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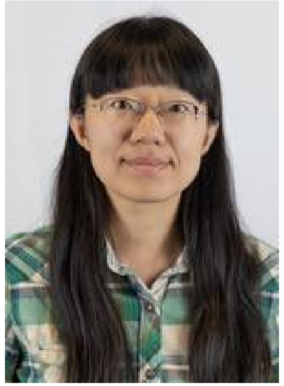
A reinforcement learning approach to personalized learning recommendation systems



Xueying Tang[1], Yunxiao Chen[2]*, Xiaoou Li[3], Jingchen Liu[1] and Zhiliang Ying[1]

[1]Department of Statistics, Columbia University, New York, New York, USA
[2]Department of Psychology, Institute for Quantitative Theory and Methods, Emory University, Atlanta, Georgia, USA
[3]School of Statistics, University of Minnesota, Minneapolis, Minnesota, USA

Reporter: Yingshi Huang

Introduction

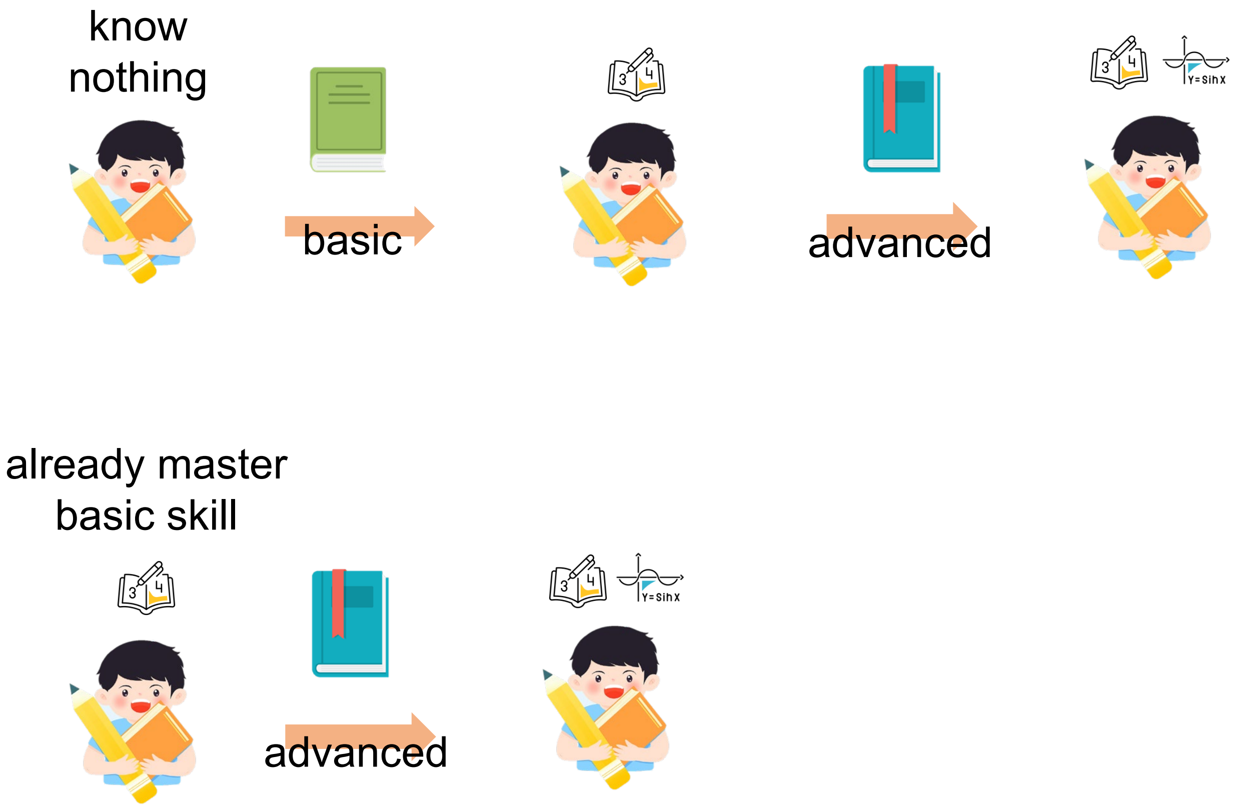
- Personalized/adaptive learning

Feeling boredom because you already mastered the classroom material?

Experiencing stress because the teacher was teaching too fast for you?

