Cognitive Modeling and its application in Intelligent Education

(认知建模及其在智慧教育中的应用)

Enhong Chen (陈恩红)
cheneh@ustc.edu.cn
University of Science and Technology of China

Outline

1 Background

2 Cognitive Diagnosis

3 Issues of Cognitive Diagnosis

4 Application

5 Conclusion and Discussion

Background

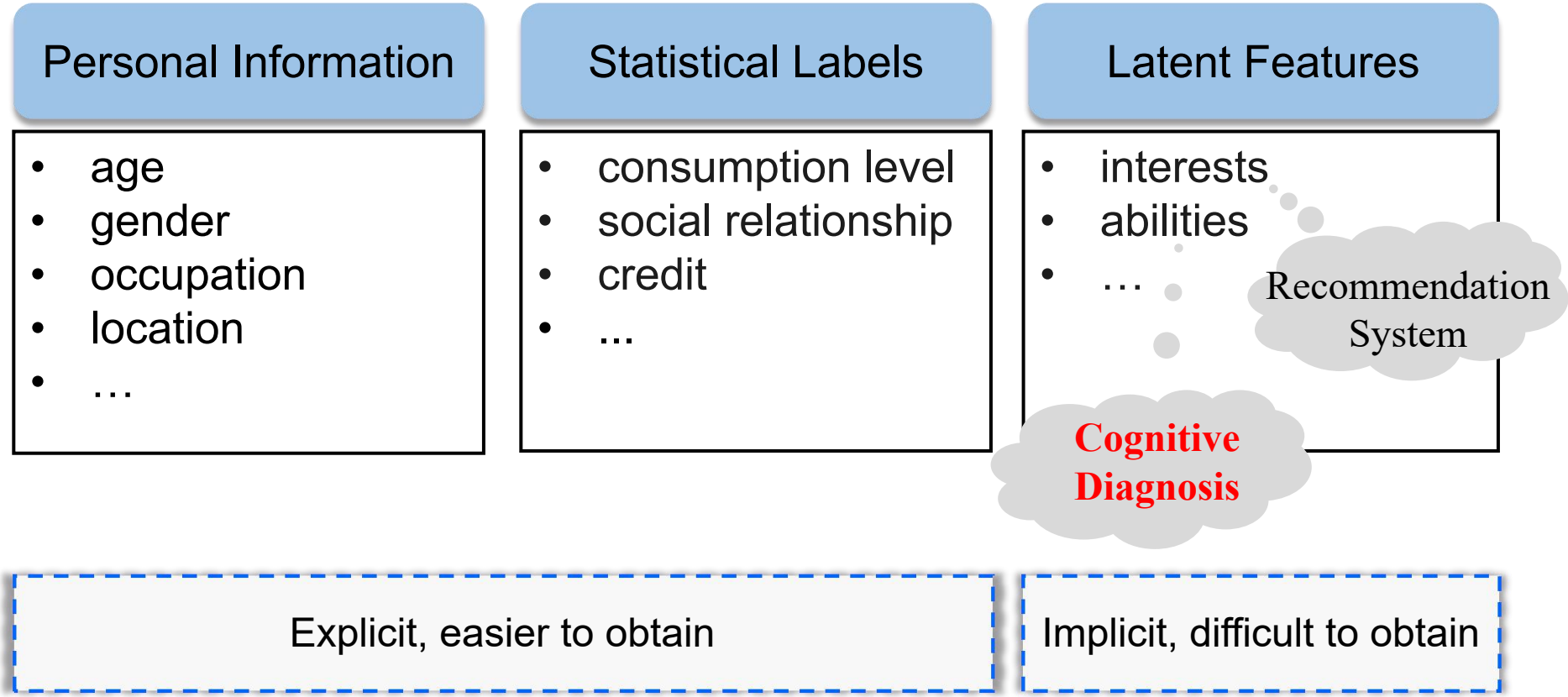
- What is a user portrait (persona)?
  - A visual display of personal data associated with a specific user.
  - Each specific information of users is abstracted into labels, which characterize users' behaviors and preferences.
  - Connect users' demands and design directions.





Background

- Labels in user portrait



Background

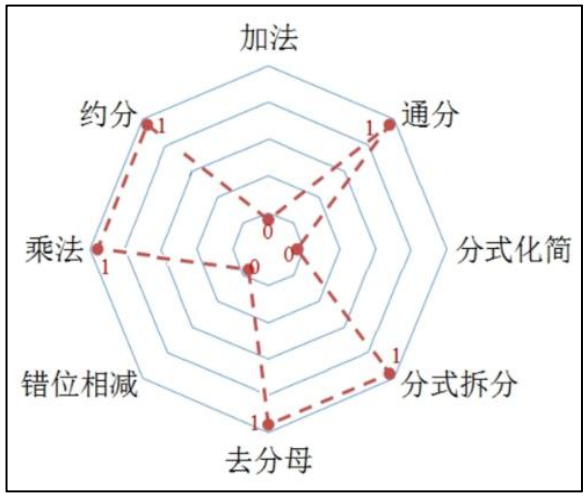
- Needs for cognitive diagnosis（认知诊断）
  - Real-world scenarios: games, sports, recruitment, education, etc.
  - Necessary: diagnose the proficiency of participants on specific skills/concepts
    - Application: exercise recommendation, adaptive learning, team formation

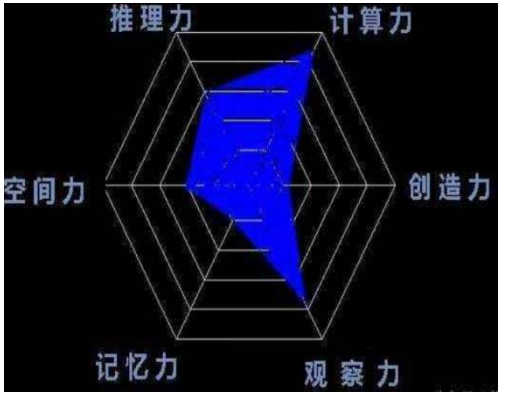
Cognitive diagnosis is a necessary and fundamental task.













Outline

1 Background

2 Cognitive Diagnosis

3 Issues of Cognitive Diagnosis

4 Application

5 Conclusion and Discussion

Definition

- **Problem Definition** of Cognitive diagnosis
  - Take Education as an example

- **Given (Input):**
  - Student-Exercise matrix R
    - R_{ij}: response score of student i on exercise j
  - Exercise-Concept Q-matrix
    - If exercise j relates to concept k, $Q_{jk} = 1$, otherwise $Q_{jk} = 0$

Response matrix R

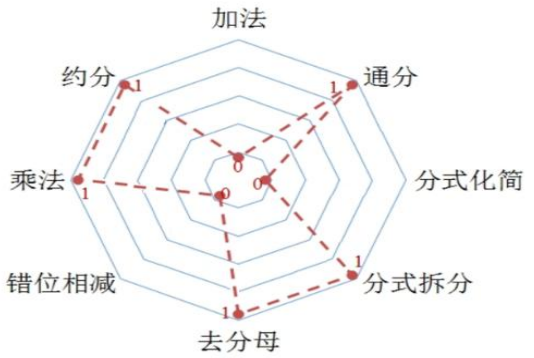
1	0	1	2	3	4
0	1	0	0	5	3
0	1	0	1	6	5

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
……			

Cognitive diagnosis

- **Goal (Output):**
  - Students' proficiency on each concept/skill
    - E.g. in the range of [0,1]



