AI and Cognitive Diagnostic Models for Educational Assessment:

Connections, Integrations, and New Directions

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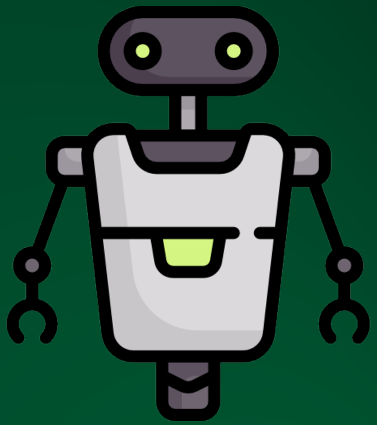
Some Benefits of Artificial Intelligence for Education Assessment

- Automated Essay and Constructed Response Data Scoring
  (Flor and Hao, 2021)
- Adaptive Personalized Learning/Intelligent Tutoring Systems
  (Almond, 2007; Green et al., 2011; Reichenberg, 2018; Madison and Bradshaw, 2018; Levy, 2019)
- Automated Item Generation
  (including programming problems and items with images)
  (Lauc et al., 2016; Song and Du, 2025; Popescu et al., 2023)



Challenges in using AI for Assessment

- Assessment using Testable, Transparent Explanatory Models
- Assessment results/explanations should (ideally) be unique
- Assessment Task Invariance
- Assessment Diverse Group Invariance
- Diverse Subpopulation Predictive Model Fit
- Causal Model Fit

Assessment as Evidential Reasoning

(Messick, 1994; Mislevy et al., 2006)

STEP 1: CONSTRUCTS:

What skills or other attributes should be assessed and WHY?

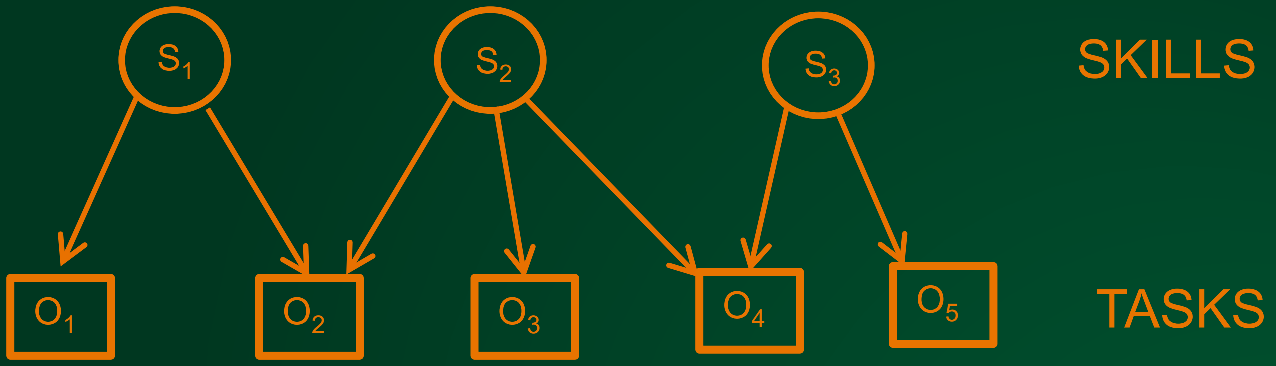
STEP 2: TASKS:

What behaviors or performances reveal those constructs?

STEP 3: CONNECTIONS: How are Tasks and Constructs related?

This methodology implies the existence of a causal chain of evidence which can be inspected, tested, and documented.

Cognitive Diagnostic Models



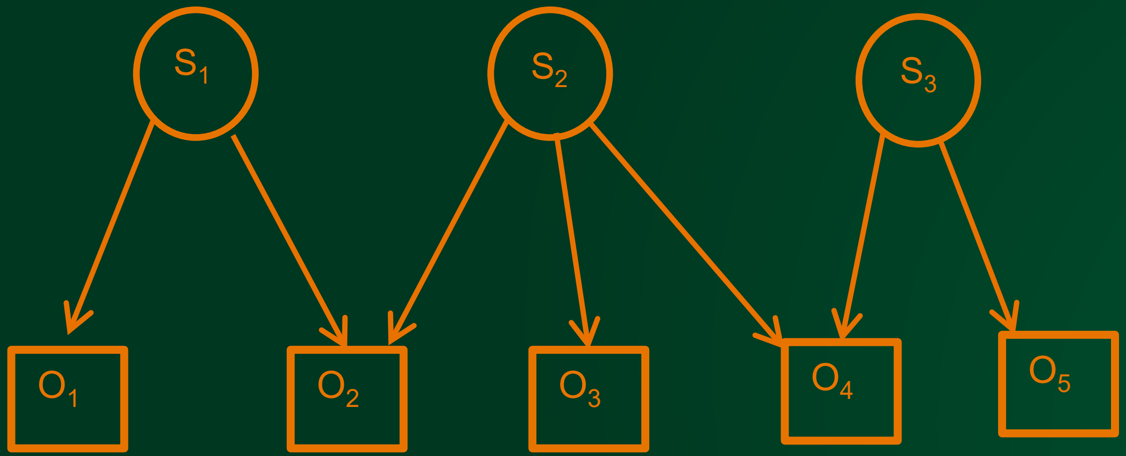
Proficiency Model: joint distribution of skills (model of student population)

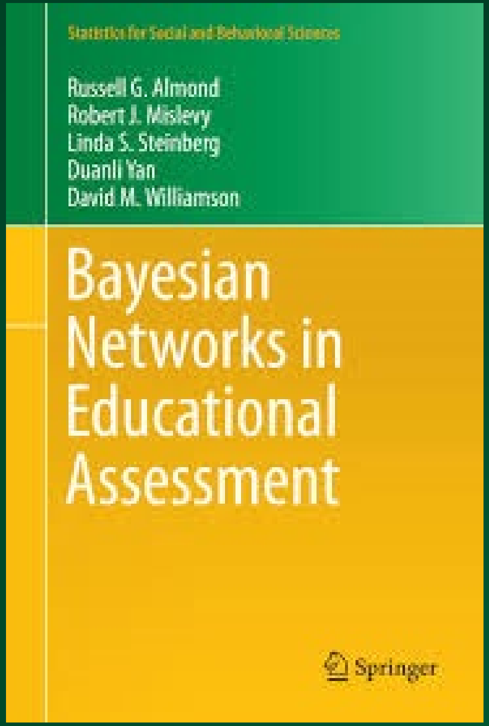
Evidence Model: conditional distribution of responses given skills (model of items)

Inference: Given behavioral observables O_1 O_2 O_3 O_4 O_5 compute probable values of S_1 S_2 S_3

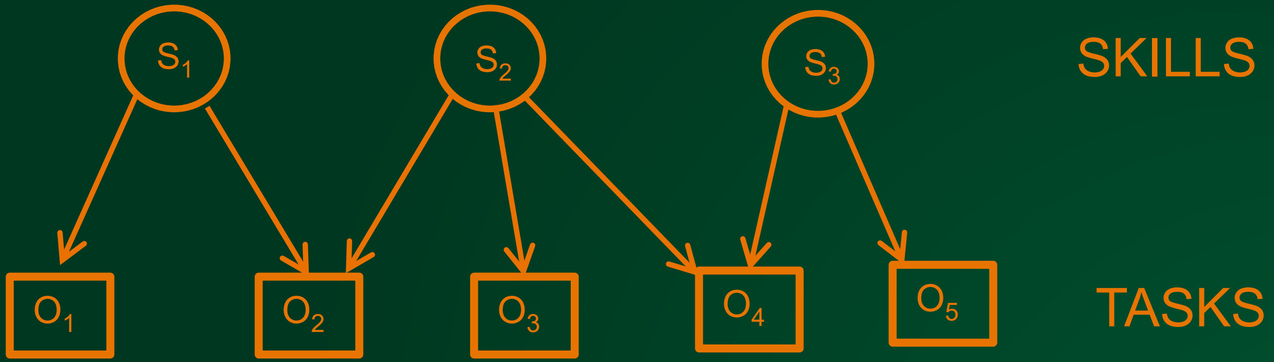
Supports: Form Invariance, Detection of DIF, Assessment through Evidence based reasoning

