# ARE TEACHERS OBSOLETE?

Emily Jensen's Area Exam
12 November, 2021

Full bibliography at the end

# How can adaptive systems train humans to perform complex tasks?

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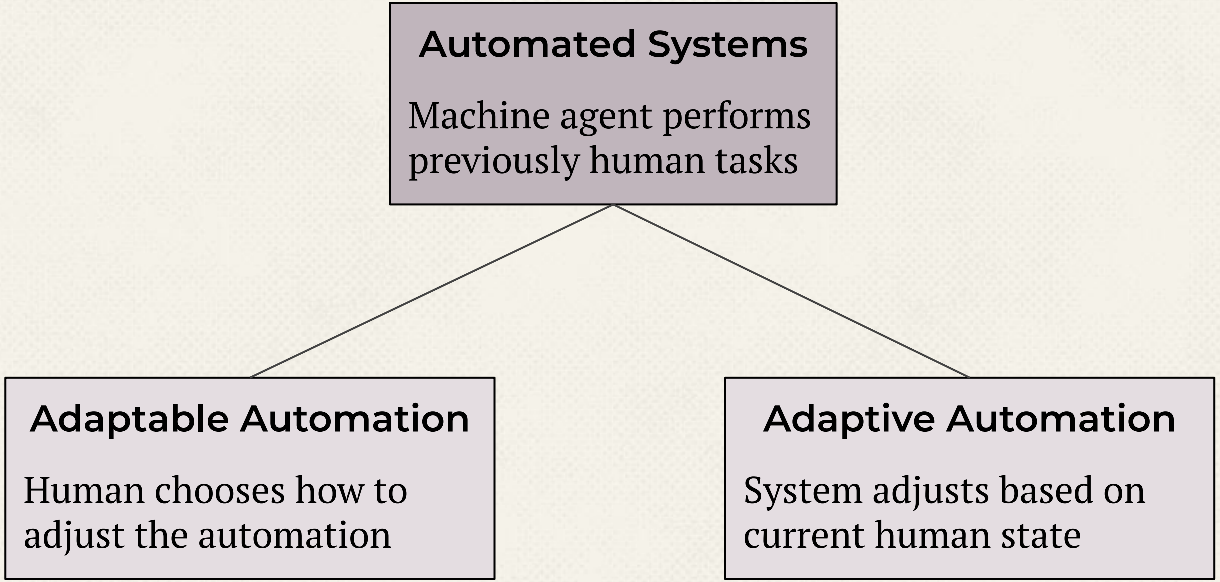
# ADAPTIVE SYSTEMS