Introduction

- Personalized/adaptive learning



Introduction

- How to determine the tailored learning path for each learner?
  - Goal:
    maximize the overall reward along the whole learning process for each learner
  - Key question:
    makes decisions on what to learn at the next step

Introduction

- How to determine the tailored learning path for each learner?

  - Three components:

    Measurement model
    (students' current knowledge profile)

    Learning model
    (the learning process: relationship between learning materials and changes of knowledge profiles)

    Recommendation strategy
    (the selection of learning materials)

Introduction

- How to determine the tailored learning path for each learner?
  - Three components:

    Measurement model
    (students' current knowledge profile)

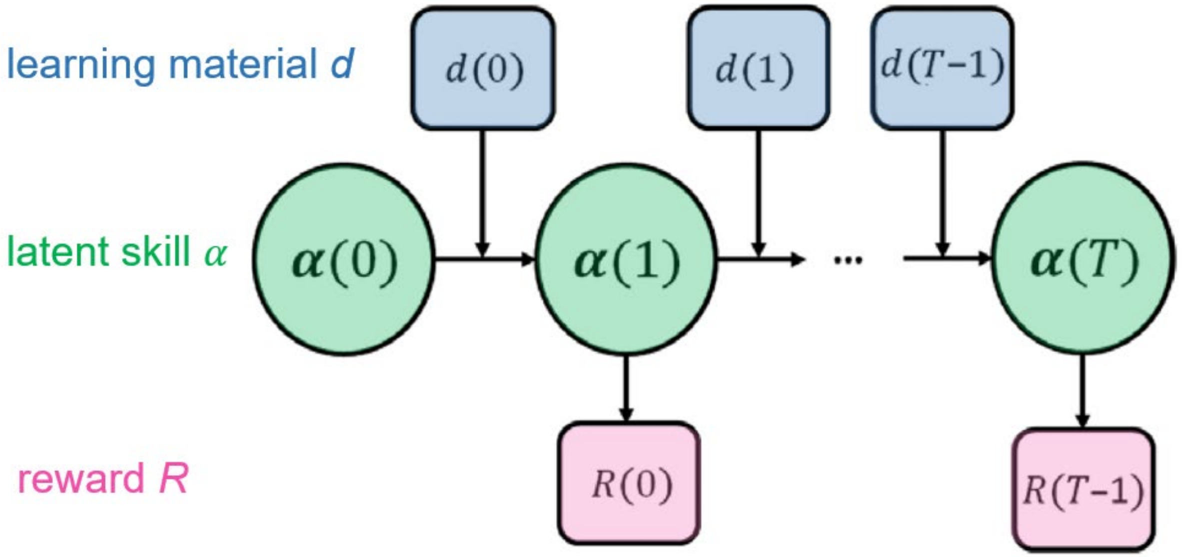
    Learning model (prior): complex & require large sample size to calibrate
    (the learning process: relationship between learning materials and changes of knowledge profiles)

    Recommendation strategy
    (the selection of learning materials)

➡ Purpose:
simultaneously build the learning model and recommendation strategy

Background

- K skills: $\alpha_1, \alpha_2, \ldots, \alpha_k$ (mastery = 1, non-mastery =0)
- T time epochs: $0,1,\ldots,T-1$
- Learning material pool: $\mathcal{D}$
- Reward
  - the number of skills being mastered at learning stage t:
  - $R(t) = \sum_{k=1}^{K}[\alpha_k(t+1) - \alpha_k(t)]$
  - the entire learning process:
  - $E(\sum_{t=0}^{T-1} R(t))$



Background

- Measurement model:
  - the probability of a specific response on item j: $P(Y_j = y|\boldsymbol{\alpha})$
  - diagnostic models (discrete) or multidimensional IRT (continuous)

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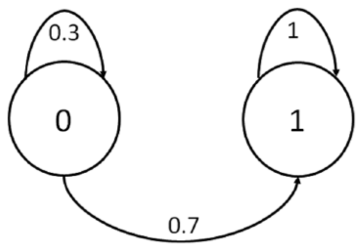
- Learning model:
  - the effectiveness of each learning material
  - a Markov chain (with no retrogression assumption): $P_d(\boldsymbol{\alpha}(t+1) = \boldsymbol{\alpha}|\boldsymbol{\alpha}(t) = \tilde{\boldsymbol{\alpha}})$

