

2018

Continuous improvement: How systems design can benefit the data-driven design community

Lomas, James, Patel, Nirmal and Forlizzi, Jodi

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Designing for Continuous Improvement in K12

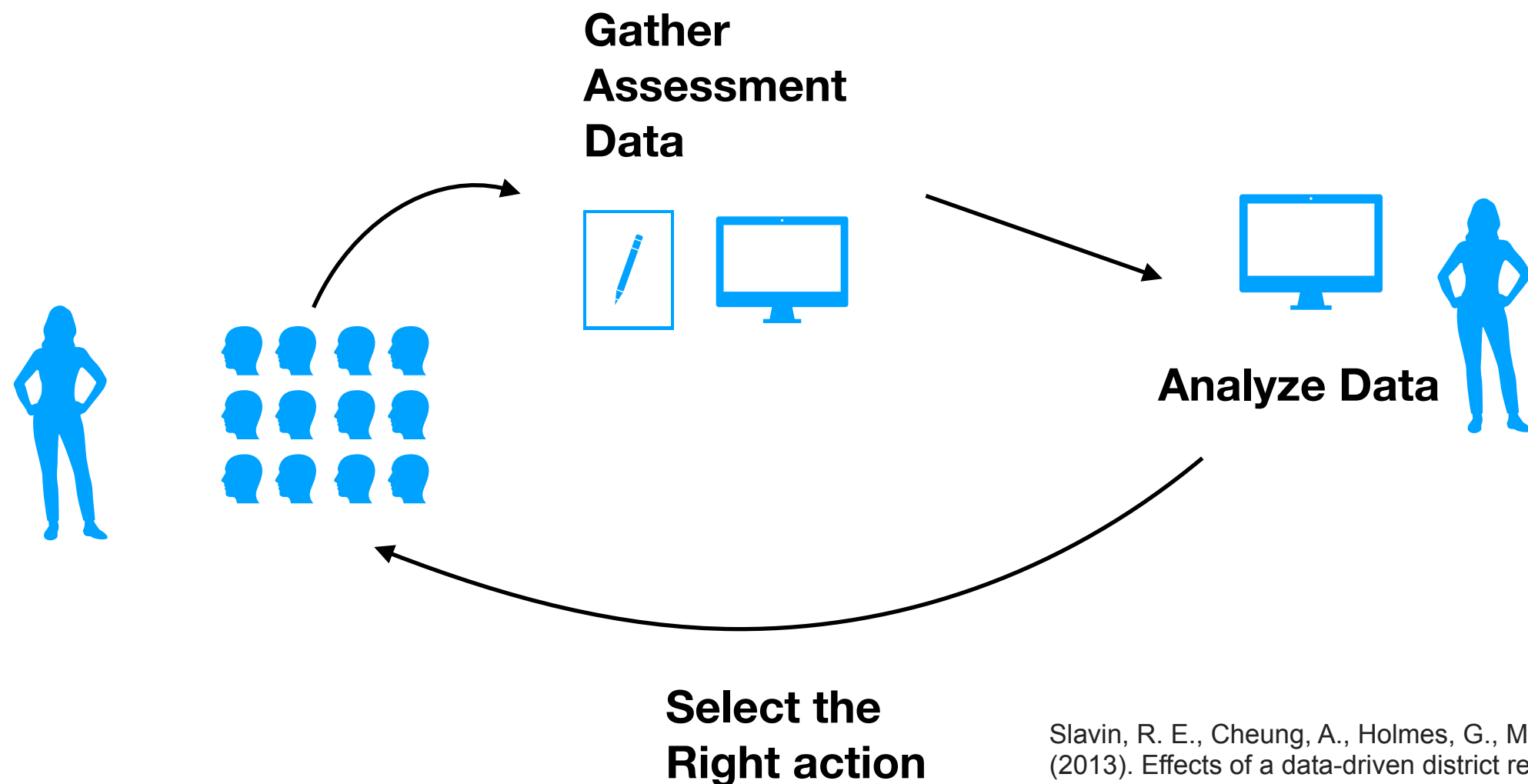
How systems design can help data-driven design in complex-technical systems

Data-Driven Continuous Improvement in K12

"Data-Driven Decision-Making"

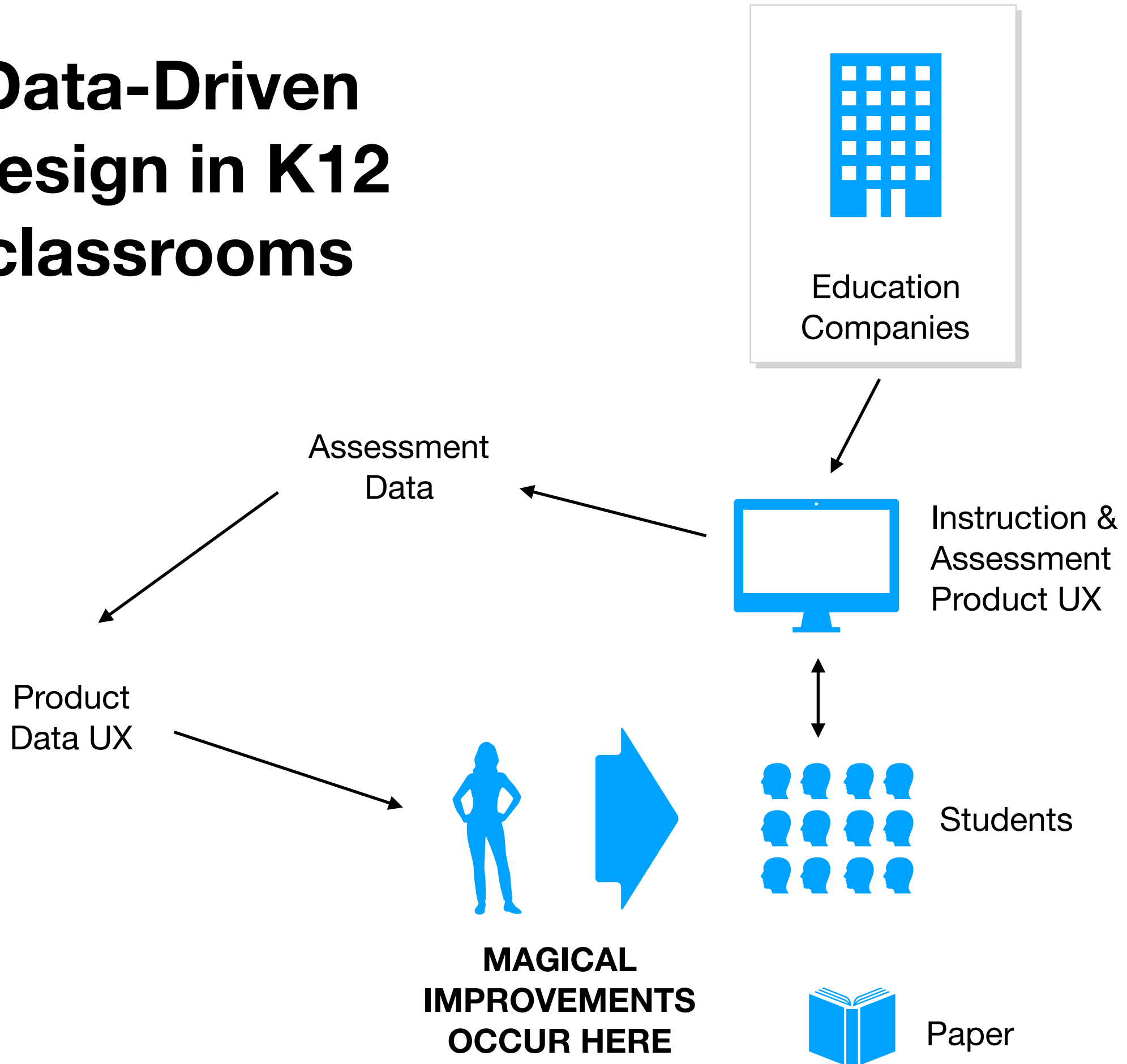
Slavin et al, 2013

1. Gather assessment data
2. Analyze data to identify problems and their causes
3. Select actions to address those problems



Slavin, R. E., Cheung, A., Holmes, G., Madden, N. A., & Chamberlain, A. (2013). Effects of a data-driven district reform model on state assessment outcomes. *American Educational Research Journal*, 50(2), 371-396.

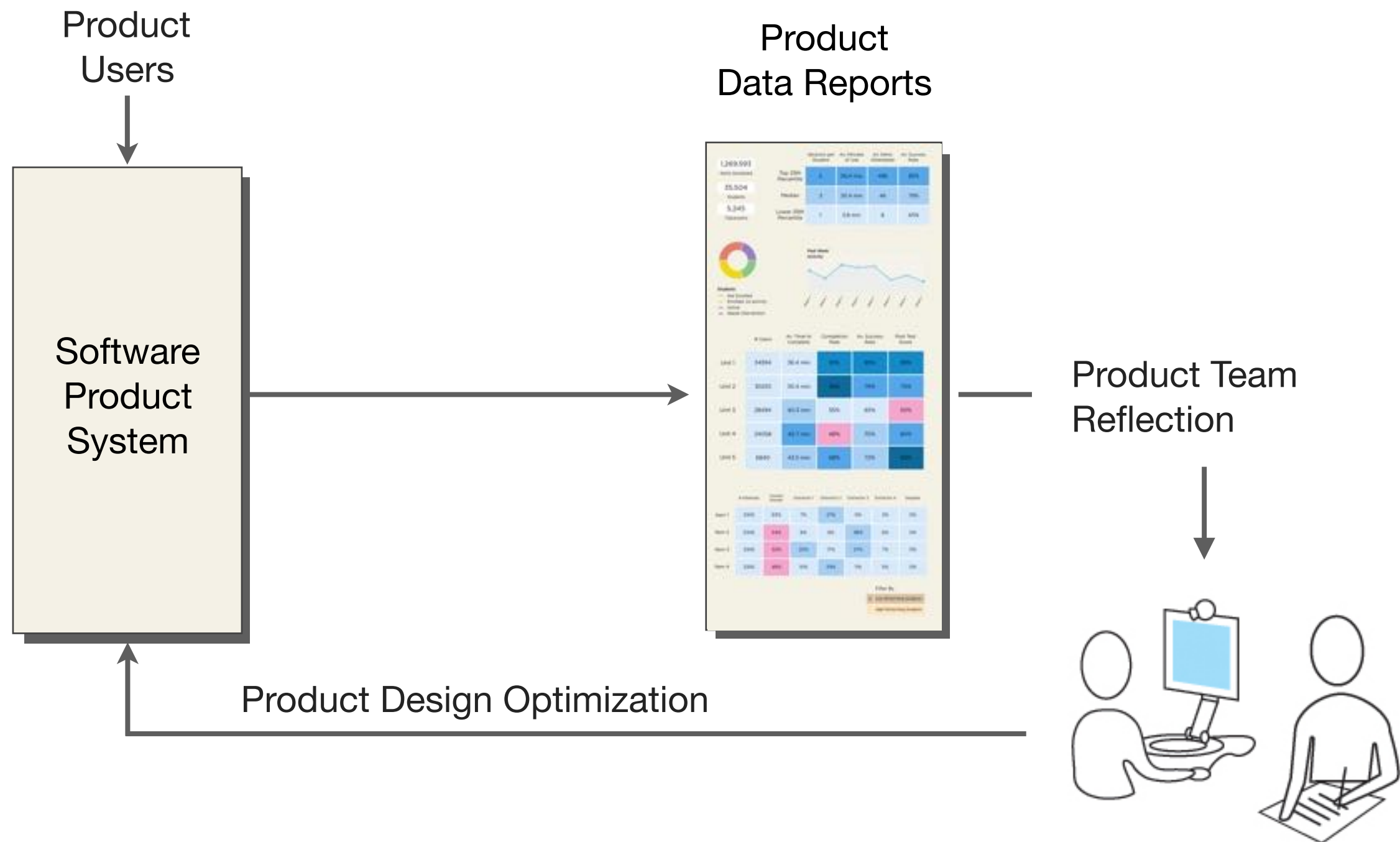
Data-Driven Design in K12 classrooms



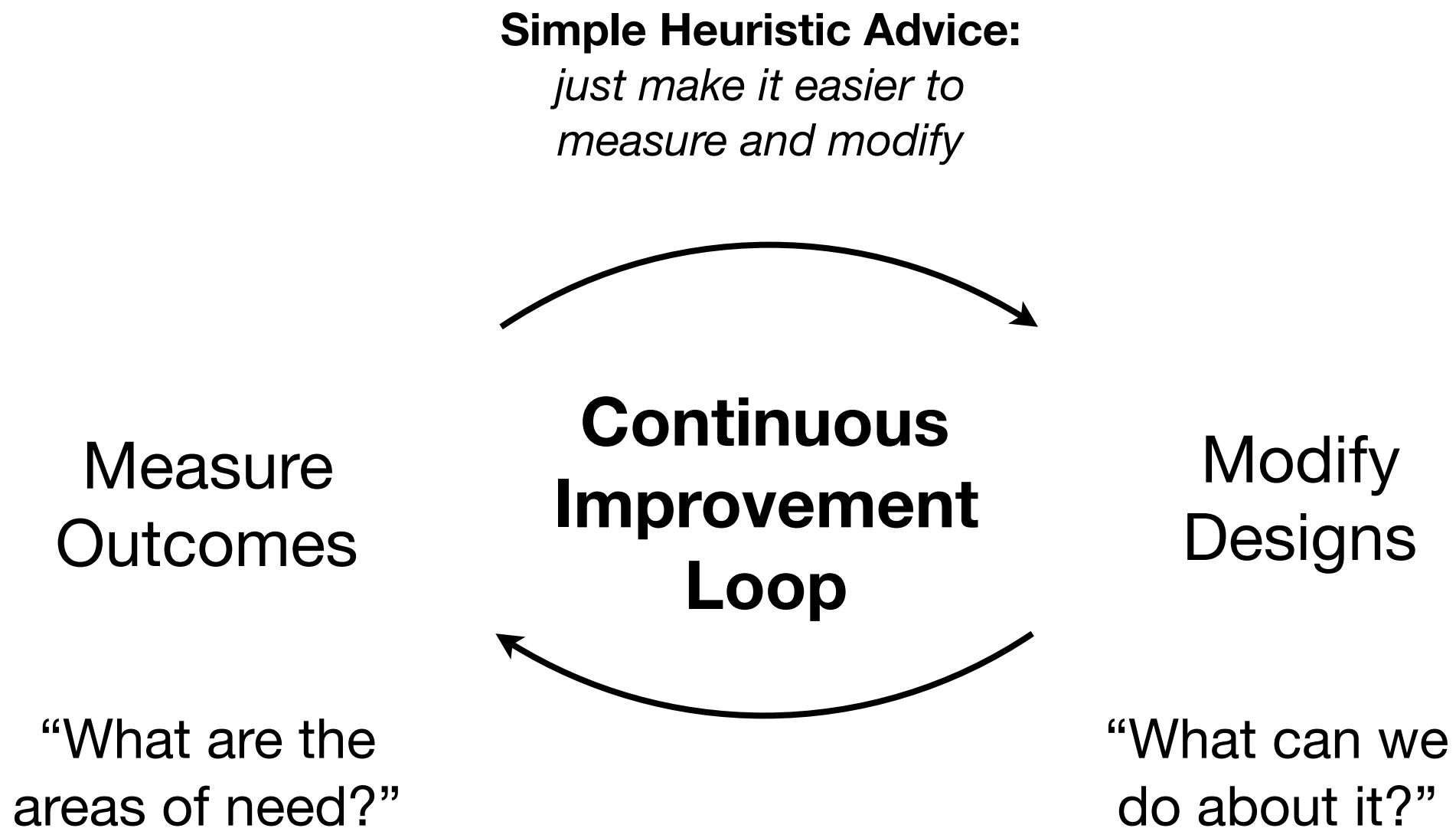
What is Data-Driven Design?