*A brief overview*

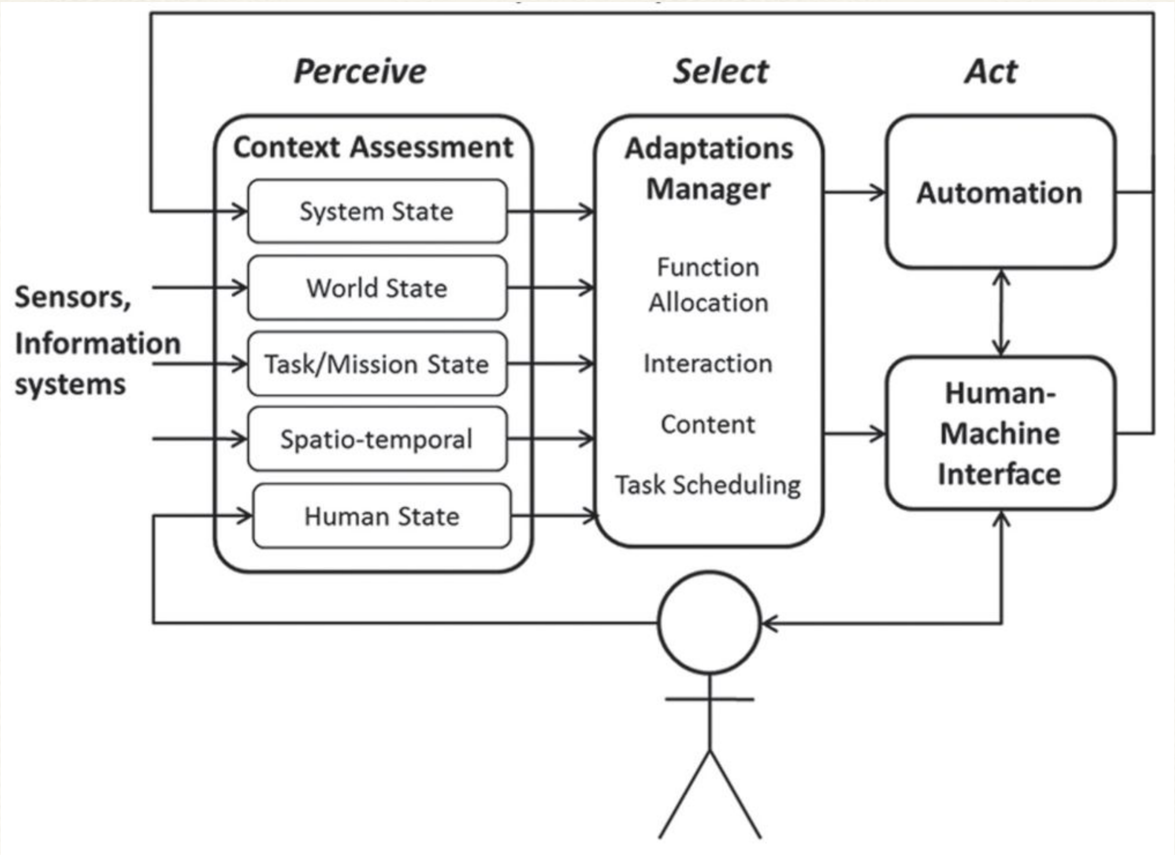
**Automated Systems**

Machine agent performs previously human tasks



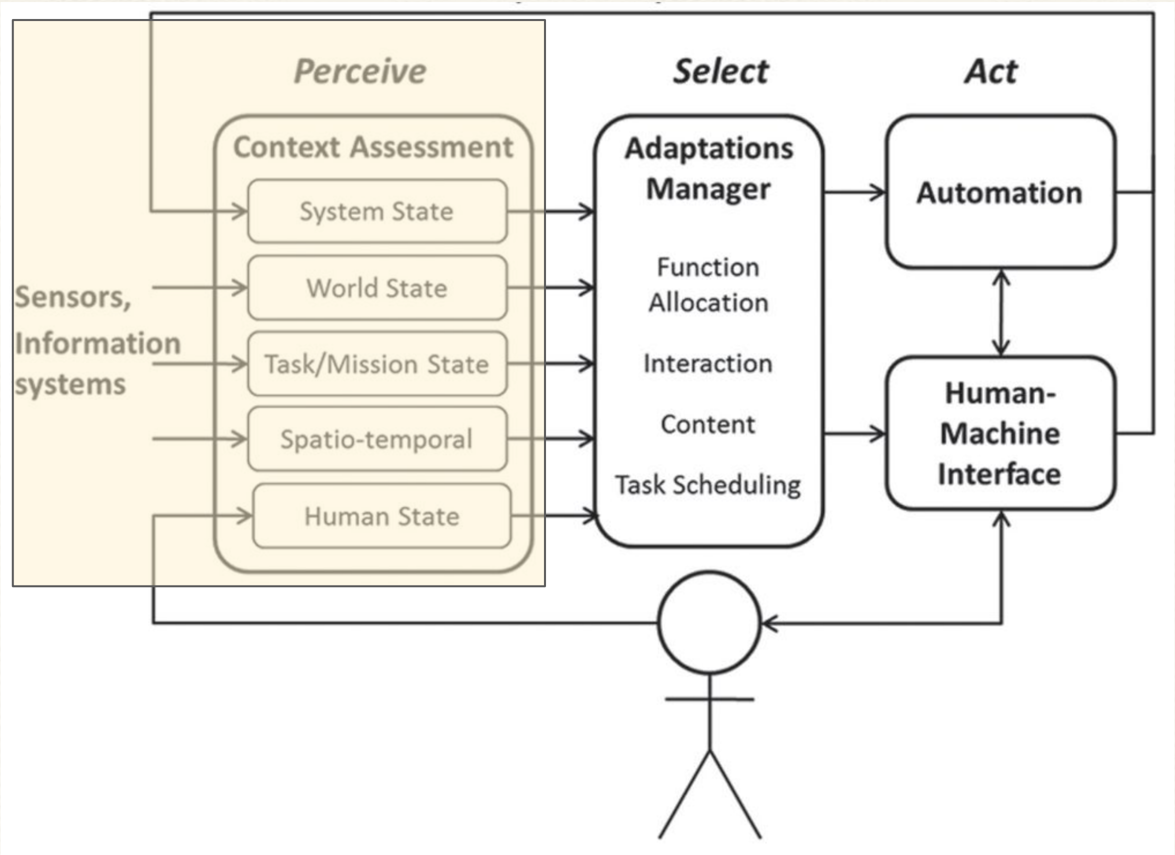

(Parasuraman, 1997; Feigh, 2012)

