

Personalization

Goals

- Overall: Help us be more intentional about personalization systems we design
- Introduce a framework for creating automated personalization projects
- Work on a personalization project that you care about
- Practice these projects on a few data sets
- Work on a project using the LASI Dataset

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 you are right

Plan

Day 1

- Definitions...
- Narrative Models
- Operational Models
- Choose your own adventure

Day 2

- Validation Models
- Presentations

In the News

EDUCATION WEEK

Gates, Zuckerberg Philanthropies Team Up on Personalized Learning

TIME | U.S.

Why Mark Zuckerberg Wants to Spend on Personalized Learning

As ed reformers urge a 'big bet' on personalized learning, research points to potential rewards — and risks

The Washington Post
Democracy Dies in Darkness

A primer for Mark Zuckerberg on personalized learning — by Harvard's Howard Gardner

Smithsonian.com

Is Artificial Intelligence the Key to Personalized Education?

USA TODAY

Is personalized learning the future? This high school thinks so.

 **Chalkbeat**
Education news. In context.

Forbes

Transforming Education, One Student At A Time

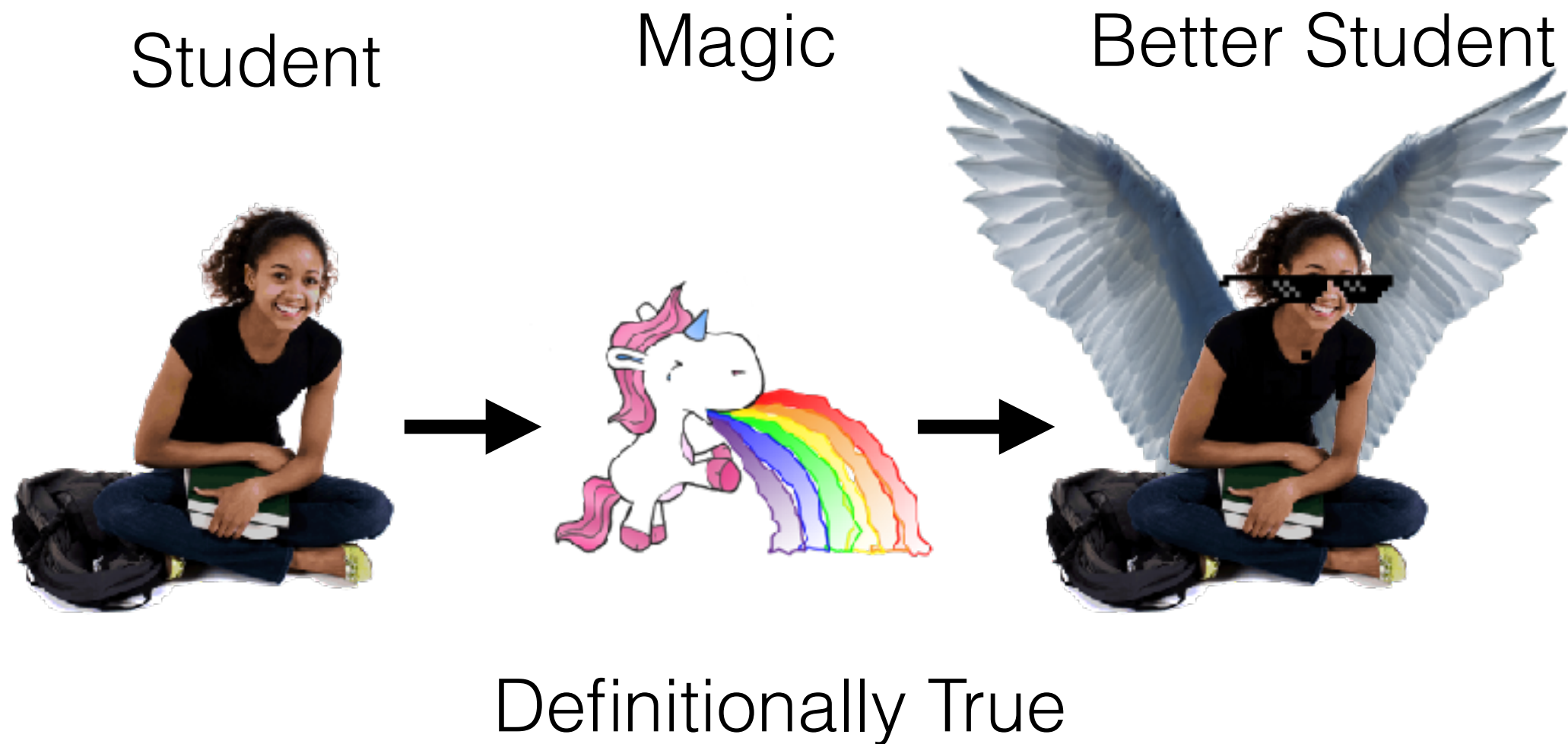
EdTech
Focus On K-12™

IBM and Sesame Workshop Aim to Personalize Learning for Preschoolers

Exercise 1: Define These Terms (without Googling)

- Personalization:
- Differentiation:
- Individualization:
- Adaptivity:

Best Definition



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



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

329 BC, Xue Ji

Not Xue Ji

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

Charles Eliot, 1899

Vocabulary

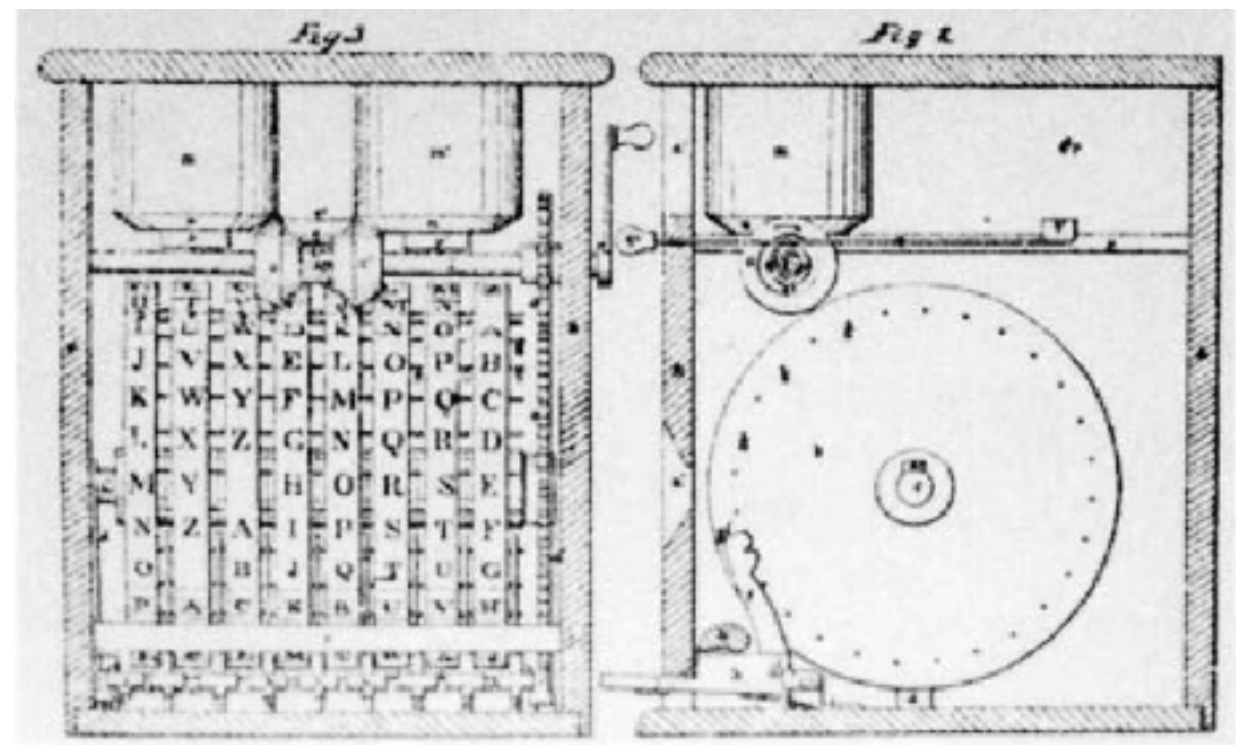
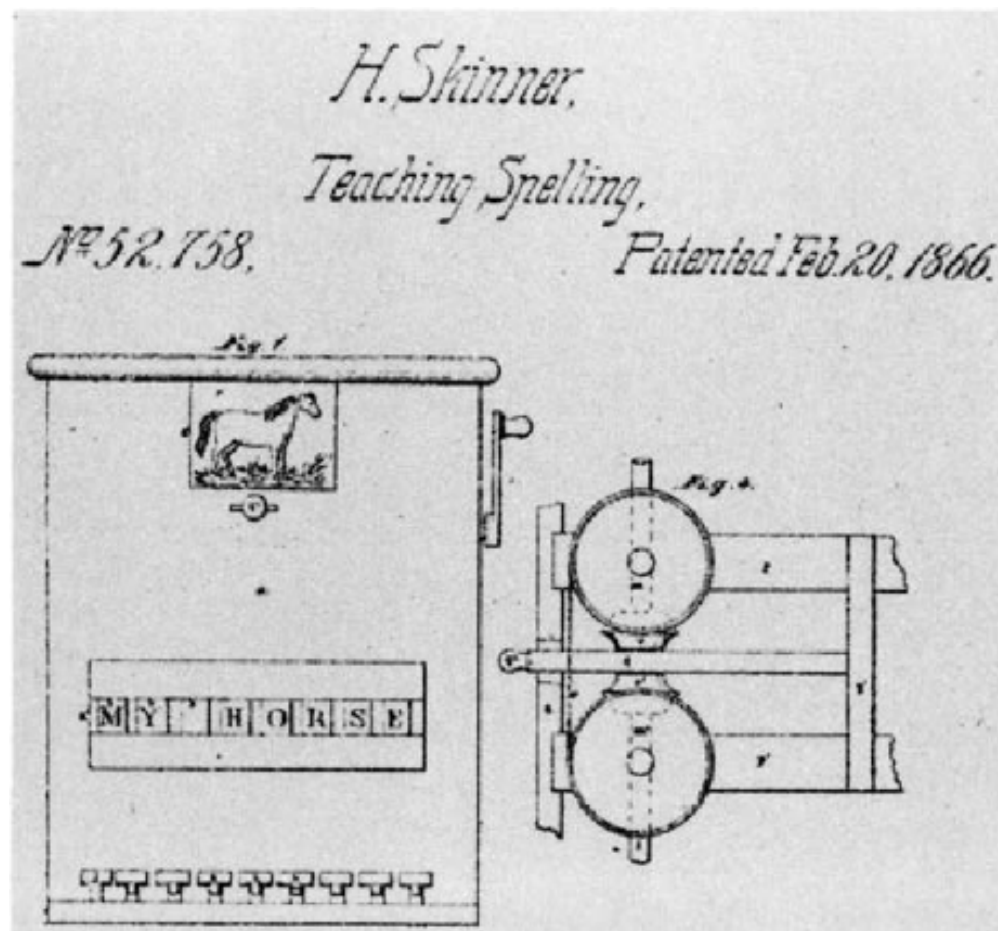
Individualization: learning goals are the same for all students, but students can progress through the material at different speeds

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)

Teaching Machines



Teaching Machines

- Automatic or self-controlling device
- Presents a unit of information
- Provides some means for the learner to respond to the information
- Provides feedback about the correctness of the learner's responses

(Benjamin, 1988)



Skinner's Teaching Machines

Intelligent Tutoring Systems

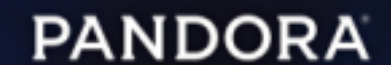


- Simulate a human tutor
- Interpret complex behavior
- Respond differently to different students
- Offer hints
- (Learn from the student)

Adaptive

- Originally = assistive
- ~1990s = sequential estimate of aptitude (IRT)
- ~2012 = a system that adapts the educational environment according to students' learning needs
- Distinct from Cognitive Tutors in terms of methods employed
- A Cognitive Tutor built in San Francisco

Adaptive Systems

The Netflix logo, consisting of the word "NETFLIX" in a bold, red, sans-serif font, is centered on a light gray rectangular background.The Amazon.com logo, featuring the text "amazon.com" in a black, sans-serif font with a registered trademark symbol, and a curved orange arrow underneath the word "amazon". It is centered on a white rectangular background.The Pandora logo, with the word "PANDORA" in a white, sans-serif font, is centered on a dark blue background with a bokeh effect of light blue and white circles.The last.fm logo, with the text "last.fm" in a red, lowercase, sans-serif font, is centered on a white background.The Hulu logo, with the word "hulu" in a green, lowercase, sans-serif font, is centered on a dark gray rectangular background.The LinkedIn logo, with the word "Linked" in a black, sans-serif font and "in" in white inside a blue square, followed by a registered trademark symbol, is centered on a white background.

Adaptive Engines



adapt
courseware

Recommender Systems

Collaborative filter: build a model from a user's past behavior + similar decisions made by other users



Content filter: utilize a series of discrete characteristics of an item in order to recommend additional items with similar properties



Definitions

- Must involve **time** (or at least two time points)
- Make inferences about **relevant groups** or **individuals**
- Requires a **defined goal/standard**
- Inherently **causal**
- **Automate**

Personalization/Differentiation/ Individualization

Underlying characteristic (for quant models):

Make probability statements about individual students

Underlying problem:

Students are bound by the arrow of time - they can only do any task once under the exact same conditions