A Cognitive Diagnostic Model is an example of the well-studied Bayesian Network in AI



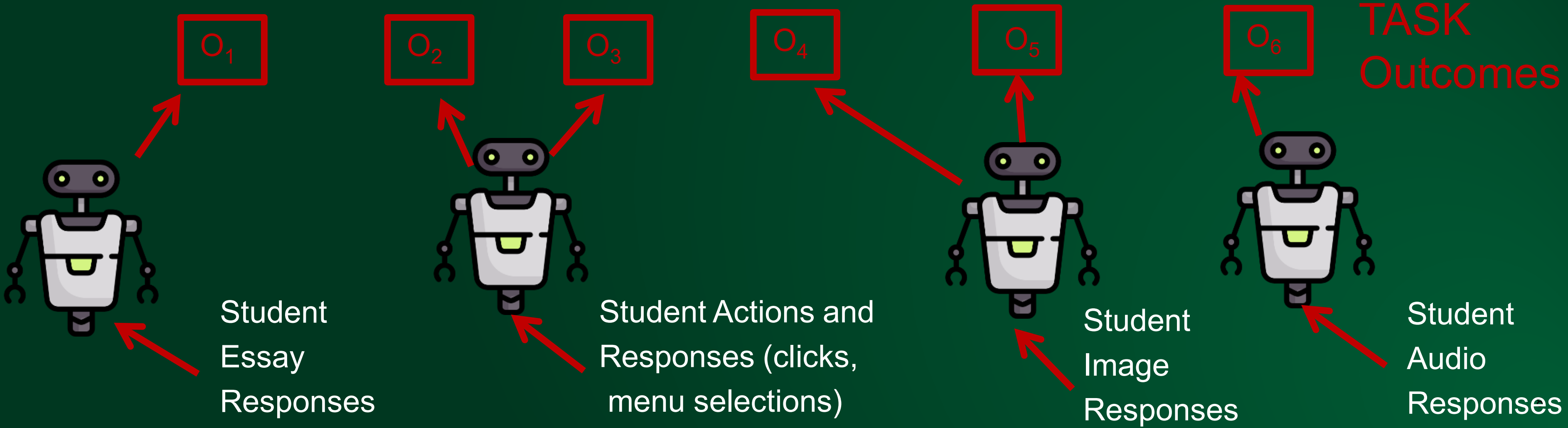


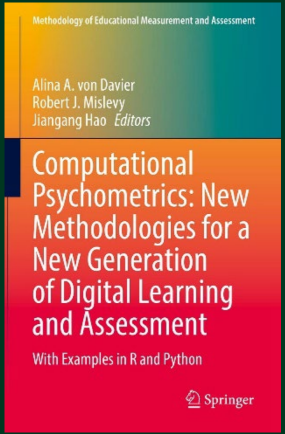
Cognitive Diagnostic Models: Applications



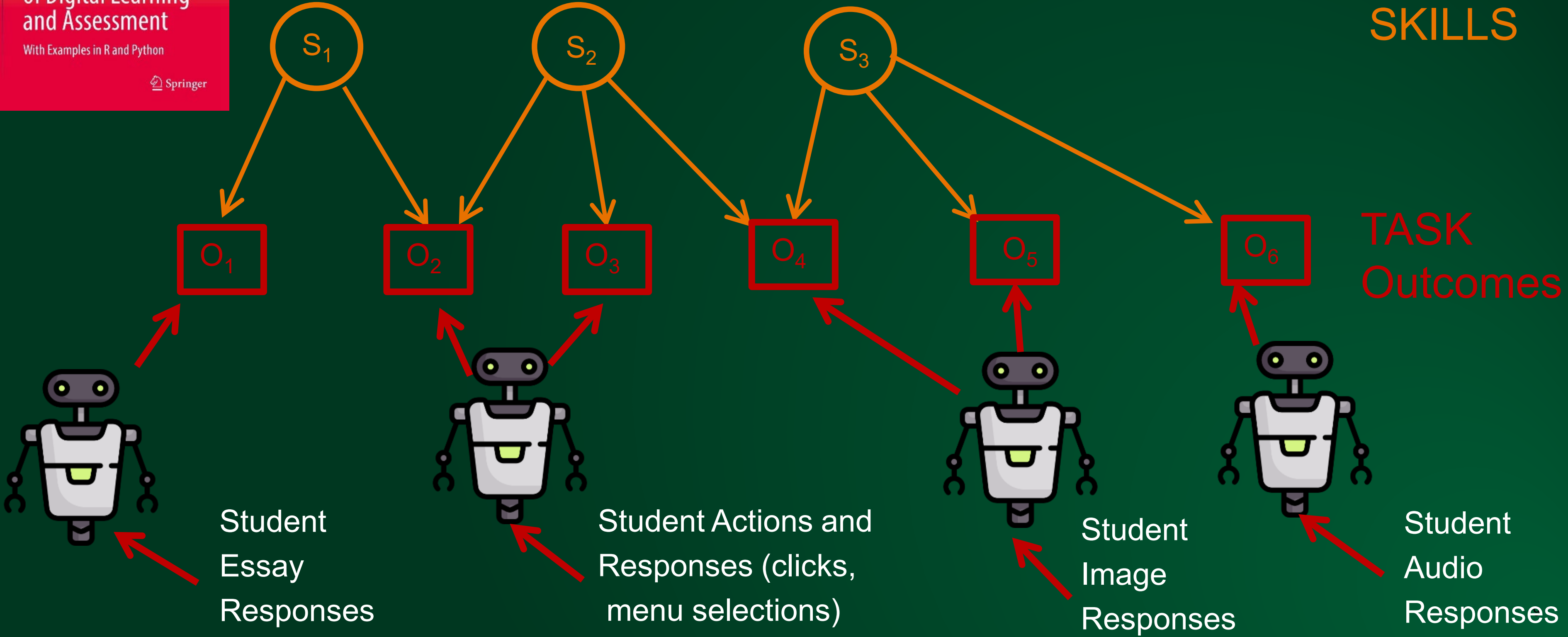
- Navvy Assessments (Laine Bradshaw)
- Dynamic Learning Maps (Jake Thompson)
- Education Companion App by ACTNext (Deonovic et al., 2019)
- Recent Reviews (Deonovic et al., 2019; Williamson, 2023; Wang et al., 2024)
- Evaluating LLMs and other AI systems using CDM methods

Typical Deep Learning Network in AI is a Predictive (not Explanative) Learning Machine



