Lessons from Autonomous Personalization

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Charles Lang
Visiting Assistant Professor
Teachers College Columbia University

Slides available at:
https://github.com/charles-lang/georgetown

Structure of Talk

- Personalization algorithms
- Three lessons: goals, models and implementation
- Applied to teaching
- Masters Degree

Autonomous

Personalization

The success of education depends on adapting teaching to individual differences among learners

329 BC, Xue Ji

“Uniformity is the curse of American schools...Individual instruction is the new ideal.”

Charles Eliot, 1899

Best Definition

Student

Magic

Better Student

Definitionally True

If we provide what the student needs, when they need it, they will learn better

Vocabulary

Individualization: learning goals are the same for all students, but students can progress through the material at different speeds

Differentiation: learning goals are the same for all students, but the method or approach of instruction varies according to the preferences of each student

Personalization: learning goals and content as well as the method and pace may all vary (so personalization encompasses differentiation and individualization)

ed.gov (2010)

Autonomous

We trust the machine to do some of the decision making

Fuel for machines = variation

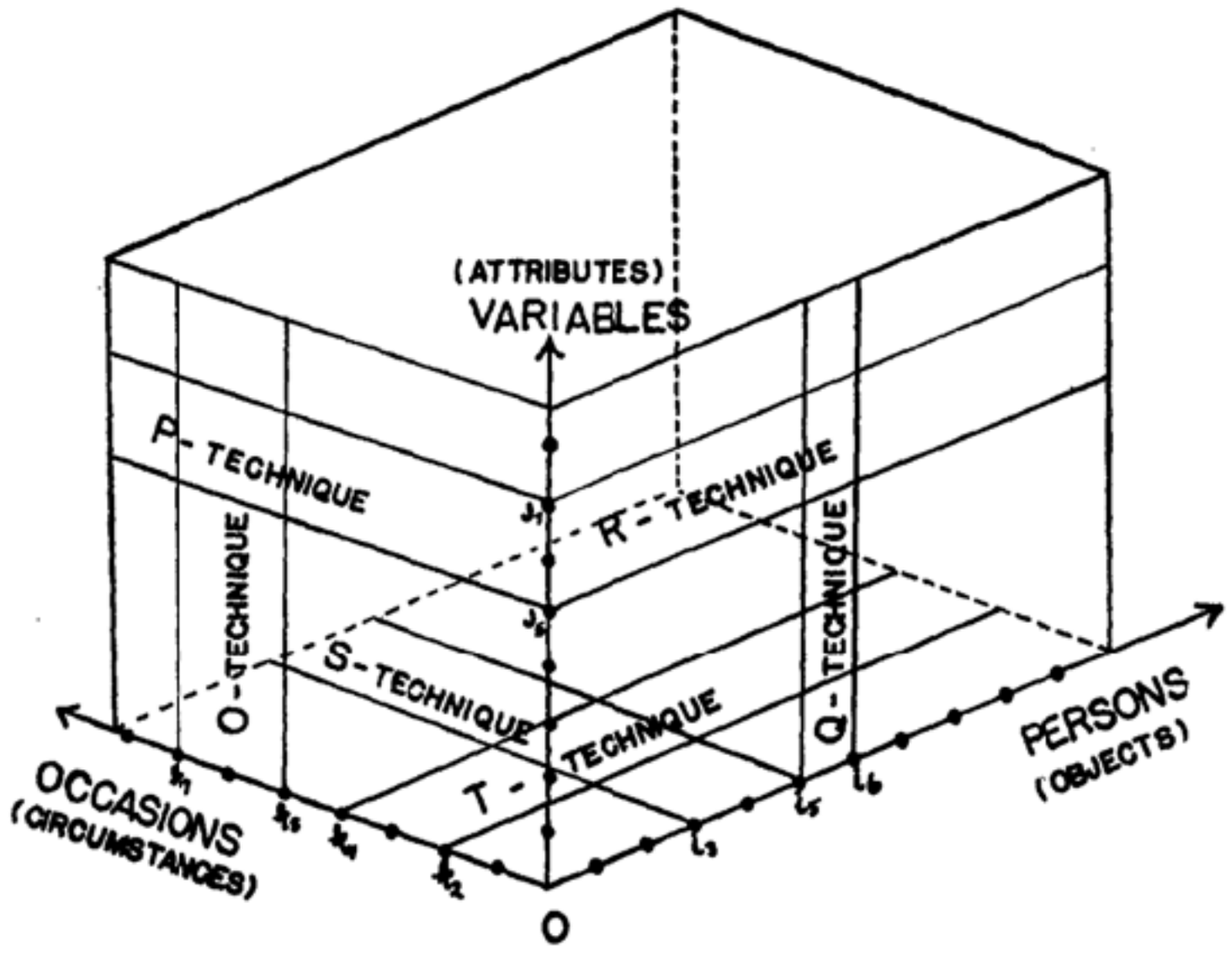


FIG. 1. THE COVARIATION CHART

Cattell, 1952

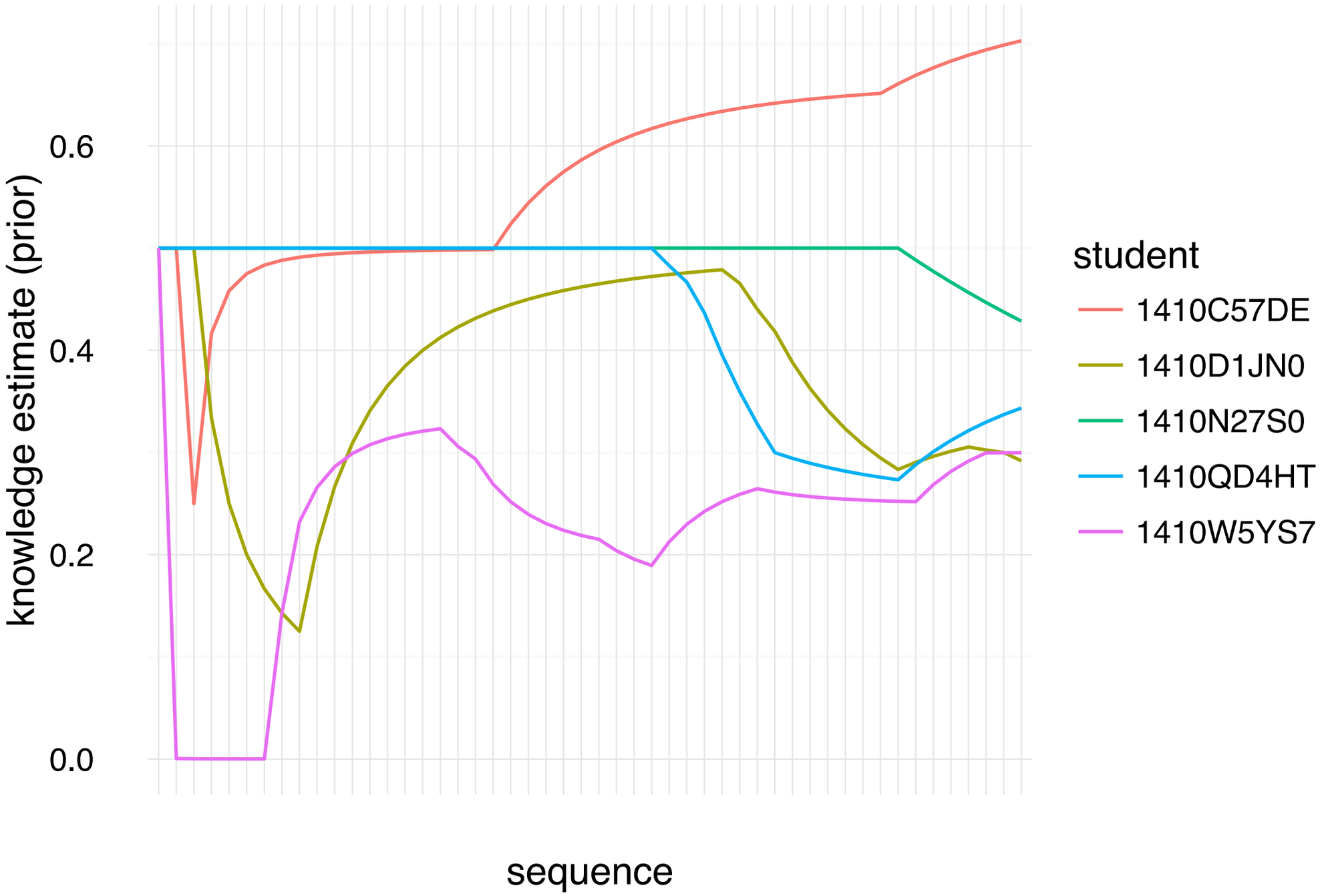
Bayesian Student

$$P(K|D) \propto P(D|K).P(K)$$

behavior (posterior) | context (likelihood) | knowledge (prior)

