experiment of Chapter 9[2].

[2] All algorithms from Chapter 9 except Q-Matrix placed questions in exactly one group

10.2 Algorithms

In this investigation we are looking at a subset of the algorithms utilized in Chapter 9. Specifically we are looking at the following algorithms:

10.2.1 *k*-means

The *k*-means clustering algorithm can be extended to utilize partial relevance by providing it a listing of questions that must be placed together. Given the set of correctly-grouped questions, we can move each known question to the mean of the group it appears in. Thus if three questions are known to be grouped together, we replace the original coordinates for each of them with a new vector at their mean. Correct weighting of the importance of that point is ensured by retaining three copies of it in the dataset.

This is equivalent to leaving the points in place and altering the code to ensure that those points are always grouped together. By moving the points to be co-located, we are guaranteed they will be placed into the same group. By choosing that point to be at their mean, we ensure that they have the same effect on their assigned cluster center that the three of them together would have. Performing the alteration this way allows the partial-information result to be done as a pre-processing step, without altering the code itself.

10.2.2 Agglomerative Clustering

Both the raw (Euclidean) and correlated agglomerative clustering algorithms can easily be extended with partial information by simply changing the starting condition from having every question independently grouped, to initializing groups of questions that must be paired together. The algorithms proceed as normal after initialization.

10.2.3 NNMF

During each round of the gradient ascent for the NNMF algorithm, we can overwrite entries in the relevance vectors for those questions that need to be placed together. As in the *k*-means case, this is done by finding the factor to which the set of questions can most easily be assigned to. For each question whose assignment is "known," we ensure at each step that the entry corresponding to the correct group is set to 1 and the other entries for that question are set to 0.

10.2.4 Q-Matrix

Modification of Q-Matrix is easy, as the output from Q-Matrix most closely represents what we are looking for: a binary assignment of questions into topic groups. Here the Q-Matrix is initialized such that the desired group memberships are guaranteed. As in the NNMF case, the entry for the correct group for each known question is set to 1 and all other entries are set to 0. Questions that are known are not updated during the gradient ascent.

10.3 Results

When evaluating results for this experiment, we are focused primarily on the final precision values. Since the algorithms tested are assigning each question to exactly one group, and some of the questions are assigned to more than one group in the human-generated answer, recall values have less absolute meaning. However, every algorithm should be able to produce 100% accuracy when presented with 100% of the correct answer. The hope is to discover one or more algorithms that can produce perfect or near-perfect accuracy with a small amount of the answer provided.

The graphs shown in this section are the best four overall algorithms for each dataset. The lines plotted are final precision (that is, the full output of each algorithm) as a function of the percentage of the correct answer that was provided. Each point on these curves is the average of 20 runs with newly generated partial information. Lines in blue have higher average precision than lines in red. In the course datasets, eight factors were extracted, in the baseline datasets the known correct number was used.

Figures 10.1 and 10.2 show the response to partial information on course datasets. Figure 10.3 shows a very similar result for the trivia dataset. Figure 10.4 shows the results for the Math & French data. On the majority of datasets, the lines are monotonically increasing as the amount of partial information increases, as would be expected. Only on the Math & French dataset, and to a lesser extent the full Academic dataset, are there any segments where precision decreases. This phenomenon is surprising, possibly indicating a slight discrepancy between the model implied by the provided data and the model implied by the algorithm.

Across all of the datasets, the Non-Negative Matrix Factorization emerges as the clear winner, appearing in the top four performers on every plot, usually as the top algorithm overall. A numeric comparison of precision vs. α is is provided in Table 10.1, which demonstrates quite clearly that the most suitable algorithm in our survey is NNMF.