# Adaptive Systems



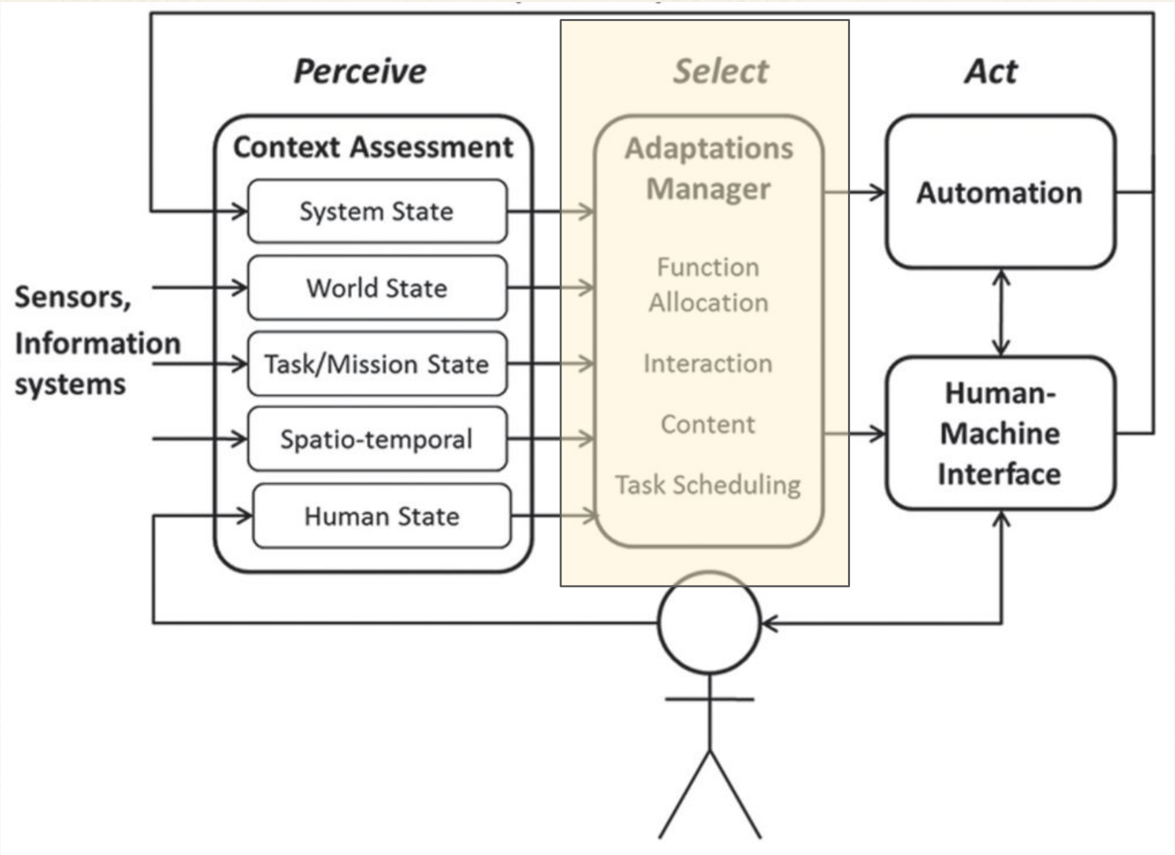

(Fig. from Feigh, 2012; Heard, 2020)

# Adaptive Systems



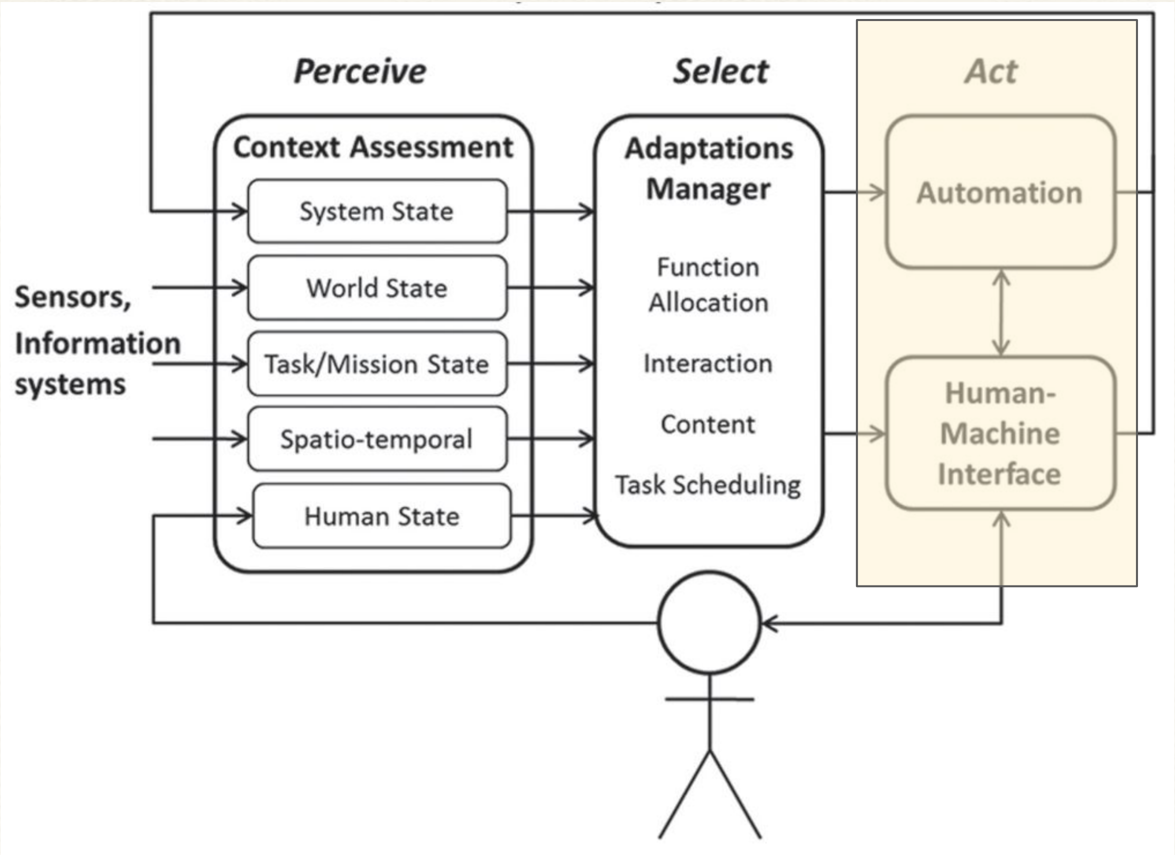

(Fig. from Feigh, 2012; Heard, 2020)