Results

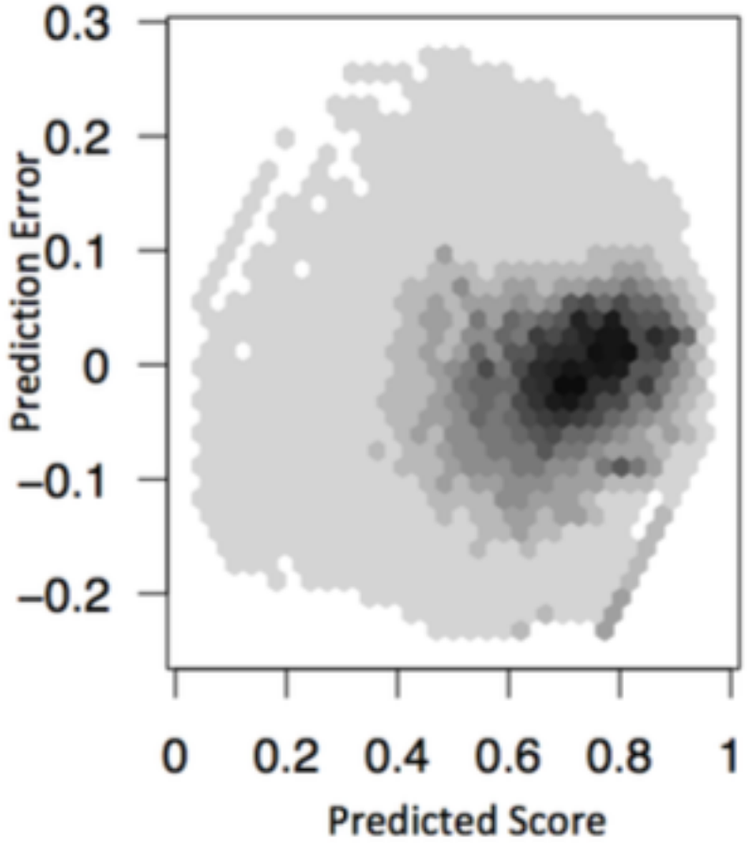
Real Students



Real Students

Model	Overall	Per Student	Per Skill
BKT	0.28	0.39	0.28
Bayes	0.29	0.25**	0.31

** $p < .01$

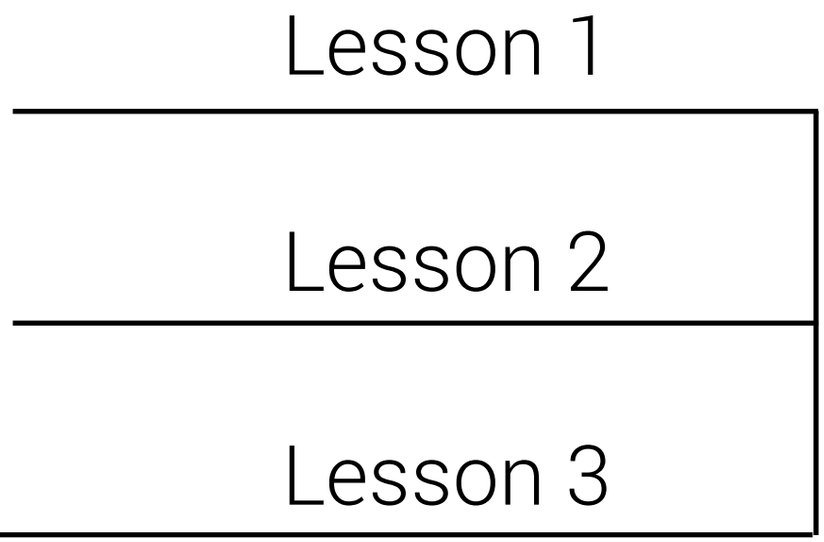


Why?

- Being able to predict student behavior is useful
- Data collection parsimony is *more* useful

Success?