10.4 Partial Information Conclusions

These results are disheartening: Chapter 9 showed that the relevance matrix R cannot be extracted automatically from the score matrix. Here we see that providing partial information provides undoubted benefit, but that benefit is at best linear in the amount of information provided on the datasets we are most concerned with. Based on the results presented here,

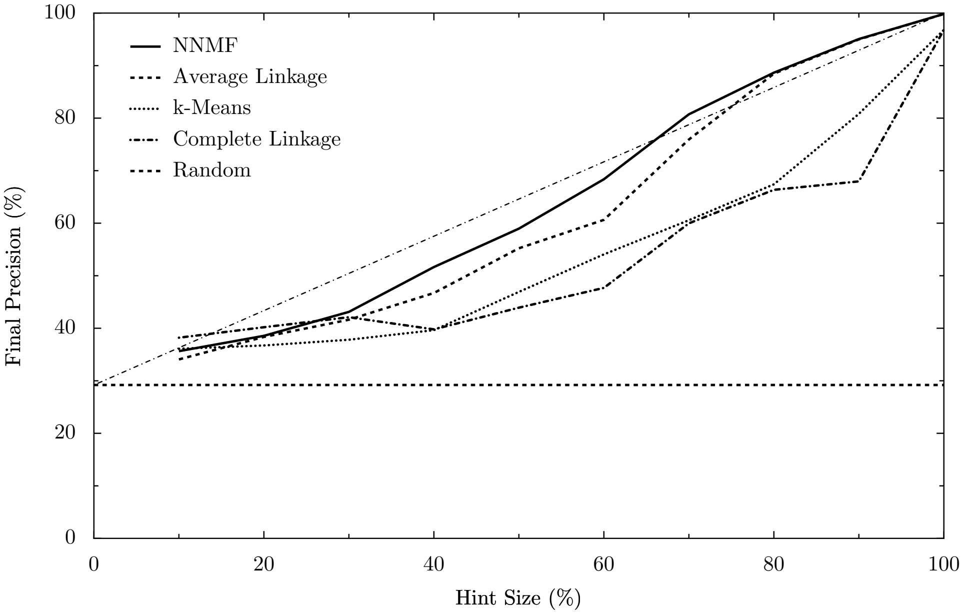


Figure 10.1: Best four algorithms, 008 dataset

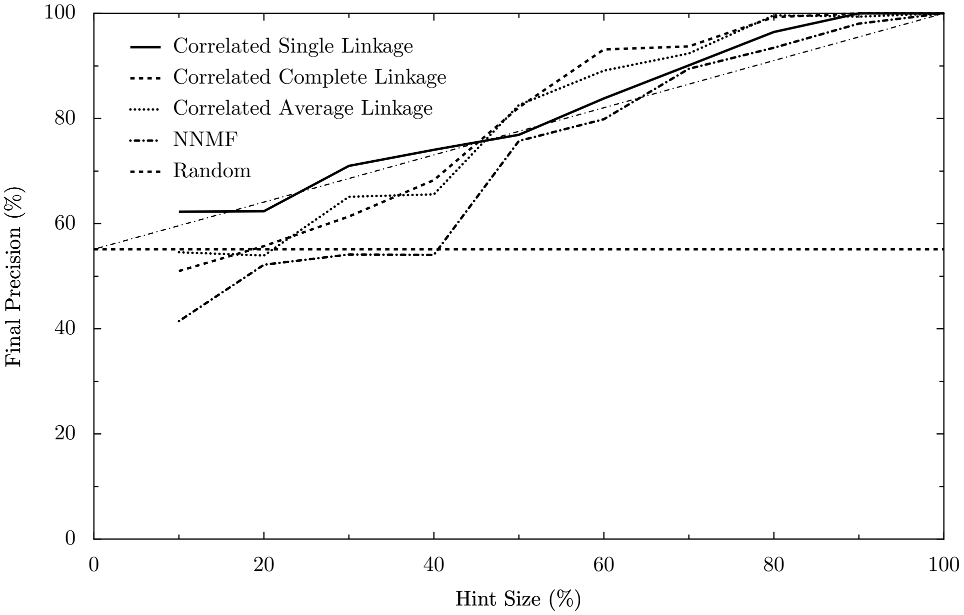


Figure 10.2: Best four algorithms, 141 dataset

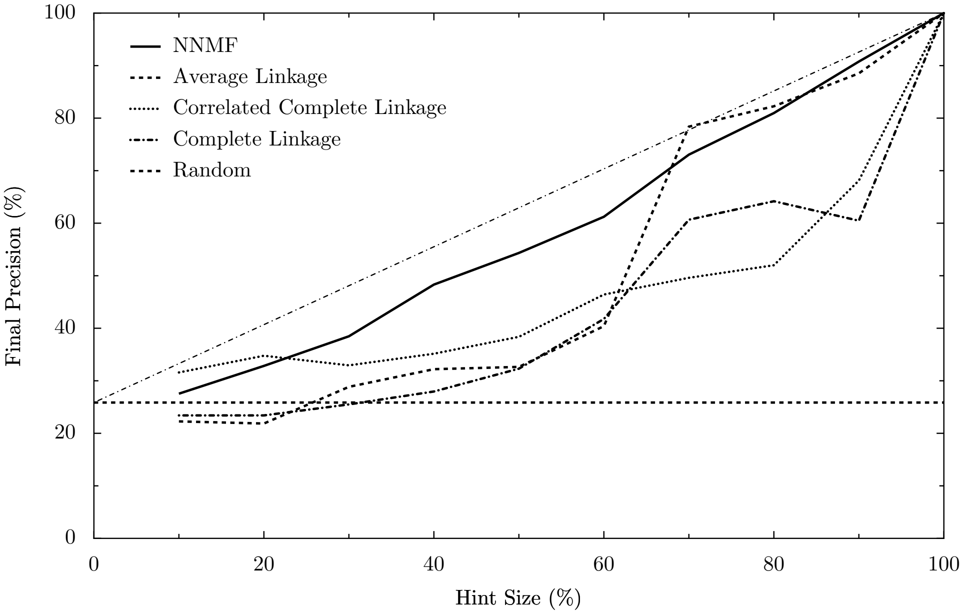


Figure 10.3: Best four algorithms, Trivia dataset

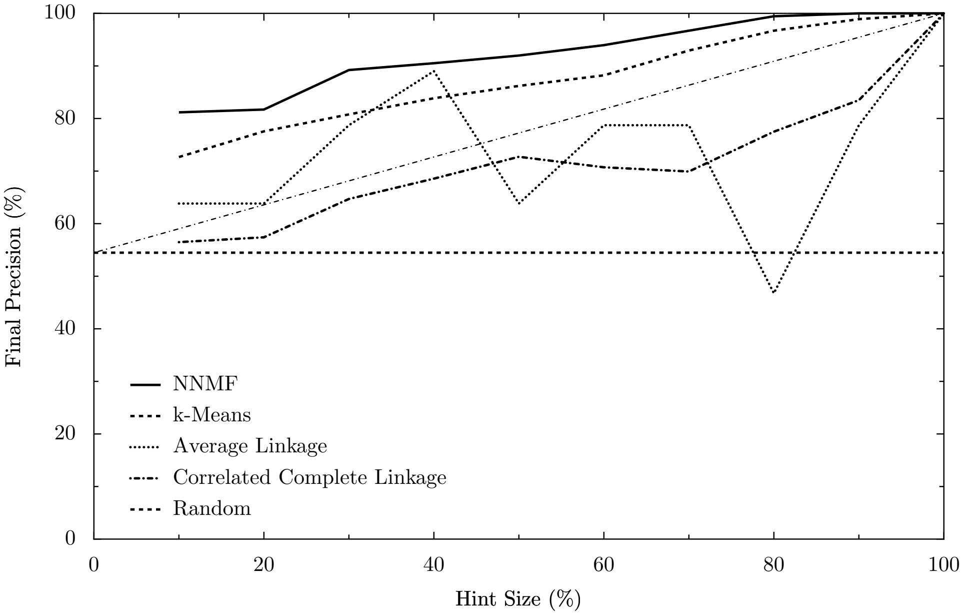


Figure 10.4: Best four algorithms, Math & French dataset

Algorithm	0 to 20	20 to 40	40 to 60	60 to 80	80 to 100	AVG
nnmf	**35.2**	**41.7**	**55.1**	**72.0**	**91.8**	**64.8**
avgLink	30.7	36.3	45.6	62.7	81.2	56.1
corrclink	33.9	36.7	46.0	57.6	79.9	55.4
kmeans	33.7	36.5	43.5	55.2	79.1	54.2
corrmlink	**35.2**	36.0	42.8	52.9	77.2	53.0
completeLink	33.0	32.2	37.0	50.3	71.0	48.3
corrslink	30.8	32.8	39.1	48.8	70.0	48.2
singleLink	31.2	30.0	29.0	29.2	42.5	33.4

Table 10.1: Average precision across datasets as a function of amount of partial information provided.

there is no silver bullet for clustering questions in a way related to the human concept of topic. This has deep implications for pedagogy and assessment in general. Topic clustering and the issue of why some data is easily partitioned are likely to remain active areas of research in EDM for some time.

Chapter 11

Future of EDM