# Adaptive Systems




(Fig. from Feigh, 2012; Heard, 2020)

# Adaptive Systems




(Fig. from Feigh, 2012; Heard, 2020)

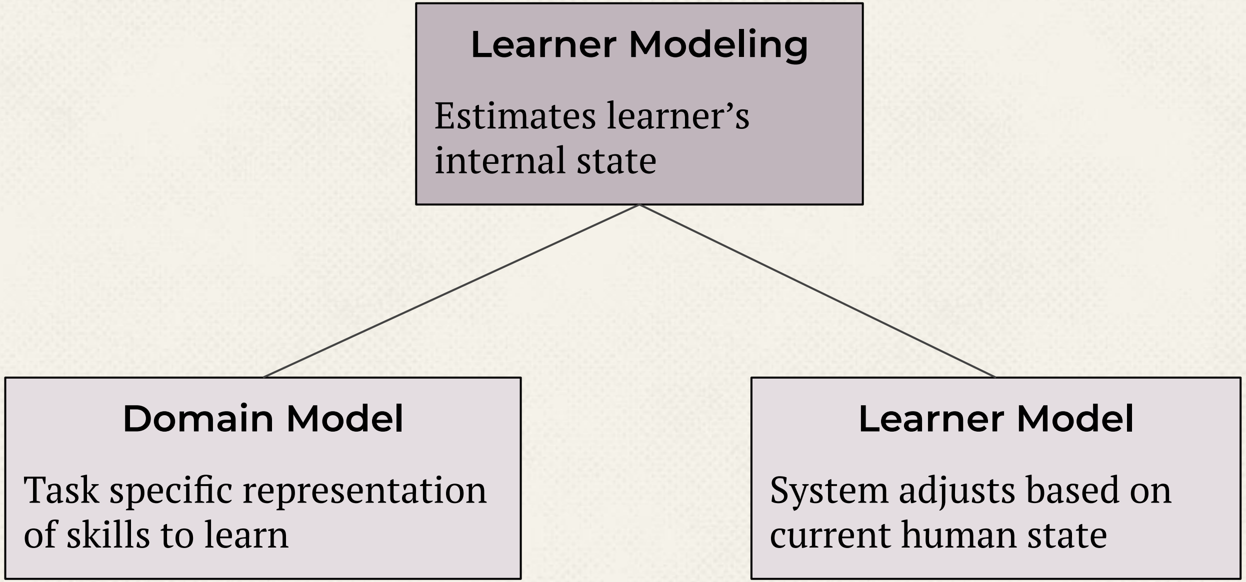
# TRAINING HUMANS

*Efficiently and at scale*

**Learner Modeling**

Estimates learner's internal state

(Pelánek, 2017)

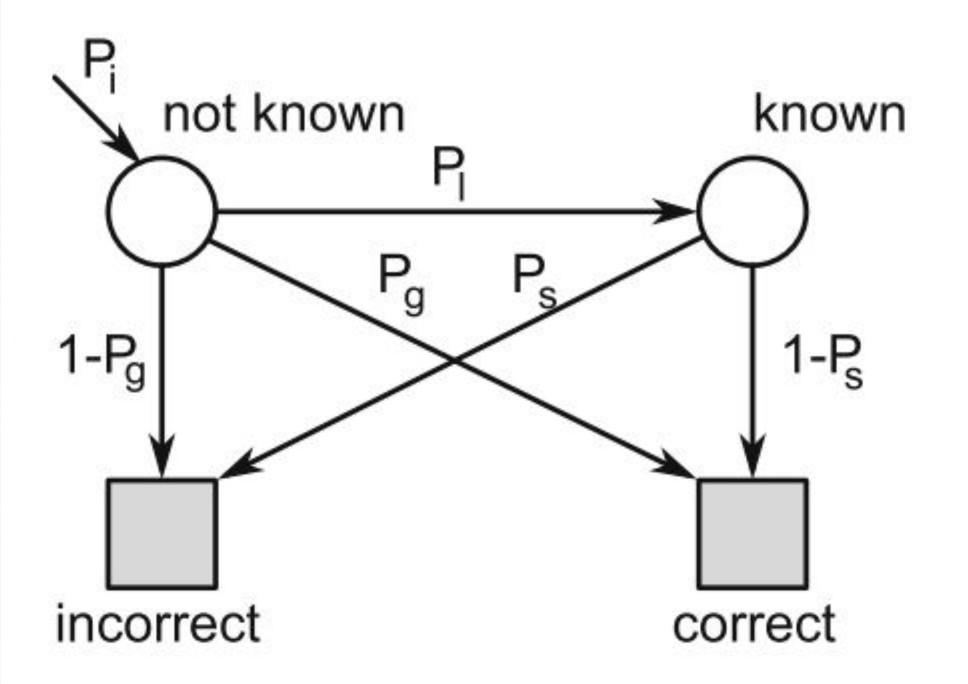



(Pelánek, 2017)

## Learner Modeling
## Bayesian Knowledge Tracing

(Pelánek, 2017)