Traditional Cognitive Diagnosis Models

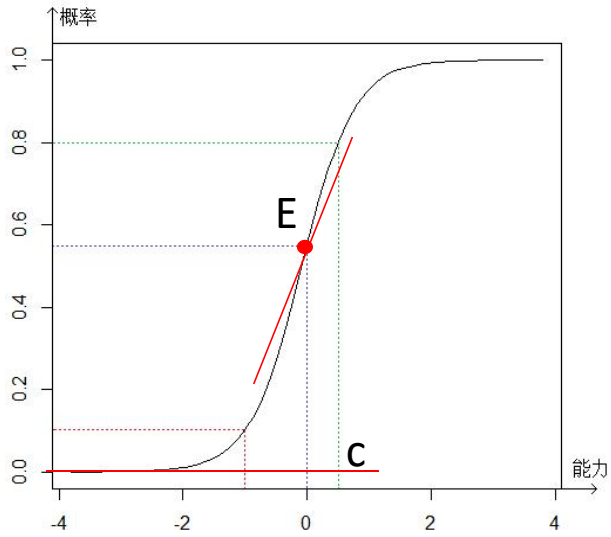
Traditional Cognitive Diagnosis Models （CDM）

Item Response Theory (IRT)

Skill proficiency Discrimination

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

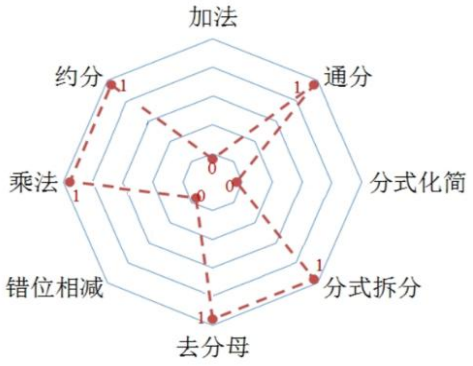
Difficulty Guess factor



DINA

$$P(Y_{ij}=1|\alpha_i)=(1-s_j)^{\eta_{ij}}g_j^{1-\eta_{ij}}$$

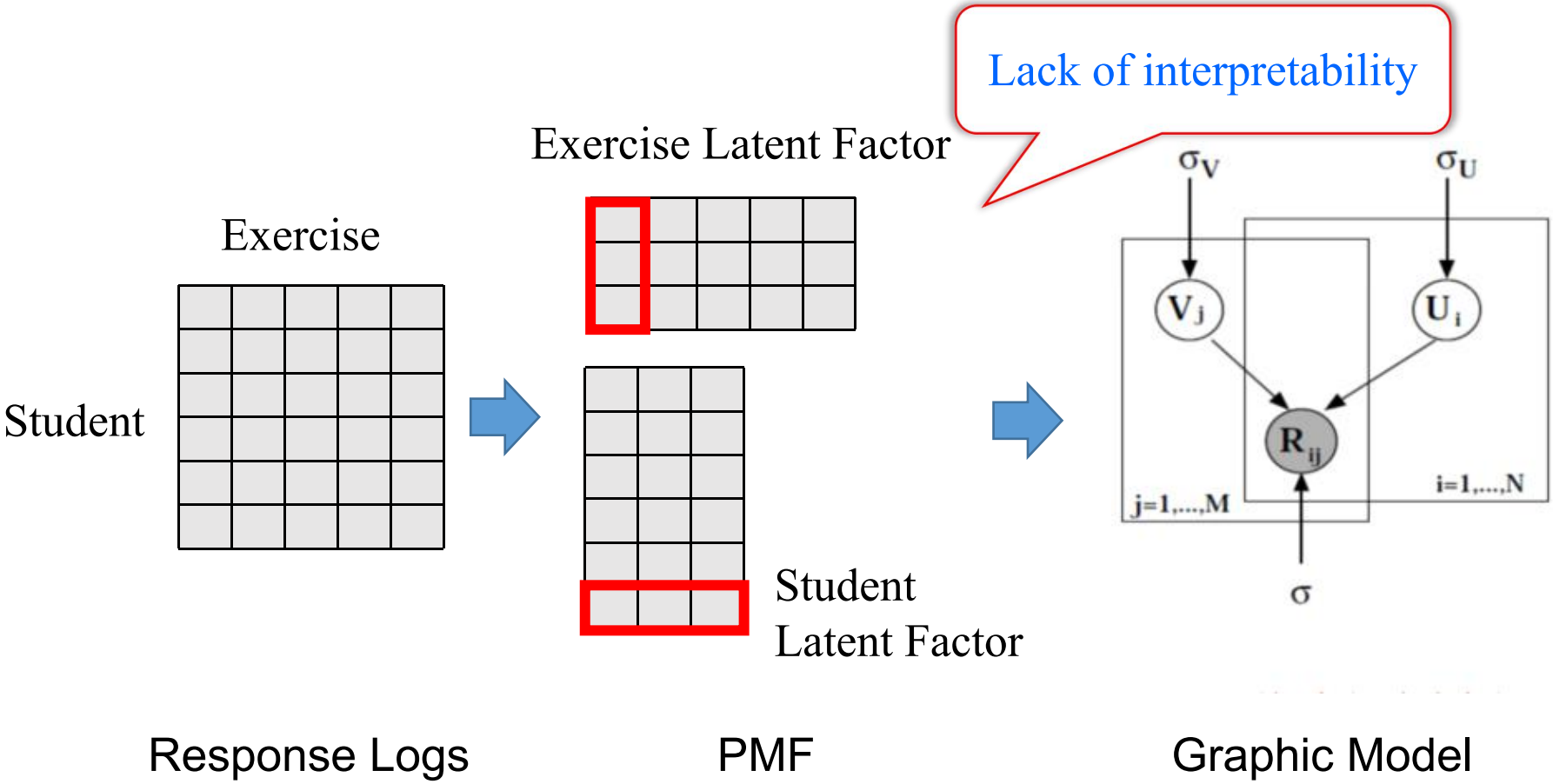
Skill proficiency vector Slip Guess



- 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.

Limitations of traditional data mining

- **Probabilistic Matrix Factorization (PMF)**
  - Problem: the meaning of latent factor is ambiguous



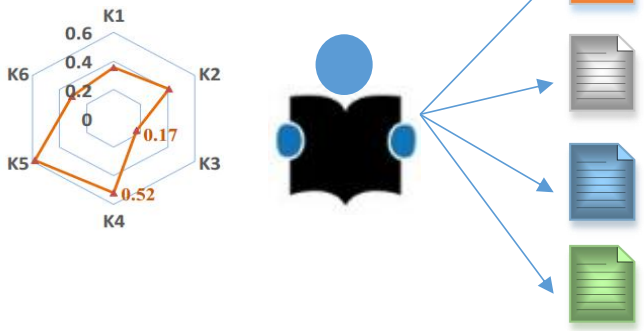
- Andriy Mnih and Ruslan Salakhutdinov. 2007. Probabilistic matrix factorization. In Advances in NIPS. 1257–1264

Review of Traditional Models

- Assumptions in traditional cognitive diagnosis
  - Same response type (score manner)

Correct  or Incorrect 

  - Manually designed (mostly linear) interaction function
  - static student states
    - students' knowledge states do not change during the answering process



Outline

1 Background

2 Cognitive Diagnosis

3 Issues of Cognitive Diagnosis

4 Application

5 Conclusion and Discussion

Issues of Cognitive Diagnosis

- **How to model different response types of exercises**: different types of exercises need to be modeled differently