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

Narrative Model

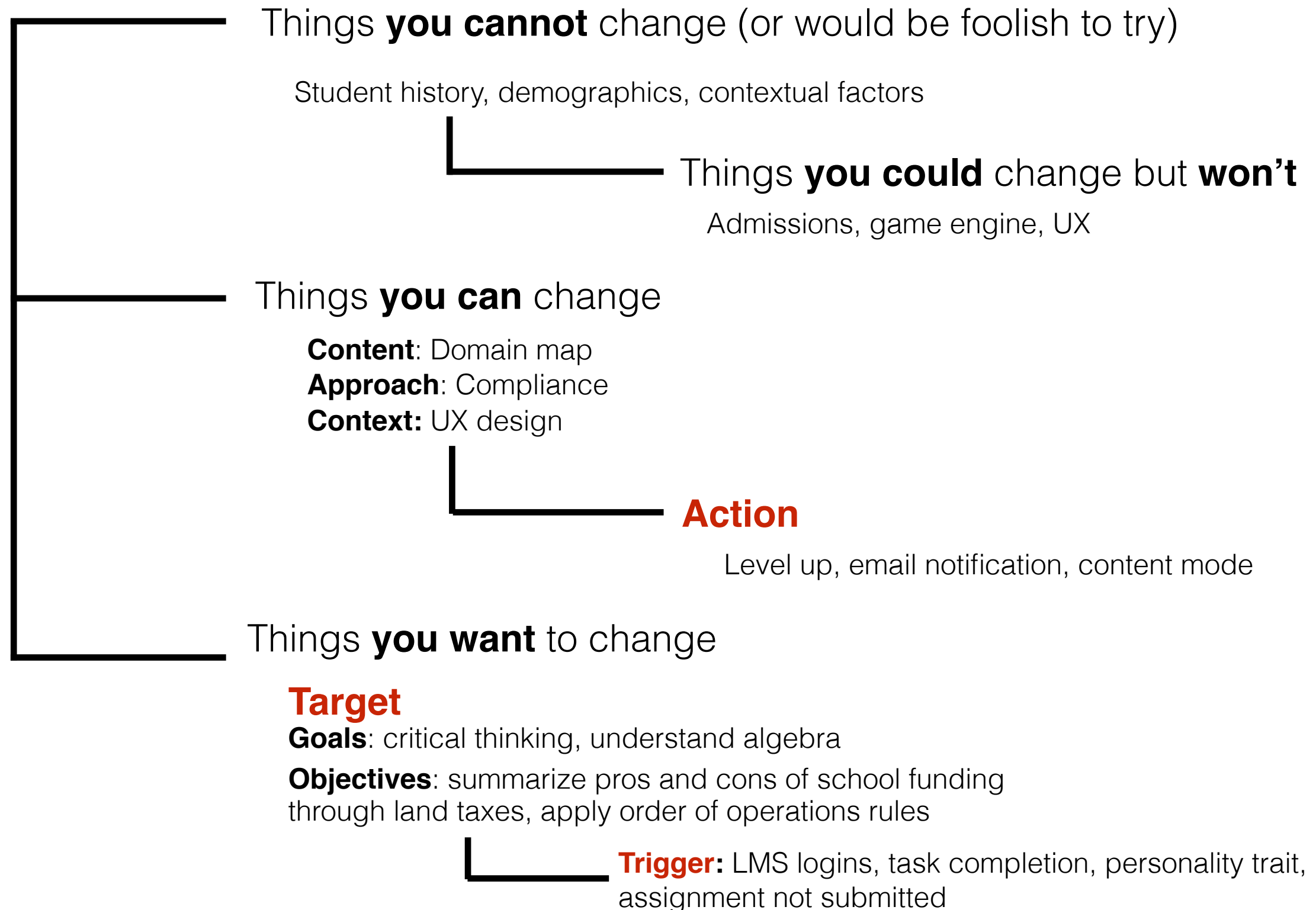
If we alter the **environment by W**, for **subgroup X**,
then **learner Y** will do **Z**

**If learner X does Y in environment W, they get
result Z (vs. Z')**

Exercise 2: Devise an Example

Take five minutes to invent a personalization example
and write the narrative model

Narrative Model



Narrative Model

Cannot change

Can change

Want to change

Action

Trigger/Target

incoming student
study habits

email deadline
reminders

student logins
meet deadline

incoming student
knowledge

content

understanding
progress

student anxiety

content difficulty

correctness

Exercise 3: Categorize the aspects of your example into:

- Cannot change
- Can change
- Want to change

Narrative Model

Action

Trigger

If we alter the **environment by W**, for **subgroup X**,
then **student Y** will do **Z**

Target

If we **send email deadline reminders** to **students who do not login** then **those students** will **hand in their assignments on time**

Exercise 4: Convert your example into the following form:

If we alter the **environment by W**, for **subgroup X**,
then **student Y** will do **Z**

Narrative Model

Part theory, part causal model, part guess

If you put “if” in front of it, this is the hypothesis
that you are continuously testing

In what way does the narrative model matter?

Operational Model

Operational Model

What are you counting?

Cannot change

incoming student
study habits

- student demographics
- previous courses
- previous LMS use

Can change

Action

email deadline
reminders

- send/not send
- time sent

Want to change

Trigger/Target

student logins
meet deadline

- logins
- submissions
- timestamp
- grades
- completion

Exercise 5: Define what you
are counting

Operational Model

What variation are you mining?

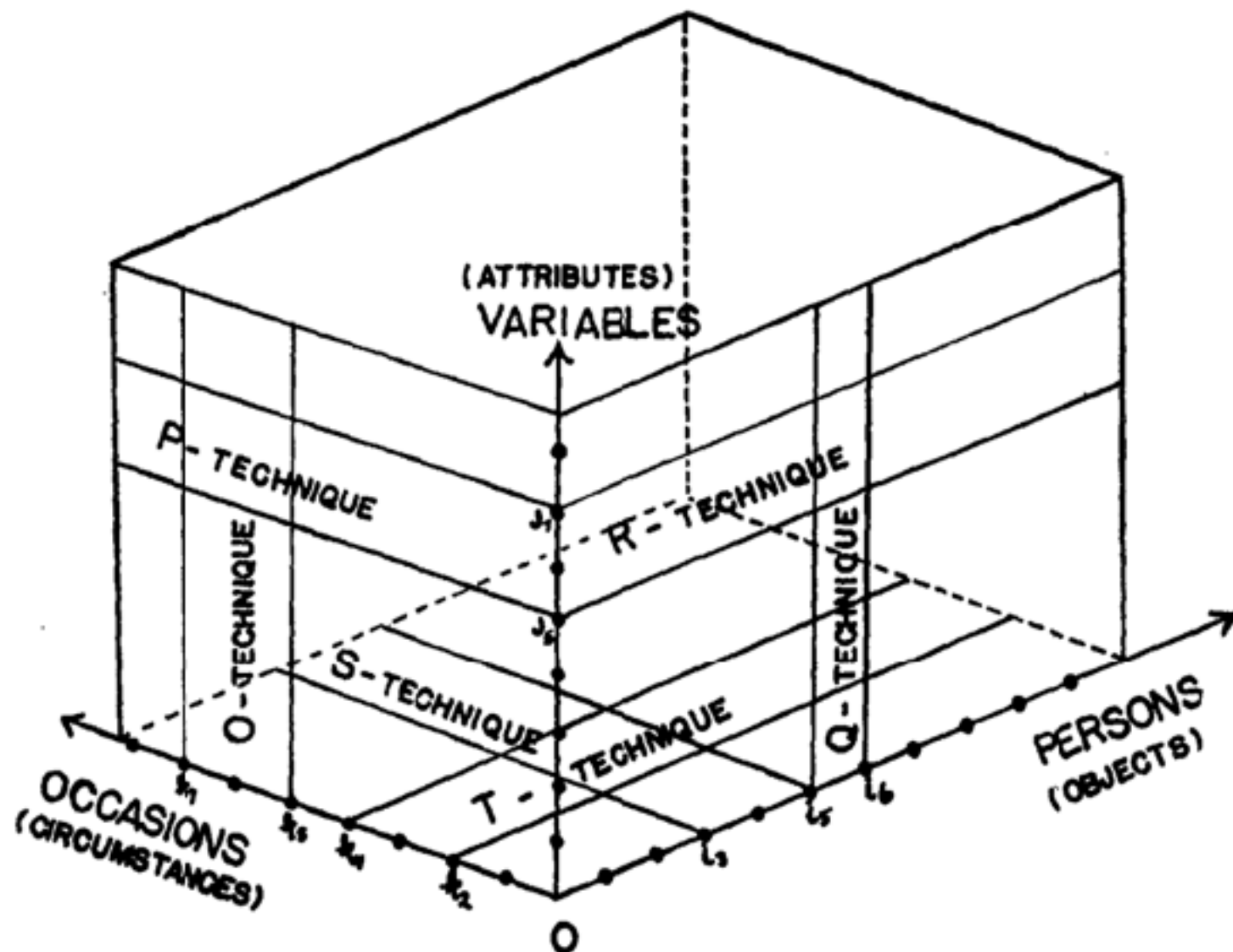


FIG. 1. THE COVARIATION CHART

Cattell, 1952

Exercise 6: Variation

Questions to ask:

- On what planes is the variation?
- What comparisons are available?
- What **relevant information** is available in that variation that we can draw **inferences** about **triggers** from?

