A GRAPH-BASED TAXONOMIC INTELLIGENT TUTORING SYSTEM UTILIZING BLOOM'S TAXONOMY AND ITEM-RESPONSE THEORETIC ASSESSMENT

A Thesis/Dissertation

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Abstract

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Chapter 1
Background Information

1.1 Introduction

1.1.1 Problem Definition

A *content item* is some unit of information, such as a statement, graph, table, example, and so forth. An educationl television program, interactive tutorial or university lecture (generally, these may all be called programs) can be broken down into these units of information. Call an item χ; then the i^{th} item to be seen is χ_i, and the time at which it is seen t_i. Then (χ_i, t_i) represents the i^{th} item and its scheduled time.

For that matter, any program can be thought of as a sequence of these tuples, thereby forming a schedule of items:

$$X = \langle(\chi_1, t_1), (\chi_2, t_2), \ldots (\chi_n, t_n)\rangle. \tag{1.1}$$

Furthermore χ could be a question, which could be thought of as an item which accepts a response back that has a correct answer. Items and questions share many similar properties which help to distinguish them, such as the ones in Fig **??**.

The main question this body of work seeks to answer is this: *based on input from the student on any subset of questions in an item schedule, how should the remaining questions be scheduled*?

1.1.2 Novel Contributions

The answer to this question required a series of novel contributions to the fields of intelligent tutoring systems (ITS) and computer-aided assessment (CAT). Specifically:

- The creation of a data structure in the form of a graph, whose nodes contain information relevant to the assessment process, and whose edges capture dependency relationships among questions;

- A modification to an existing assessment theory known as Item Response Theory, which however providing a mature means of assessing student ability, benefited from an account of dependency relationships;

- A scheduler, or algorithm whose purpose was to determine what the questions should be given the item parameters and the students' response sets;

- An addendum to an existing theory of memory, forgetting, and practice, which could then be integrated into the scheduler to provide a fuller-featured system.

In addition to this, the body of work rests upon other incidental novel contributions, such as the separation of Bloom level and difficulty [**?**].

1.2 Bloom's Taxonomy

Bloom's cognitive taxonomy organizes questions into levels depending on the cognitive functions required of the answerer. The levels are: knowledge, comprehension, application, analysis, evaluation, and synthesis. A brief overview is given in Table 1.2, with definitions and examples of questions covering the concept of for-loops:

Each category depends on the cognitive functions used in the previous category. That is, comprehension requires knowledge, application requires comprehension, and so forth.

Table 1.1: The levels of Bloom's taxonomy defined

Level	Explanation	Example Question
Knowledge	Recalling factual information.	What is a for-loop?
Comprehension	Assigning meaning to information.	What does the example for-loop output? (Give example.)
Application	Applying a rule to a specific instance.	How can the update statement of the loop be changed to print only even numbers?
Analysis	Breaking information into parts and exploring relationships.	What would happen if the update statement decremented instead of incremented the counter?
Evaluation	Judging the use of knowledge or the validity of an argument.	Which is better for reading user input: a for-loop or a while-loop? Why?
Synthesis	Utilizing knowledge to create a new solution to satisfy a goal.	Write a for-loop to print only even numbers up to ten.

Furthermore the mastery of one of the levels is with respect to a given concept. A student may be able to synthesize solutions to problems dealing with expressions, but may not possess knowledge of equations, and thus could not solve problems involving equations.

The utility of Bloom's taxonomy lies in its ability to pinpoint the underlying cause of the student's problem-solving impasses [17]. Suppose a test of mastery of loops is given with the comprehension question "What does such-and-such loop output?" is given, and the student reaches an impasse. If the question "What are the three expressions of the loop and what do they do?" is asked and the student does not know, the impasse can be attributed to a lack of knowledge about loops. If the student does know about the loop expressions but still cannot answer, one might instead attribute it to a comprehension difficulty *as such*; which might be remedied by giving some examples to build intuition, then continuing to test at the comprehension level.

Educators may have an intuitive notion of how to do this, but Bloom's taxonomy gives the ability to examine the impact of questions scientifically. By identifying the tested concept and the Bloom level of exercises, one can then form hypotheses about student responses to questions.

1.2.1 The Interpretation in Computer Science

Bloom's taxonomy has been proven to be useful at the undergraduate level, and particularly in the field of software engineering [3, 15]. It has seen success in program comprehension [4], where the asking of comprehension questions fosters code reading [9]. In addition, it has been useful for pinpointing the difficulties of novice programmers in a guided learning approach [17]. It been used to identify a marked preference for higher-level problems for those able to solve them [6] [8]. At least two experiments have shown the effect of item ordering on performance [14, 5], and the taxonomy has even been applied to create ratings of courses based on the average Bloom levels of tasks and questions in the course [16].

In spite of all this, there is an ongoing debate regarding the applicability of Bloom's taxonomy to computer science [11, 7, 19]. The crux of this debate centers around the interpretation of Bloom levels: not only how questions map to Bloom levels, but also regarding the progression of Bloom levels over the span of a course or curriculum.

A tacit assumption in much of the research is that Bloom levels equate to difficulty levels. While there is certainly a relationship between Bloom level and difficulty in the "ordinary course" of devising problems, a distinction can be made between the two.

1.2.2 Assumptions of this Work

Prior research by the author supports the view that Bloom level and difficulty are separable parameters of a content item. This work will proceed on the assumption to that effect.

In addition, some of the components of this body of work, particularly those pertaining to memory and recall, are supported by many decades of empirical research [?]. While the study of intelligent tutoring systems has seen attempts to validate addendums to these theories which accommodate re-activation of forgotten knowledge, none have undergone extensive empirical testing as is typical for psychological models. The components of this body of work regarding re-activation introduce hypotheses.

1.3 Item Response Theory

Here is introduced a mature assessment theory known as Item Response Theory, an alternative to Classical Test Theory (CCT). Whereas Classical Test Theory assigns a student a grade based on the student's position in a distribution of composite test scores, Item Response Theory accounts for item difficulty, item discrimination, the probability of guessing the question correctly.

One of the main appeals of IRT is its incorporation of item difficulty. As will be shown later, this is pertinent to the interpretation of Bloom levels.

According to Item Response Theory (IRT), the probability p_i that a student answers correctly the i^{th} question on a test, is given by:

$$p_i(\theta_s) = \gamma_i + \frac{1 - \gamma_i}{1 + e^{\alpha_i(\theta - \beta_i)}} \tag{1.2}$$

where:

- α is the item discrimination, or how well the item can distinguish students of varying trait ability;
- β is the question difficulty, an initial estimate of which can be obtained from the proportion of students with average trait ability who pass the question;
- γ is the probability of guessing the answer correctly, which for n-choice questions is

$1/n$;

- and θ is the *trait ability* of the student, or the student's particular ability to answer that question correctly.

A graph of the IRT curve for the parameters $\alpha = 1, \beta = 0, \gamma = 0$ is shown 1.3.

Note that α_i, β_i, and γ_i are parameters of the item i; however θ_s is particular to the student s. If the trait ability of the student is known in addition to the item parameters, then the probability of a correct response can be calculated. However, it is more often than not the case that the response set of the student is known, and trait ability is unknown. In such a case, a variety of techniques are deployable.

Trait ability in IRT can be obtained using a maximum likelihood estimation (MLE) method, which finds a maximum-likelihood estimate of θ by testing a range of θ values with the IRT formula [1]. Later it will be shown how θ can be estimated. Another potential technique is Newton-Raphson, which in most other applications would be the more efficient and desirable method. It will later be discussed why the MLE method is preferred.

Until now, the fusion of IRT and Bloom's taxonomy has only existed in the literature as a possibility [18]. This work seeks to reconcile the two by offering a compatible interpretation of Bloom's taxonomy.

1.3.1 Evaluation of Trait Ability

Consider a set of content items or questions for which the answer is either incorrect or correct. This is true in the case of multiple choice questions (as well as true-false, which is a subset of multiple-choice questions).

Suppose the student has a response set for content items:

$$X_s = x_{s1}, x_{s2}, \ldots, x_{si}, \ldots x_{sn} \tag{1.3}$$

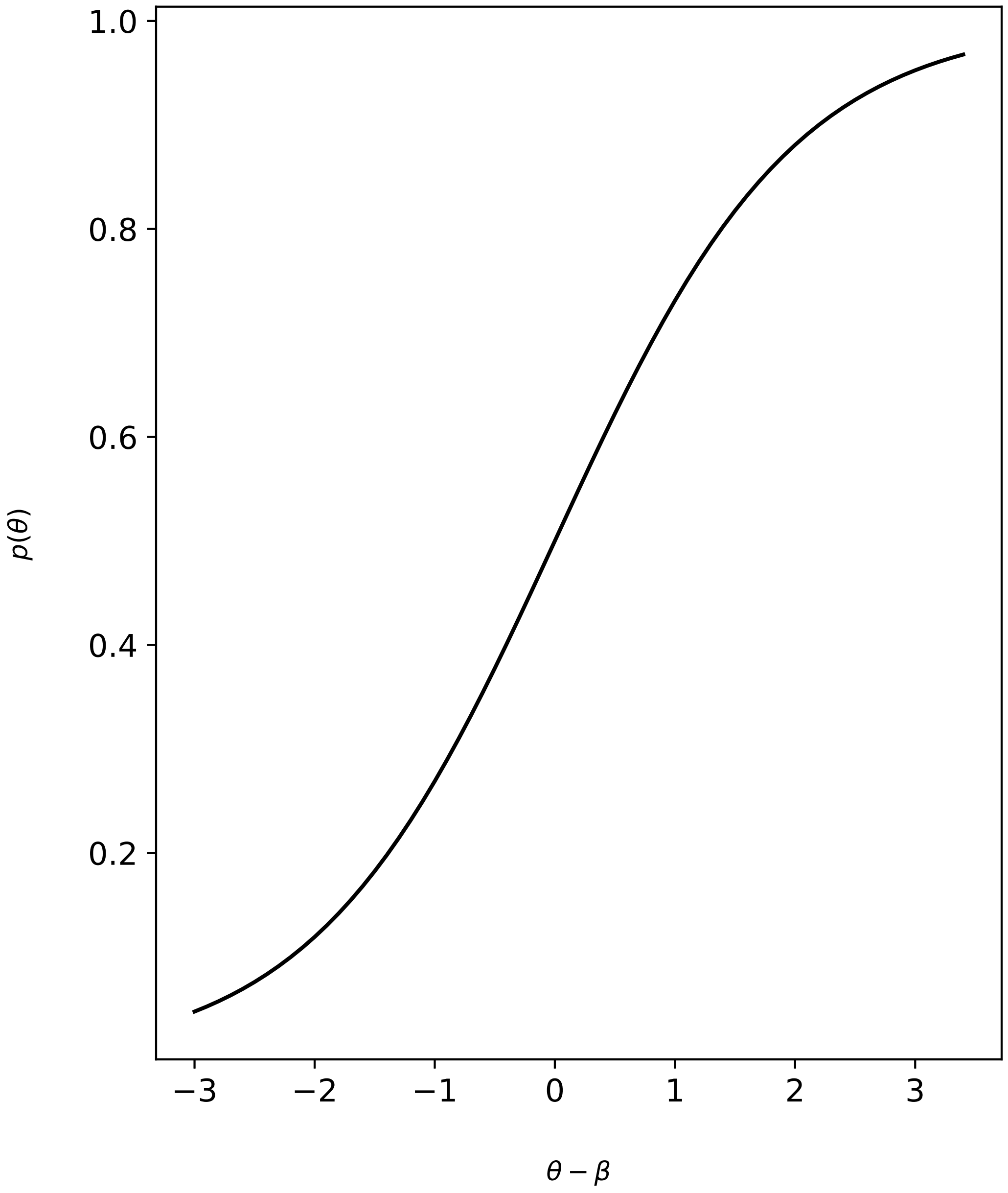

Figure 1.1: A probability curve in Item Response Theory.

