Adaptive Learning with Cognitive Contexts Modeling

(基于认知情境建模的自适应学习方法)

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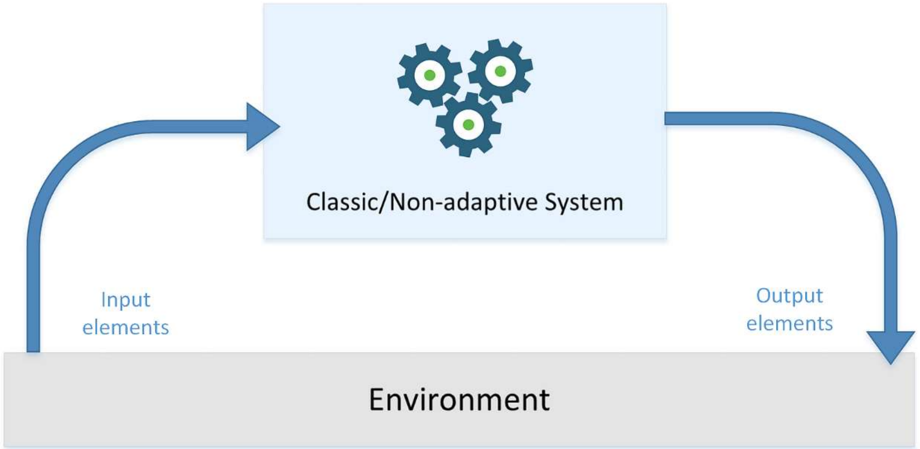
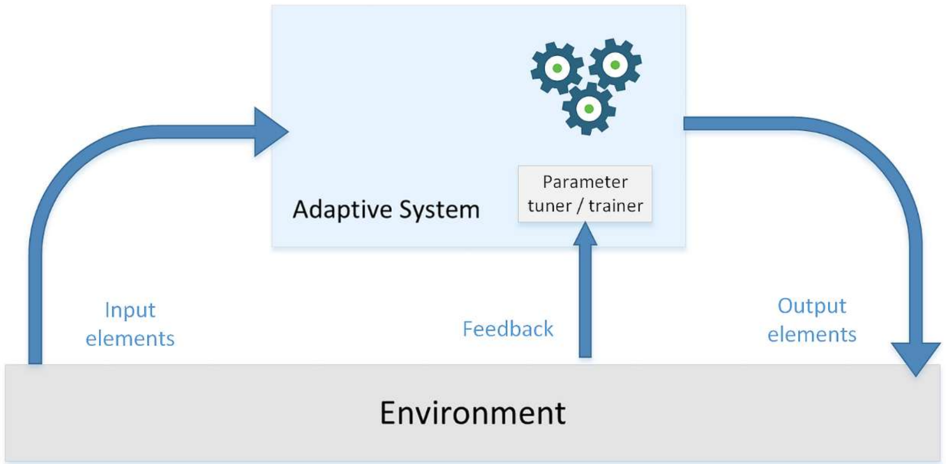
Outline

Background

- Adaptive is important for “learning”



(a) Non-adaptive learning



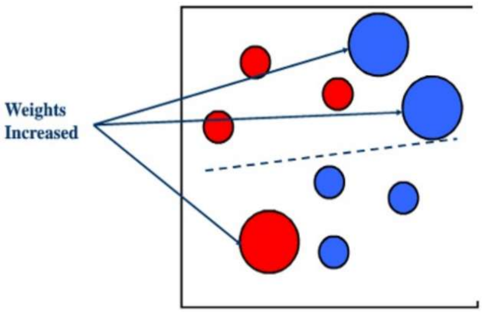
(b) Adaptive learning

➢ **Adaptive learning** is an educational method which uses computer algorithms to orchestrate the interaction with the learner and deliver customized resources and learning activities to address the unique needs of each learner [1].

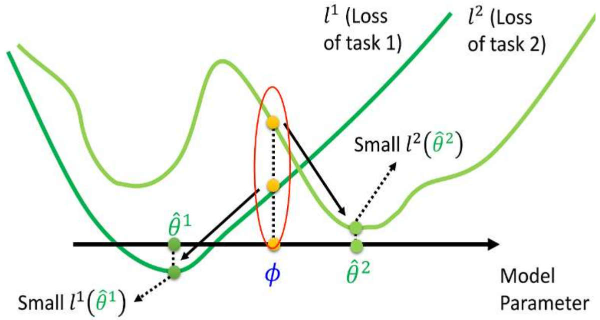
[1] https://www.smartsparrow.com/what-is-adaptive-learning/

Background

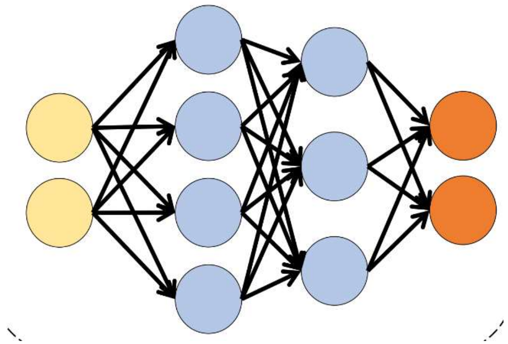
Data Selection



Parameter Training



Architecture Optimization



- ✓ Adaptive Sampling[AdaBoost' EuroCOLT'95]
- ✓ Re-weighted cost[BAN'ICML'18]

- ✓ Adaptive learning rate[Adam, ICLR'15]
- ✓ Parameter initialization [MAML, ICML'17]

- ✓ Dropout [AE, NIPS'13]
- ✓ Model layer selection [AdaShare, ArXiv'19]

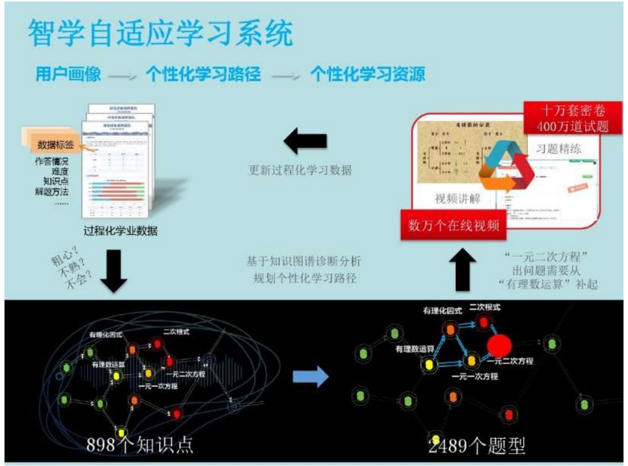
Some representative "adaptive cases" in machine learning

Background

- Adaptive in human learning

智学网

Adaptively teach few students



Adaptively teach more students

流利说

松鼠Ai

猿题库

可汗学院 khanAcademy

- "Adapts" based on the responses of the individual student, which dynamically adjusts the level or types of instruction based on individual student abilities or preferences. [Wikipedia]

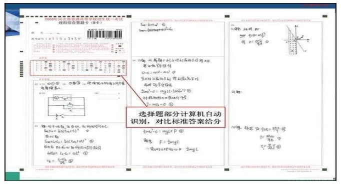
Background

Experienced teacher

Adaptive Learning Algorithms

Evidence

Limited learning records



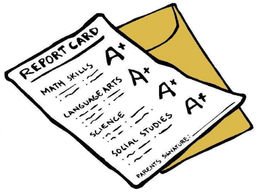
Large number of learning records

1	0	1	2	3	4
0	1	0	0	5	3
0	1	0	1	6	5

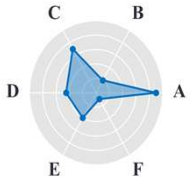
	一次函数	函数求导	线性规划
试题1	1	0	1
试题2	1	1	0
试题3	0	1	0
试题4	0	0	1
……			

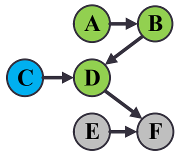
Evaluation

via score



via Cognitive diagnosis





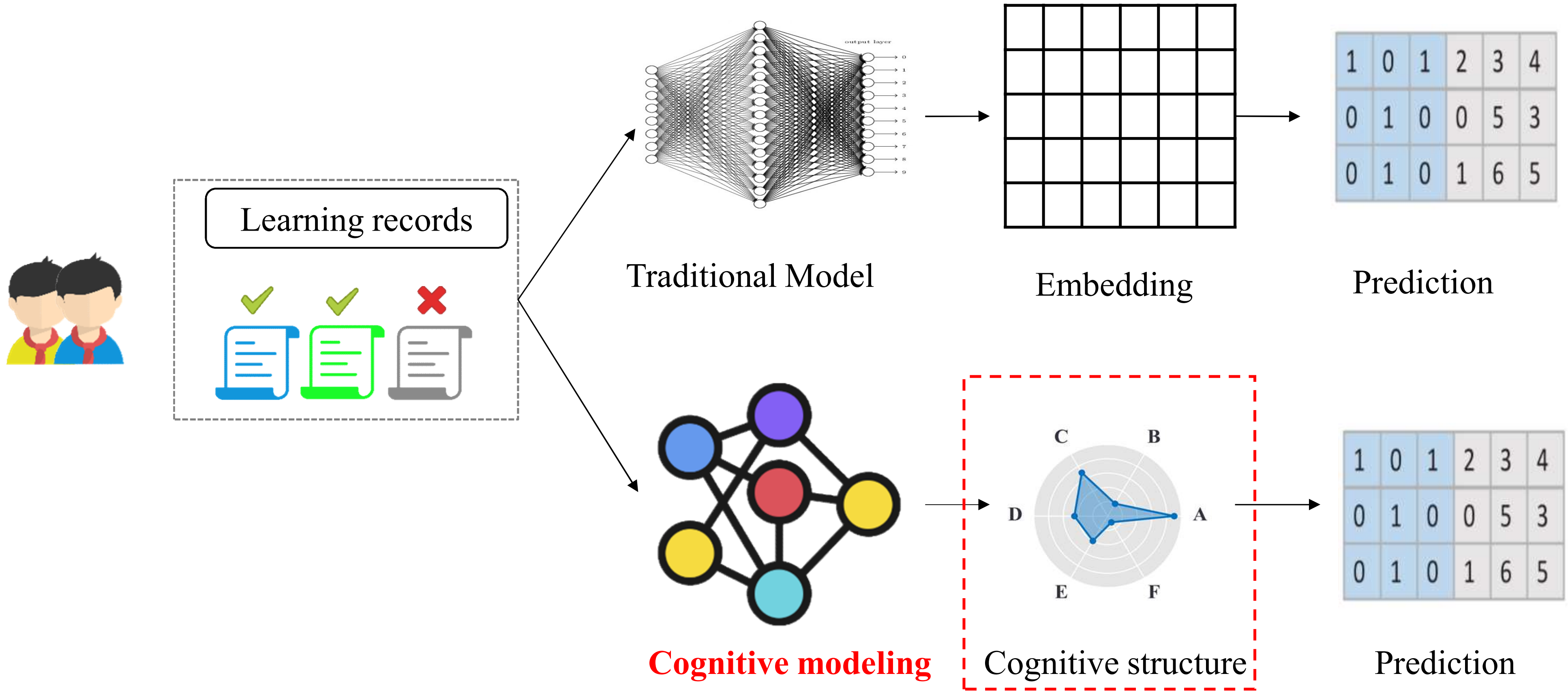
Solution

Offline teaching

Adaptive teaching

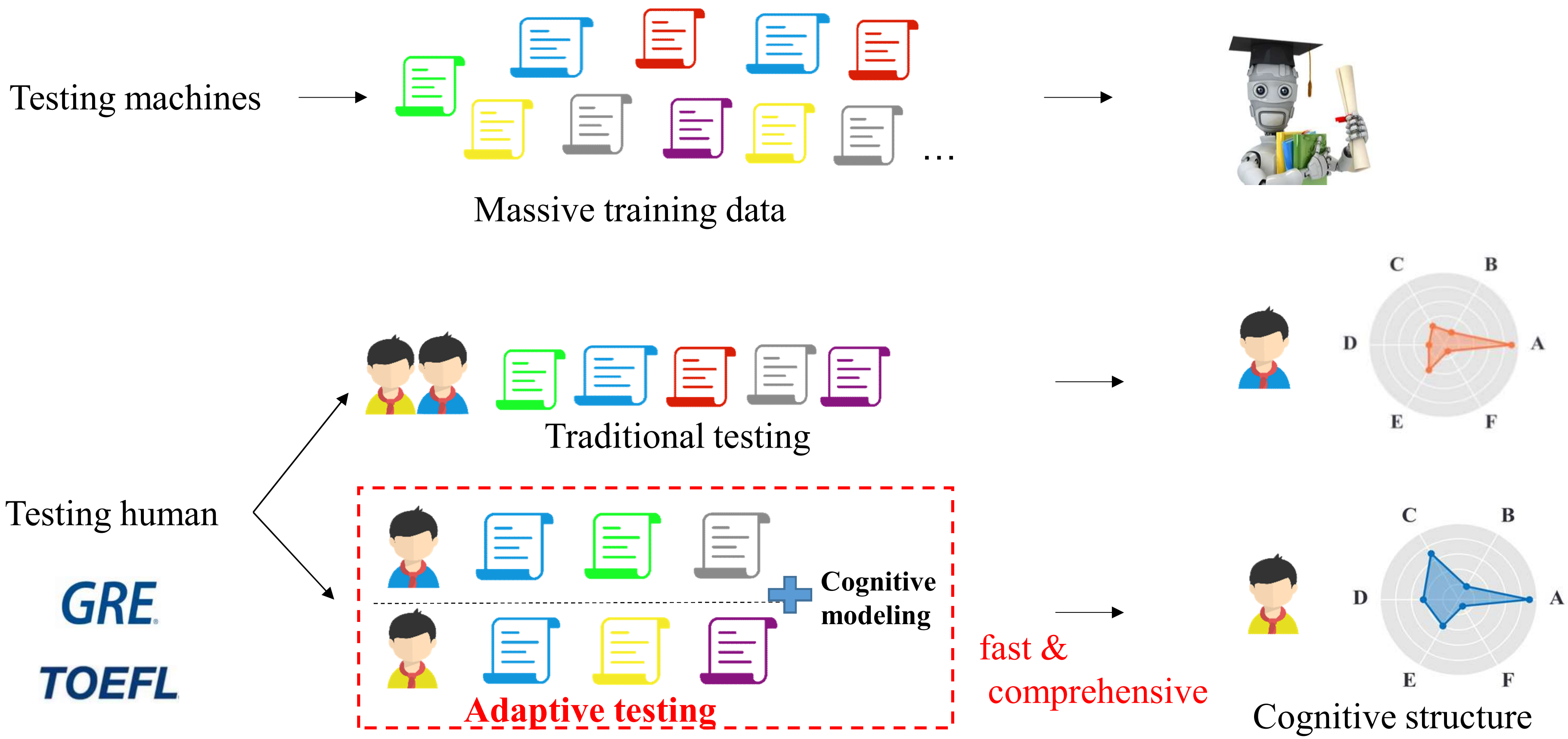
Background

➢ How to accurately evaluate the cognitive level of each student?