The field of Educational Data Mining is ripe for explosive growth. Machine learning and data mining have developed a vast array of tools and techniques that have been well-studied and examined in myriad contexts. However, as seen in earlier chapters, EDM is still an extremely small field, with an estimated thirty researchers worldwide identifying as being interested in it. Given the strong ITS background for many EDM researchers, it is certain that the ITS community will have a strong presence in EDM in years to come, but the focus is likely to shift from being a sub-division of the ITS community into a broader discipline operating in the overlap between education, pedagogy, machine learning, and statistics. In this chapter we will discuss some avenues for future work based on the research presented in this dissertation, as well as general predictions of where EDM as a whole will go during the next few years.

11.1 Future Work

As with any other significant research project, it is difficult or impossible to find a point at which the research presented in this dissertation is “done.” In this case, there are a number of avenues for future work that have already presented themselves. It is unlikely that I will be able to follow up on every one of these research paths, but I hope to investigate the majority of the following.

11.1.1 Other “Baseline” Topics

In the academic baseline dataset presented in the topic clustering experiment, why is it that Math and French are separable, but Biology and World History are not? What other subjects are separable? It seems obvious that languages ought to be separable from sciences, given that Math is separable from French. Are languages separable from one another? Is Italian separable from French? Is Japanese separable from Spanish? Within the more technical areas, are highly-mathematical subjects like Physics separable from Math? Performing follow-up data collection and experimentation with the topic clustering framework developed for this dissertation should provide some insight into what subjects are fundamentally separable. Of particular interest to the CS Education research community would be whether an online quiz of this type that focused purely on computer science topics are separable. The results of that would indicate whether or not it is the type of assessment we perform in class, in relation to *when* we perform that assessment relative to the initial introduction of the knowledge, that is truly important. There is a significant amount of research that could be performed in this vein, with applicability to cognition, education, assessment, and education, in addition to EDM.

11.1.2 Distinct Sizes of Cognitively Related Information

Another interpretation of the results of the topic clustering analysis experiment is that there is a fundamentally different behavior for questions that are related at the “topic” level than those that are related at the subject level. Obviously, a test that was checking for the presence or absence of individual pieces of isolated knowledge can determine whether a student has learned those pieces of knowledge. The results from the topic clustering experiment suggest that we can determine who has studied Math or French (and still remembers it), but for some reason cannot determine who understands linked lists but not hash tables.

It is possible that there is some emergent reason for this discrepancy that could be modelled using a cognitive architecture like ACT-R or SOAR. This style of cognitive experiment is not unheard of in the cognition community, as shown by research like (Peterson and Simon, 2000).