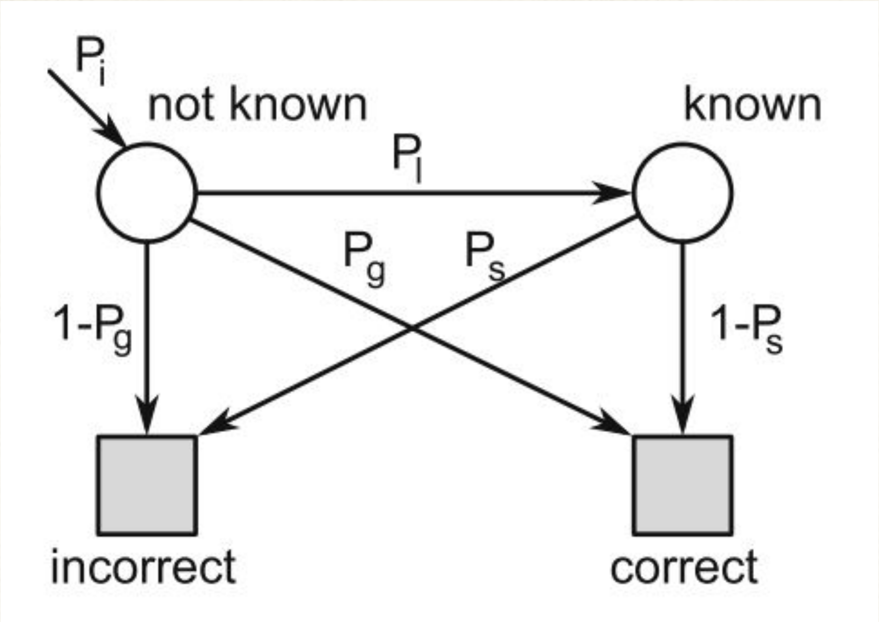
# Learner Modeling
# Bayesian Knowledge Tracing




(Fig. from Pelánek, 2017; orig. Corbett & Anderson 1995)

$P_i$ = initial
$P_l$ = learn
$P_g$ = guess
$P_s$ = slip

# Learner Modeling
# Bayesian Knowledge Tracing




(Fig. from Pelánek, 2017)

- Learning individual $P_i$ (Pardos, 2010)
- Relationship between carelessness + affect (San Pedro, 2011)
- Cf. Deep Knowledge Tracing (Khajah, 2016)

$P_i$ = initial
$P_l$ = learn
$P_g$ = guess
$P_s$ = slip

# Learner Modeling
# Inverse Reinforcement Learning

## Learner Modeling
## Inverse Reinforcement Learning

Infer knowledge based on a sequence of actions

- Ex: solving algebraic equations
- Learner is modeled as an MDP

$$\mathbb{P}(a|s) \propto \exp(\beta \cdot Q_h(s, a))$$

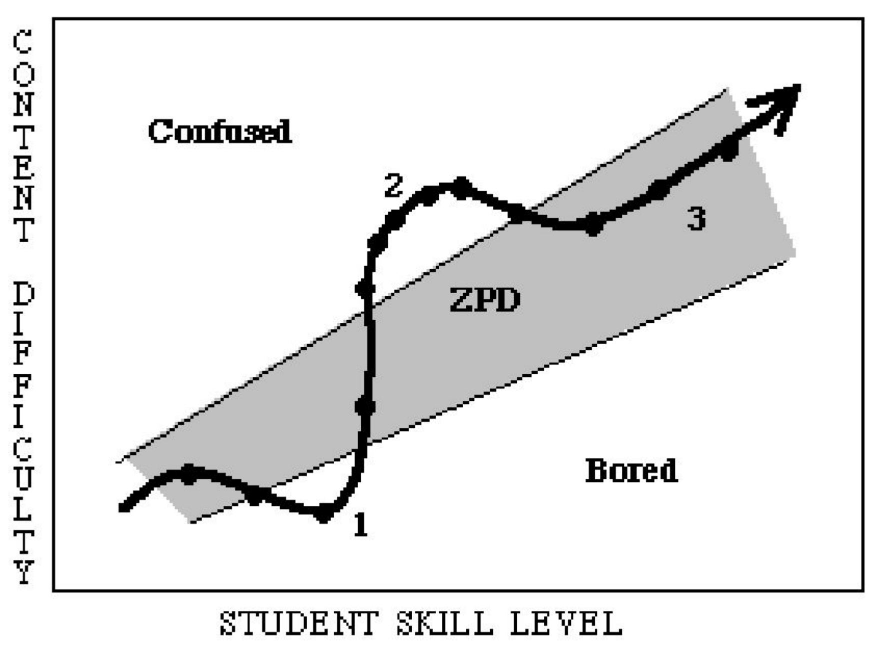
(Rafferty, 2016)

Gold standard: human tutors

- Curriculum development
- Personalization
- But, it's not scalable. Can we automate problem generation? (Gulwani, 2014)

Make it challenging, but not too hard

- Scaffolding! (Shute, 2008)
  - Deliberate Practice (Ericsson, 1993)
  - Zone of Proximal Development (Vygotsky, 1978)