→ no arrow pointing from 1 to 0

only depends on time t



$$P(\alpha(t+1) = 0|\alpha(t) = 0) = 0.3$$

  - contain a large number of parameters: $|\mathcal{D}| \times 2^K$

(the number of learning materials × all possible states of knowledge profiles)

Background

- Recommendation strategy:
  - the probability that material d will be recommended at time t: policy π
  - $\pi_t(d) \geq 0$ & $\sum_{d \in \mathcal{D}} \pi_t(d) = 1$

  - lower benchmark: $1/|\mathcal{D}|$
  - upper benchmark: oracle strategy π^*
    - when no measurement error and learning model is known, that is, outperform any policy under imprecise information

➡

approximate π^* by collecting students' learning data in a strategic way

Reinforcement Q-learning

- Objective:
  - (1) bypass the estimation of learning model & (2) approximate π^*
    → how to optimize the policy without the learning model

Reinforcement Q-learning

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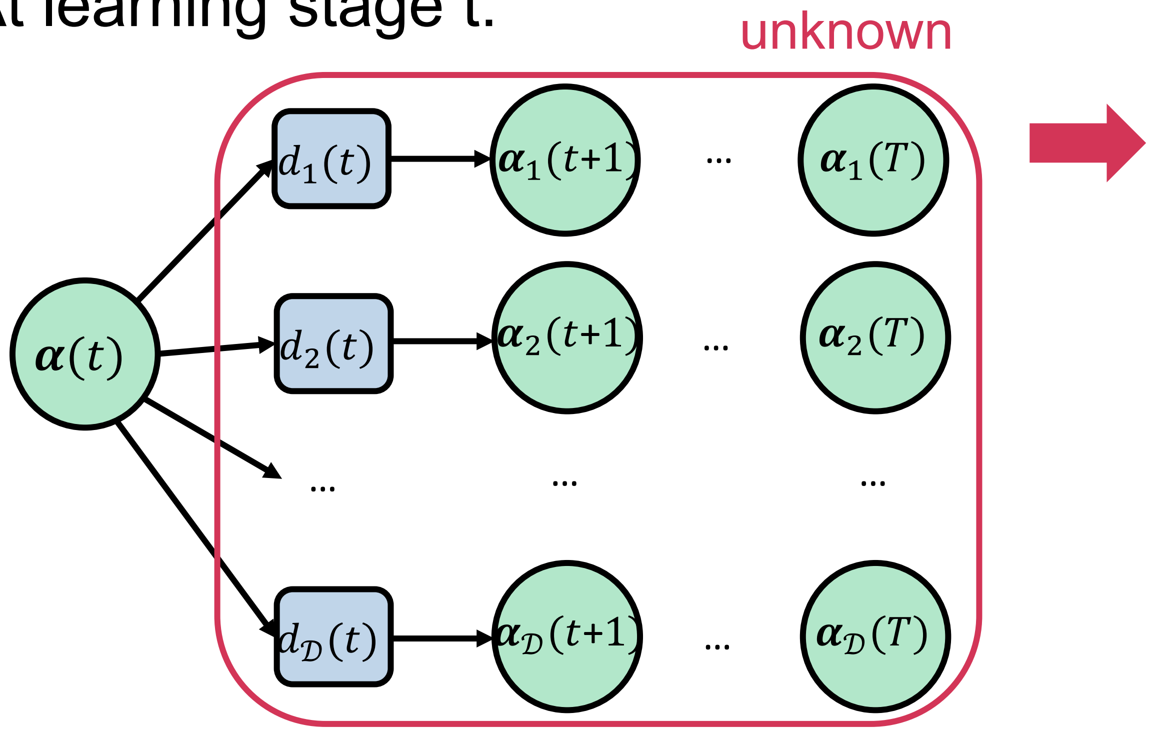
    $\rightarrow$ how to optimize the policy without the learning model

- At learning stage t:

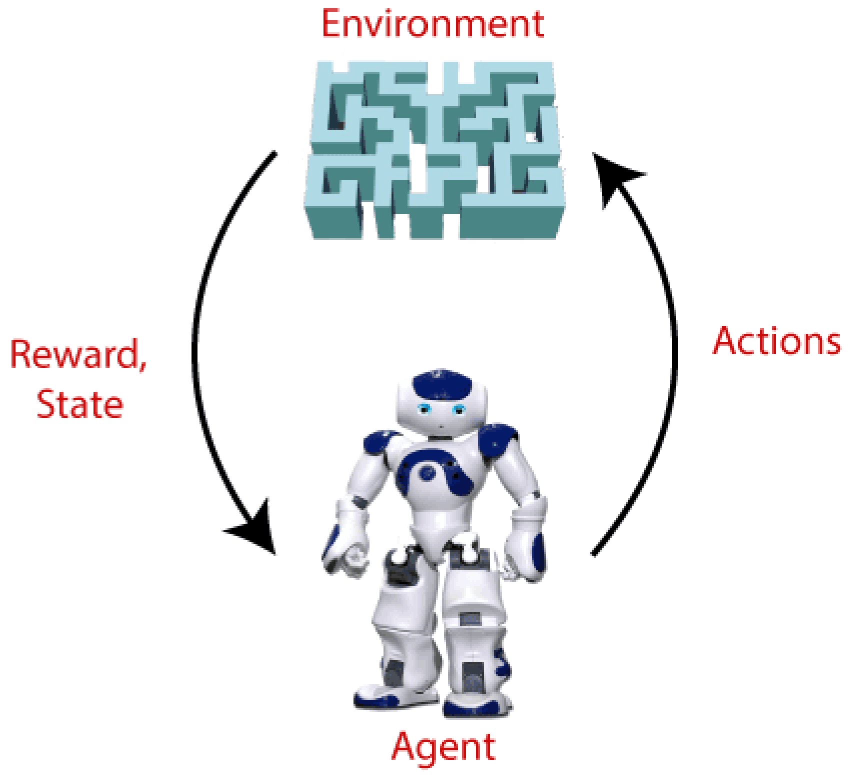


What would happen after selecting different learning materials is unknown

But we need to maximize the overall reward

Reinforcement Q-learning

- The principle of reinforcement learning:
  - learn in an interactive environment by trial and error
  - find a suitable action model (sequential actions) that would maximize the total cumulative reward (a long-term goal) of the agent