Objective Exercise

对或错

1. $|-2|$等于（　）

A. -2　　B. $-\frac{1}{2}$　　C. 2　　D. $\frac{1}{2}$

2. 在墙壁上固定一根横放的木条，则至少需要钉子的枚数是（　）

A. 1枚　　B. 2枚　　C. 3枚　　D. 任意枚

3. 下列方程为一元一次方程的是（　）

A. $y+3=0$　　B. $x+2y=3$　　C. $x^2=2x$　　D. $\frac{1}{y}+y=2$

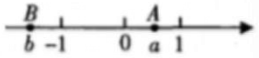
4. 下列各组数中，互为相反数的是（　）

A. $-(-1)$与1　　B. $(-1)^2$与1　　C. $|-1|$与1　　D. -1^2与1

5. 下列各组单项式中，为同类项的是（　）

A. a^3与a^2　　B. $\frac{1}{2}a^2$与$2a^2$　　C. $2xy$与$2x$　　D. -3与a

6. 如图，数轴A、B上两点分别对应实数a、b，则下列结论正确的是



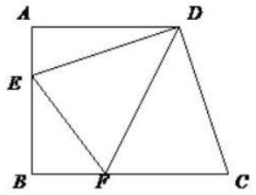
（第6题）

A. $a+b>0$　　B. $ab>0$　　C. $\frac{1}{a}-\frac{1}{b}<0$　　D. $\frac{1}{a}+\frac{1}{b}>0$

Subjective Exercise

连续分值

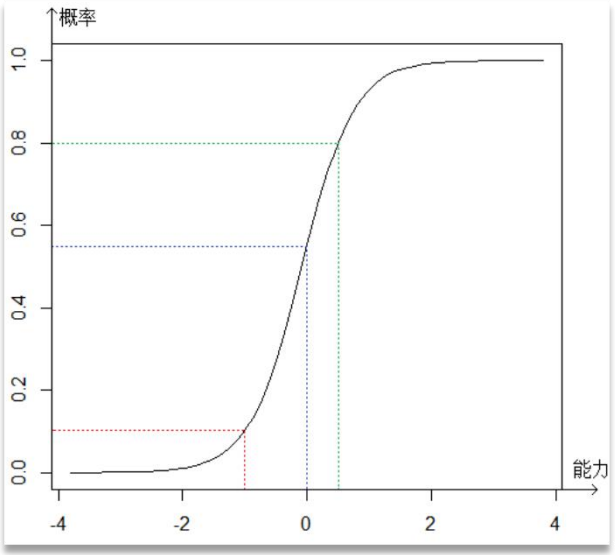
1.如图，在直角梯形ABCD中，AD∥BC，∠A＝90°，AB＝AD，DE⊥CD交AB于E，DF平分∠CDE交BC于F，连接EF．证明：CF＝EF

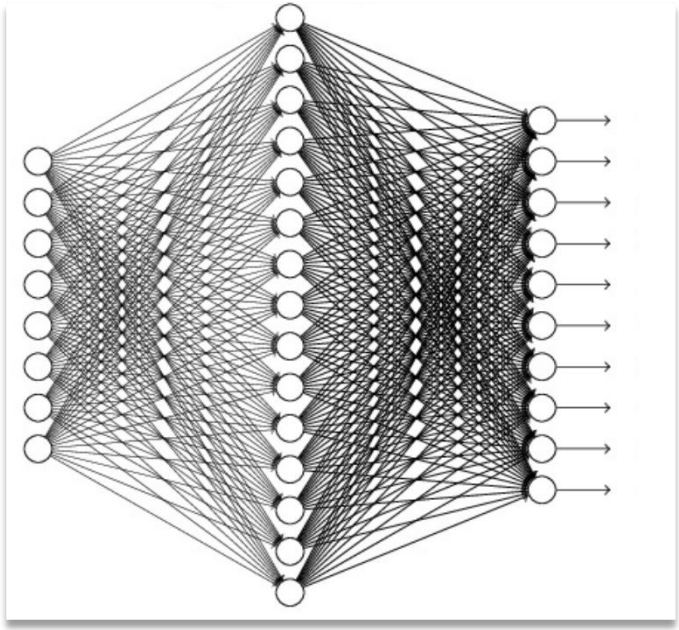


解：
过D作DG⊥BC于G．
由已知可得四边形ABGD为正方形，
∵DE⊥DC
∴∠ADE+∠EDG=90°=∠GDC+∠EDG，
∴∠ADE=∠GDC．
又∵∠A=∠DGC且AD=GD，
∴△ADE≌△GDC，
∴DE=DC且AE=GC．
在△EDF和△CDF中∠EDF=∠CDF，DE=DC，DF为公共边，
∴△EDF≌△CDF，
∴EF=CF

Issues of Cognitive Diagnosis

- How to model different response types of exercises
- **How to model the complex relations**
  - manually designed, limited ability → automatically learned, high ability





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

针对不同场景人工设计，例如IRT

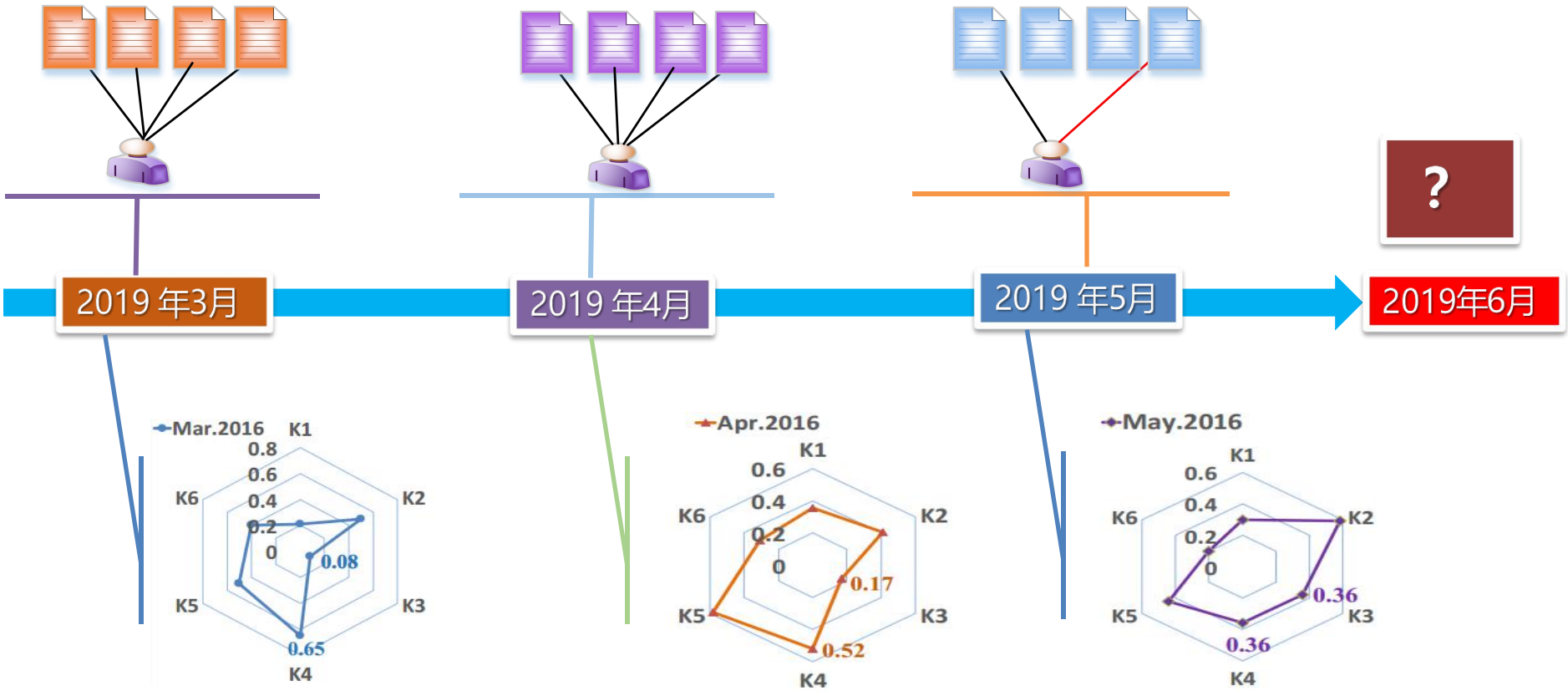
- manually designed: labor intensive
- mostly linear: limited ability

模型简单，不足以建模复杂关系

- ✓ automatically learned from data
- ✓ high ability

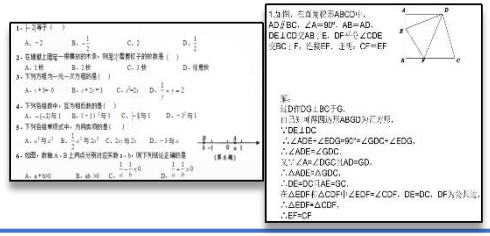
Issues of Cognitive Diagnosis

- How to model different response types of exercises
- How to model the complex relations
- **How to model the evolving of students' knowledge proficiencies**: students' knowledge states change over time