Here X_s is the response vector of student s, and x_{si} is the correctness of the response to content item i by student s; it is zero if the response is incorrect, or 1 if it is correct.

These questions may be of various and sundry discriminations, difficulties, and probabilities of guessing. The first question may have $\alpha_1 = .5$, $\beta_1 = 1$, and $\gamma_1 = .25$; the second may only differ in its difficulty, for example $\beta_2 = -1$. However, it shall be assumed that the set of content items for which the student has provided responses are for the same concept and the same Bloom taxonomic level. The reason for this assumption will become apparent later.

Recall that the probability p_{si} of student s answering the i^{th} question correctly is:

$$p_{si}(\theta_s) = \gamma + \frac{1-\gamma_i}{1+e^{\alpha_i(\theta-\beta_i)}} \tag{1.2}$$

Since θ_s is unknown but the response set is known, one method for determining θ_s is by guessing all possible values. First, one can define a function f_{si}:

$$f_{si}(\theta_s) = \begin{cases} p_i(\theta_s) & \text{if } x_{si} = 1 \\ q_i(\theta_s) & \text{otherwise} \end{cases} \tag{1.4}$$

where

$$q_{si}(\theta_s) = 1 - p_{si}(\theta_s). \tag{1.5}$$

That is, f_{si} assumes the probability p_{si} if answered correctly and q_{si} if not answered correctly. Proceeding on the assumption that each of the observations (that is, responses in the response set) is independent, the probablity of observing a total response set given a particular θ_s value is the product of the probabilities f_{si} for all i, $1 \leq i \leq n$, or

$$\prod_{i=1}^{n} f_{si}(\theta_s). \tag{1.6}$$

Supposing that there exists some θ_s which maximizes this product, the most likely value for the student's true trait ability θ_s is defined by:

$$\theta_s = \underset{\theta}{\operatorname{argmax}} \left[\prod_{i=1}^{n} f_{si}(\theta). \right] \tag{1.7}$$

that is, that value of θ_s which maximizes the product which gives the probability of all the observations occuring together, given θ_s. To obtain this, products for a range of possible θ values are calculated.

In the intelligent tutoring system which has been constructed, there are only thirteen such values, drawing from the +/- system. The mapping of grades to trait ability levels is given in Table 1.3.1. This mapping could also be applied to difficulty levels of questions. A "C question" is one which students of average trait ability (and perhaps just more than half the class) may be expected to answer; an "A+ question" is a very difficult question which students of only A+ ability at the time of asking may be expected to answer; and an "F question" is one which may be used to determine if a student's trait ability is minimally satisfactory. This mapping lends to a intuitive understanding of trait ability–as the familiar letter grade. An MLE may thereby effectively grade the student.

To that end, rather than using a fine-grained MLE, it makes practical sense to calculate products for these thirteen values of θ, since higher granularity than the +/- system is not useful for final grade assignment, nor is necessarily more intuitive for the student or instructor. Restricting the products calculated to this set of values also makes sense from an efficiency standpoint. The total time complexity of the MLE is linear in the size of the response set, regardless of the number of guesses in θ; while not asymptotically reduced from using a smaller step size, it is five times faster than 10^{-1}, and fifty times faster than 10^{-2}. A graph calculating likelihoods for MLE is depicted in Figure 1.3.1.

The total number of MLE estimations for trait ability throughout a course is equal to the total number of responses for all questions throughout a course, which can be quite large; it is proportional to the number of students times the number of items.

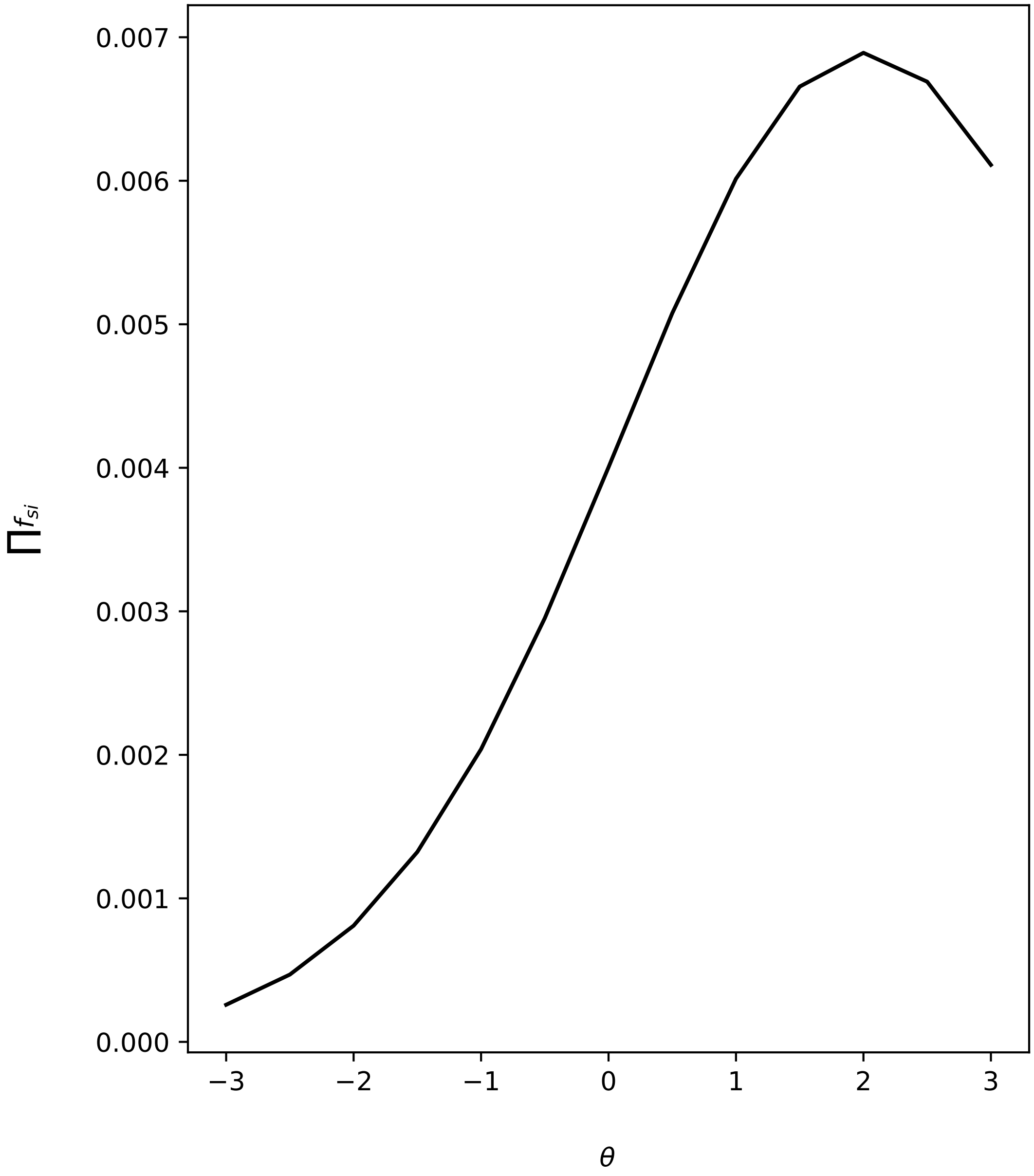

Figure 1.2: A maximum-likelihood estimation for IRT

Table 1.2: Grades mapped to trait ability levels

Letter	θ	Explanation
F	-3.0	unsatisfactory
D-	-2.5	minimal
D	-2.0	
D+	-1.5	
C-	-1.0	acceptable
C	-0.5	
C+	0.0	
B-	0.5	good
B	1.0	
B+	1.5	
A-	2.0	distinguished
A	2.5	
A+	3.0	

1.4 Factor Analysis

Suppose Y is a vector of m observed random variables. It is posited that there are $n : n \leq m$ latent, or hidden variables which explain Y, in addition to item-specific variables ϵ. Y may be scores on test questions (what is directly measured); latent variables may be degree of understanding, amount of time spent studying, alertness, verbal intelligence, and so forth (what is indirectly measured). An example of a factor analysis diagram is given in Figure **??**.

This relationship may be expressed this using the following system of equations [**?**]:

$$\begin{aligned} y_1 = &\quad \lambda_{11}\zeta_1 + \lambda_{12}\zeta_2 + \dots \lambda_{1n}\zeta_n + \psi_1\epsilon_1 \\ y_2 = &\quad \lambda_{21}\zeta_1 + \lambda_{22}\zeta_2 + \dots \lambda_{2n}\zeta_n + \psi_2\epsilon_2 \\ \vdots & \\ y_m = &\quad \lambda_{m1}\zeta_1 + \lambda_{m2}\zeta_2 + \dots \lambda_{mn}\zeta_n + \psi_m\epsilon_m \end{aligned} \tag{1.8}$$

Here, ζ represents a factor, or latent variable. The λ weight represents a factor loading, or extent to which the factor influences y; ϵ is an item-specific random variable, and ψ is its loading. This above system may be expressed in matrix notation:

$$Y = \Lambda X + \Psi E \tag{1.9}$$

This is known as the fundamental equation of factor analysis. Here, Λ is known as the loading matrix of the factors. For normalized Y, it gives the amount of variance accounted for by each factor in X.

The means by which Λ is obtained:

It suffices to say that factor analysis involves the interpretation of Λ, and may be one of two types: confirmatory or exploratory.

1.4.1 Confirmatory vs. Exploratory

Confirmatory factor analysis (CFA) seeks to confirm that hypothesized factors accounted for a certain threshold of variance. Exploratory factor analysis (EFA) seeks to find factors which account for unexplained variance.

In this thesis, the use of CFA is to confirm that dependency relationships among items exist. It is also used to find the extent of variance accounted for by those dependency relationships.

1.5 Previous Research

Chapter 2
Items and Sets

2.1 Representing Items

A database was used to represent items, item sets, students, and student responses. A full diagrammatic representation of the database is shown in Figure 2.1.

The database contains items of the following nature:

- *Content.* These include facts (which may be arranged into paragraphs, subsections, and sections), definitions, diagrams, and source codes.

- *Assessment.* These include questions, which may be true/false, multiple-choice, code writing, code simulation, short answer, and freewriting; also Likert scale items.

2.1.1 Taxonomic Information

Any output from this database to the student which is intended to solicit input from the student has the following ordinal dimensions:

- *Difficulty.* Following the +/- grading system, difficulties range from -3 (very easy) to +3 (very hard), with 0 being medium. As alluded to earlier, difficulty determines the probability that a given student in the class will answer the item correctly.

- *Bloom level.* The Bloom levels of cognitive functioning are Knowledge, Comprehension, Application, Analysis, Evaluation, and Synthesis.