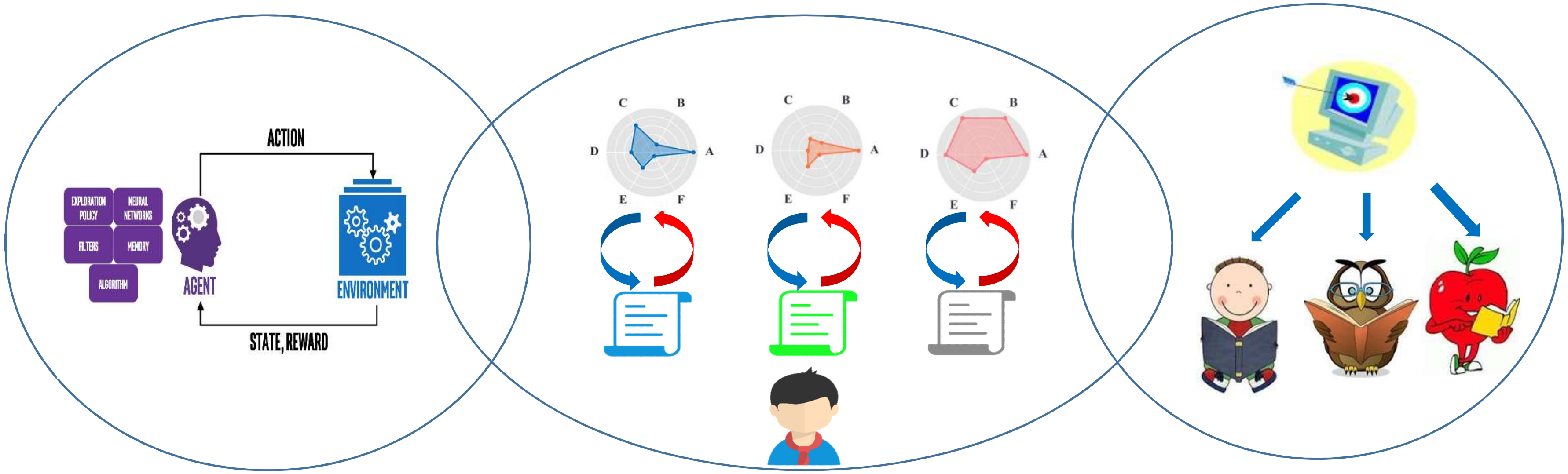
Background

➢ How to make fast & comprehensive testing to evaluate the cognitive level of student?



Background

- Given the cognitive level of each student, how to adaptively recommend personalized educational resources?



- Implicit context

- **Explicit cognitive context**
- **Cognitive context-aware**

- User interest-aware

Adaptive in machine learning

Adaptive in human learning

Traditional personalized recommendation

Background

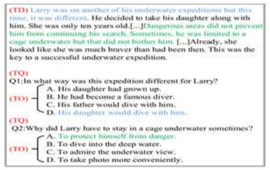
Response matrix R

1	0	1	2	3	4
0	1	0	0	5	3
0	1	0	1	6	5

Q-matrix

	一次函数	函数求导	线性规划
试题1	1	0	1
试题2	1	1	0
试题3	0	1	0
试题4	0	0	1
……			

Exercise Text



Challenges

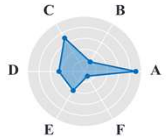
How to accurately evaluate the cognitive level of each student?

How to make fast & comprehensive testing to evaluate the cognitive level of student?

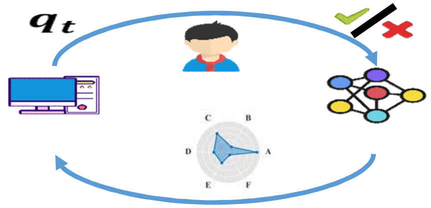
How to adaptively recommend personalized educational resources?

Solutions

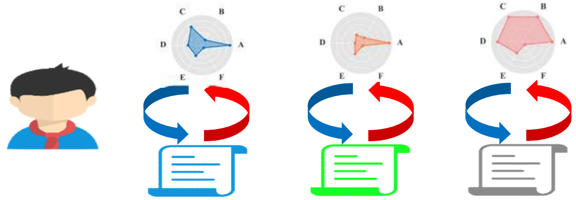
Cognitive Diagnosis



Adaptive Testing



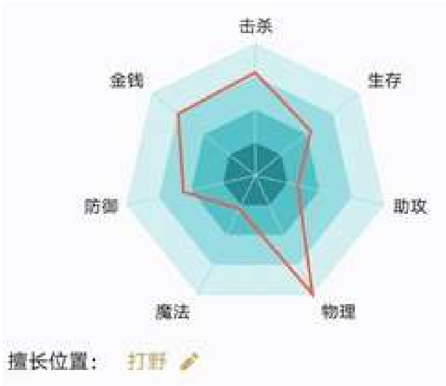
Cognitive Context-aware Recommendation

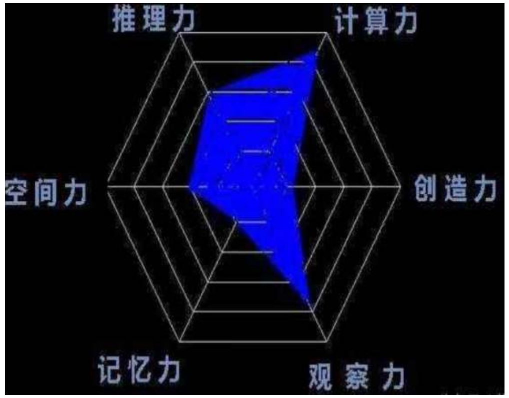


Outline

Cognitive Diagnosis

- Cognitive diagnosis（认知能力诊断）
  - Defination: diagnose the proficiency of participants on specific skills/concepts
  - Necessary: **adaptive learning is based on cognitive diagnosis**
    - Real-world scenarios: games, sports, recruitment, education, etc.





Cognitive diagnosis is a necessary and fundamental task.

Cognitive Diagnosis

- Problem Definition of Cognitive diagnosis
  - Given (Input):
    - Student-Exercise matrix R
      - R_{ij} denotes the response score of student i on exercise j
    - Exercise-Concept Q-matrix
      - If exercise j relates to concept k, $Q_{jk} = 1$
  - Goal (Output):
    - Student's proficiency on each concept/skill
      - E.g. in the range of [0,1]

Response matrix R

试题

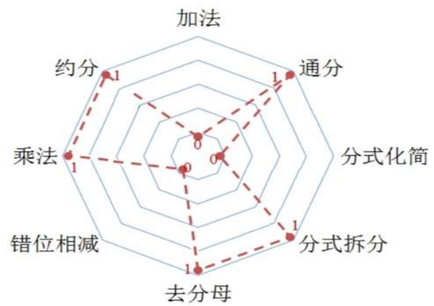
学生						
	1	0	1	2	3	4
	0	1	0	0	5	3
	0	1	0	1	6	5

Q-matrix

技能/知识点

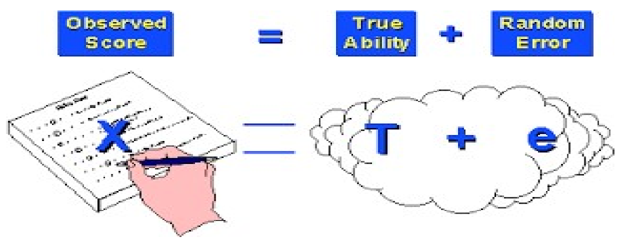
	一次函数	函数求导	线性规划
试题1	1	0	1
试题2	1	1	0
试题3	0	1	0
试题4	0	0	1
……			

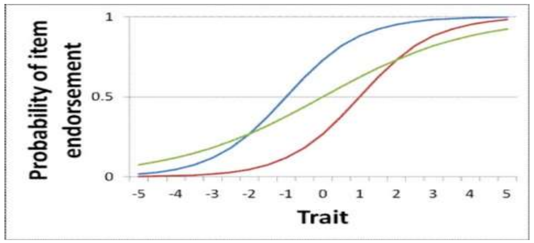
Cognitive diagnosis

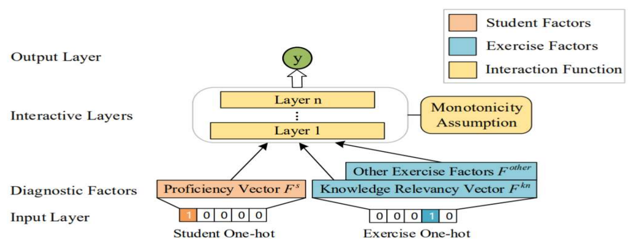


Cognitive Diagnosis

- Technological development







- early 20th century~ 1960s:
  - **Ability level paradigm**
  - Classical Measurement Theory (CTT)
  - Item Response Theory (IRT)
  - Describe the relationship among true score, errors and observation score

- 1960s~2010s :
  - **Cognitive level paradigm**
  - Multidimensional IRT(MIRT)
  - Describe the relationship between latent trait and item characteristics

- Now~ :
  - **Deep cognitive diagnosis paradigm**
  - deep learning-based cognitive diagnosis
  - Describe complex relationships

- Harold Gulliksen. 1950. Theory of mental tests
- A. Birnbaum. 1968. Some latent trait models and their use in inferring an examinee' s ability. Statistical theories of mental test scores (1968).
- J. De La Torre. 2009. DINA model and parameter estimation: A didactic. Journal of educational and behavioral statistics 34, 1 (2009), 115–130.
- Fei Wang, Qi Liu, Enhong Chen, et al. Neural Cognitive Diagnosis for Intelligent Education Systems. AAAI2020, Accepted.

Cognitive Diagnosis

- Item Response Theory (IRT)

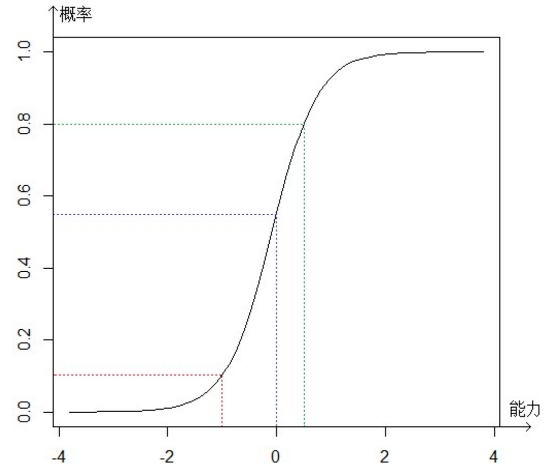
Guess factor

Skill proficiency

$$P(R_{uv} = 1|\theta_u, a_v, b_v, c_v) = c_v + \frac{1 - c_v}{1 + \exp(-1.7a_v(\theta_u - b_v))}$$

Discrimination

Difficulty



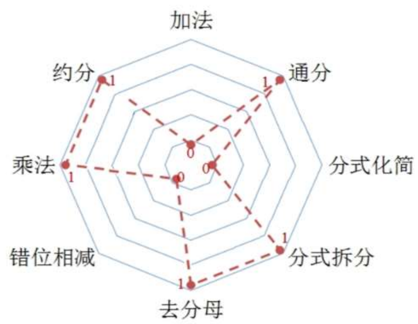
- DINA

$$P(Y_{ij} = 1 \mid \boldsymbol{\alpha}_i) = (1 - s_j)^{\eta_{ij}} (g_j)^{1-\eta_{ij}}$$

Skill proficiency vector

Slip

Guess



- A. Birnbaum. 1968. Some latent trait models and their use in inferring an examinee’ s ability. Statistical theories of mental test scores (1968).
- J. De La Torre. 2009. DINA model and parameter estimation: A didactic. Journal of educational and behavioral statistics 34, 1 (2009), 115–130.

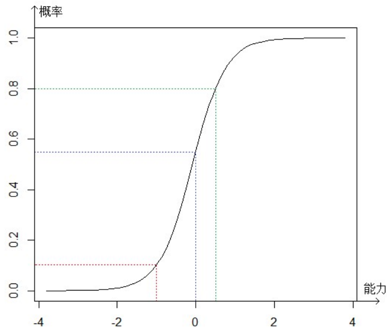
Cognitive Diagnosis

- Summary of existing methods
  - **Problems** in the interaction functions of traditional methods:
    - manually designed → labor intensive
    - mostly linear function → limited approximation ability
    - just numerical data → cannot mine heterogeneous big data

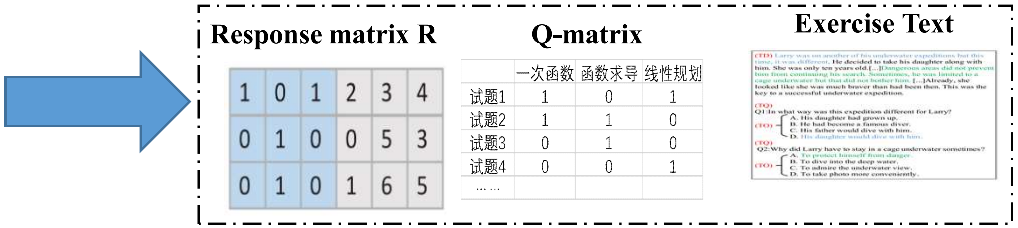
Deep cognitive diagnosis paradigm

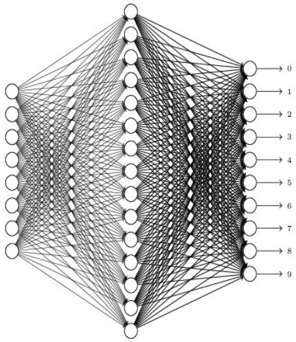
- Learn interaction function automatically from data with deep learning
  - manually designed, limited ability → automatically learned, high ability

IRT



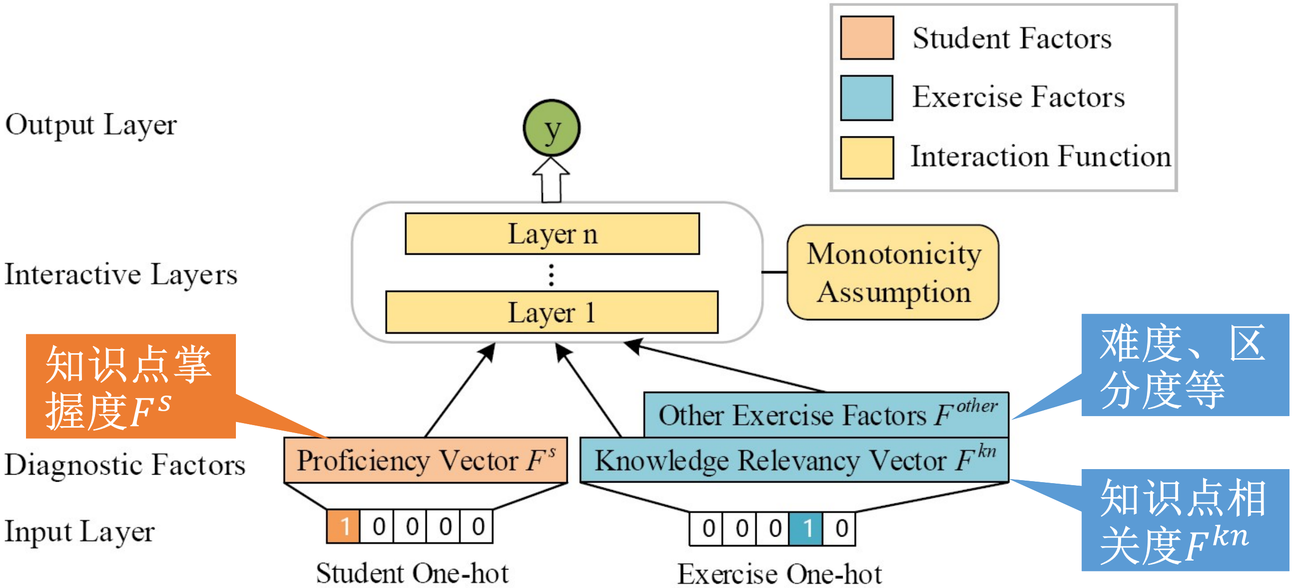
$$P(R_{uv}=1|\theta_u,a_v,b_v,c_v)=c_v+\frac{1-c_v}{1+\exp\left(-1.7a_v(\theta_u-b_v)\right)}$$