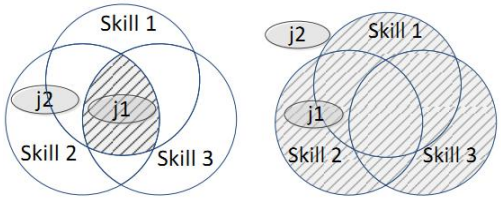


Research Overview

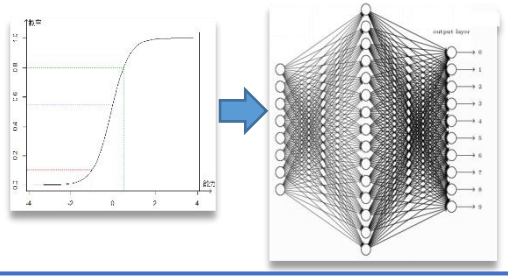
Model different response types of exercises



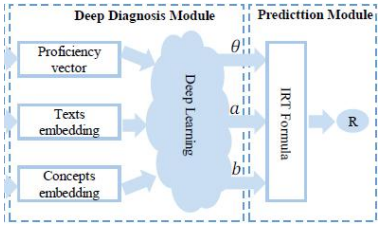
Fuzzy Cognitive Diagnosis (IJCAI 2015, TIST 2018)



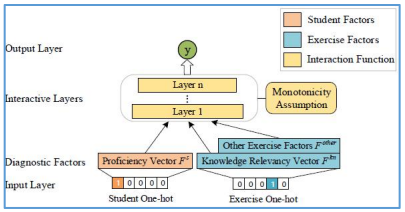
Model the complex relations



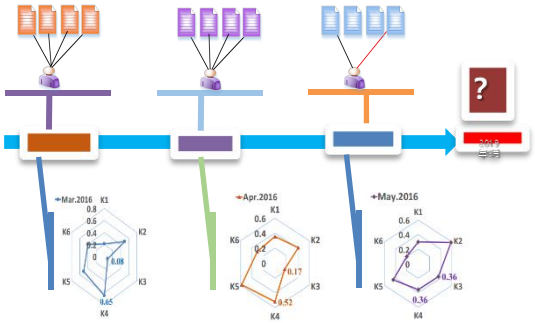
DIRT(CIKM2019)



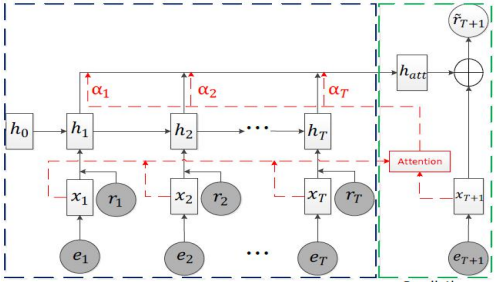
Neural Cognitive Diagnosis (AAAI 2020)



Model the evolving proficiencies

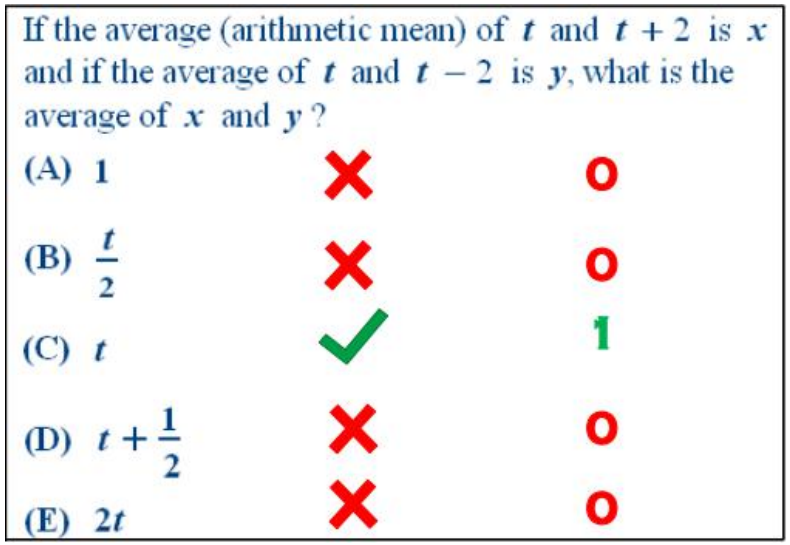


Knowledge Tracing (AAAI 2018, TKDE 2019)

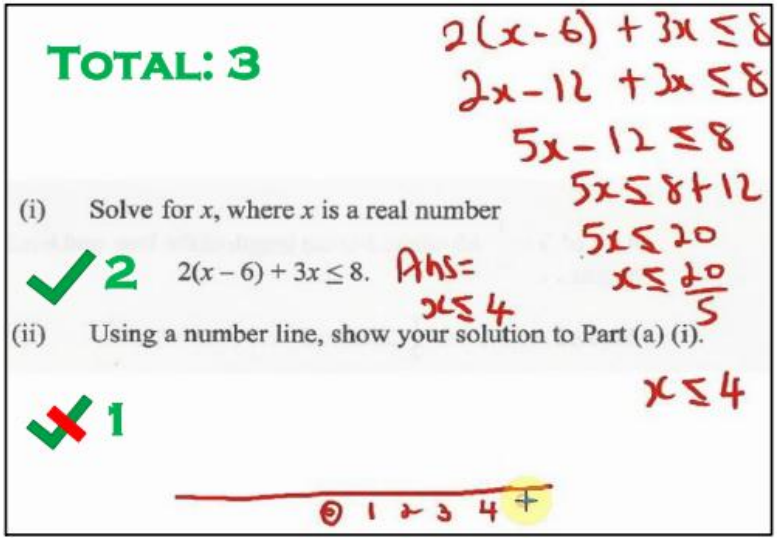


Fuzzy Cognitive Diagnosis

- **Fuzzy Cognitive Diagnosis Framework (Liu et al. 2018)**
  - handle **objective problems** with two score categories and **subjective problems** with multi score categories simultaneously



objective problems



subjective problems

Liu Q, Wu R, Chen E, et al. Fuzzy cognitive diagnosis for modelling examinee performance[J]. ACM Transactions on Intelligent Systems and Technology (TIST), 2018, 9(4): 48.

Fuzzy Cognitive Diagnosis

- **4-tier fuzzy cognitive diagnosis framework (FuzzyCDF)**
  - Fuzzify the skill proficiency of examinees using fuzzy set theory
  - Fuzzify the mastery of objective and subjective problems based on conjunctive and compensatory hypotheses
  - Consider slip and guess factors