- *Concept.* Concepts covered in computer science courses; for example in a programming course, these may include: Variables, Expressions, Control Structures, etc.

Any output to the student also has the following categorial dimensions:

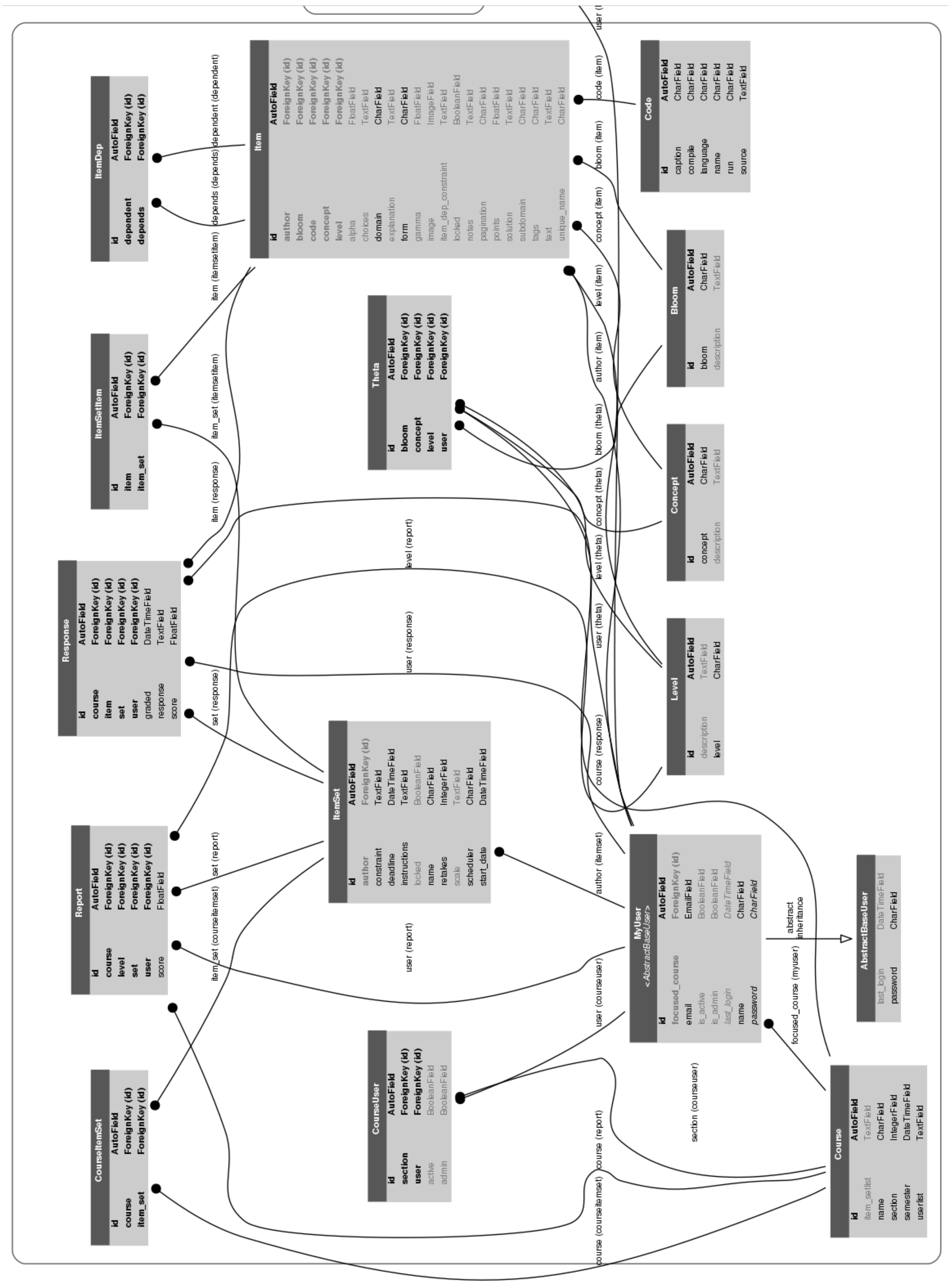

Figure 2.1: The database layout.

- *Context.* A problem may have a domain-specific context, e.g. it may be a problem relevant to biology, chemistry, physics, mathematics, etc.
- *Type.* The problem may be true/false, multiple-choice, short answer.

Each output may also have a dependency list, that is a list of IDs of, or a rule describing, other output entries which the student should be exposed to prior to that output. For this system, Bloom level, subject domain, concept, and difficulty are dimensions of a test question.

It is important to note that the dimensions of the data are not necessarily limited to the above; an exploratory factor analysis (EFA) could be used to extend the dimensionality of the data semi-automatically. This functionality has not been implemented, but there exists a potential for it.

2.1.2 Examples of Content Items

2.2 Reconciling Bloom's Taxonomy with Item Response Theory

A popular interpretation of Bloom's cognitive levels is that they are difficulty levels, and that these difficulty levels are fixed [14, 16, 13, 11, 7]. Knowledge is easy; synthesis is hard. We will call this the Bloom-equals-difficulty hypothesis.

A creative interpretation of this hypothesis is that per-student difficulty can be explained in terms of the demotion of Bloom levels. The synthesis *and therefore difficult* questions, once the solution is obtained, are reduced to knowledge *and therefore easy* questions. Certainly, this is one possible scenario. However, it does not explain a student's ability to answer altogether distinct synthesis problems; this is to suggest students engage the cognitive functions of synthesis, presumably as an effect of learning the use of those functions. To maintain that Bloom equals difficulty would either require sustaining the view that students are able to pass the questions because of a demotion of the cognitive functions required (which poses a rather cynical view of cognition and of education); or else some notion of trait ability–in particular one which offsets difficulty, allowing an increase in the probability of passing the question.

The latter option takes the shape of a primeval form of IRT, mapping Bloom levels to β. This is highly convenient for the hypothesis that Bloom equals difficulty, as it becomes agreeable to evaluation with IRT. Nontheless, there are still several issues with the hypothesis.

Consider first that exposure to knowledge and knowledge questions causes an increase in θ, provided the student acquires the knowledge. According to Bloom's theory, this would increase the probability of answering comprehension questions correctly. This agrees with the theory. However, according to IRT, it would also increase the probability of answering application questions correctly even if no comprehension-level questions are asked. In fact, it is theoretically possible to design tests with sufficient numbers of knowledge questions to place, for any β, $\theta - \beta$ much greater than zero–that is for example to say, asking a sufficient number of knowledge questions should give the reasonable assurance that application-level ability is high enough not to bother testing it.

As many educators will no doubt agree, this is not the case. Even if a student scores exceptionally well on knowledge questions, it gives no such assurance that the student will score similarly on application-level questions. Even if knowledge and application scores are found to be correlated, there may be an additional underlying factor contributing to both scores (such as intelligence). The application level is *qualitatively* different; hence it needs to be tested in spite of the value of θ.

Second, if the hypotheses is strictly true, then there can exist no counterexample to the claim. That is to say that there exists no problem on a lower Bloom level which is more difficult than a problem on a higher Bloom level. To take an example, it would be mistaken to call an application problem easier than any comprehension problem.

Counterexmaples with intuitive appeal can be constructed. Take for-loops for example. To ask a student to print out the result of a simple loop which prints numbers 1 to 10 should present an easy enough task. This is an application of the many rules of for-loops, but which does not require creative synthesis or critical thinking on the part of the student (hence it is an application problem).

Consider then asking the student to impose a flowchart over the same code, including the initialization, condition and update statements and the body of the loop, and to indicate the start and stop of the loop. Suppose the student has seen flowcharts over similar loops before. This is a test of comprehension–in particular, comprehension of the internal workings (the control flow) of the loop.

The application problem above requires only an intuitive comprehension of the loop: "*It prints the sequence from 1 up to 10 in steps of 1*", the student may realize. It demands only shallow comprehension and the rule to be applied is simple. In the comprehension problem, on the other hand, a higher degree of precision in comprehension of the loop is demanded to solve the problem. The comprehension problem also depends on mastery of the knowledge, comprehension, and application of flowchart symbols. Regardless, explaining the control flow of the loop in full detail is a more difficult undertaking than simply printing its output.

Likewise, it is possible to ask the student to synthesize a loop printing the first ten powers of two, then ask a comparatively difficult analysis question in the form of an obfuscated loop code. Impasses in this situation may be attributed to a lack of knowledge or comprehension of the constructs used in the presented code. In the synthesis problem, the student has the advantage of using known syntax.

Third, by Bloom's own admission, it is possible to skip levels for certain concepts [2]. In this case, the ordinality of Bloom levels breaks down. A plausible example is given above. It is possible to teach how to obtain the numeric sequences printed by for-loops before covering in full detail the control flow of the loop. In that particular case, application of the rule does not depend on comprehension of the code construct.

Alternative interpretations of Bloom levels distinguish between facility or difficulty and complexity of a problem [10, 19]. In such interpreations, the cognitive complexity has an orthogonal relationship to the item difficulty. The problem with such interpretations, however, is that they do not readily explain the moderate correlation that does exist between mean performance and Bloom level [10].

2.2.1 Difficulty vs. Bloom Level

Chapter 3
Trait Ability

3.1 Representing Ability

To form a statistical basis for content scheduling, the measure of trait ability should be done per-concept and Bloom level. Therefore if there are m concepts and n levels, there are then nm number of θ values. This shall be called Θ, the trait ability matrix; and Θ_s will denote the trait ability matrix of student s. Let j be the index of a Bloom level and k be the index of a concept, then:

$$\Theta_s = \begin{bmatrix} \theta_{s11} & \cdots & \cdots & \cdots & \theta_{sn1} \\ \vdots & \ddots & & & \\ \vdots & & \theta_{sjk} & & \\ \vdots & & & \ddots & \\ \theta_{s1m} & & & & \theta_{snm} \end{bmatrix} \tag{3.1}$$

While not strict, there is certainly an ordering about Θ. Lower-level concepts come before higher-level concepts, and lower Bloom levels come before higher Bloom levels. Conceivably a Θ may look like the following:

$$\Theta_1 = \begin{bmatrix} 3 & 2.5 & 1 & 0 & -1 & -2 \\ 2 & 1.5 & 0 & -.5 & -1.5 & -2.5 \\ 1 & .5 & 0 & -1 & -2 & -3 \\ 1 & 0 & -.5 & -1 & -2.5 & -3 \end{bmatrix} \tag{3.2}$$

Highlighted are areas where $\theta_{sjk} = 0$. These are the areas where the student has roughly .5 probability of answering a question at difficulty $\beta = 0$ correctly. Now the question arises:

given a rich content item set with questions in all (Bloom × concept × difficulty) categories, which categories should be selected? Many factors are taken into account.

3.2 Proximal Zone of Development

Clearly the higher θ_{sjk} values should be left alone, particularly those nearing 3, since this demonstrates exceptional mastery of that (Bloom × concept) category. In particular, if $\theta_{sjk} = 3$, there is no sense in asking at all since trait abilities are capped at 3. In probabilistic terms and relative to questions, asking questions for which the estimated probably is overwhelmingly high, for example $p > .9$, serves no purpose, since probability estimates of that degree require $\theta - \beta$ significantly greater than 0.