11.1.3 Voting Methods for Topic Clustering

Since the algorithms presented in the experiment on topic clustering with partial information all perform better than random chance given 25% to 30% of the answer, there is a possibility of leveraging this into creating a more precise aggregate answer. Voting methods are based on the idea of giving votes to a number of classifiers, each of which is better than random. Not all voters have equal sway in the final results, but the answer with the most votes is the final prediction. In this case algorithms would be voting for individual question pairings, and it is possible that from those pairings an aggregate answer could be produced. One requirement for this to work would be that the algorithms produce distinct pairings, rather than all producing the same (relatively inaccurate) answer. Preliminary investigations into this indicate that the overlap between pairings produced by the algorithms in the topic clustering experiment are relatively slight, so this should not be much of a concern. This recalls some of the work done recently on mixing clustering algorithms (Gionis et al., 2005).

11.1.4 Alternate UI Platforms for Agar

Although rather more mundane that some of the other research, the focus on usability that went into the development of Agar makes it a prime candidate for experimentation into other UI platforms. Two user interface platforms in particular are of great interest: development of an Agar variant for use with Tablet PC technology, which enables the "red-pen" metaphor to an even greater extent, and an online version of Agar using the currently popular AJAX (asynchronous Javascript and XML) suite of technologies, allowing for easy onetime backend setup and ubiquitous access to CAA systems from any network-enabled host. While certainly less research-oriented than other avenues of future work, development of systems like these would undoubtedly be a benefit for the academic community at large.

11.2 The Road Ahead

The current dominance of ITS-related research and datasets is clear in the EDM community. Of the two past EDM workshops, one was at the International Conference on Intelligent Tutoring Systems, and the other was at the AAAI yearly conference. As of this writing there are calls for papers for two new EDM workshops in 2006. Again, one is located at ICITS and the other is at AAAI.

However, this dominance is dimming somewhat as the community grows and diversifies. More EDM research is being presented from non-ITS data sources, ranging from the unit-test score matrices (Spacco et al., 2006) of the Marmoset project (Spacco et al., 2005) to standardized test data. Indeed, the full cross-product of educational data sources and machine learning techniques provides a fertile ground for future EDM research.

Perhaps the single most intriguing data source that has yet to be taken advantage of is the collection of novice programmer code snapshots stored by the Marmoset project. These snapshots are taken during the development of the students' first programming projects, stored every time each student saves their code. There are literally hundreds of thousands of these snapshots available. Obviously, dealing with such a rich data source will require some advanced techniques, as hand-coding for descriptive features of each snapshot is quite infeasible. However, such a large and rich source of data is quite tantalizing: behavior of first-year programming students has been a continual theme of investigation in the CS Education community for decades (Gruener and Graziano, 1978; McCracken et al., 2001). Given the resources to investigate the behavioral patterns shown in such data, the Marmoset data could easily become a seminal hallmark of the EDM community.

If data mining is really "statistics on steroids," by analogy, educational data mining must be educational statistics on steroids. If there is any truth in this analogy, then an obvious and critical step in the development of EDM is to look at the techniques that have come out of educational statistics or psychometrics to see where EDM techniques can be applied. A prime example of this is the research presented on estimating difficulty and discrimination statistics for student population sizes too small to utilize IRT (Chapter 7). Statistical techniques that need to be examined by the EDM community include CFA, Cronbach's Alpha (Cronbach, 1951), validity, and reliability.

One of the major outstanding questions in the future of EDM is with which fields it will develop significant ties. While it is almost certain that EDM will retain ties with the ITS community for quite some time, the possibility of overlap with other areas will bring EDM into the awareness of a broader audience. The growth of EDM will obviously be affected by the areas that EDM becomes connected with. EDM could easily see growth in the field of machine learning, CS Education Research (which is itself somewhat distinct from CS Education in general), AI in Education, or even general AI, as the issues of prediction, cognition, and learning that surround EDM are central components of much of AI. The fields that EDM overlaps with will depend very heavily on the EDM-related conferences and workshops that EDM researchers try to publish in over the next few years. The acceptance or rejection of all of these fields individually bring independent benefits and drawbacks for the development of the field as a whole. Stronger connections with machine learning and AI will bring better experimental procedure to the field, but will pull it further away from the majority of the instructors that could benefit from ideas coming out of EDM. Inclusion in the CS education or CS education research communities will bring greater attention to a broad audience of people interested in improving teaching, assessment, and pedagogy, but these fields carry with them some stigma of being lower quality research when compared to more traditional Computer Science.