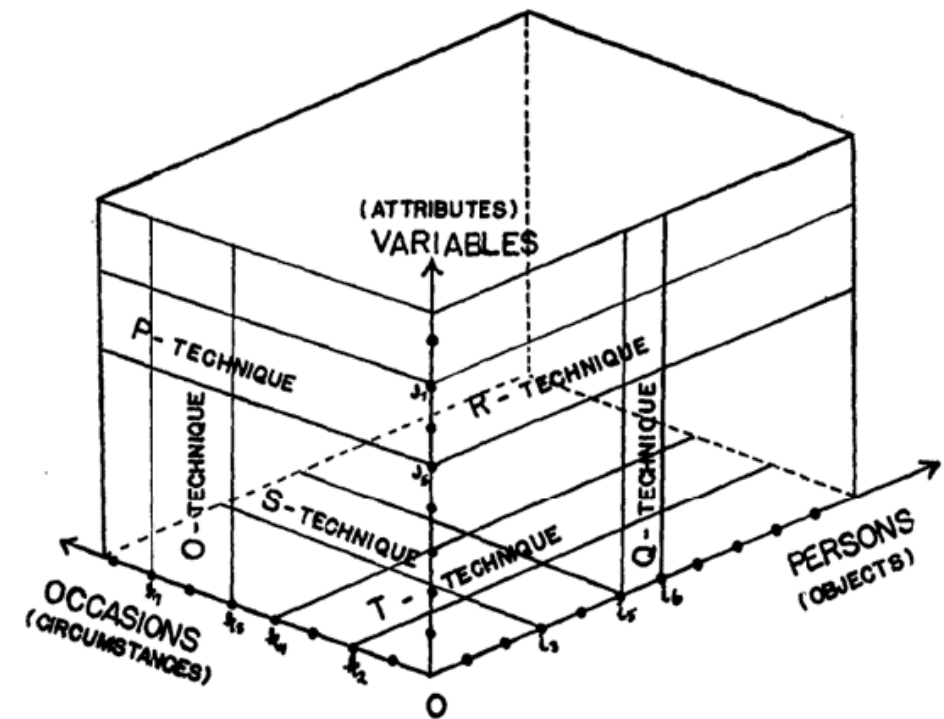


FIG. 1. THE COVARIATION CHART

Operational Model

- How are you making meaning from that variation?
- What is the trigger?
- What is the action?

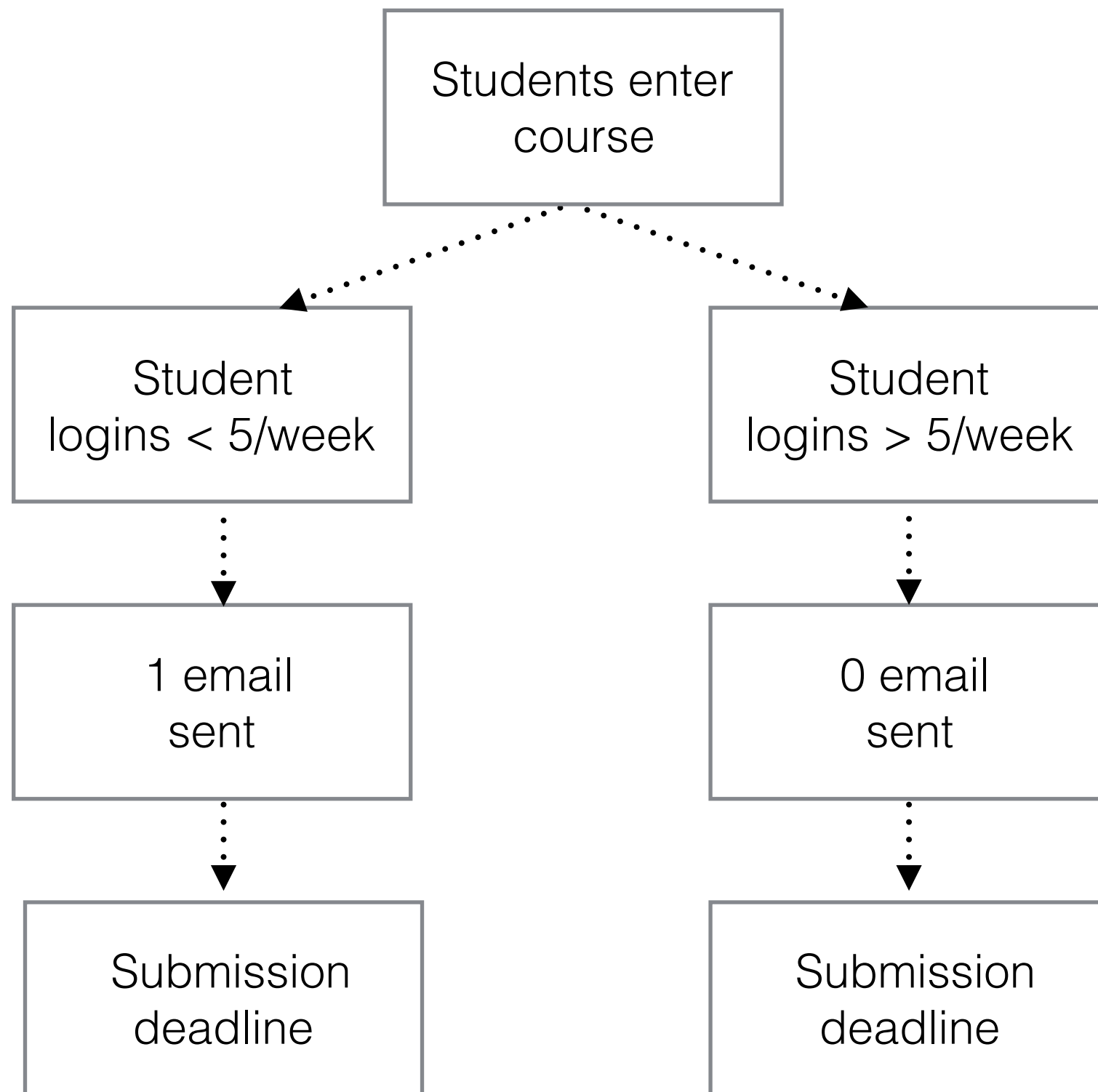
Exercise 7: Simulate Data

- Using R, simulate and visualize the variables for your example

Operational Model

- How does the machine make decisions?