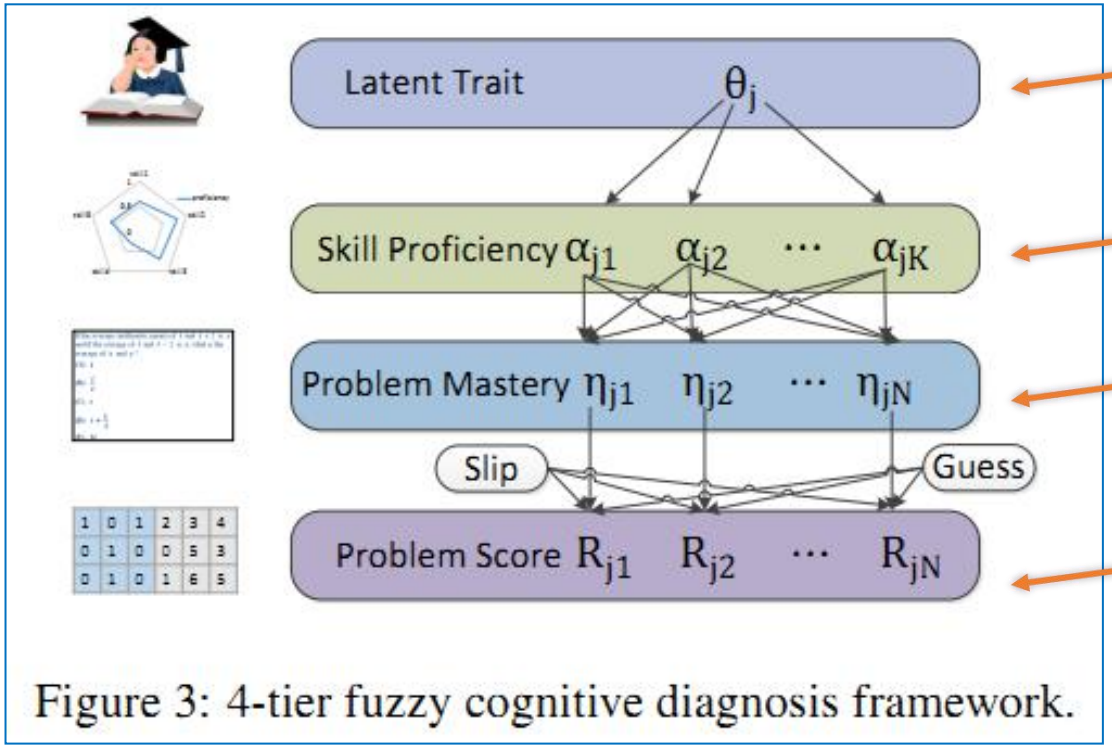


Figure 3: 4-tier fuzzy cognitive diagnosis framework.

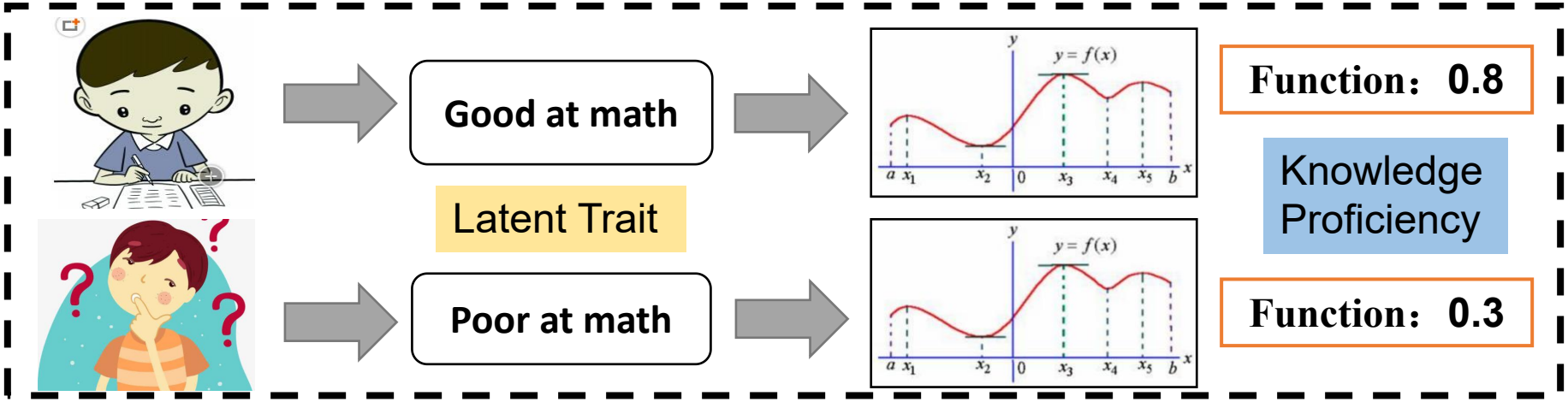
Fuzzy Cognitive Diagnosis

- **Student's skill proficiency**
  - Influenced by latent trait
  - Randomize student knowledge proficiency based on IRT

Item Response Function:

$$\alpha_{jk} = \mu_k(j) = \frac{1}{1 + \exp[-1.7 a_{jk}(\theta_j - b_{jk})]}$$

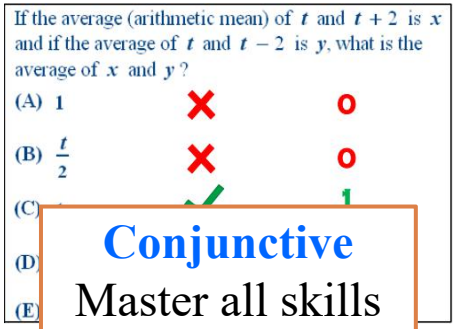
Knowledge Proficiency | Education Prior | Latent Trait

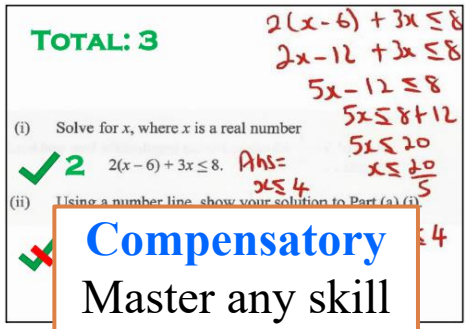


Fuzzy Cognitive Diagnosis

Student's problem mastery

Objective problem VS. **Subjective problem**



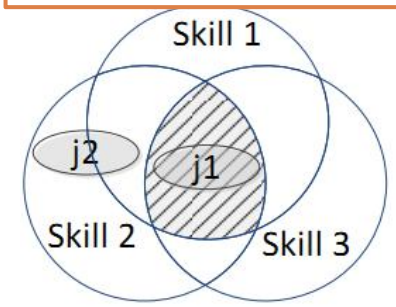


Conjunctive
Master all skills lead to be correct

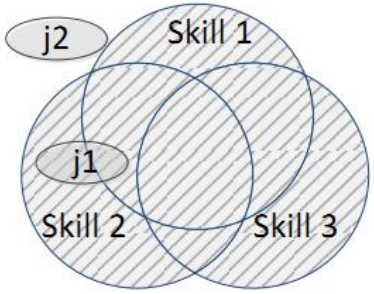
Compensatory
Master any skill can correct

Fuzzy theory

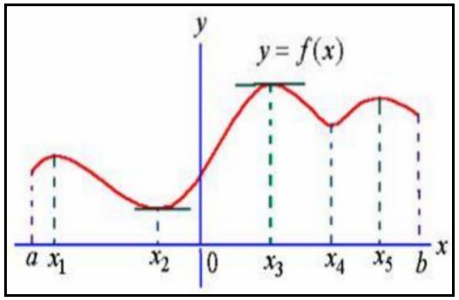
Fuzzy intersection



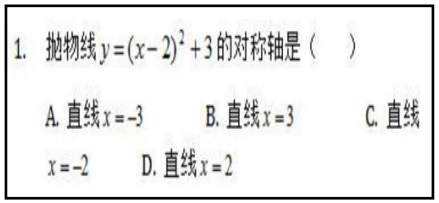
Fuzzy Union



Knowledge proficiency



Function: 0.8



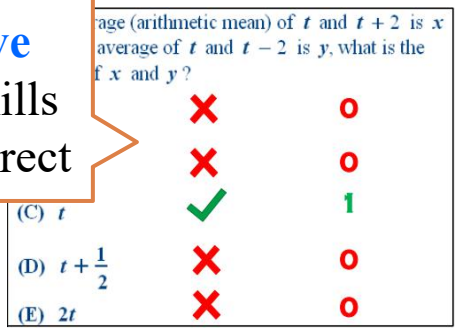
Problem master: 0.7

Fuzzy Cognitive Diagnosis

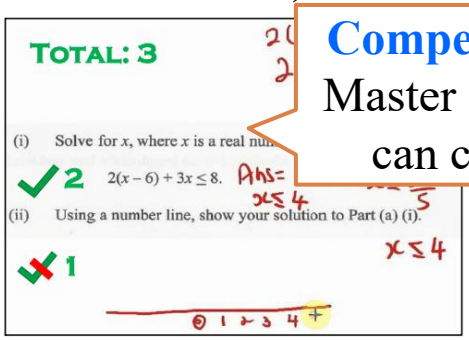
- **Student's problem mastery**
  - Model **subjective and objective** problems with different hypotheses (**conjunctive vs. compensatory**)
  - Fuzzy theory (**interaction vs. union**)