Neural Cognitive Diagnosis

- **Model Design :**
  - **Student Factors**: knowledge proficiency vector F^s
  - **Exercise Factors**: knowledge relevancy vector F^{kn}
    - other exercise factors F^{other} (optional): e.g., difficulty, discrimination
  - **Interaction Function**: interactive multi-layers
  - **Output**: The probability that the student would correctly answer the exercise

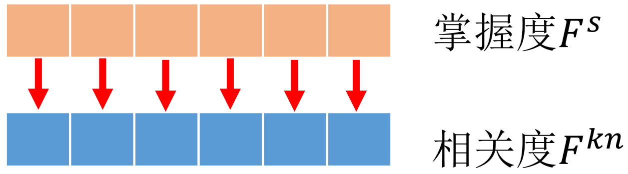


Fei Wang, Qi Liu, Enhong Chen et al. Neural Cognitive Diagnosis for Intelligent Education Systems. *AAAI2020, Accepted.*

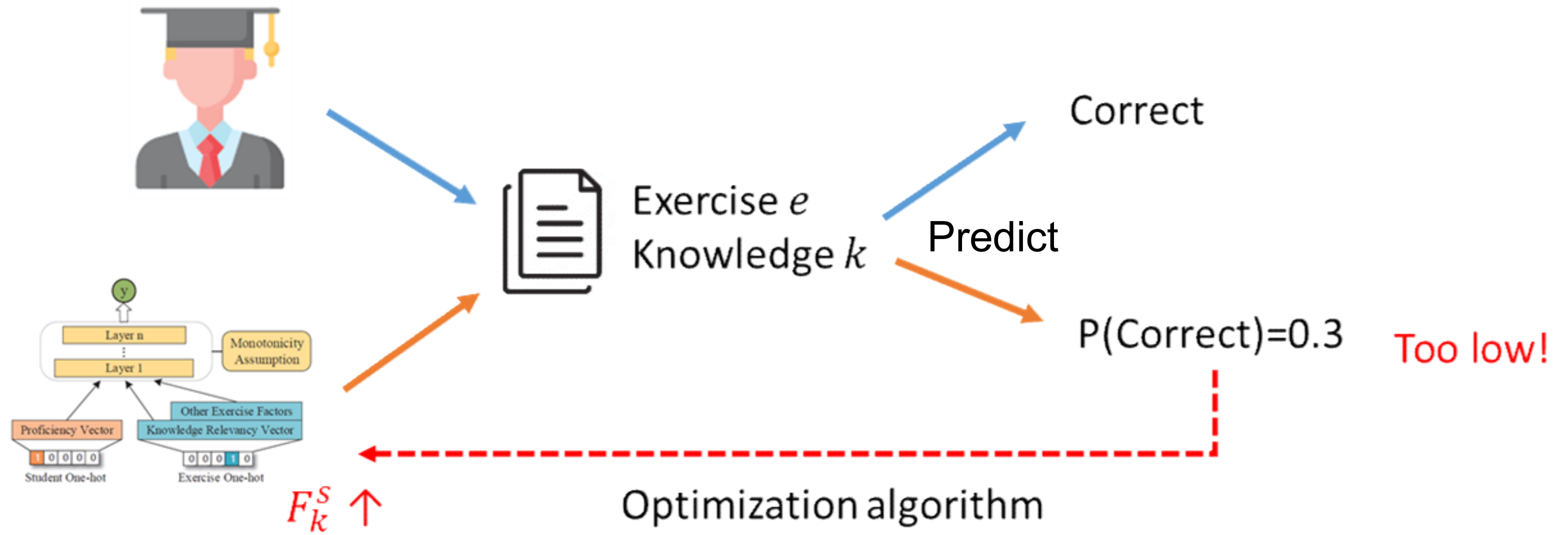
Neural Cognitive Diagnosis

➢ Explainable

- ➢ Explainably model student knowledge states
- ➢ $\boldsymbol{F^s} \circ \boldsymbol{F^{kn}}$: attach each entry of F^s to a specific knowledge concept

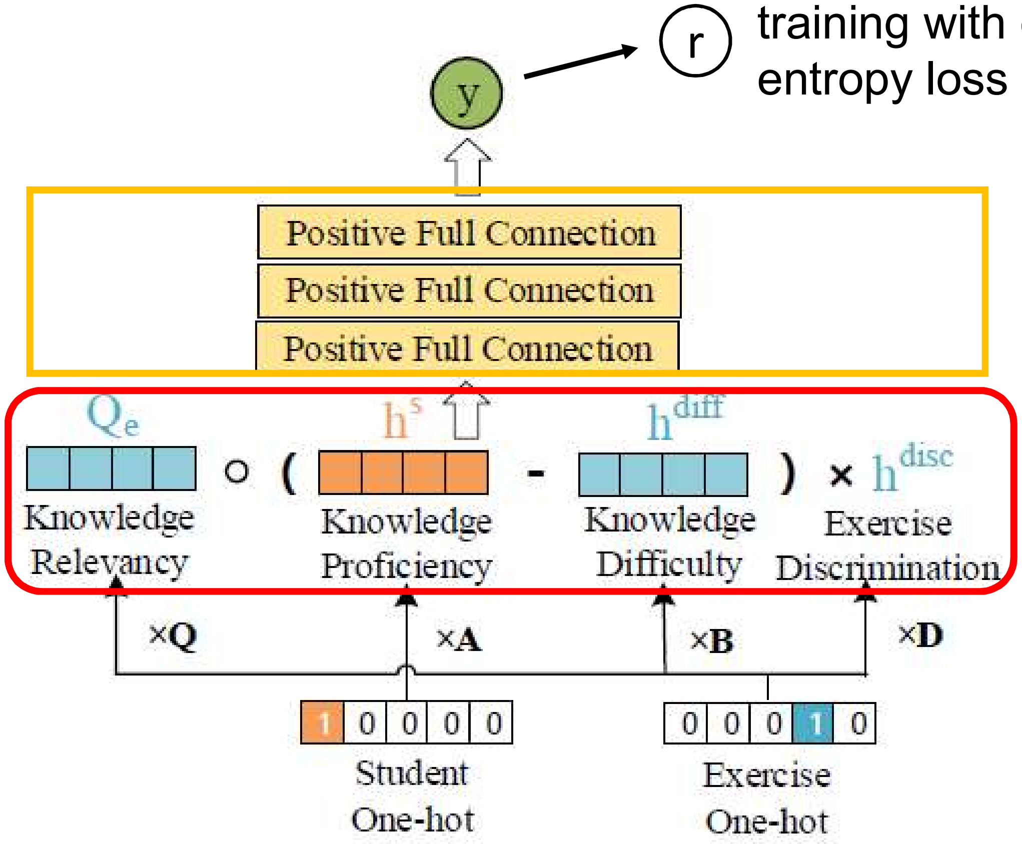


- ➢ **Monotonicity Assumption**: *The probability of correct response to the exercise is monotonically increasing at any dimension of the student's knowledge proficiency.* (widely applicable)



Neural Cognitive Diagnosis

➢ **NeuralCDM:** One basic implementation of NeuralCD with Q-matrix



interaction layer:
- full connection
- positive weights

Monotonicity Assumption

input layer:

$Q_e \circ (h^s - h^{diff}) \times h^{disc}$

$F^{kn} \circ F^s$

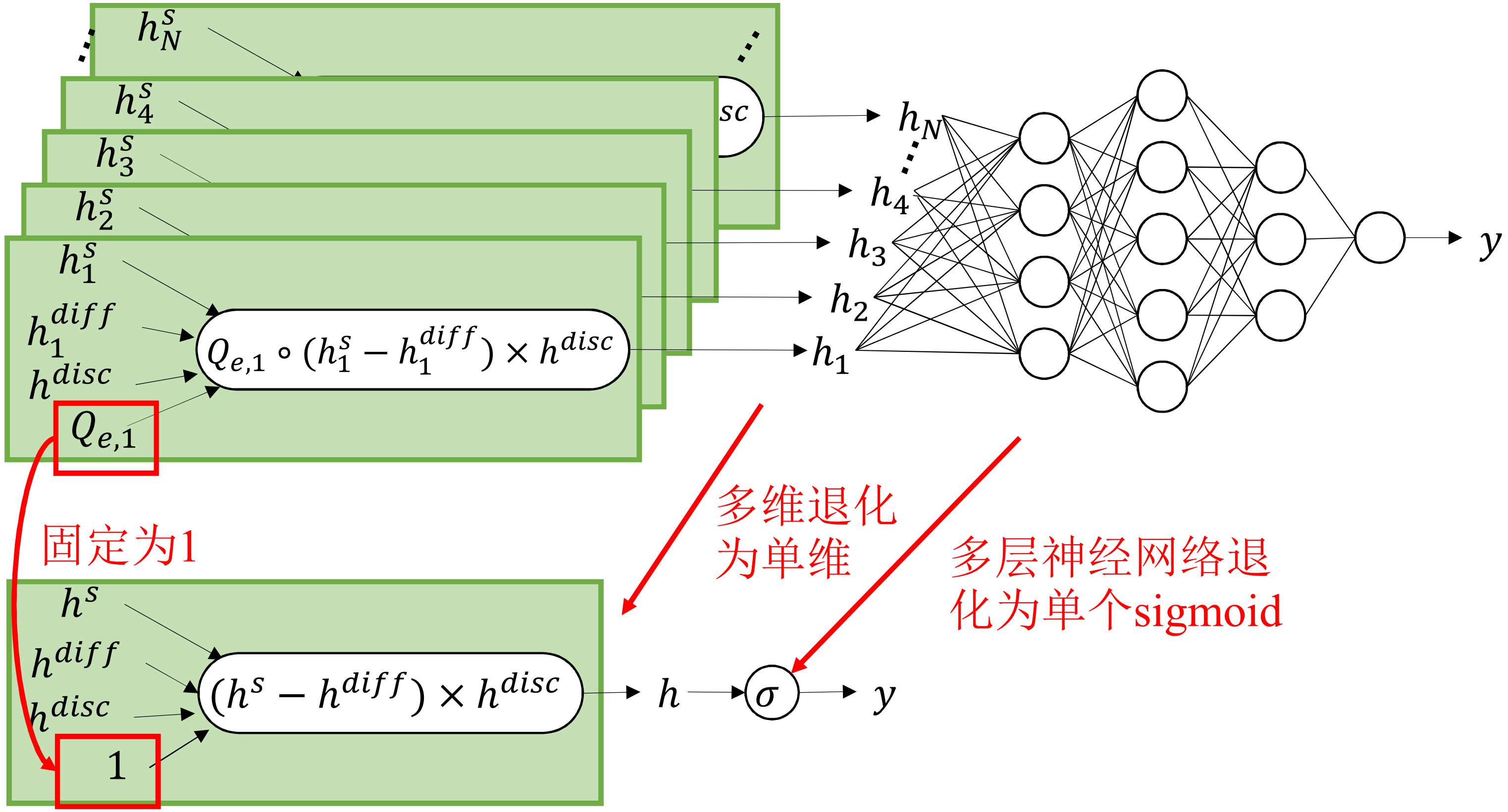
Directly from Q-matrix

	一次函数	函数求导	线性规划
试题1	1	0	1
试题2	1	1	0
试题3	0	1	0
试题4	0	0	1
……			

Neural Cognitive Diagnosis

- **General**:
  - NeuralCD framework is general and can cover some traditional models
  - e.g., MF, IRT, MIRT

NeuralCDM



IRT

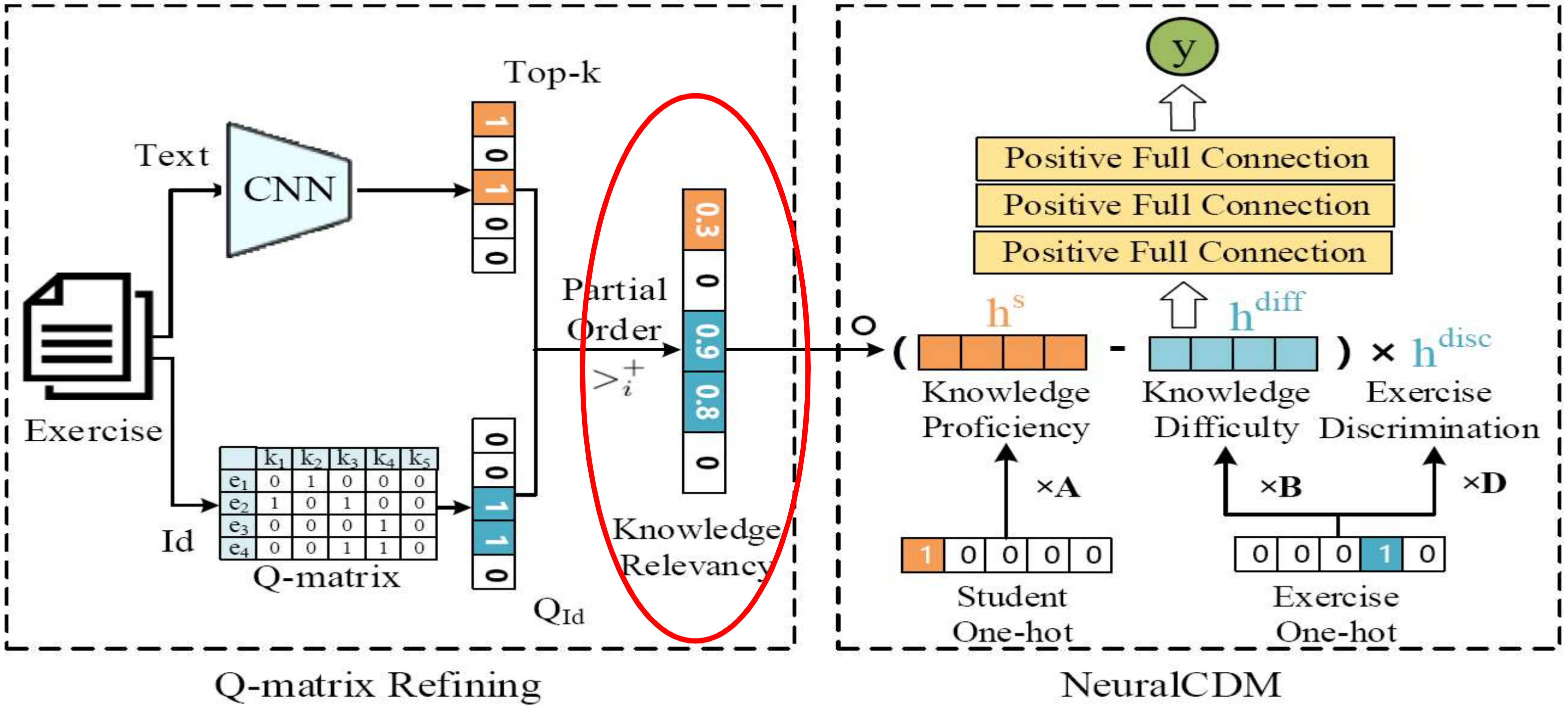
$$P(R_{uv} = 1|\theta_u, a_v, b_v, c_v) = c_v + \frac{1 - c_v}{1 + \exp\left(-1.7a_v(\theta_u - b_v)\right)}$$