If $\theta_{sjk} = x$ then it would be "unfair" to ask questions in that category which have $\beta > x$. According to Equation 1.2, if $\beta > x$ and $\theta_s < x$, then $\theta - \beta < 0$ and therefore $p(\theta_s) < .5$, which means the student has less than .5 probability to answer correctly. Asking questions for which $p(\theta_s) < .5$ has psychological ramifications, and potential problems for the updated MLE of θ_s.

It is true that correct answers of more challenging questions raise the ability returned by a maximum likelihood estimate, however if the probability of answering them is consistently less than chance and the student responds accordingly, it is unlikely the estimate will return any $\theta_{sjk} > x$ for those problems. Also, given the information Θ_s about the student, if it is known that the particular student will more than likely fail a particular question, it would not make sense to ask it from a psychological standpoint, provided that the intention of asking is to raise trait ability levels. If the student consistently experiences more failures than successes, the student is more likely to be discouraged by the testing.

There is another consideration: the concept tier and Bloom levels. The course is a progression of concepts across Bloom levels. Ideally, the student should see steady progress in the course. The set of questions asked at any given time in a course of study typically range over a subset of concepts. Testing for all concepts begins at the Knowledge level; as new concepts are introduced over time, the tested Bloom level for earlier-introduced concepts rises. In a "perfect" situation, we might observe a trait ability matrix as in Equation 3.3, which shows a clear diagonal reflecting a progression in both concepts and Bloom levels.

$$\Theta_2 = \begin{bmatrix} 3 & 3 & 2 & 1 & 0 \\ 3 & 2 & 1 & 0 & -1 \\ 2 & 1 & 0 & -1 & -2 \\ 1 & 0 & -1 & -2 & -3 \\ 0 & -1 & -2 & -3 & -3 \end{bmatrix} \tag{3.3}$$

With all this in mind, the most logical subset of (Bloom × concept) categories to select questions from are those in the neighborhood of $\theta_{sjk} = 0$. One interpretation of this subset is that it is the student's proximal zone of development. In the psychology of learning, the proximal zone of development is the area or areas in which a student can perform a task with assistance, but could not perform the task without assistance. This is consistent with $p \approx .5$.

However, any question can potentially be asked for any (Bloom × concept) category while still placing p at or just slightly above .5 by manipulating difficulty. In fact, a matrix of difficulties for desired target questions could be calculated from the ability matrix:

$$B_s = \Theta_s - \delta \tag{3.4}$$

where δ is a sufficiently low value, such as .5. In the case of student $s = 1$, B would then equal:

$$B_1 = \begin{bmatrix} 2.5 & 2 & 1 & -.5 & -1.5 & -2.5 \\ 1.5 & 1.5 & -.5 & -1 & -2 & -3 \\ .5 & 0 & -.5 & -1.5 & -2.5 & -3.5 \\ .5 & -.5 & -1 & -1.5 & -3 & -3.5 \end{bmatrix} \tag{3.5}$$

Then, it is possible to threshold the matrix so as to eliminate (Bloom × concept) categories after this stepladder, but include some lag up to and not including those β_{sjk} values for which the student has θ_{sjk} indicating distinguished mastery:

$$B_1 = \begin{bmatrix} & 2 & 1 & -.5 & & \\ 1.5 & 1.5 & -.5 & & & \\ .5 & 0 & -.5 & & & \\ .5 & -.5 & & & & \end{bmatrix} \tag{3.6}$$

From here, the density of questions asked may be in proportion to the distance from -.5. Eventually, either the student will reach $\theta_{sjk} = 3$ or else the tutoring system will run out of questions for that (Bloom × concept), in which event the trait ability level will stay.

This structure, Θ, therefore shows where to begin asking questions. It also helps to define the goal of the intelligent tutoring system: to increase values in Θ successively along its diagonal, thereby engineering an experience similar to course progression.

3.3 Updating Ability

The trait ability matrix must be refreshed (either after a student response, for a more fine-grained scheduling, or after a total assessment for course-grained scheduling). Therefore the student responses must be auto-graded, and an MLE for each element in Θ must be performed.

3.3.1 Short Answer

For short answer questions, γ is set to 0, since it is assumed that there are infinitely many possible responses to the short answer question, unless otherwise indicated in the problem specification.

Support for auto-grading short answer questions was easily obtained. Short answer questions can be graded using the Levenshtein distance, also known as the edit distance. Essentially, the Levenshtein distance gives the number of edits (insertions, substitutions and deletions) required to arrive from the student input to the solution. If the Levenshtein distance is below a threshold, the answer is marked correct; otherwise it is marked incorrect.

Chapter 4
Item Dependencies

4.1 Dependency Information

No representation of trait ability mentioned so far specifically accounts for dependency relationships between questions. There are certainly dependency relationships between whole (Bloom × concept) catogories. For example, one must be able to execute a for-loop (Comprehension of Loops) well before gaining the ability to write one which satisfies an intended goal (Synthesis of Loops). This is a course-grained dependency.

Other course-grained dependencies might be less obvious; questions in categories for which concept is high-level and Bloom is low-level, depending on questions in categories for which concept is lower-level and Bloom is high-level. For example, understanding a for-loop (Comprehension of Loops) is predicated on being able to evaluate expressions (Application of Expressions). In a trait ability matrix, these categories might even lie on a diagonal, which would otherwise seem to suggest their independence.

Consider finer-grained dependency relationships among the following specific questions regarding expressions:

```
(a) What is (5 % 2)?
(b) What is (5 / 2)?
(c) What is (5 % (5 / 2))?
```

The intuition captured by this example is that Part (c) could not be answered correctly, at least not by any logical chain of reasoning, without possessing the specific application ability that Part (a) and Part (b) test for.

It is probably true that Part (c) is more difficult than Part (a) or Part (b), but this is not the reason for the dependency; rather it would appear the dependency is the reason for the higher difficulty. In terms of questions which test application ability for expressions, all of the questions are in the same neighborhood of difficulty; it is even possible albeit unlikely for the β values for all of these to be equal.

However, if dependencies of the form $c \rightarrow a$ and $c \rightarrow b$ exist (that is, c depends on a and b), they would be indicated by high binary correlations between c and a and c and b.

Even more telling than the coefficients of determination are the loadings from a confirmatory factor analysis, which when squared give the proportions of variance attributable to a and b. This technique gives an indication of the degree to which c depends on a and b, and the relative proportions of this dependency.

4.1.1 Probability Estimates Using Dependees

Consider the vector of squared factor loadings for a set of content items, where the depender is a content item j. Suppose these content items are independent.

$$\Lambda = \begin{bmatrix} \lambda_1^2 & \lambda_2^2 & \dots & \lambda_n^2 \end{bmatrix} \tag{4.1}$$

The total amount of explained variance is given by:

$$E = \sum_{i=1}^{n} \lambda_i^2 \tag{4.2}$$

And the unexplained variance by:

$$U = 1 - E. \tag{4.3}$$

Suppose a student gives a unique one-time response to each question, thereby producing a response set vector:

$$X = \begin{bmatrix} x_1 & x_2 & \dots & x_n \end{bmatrix} \tag{4.4}$$

The regression model used to obtain the probability that the student answers the depender question correctly is:

$$p_j = x_1\lambda_1^2 + x_2\lambda_2^2 + \ldots + x_n\lambda_n^2 + U\epsilon \tag{4.5}$$

Alternatively:

$$p_j = \sum x_i\lambda_i^2 + U\epsilon \tag{4.6}$$

where ϵ is some error function not accounted for by the dependencies, having range $0 \leq \epsilon \leq 1$. It accounts for factors not explained in the confirmatory factor analysis which nevertheless influence the test; these could be the student's intelligence, aptitude for that particular problem, or how many hours of sleep were had the night before; or other, inconceivable factors.

The proceeding assumption is that the unexplained variance is due to item discrimination, problem difficulty, and trait ability. That is:

$$\epsilon = \gamma_j + \tfrac{1}{1+e^{\alpha_j(\theta_s^* - \beta_j)}}, \tag{4.7}$$

which is to say that the remainder of the probability can be estimated using Item Response Theory and what is known about the student's trait ability from other problems which, while not strictly dependencies, inform the probability that a student will be able to answer a question of this nature. A caveat is that the θ_s used in this calculation should not include any of the depenedencies in its MLE, since they are accounted for in the formula. This value is denoted as θ_s^*

And therefore the estimated probability is:

$$p_j = \sum x_i\lambda_i^2 + U\left[\gamma_j + \frac{1}{1+e^{\alpha_j(\theta_s^* - \beta_j)}}\right]. \tag{4.8}$$

This assumes, however, an atemporal view. It assumes a scenario in which memory is flawless; that all of the dependencies reside in memory at the time of the asking of the target (depender) question. Also, it assumes that there is no feedback given for incorrect responses to questions.

Rather than a response x_i, instead a probability p_i can be modeled by a combination of Item Response Theory and theories of memory and forgetting. In that case:

$$p_j(t) = \sum p_i(t)\lambda_i^2 + U\left[\gamma_j + \frac{1}{1 + e^{\alpha_j(\theta_s^* - \beta_j)}}\right]. \tag{4.9}$$

That is, the probability of answering a target question correctly is the product of the probabilities of answering the dependencies correctly by the proportions of variance explained by the dependencies, plus the remainder of variance explained by Item Response Theory: the item parameters and the student's trait ability.

What remains is a temporal account of questions, in particular the role of memory and forgetting.

Chapter 5
Memory

5.1 Models of Memory

Ebbinghaus is credited with a theory of memory and forgetting which has withstood empirical study for over a century [?]. It is known as the power law of forgetting. According to the power law of forgetting, the strength of a memory after a time t falls off exponentially:

$$S(t) = ae^{-bt} \tag{5.1}$$

In this model, a is the initial strength of the memory, and b^{-1} is a decay rate. The curve drawn by this function is known as the curve of forgetting, which is depicted in Figure 5.1. If $a = 1$, the function may be interpreted as a probability function:

$$p(t) = e^{-bt} \tag{5.2}$$

According to the theory, if the memory strength falls below a certain threshold, then in the absence of any intervening information (that is, information which re-activates the memory via association), the individual will be unable to spontaneously recall the information. In a probabilistic model, one may set the threshold at .5 probability—the probability below which the individual has more than likely forgotten the information.