Conjunctive
Master all skills lead to be correct

Compensatory
Master any skill can correct

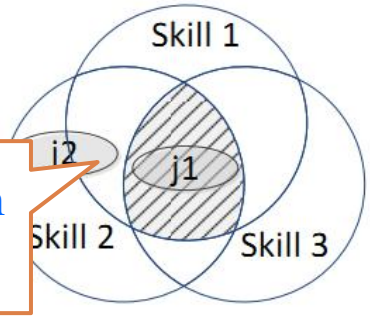


Objective problem

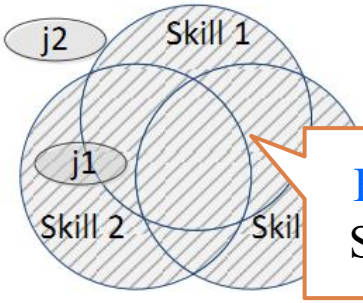


Subjective problem

Fuzzy theory

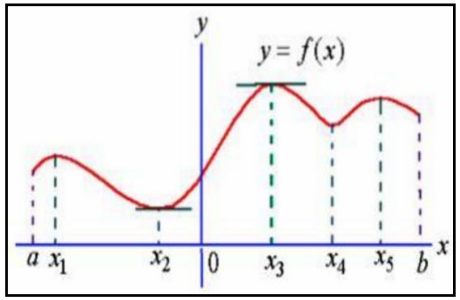


Fuzzy intersection
Obj. problem

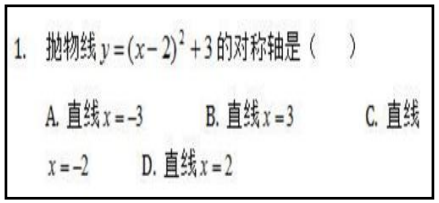


Fuzzy Union
Sub. problem

Knowledge proficiency



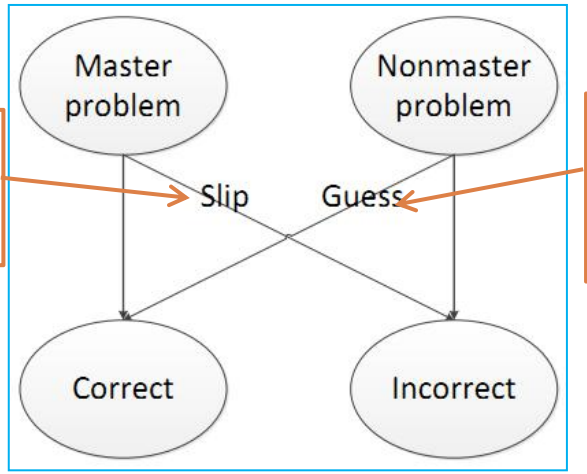
Function: 0.8



Problem master: 0.7

Fuzzy Cognitive Diagnosis

- **Student's scores on problems**
  - slip and guess factors



粗心：胜券在握也会“大意失荆州”

猜测：东郭先生也能“瞎猫碰死耗子”

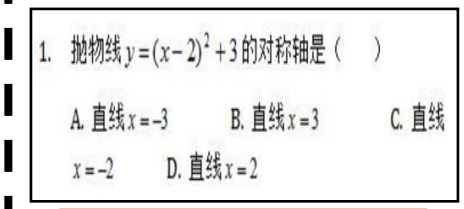
Objective (Bernoulli distribution):

$$P(R_{ji}=1|\eta_{ji},s_i,g_i)=(1-s_i)\eta_{ji}+g_i(1-\eta_{ji})$$

Subjective (Gaussian distribution):

$$P(R_{ji}=1|\eta_{ji},s_i,g_i)=\mathcal{N}(R_{ji}|[(1-s_i)\eta_{ji}+g_i(1-\eta_{ji})],\sigma^2)$$

slip **guess**


1. 抛物线 $y=(x-2)^2+3$ 的对称轴是（　）

A. 直线 $x=-3$　B. 直线 $x=3$　C. 直线 $x=-2$　D. 直线 $x=2$

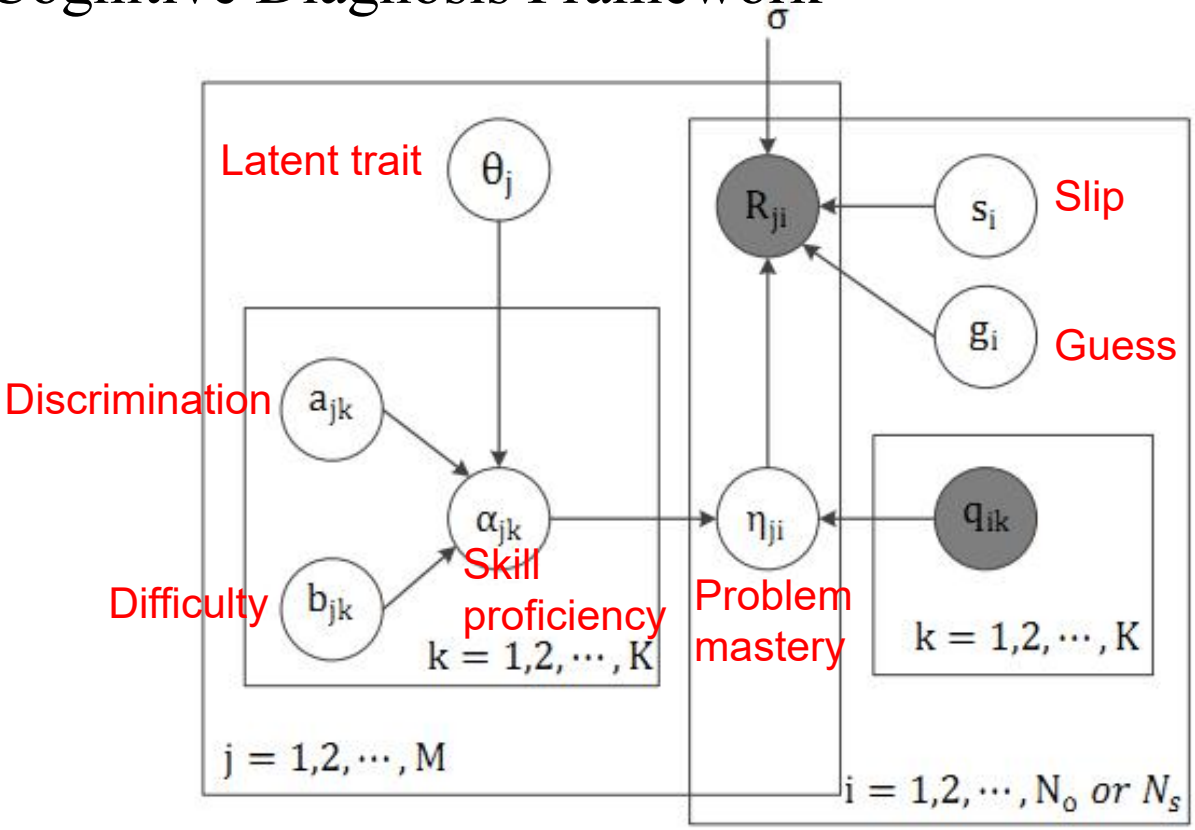
Mastery degree: 0.7



Real score：0.5

Fuzzy Cognitive Diagnosis

Fuzzy Cognitive Diagnosis Framework



Parameter prior distribution

$$\theta_j \sim \mathcal{N}(\mu_\theta, \sigma_\theta^2), a_{jk} \sim ln\mathcal{N}(\mu_a, \sigma_a^2), b_{jk} \sim \mathcal{N}(\mu_b, \sigma_b^2);$$
$$s_i \sim Beta(v_s, w_s, min_s, max_s),$$
$$g_i \sim Beta(v_g, w_g, min_g, max_g);$$
$$1/\sigma^2 \sim \Gamma(x_\sigma, y_\sigma).$$

Fuzzy Cognitive Diagnosis

- **Datasets**
  - Student test records
  - Test set: random 20%, 40%, 60%, 80%

Table 2: Datasets Summary.