Perhaps the single most important field for cross-pollination with EDM is that of educational statistics and psychometrics. Given the relative dissimilarity of techniques and experimental methods, this may also be the hardest area for EDM to break into. However, EDM cannot really be considered a success in its ostensible mission to find non-obvious information in educational data until the educational statisticians become comfortable with the results being produced within the EDM community. Without being able to provide the next generation of tools for organizations like the Educational Testing Service (ETS) and The College Board to generate and analyze test questions, EDM can only be considered a partial success at best.

Chapter 12

Conclusions

This dissertation describes a method for performing data-driven course assessment and program assessment as a motivation for a series of investigations into Educational Data Mining. This type of assessment, both at the course and program levels, is a popular issue in education today, with renewed emphasis being placed on assessment by accreditation agencies, parents, administrators, and governments. EDM is uniquely positioned to provide solutions for difficult assessment problems, such as quantifying student learning, or the effectiveness of different teaching methods, while still causing only minimal impact on individual instructors. In situations where standardized testing is too difficult or invasive, EDM may provide the key to better quantitative assessment.

The bulk of this dissertation focuses on tools and techniques for collection and analysis of score matrices. Although the analysis fails to provide a solution for low-impact generation of the relevance matrix *R*, our collection techniques have proven quite successful, and automatic generation of *R* is merely desirable, not critical, for our program assessment.

12.1 Collection

Since most instructors do not currently record scores at the per-item level, it is necessary to provide methods for gathering S that make this palatable. In Chapter 4 we introduced two programs that were developed for this task. The first is Agar, a Computer-Aided Assessment (CAA) system designed with usability in mind by focusing on existing usage patterns. The philosophy behind Agar is unique among CAA systems in that Agar works to fit in with the usage paradigms of instructors, rather than forcing instructors to work within the restricted usage of the CAA system.

Agar has been deployed and actively used within our department for nearly three years. The majority of the current users of the system use it voluntarily, and have no connection to the development of the project. Users are responsible for a slow but steady stream of minor feature requests, allowing Agar to function more easily in situations that its original design was never intended to cover. For an academic tool, Agar has seen remarkable success, growing into a critical component of the departmental teaching infrastructure, rather than falling by the wayside.

In Chapter 4 we also introduced HOMR, the Homebrew Optical Mark Recognition system. HOMR allows forms for fill-in-the-bubble surveys, quizzes, and tests to be developed using a variety of word-processing systems ranging from LaTeX to Microsoft Word, printed on any printer, distributed to students, and scanned on any scanner. With accuracy rates significantly higher than those utilized by the US Census (Bureau, 2004), HOMR provides powerful OMR using commodity hardware and an easy programming interface. Such a tool is ideal for recording scores, either directly by grading multiple-choice tests or by providing OMR forms for graders to record scores.

12.2 Analysis

With tools like Agar and HOMR available to help collect score matrices, it falls to EDM analysis techniques to determine what assessment information can be extracted from S. The analysis techniques presented in this dissertation show a clear progression of what assessment information can be extracted from these score matrices. In Chapter 7 we introduced a method for assessing the difficulty and discrimination of the individual questions, assuming that the contents of the entire course were related. This is an obvious simplification, but provides an ability to determine, at minimum, which questions were particularly bad and possibly which questions were particularly good. By providing estimates of the difficulty of the question, instructors can ensure that students are understanding concepts at a reasonable level. By investigating which questions had the worst discrimination, instructors can begin to train themselves to ask better, more insightful questions, which leads directly to more meaningful assessment of students.