5.2 ACT-R

John Anderson developed a model for process-based learning which could provide the foundation for an intelligent tutoring system [?]. He called this Adaptive Control

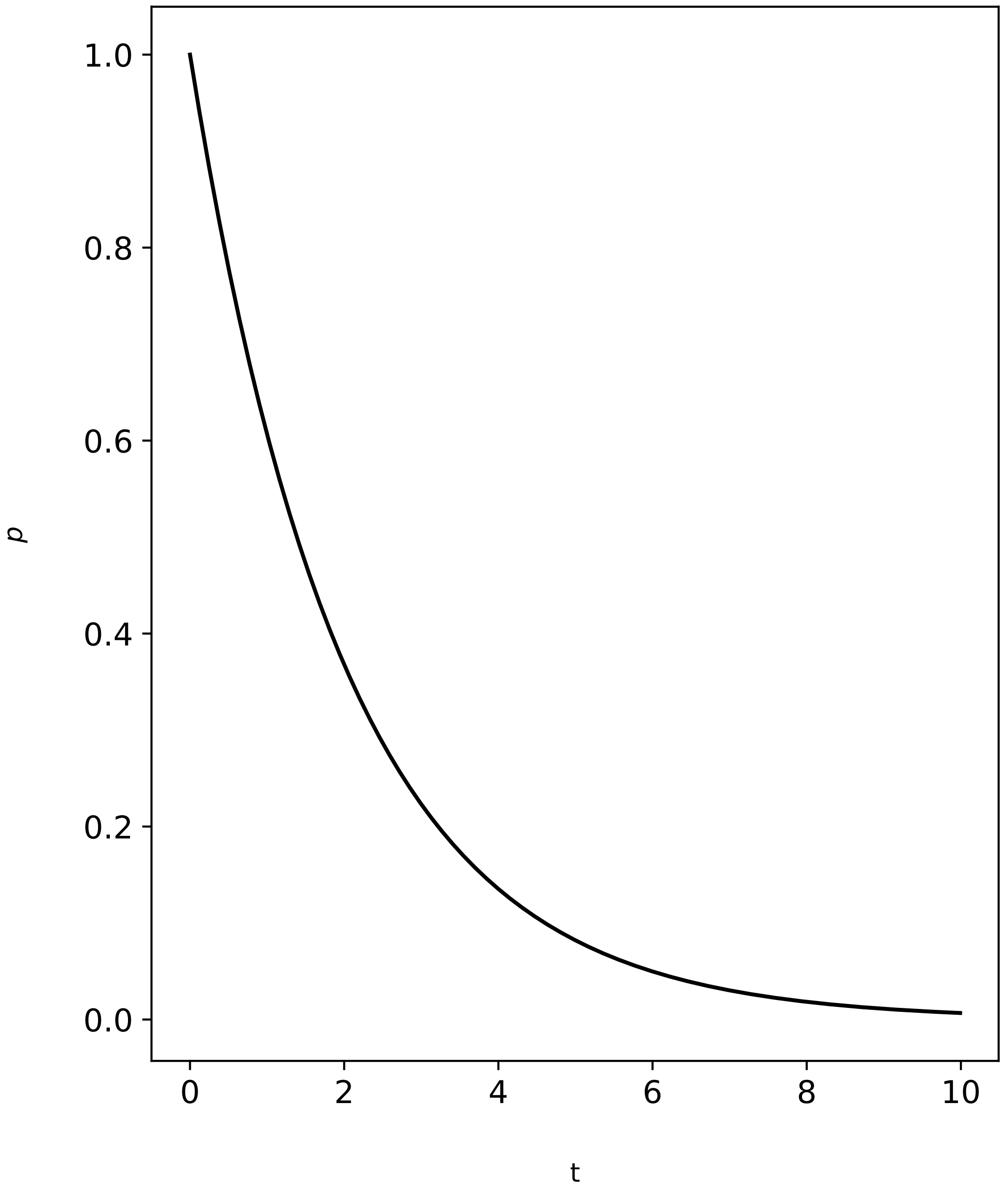

Figure 5.1: The curve of forgetting

of Thought-Rational (ACT-R). In ACT-R, there are goals, akin to problem statements; and rules, or processes used to solve problems; and finally facts, or knowledge utilized in the course of applying rules. In this regard, the structure of an ACT-R model resembles a logic program.

In addition to this, however, Anderson added models for memory and forgetting to support realistic recall probabilities and latencies. The memory component is based on Ebbinghaus' model of memory retrieval. Anderson added a component to explain memory re-activation of a memory. According to Anderson's model, a chunk of memory i is re-activated (or additionally activated) to the extent that other chunks of information (related concepts, words, ideas, etc.) which have some association to i are attended to. This notion is captured in the following equation:

$$a_i = b_i + \sum_{i=j}^{n} w_j s_{ji} \tag{5.3}$$

In this equation, known as the activation equation, the activation of a chunk i is equal to its base activation b_i, plus the products of the attentional weights w_j by the associative strength of s_{ji} to other chunks. This provides an intuitive explanation for the manner in which recall of a target chunk can be stimulated by dropping hints, using certain key words or phrases, or mentioning related material.

Practice has the effect of causing the base strength of the memory to increase, and delays cause the strength of the memory to drop off:

$$b_i = \ln\left(\sum_{j=1}^{n} t_j^{-d}\right) \tag{5.4}$$

Here, t_j is the time since the jth practice of an item, and d is a decay rate. . . .

Some concepts, particularly the notion of re-activation of memories, have been borrowed from ACT-R and modified to fit the more coarse-grained intelligent tutoring system presented in this work. In particular, total problems rather than individial processes will have probabilities of recall associated with them. Also, associative strenghts are established using a factor analysis.

5.3 Alterations to Memory Model

A slight modification to this theory accounts for short-term memory and short-term memorization, which allows for a small time window for the student to enjoy a high probability of recollection before dropping off sharply, as in the original curve:

$$p(t) = \frac{1}{1 + e^{m(t-\lambda)}} \tag{5.5}$$

In this equation, λ is the lifespan of the memory; or, the amount of time that passes until there remains only a .5 probability that the student recalls the information. The value m is a parameter which controls the rate of dropoff, much like the decay rate in Ebbinghaus' model. An example curve for this equation is given in Figure 5.3.

5.4 Re-Activation

To account for re-activation, a simple model for the extension of half-life may be used:

$$\lambda_n = \rho_s \lambda_{n-1} \tag{5.6}$$

Here, n refers to exposure or trial number n. In the intelligent tutoring system, this is the nth time that the student has seen the problem. λ_{n-1} is the former lifespan of the memory. ρ_s is a learning rate, which is a parameter particular to the student; its domain is $(1, \infty]$. The intuition captured by this formula is that with an increased number of trials,