Dataset	# Examinee	# Skill	# Problem Obj.	# Problem Sub.
FrcSub	536	8	20	0
Math1	4,209	11	15	5
Math2	3,911	16	16	4

- **FracSub**: fraction subtraction objective problems for middle school students
- **Math1** and **Math2**: mathematical exams for high school students

单元测评(二)　点、直线、平面之间的位置关系

(时间：90 分钟　满分：120 分)

第Ⅰ卷(选择题，共 50 分)

一、选择题：本大题共 10 小题，共 50 分.

1．室内有一直尺，无论怎样放置，在地面上总有这样的直线，它与直尺所在的直线(　　)

A．异面　　B．相交

C．平行　　D．垂直

解析：当直尺与地面垂直时，地面上的任意一条直线都和直尺所在的直线垂直；

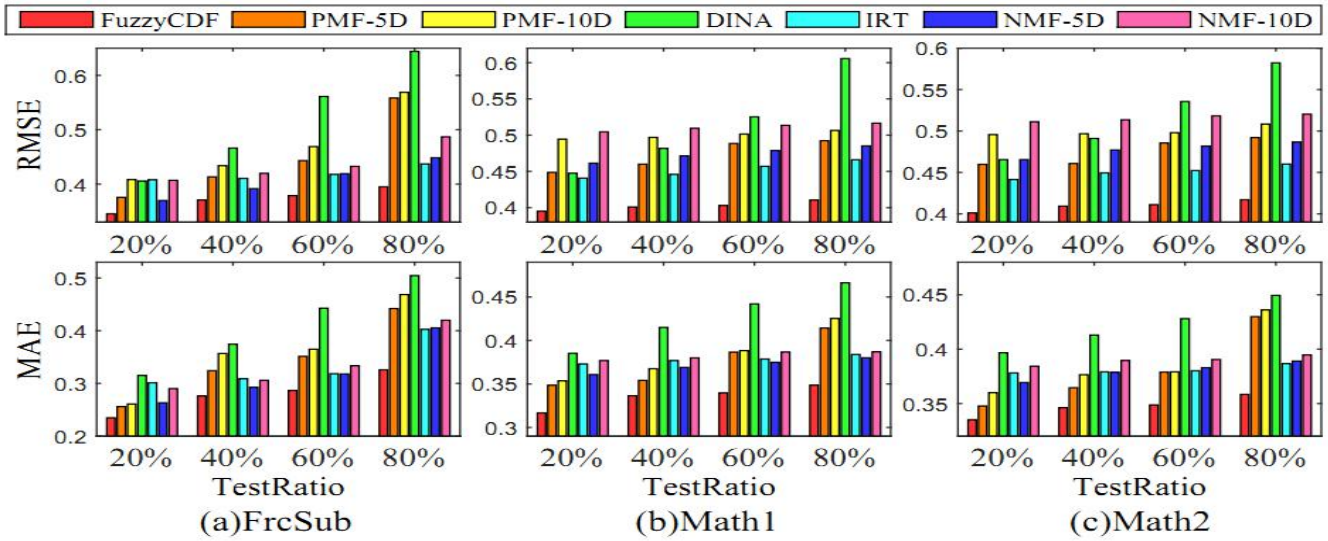
当直尺所在的直线与地面不垂直时，过直尺所在的直线作一与地面垂直的平面，此平面与地面的交线设为 a，则地面内任一与交线 a 垂直的直线都与直尺所在的直线垂直．

答案：D

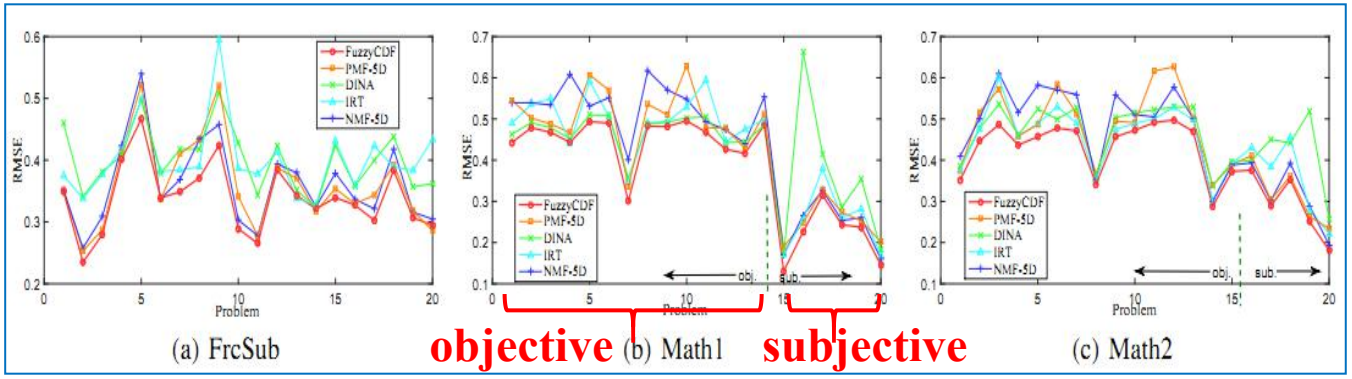
2．设 P 是△ABC 所在平面 α 外一点，H 是 P 在 α 内的射影，且 PA，PB，PC 与 α 所成的角相等，则 H 是△ABC 的(　　)

Fuzzy Cognitive Diagnosis

- **Student performance prediction**
  - Baselines: IRT, DINA, PMF, NMF
  - Evaluation: RMSE



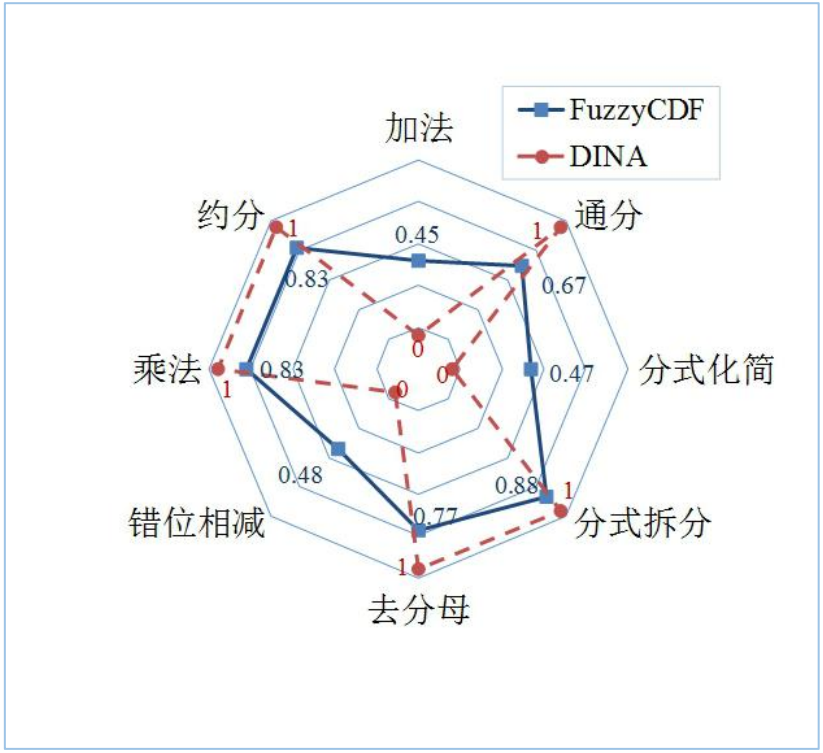
FuzzyCDF performs the best on all the datasets.