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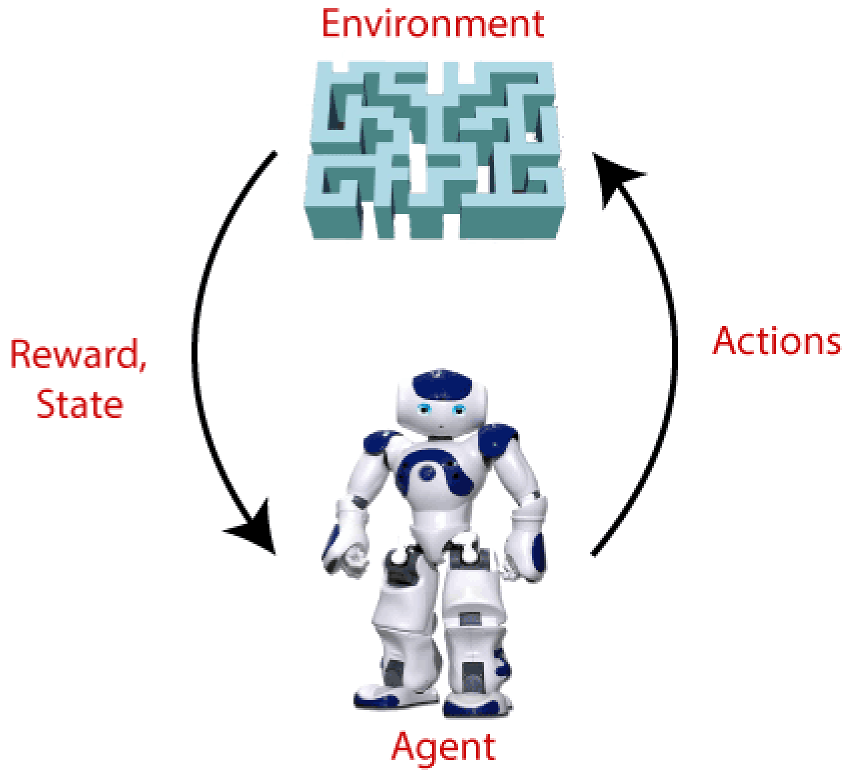
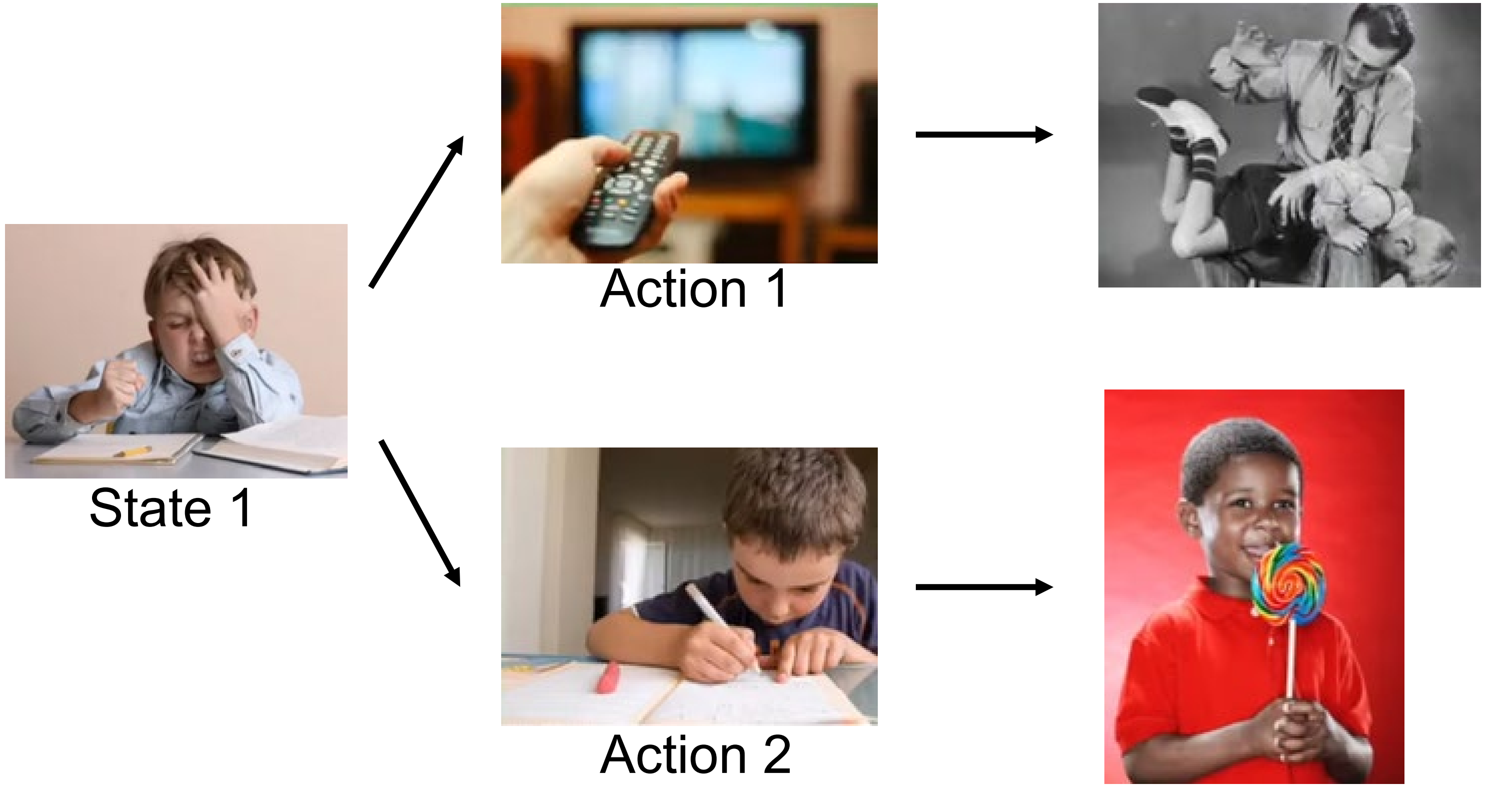
- In this case:
  - Agent → online learning platform
  - State → knowledge profile $\alpha(t)$
  - Action → selection of learning material
  - Environment → learners
  - Reward → the changes of knowledge profile