Example 1: Arbitrary Decision

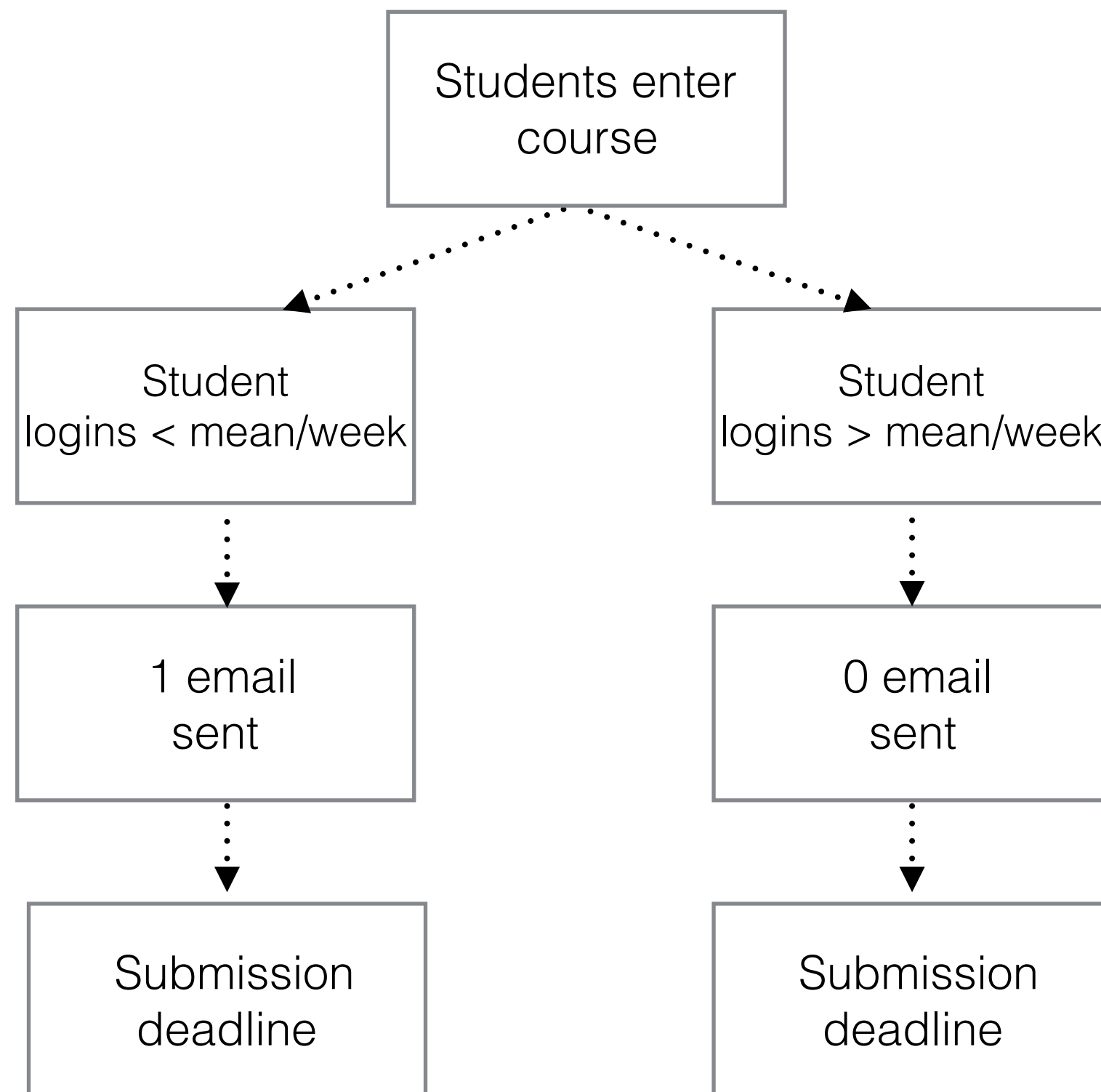


Count: logins

Variation: theoretical/time

Information: priorities

Example 2: Mean Decision



Count: logins

Variation: between-individual

Information: priorities

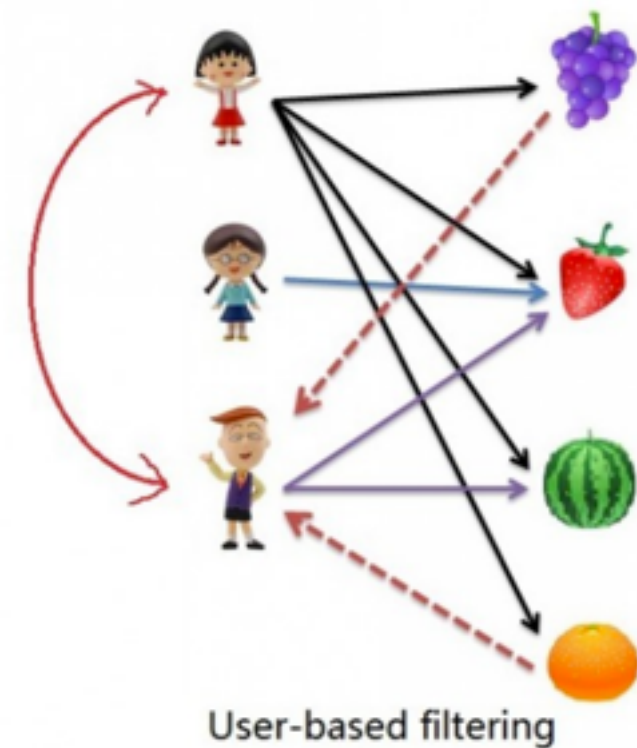
Example 3: User Based Collaborative Filter

	student A	student B	student C
podcast	score improved = yes	yes	no
game	yes	no	no
quiz	yes	yes	no

Count: score change, tasks, students

Variation: between-individual

Information: learning



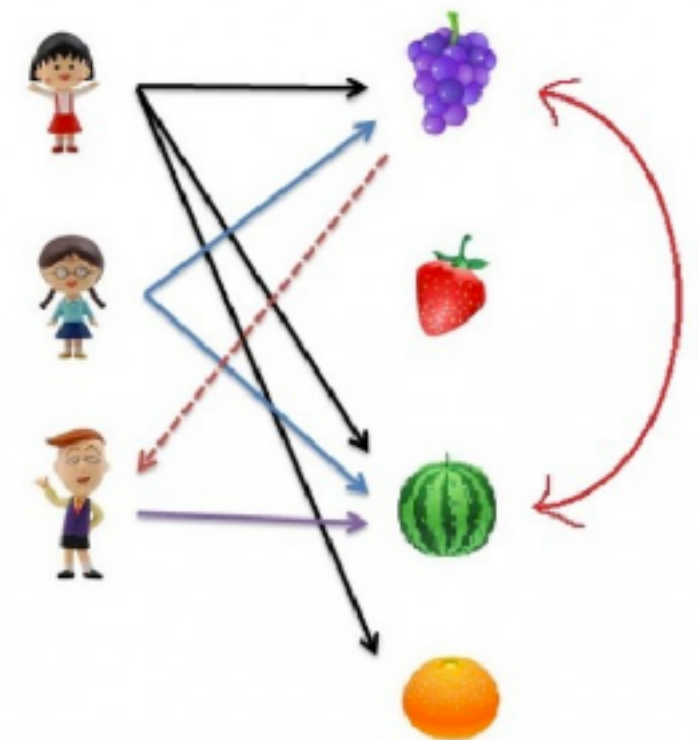
Example 4: Item Based Collaborative Filter

	student A	student B	student C
podcast	score improved = yes	yes	no
game	yes	no	no
quiz	yes	yes	no