- 1. Define “the right” goals (or needs).**
- 2. Define “the right” measures of those goals.**
- 3. Take actions to modify the current system when goals aren’t met.**

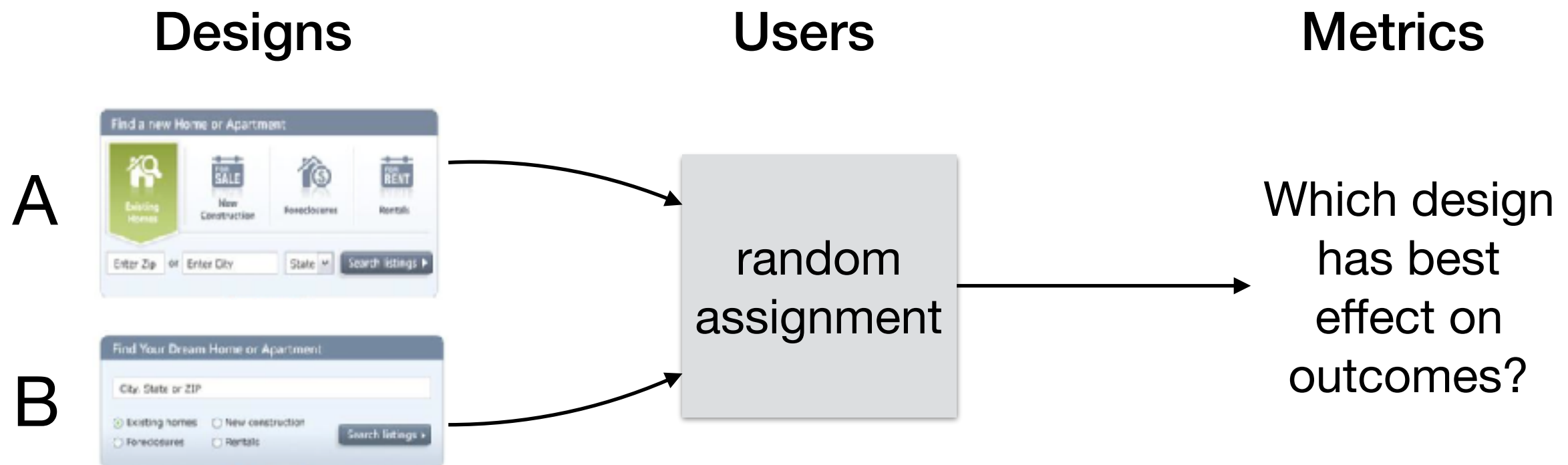
Software Model of Data-Driven Continuous Improvement



How Might We Design Systems to Support Data-Driven Continuous Improvement?



Online Product Experiments (A/B Tests): A Method for Continuous Improvement



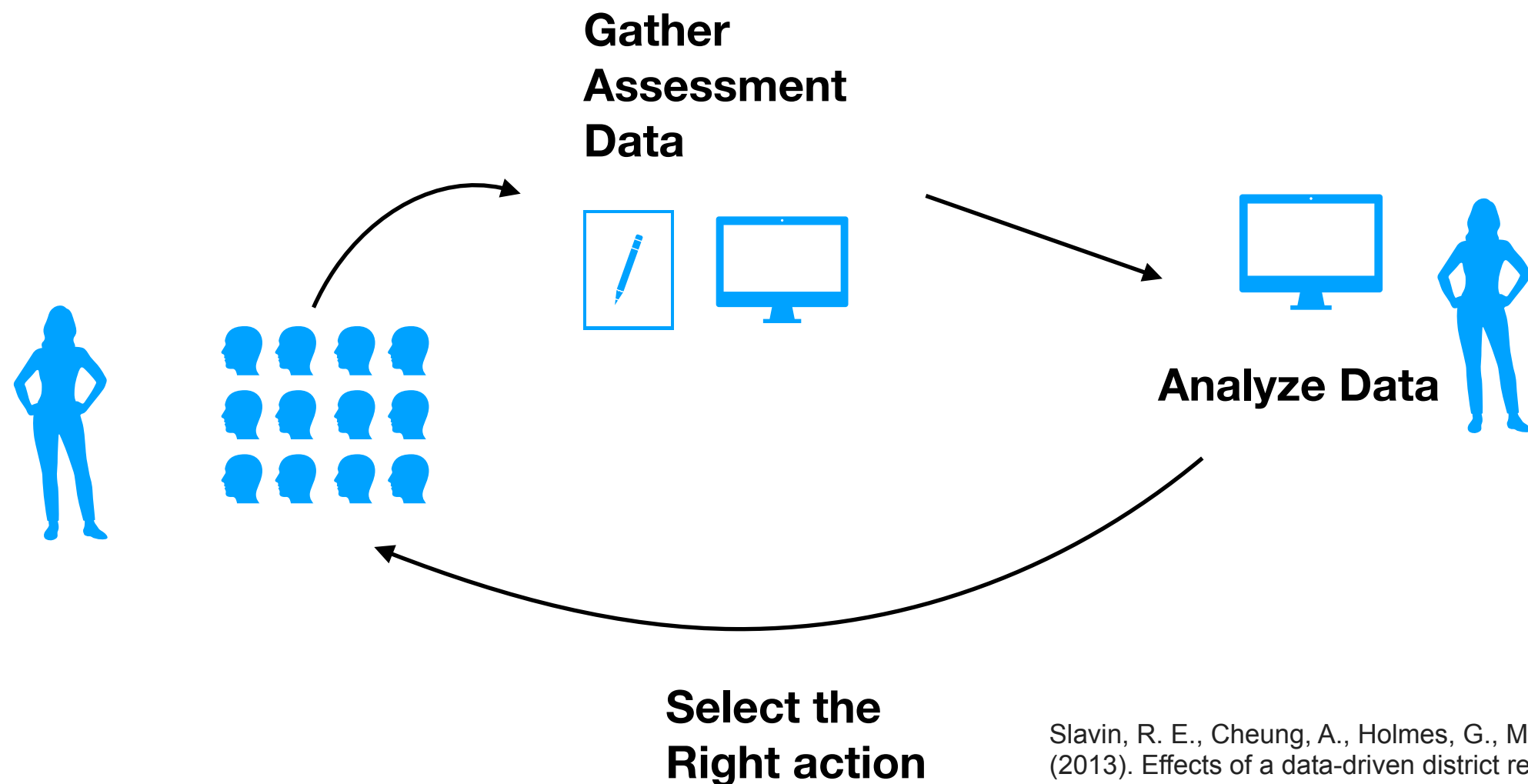
Over 10,000/day run by Google, Facebook, Amazon, etc

Continuous Improvement in K12

"Data-Driven Decision-Making"

Slavin et al, 2013

1. Gather assessment data
2. Analyze data to identify problems and their causes
3. Select actions to address those problems



Slavin, R. E., Cheung, A., Holmes, G., Madden, N. A., & Chamberlain, A. (2013). Effects of a data-driven district reform model on state assessment outcomes. *American Educational Research Journal*, 50(2), 371-396.

Why is there desire for “Data-Driven Decision Making” (DDDM) in K12?

Very few interventions have been found to be effective in addressing the poverty achievement gap.

In a review of 196 randomised field experiments, Data-Driven Decision Making was found to be one of the most effective approaches for improving high-poverty schools (Fryer, 2017).

Fryer Jr, R. G. (2017). The production of human capital in developed countries: Evidence from 196 randomized field experimentsa. In Handbook of Economic Field Experiments(Vol. 2, pp. 95-322). North-Holland.

Van Geel, M., Keuning, T., Visscher, A. J., & Fox, J. P. (2016). Assessing the effects of a school-wide data-based decision-making intervention on student achievement growth in primary schools. *American Educational Research Journal*, 53(2), 360-394.

DDDM is not “disruptive” or radical change.

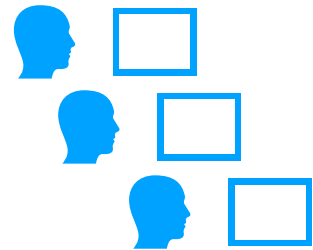
DDDM is all about small incremental improvements... ideal for complex social-technical systems

**K12 Education is a
Complex-Technical System**

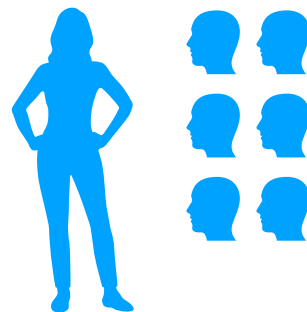
K12 Education is a Complex-Technical System



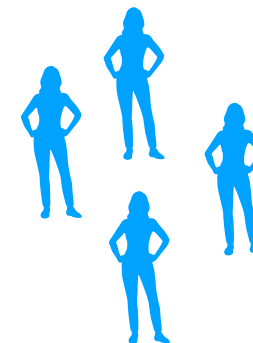
Family
Interactions



Computer
Interactions



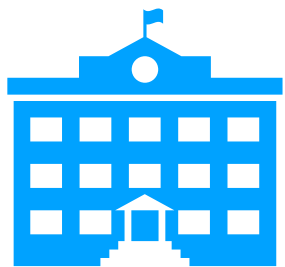
Teacher
Interactions



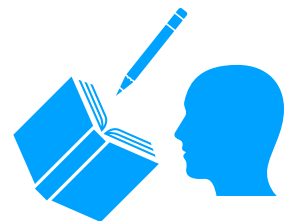
PLCs



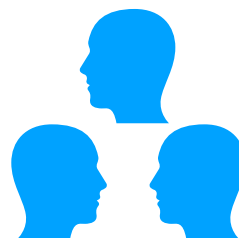
Government
Policy



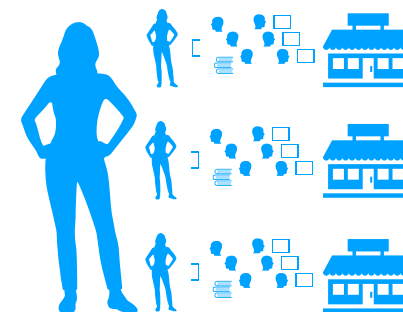
Out-of-School
Programs



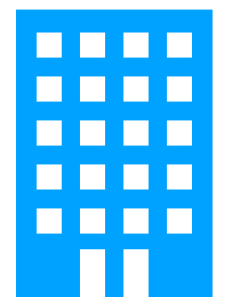
Text
Interactions



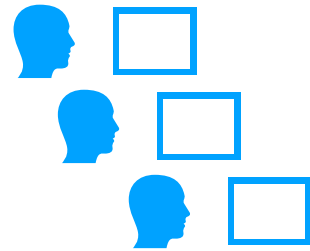
Small-Group
Interactions



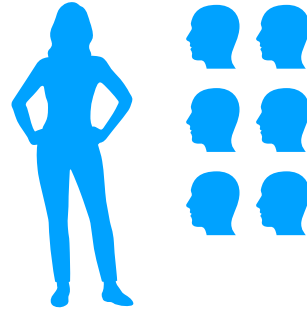
Administrative
Interactions



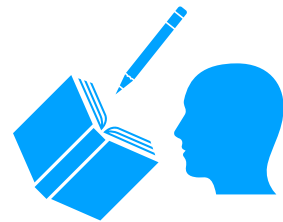
Education
Companies



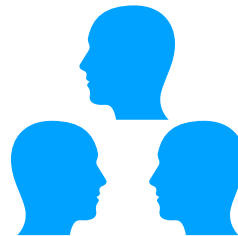
Computer
Interactions



Teacher
Interactions

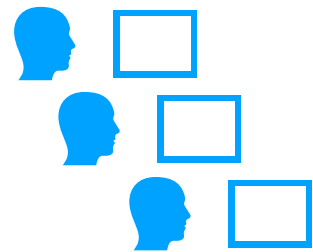


Text
Interactions

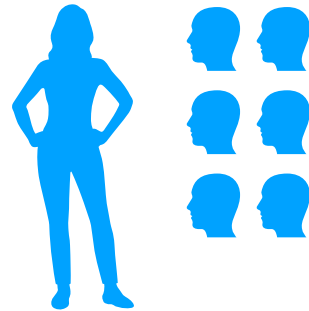


Small-Group
Interactions

The Modern Classroom



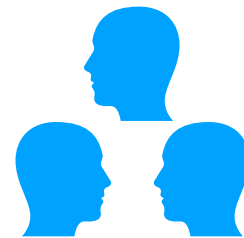
Computer Interactions



Teacher Interactions

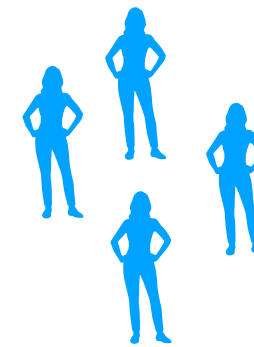


Text Interactions



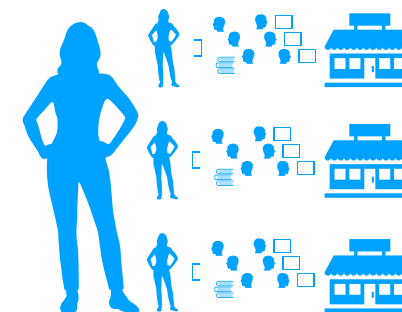
Small-Group Interactions

+



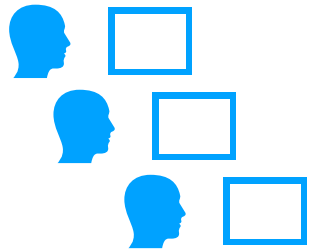
PLCs

“Professional Learning Communities”