Reinforcement Q-learning

- Q-learning algorithm:
  - Determine action sequence with Q table

	Action 1	Action 2
State 1	-5	10



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- Q-learning algorithm:
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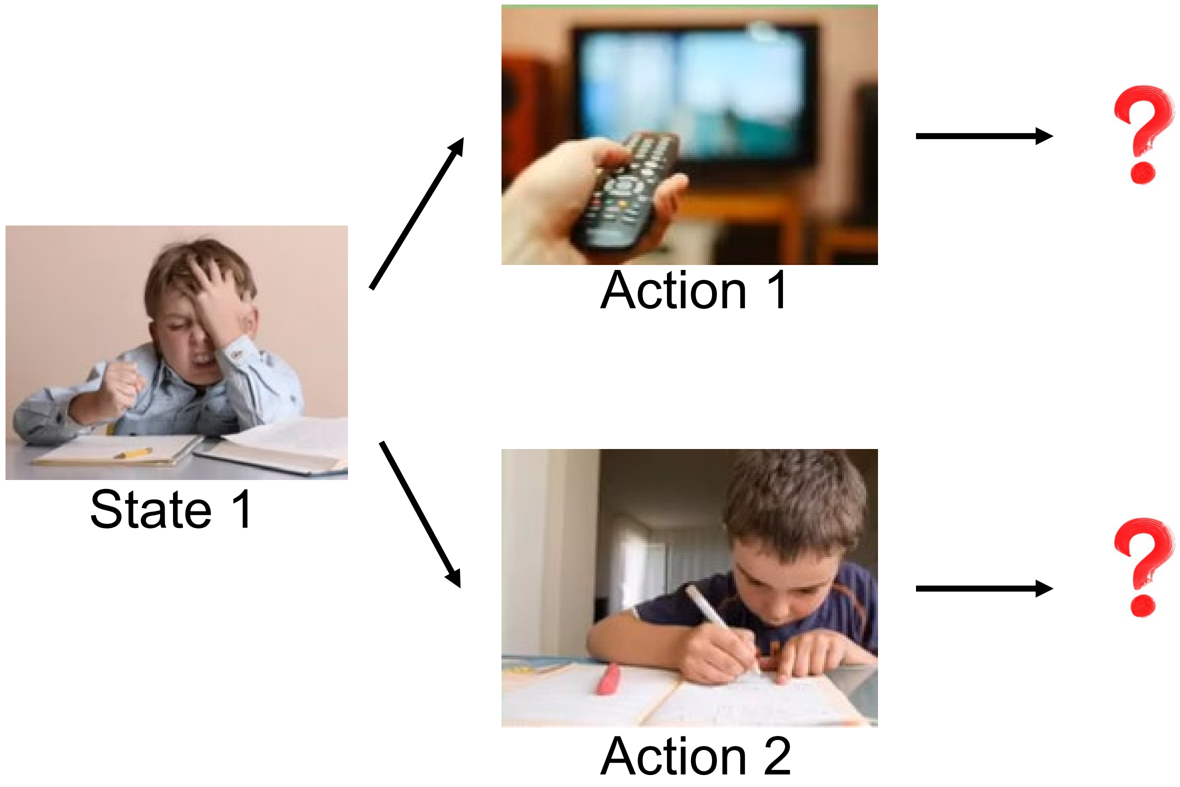
	Action 1	Action 2
State 1	0	0



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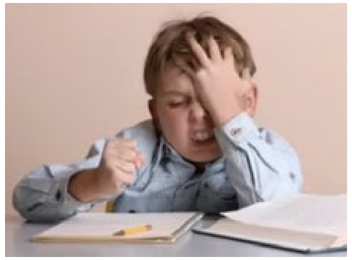

State 1

Action 1

Action 1

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Reinforcement Q-learning

- Q-learning algorithm:
  - Determine action sequence with Q table
  - The sum of the expected reward gained in the remaining training epochs

$$Q_t^*(\boldsymbol{\alpha}, d) = E\left(\sum_{s=t}^{T-1} R(s) | \boldsymbol{\alpha}, d, \pi^*\right)$$

  - Maximize $Q_t^*(\boldsymbol{\alpha}, d)$ to select the next learning material

$$d^* = \operatorname*{argmax}_d Q_t^*(\boldsymbol{\alpha}, d)$$

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  - Example: two skills (K = 2) with two set of learning materials in two time epochs (T = 2)

	$t = 0$		$t = 1$	
$\boldsymbol{\alpha}$	$d = 1$	$d = 2$	$d = 1$	$d = 2$
(0, 0)	**1.26**	0.60	**0.60**	0.00
(1, 0)	0.70	**0.91**	0.00	**0.70**

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$T \times 2^K \times |\mathcal{D}|$

So complex!