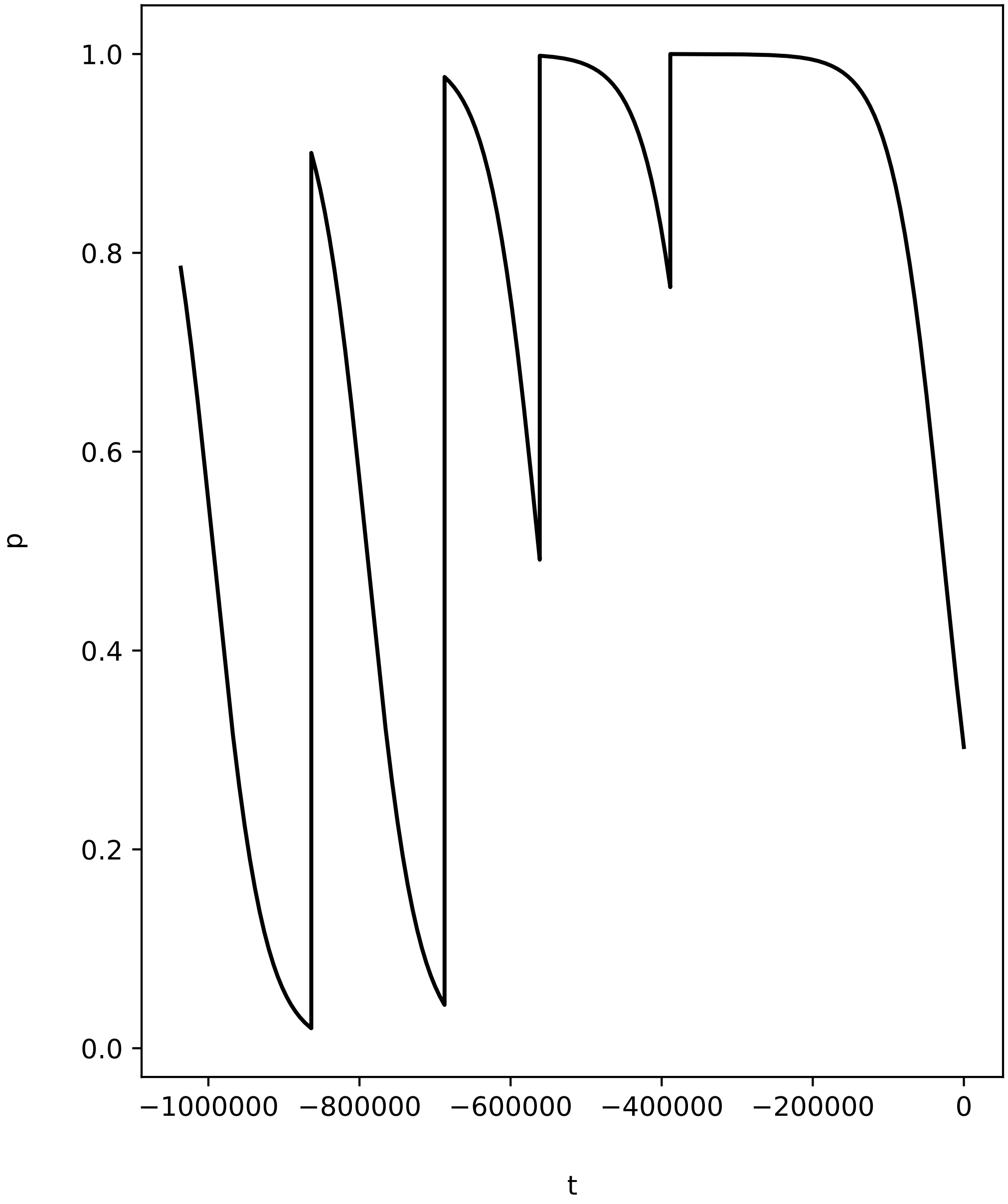

Figure 5.2: Forgetting with re-activation

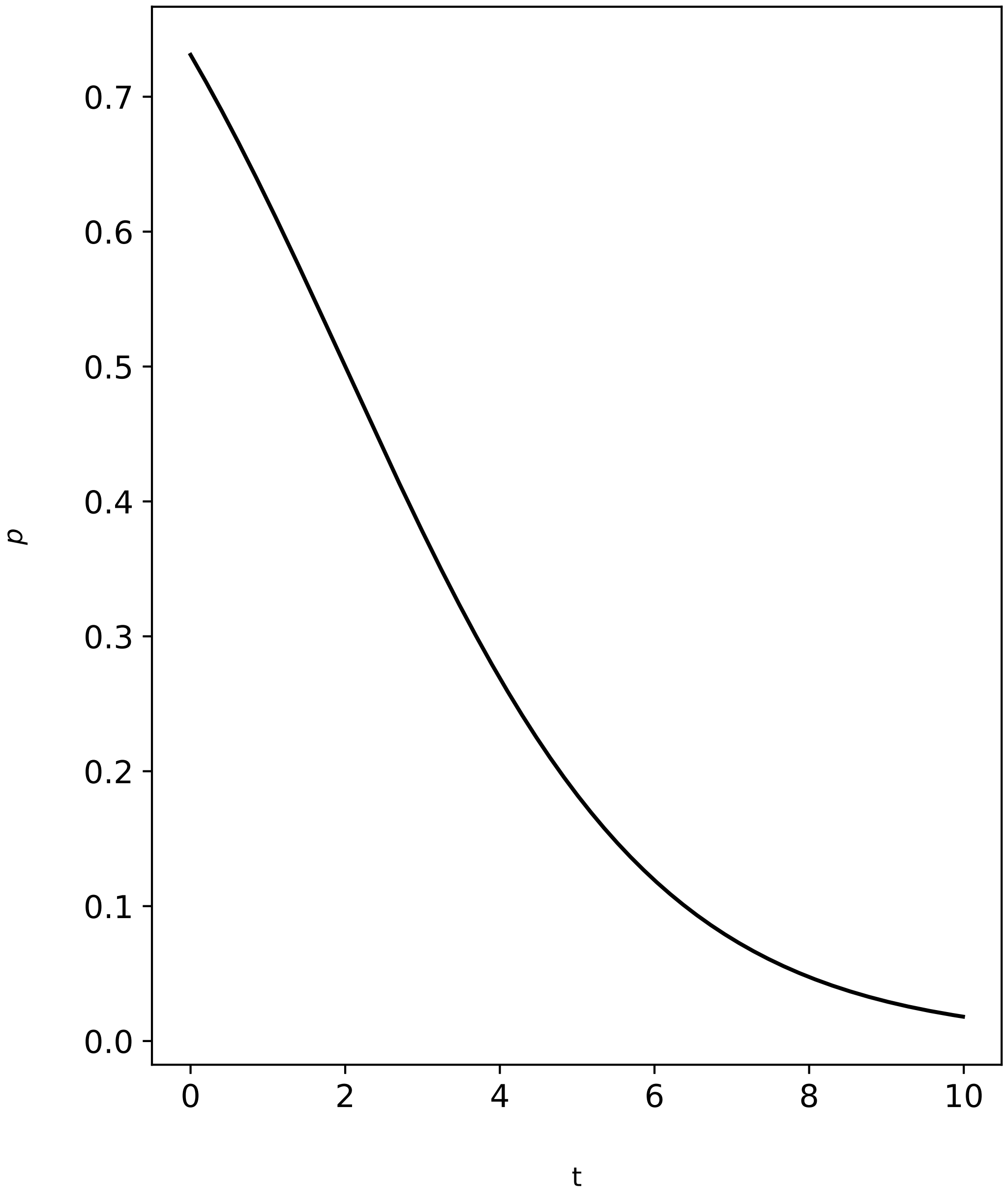

Figure 5.3: The modified curve of forgetting

the lifespan of the memory increases.

Apparently there is a difference in problems in the ease with which they are learned. An addendum to this can be used to account for individual differences in problems:

$$\lambda_n = \mu_i \rho_s \lambda_{n-1} \tag{5.7}$$

Here, μ_i represents the memorability of the problem, or the ease with which the problem solution can be committed to memory.

5.4.1 Spacing Effect

The spacing effect is the effect that the amount of time in between trials has on the memorization of a chunk of memory. In the above model, memorization is interpreted as an increase in the lifespan of a memory. If only a short amount of time passes between the last trial, the effect will not be as great as if a longer time has passed. One consequence of this is that, according to the spacing effect hypothesis, cramming is ineffective (where cramming is namely repeating trials in short bursts).

The spacing effect can be accommodated in the memory model used by the intelligent tutoring system. We define a function for the dropoff:

$$\sigma(t) = \rho_s(1 - e^{-t}) \tag{5.8}$$

$$\lambda_n = \sigma(t) \mu_i \rho_s \lambda_{n-1} \tag{5.9}$$

Chapter 6
Scheduling

6.1 Item Scheduling

The general procedure for scheduling content and assessments can be stated as follows. First, the trait ability matrix for the student is initialized:

$$\Theta \leftarrow -\infty \tag{6.1}$$

That is, the algorithm initially proceeds on the assumption that it is not possible for any student to answer any question with probability greater than zero. In the first iteration, schedule a preliminary test consisting of a diagonal block of the trait ability matrix, for example:

$$\Theta_s = \begin{bmatrix} \theta_{s11} & \theta_{s21} & \theta_{s31} & \dots \\ \theta_{s12} & \theta_{s22} & & \\ \theta_{s13} & & \ddots & \\ \vdots & & & \end{bmatrix} \tag{6.2}$$

The test should be small enough to be feasible while having enough questions to support an MLE. At least two questions are needed per (Bloom × concept) for an MLE. A 3×3 or triangle is sufficient.

Once the data is collected, it is then possible to calculate α_i and β_i for all items.

With respect to α_i, it is desirable to discard any question i for which $\alpha_i < 0$. Recall that negative values of α indicate a negative biserial correlation with the composite score, which means that the question asked is an indicator of whether or not the student will perform poorly on the overall measure.

It α_i is close to -1, then the question may have powerful predictive power, in which case it should be analyzed for its properties. It may be desirable to retain such questions for the purpose of predicting success. Regardless, if $\alpha_i < 0$, then it along with its subtree should be severed from the dependency graph, and should only be asked independently as part of a preliminary testing measure.

With the response set, Θ_s can be constructed and the proximal zone of development can be identified, as well as a distribution to select the category from.

Once a category is selected, the roots of the assessment tree are traversed until either a question within the neighborhood of the trait ability is found, or if no question is found, the traversal ends and another random category is selected.

6.1.1 Finding High-Impact Items

Once a node on the tree is found, a check is performed to ensure the dependencies have been asked. If not, an in-order recursive descent is done on each dependency, and this procedure is performed on the sub-dependencies. If all dependencies have been asked, the probability of the target question is evaluated. If the probability is .5, the question is asked.

If the probability is less than .5, a confirmatory factor analysis is performed on the dependencies of the node. At any time, this factor analysis may reveal a squared loading near zero, which indicates that the dependency relationship indicated by the graph is not an actual dependency. In that event, the link between the target and the "dependency" is severed and a confirmatory factor analysis is re-run on the remaining dependencies.

The most impactful dependency is sought. This dependency item i is selected as follows:

$$\underset{i}{\operatorname{argmax}} \left[(1 - p_i)\lambda_i^2 \right] \tag{6.3}$$

The value λ^2 is the proportion of variance due to that dependency, so it is preferred to start with higher proportions of variance. Also $(1 - p_i)$ is the room for improvement in the probability of the answering the dependency correctly. The intuition is that the more likely it is that the student is able to answer the dependency correctly, the probability of answering the target question rises—to the extent of the dependency relationship.

6.1.2 Finding the Next Item

The maximal value for $(1 - p_i)\lambda_i^2$ may have $p_i < .5$, in which case the above procedure is recursively applied to the dependencies with i as the target question.

Eventually, the algorithm will converge on either a question for which $p_i > .5$, or it will hit the leaves. What this means is that there is no question in the sub-tree for which p_i

6.1.3 Finding the Whole Schedule

Chapter 7
Experimental Results

7.1 Experiments Supporting the Utility of the Taxonomy

Experiment 1. Our first experiment tested to see if there is a performance difference between computer-based assessment and paper-based assessment when questions are ordered by Bloom level. Our hypothesis was that students taking the computer-based assessment would fare better than those taking the paper-based assessment because of the immediate feedback offered by the computer-based assessment.

We designed a test of 10 questions (2 concepts, each concept having questions over 5 Bloom levels) to give to students[1]. The questions were of multiple-choice and short-answer format. There were two knowledge, comprehension, application, analysis, and evaluation questions. No synthesis questions were asked because of the constrained formats allowed by the computer-based testing framework. An interrater reliability of 90% was determined by two independent raters (the authors), both computer science educators, who assessed the Bloom levels of the questions. After a point of disagreement about an evaluation-level problem, the test was adjusted to yield an 100% interrater reliability.

We designed a test of 10 questions (with 2 concepts, each concept having questions over 5 Bloom levels) to give to students. The concepts tested were on recursion and binary trees, and were written to be language-independent. The questions were of multiple-choice and short-answer format. There were two knowledge, comprehension, application, analysis, and evaluation questions. No synthesis questions were asked because of the constrained formats allowed by the computer-based testing framework. An interrater reliability of 90%

[1] All questions may be viewed at: https://steam.cct.lsu.edu/assessment/

was determined by two independent raters, both computer science educators, who assessed the Bloom levels of the questions. After a point of disagreement about an evaluation-level problem, the test was adjusted to yield an 100% interrater reliability.

Evaluation-level problems are resistant to multiple-choice and short-answer formats because of the nature of the category. Our approach was to use multiple-choice questions of the "choose the best answer" format, in which there are many proposed uses of a concept or language construct, but one stands out as the most sensible from the standpoint of experts.

The test resembled a quiz that might be given in the normal course of teaching the class. At the end of the quiz, the question "how satisfied were you with the (paper/computer)-based medium?" was asked to gauge satisfaction differences as well.

For this experiment, volunteers were recruited from a Java programming class for introductory computer science students. All students volunteered; candy was offered as an incentive for all the experiments. We split the classroom into two groups, matched based on their current grade in the course. We gave the control group the paper quiz, and the experimental group the computer-based quiz.

An answer was scored as totally correct if it coincided exactly with the solution, and otherwise scored as incorrect. Correct answers were encoded with 1, incorrect with 0. A composite score was derived by summing these scores per-student.

Experiment 2. The second experiment tested the effect of ordering the questions by Bloom level. For this experiment we designed another test of 10 questions (2 concepts, each concept having questions over 5 Bloom levels). This test also covered recursion and binary trees. In the control condition, questions were given in forward Bloom-level order. In the experimental condition, they were given in reverse order.

For both Experiments 2 and 3, participants were recruited in the same manner; however for this experiment a C++ class which followed the same conceptual track was also added to the pool. Matched-pairs were assigned to each group bsaed on their current grade in each course. The test was constructed and interrater reliability gauged in the same manner, and the test was also scored in the same manner.

Experiment 3. The third experiment tested the effect of intervening questions on the performance of later questions in the assessment. Our hypothesis was that overall performance would be improved if incorrect answers triggered the addition of new *intervention* questions from a lower Bloom level.

Experiment 3 participants were recruited from a different class. The test was this time language-dependent (MATLAB) and tested mastery of control structures, in particular for-loops. In the control condition, the control group was given an assessment of 10 questions, with 2 questions per the first five Bloom levels. The experimental group was given an adaptive measure. If at any point a student answered a question incorrectly, then a question at the next lowest level was given. This applied to all levels except knowledge. So for example if a student answered an application-level question incorrectly, a comprehension-level question (related to the application-level question) was scheduled before another application-level question of the same type. The experimental group thus had a a maximum of 4 additional questions asked for a total possible 14-question test.

7.2 Analysis and Results

Experiment 1. The experimental condition (N=27 M=6.21) did in fact show a higher mean score than the control condition (N=27 M=5.23) in overall performance. Statistical significance was tested with a one-tailed two-sample matched-pairs Student's t-test on the composite score. The result indicated a statistically significant difference (t=2.024, p=0.048). The experimental condition (M=4.93) showed a higher mean score than the control condition (M=4.38) in satisfaction as well; a similar t-test was done and was marginally statistically significant (t=1.7753, p=0.082).

Experiment 2. The experimental condition (N=48, M=4.94) showed a higher mean score than the control condition (N=48, M=4.31). Statistical significance was tested with a one-tailed parametric Student's t-test on the composite score. The result indicated a statistically significant difference (t=2.13, p=0.036).

Experiment 3. To tell the immediate effect of the intervention questions, one-tailed parametric Student's t-test on the composite score of questions starting after the first intervention question was done. It was hypothesized that the experimental condition would perform better on the remainder of the test. The experimental group (N=45, M=6.98) outperformed the control group (N=45, M=6.23). The result indicated a marginally statistically significant difference (t=1.7082, p=0.092).