In Chapter 8 we investigated methods for predicting missing entries in the student score matrix. Based on this investigation, we can see that the statistics gathered in Chapter 7 are useful in predicting scores, particularly on binary score matrices. We also gained some insight into the structure of score matrices in general, showing that for most prediction methods it is better to examine other scores on a given question, rather than other scores by a given student. This reinforces the notion that student scores are noisy, and gives some justification for the claim made by techniques like CFA that question difficulty is more important in prediction than student ability, or at least student scores on other questions.

Chapter 9 delves into one of the fundamental issues in this assessment system: whether we can group questions by topic, allowing instructors to generate a binary version of the relevance matrix R by identifying the topics for t groups of questions, rather than identifying the topics for every individual question. Although manually labelling the questions is possible, likely taking half an hour to an hour per course, it would be preferable to not add to the burden on instructors. Additionally, if the relevance information can be extracted algorithmically, we can avoid the appearance of human bias in that stage of the analysis, arguably providing better final results when producing course assessment or program assessment scores.

However, the experiments presented in Chapter 9 show that for the types of data that we expect, such a clustering cannot be done much better than random chance. There are types of data, notably the Math & French questions from our baseline datasets, that can easily be correctly clustered. The algorithms that work well on that data do perform better than most on the course data, implying that those are likely the right algorithms to be using, but the issue is complicated by some unknown factor. It may be that the difference is in the style of assessment we perform in courses: the baseline data was generated by volunteers, many or most of whom were not taking either Math or French at the time. In contrast, we assess student knowledge on each topic immediately after teaching it, and rarely if at all after that course has ended. It may be that the timing of our assessment is off, in terms of partitioning the topics. Having not given students sufficient time to fully integrate the new information with their existing knowledge means that scores for “related” questions remain uncorrelated, much like the trivia data. This is certainly not the only hypothesis for why Math and French questions can easily be separated but the questions about the scheduler cannot be separated from questions about system calls in operating systems. Other interpretations call into question issues of cognition, question-writing technique, or simply having not found the right algorithm in our survey. However, this constructivist notion of timing seems quite likely, is the most readily verified, and thus serves as our working theory as to our failure at the topic clustering problem.

Given that we cannot cluster topics without any information other than scores, and preliminary experiments at incorporating question text were unsuccessful, Chapter 10 provides the next logical step: rather than require instructors to identify groups after they are produced by the algorithms, if partial information is provided ahead of time, can the algorithm finish the grouping accurately? Again we are confronted with results that indicate this is possible, but not likely to be worth deploying. The response of the algorithms surveyed in this experiment to partial information is consistently linear or sublinear. An ideal result would be to find some algorithm that provides near 100% precision when provided with some small fraction of the correct answer. This would allow for generation of the full relevance matrix with minimal imposition on the instructor. However, this does not appear to be possible.

12.3 Assessment

Given the results of Chapters 9 and 10, it is clear that for our outcomes-based assessment system, it is necessary to prompt instructors for the full relevance matrix R. Scores can be filled in automatically, and questions can be assessed to help instructors ask better questions, but relevance information must be a manual input to the system. This will likely remain an area of interest for the EDM community, as this type of assessment is quite valuable, and as shown in our experiment on prediction, knowing topic information for the questions can provide notably better results. Further, these experiments provide something that could easily become one of the first great questions for EDM: why are some topics separable, but not others? Finding an answer to this question may provide a significant result, not just for the EDM community but for cognitive science, assessment, and pedagogy.

Given the results of these clustering experiments, we rely on the instructors to manually provide the contents of *R*, mapping from questions to the topics of a course. Given *S* and *R*, it is easy to generate statistics describing the performance and assessment of a single course. Simply counting the entries in *R* that are relevant to each topic gives a notion of *coverage*, showing which topics were tested more heavily. Given *R* and *S* it is also easy to calculate average scores for each topic, which could be used to show when a particular subject was poorly understood by the students. If *R* and *S* are being kept up-to-date as the course progresses, targeted study suggestions could be sent to students based on which topics they are performing worst in.