- Objective setting
- Models of learning
- Data location



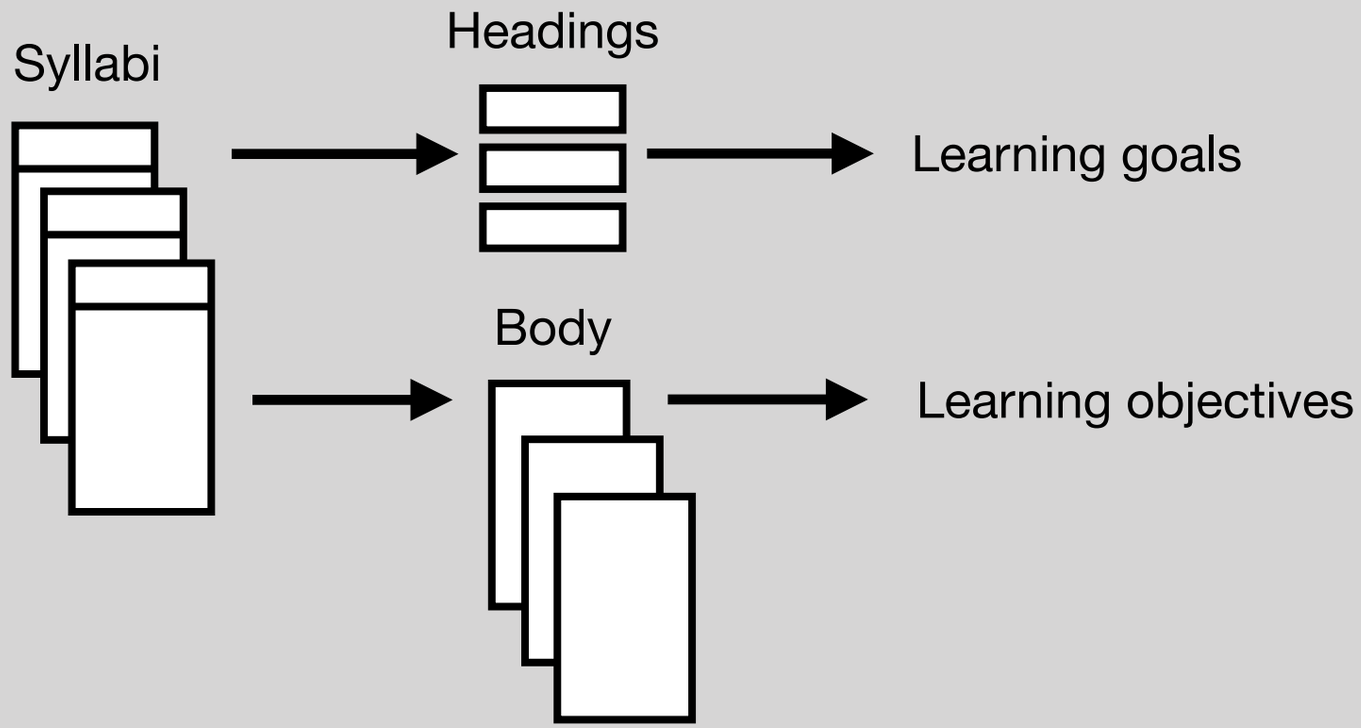
Lesson 1: Objective setting is non-trivial