Count: score change, tasks, students

Variation: between-tasks

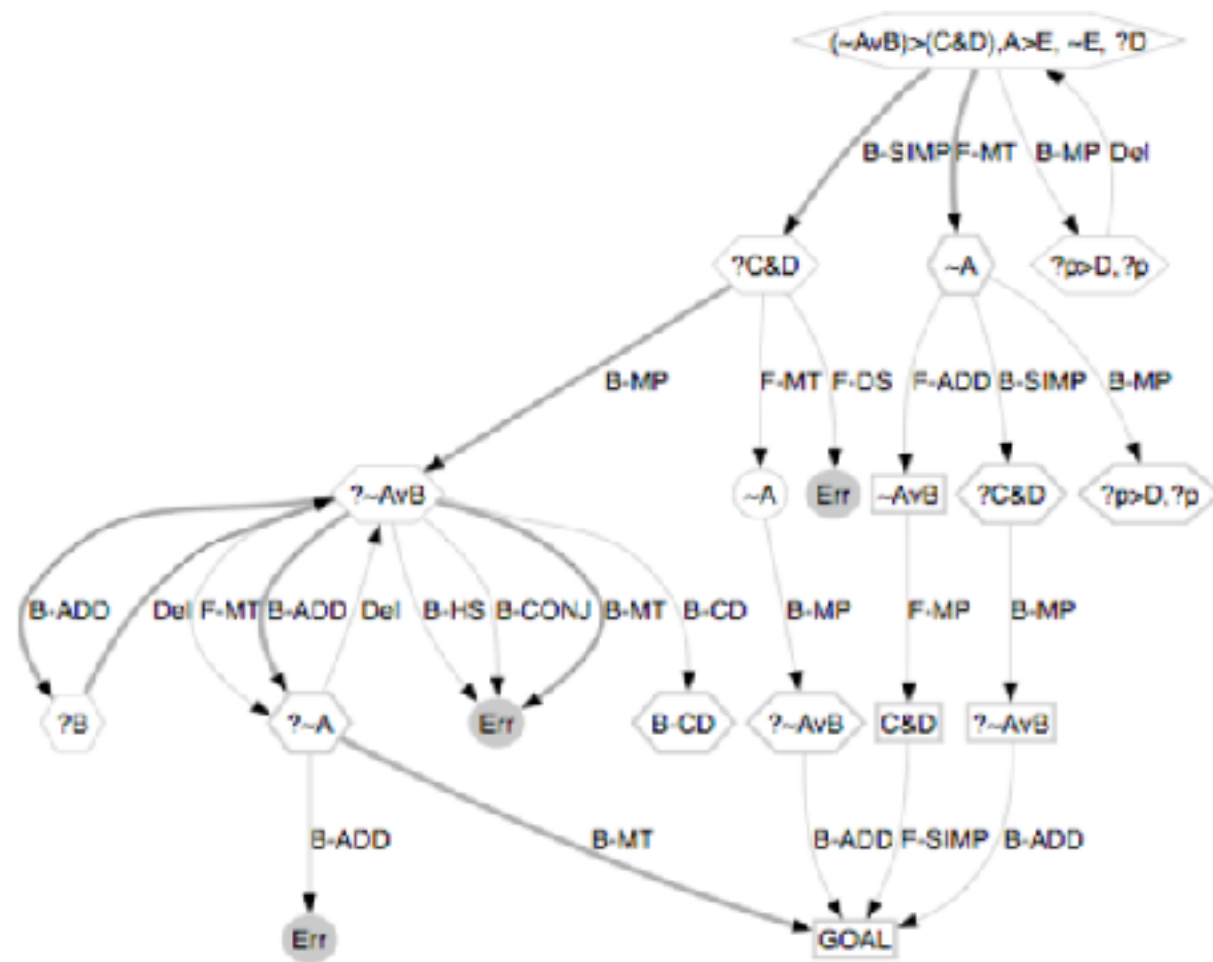
Information: learning



Item-based filtering

Example 5: Model Tracer

Compare models of **how** people **know**



Count: decisions,
pathway, success

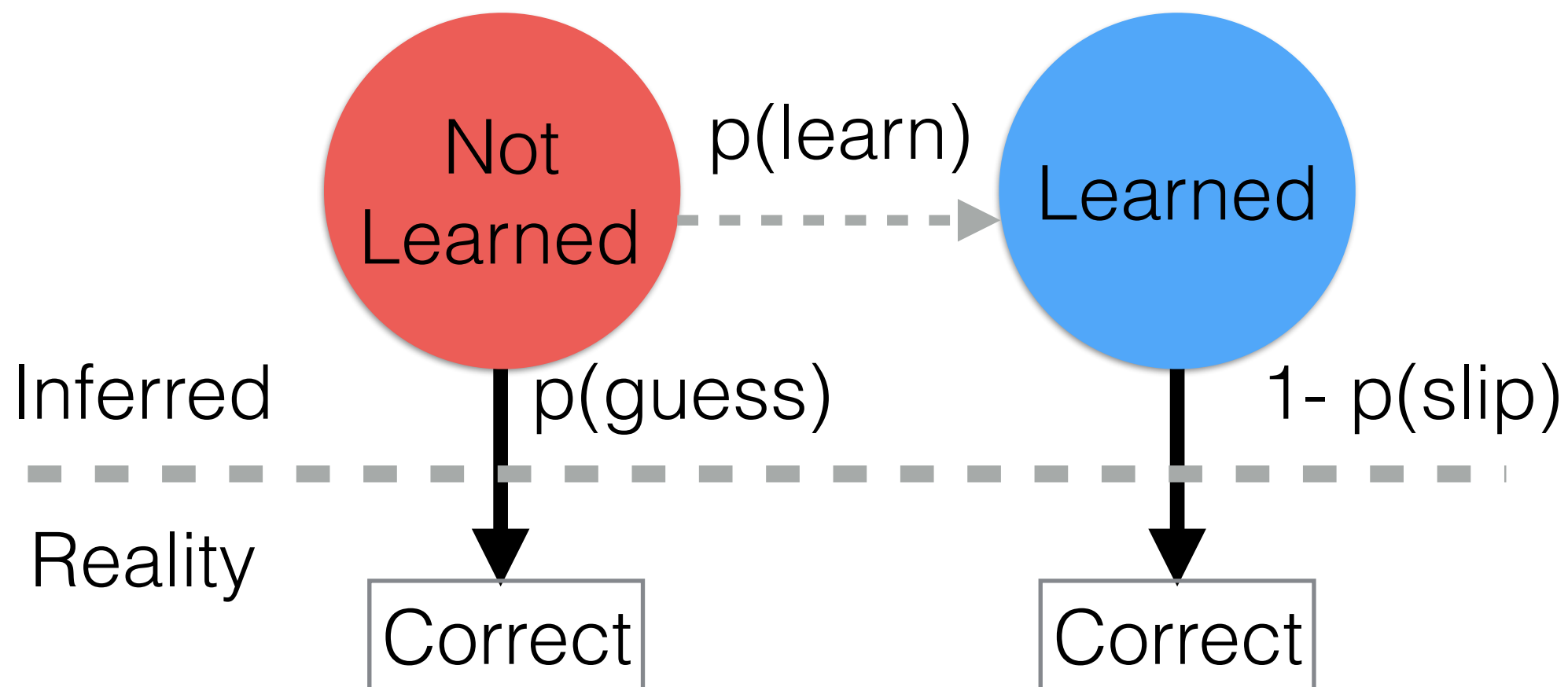
Variation: between-
students

Information: learning

Example 6: Knowledge Tracer

- Operational model can be very complex
- Can involve latent traits
- Can merge axes of variation

Count: correct/
incorrect, student
Variation: between-
students, over-time
Information: latent trait
model



Exercise 8: Choose a Methodology

- Choose a methodology appropriate to the variation you have defined and the inference you believe you need to make for your trigger

End Day I

Operational Model

- What are you counting?
- What variation are you mining?
- What relevant information is available in that variation?
- How are you making meaning from that variation?
- What is the trigger?
- What is the action?
- How does the machine make decisions?