Finally, program assessment in this situation is easy, given *S*, *R*, and a mapping *C* of course topics to program outcomes. To determine a numeric value for each program outcome, simply find the average score for each topic (as above) and multiply that vector by the matrix *C*. As *C* is completely independent of students or questions, *C* can remain relatively constant over time, only being updated as course topics change. Developing *C* represents little or no work for the instructor. By summing up the resulting vectors across all courses, program-wide assessment values can be produced, relating students performance on the questions in the program indirectly to the general skills and abilities we would like them to have upon graduation.

12.4 Impact

The significance of this dissertation goes far beyond the development of this assessment technique. Many of the individual components that went into this are significant in their own right. Agar represents a notable advance in the development of CAA systems, approaching the problem with more widespread use and adoption in mind, rather than automating a single, specific type of programming assignment assessment. HOMR, while not groundbreaking, appears to be the most accurate free OMR system available, and has already found usage and adoption outside of UCR. Both of these systems contribute to the teaching community above and beyond their function as score-collection utilities for our EDM system.

The real contribution of this dissertation, however, is the EDM analysis of the score matrix S. The technique for producing estimates of difficulty and discrimination has already provided anecdotal evidence of instructors bettering their courses both here and in other institutions. It is further verified as a valid and useful technique by its strong showing in score predictions. The score prediction investigation itself is useful for providing some basic methodology for EDM researchers to deal with a problem that is likely to be all-too-common in this area, that of dealing with missing entries in S. Even if these methods are not those that are eventually settled upon, discussion of these methods is a necessary step for the community to take on the path to common experimental methodologies.

Most important of all is the investigation into topic clustering. The fact that most algorithms perform quite well on the Math and French data indicates that there ought to be solutions to this problem. The non-performance on the Trivia data is unsurprising, given that the correlations between scores on questions like “What farm creature is tapped for the antibodies used in the miracle snakebite antidote CroFab?” and “What daredevil plains state had the lowest rate of car seatbelt use, at 47.7%, in 2000?” even though these questions both derive from the same overall category. The fact that both the Biology and the World History data behave like the Trivia implies very strongly that what we are seeing is a difference between questions testing a skill and questions that are testing isolated fact retrieval. This is not to imply that Biology or History do not have associated skills, but the types of questions asked on an SAT subject test in those categories are based more on memorization than practice of a skill. Given this interpretation of the baseline data, it is still striking that questions taken from *across the CS curriculum*, ranging across four instructors, and sampling a variety of question types, show little difference from the behavior of the Trivia data. Elimination of the low-discrimination questions allows for *some* correct structure to be produced by the algorithms surveyed, but the precision of the best algorithm on the reduced data is still worse than the precision of the worst algorithm on the Math and French data. Admittedly this is a bit of an apples-and-oranges comparison, as the random-chance precision for the Math & French data is higher than any other dataset, but the fact still remains: the inability to produce an accurate topic clustering is more probably due to bad input data than to choice of algorithm.

The question that remains to be determined is why the CS course data is so problematic. It is not obvious, as shown in numerous discussions with interested parties, why the presumed topics in CS should be as hard to reproduce as the Trivia topics. A likely explanation, given the current climate of constructivism in education, is that students have not had sufficient time to merge the information being tested into their overall mental model of the subject. Another hypothesis would be that topics at the course level behave differently, in a cognitively distinct way, than individual facts (which are known or not known), or larger skills like Math or French. If this is the case, and there is a reason based on the cognitive architecture of the human mind for why the topic clustering failed, that would imply that a generative mathematical model for the question scores should be built on factors other than topic, which is somewhat counterintuitive.

This issue of determining why there is this fundamental difference in behavior for datasets so similar on the surface is an important issue to be faced by the Educational Data Mining community, and by the educational community as a whole. An answer to this question may reveal a great deal of information about teaching and the human mind. Such an investigation is, at some grand level, the earliest foundation of the academic enterprise. In this way, it can be hoped that one of the newer academic disciplines, educational data mining, can make a significant contribution to the oldest questions in the academic endeavor.

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