Objective Setting is Non-Trivial

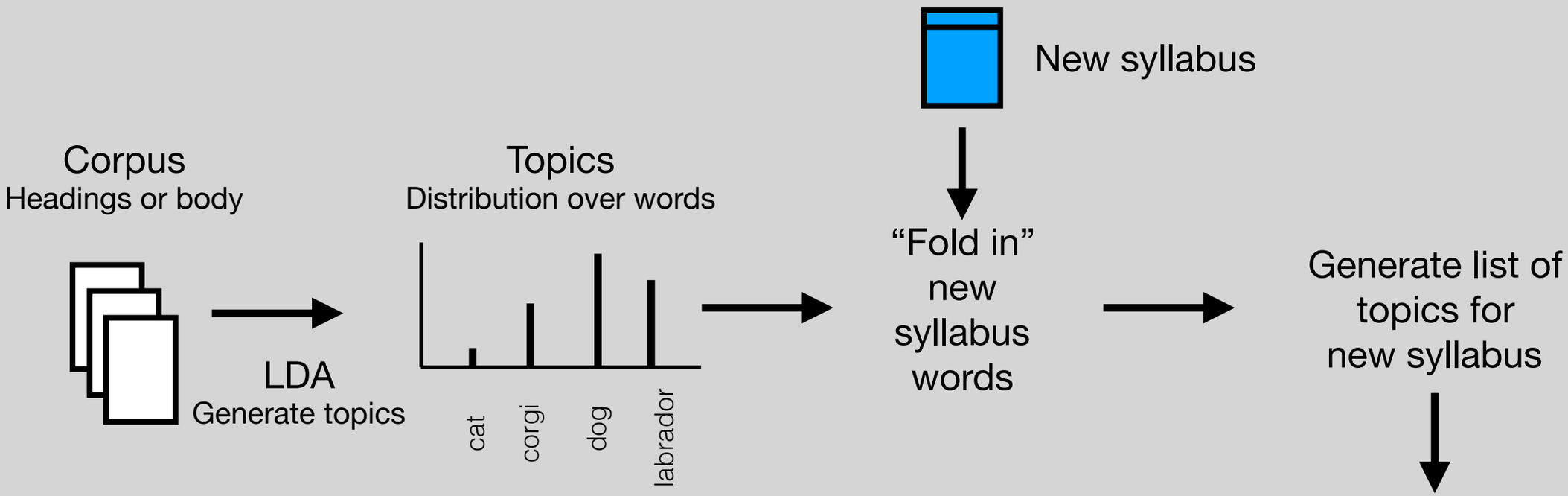
- **Model requires that a desired behavior is defined**
- Time consuming
- Conceptually difficult
- Requires training

Syllabus Project

Can we auto-generate learning goals and objectives from syllabi?



Syllabus Project



Objectives

- **Not to prove The Answer**
- Provide suggestions
- Reduce friction
- Reduce time spent

Lesson 2: The need for (at least) three models of learning

General Framework

- **Narrative Model**: Dinner party version of your personalization model or theory

- **Operational Model**: What you count and how you count it

- **Validation Model**: Convincing yourself there is a connection between your narrative and operational models

Swimming Expert

Experimental Psych Context

Classroom

Ed Stat, Economics

Bad

Social Psych

Good

Spell “cat”