7.2.1 Limitations

A few validity concerns are to be pointed out. No random order was given in Experiment 2 because of a lack of available subjects; hence it cannot be inferred that forward order is no different from random order. The experimenters (paper authors) designed the tests. The number of items per test was small to allow for a conservative testing time. For Experiment 1, confounding variables (those other than immediate feedback) may have played a role in test-taking because the test-taking media were different.

7.3 Experiments Supporting the Reconciliation of the Taxonomy with IRT

7.3.1 Experiment 1

Experiment 1 Design. In the first experiment, a selection of 16 multiple-choice questions on topics in operating systems concepts were asked to a sample group of students (N=54) in an undergraduate-level operating systems class. Each question had 5 choices (γ=.2). These questions were tagged with Bloom levels, and interrater reliability was calculated between two independent raters with experience in curricular and course design. Questions were tagged with hypothesized difficulty levels, which were targeted to be inversely proportional to the Bloom levels. Hence the question author intended for the knowledge questions to be difficult relative to analysis questions, while still maintaining the appropriate Bloom category.

Analysis of Experiment 1 Data. Interrater reliability on Bloom levels was calculated to be 93%. Means for each Bloom level are reported below. Clearly

	Knowledge	Comprehension	Appplication	Analysis
M	.42	.53	.67	.82

One-tailed Student t-tests were performed on the three consecutive pairs of means. The mean for comprehension was statistically significantly greater than the mean for knowledge (t = 2.00), the same held true for application and comprehension (t = 2.33), and analysis and application (t = 2.64). These statistics, in conjunction with the interrater reliability for the assignment of Bloom levels, support the view that Bloom level and difficulty are distinguishable.

In light of this data, a modification of IRT was sought in order to account for the dependency relationships that existed among the questions. Intuitively, this modification of p_i should possess the properties that: (a) if a question x_j is unrelated, p_i should be unaffected; and (b) if x_j is fully related, p_i should be equal to the response value for x_j.

The degree of relationship may be expressed with Pearson's r, where $r_{ij} = 0$ indicates no relationship between x_i and x_j and $r = 1$ indicates a full positive correlation. An even more viable metric is the coefficient of determination r^2, which indicates the proportion of variance in the depender which is attributable to the dependee. Intuitively, it is this proportion of the probability which should be associated with the correctness of j. The remainder may be left to item response theory. In the event of a negative correlation, the response should be opposite.

$$\begin{aligned} p_i(\theta) = & \quad (1-r^2)\Big(\gamma_i + \frac{1-\gamma_i}{1+e^{\alpha_i(\theta-\beta_i)}}\Big) \\ + & \quad (r^2)\Big(\mathbf{sgn}(r)x_{sj} + \frac{1-\mathbf{sgn}(r)}{2}\Big) \end{aligned}$$

The above formula satisfies our needs. The **sgn** function gives the sign of r. For $r = 1$, p_i defaults to the correctness of the dependee's answer (0 or 1, depending on whether or not the dependee was answered correctly); and for $r = -1$, p_i assumes the flip of the dependee's answer. For $r = 0$, p_i assumes the form of original IRT.

In the MLE estimation of θ, we would omit question j, since it is included already in the above formula.

7.3.2 Experiment 2

Experiment 2 Design. To test this modified theory, another experiment was conducted. The purpose of this experiment was to explore the relationship among the probability predicted by unmodified IRT, the probability predicted by modified IRT, and the correctness of the actual response. It was hypothesized that modified IRT should produce a more accurate output than unmodified due to its account of dependency relationships.

As in the first experiment, a selection of 16 multiple-choice questions on topics in operating systems concepts were asked to the same sample group of students (N=54) in the same manner (γ=.2). The questions covered 4 concepts, and each concept had 4 questions, each of different Bloom levels (Knowledge, Comprehension, Application, Analysis), where each question of a Bloom level higher than Knowledge was dependent on a question of an immediately-lower Bloom level (e.g. the Application question was dependent on the Comprehension question of the same concept). These questions were asked in forward Bloom order. The hypothesized difficulties were held equal across Bloom levels.

Analysis of Experiment 2 Data. . . . Interrater reliability on Bloom levels was once again calculated to be 93%.

	Knowledge	Comprehension	Appplication	Analysis
M	.78	.62	.48	.41

To test the hypothesis that modified IRT leads to an increase in accuracy, a t-test on the increase in accuracy of probability was conducted at the .05 significance level.

First the probabilities $p_i^{irt}(\theta)$ (for original IRT) and $p_i^{mod}(\theta)$ (for modified IRT) were calculated. Note that each of these formulas require θ. The value for θ was calculated per-student using the MLE method on the first data set. To determine whether or not $p_i^{mod}(\theta)$ was on the whole more accurate than p_i^{irt}, the result

$$\Delta p_{si} = (2x_{si} - 1)(p_i^{mod} - p_i^{irt})$$

was calculated. Here p_{si} represents the probability that student s will answer item i correctly. Then Δp_{si} represents the increase in accuracy of the probability; for example, it is positive if $p_i^{mod} > p_i^{irt}$ and $x_{si} = 1$.

Finally, to test the effectiveness of p_i^{mod}, a one-tailed Student's t-test was calculated on Δp_{si} for the dependee questions (N=648). The test revealed that Δp_{si} is statistically significantly greater than zero ($t = 2.05$), implying that p_i^{mod} indeed produces a more accurate estimate than IRT alone.

As the data reveals, the proportion of students who passed a question did not agree with the hypothesized difficulties. It was suspected that this may be due to the effect of item dependencies, which the next experiment investigates in further detail.

7.3.3 Experiment 3

Experiment 3 Design. One question remains: can p_i^{mod} be used in some meaningful way? Suppose we wish to maximize the probability that a student answers an Analysis question correctly, and that this Analysis question depends on an Application question. For that matter, it may depend on more questions, each of which having its own degree of relatedness to the depender.

We thus posit a more general form of modified IRT which takes into account multiple dependencies using factor analysis [12]. From a factor analysis, it is possible to obtain the proportion of variance explained by each dependency by squaring the factor loading. A factor analysis was performed on the dependent question using dependees as factors to obtain these proportions of variance explained.

Those proportions of variance could then be used as part of a more generalized modification to IRT:

$$\begin{aligned} p_i(\theta) = & \qquad (1 - (\sum_j v_j))\Big(\gamma_i + \frac{1-\gamma_i}{1+e^{\alpha_i(\theta-\beta_i)}}\Big) \\ + & \qquad \sum_j (v_j)\Big(\mathbf{sgn}(r)x_{sj} + \frac{1-\mathbf{sgn}(r)}{2}\Big) \end{aligned}$$

In this generalized formula, v_j refers to the proportion of variance explained by the dependee j (the squared factor loading for j). Therefore the sum of these is the total explained variance; one minus the sum is the total unexplained variance. Intuitively the probability is proportional to the amount of variance explained by a dependee. On the one hand, if one dependee explains 90% of the total variance, and the student answers this dependee correctly, the probability should depend heavily on whether or not the dependee was correct. On the other hand, if the total unexplained variance is 1, this would imply the dependees are not dependees at all. In this case, the probability defaults to the item response theory calculation, which uses the best available information (trait ability and question parameters).

In our experiment to test the utility of this formula, we first required a small problem set with one depender and multiple dependees. The experiment was intended to test whether or not the asking of highly-dependent questions increased mean scores.

For this we first required proportions of variance between depender and dependees. We created 4 questions, where the 4th question had three dependees. We then asked some of our students (N=22) to answer all of these questions to obtain proportions of variance, which are listed below.

	q1	q2	q3	q4
v_j	.02	.23	.30	
M	.67	.66	.43	.34

The others would receive a combination of questions. Each student was randomly assigned to one of eight groups. Four students received each combination of three questions, such that 4 received the depender outright, 12 received one of the three dependees (4 each) before the depender, 12 received two of the three dependees (6 each) prior, and 4 received all three dependees. The purpose of this was to test the effect of exposure of each dependee. Thus each dependee question appeared in half of the students' assessments. The total number of respondents for the depender was 32, and the total number of respondents for each dependee was 16.

Analysis of Experiemnt 3 Data. The analysis of this data required examining the relationship between dependent response and dependee exposure.

Let E_{sj} be 1 if student s was exposed to j, 0 otherwise. Then, our hypothesis was that exposure of dependee questions should result in an increase in the probability that the student answers the depender correctly, in proportion to the amount of variance explained by the dependee. Below in the table is the number of times the depender was answered correctly given exposure to a set of dependees. Though the data set is small, there does appear to be a trend in the data. A clearer trend can be observed by summing the number of correct responses per exposure to a given question.

dependees	#correct	percent	#correct	percent
none	1	.25	1	.06
q1	1	.25	8	.50
q2	2	.50	10	.62
q3	3	.75	11	.69
q1, q2	2	.50		
q1, q3	2	.50		
q2, q3	3	.75		
q1, q2, q3	3	.75		

The table shows the percent of students who answered the depender correctly given a particular set of questions (left), as well as the percent of students who answered the depender correctly given exposure to a given question (right). It is interesting to note that to an extent, the proportions of variance explained by a given question appear to be co-related to the percentage of students who answered the depender correctly. However, the numbers are too small to draw a definitively conclusion.

Due to the low N in Experiment 3, the results do not present *conclusive* evidence that the intervention of the dependee questions was responsible. However, there is enough preliminary evidence to warrant further investigation. If there is an effect, it is suspected that exposure to the dependee problem solution by the ITS plays a larger role than simply the question itself.

7.4 Experiment Supportng the Utility of the Scheduler

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Appendix A
Appendix A: Algorithms

Appendix B

Appendix B: Mathematics

Appendix C
Appendix C: IRB Documents

Application for Exemption from Institutional Oversight

Institutional Review Board
Dr. Dennis Landin, Chair
130 David Boyd Hall
Baton Rouge, LA 70803
P: 225.578.8692
F: 225.578.5983
irb@lsu.edu | lsu.edu/irb

Unless qualified as meeting the specific criteria for exemption from Institutional Review Board (IRB) oversight, ALL LSU research/ projects using living humans as subjects, or samples, or data obtained from humans, directly or indirectly, with or without their consent, must be approved or exempted in advance by the LSU IRB. This form helps the PI determine if a project may be exempted, and is used to request an exemption.

– Applicant, Please fill out the application in its entirety and include the completed application as well as parts B-F, listed below, when submitting to the IRB. Once the application is completed, please submit the completed application to the IRB Office by e-mail (irb@lsu.edu) for review. If you would like to have your application reviewed by a member of the Human Subjects Screening Committee before submitting it to the IRB office, you can find the list of committee members at http://sites01.lsu.edu/wp/ored/human-subjects-screening-committee-members/.

– A Complete Application Includes All of the Following:

(A) This completed form

(B) A brief project description (adequate to evaluate risks to subjects and to explain your responses to Parts 1&2)

(C) Copies of all instruments to be used.

*If this proposal is part of a grant proposal, include a copy of the proposal and all recruitment material.

(D) The consent form that you will use in the study (see part 3 for more information.)