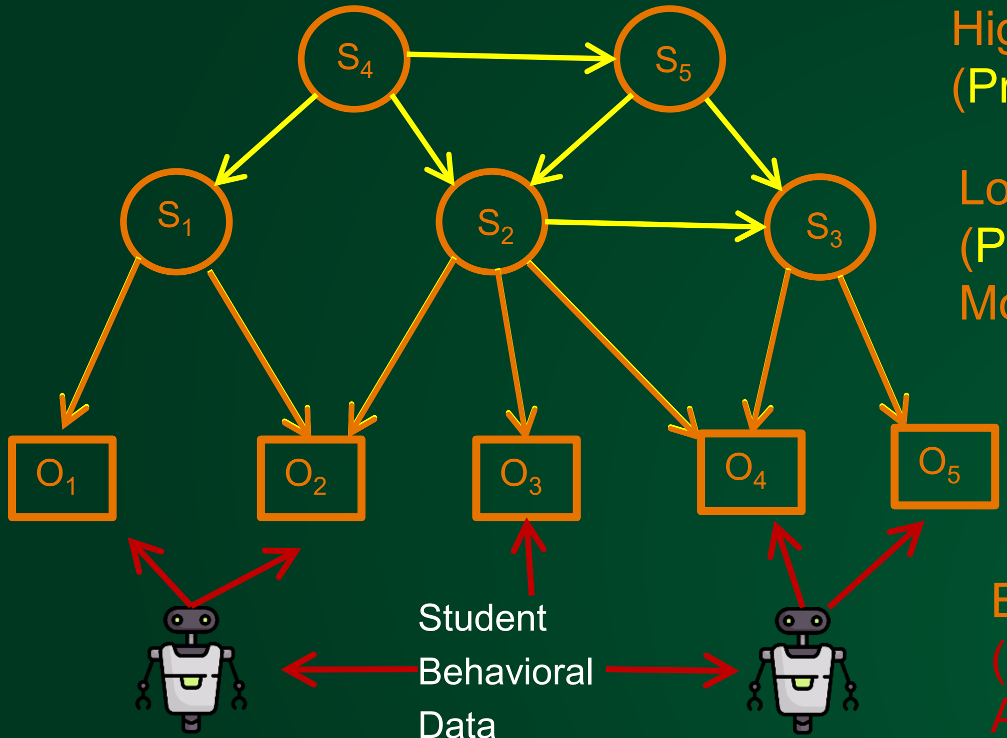


Cognitive Diagnostic Models: Evidence Identification



Cognitive Diagnostic Models: Deep Proficiency Models

(Almond et al., 2015; Kim et al., 2016;Gu, 2024)



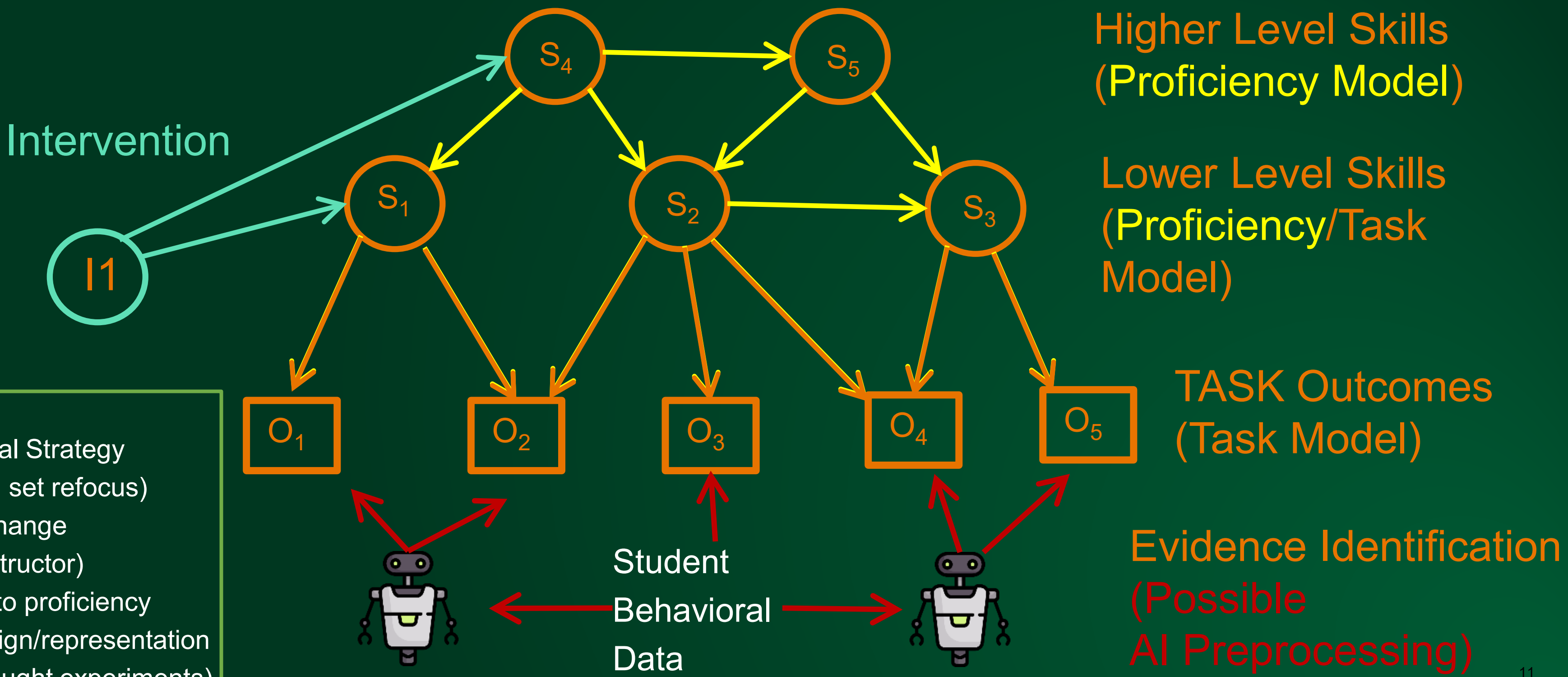
Higher Level Skills (Proficiency Model)

Lower Level Skills (Proficiency/Task Model)

TASK Outcomes (Task Model)

Evidence Identification (Possible AI Preprocessing)