Neural Cognitive Diagnosis

➢ Extendible

- refine Q-matrix with exercise texts
- pre-train a CNN to predict knowledge concepts of the input exercise
- combine with Q-matrix through a partial order probabilistic scheme:

NeuralCDM+



knowledge relevancy: Q-matrix >= predicted > other = 0

Neural Cognitive Diagnosis

- **Experiment**
  - **Datasets**

Dataset	Math	ASSIST
#Students	10,268	4,163
#Exercises	917,495	17,746
#Knowledge concepts	1,488	123
#Response logs	864,722	324,572
#Knowledge concepts per exercise	1.53	1.19
$AVG_{\#log}$	2.28	8.05
$STD_{\#log>1}$	0.305	0.316

- **Math**: private, mathematical exercises (with texts) and logs
- **ASSIST**: public, mathematical exercises (without texts) and logs

  - **Student performance prediction**

Model	Math			ASSIST		
	Accuracy	RMSE	AUC	Accuracy	RMSE	AUC
DINA	0.593±.001	0.487±.001	0.686±.001	0.650±.001	0.467±.001	0.676±.002
IRT	0.782±.002	0.387±.001	0.795±.001	0.674±.002	0.464±.002	0.685±.001
MIRT	0.793±.001	0.378±.002	0.813±.002	0.701±.002	0.461±.001	0.719±.001
PMF	0.763±.001	0.407±.001	0.792±.002	0.661±.002	0.476±.001	0.732±.001
NeuralCDM	0.792±.002	0.378±.001	0.820±.001	**0.719±.008**	**0.439±.002**	**0.749±.001**
NeuralCDM+	**0.804±.001**	**0.371±.002**	**0.835±.002**	-	-	-

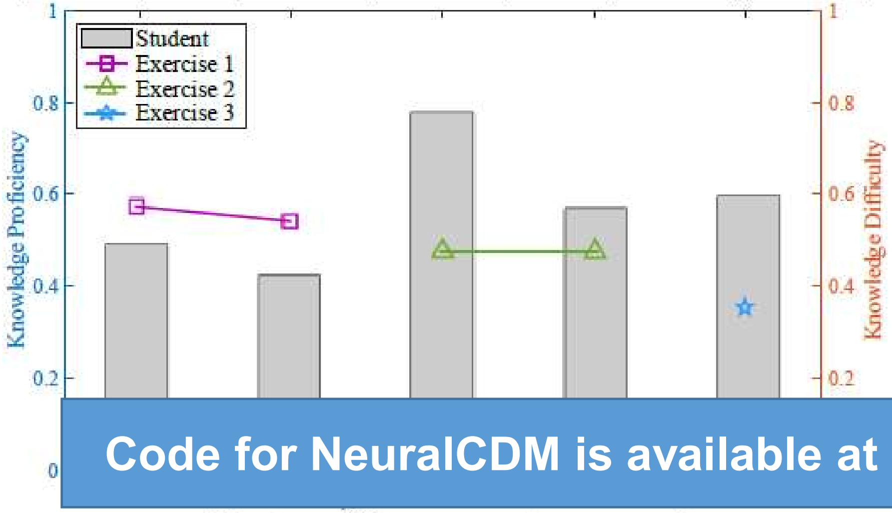
Best

Neural Cognitive Diagnosis

- **Adaptive Diagnosis**
  - a student's performance on 3 exercises in ASSIST
  - and his/her diagnosed result

Q-Matrix | Response

	Number Line	Solving Inequalities	Add Whole Numbers	Absolute Value	Ordering Fractions	Student Response
Exercise 1	1	1	0	0	0	✗
Exercise 2	0	0	1	1	0	✓
Exercise 3	0	0	0	0	1	✓



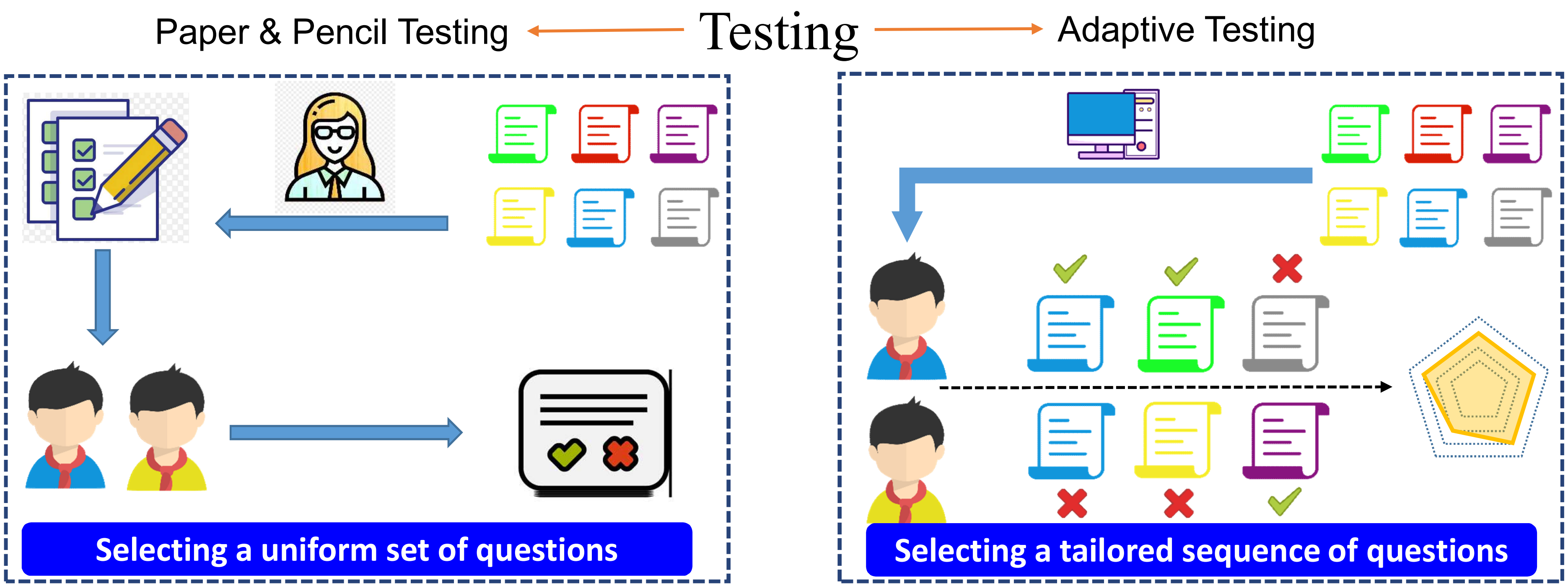
The student is more likely to answer correctly when his/her knowledge proficiency satisfies the requirement of the exercise.

Code for NeuralCDM is available at https://github.com/bigdata-ustc/NeuralCD

Outline

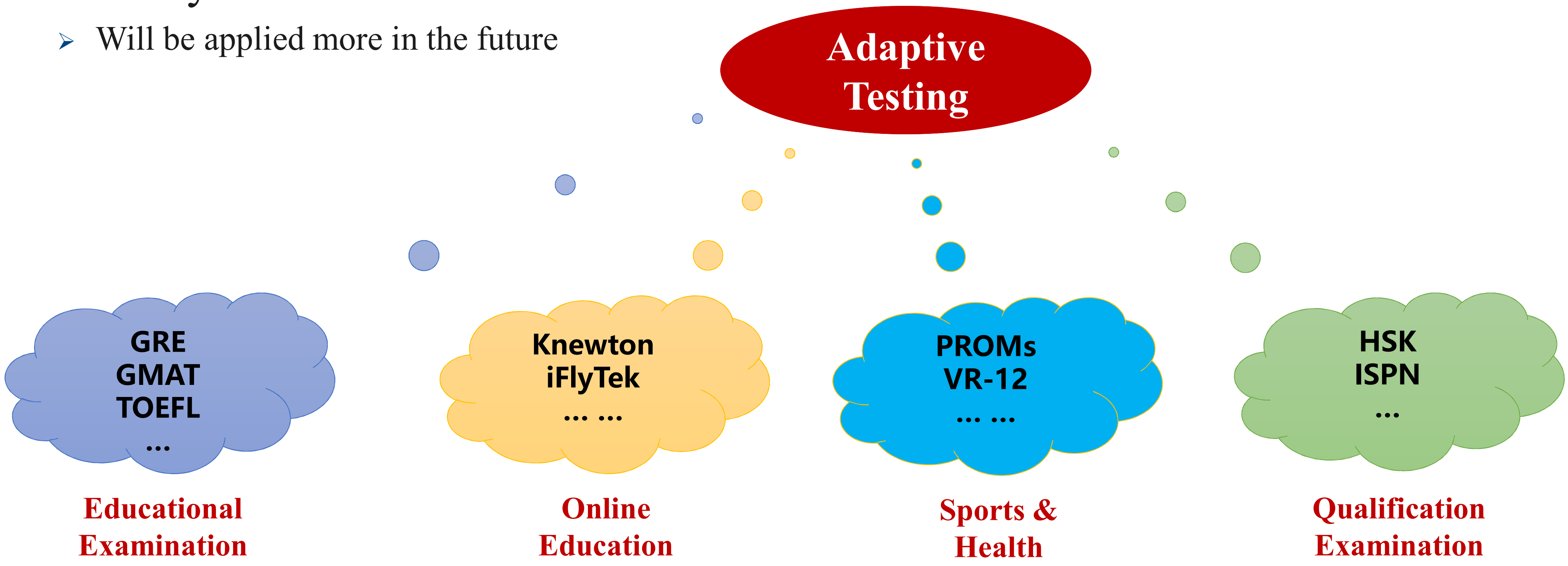
What is Adaptive Testing

- Adaptive Testing: a promising form of computer-administrated examination
  - different from traditional “ Paper and Pencil testing”
  - interactively select questions for students, based on his/her current performance



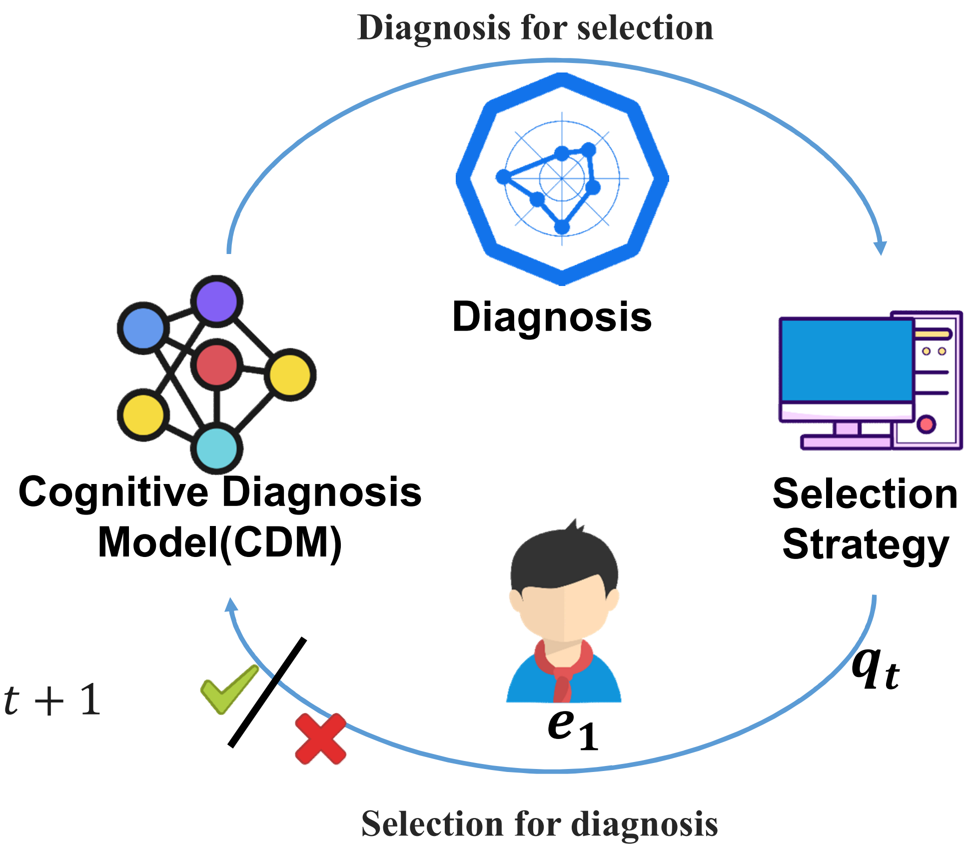
Application of Adaptive Testing

- More and more adaptive testing applications
  - Improve the experience of both examiners and examinees
- Not only in educational exams
  - Will be applied more in the future



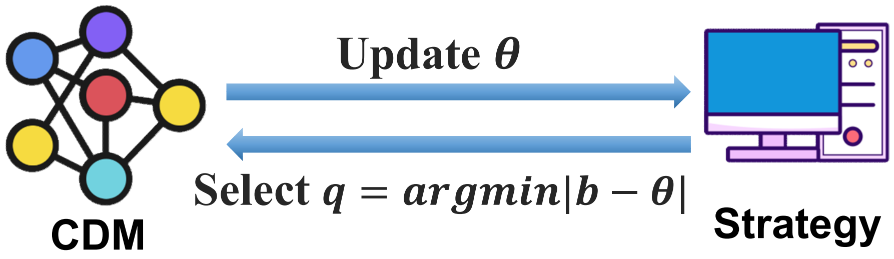
Formalization of Adaptive Testing

- Adaptive Testing Framework
  - **Cognitive Diagnosis Model (CDM)**
    - Input: examinee records
    - Output: diagnosis for examinee ability
    - Example: IRT, NeuralCD
  - **Selection Strategy**
    - Input: examinee ability
    - Output: the next question
- Adaptive Testing Procedure
  - Input: new examinee e_1
  - Procedure: step t → select → answer → diagnose → step $t+1$
  - Output: diagnosis for e_1