(E) Certificate of Completion of Human Subjects Protection Training for all personnel involved in the project, including students who are involved with testing or handling data, unless already on file with the IRB. Training link: (http://phrp.nihtraining.com/users/login.php)

(F) Signed copy of the IRB Security of Data Agreement: (https://sites01.lsu.edu/wp/ored/files/2013/07/IRB-Security-of-Data.pdf)

1) Principal Investigator: Steven R. Brandt **Rank:** Adjunct Professor

Dept: Computer Science **Ph:** (225) 287-8548 **E-mail:** sbrandt@cct.lsu.edu

2) Co Investigator(s): please include department, rank, phone and e-mail for each
*If the Principal Investigator is a student, identify and name supervising professor in this space

Dennis Castleberry, Ph.D. Student of Computer Science, (225)-578-5912, dcastl2@lsu.edu

3) Project Title: EDUCAT: Educational Data Modelling for Unified Computerized Assessment and Tutoring

4) Proposal? (yes or no) yes **If Yes, LSU Proposal Number**

Also, if YES, either

● **This application completely matches the scope of work in the grant**

OR

○ **More IRB Applications will be filed later**

5) Subject pool (e.g. Psychology students) Computer Science students

*Indicate any **"vulnerable populations" to be used**: (children <18 the mentally impaired, pregnant women, the ages, other). Projects with incarcerated persons cannot be exempted.

6) PI Signature **Date** 12/14/15 (no per signatures)

**** I certify my responses are accurate and complete.** If the project scope or design is later changes, I will resubmit for review. I will obtain written approval from the Authorized Representative of all non-LSU institutions in which the study is conducted. I also understand that it is my responsibility to maintain copies of all consent forms at LSU for three years after completion of the study. If I leave LSU before that time the consent forms should be preserved in the Departmental Office.

Screening Committee Action: ○ Exempted ○ Not Exempted Category/Paragraph

Signed Consent Waived?: ○ Yes **or** ○ No

Reviewer __________ **Signature** __________ **Date** __________

Continue on the next page

Abstract. The purpose of this study is to design a metric of success for an Intelligent Tutoring System (ITS) which gives programming problems for students to solve.

Description. We have partially constructed an ITS (intelligent tutoring system) which can issue problems for the student to solve. We would like to examine the differences (particularly in performance) between solving the problems through an ITS versus a conventional paper-based approach.

After we seat the student in a private and distraction-free conference room, the student will solve problems on the ITS or on paper for up to an hour, after which the system will cue the student that the trial is concluded. Once the trial has concluded, the test administrator will stop the ITS (if applicable) for the debriefing phase.

We will conduct at least one experiment, which is to test mean performance differences between the paper-based and computer-based contexts. Further experiments may test differences between two distinct problem sets given by the ITS; for example, performance differences due to differing progressions of Bloom taxonomic levels, problem difficulties, or concepts. All further experiments will test performance differences due to manipulations on the problems (rather than the interface, the test administrator's instructions, or other potential variables).

Consent Form

Study Title: EDUCAT: Educational Data-Modelling for Unified Computerized Assessment and Teaching

Performance Site: Louisiana State University and Agricultural Mechanical College

Investigators:

- PI: Steven R. Brandt, sbrandt@cct.lsu.edu, (225) 287-8548
- Co-PI: Dennis Castleberry, dcastl2@tigers.lsu.edu, (225) 578-5912

Purpose of Study: This study seeks to measure the success of an intelligent tutoring system (ITS).

Subject Inclusion: Individuals between the ages of 18 and 65 with normal or corrected to normal vision, who are enrolled in introductory-level programming courses.

Number of subjects: 300

Study Procedures: The study will take approximately 1 hour to complete. Participants will be asked to perform a programming-related tasks.

Benefits: This study will advance knowledge in intelligent tutoring systems and their effects on learning problem-solving techniques in STEM courses.

Risks: There are no known risks.

Right to Refuse: Subjects may choose not to participate or to withdraw from the study at any time without penalty or loss of any benefit to which they might otherwise be entitled.

Privacy: Results of the study may be published, but no names or identifying information will be included in the publication. Subject identity will remain confidential unless disclosure is required by law.

Compensation: Subjects will be given extra credit simply for showing up to their appointment. As incentive for solving problems, they will be given additional extra credit for problems they solve correctly.

****Please sign and submit this document with your IRB application****

Security of Data

Number: PS06.20

SECURITY OF DATA

PURPOSE

I certify that I have read and will follow LSU's policy on security of data – PS06.20 (http://sites01.lsu.edu/wp/policiesprocedures/policies-procedures/6-20/) and will follow best practices for security of confidential data (http://www.lsu.edu/it_services/its_security/best-practices/sensitive-data.php) This Policy Statement outlines the responsibilities of all *users* in supporting and upholding the security of *data* at Louisiana State University regardless of *user's* affiliation or relation with the University, and irrespective of where the *data* is located, utilized, or accessed. All members of the University community have a responsibility to protect the confidentiality, integrity, and availability of *data* from unauthorized generation, access, modification, disclosure, transmission, or destruction. Specifically, this Policy Statement establishes important guidelines and restrictions regarding any and all use of *data* at, for, or through Louisiana State University. This policy is not exhaustive of all *user* responsibilities, but is intended to outline certain specific responsibilities that each *user* acknowledges, accepts, and agrees to follow when using *data* provided at, for, by and/or through the University. Violations of this policy may lead to disciplinary action up to and including dismissal, expulsion, and/or legal action. It is recommended that all personnel on your project be familiar with these policies and requirements for security of your data.

In addition it is recommended that PIs review any grant, non-disclosure/confidentiality agreement, or restricted data agreements before publishing articles using the data.

I certify that I have read and understand these policies

Name: Dennis G. Castleberry II

Date: 12/11/15

Please sign and submit this document with your IRB application

Security of Data

Number: PS06.20

SECURITY OF DATA

PURPOSE

I certify that I have read and will follow LSU's policy on security of data – PS06.20 (http://sites01.lsu.edu/wp/policiesprocedures/policies-procedures/6-20/) and will follow best practices for security of confidential data (http://www.lsu.edu/it_services/its_security/best-practices/sensitive-data.php) This Policy Statement outlines the responsibilities of all *users* in supporting and upholding the security of *data* at Louisiana State University regardless of *user's* affiliation or relation with the University, and irrespective of where the *data* is located, utilized, or accessed. All members of the University community have a responsibility to protect the confidentiality, integrity, and availability of *data* from unauthorized generation, access, modification, disclosure, transmission, or destruction. Specifically, this Policy Statement establishes important guidelines and restrictions regarding any and all use of *data* at, for, or through Louisiana State University. This policy is not exhaustive of all *user* responsibilities, but is intended to outline certain specific responsibilities that each *user* acknowledges, accepts, and agrees to follow when using *data* provided at, for, by and/or through the University. Violations of this policy may lead to disciplinary action up to and including dismissal, expulsion, and/or legal action. It is recommended that all personnel on your project be familiar with these policies and requirements for security of your data.

In addition it is recommended that PIs review any grant, non-disclosure/confidentiality agreement, or restricted data agreements before publishing articles using the data.

I certify that I have read and understand these policies

Name: ______________________

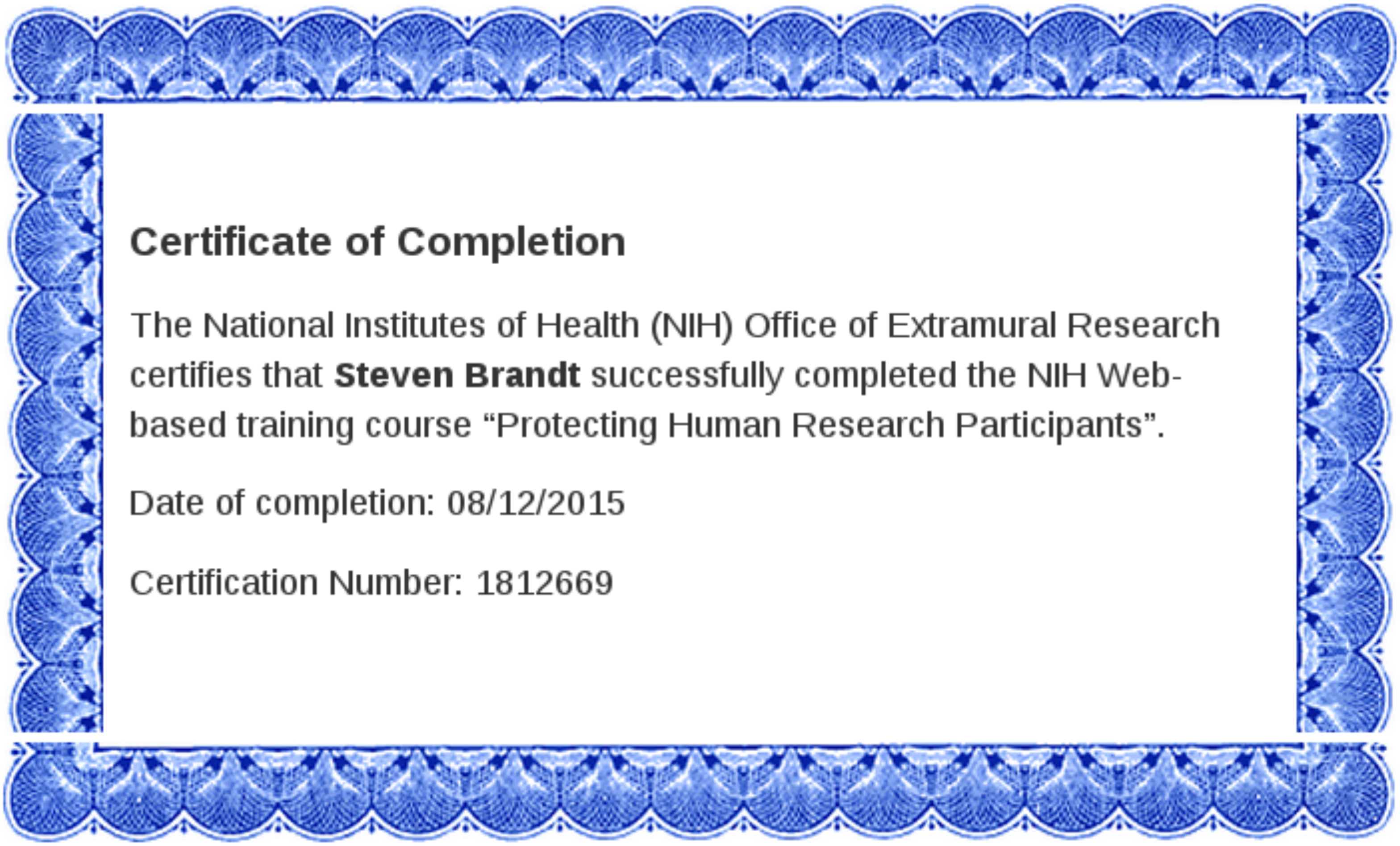
Date: 12/14/15

Certificate of Completion

The National Institutes of Health (NIH) Office of Extramural Research certifies that **Dennis Castleberry** successfully completed the NIH Web-based training course “Protecting Human Research Participants”.

Date of completion: 03/06/2009

Certification Number: 184387



Certificate of Completion

The National Institutes of Health (NIH) Office of Extramural Research certifies that **Steven Brandt** successfully completed the NIH Web-based training course “Protecting Human Research Participants”.

Date of completion: 08/12/2015

Certification Number: 1812669

Vita

Insert the text of your vita, which is basically a description of yourself and your academic career.