Reinforcement Q-learning

- Q-learning algorithm:
  - $Q_t^*(\boldsymbol{\alpha}, d)$ is approximated by a linear model

$$Q_t(\hat{\boldsymbol{\alpha}}, d, \boldsymbol{\beta}) = \sum_{l=1}^{p} \beta_l^{(td)} f_l(\hat{\boldsymbol{\alpha}})$$

finite dimensional vector

functions summarizing features of $\hat{\boldsymbol{\alpha}}$

→ from $T \times 2^K \times |\mathcal{D}|$ to $T \times p \times |\mathcal{D}|$ $(p \ll 2^K)$

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$\rightarrow$ from $T \times 2^K \times |\mathcal{D}|$ to $T \times p \times |\mathcal{D}|$ $(p \ll 2^K)$

  - Example: a main effect linear model

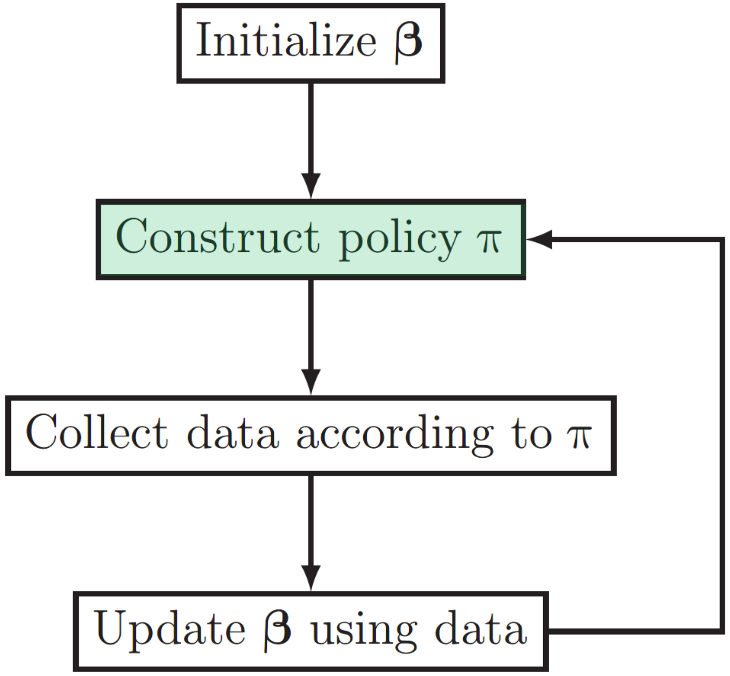
$$Q_t(\widehat{\boldsymbol{\alpha}}, d, \boldsymbol{\beta}) = \beta_0^{(td)} + \sum_{k=1}^{K} \beta_k^{(td)} f_k(\widehat{\boldsymbol{\alpha}})$$

the posterior probability of $\alpha_k(t) = 1$

➡ Our problem becomes the estimation of $\boldsymbol{\beta}$

Reinforcement Q-learning

- The estimation of $\boldsymbol{\beta}$:
  - the balance between exploration (exploring new path) and exploitation (following the current "best" path)



$$\beta_l^{new} = \beta_l^{old} + \text{learning rate} \times \Delta_l$$

$$\pi_t(d|\hat{\boldsymbol{\alpha}}) = \frac{\exp\left(\gamma_1 Q_t(\hat{\boldsymbol{\alpha}}, d', \boldsymbol{\beta})\right)}{\sum_{d' \in \mathcal{D}} \exp(\gamma_1 Q_t(\hat{\boldsymbol{\alpha}}, d', \boldsymbol{\beta}))}$$

exploration parameter ≥ 0

$\gamma_1 = 0$: purely random

$\gamma_1 = \infty$: completely follows the current Q-function

Take home message

- Adaptive Learning aims to provide tailored learning trajectory for every individual

- Three key components in personalized learning
  - Measurement model, learning model, and recommendation strategy

- Facilitating a solution with reinforcement Q-learning
  - Determine an optimal action sequence that maximizes the long-term reward through collecting feedbacks from the environment

The End. Thanks for Listening!

School of Education & Information Studies

Thanks
감사합니다
Grazie
谢谢大家

Reporter: Yingshi Huang

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