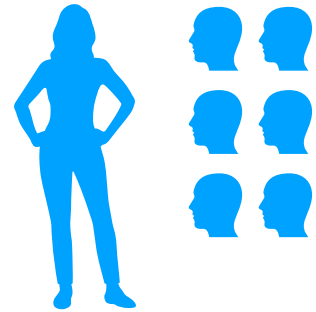


Administrative Interactions

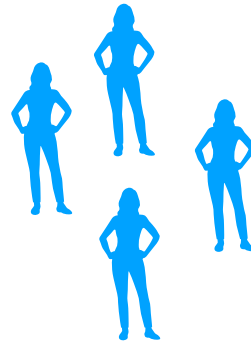
- Curriculum Coordinators
- Schools
- Districts
- State Admin



Computer Interactions



Teacher Interactions

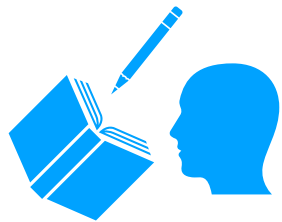


PLCs

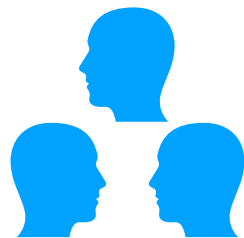


Government Policy

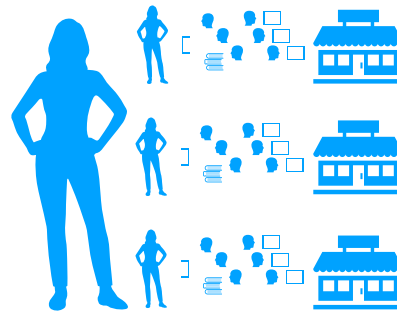
- Learning Standards



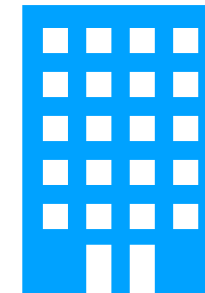
Text Interactions



Small-Group Interactions



Administrative Interactions



Education Companies

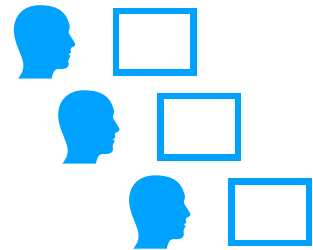
- Textbooks
- Assessments
- Paper & Digital Products

K12 Education is a Complex-Technical System

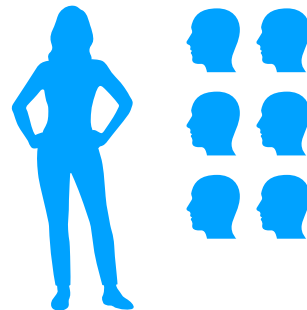
Opportunities from Systems Design?



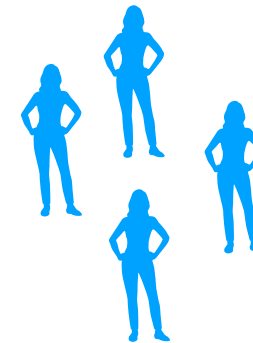
Family
Interactions



Computer
Interactions



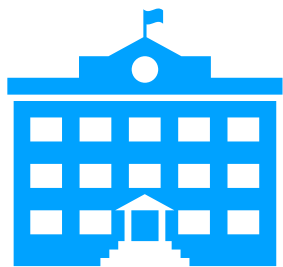
Teacher
Interactions



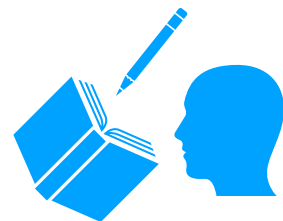
PLCs



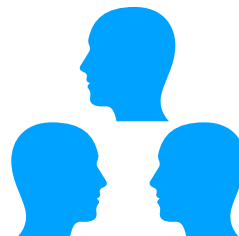
Government
Policy



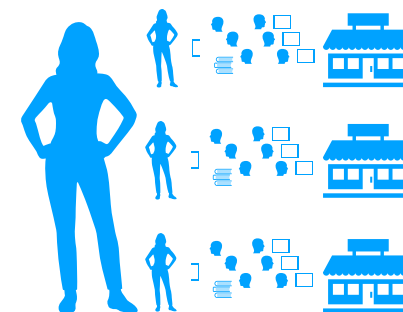
Out-of-School
Programs



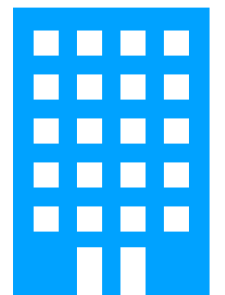
Text
Interactions



Small-Group
Interactions



Administrative
Interactions



Education
Companies

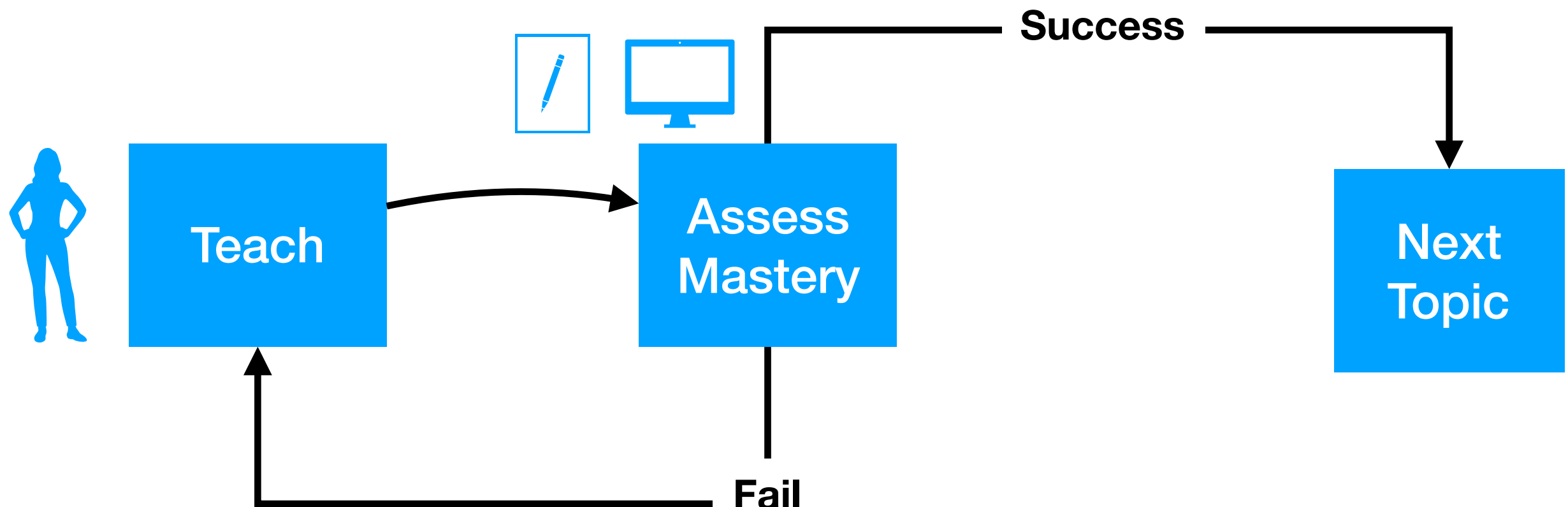
Systems Design

Role of data in systems design

- Systems use data as feedback to guide action.
- Measurements provide data to inform systems whether goals have been achieved.
- Cybernetic systems?