Validation Model

Reasoning

Statistics

Counterfactual

Predictive

Frequentist

Bayesian

Fiducial

Education

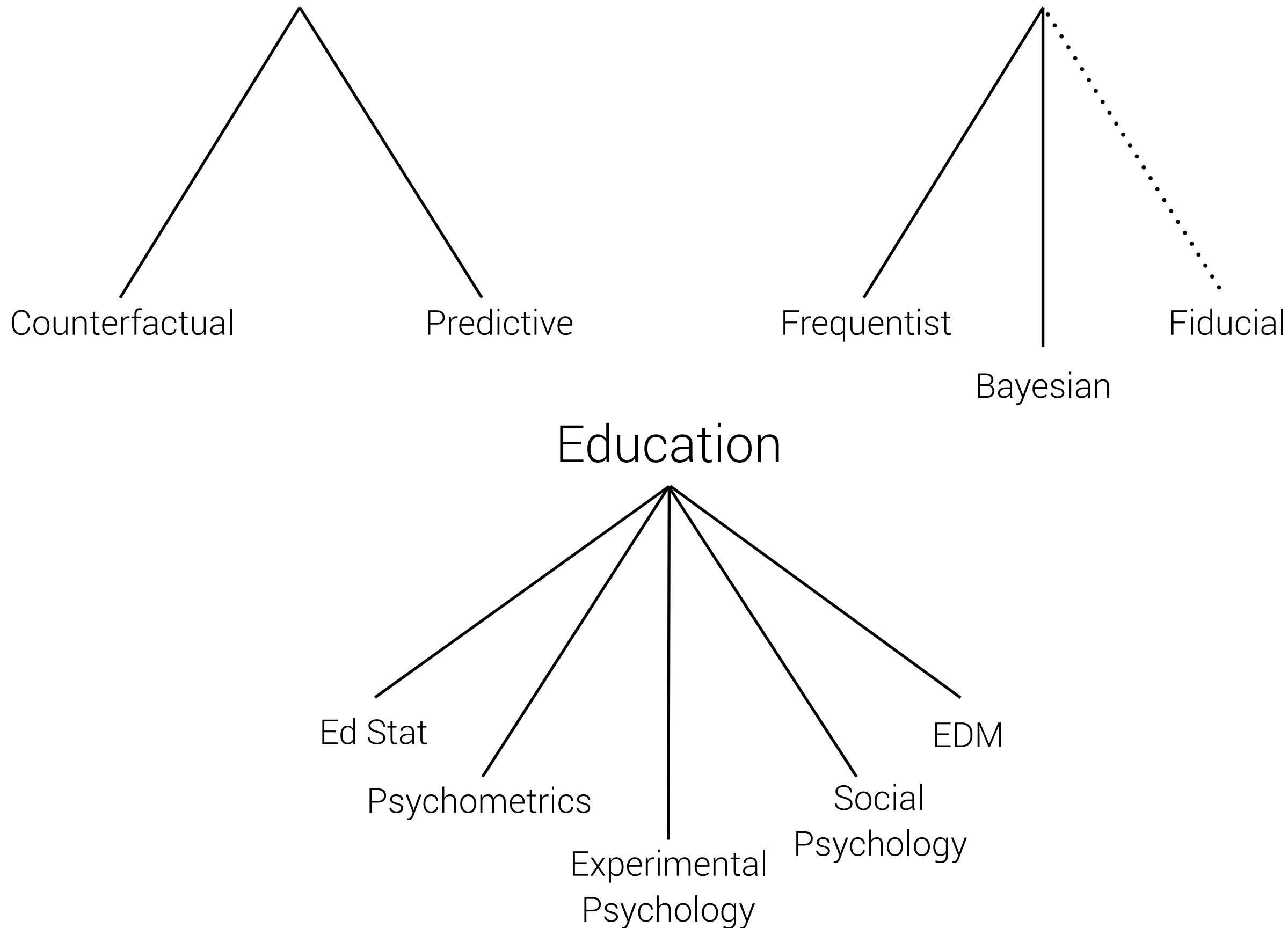
Ed Stat

Psychometrics

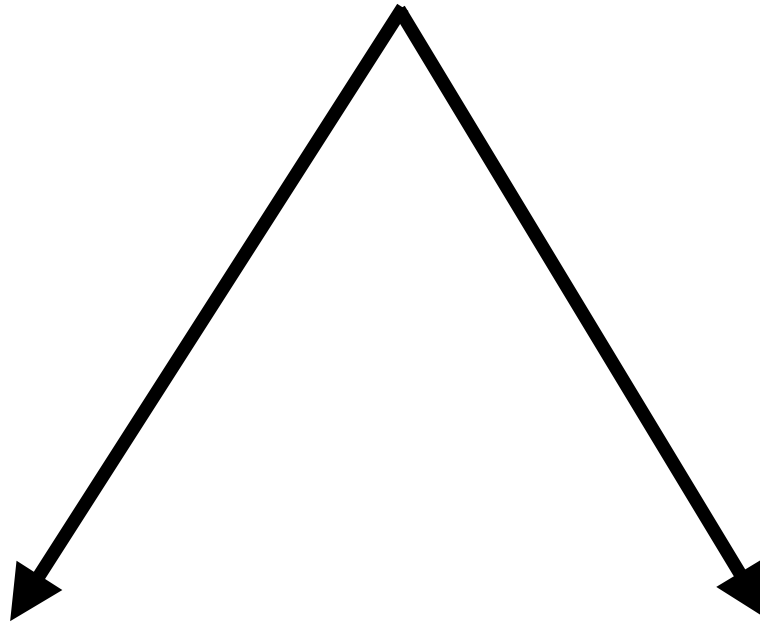
Experimental
Psychology

Social
Psychology

EDM



Variation



Patterns

Uncertainty

Swimming Experience

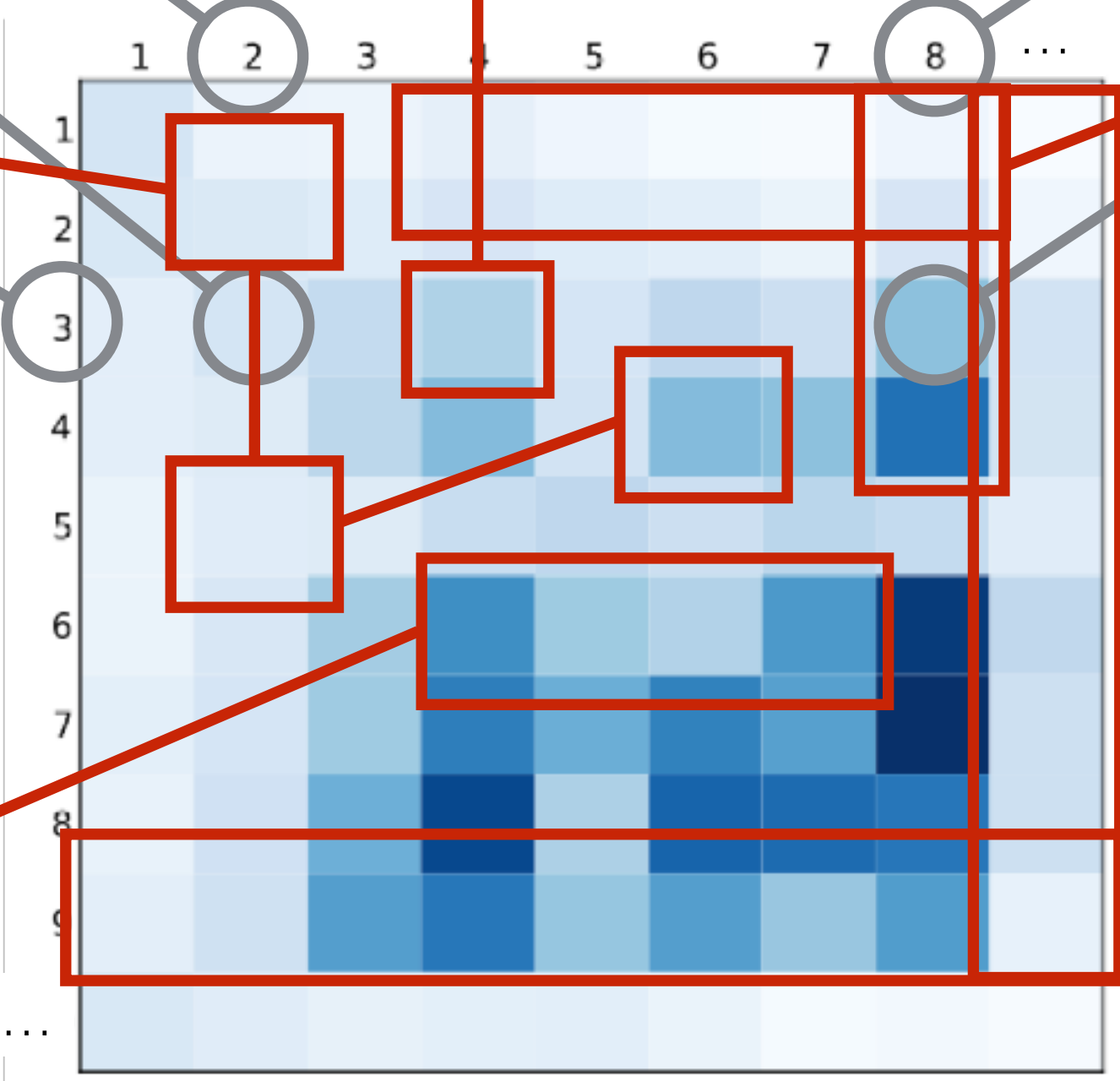
Experimental Psych

Classroom

Context

Social Psych

Ed Stat,
Economics
Bad
Spell "cat"



Psychometrics/
BKT

Adaptive

Behavior

Narrative Model

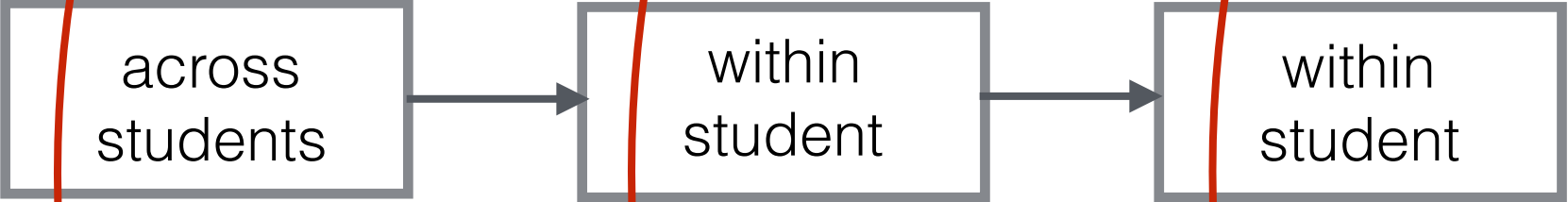


Operational Model

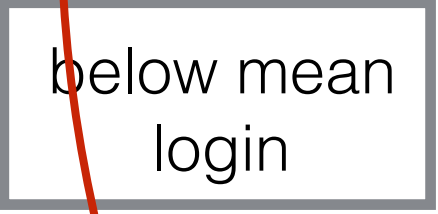
Count



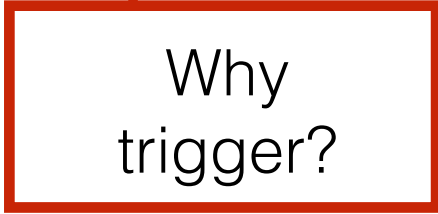
Variation



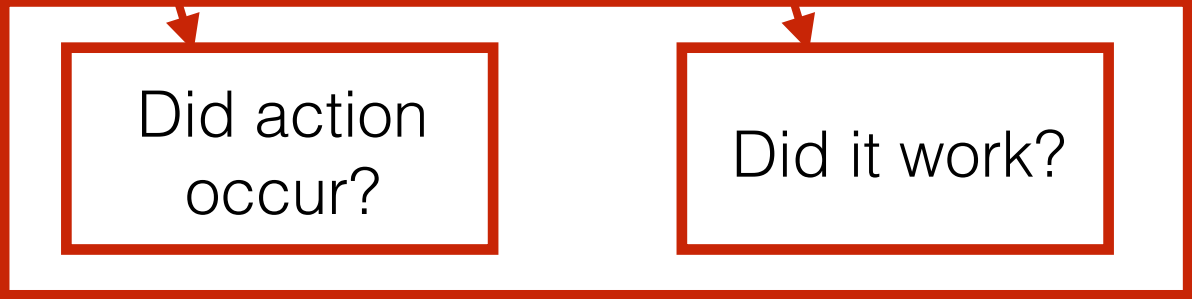