Related Work in Adaptive Testing

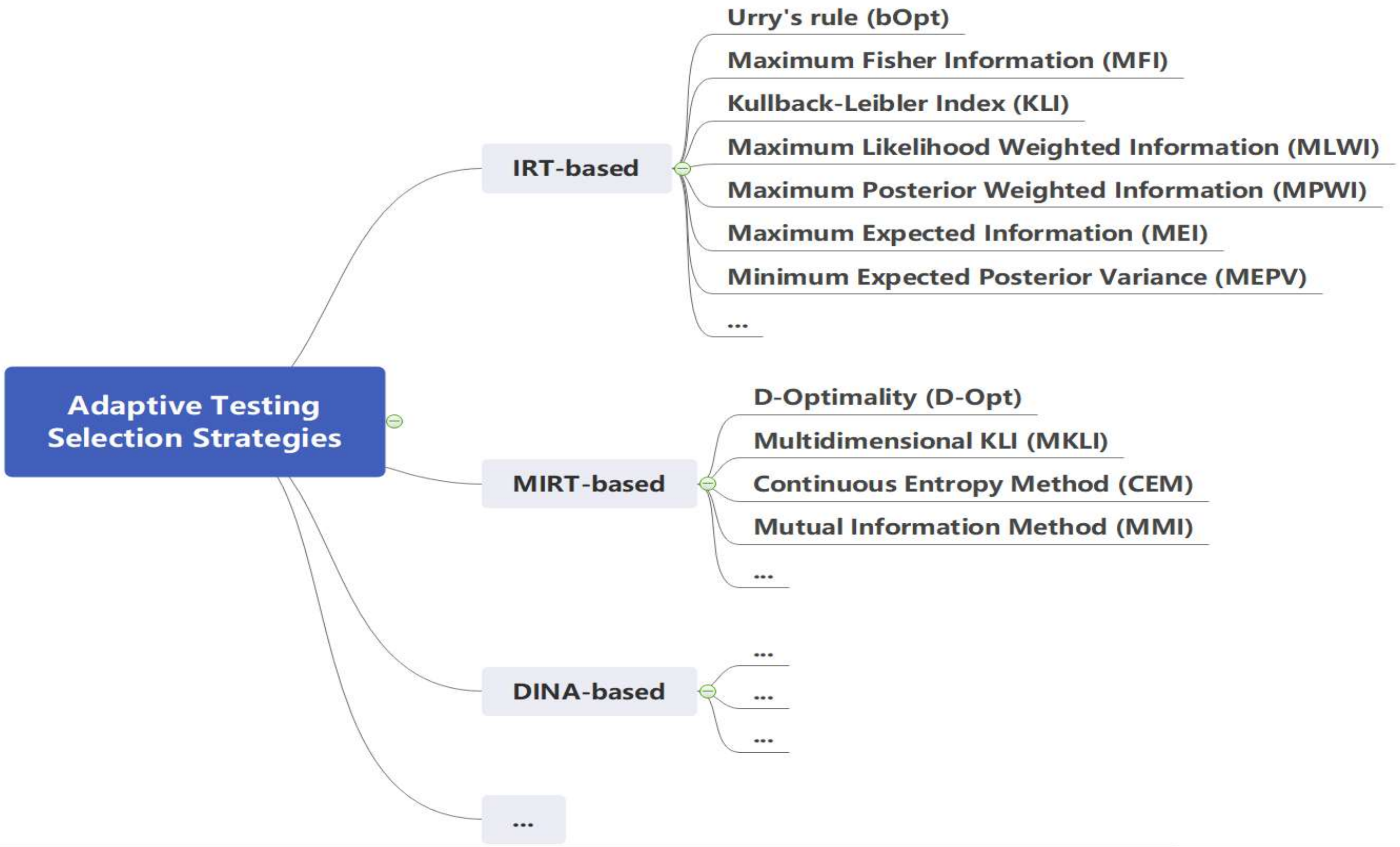
- Methodology:
  - Heuristic: $h(q)$ = informativeness of question
  - Greedy: $q_t^* = argmax_{q\in Q} h(q)$
- By informativeness we mean
  - Generally: information a question offers while answered by the examinee
  - Specifically: accuracy of parameter estimation of the CDM
- Example: a simple IRT-based strategy
  - Intuition: matching difficulty with ability
  - Procedure: (bOpt)



$$\overbrace{\boxed{\boldsymbol{p}}}^{\text{Prob done right}}(\boldsymbol{a},\underbrace{\boxed{\boldsymbol{b}}}_{\text{difficulty}}|\overbrace{\boxed{\boldsymbol{\theta}}}^{\text{ability}}) = \frac{\mathbf{1}}{\mathbf{1} + \boldsymbol{e}^{-\boldsymbol{a}(\boldsymbol{\theta}-\boldsymbol{b})}}$$

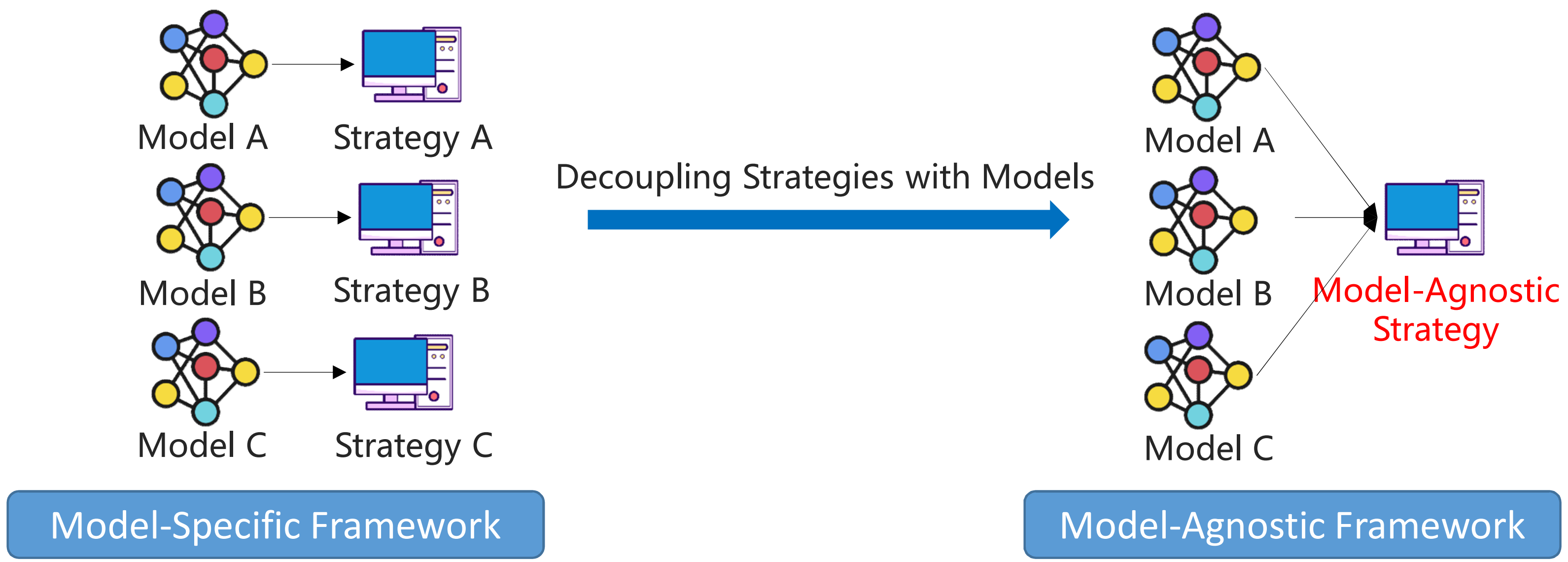
Development of Adaptive Testing

- Following the same idea, there are a number of adaptive testing strategies
  - Categorized by their underlying CDMs



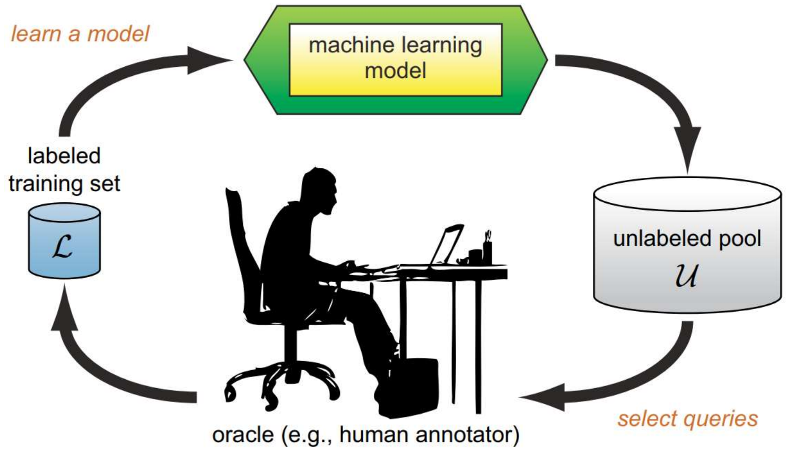
Challenge in Adaptive Testing

- Model-specific methodology leads to inflexible framework
  - IRT model → IRT-based strategy → only dedicated to IRT
  - MIRT → redesign MIRT-based strategy → only dedicated to MIRT
  - NeuralCDM → hard to redesign → no suitable strategy currently
- We need a model-agnostic framework



Inspiration from Machine Learning

- Adaptive Testing: from a data scientist's perspective
  - Selects valuable data samples for models
- Active Learning: Inspire us with a model-agnostic solution
  - Applies data querying strategies to a wide range of models and tasks
  - ① Abstract the underlying models without specific assumptions
  - ② Uplift the objectives to a high level



Active Learning Concepts	Adaptive Learning Counterparts
Labeled dataset	Tested question set
Unlabeled dataset	Untested question set
Learning model	Diagnosis model
Active query selection	Question selection
Person annotator	Student

How to Achieve Model-Agnostic

- CDM abstraction from specific models
  - Ability parameters without interpretation assumption

IRT $p(\boxed{\boldsymbol{\theta}}) = \frac{1}{1+e^{-a(\theta-b)}}$

MIRT $p\left(\boxed{\vec{\theta}}\right) = \frac{1}{1+e^{-\vec{a}^T\left(\vec{\theta}-\vec{b}\right)}}$

…… ……

$\Rightarrow \mathcal{M}(\boldsymbol{\theta})$

- Optimization objective at a high level
  - Original objective: make parameters estimated accurately
  - From an educational perspective, is that enough ?

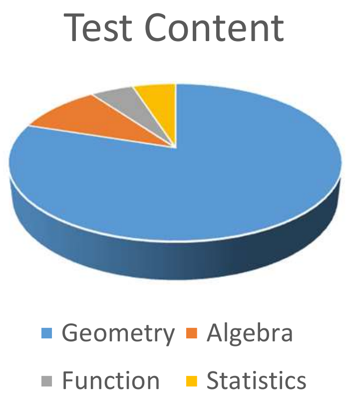
Quality and Diversity: Proper Objectives

What should appropriate questions look like ?

$\mathcal{M}(\boldsymbol{\theta}) \updownarrow ?$

- High-quality: contains enough information
  - Understand examinees accurately
  - The more information, the more uncertainty in the change of model parameters
- Diverse: covers enough knowledge points
  - Understand examinees comprehensively

Nothing useful if the student will definitely answer the question right/wrong



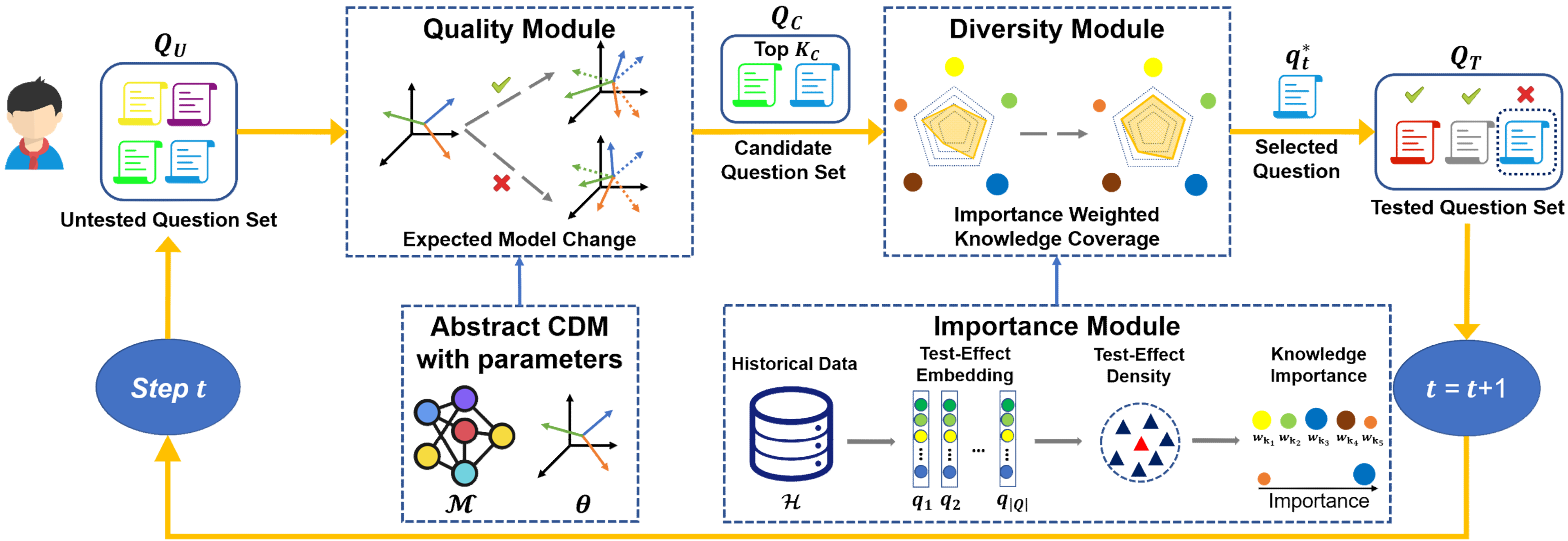
Biased results if the knowledge coverage is imbalanced