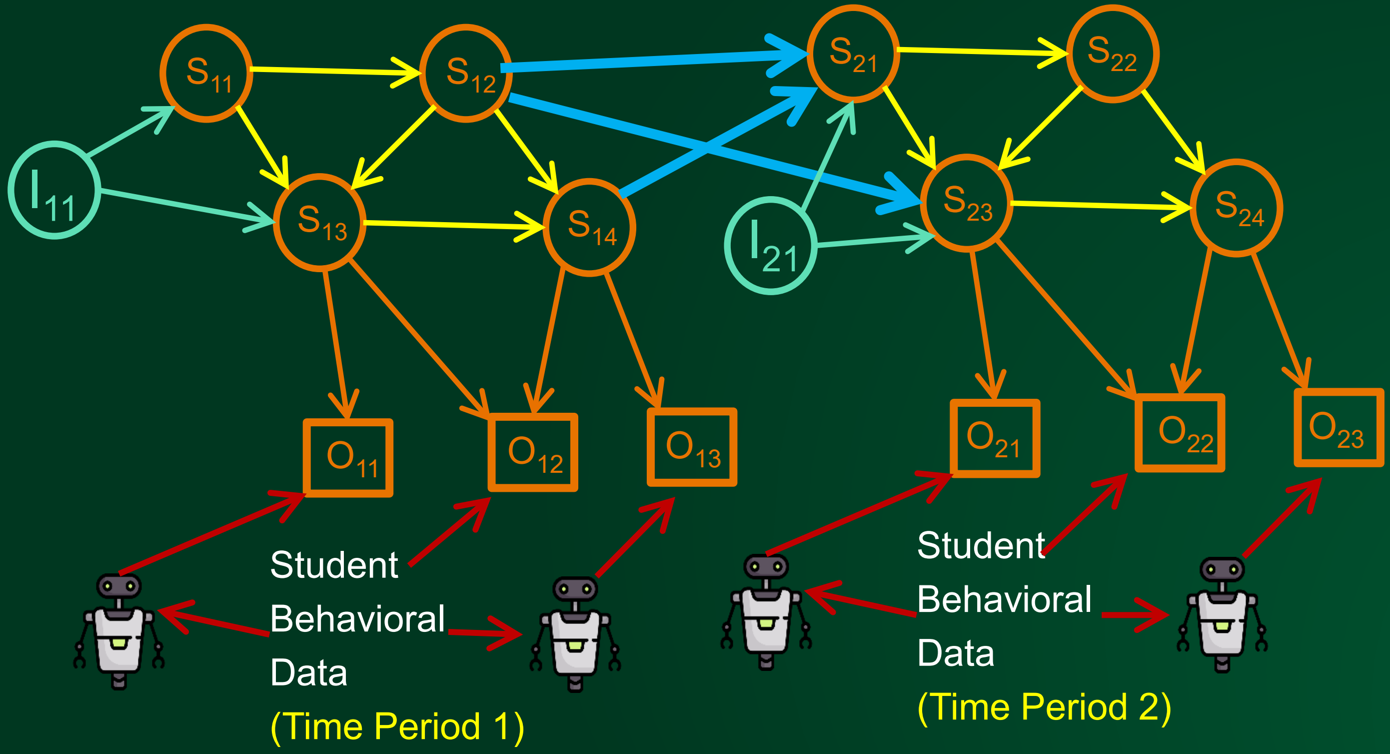
Cognitive Diagnostic Models:
Deep Proficiency Models+Intervention



Interventions
- Instructional Strategy
  (e.g., skill set refocus)
- Context Change
  (e.g., Instructor)
- Insights into proficiency model design/representation
  (e.g., thought experiments)

Cognitive Diagnostic Models: Dynamic Bayes Net

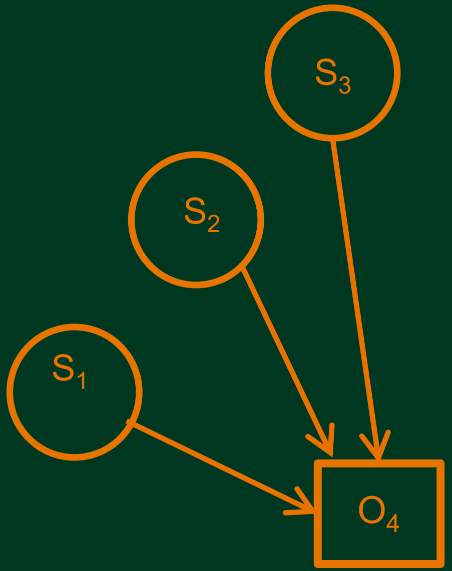
(Almond, 2007; Green et al., 2011; Reichenberg, 2018; Madison and Bradshaw, 2018; Levy, 2019)



This type of Architecture is Common in the AI Reinforcement Learning Literature
It is used for Planning and Control (Golden, 2020, Ch.1 and Ch.12)

This architecture can be used to analyze and design curricula And AI-driven personalized Learning environments (e.g., Intelligent Tutoring systems)

Reducing Parameter Redundancy to Support Assessment Reliability
(Almond et al., 2001; Levy & Mislevy, 2004; Bradshaw & Templin, 2014)



$$p\left(O_4=1|S_1,S_2,S_3\right)=\frac{1}{1+exp\left(-a_4\theta+b_4\right)}$$

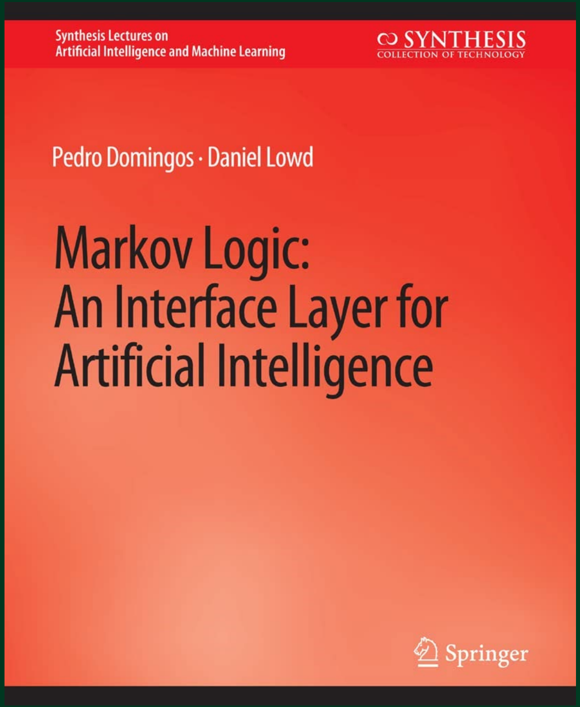
$$\theta=\sum_{j=1}^{3}\beta_j S_j+\beta_{1,2}S_1S_2+\beta_{1,3}S_1S_3+\beta_{2,3}S_2S_3+\beta_{1,2,3}S_1S_2S_3 \quad GDINA$$

$$\theta=S_1\vee S_2\vee S_3 \quad DINO$$

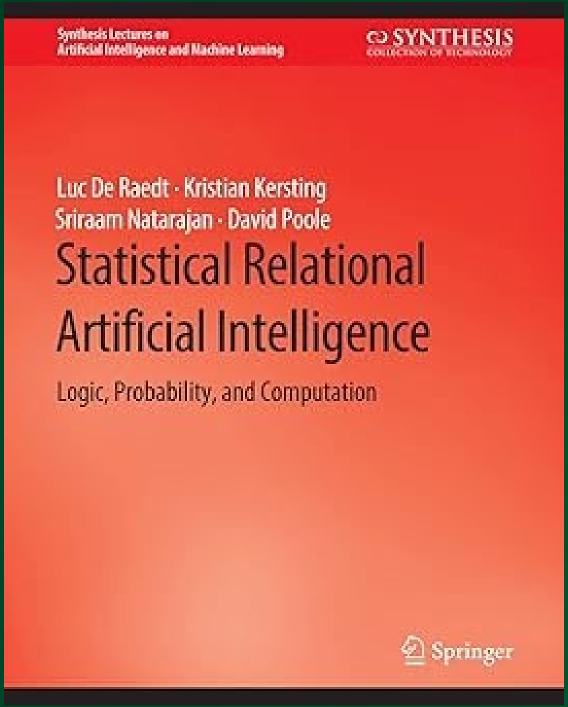
$$\theta=S_1\wedge S_2\wedge S_3 \quad DINA$$

$$\theta=\left(S_1\wedge S_2\right)\vee S_3 \quad MARKOV\ LOGIC\ NET$$

Markov Logic Nets in AI Literature



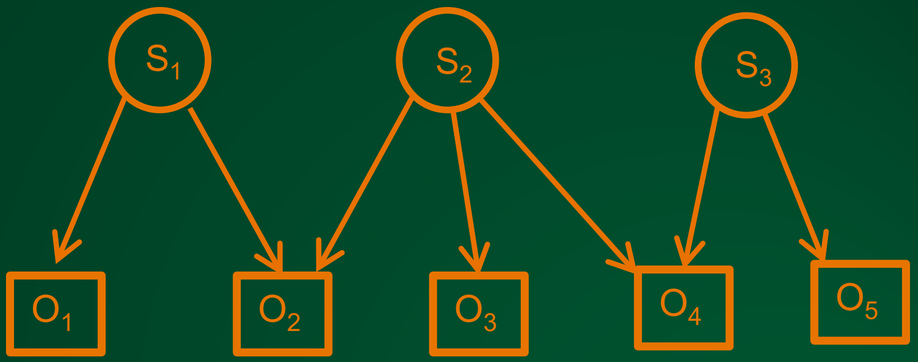
2009



2016

Dealing with Estimation and Inference in Possible Presence of Model Misspecification, Parameter Redundancy, and Empirical Non-Identifiability
(Golden, 2024, under review)