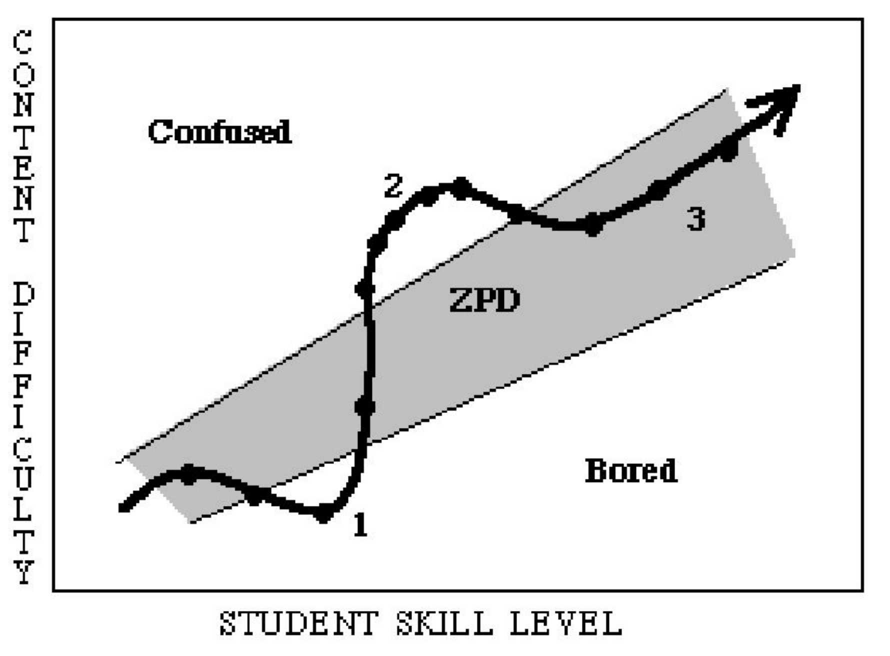



(Fig. from Murray, 2002)

# Giving Feedback

Make it challenging, but not too hard

- Scaffolding! (Shute, 2008)
  - Deliberate Practice (Ericsson, 1993)
  - Zone of Proximal Development (Vygotsky, 1978)
- Some concrete examples
  - Bayesian Knowledge Tracing based "ready to learn" (Baker, 2020)
  - Address a misunderstood skill (Rafferty, 2016)
  - ZPD based on hint use (Murray, 2002)




(Fig. from Murray, 2002)

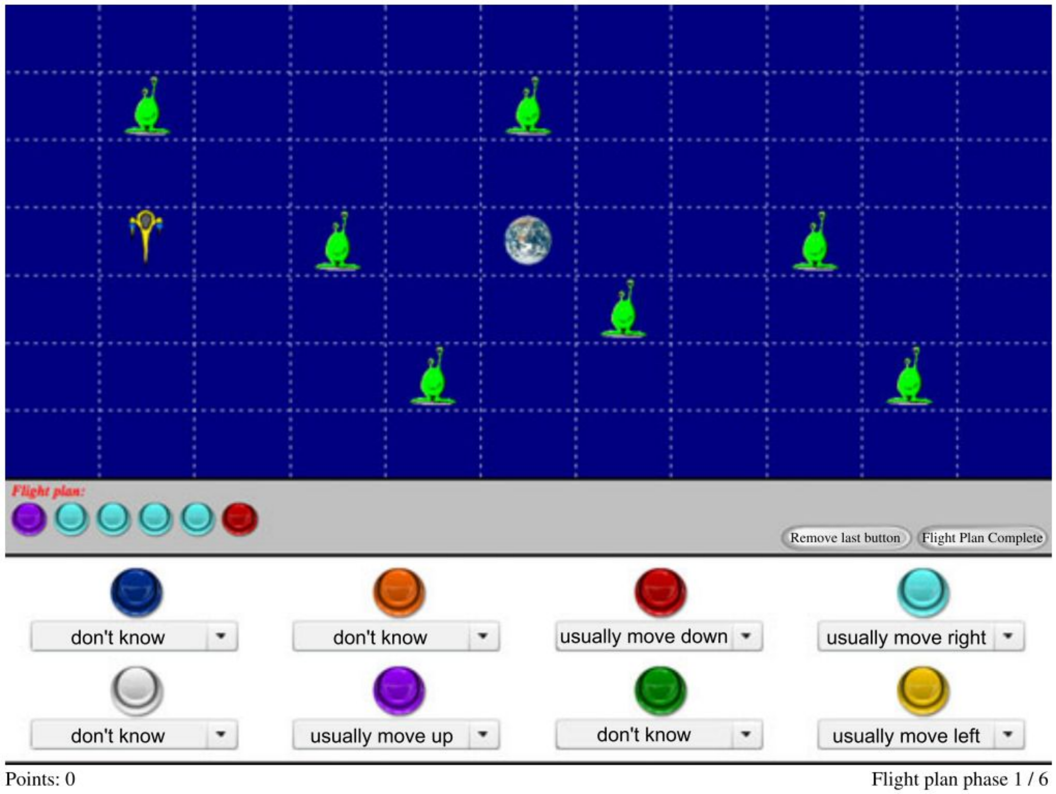
# COMPLEX TASKS

*Current work and opportunities*

How do we measure the internal state of the user?