Behavior

1 2 3 4 5 6 7 8 …

1 2 3 4 5 6 7 8 9 …

Psychometrics/ BKT

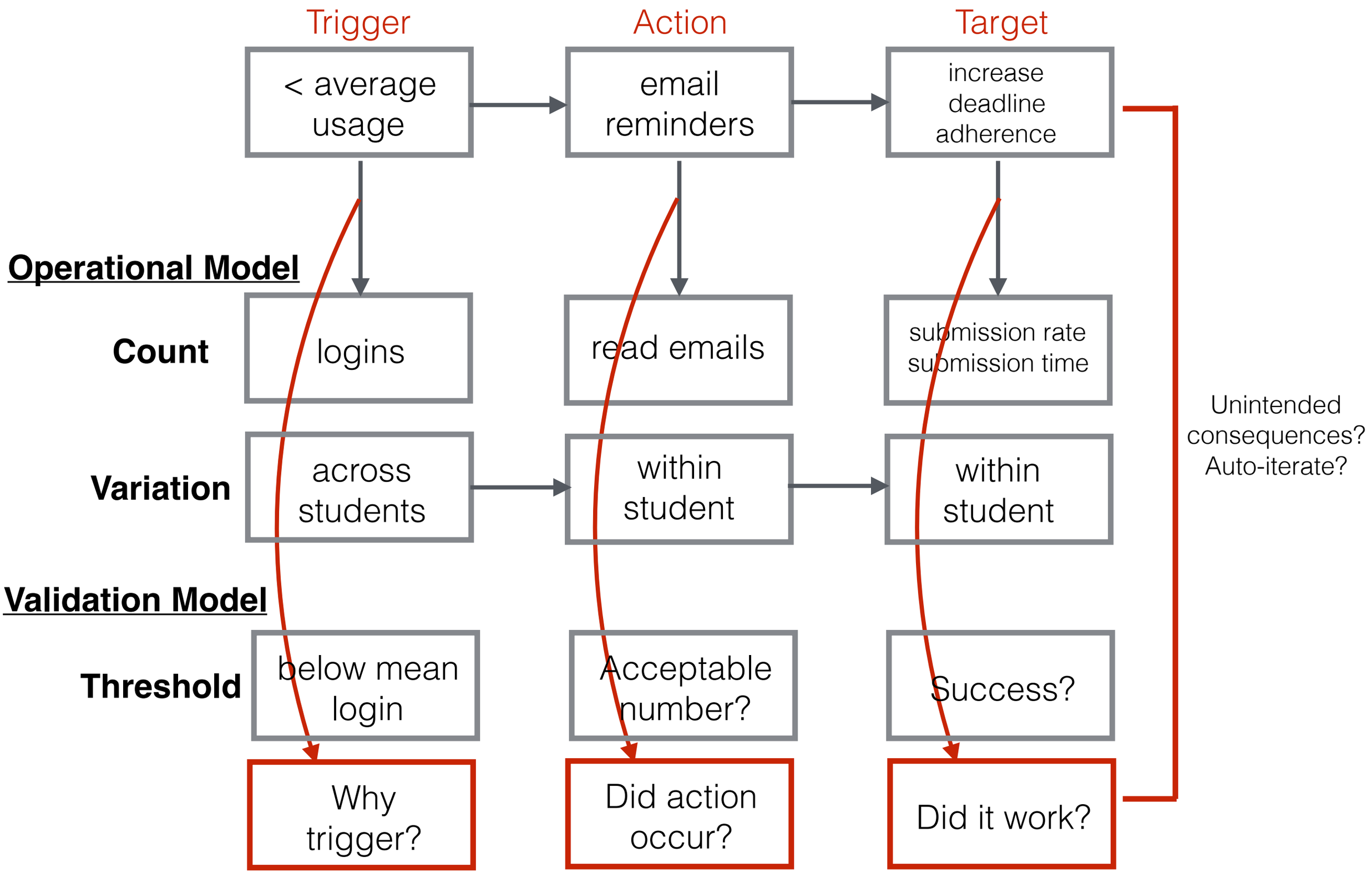
Qual/Big Data

Pragmatic Validity

- Relax pursuit of generalizability to other populations
- Concentrate on internal validity and prediction of future events

Grapentine, T. (1995)

Narrative Model



Lesson 3:

Implementation is everything

Implementation

- Data sources are controlled by different groups within an institution

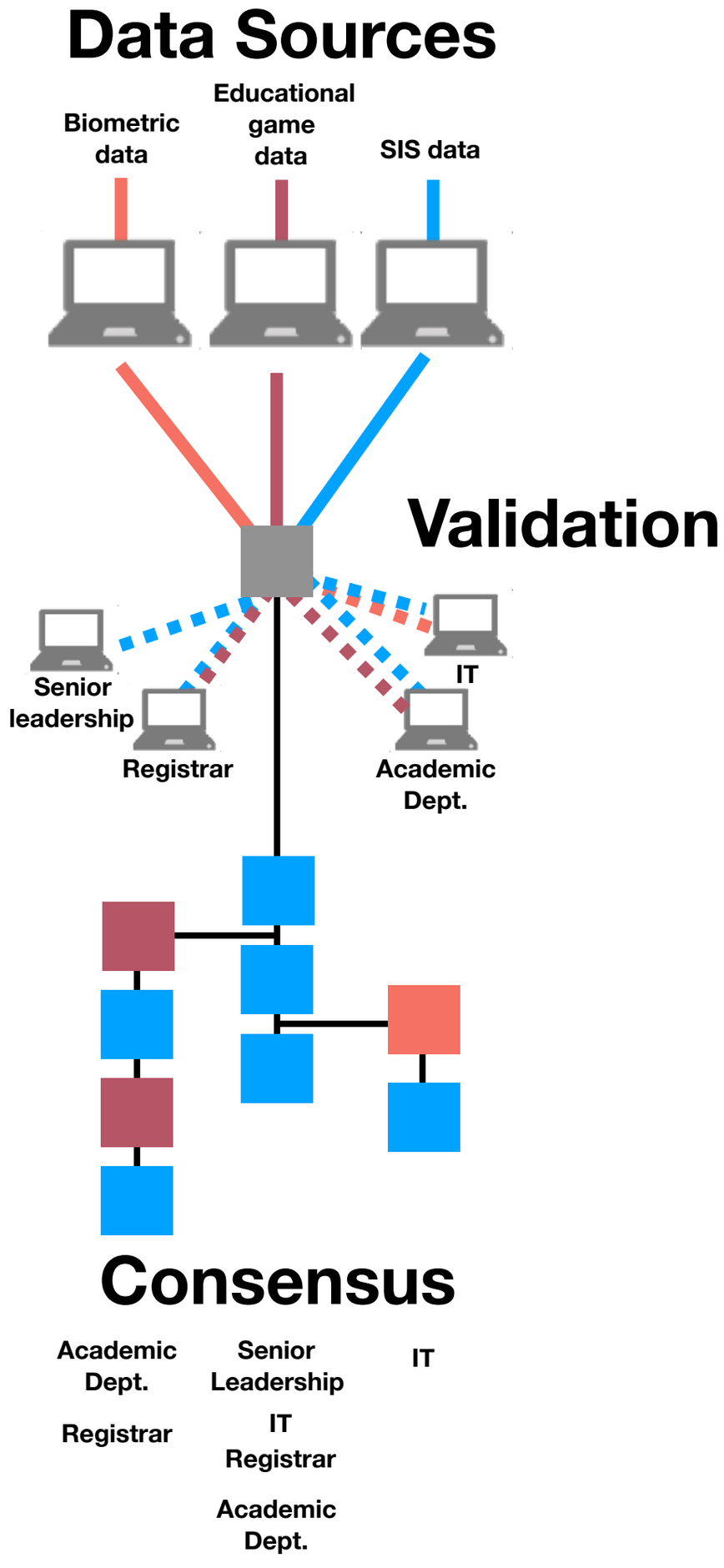
- Negotiation between groups is a major stumbling block to utilizing data