- CDM with many tasks
- Misspecification possible if just 1 task model skill specification is wrong
- Non-identifiability/Parameter Redundancy if just 1 task model too easy or difficult
- Not desirable to reparameterize by deleting task models or linking parameters across task models



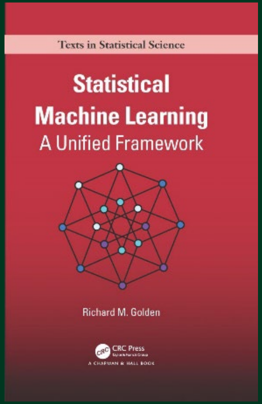
Estimation And Inference In the Presence of Possible Model Misspecification and Parameter Redundancy (Golden, under review)
Technical Report: /https://labs.utdallas.edu/coinslab/files/2024/08/PsychoRedundancyV13_arxivstatTH-1.pdf

Dealing with Inevitable Presence of Redundancy, Non-Identifiability, and Model Misspecification

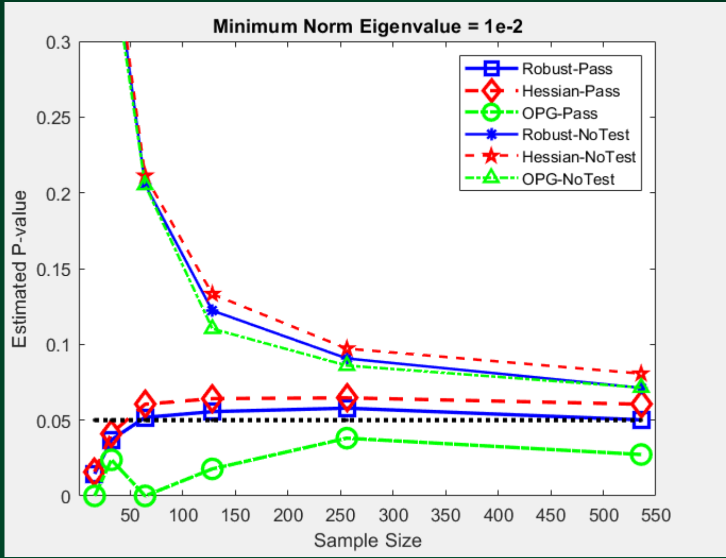
Golden (2024, under review)

- Assume parameters locally identifiable asymptotically
- Non-identifiability for finite samples is ok
- Parameter redundancy for finite samples is ok
- Model may be possibly misspecified
- THEN:

  Theorem shows how to identify permissible inferences (e.g., confidence intervals on individual parameters) and how they can be computed



Proof method involves modifying Huber (1967) analysis of asymptotic distribution of M-estimators (see Golden, 2020, Ch. 15)



Simulation Study showing estimated P-value as a function of sample size for a 30 parameter CDM. New method effective for smaller sample sizes unlike standard inference methods.

Assessment as Evidential Reasoning

(Messick, 1994; Mislevy, 2021)

STEP 1: CONSTRUCTS:

What skills or other attributes should be assessed and WHY?

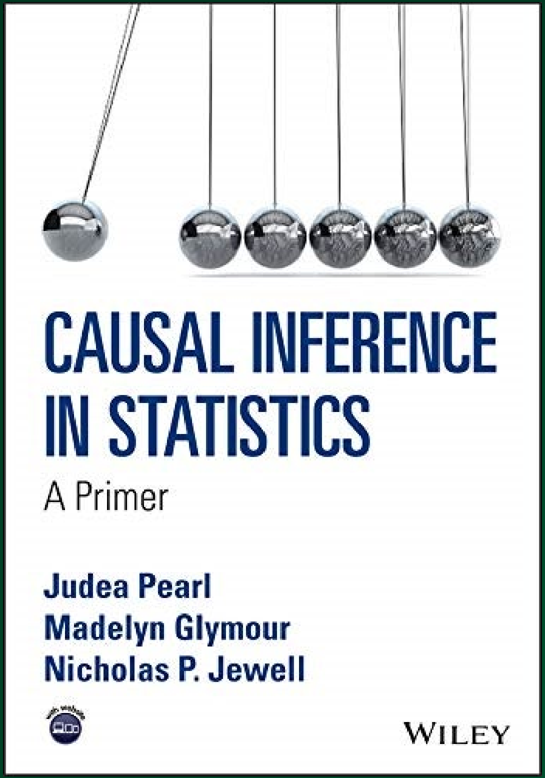
STEP 2: TASKS:

What behaviors or performances reveal those constructs?

STEP 3: CONNECTIONS: How are Tasks and Constructs related?

INTERVENTIONS: (1) Test the theory, and (2) Exploitthe theory

Causal Modeling has been around for decades but only in past five or ten years has it become a hot area in Artificial Intelligence

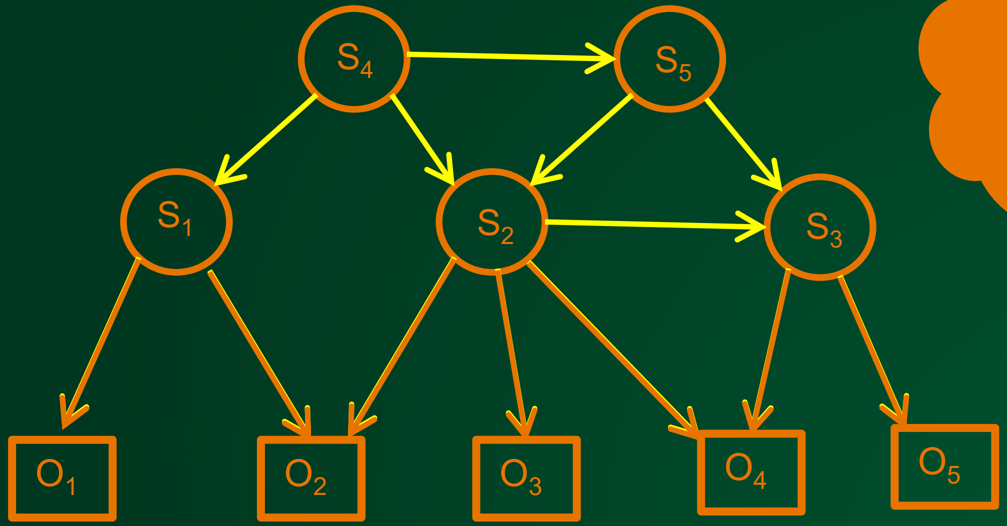


Golden, R. M. *Inferring Causal Relationships from Observational Data Sets*. Talk presented at the Frontiers in Brain Health Lecture Series, Center for Brain Health, University of Texas at Dallas, Dallas, Texas, May 19, 2023. Click here to watch the lecture! (https://www.youtube.com/watch?v=lewmQtYfsSY&list=PLlVrJgppjfmJ0v_-iak0vNFOCLU8A4Nlh&index=2)