- Driving - Actively force user to display behavior (Sadigh, 2016)
- Gaming - Assume actions are rational wrt internal dynamics (Reddy, 2018)
- Measure physiological responses (Heard, 2020)

# Case Study: Rafferty 2015



## Case Study: Rafferty 2015

- Modeled complex user actions as a Markov Decision Process
- Users may have misconceptions about how their actions change the current state
- Used inverse planning to reason about knowledge

# Review of Markov Decision Processes

- Agent is currently in state $s$ and chooses to take action $a$
- Next state $s'$ is determined by transition model $T = Pr(s' \mid s, a)$
- The result of the action is given a cost/reward $r(s, a, s')$

## Review of Markov Decision Processes

- Expected long-term value is given by *Q(s, a)*
- Chosen action is determined by policy *Pr(a | s)*

(optimal policy will maximize Q)

$$Q(s,a) = \underbrace{\sum_{s' \in S}}_{\text{Sum over all possible next states}} \underbrace{\mathbb{P}(s'|a,s)}_{\text{Prob. of getting to the state}} \left( \underbrace{r(s,a,s')}_{\text{Reward at the state}} + \underbrace{\gamma \sum_{a' \in A} \mathbb{P}(a'|s') Q(s',a')}_{\text{Discounted result of future actions}} \right)$$

## Inferring User Beliefs

- Assume reward function is given
- Goal: infer user's transition model given action sequence

$$\boxed{\mathbb{P}(T|\mathbf{a}, s_1, R, \gamma)} \propto \boxed{\mathbb{P}(\mathbf{a}|s_1, T, R, \gamma)}\boxed{\mathbb{P}(T)}$$

Posterior: prob of a given transition model

Likelihood: prob of action sequence given model

Prior: distribution over transition models. Can encode misconceptions, set as uniform here

## Inferring User Beliefs

- Need approximation of policy to calculate likelihood
- Use Boltzmann noisily optimal policy
- Higher $Q$ represents better choices
- Marginalize over various values of β

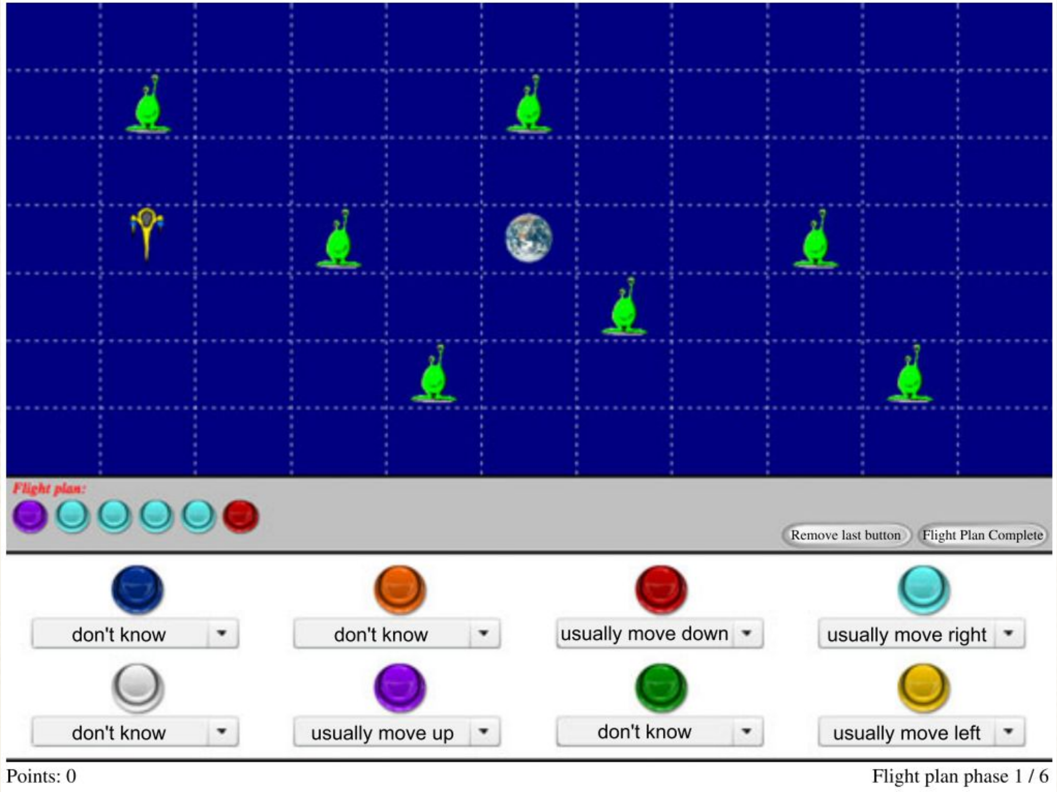
$$\mathbb{P}(a|s, T, R, \gamma) \propto \exp\left(\boxed{\beta} \cdot \boxed{Q(s, a|T, R, \gamma)}\right)$$

Determines how close to optimal

Q-value of choosing action in state

## Key Results

- 73% match of Maximum A Posteriori with beliefs
- Distinguishes plans with misconceptions
- Similar performance to human raters



# How can adaptive systems train humans to perform complex tasks?

# Adaptive Automation

Perceive

Select

Act

# Adaptive Automation

## Perceive

- Great strides in sensing technology (Feigh, 2012)
- Theoretical frameworks for assessing knowledge (Pelánek, 2017)
- Are humans really rational? (Reddy, 2018; Rafferty, 2015/2016)
- How do we represent complex domain models?
- Need to address the social-emotional and cultural side of learning

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## Select

- Triggers and adaptations based on heuristics (Heard, 2020; Murray, 2002; Shute, 2008)
- Need to go beyond metrics like performance (Khasawneh, 2019; Heard, 2020)
- How do we plan for how humans change over time? (Kress-Gazit, 2021)