BUT

- Job is too big for any one group, there is more work than can possibly be achieved by one person, unit, department, university, government…

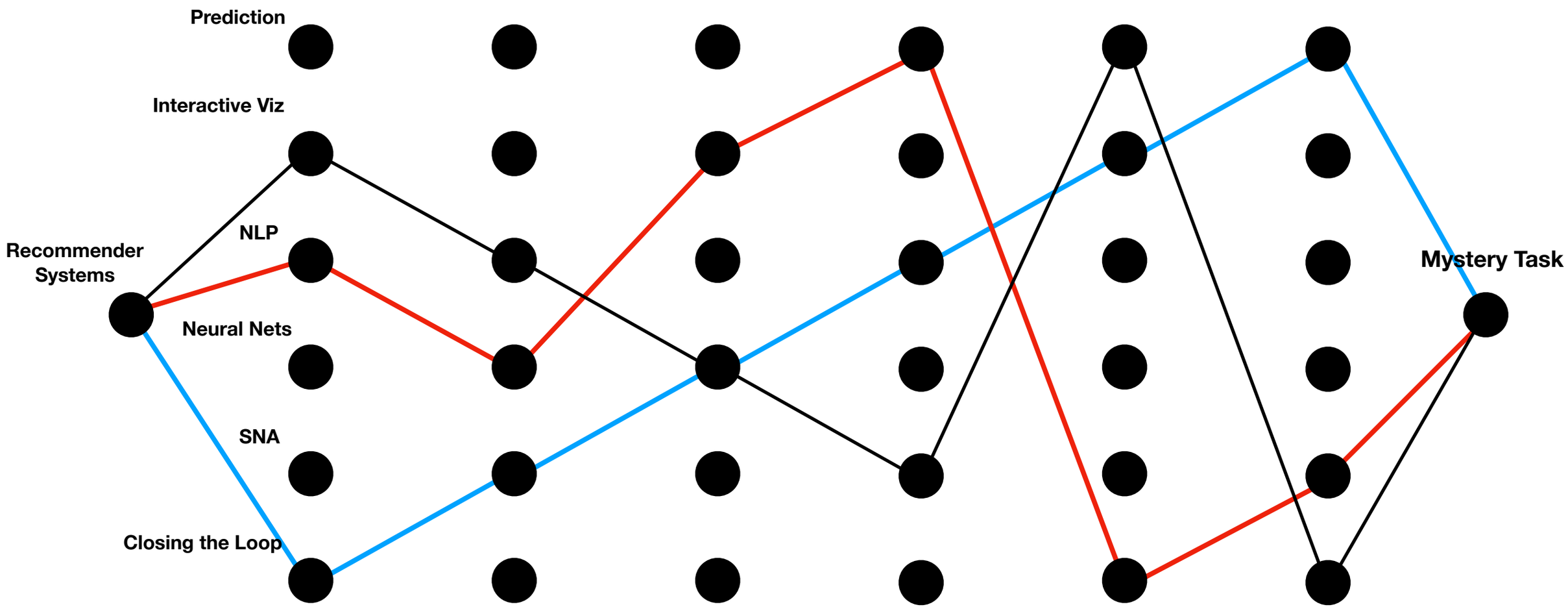
Blockchain Project

Can we use a distributed data base (Blockchain) to build consensus about what data to collect?