It is expected that causal modeling will play an increasingly important role in our cognitive diagnostic models of assessment

Technical (Mathematical) Definition:

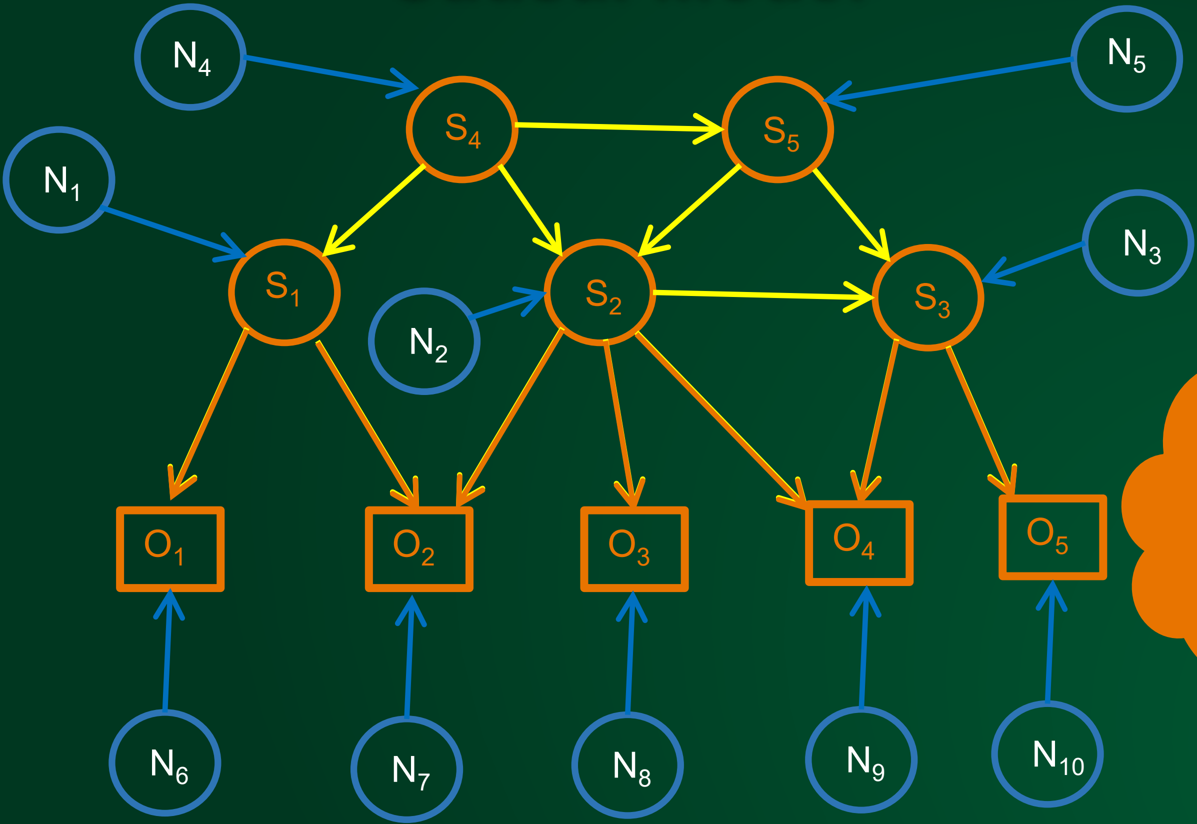
Bayes Net Probability Model



Arrows specify Conditional Independence Assumptions

Technical (Mathematical) Definition:

Causal Model



Arrows specify Causal Modeling Assumptions

Confounder Problem in Causal Inference

Student Motivation	Reading Performance
3	8
0	4
1	2
2	3
1	4

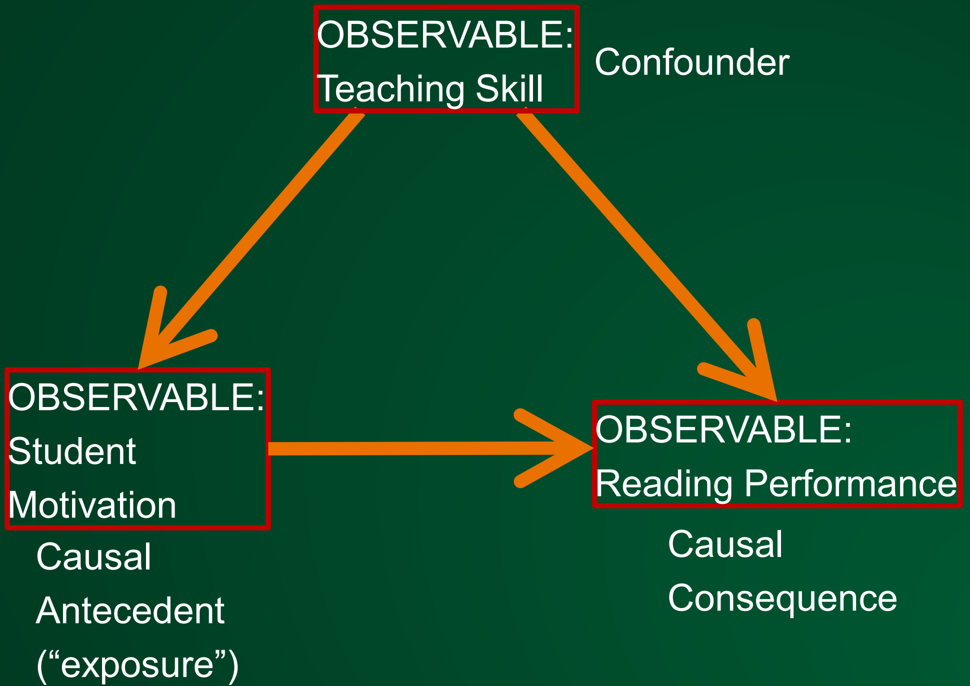
$\boxed{\text{OBSERVABLE: Student Motivation}} \longrightarrow \boxed{\text{OBSERVABLE: Reading Performance}}$

Causal Antecedent ("exposure")