Mastery Learning

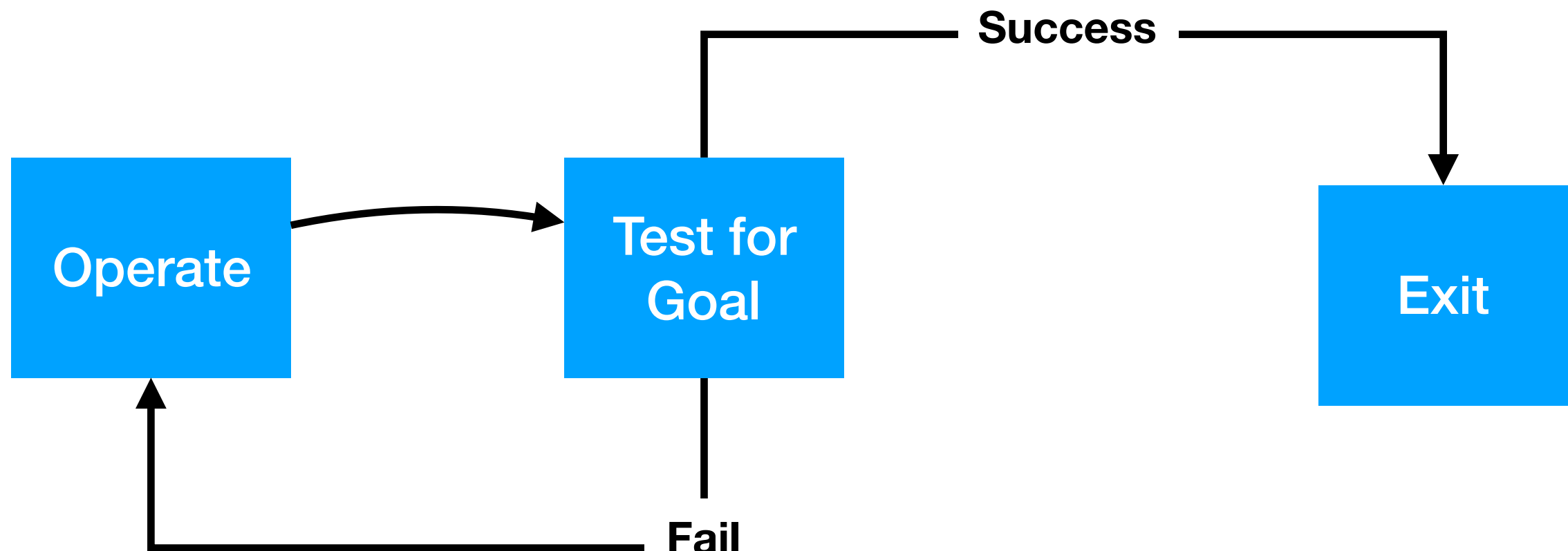
as a cybernetic system



Closed System

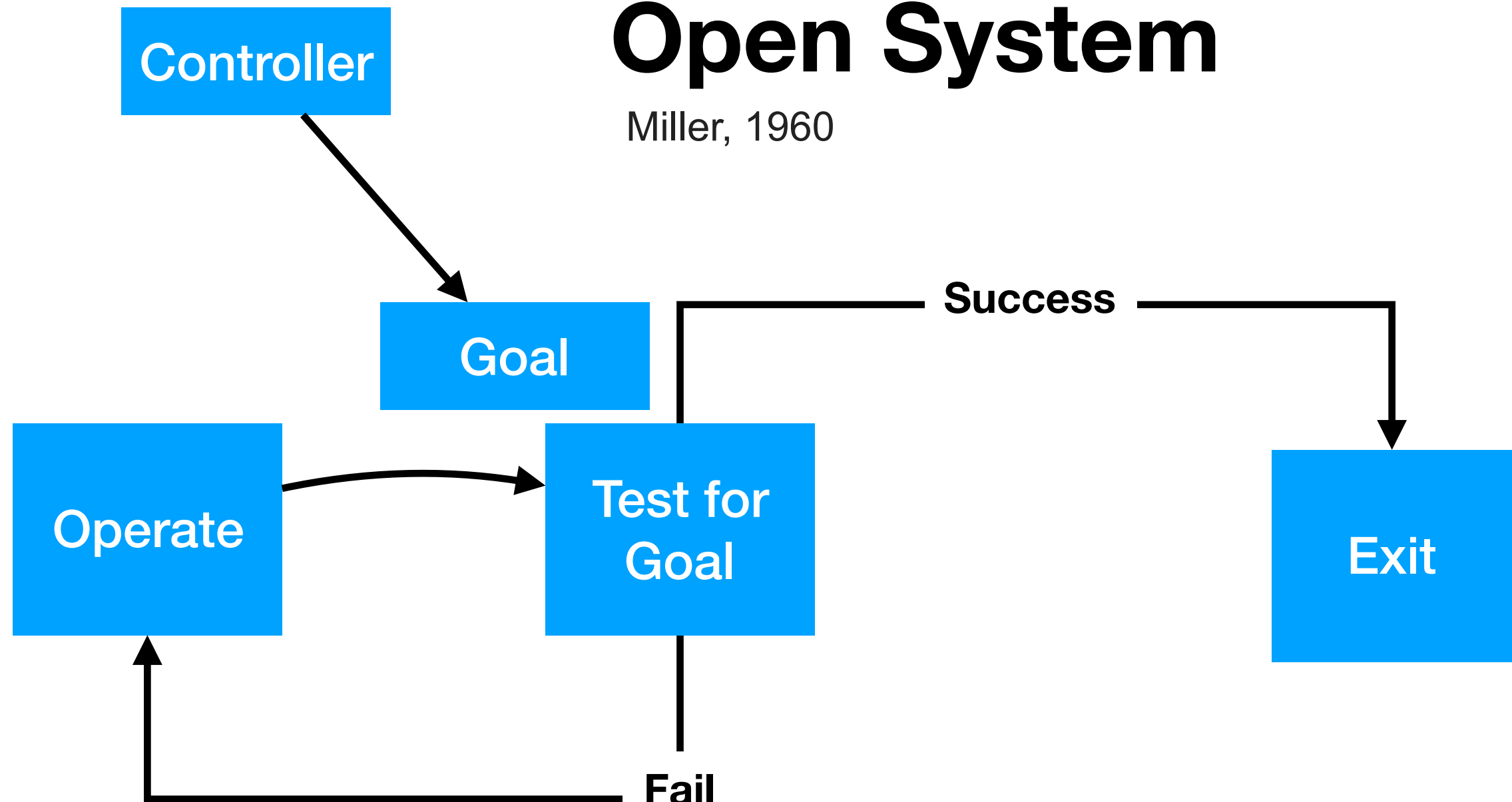
TEST, OPERATE, TEST, EXIT

Miller et al, 1960



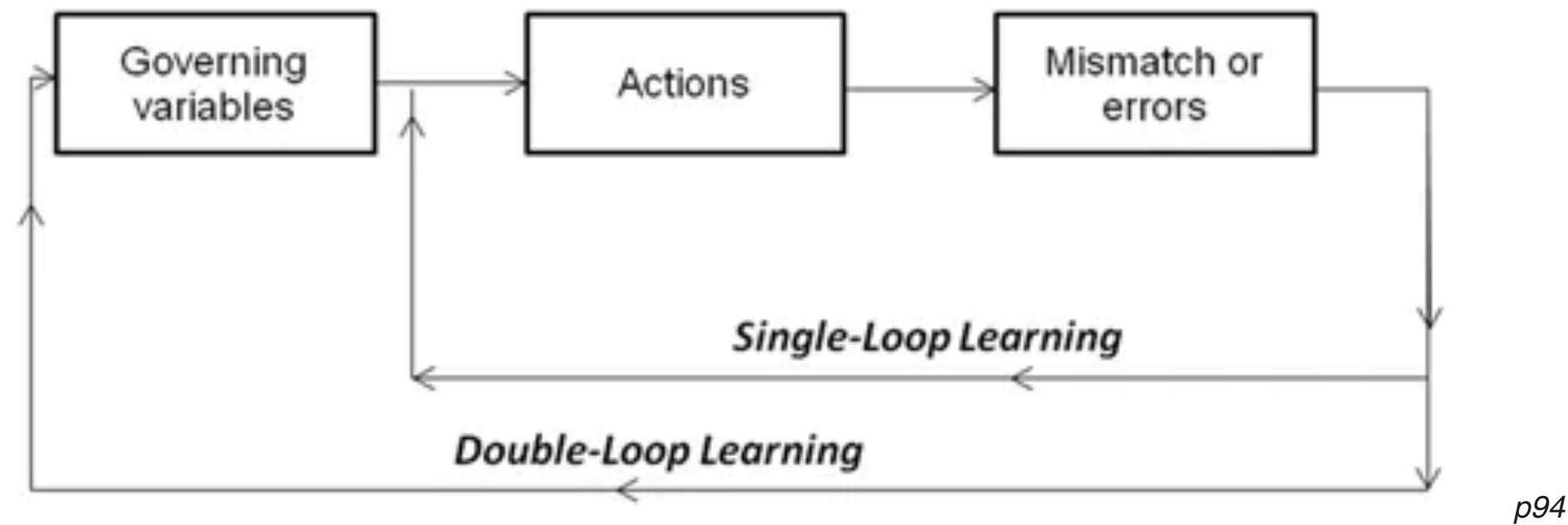
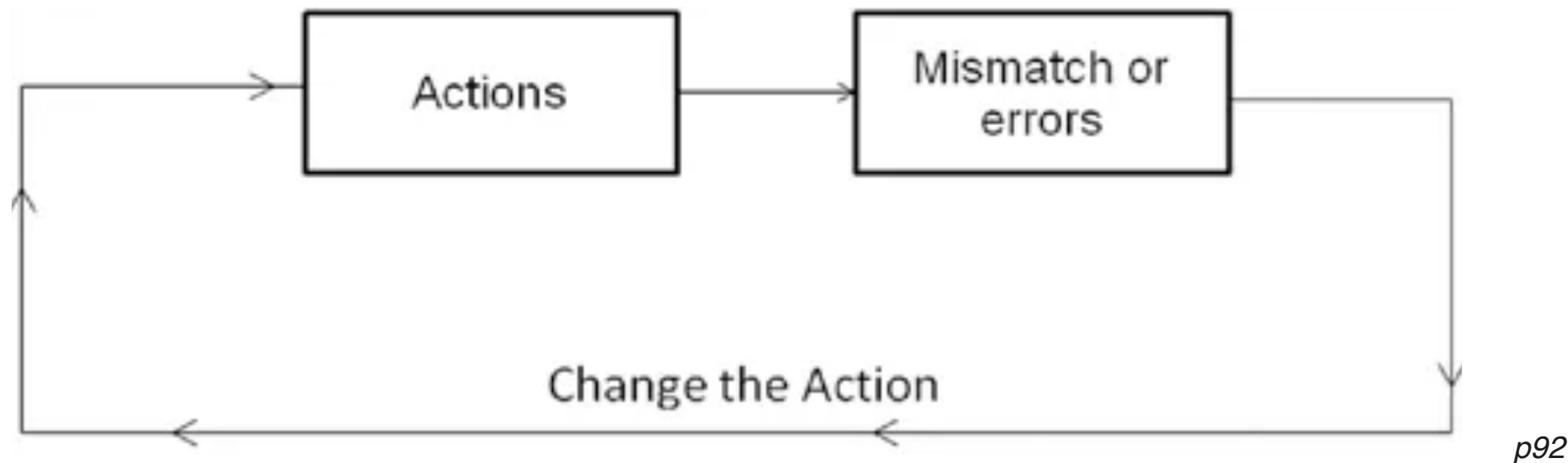
Open System

Miller, 1960

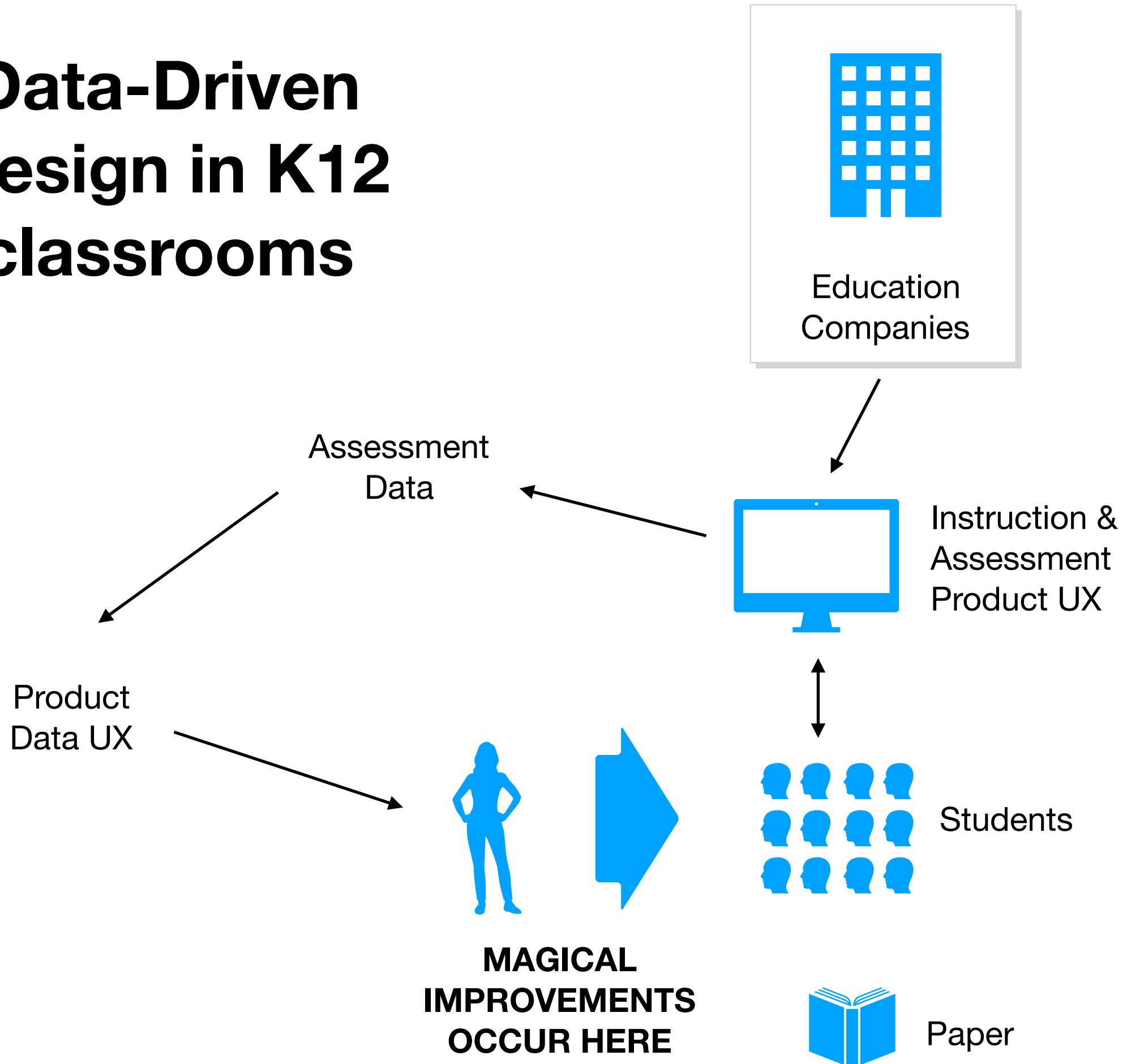


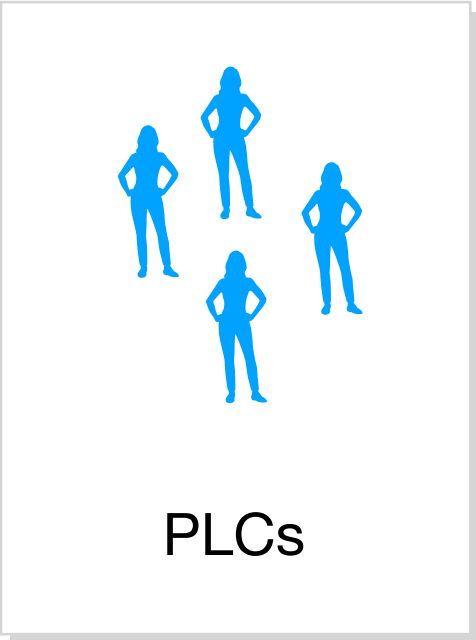
Single and Double Loop Learning

Argyris 1990

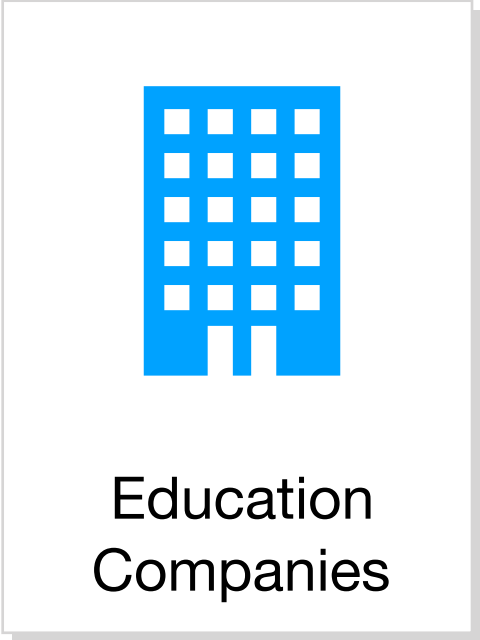


Data-Driven Design in K12 classrooms

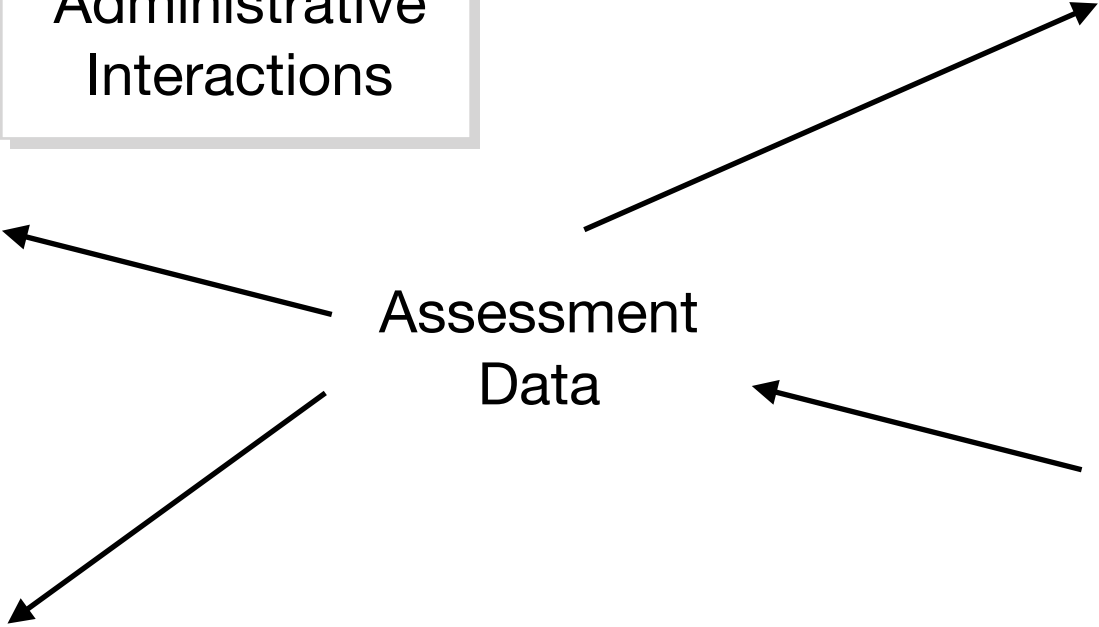




Admin Actions in Response to Data?