Machine decision



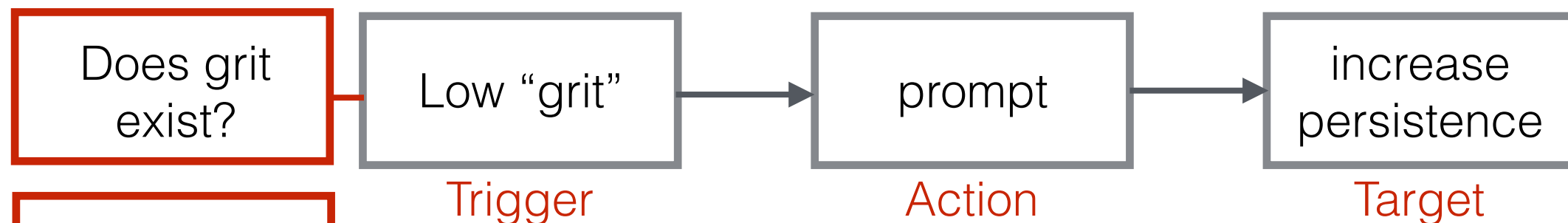
Validation Model



Prediction?
Counterfactual?



Narrative Model



Does logout
= grit?

Operational Model

Count

logout/time

engage with
prompt

Session time

Variation

across/within
students

within
student

across
students

**Machine
decision**

below defined
logout

Do these reasonably
correspond?

Validation Model

Why
trigger?

Did action
occur?

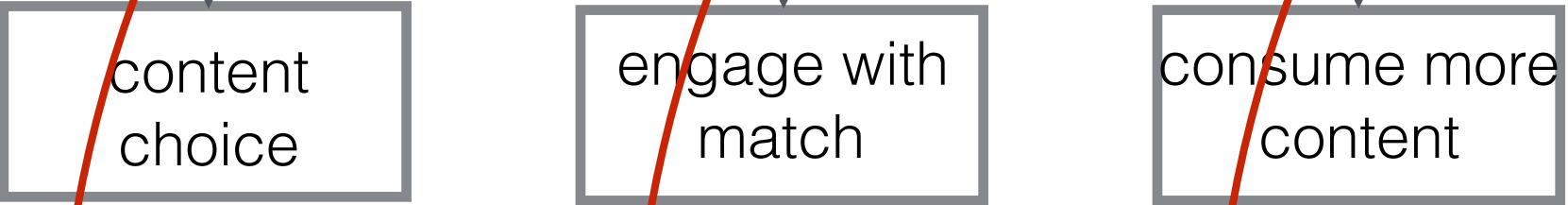
Did it work?

Narrative Model



Operational Model

Count



Variation



Machine decision



Validation Model

Do these reasonably correspond?

Similarity,
sparsity,
neighborhood

Why
trigger?

Did action
occur?

Did it work?