Our Work: Framework Overview

- Model-Agnostic Adaptive Testing (MAAT)
  - Work with an abstract model to achieve model-agnostic
  - Aim at the two high-level objective in a two-stage method

high-quality questions

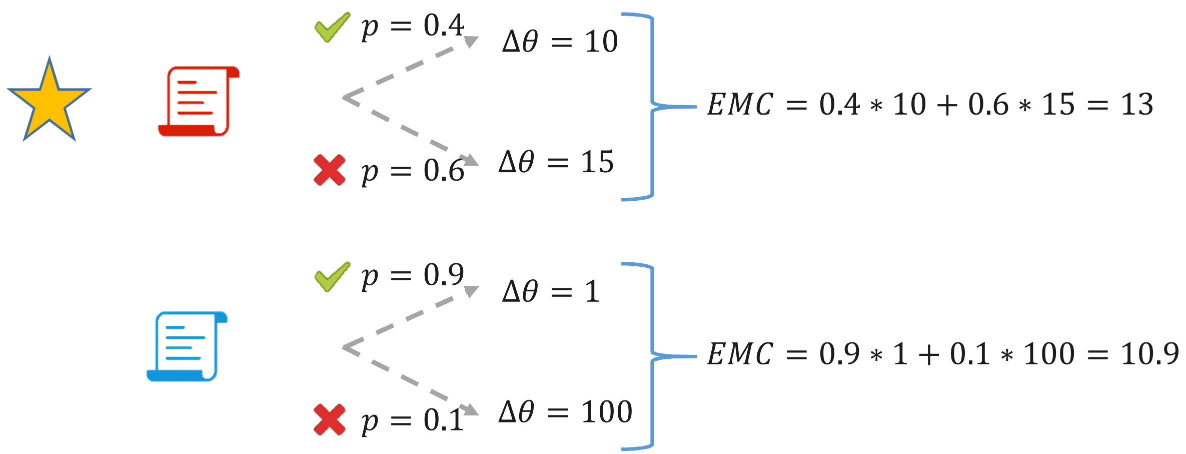
diverse questions

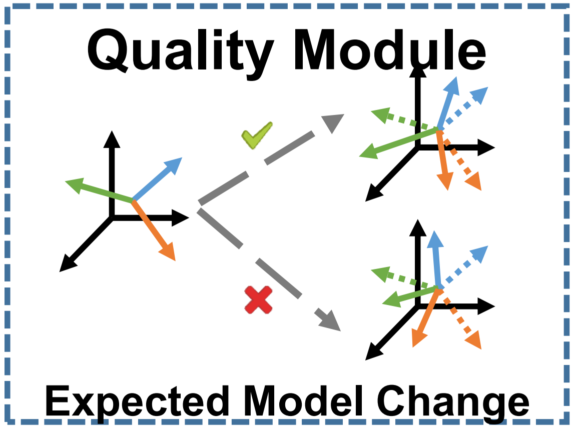


Quality Module: Select High-quality Questions

- Quantify the quality of a question
  - How we measure the information the abstract CDM obtains
- Expected Model Change (EMC)
  - Idea: the more information of question, the more uncertainty in the change of model parameters
  - Challenge: change is unknown before the student answer the question
    - Solution: estimate with expectation

$$\mathrm{EMC}(q_j) = \mathbb{E}_{a_{ij} \sim p} \Delta \mathcal{M}(< e_i, q_j, a_{ij} >)$$



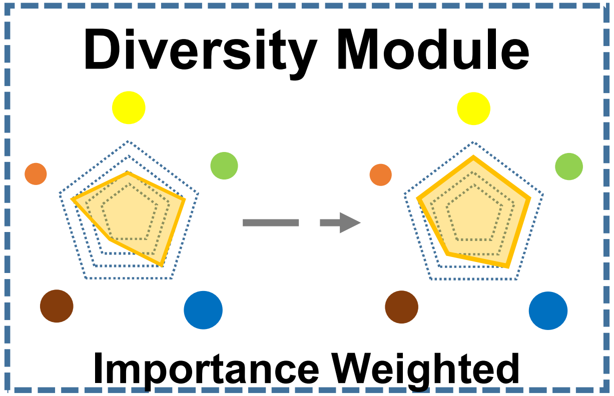


Diversity Module: Select Diverse Questions

- Quantify the diversity of the candidate questions
  - Intuitively done with knowledge concepts related to questions
- Importance Weighted Knowledge Coverage (IWKC)
  - Idea: the more knowledge concepts covered, the more diverse of the questions

$$\mathrm{IWKC}(Q_T) = \frac{\sum_{k \in K} w_k * IncCov(k, Q_T)}{\sum_{k \in K} w_k},$$

$$IncCov(k, Q_T) = \frac{cnt(k, Q_T)}{cnt(k, Q_T) + 1},$$

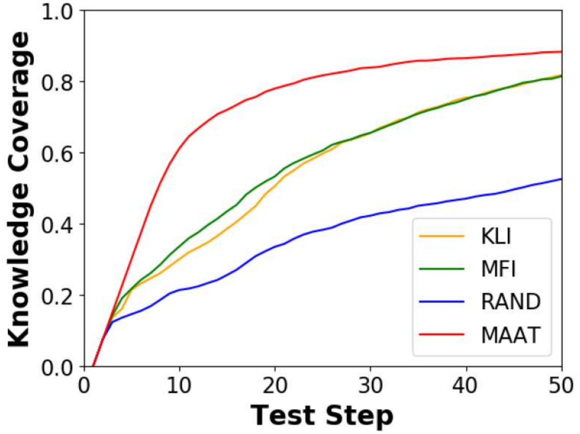


- Challenge:
  - Difficulty: subset selection with maximizing IWKC is NP-hard
  - Solution: fortunately with the submodular property of IWKC, the simple greedy algorithm can achieve a suboptimal solution with optimal ratio $1 - \frac{1}{e}$

Theoretically Guarantee

Experiments

- Two real datasets on education
- Quality comparison
  - AUC on performance prediction
- Diversity comparison
  - Coverage on knowledge



(a) IRT on EXAM

TABLE III
QUALITY COMPARISON WITH AUC METRIC

(a) EXAM

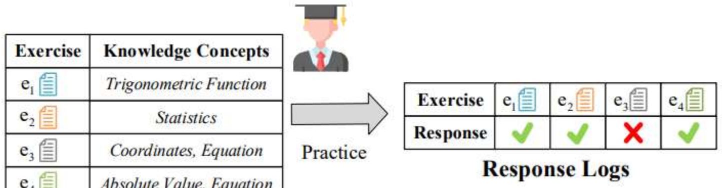
Methods	IRT		MIRT		NCDM	
	@25	@50	@25	@50	@25	@50
RAND	0.6435	0.7076	0.7426	0.7767	0.7081	0.7566
MFI	0.7092	0.7207	-	-	-	-
KLI	0.7081	0.7257	-	-	-	-
D-Opt	-	-	0.7515	0.7710	-	-
MKLI	-	-	0.7502	0.7747	-	-
MAAT	**0.7192**	**0.7319**	**0.7600**	**0.7861**	**0.7614**	**0.7868**

TABLE IV
RESULTS ON A TYPICAL EXAMINEE FOR CASE STUDY

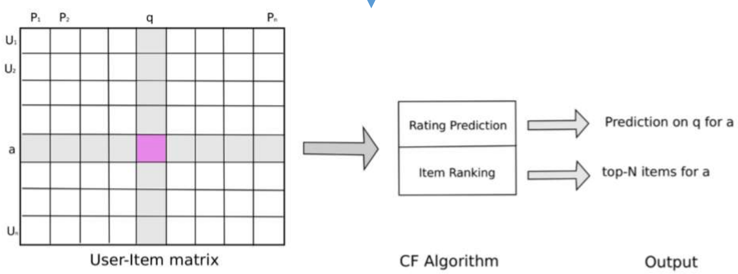
MAAT		D-Opt		MKLI	
Function	0.6666	Function	0.6652	Triangle	0.6645
Set	0.6710	Equation	0.6686	Algebra	0.6689
Equation	0.6763	Equation	0.6717	Equation	0.6732
Triangle	0.6841	Triangle	0.6756	Function	0.6774
Algebra	0.6905	Geometry	0.6801	Algebra	0.6810
Triangle	0.6961	Function	0.6857	Function	0.6843
Coordinates	0.7022	Geometry	0.6914	Function	0.6887
Geometry	0.7087	Triangle	0.6956	Triangle	0.6929
Real Number	0.7136	Algebra	0.6963	Inequality	0.7001
Equation	0.7188	Function	0.6998	Geometry	0.7057

Outline

Traditional recommendation

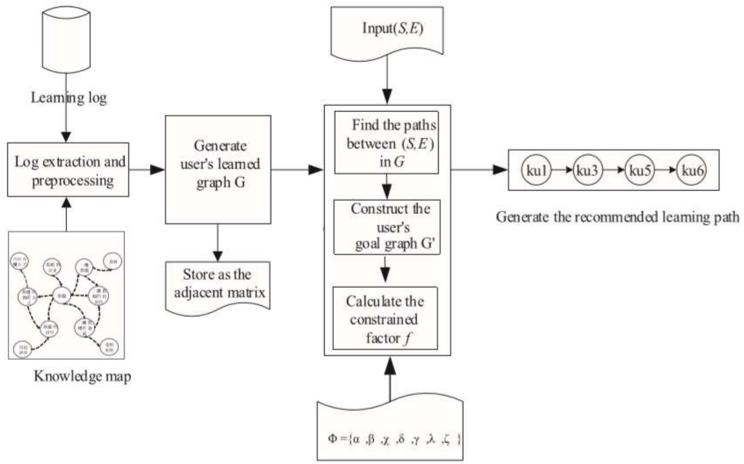


Collaborative filtering on student response matrix and recommend the exercise more likely to be correctly answered.



Thai-Nghe et al. 2010

Based on learning trajectory and knowledge structure, adopt expert system to recommend learning path.



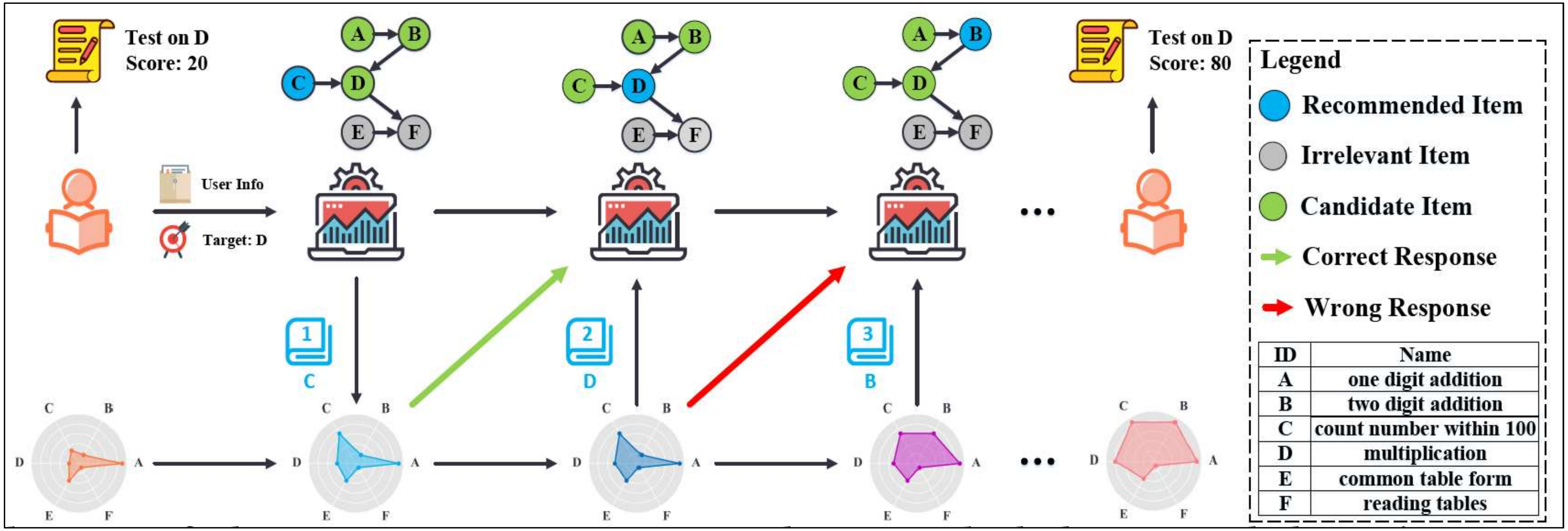
Zhu et al. 2018

Assuming student state is static makes it hard to capture the dynamic cognitive context, which impairs the model ability to provide suitable recommendation.

Cognitive Context-aware Recommendation

- Adapt to the implicit **evolving cognitive context** of the learner
- Keep the learning path be **in accordance with the logicality** determined by the knowledge structure (e.g. prerequisites)

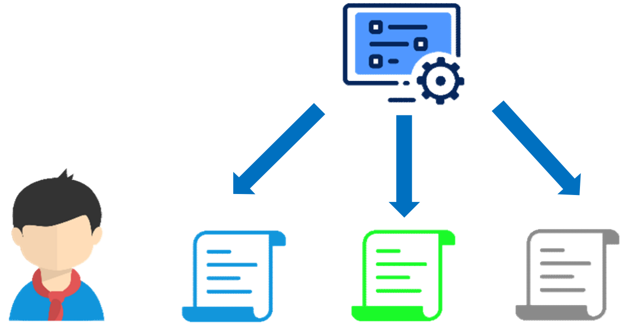
knowledge structure of items



cognitive context of learner

Cognitive Context-aware Recommendation

Traditional static adaptive recommendation



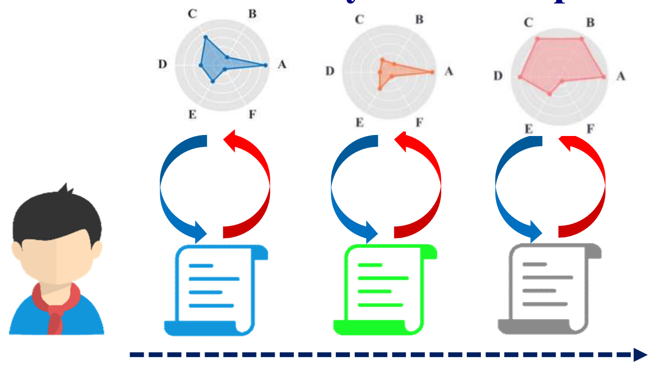
- Recommend all items at one time
- Without Interaction
- Context-blind

Limitation

Without precisely modeling cognitive context, it is hard to recommend suitable items.

Cognitive Context-aware Recommendation

Interactive dynamic adaptive recommendation



- Multi-round interaction
- Adaptively adjust recommendation strategy according to cognitive context

Challenge

How to model the evolving cognitive context?

How to stay with the logicality of knowledge structure ?

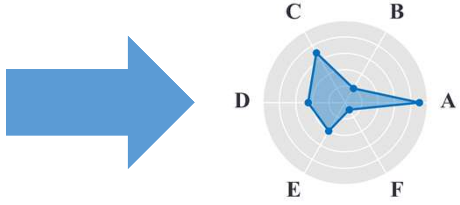
How to maximize the overall gain along the learning path?