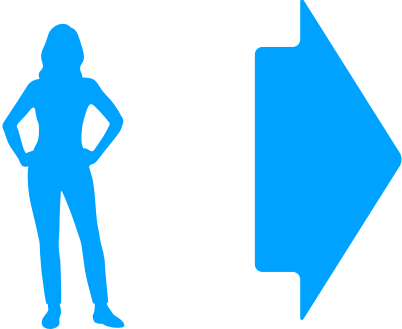
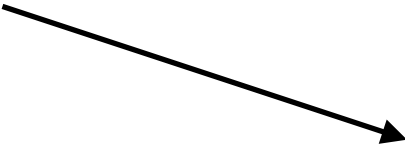


Product Team Actions in Response to Data?



Instruction & Assessment Product UX

Product Data UX



Teacher Actions in Response to Data?



Students



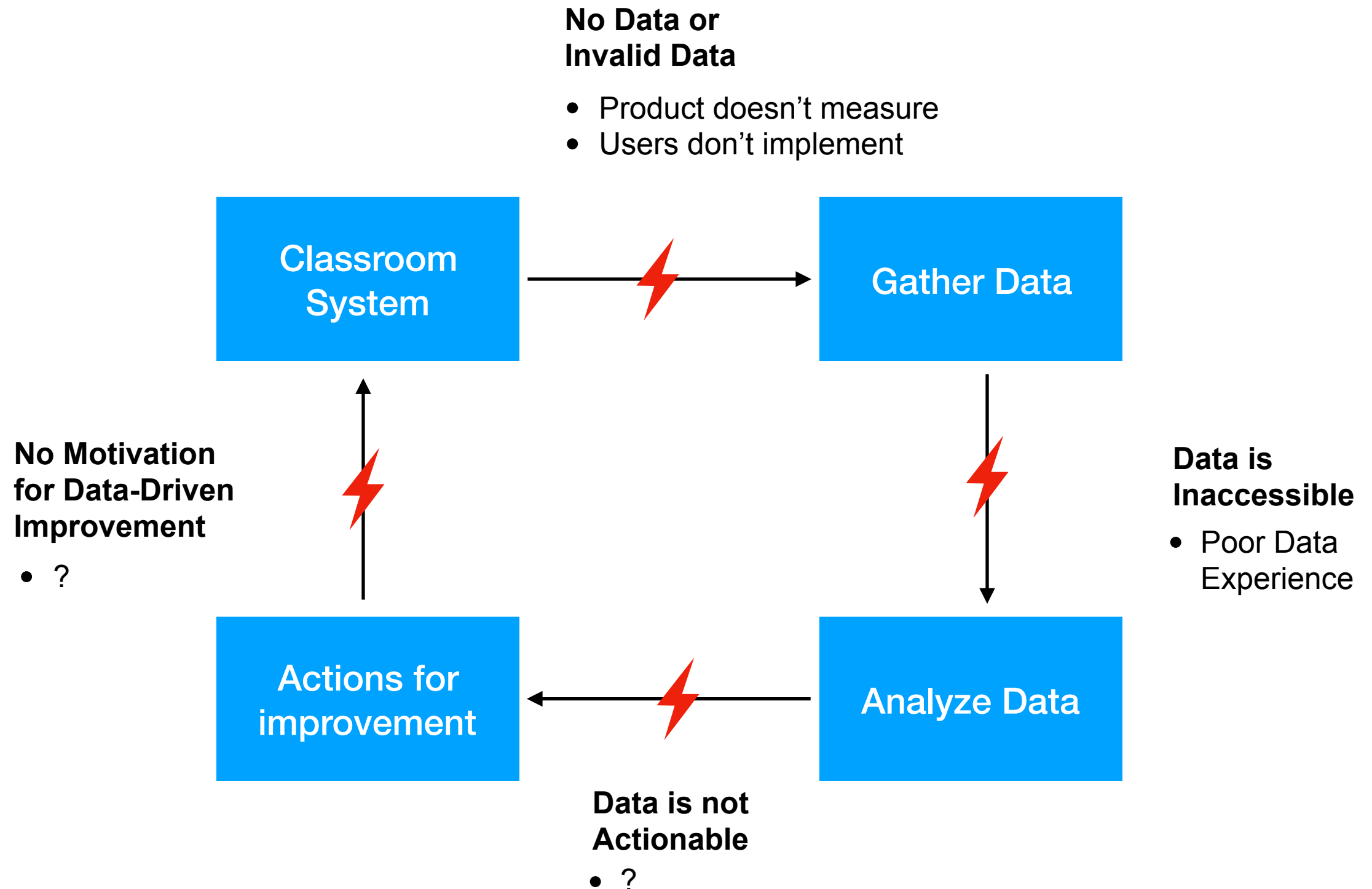
Paper

Case #1:

**Supporting Data-Driven
Improvement in Educational
Product Companies**

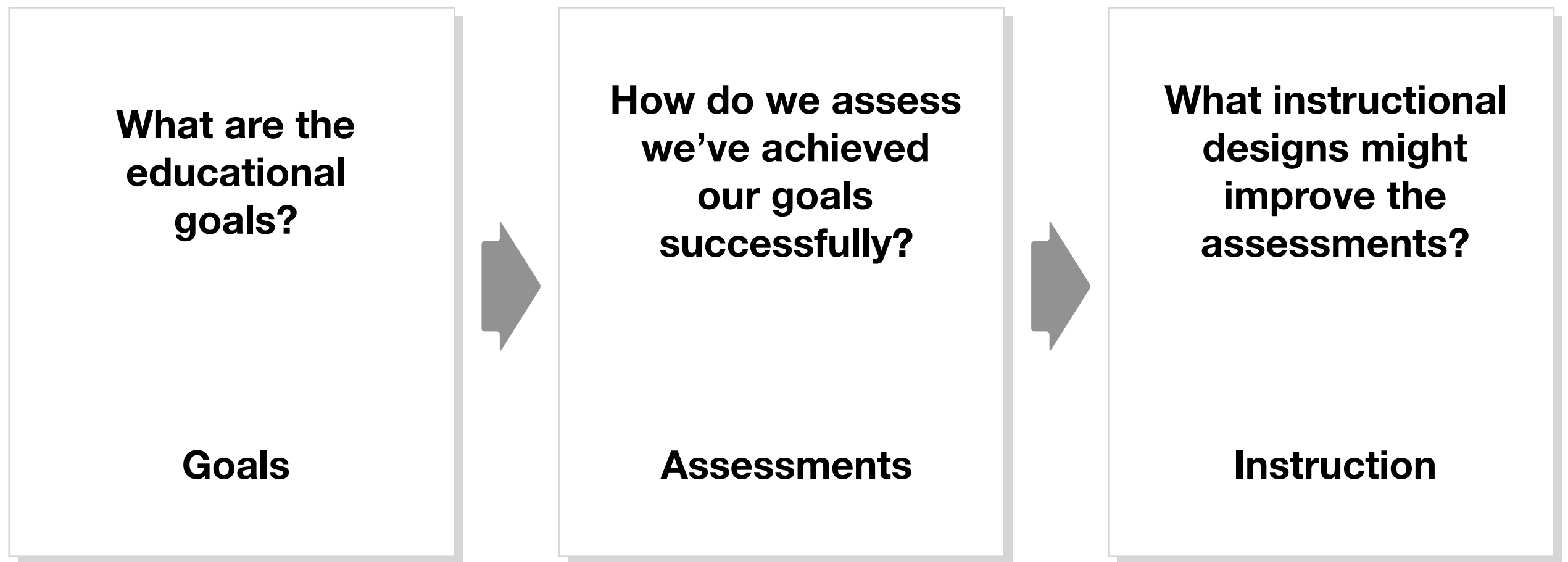
Common Barriers to DDDM

And some root causes



"Backwards Design" Methodology

(cite Understanding by Design)



Key Question #1:

Is the system capable of measuring success?

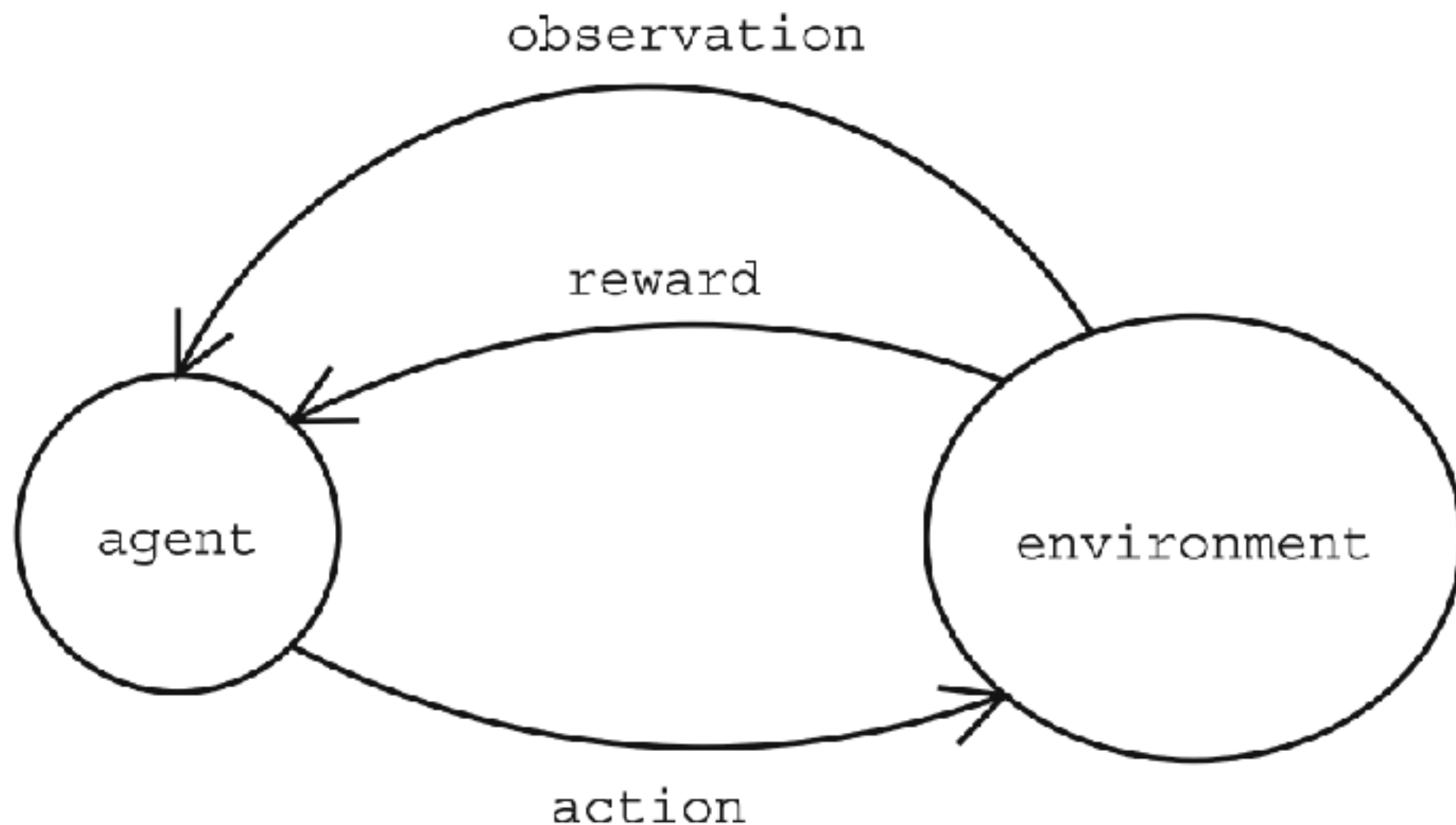
Can the system measure whether it is achieving its goals?

“If we want to report on student mastery for topic A, we need to collect valid test data on topic A”

Case #2:

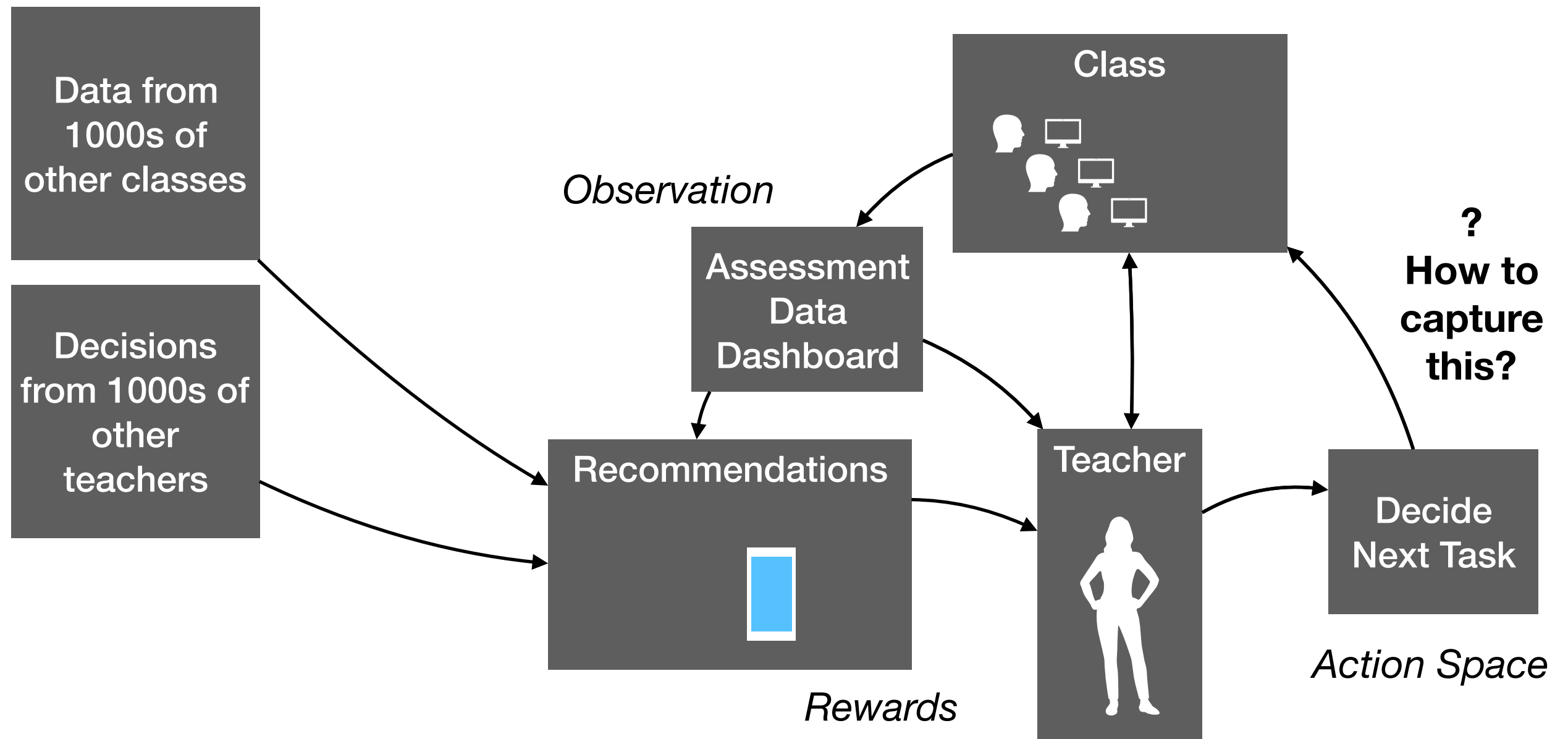
**Development plans for a
teacher-facing
recommendation system**

Mapping the System to Reinforcement Learning



- What is the space of possible observations? (what we measure?)
- What is the space of possible actions? (what can we do?)
- What is the reward metric? (how do we quantify our goals?)