Causal Consequence

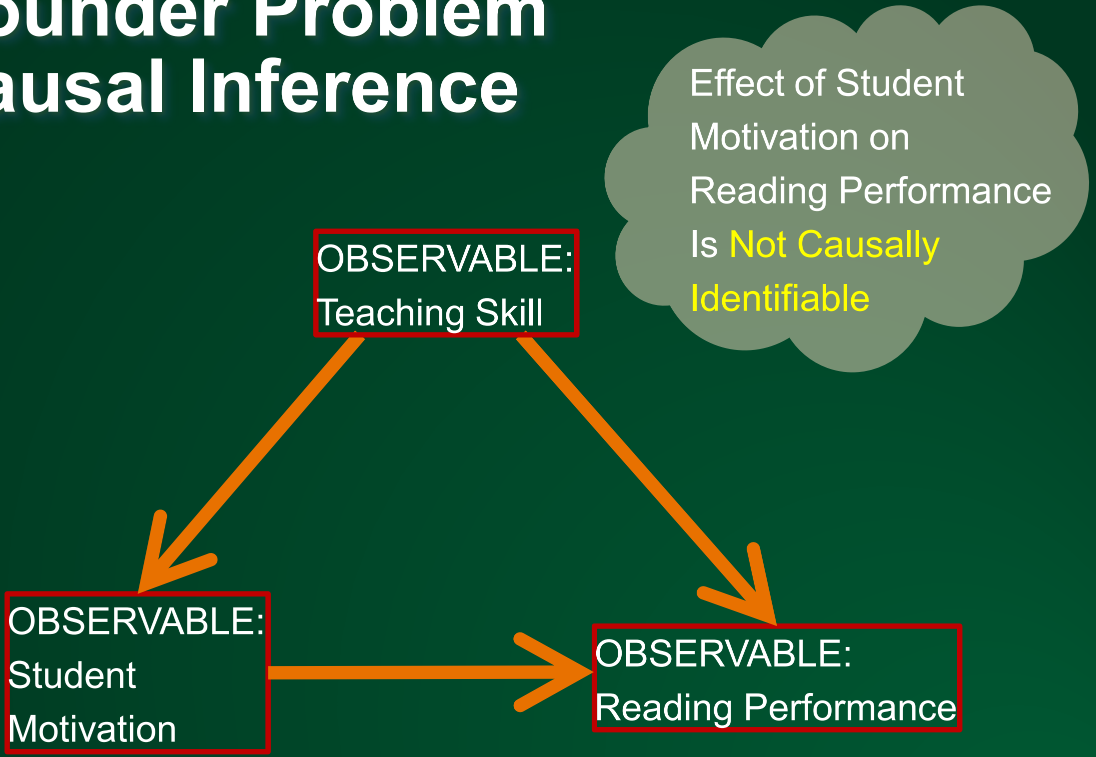
Confounder Problem in Causal Inference

Student Motivation	Reading Performance	Teaching Skill
3	8	3
0	4	0
1	2	0
2	3	5
1	4	1



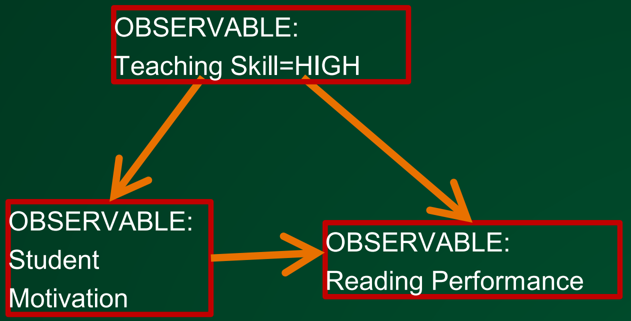
Confounder Problem in Causal Inference

Student Motivation	Reading Performance	Teaching Skill
3	8	3
0	4	0
1	2	0
2	3	5
1	4	1



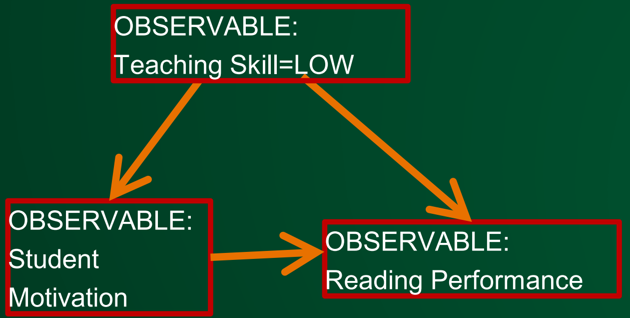
One Approach to Solving Confounder Problem in Causal Inference

Student Motivation	**Reading Performance**	**Teaching Skill**
3	8	3
2	3	5



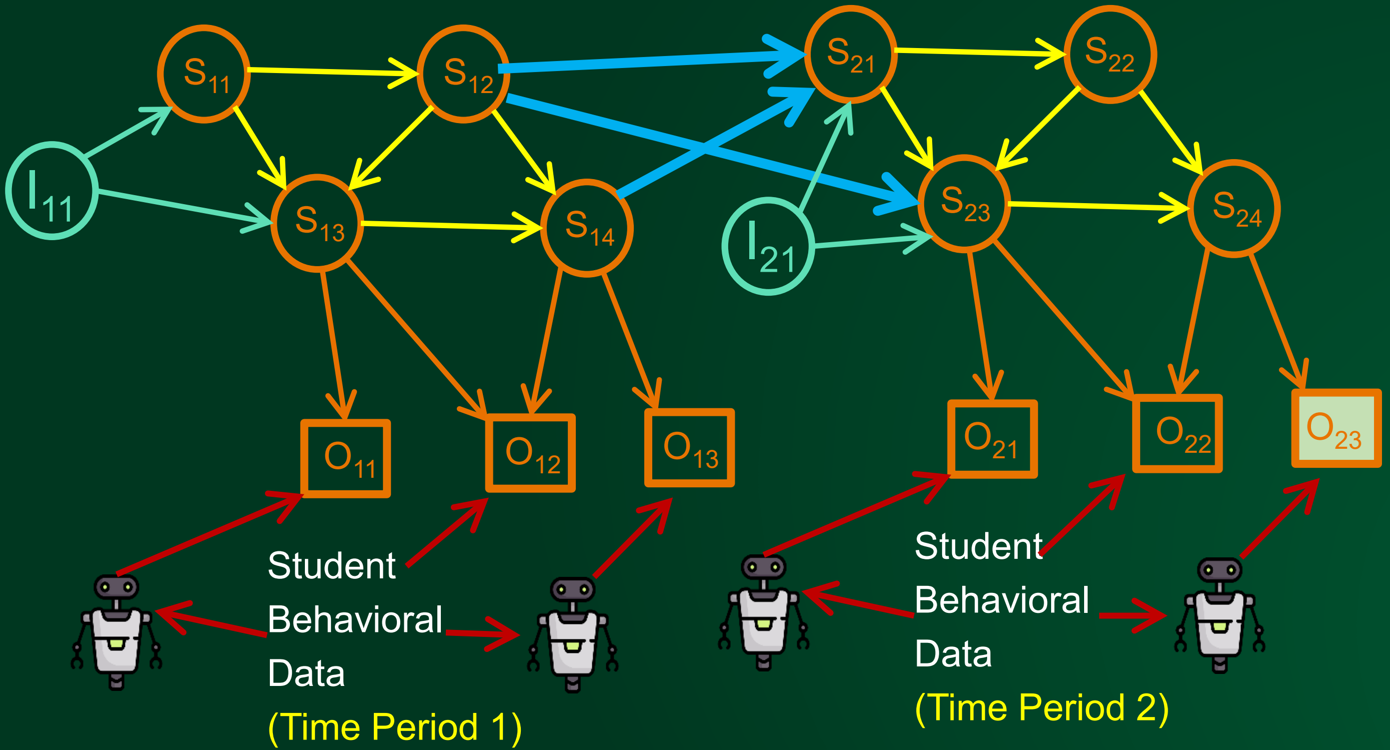
Effect of Student Motivation on Reading Performance Is Causally Identifiable