Impact on Teaching

LA: Process & Theory



https://github.com/la-process-and-theory/syllabus

Why?

- Content isn’t necessary cumulative
- Learning is more effective if you can follow your own interest
- Students are better arbiters of what they need to know than instructor
- Promotes self-motivated learning
- More time getting instructor feedback
- Get to test the tool you build in unit 1

Narrative Model

	Trigger	Action	Target
	Recommend	Choose content	Motivation

Operational Model

Count	Recommend-ations	Choice patterns	Commits Additions
Variation	across students	across students	across students

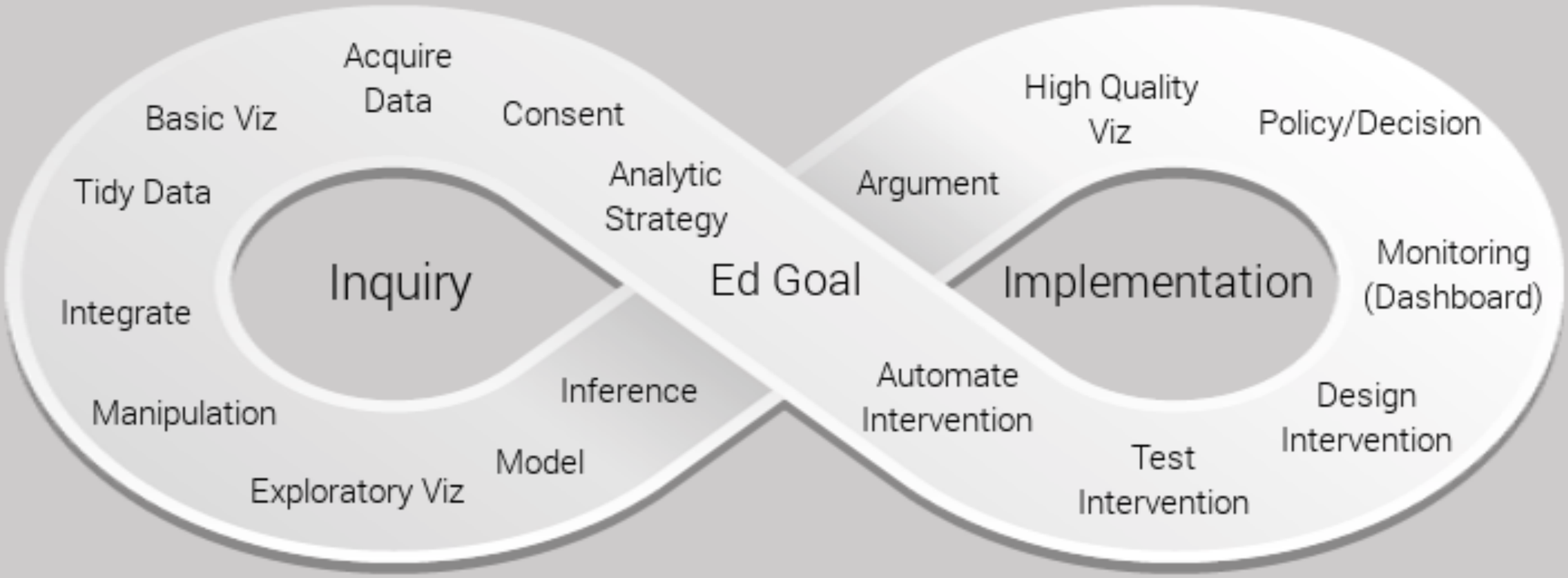
Validation Model

Threshold	Variation in recommend	Correlation choices/recs	Do I care?
	Why trigger?	Did action occur?	Did it work?

Affect?

Differential use/utility by subgroup?

Ed Data Science Cycle



MSc in Learning Analytics

MSc in LA

- 18-24 months
- 3 course methods sequence: Intro, Intermediate, job readiness
- Required courses in sociology, cognition & learning, data visualization, statistics
- Placed with employers for group based capstone projects

Example Capstone Projects

- Which modalities within platform correlate with highest engagement?
- Interpreting clustering of students within personalized learning platform
- College math readiness personalized tutor evaluation
- Patterns within admissions system usage among applicants