Mapping Classrooms to Reinforcement Learning



1. Assessment Data Dashboard (*Observation*)
2. Digital Assignment Possibilities (*Action Space*)
3. Recommendation Success (*Rewards*)

Key Question #2:

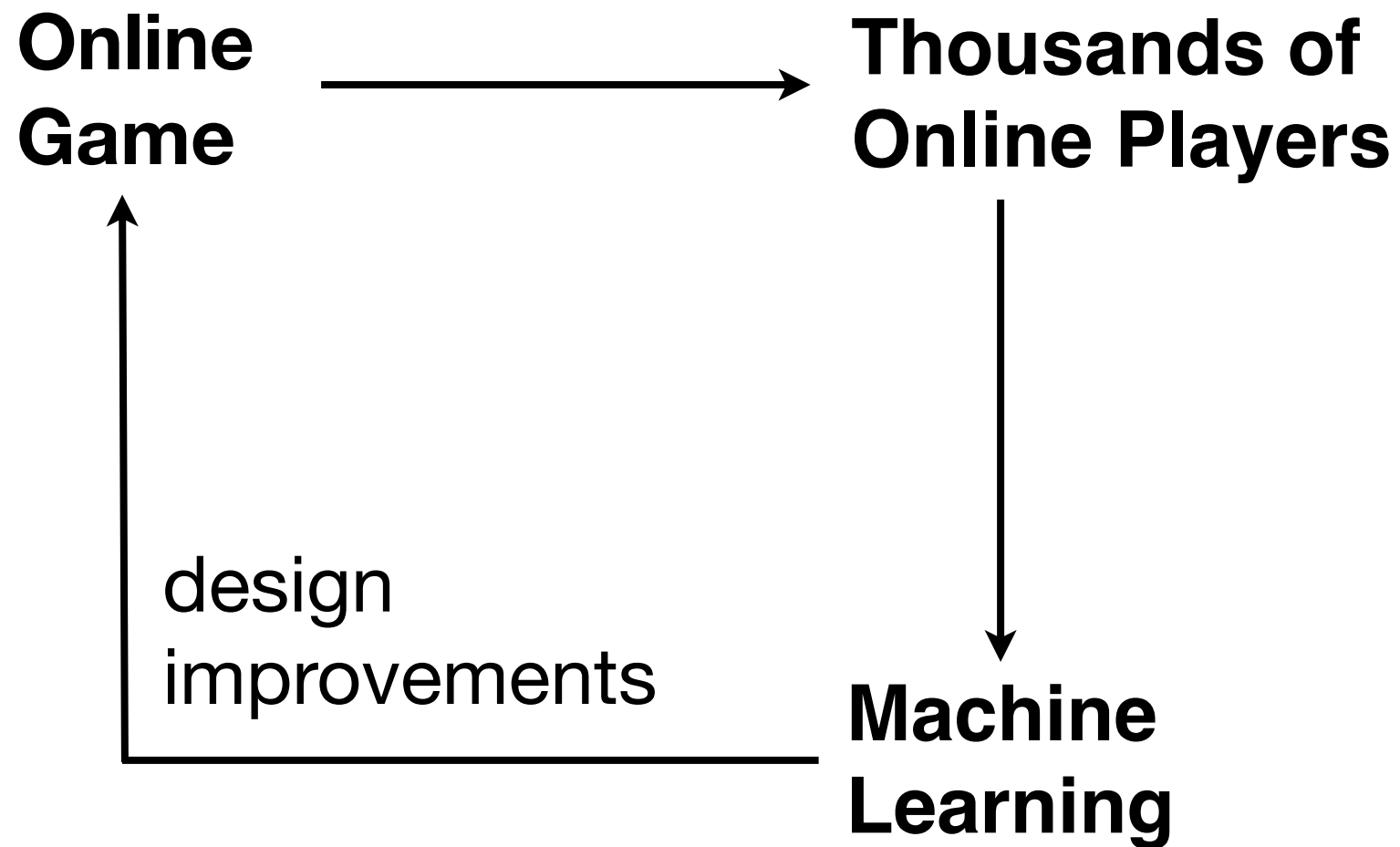
Is the action space sufficiently defined?

The right data might be gathered and analysed appropriately ...but is there a defined action in response?

NEED methods for scaling-up system learning from rich human decision-making

Case #3:

Automated Machine-Learning Optimization of an Educational Game



An AI system for design optimization successfully increased game engagement...

...but then spun out of control!

Lomas, D., Forlizzi, J., Poonwala, N., Patel, N., Shodhan, S., Patel, K., Koedinger, K., Brunskill, E. (2016) Interaction Design as a Multi-Armed Bandit Problem. *ACM CHI*

Multi-Armed Bandit Problem

Goal is to maximize payout from row of slot machines with unknown rates of reward (some machines pay out more)

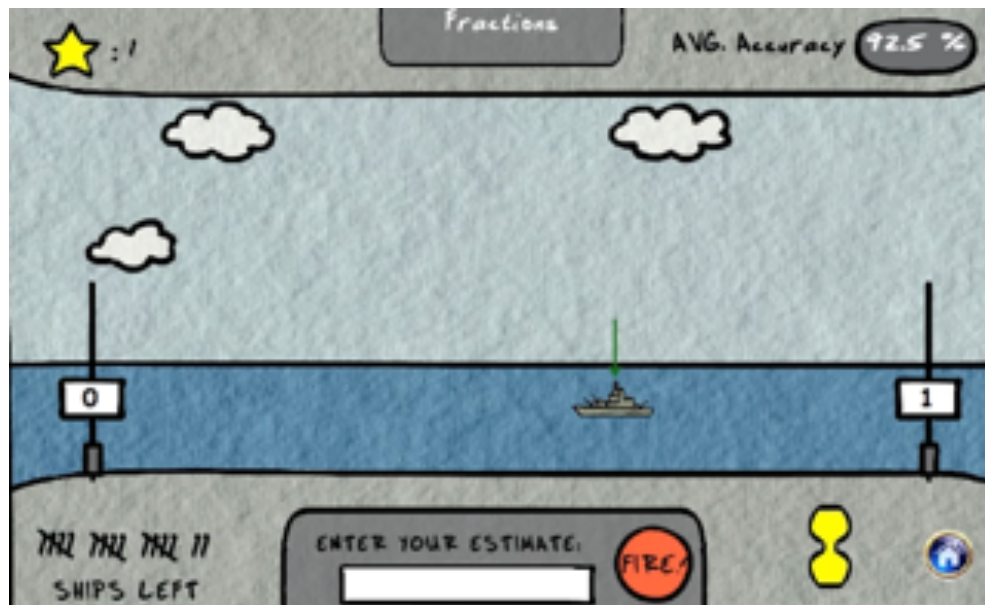
Need to balance *exploration* with *exploitation*



Interface design as a multi-armed bandit problem...

Lomas, J. D., Forlizzi, J., Poonwala, N., Patel, N., Shodhan, S., Patel, K., Koedinger, Brunskill, E. (2016).
Interface Design Optimization as a Multi-Armed Bandit Problem. In CHI'16.

Instructional Design of “ Battleship Numberline”



Ship targets

Type to name a fraction



Submarine targets

Click to locate a fraction

Design Factors

Target Type: Ship or Sub

Target Size: Small to large targets

Time Limits: Small to large time limits

Item Sets: The fractions to be estimated

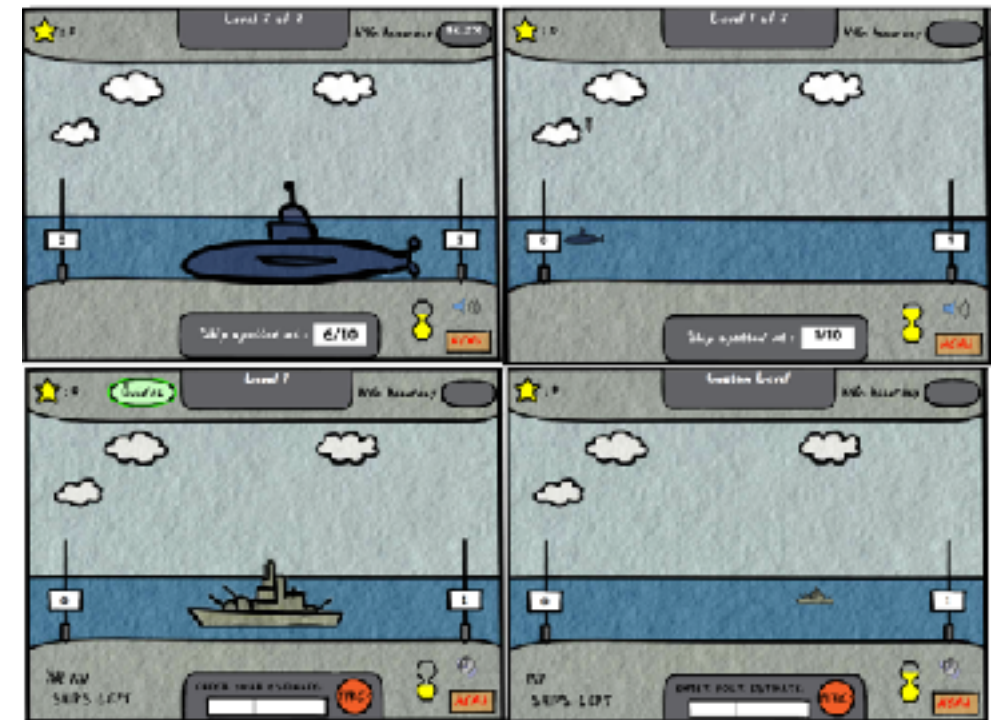
Tickmarks: Scaffolds for estimating

Sequencing: Algorithms for presentation

Experiment 1: Assigned 10,832 players to 3 simultaneous experiments, each testing 6 different design factors (2x3: target type and target size)