Student Motivation	**Reading Performance**	**Teaching Skill**
0	4	0
1	2	0
1	4	1

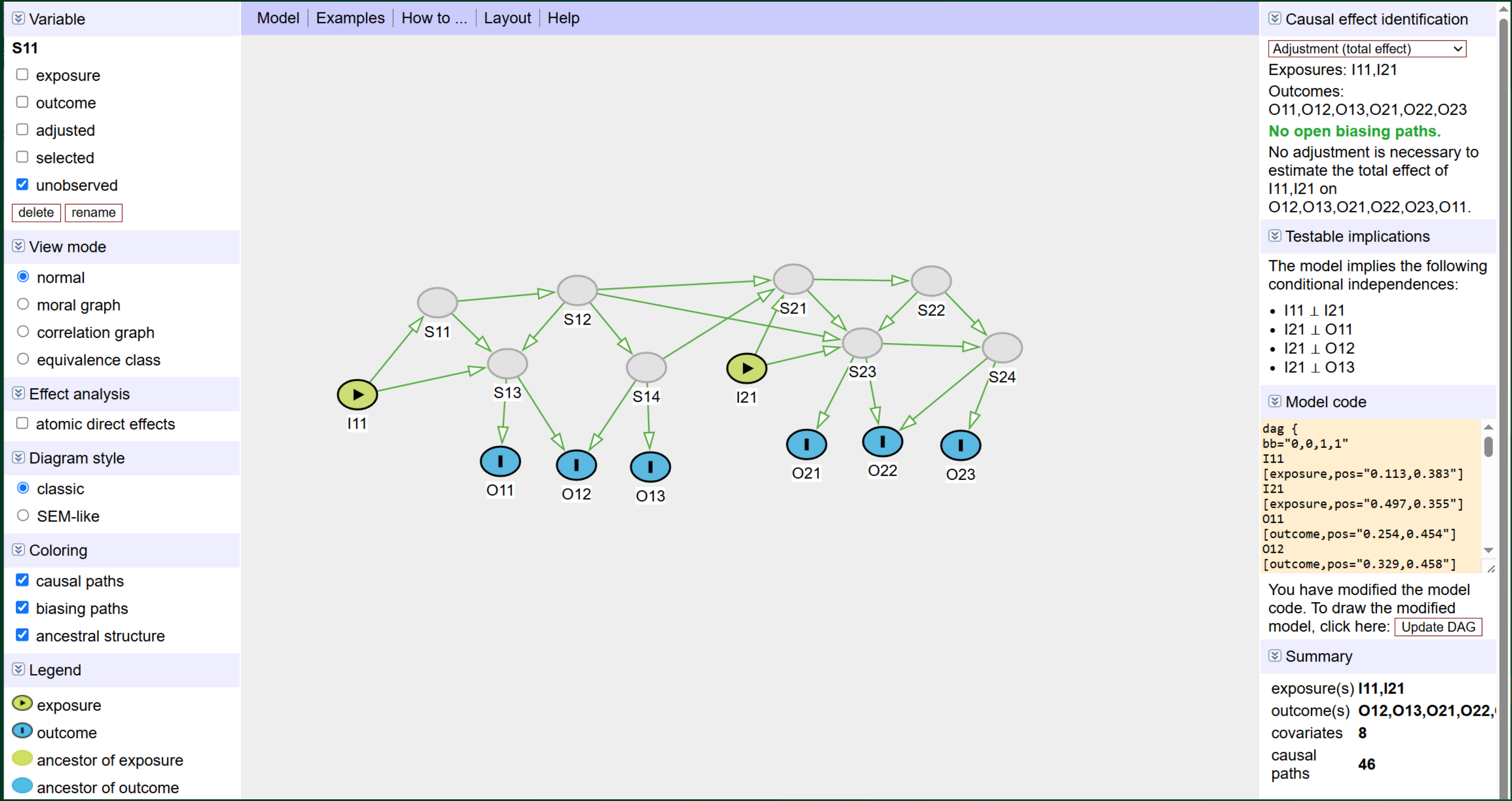


Cognitive Diagnostic Models: Causal Models

Does the Time 1 Intervention I1 **CAUSE** Student Behavioral Time 2 Outcome O3?



WEBSITE:https://www.dagitty.net/



WEBSITE:https://www.dagitty.net/

Variable

S11

- [x] exposure
- [ ] outcome
- [ ] adjusted
- [ ] selected
- [ ] unobserved

delete rename

View mode

- (•) normal
- ( ) moral graph
- ( ) correlation graph
- ( ) equivalence class

Effect analysis

- [ ] atomic direct effects

Diagram style

- (•) classic
- ( ) SEM-like

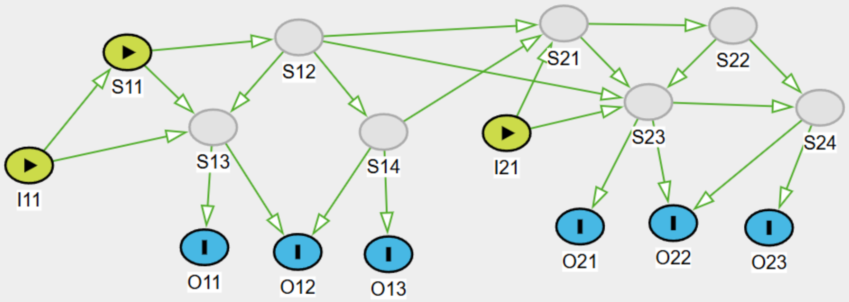
Coloring

- [x] causal paths
- [x] biasing paths
- [x] ancestral structure

Legend

- exposure
- outcome
- ancestor of exposure
- ancestor of outcome
- ancestor of exposure and

Model | Examples | How to ... | Layout | Help



Counterfactual Analysis:

Suppose everybody at time 1 has Skill 1?

Is the effect of the intervention causally identifiable?

What is the magnitude of the intervention effect?

Causal effect identification

Adjustment (total effect)

Exposures: I11,I21,S11

Outcomes: O11,O12,O13,O21,O22,O23

No open biasing paths.

No adjustment is necessary to estimate the total effect of I11,I21,S11 on O12,O13,O21,O22,O23,O11.

Testable implications

The model implies the following conditional independences:

- I11 ⊥ I21
- I11 ⊥ O13 | S11
- I11 ⊥ O21 | S11
- I11 ⊥ O22 | S11
- I11 ⊥ O23 | S11
- I21 ⊥ O11
- I21 ⊥ O12
- I21 ⊥ O13
- I21 ⊥ S11

Model code

```
S21 -> S22
S21 -> S23
S22 -> S23
S22 -> S24
S23 -> O21
S23 -> O22
S23 -> S24
S24 -> O22
S24 -> O23
}
```

Summary

exposure(s)	**I11,I21,S11**
outcome(s)	**O12,O13,O21,O22,**
covariates	**7**
causal paths	**76**

Summary

- Cognitive Diagnostic Models (CDMS) are AI Bayesian Networks
- Student Responses → AI→Evidence Indicators (observables in CDM)
- More complicated proficiency (e.g., Deep Proficiency models) and more complicated evidence models should continue to be explored as extensions of usual CDM. AI methods for inference and learning can be used.
- Dynamic Bayes Network Architecture is a CDM extension and well-studied in AI as a “planning algorithm” which is learned using “reinforcement learning”
- The strategy of reducing parameter dimensionality using DINO and DINA methods has been explored in AI in the areas “Markov Logic Nets” and “Statistical Relational AI”
- Continued work in statistical inference involving possibly misspecified, empirically non-identifiable, parameter redundant models is required as our psychometric models become more complicated…
- An important goal of assessment is to create a causal evidentiary reasoning chain and use that chain to guide curriculum design, automated AI personalized learning. Results from AI in the area of causal modeling are relevant here…

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