

DISSERTATION

by

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## ACKNOWLEDGEMENTS

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## ABSTRACT

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The public abstract is to be placed at this point in your first and final deposit and submitted via webform at final deposit. This abstract may be up to 250 words and should be written for a non-academic lay audience. In writing your public abstract, avoid jargon and technical language as much as possible.

The ability to communicate research simply and clearly is an important skill when interviewing for faculty positions, as well as for positions in industry and alt-ac sectors. The public abstract helps convey ideas beyond one's immediate academic circle, facilitating communication with colleagues who do different kinds of work and possess different dimensions of training.

Think of your public abstract as your “elevator pitch” or what you might tell someone who asks, “What is your thesis about?” You may only have a few minutes to explain it to them while keeping their attention and using terminology you are sure they will understand without further lengthy explanation.

Another way to think of your public abstract is like the description you would read on the inside of a book cover.

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## LIST OF FIGURES

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## BACKGROUND - IRT PARAMETER ESTIMATION

In educational measurement, a common goal is to quantify the knowledge of students from the results of some assessment. In a classroom setting, grades are typically assigned based on the percentage of questions answered correctly by a student assignments. The letter grades assigned from these percentages can serve as a naive measure of student knowledge; “A” students have completely mastered the material, “B” students have a good grasp of material, “C” students are fairly average, and “D” and “F” students have significant gaps in their knowledge.

The practice of evaluating student ability purely from a raw percentage score is known as true score theory [thissen] [thissen] thissen. But there are clear issues with this approach. Not all questions on an exam or homework assignment is created equally: some questions are easier, and some more difficult. Consider a scenario where two students both answer 17 out of 20 questions correctly on a test for a raw score of 85%. But if Student A answered questions 1, 8, and 9 wrong while Student B answered 4, 17, and 20 incorrectly, it is not likely that that Student A and Student B possess the same level of knowledge. For example, questions 1, 8, and 9 could be much more difficult than questions 4, 17, and 20. Additionally, the two sets of problems could cover different types of material. True score theory does not account for either of these situations, and naively quantifies the knowledge of Student A and Student B as equal.

More sophisticated methods have been studied which attempt to more accurately quantify student learning. Cognitive Diagnostic Models (CDM) (TODO: citation) aim to classify whether students possess mastery of a given skill or not. This discrete classification can be useful in determining whether or not a student meets a prerequisite, or deciding whether or not they are ready to move on to the next level of coursework. We focus instead on Item Response Theory, where student knowledge is assumed to be continuous.

## Item Response Theory

Item Response Theory (IRT) is a field of quantitative psychology which uses statistical models to model student ability. These models often give the probability of a question being answered correctly as a function of the student's ability.

Rasch Model

The Method With The Integral Thing

2-parameter Logistic Model

## Parameter Estimation Methods

### Artificial Neural Networks

In recent years, artificial neural networks (ANN) have become an increasingly popular tool for machine learning problems. Though they have been around since the 1960's (TODO: citation), GPU technology has become more accessible and modern computers are more powerful, allowing anyone interested to train a basic neural network on their machine. ANN can be applied to a diverse set of problems, including regression, classification, computer vision, natural language processing, function approximation, data generation, and more (TODO: citations).

One of the biggest critiques of ANN is their black-box nature, meaning that the decision process that a trained model uses is typically not explainable by humans. As opposed to simpler methods such as decision trees or linear regression, neural networks are not interpretable. This makes them less desirable in certain applications where researchers wish to know why a model predicts a particular data sample the way that it does. For example, if a financial institution is using data science methods to determine whether or not to approve someone's loan, the institution should be able to explain to the customer why they were denied. Most customers will not be satisfied with "the computer told us so," and

there is a possibility that a black-box neural network could learn and use features such as race or gender in its prediction, which is illegal in the United States (TODO: definitely need citation or delete).

Autoencoders

Variational Autoencoders

## METHODS - IRT PARAMETER ESTIMATION

### Ml2p-vae Description

One-parameter Logistic

2-parameter Logistic

3-parameter Logistic

tbd on this

Full Covariance Matrix Implementation

### Software Package In R Description

Plug that I made this and it is publicly available

Example of a table:

Table 1. My first table.

column	column	column	column	column	column	column	column	column	column
12.34	12.34	12.34	12.34	12.34	12.34	12.34	12.34	12.34	12.34
12.34	12.34	12.34	12.34	12.34	12.34	12.34	12.34	12.34	12.34

## RESULTS - IRT PARAMETER ESTIMATION

### Description of Data Sets

1-pl Results

2-pl Results

3-pl Results

(maybe)

## KNOWLEDGE TRACING BACKGROUND

Application Goal

Mathematical Setup

Literature Review

Bayesian Knowledge Tracing

Deep Knowledge Tracing

Dynamic Key-value Memory Networks

## REFERENCES