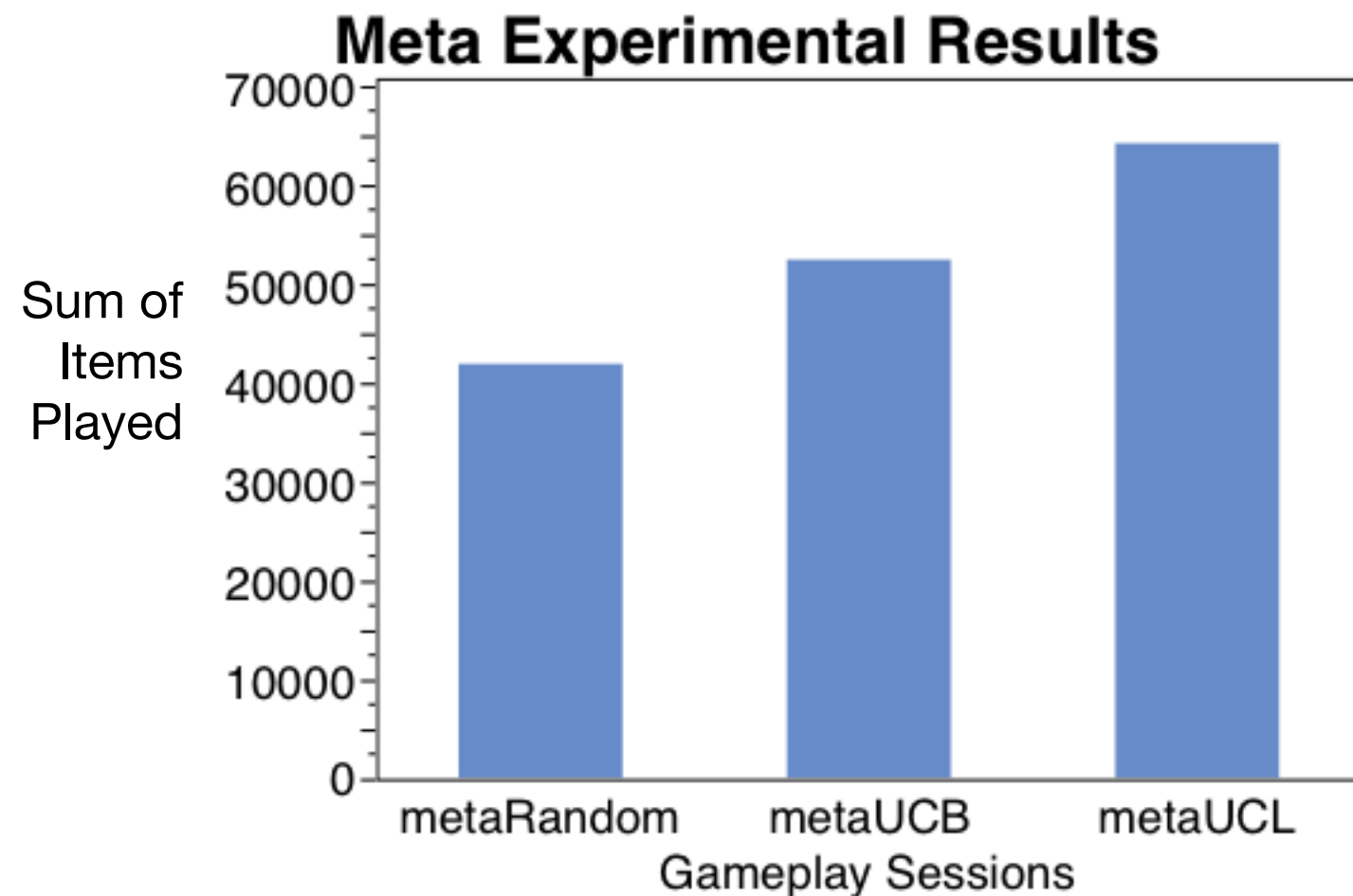
Target Type

Target Size



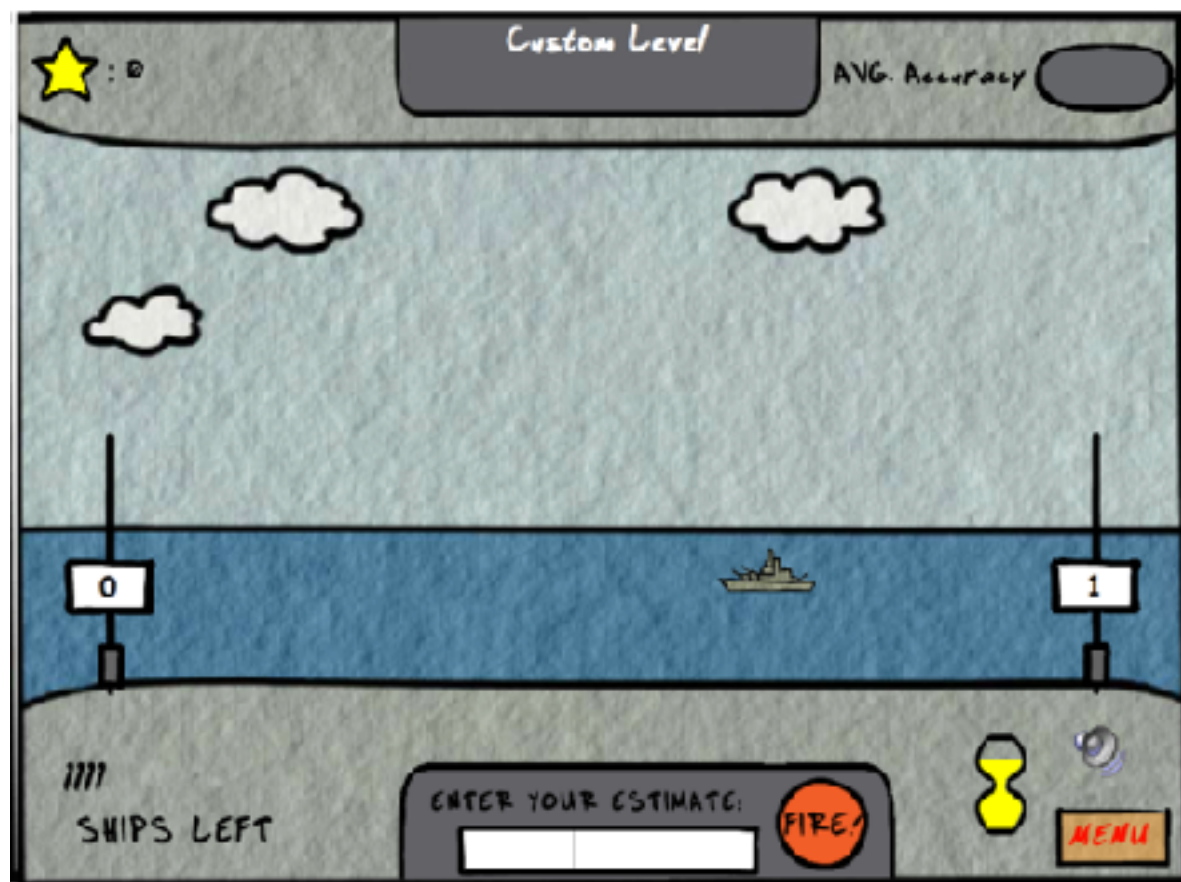
Success!

Automatic optimization algorithms produced more engagement

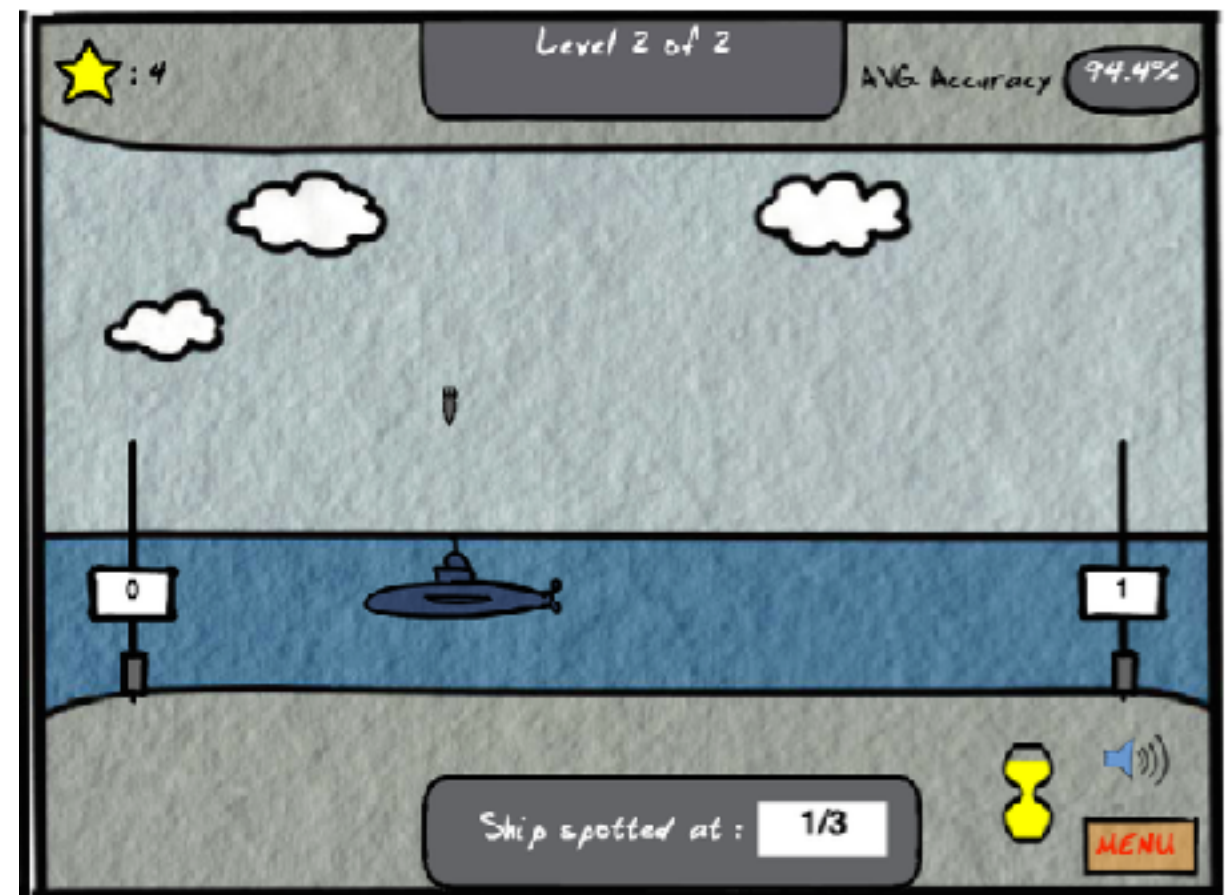


Bandit experiments
produce greater
total engagement

Meta Experiment 1



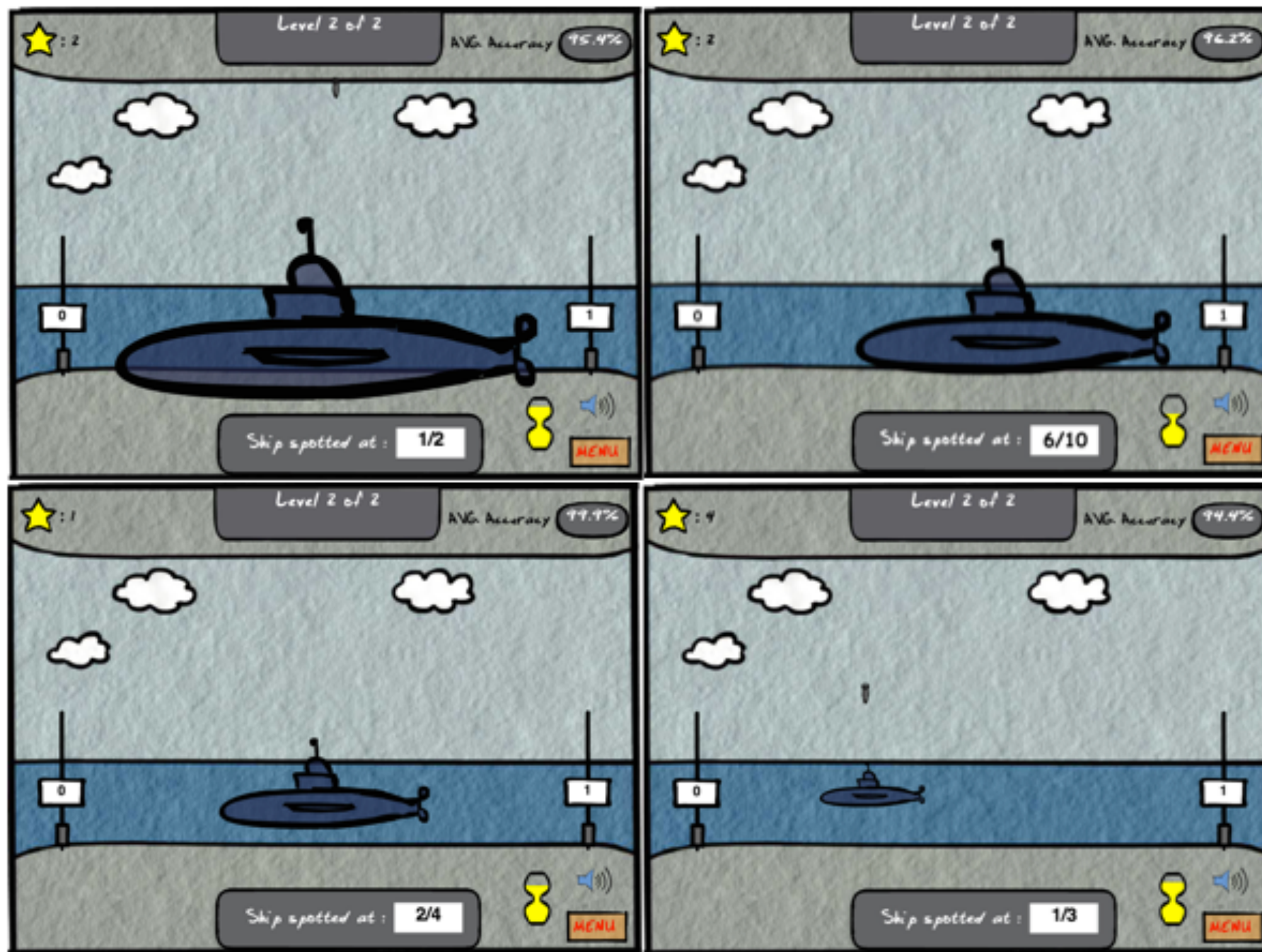
Worst Design
Ship 97

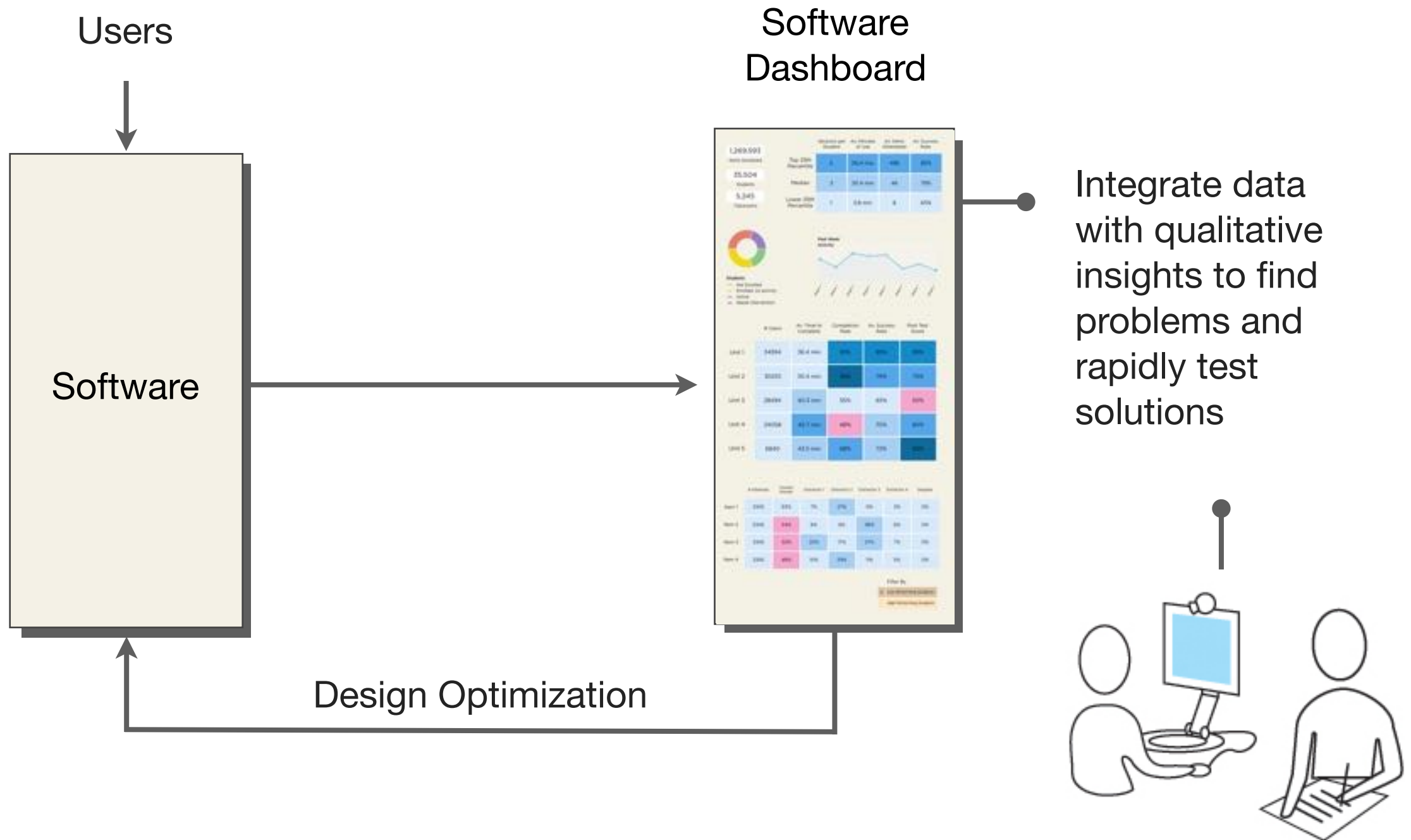


Best Design
Ship 90

Meta Experiment 2

Introduced ridiculously large “Bad Designs”





The Data-Experience Dialectic
Data and qualitative insights must be integrated

With 10,000 subjects a day, we could run thousands of experiments each year

But setting up, analyzing and acting upon experiments is hard.