Evolving Cognitive Context Modeling

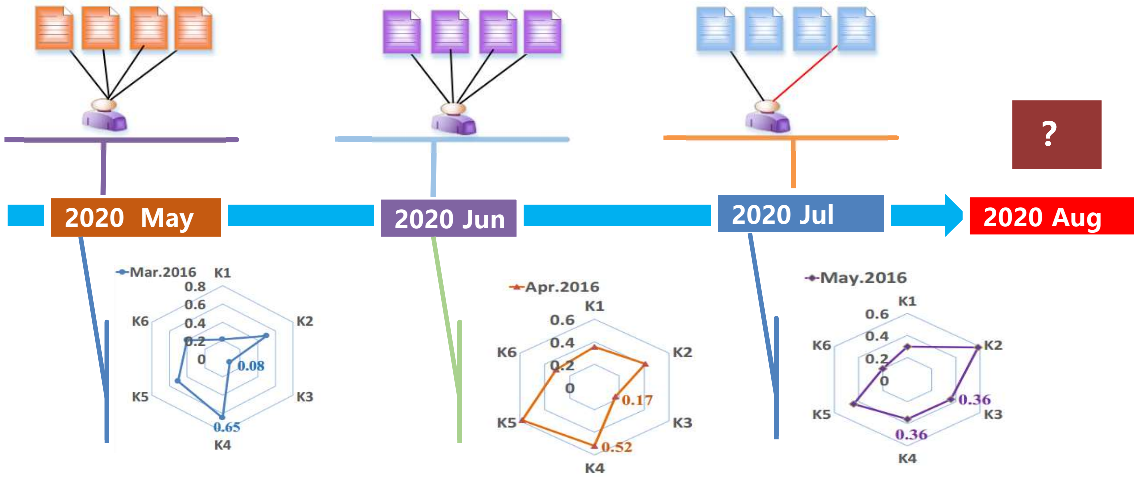
- Cognitive Diagnosis
  - IRT, MIRT, …
  - DIRT, NeuralCD
  - …
  - Problem: only model the static cognitive context
- Knowledge Tracing (Dynamic Cognitive Diagnosis)
  - BKT (Bayesian knowledge tracing)
  - DKT
  - EKT
  - …

Exercise	e_1	e_2	e_3	e_4
Response	✓	✓	✗	✓

Response Logs



Student ability keeps evolving during learning

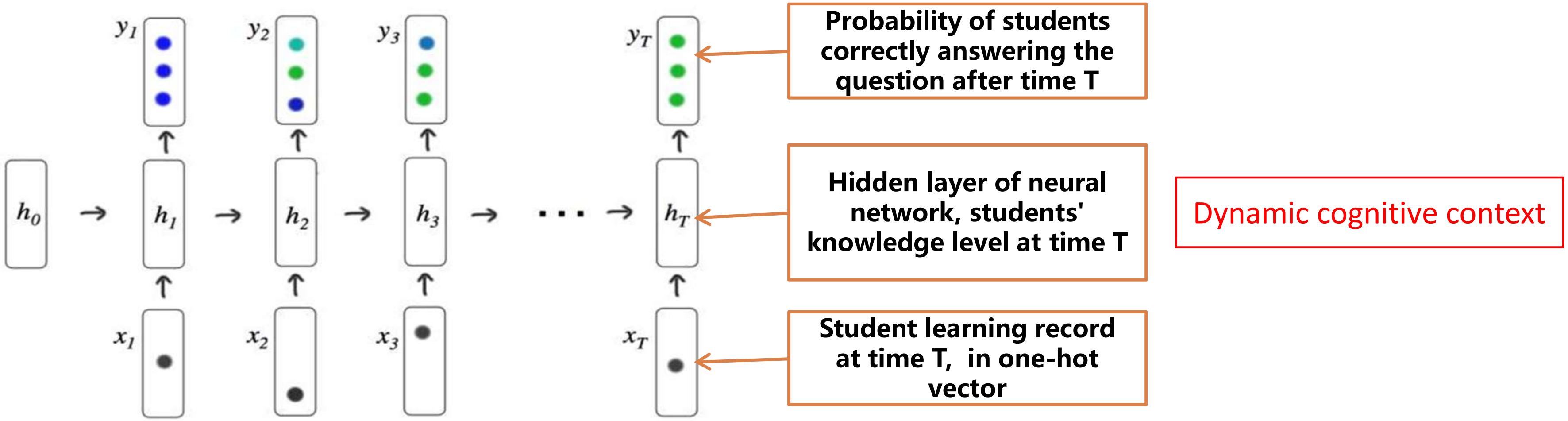


How to model the dynamic evolving cognitive context along time?

- Corbett A T, Anderson J R. Knowledge tracing: Modeling the acquisition of procedural knowledge[J]. User modeling and user-adapted interaction, 1994, 4(4): 253-278.

Evolving Cognitive Context Modeling

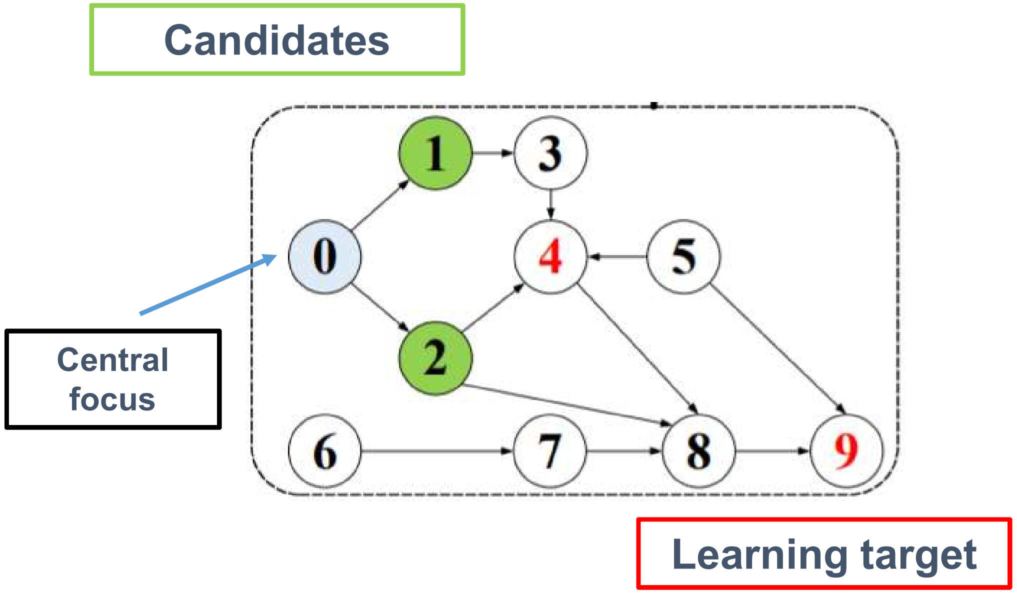
- Deep Knowledge Tracing（DKT）
  - Use RNN to Model the dynamic evolving cognitive context according to the learning records
  - The hidden state vector in RNN：dynamic cognitive context



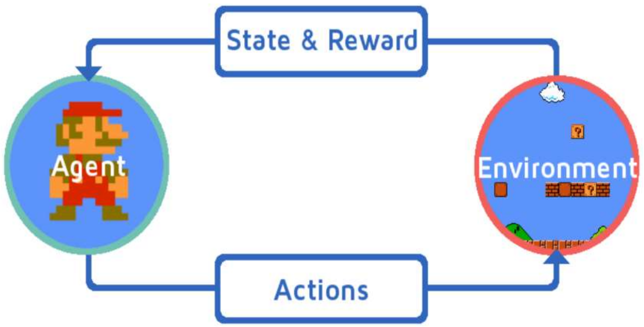
□ Piech C, Bassen J, Huang J, et al. Deep knowledge tracing. NIPS 2015: 505-513

Learning Path Recommendation

- The learning path should be **in accordance with the logicality** determined by the **knowledge structure**
  - Avoid exploring the effect of recommending *calculus* to *junior students*
- Learning path recommendation should **maximize the overall gain** along the whole learning path instead



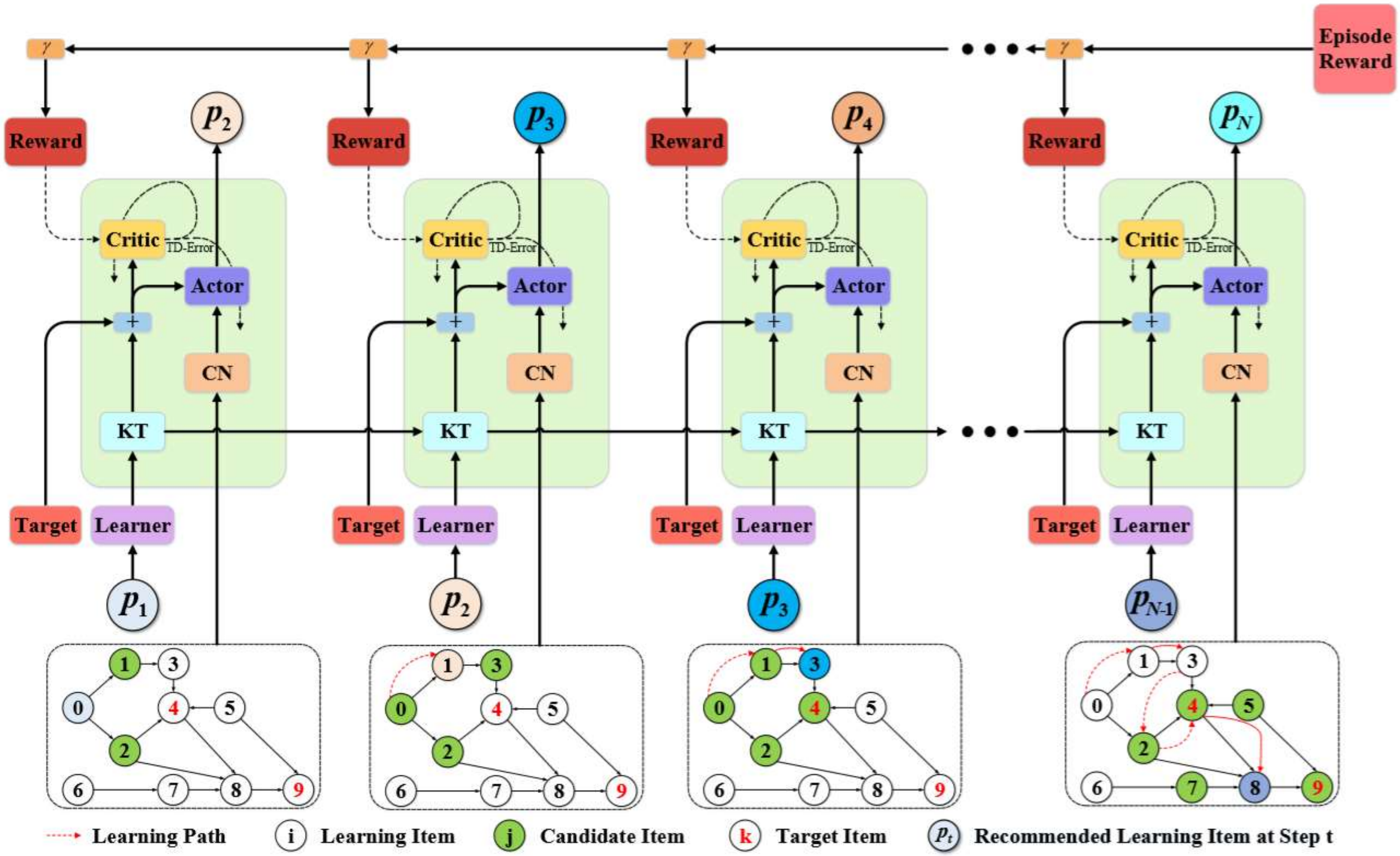
Cognitive Navigation algorithm



Actor-critic recommender

Cognitive Context-aware Recommendation

- CSEAL: Cognitive Structure Enhanced framework for Adaptive Learning



Cognitive Context-aware Recommendation

- CSEAL: Cognitive Structure Enhanced framework for Adaptive Learning

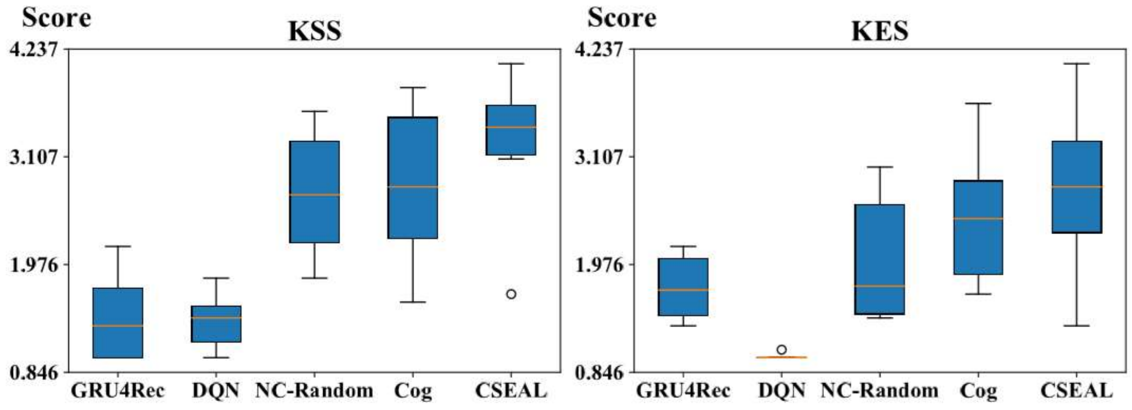
Table 3: Overall results of $E_{\mathcal{P}}$.

	KSS	KES
KNN	0.000700	0.257919
GRU4Rec	0.007727	0.201219
MC-10	0.110577	0.002236
MC-50	0.108636	-0.005103
DQN	0.100610	0.002688
CSEAL-NCN	0.222363	0.003354
CN-Random	0.272784	0.138526
Cog	0.164128	0.166560
CSEAL	**0.346883**	**0.405823**

$$E_{\mathcal{P}} = \frac{E_e - E_s}{E_{sup} - E_s},$$

Student performance improves in simulated environments

Better evaluation results given by experts



Cognitive Context-aware Recommendation

- CSEAL: Cognitive Structure Enhanced framework for Adaptive Learning

More efficient and logical learning path

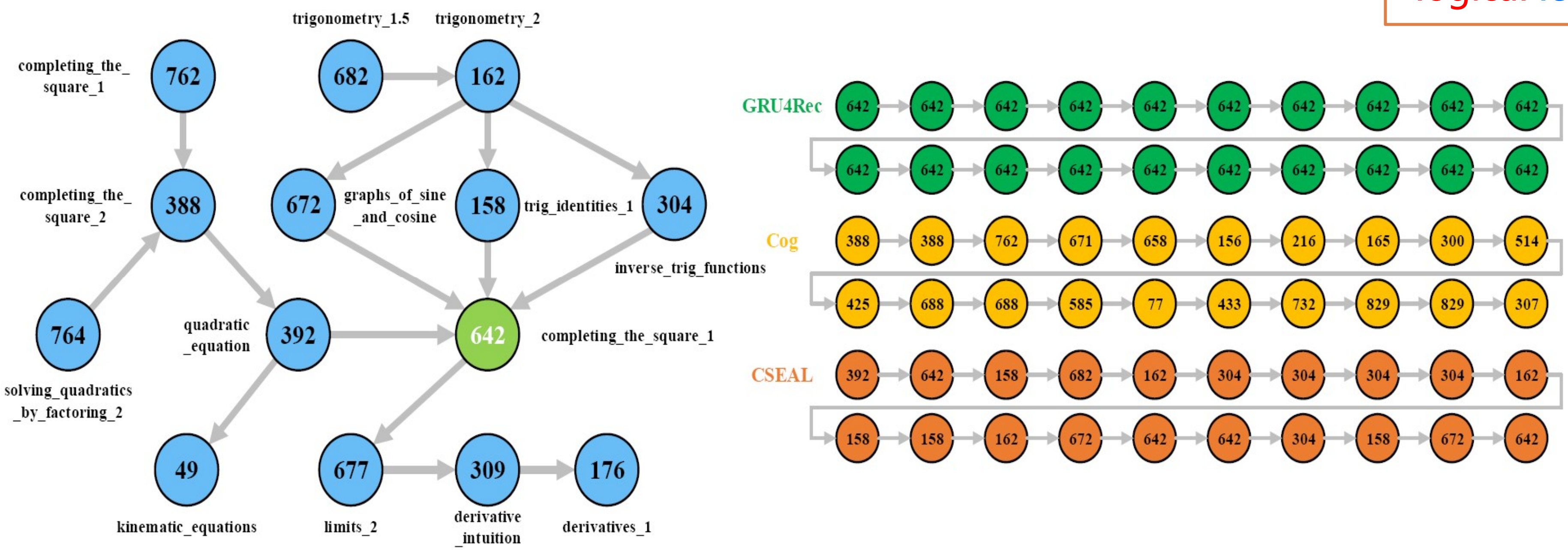


Figure 9: Visualization of different recommended learning paths for the learning item 642, i.e., *completing_the_square_1*.