# Adaptive Automation

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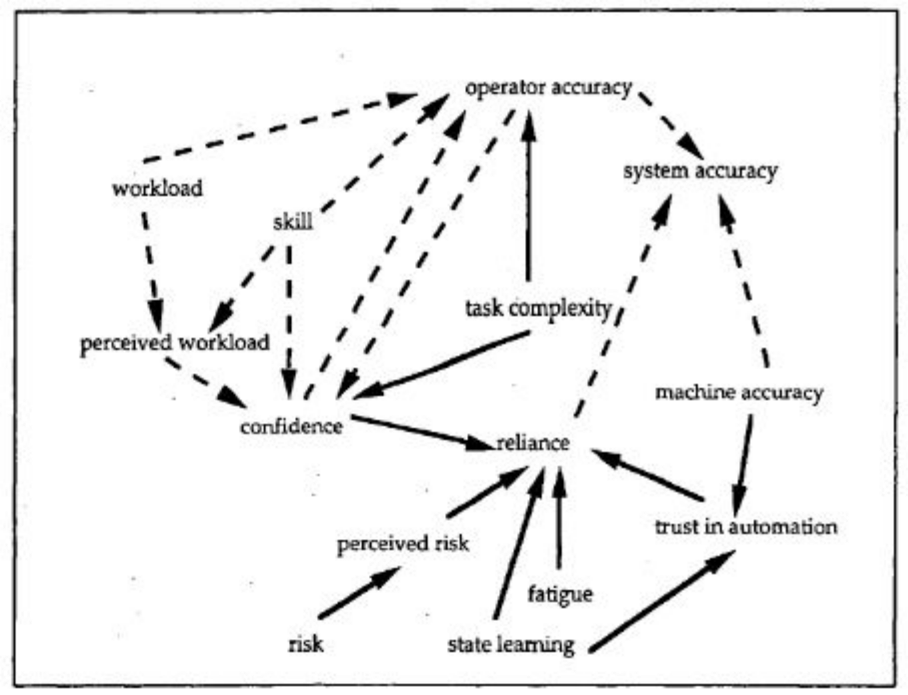
## Act

- A whole world of UX/UI and VIZ to explore
- What is the role of explainability?
- Very little focus on user experience (Khasawneh, 2019; Heard, 2020)
- How do we treat humans as an integral part of the system? (Parasuraman, 1997)

# Human-Centered Automation

Theorized
Tested




(Fig. from Parasuraman, 1997; Kress-Gazit, 2021; Khasawneh, 2019)

## How do I fit into this?

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Perceive

- Sensor-free student affect (EDM 2019; HLA)
- Teacher dialog strategies (CHI 2020; LAK 2021b)
- Cognitive engagement (LAK 2021a)

# How do I fit into this?

Perceive → Select → Act

- Sensor-free student affect (EDM 2019; HLA)
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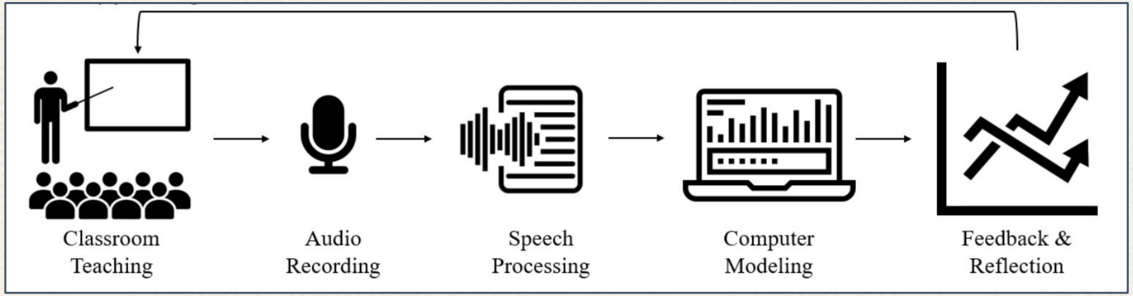


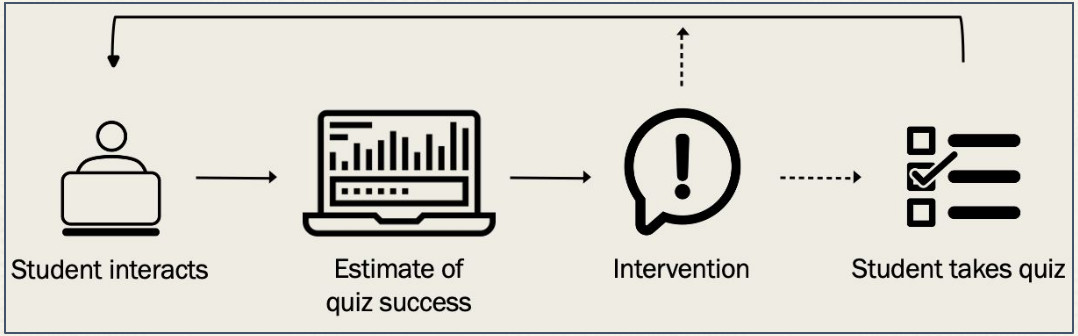

# ARE TEACHERS OBSOLETE?

*Thank you!*

**Questions?**

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