How might AI get involved? Could we partially automate design optimization and scientific experimentation?

Key Question #3:

Is there a human-in-the-loop to keep alignment?

If continuous improvement metrics are not aligned to goals and values, data-driven improvement (teams or AI) will produce unintended consequences

NEED feedback loops about suitability of success metrics

Conclusions

Takeaways

- **From Designing Artificial Intelligence to Designing Intelligent Systems**
 - **Collaboration between teams and algorithms**

(not just for AI but for products)

A Definition of Intelligence used in AI

“Intelligence measures an agent’s ability to achieve goals in a wide range of environments.”

—Legg & Hutter, 2007

“an individual’s intelligence is related to their ability to succeed...”

- Robert Sternberg

What can go wrong?

- Poor goals (misalignment with values)
- Poor metrics (misalignment with goals)
- Poor actions responding to data
- *Misleading* data and *misreading* data
- Conflicting interests in stakeholders

Unintended consequences!

Accountability can create perverse incentives

e.g. schools encourage low-performing students to drop out or to cheat (Schildkamp et al, 2012).

How can system designers help build the human into the loop?

- **UI for User Goal Setting**
- **System mapping & communicating future systems**
- **Processes to Negotiate Metrics for Success**

(not just for AI but for products)

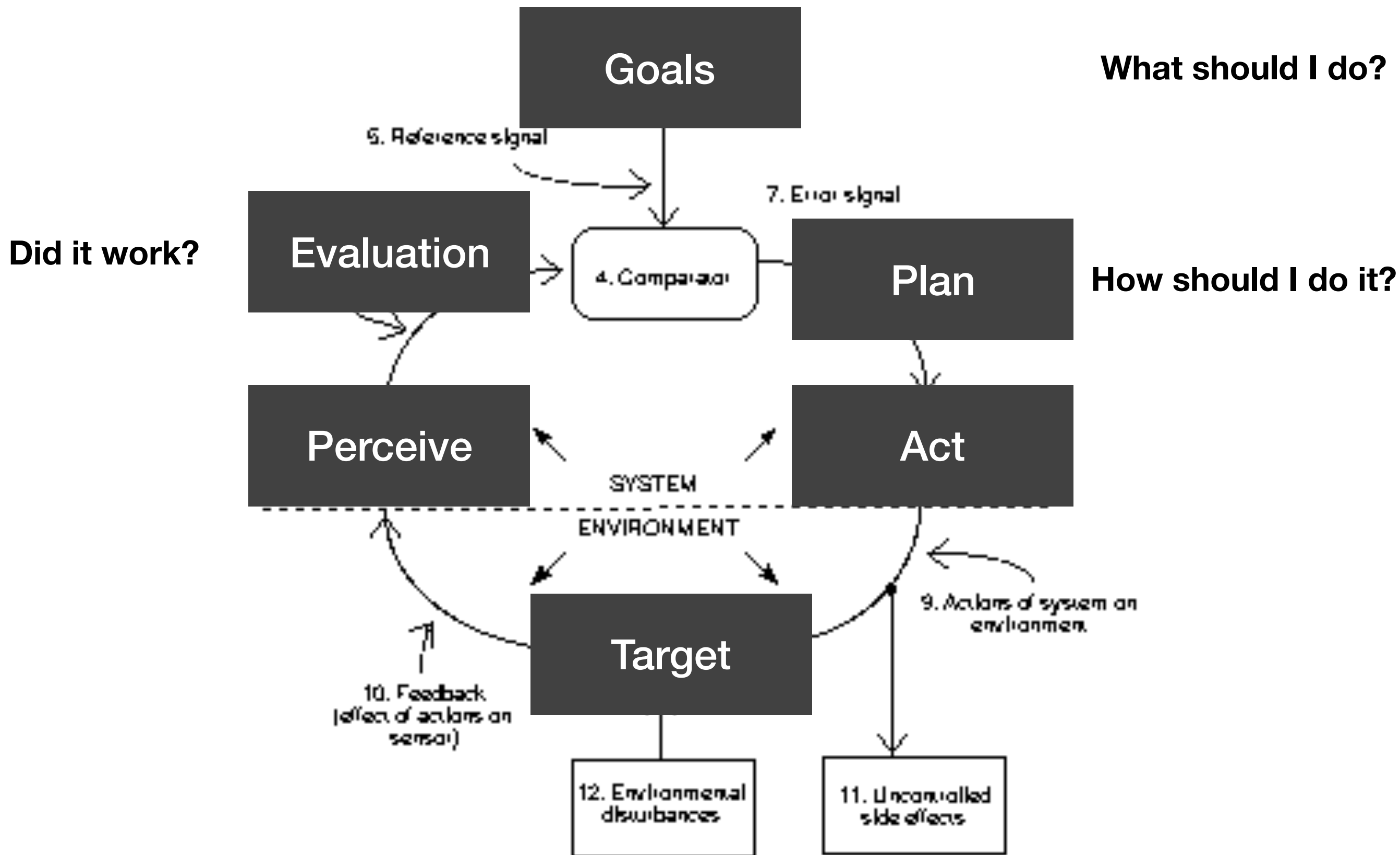
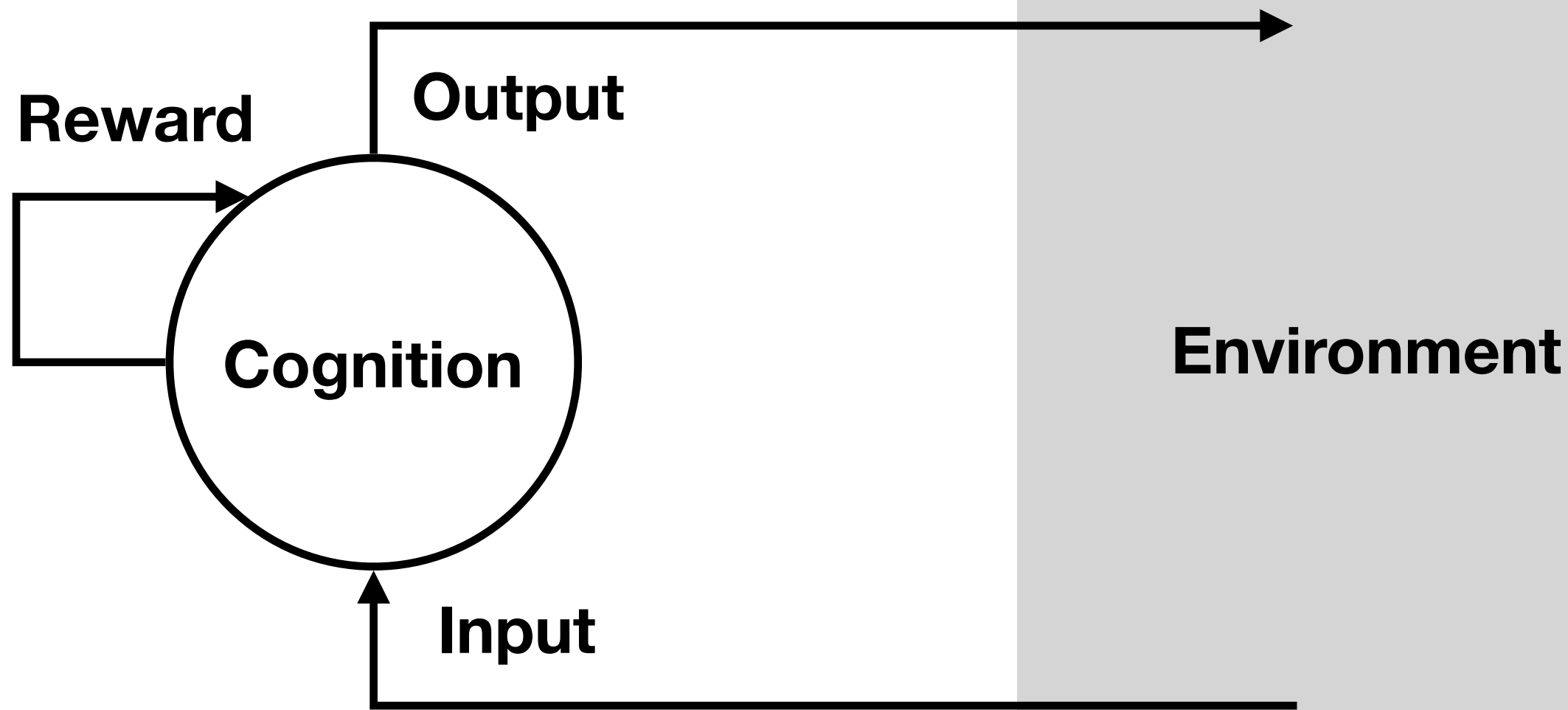


Figure 6.2
Elementary control system

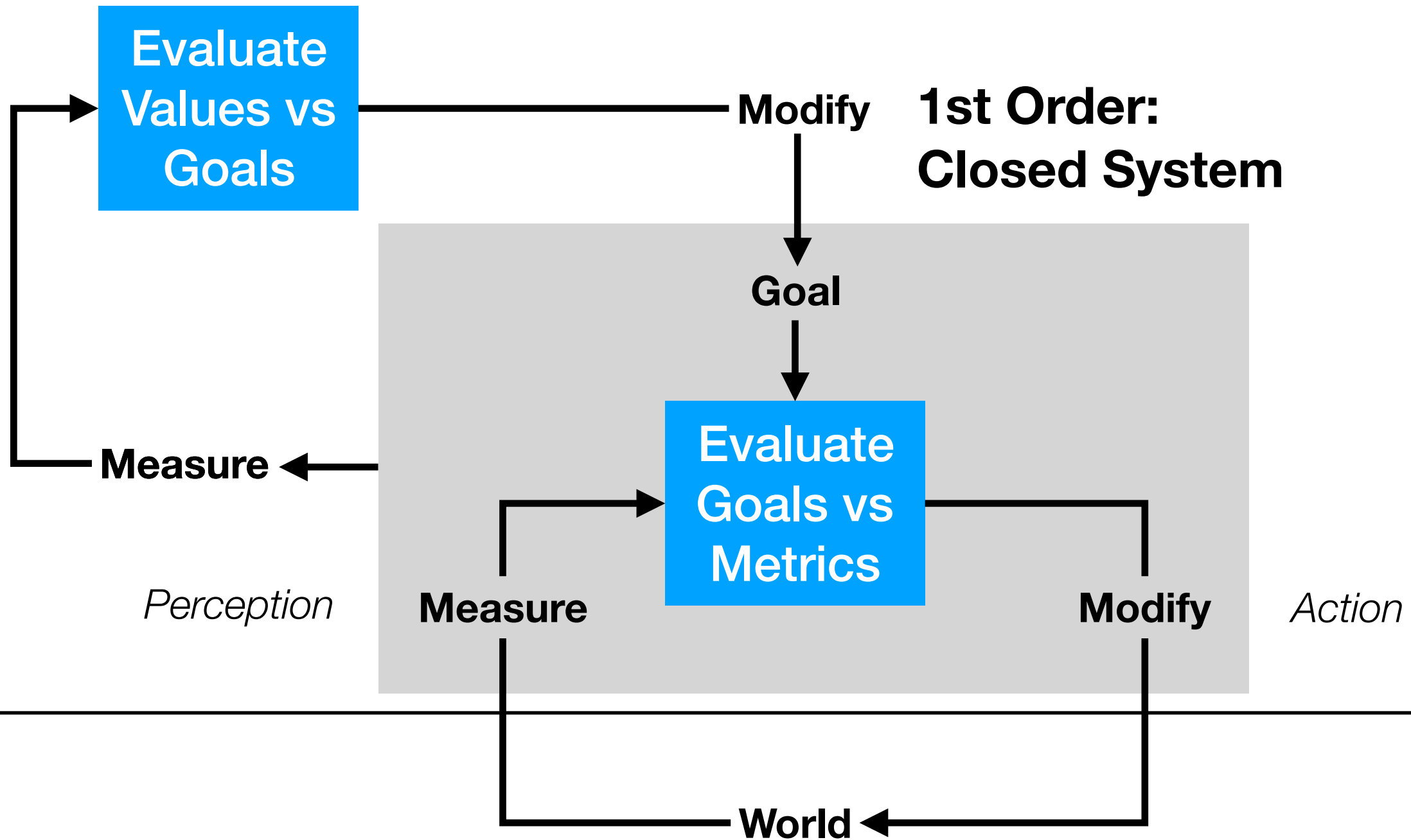


Reinforcement Learning

AI Definition of Intelligence

“Intelligence measures an agent’s ability to achieve goals in a wide range of environments.”

2nd Order: Learning System



Closed System