Outline

Conclusion

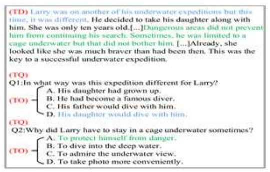
Response matrix R

1	0	1	2	3	4
0	1	0	0	5	3
0	1	0	1	6	5

Q-matrix

	一次函数	函数求导	线性规划
试题1	1	0	1
试题2	1	1	0
试题3	0	1	0
试题4	0	0	1
……			

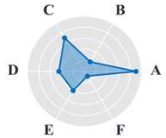
Exercise Text



Challenges | **Solutions**

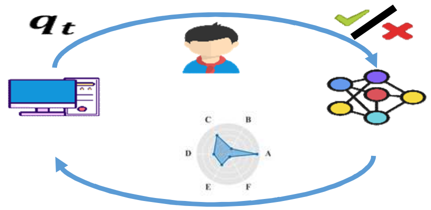
How to accurately evaluate the cognitive level of each student?

Cognitive Diagnosis



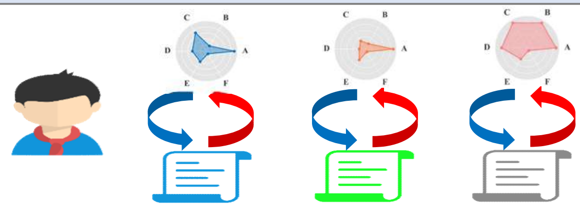
How to make fast & comprehensive testing to evaluate the cognitive level of student?

Adaptive Testing



How to adaptively recommend personalized educational resources?

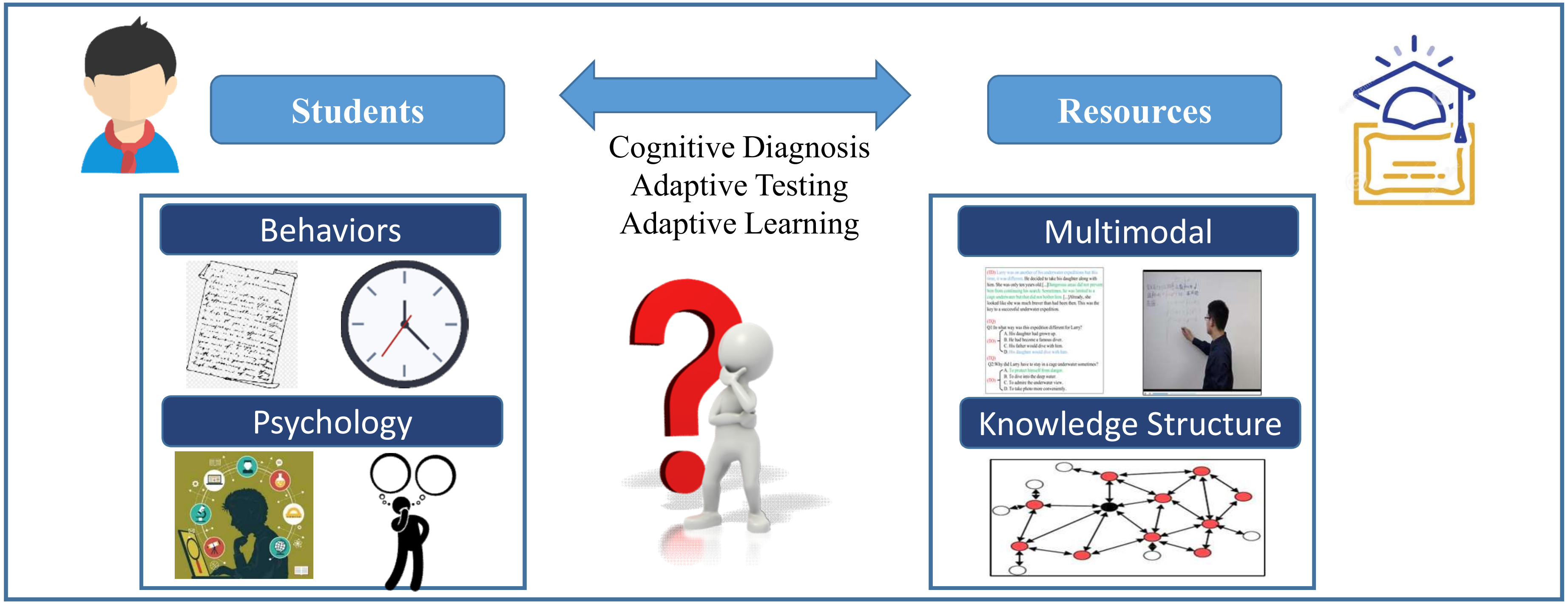
Cognitive Context-aware Recommendation



Discussion-1

- Understanding students better
  - Learning behaviors and feebacks
  - Learning psychology
  - … …

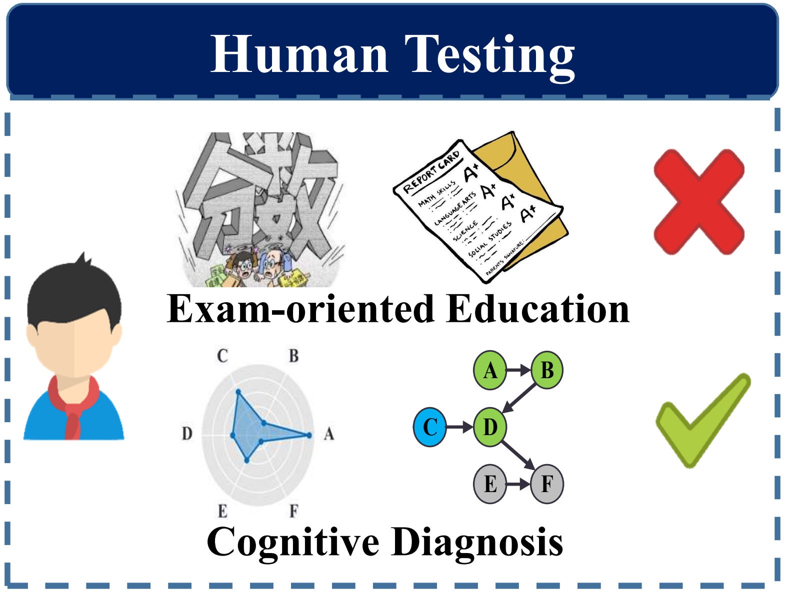
- Understanding resources better
  - Multimodal learning
  - Knowledge structure
  - … …

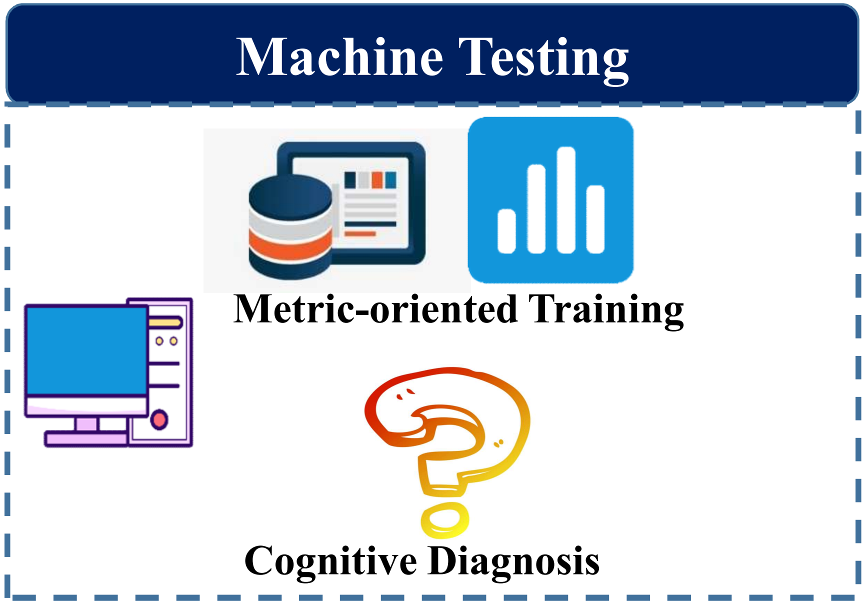


Discussion-2

- We test students with exams and diagnose them with cognitive diagnosis

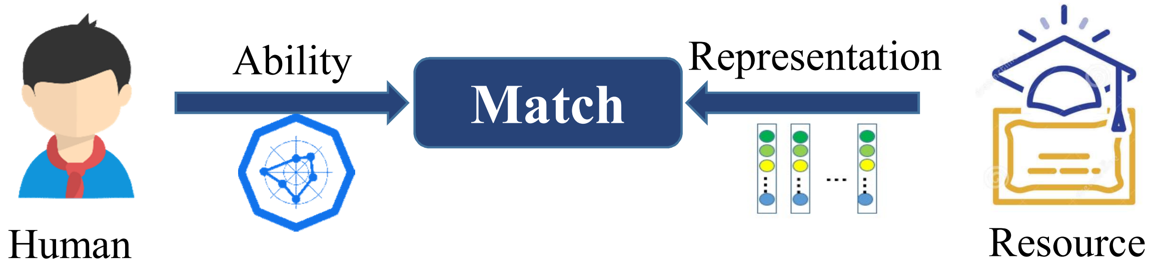
- Now we test machines with plenty of data but do not diagnose them
  - How to diagnose machines?

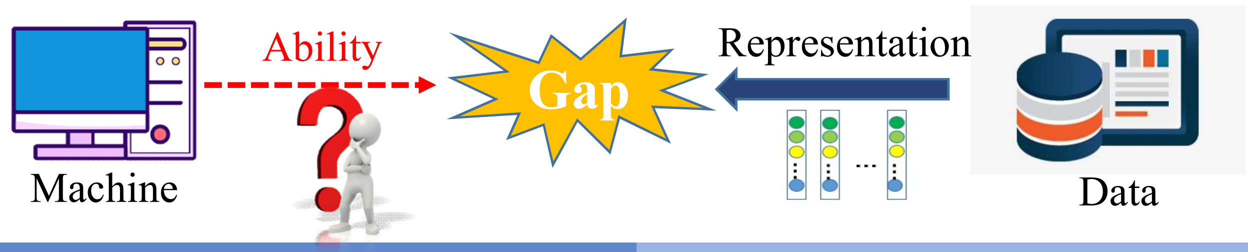




Discussion-3

- Adaptive learning enhanced with cognitive diagnosis
  - Modeling human ability and learning resources simultaneously
  - Adaptively matching resources with ability → promoting learning efficiency
- How about adaptive machine learning?





Reference

- **Fei Wang, Qi Liu, Enhong Chen et al. Neural Cognitive Diagnosis for Intelligent Education Systems. AAAI 2020.**
- **Haoyang Bi, Haiping Ma, Zhenya Huang, Yu Yin, Qi Liu, Enhong Chen, Yu Su, and Shijin Wang. Quality meets Diversity: A Model-Agnostic Framework for Computerized Adaptive Testing. ICDM 2020.**
- **Qi Liu, Shiwei Tong, Chuanren Liu, et al. Exploiting Cognitive Structure for Adaptive Learning. KDD 2019.**
- Qi Liu, Zhenya Huang, Yu Yin, Enhong Chen, Hui Xiong, Yu Su and Guoping Hu. EKT: Exercise-aware Knowledge Tracing for Student Performance Prediction.IEEE Transactions on Knowledge and Data Engineering (IEEE TKDE), accepted.
- Qi Liu, Runze Wu, Enhong Chen, Guandong Xu, et al, Fuzzy Cognitive Diagnosis for Modeling Examinee Performance, ACM TIST, accepted, 2018.
- Yu Su, Qingwen Liu, Qi Liu, Zhenya Huang, Yu Yin, Enhong Chen, Chris Ding, Si Wei, Guoping Hu, Exercise-Enhanced Sequential Modeling for Student Performance Prediction, AAAI2018, 2435-2443.
- Corbett A T, Anderson J R. Knowledge tracing: Modeling the acquisition of procedural knowledge[J]. User modeling and user-adapted interaction, 1994, 4(4): 253-278.
- Piech C, Bassen J, Huang J, et al. Deep knowledge tracing[C]//Advances in neural information processing systems. 2015: 505-513.
- Yang H, Cheung L P. Implicit heterogeneous features embedding in deep knowledge tracing[J]. Cognitive Computation, 2018, 10(1): 3-14.
- Chen P, Lu Y, Zheng V W, et al. Prerequisite-Driven Deep Knowledge Tracing[C]//2018 IEEE International Conference on Data Mining (ICDM). IEEE, 2018: 39-48.
- Nagatani K, Zhang Q, Sato M, et al. Augmenting Knowledge Tracing by Considering Forgetting Behavior[J]. 2019.
- Zhang J, Shi X, King I, et al. Dynamic key-value memory networks for knowledge tracing[C]//Proceedings of the 26th international conference on World Wide Web. 2017: 765-774.
- Allan Birnbaum. 1968. Some latent trait models and their use in inferring an examinee’s ability. Statistical theories of mental test scores (1968).
- Jimmy De La Torre. 2009. DINA model and parameter estimation: A didactic. Journal of educational and behavioral statistics 34, 1 (2009), 115–130.

Q & A

http://base.ustc.edu.cn/

https://github.com/bigdata-ustc

EduData

Forked from tswsxk/EduData

Edudata: Datasets in Education and convenient interface for downloading and preprocessing dataset in education

education dataset datasets-education

Python MIT 10 18 0 1 Updated on 10 Jun

NeuralCD

Python 9 30 0 0 Updated 3 days ago

Thanks!