FuzzyCDF outperforms almost all the baselines on both subjective and objective problems

Fuzzy Cognitive Diagnosis

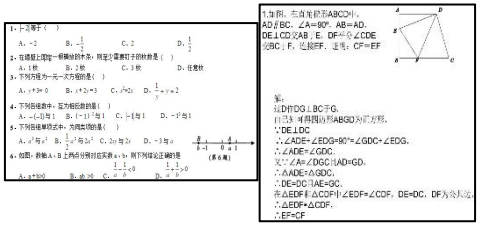
- **Diagnostic Result**
  - Explanatory and application



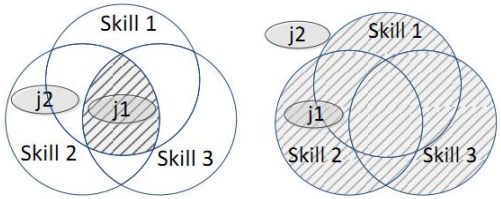
- **IRT and matrix factorization** methods describe a student with latent variables, which **cannot provide intuitive and interpretative results**
- **DINA** can only distinguish **whether an examinee masters a skill (0 or 1).**
- **FuzzyCDF** can tell **the extent to which the examinee masters a skill (0 to 1).**

Research Overview

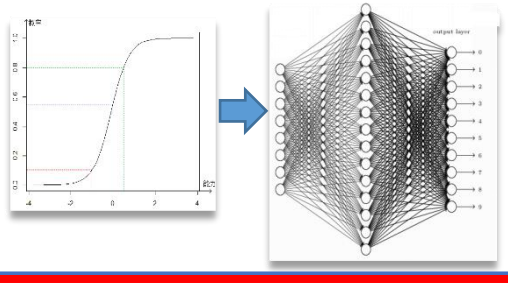
Model different response types of exercises



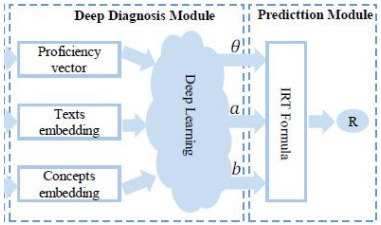
Fuzzy Cognitive Diagnosis (IJCAI 2015, TIST 2018)



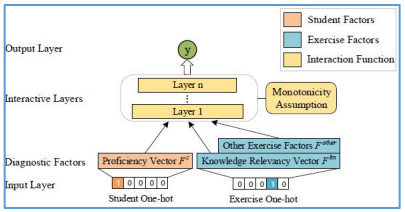
Model the complex relations



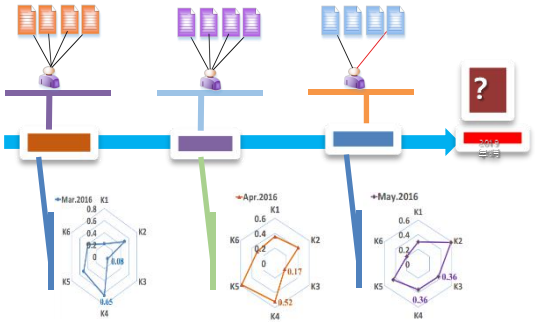
DIRT(CIKM2019)



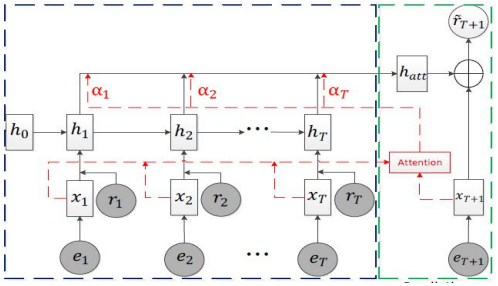
Neural Cognitive Diagnosis (AAAI2020)



Model the evolving proficiencies



Knowledge Tracing (AAAI 2018, TKDE 2019)

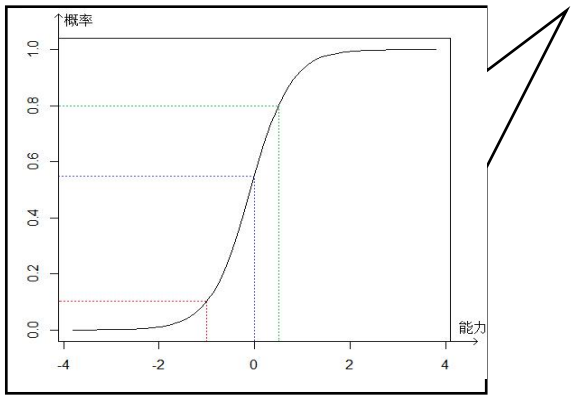


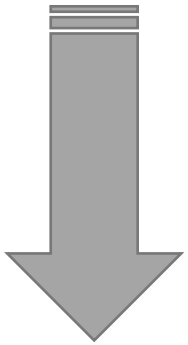
Model The Complex Relations

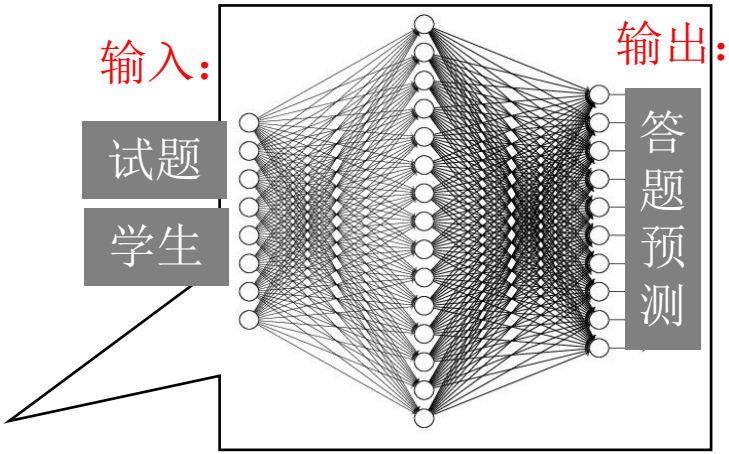
- Traditional models: manually designed, limited ability

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

2 1







- Deep models: automatically learned, high ability

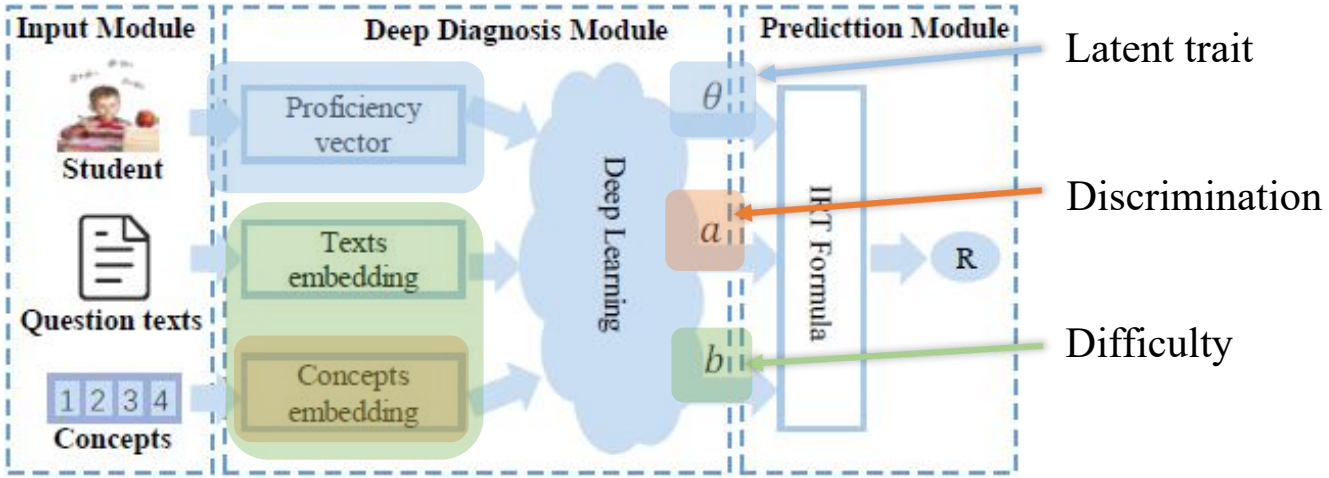
1 Estimate CDM parameters with deep learning approaches

2 Learn interaction function automatically from data with deep learning

Deep Learning Enhanced IRT

1 Estimate CDM parameters with deep learning approaches

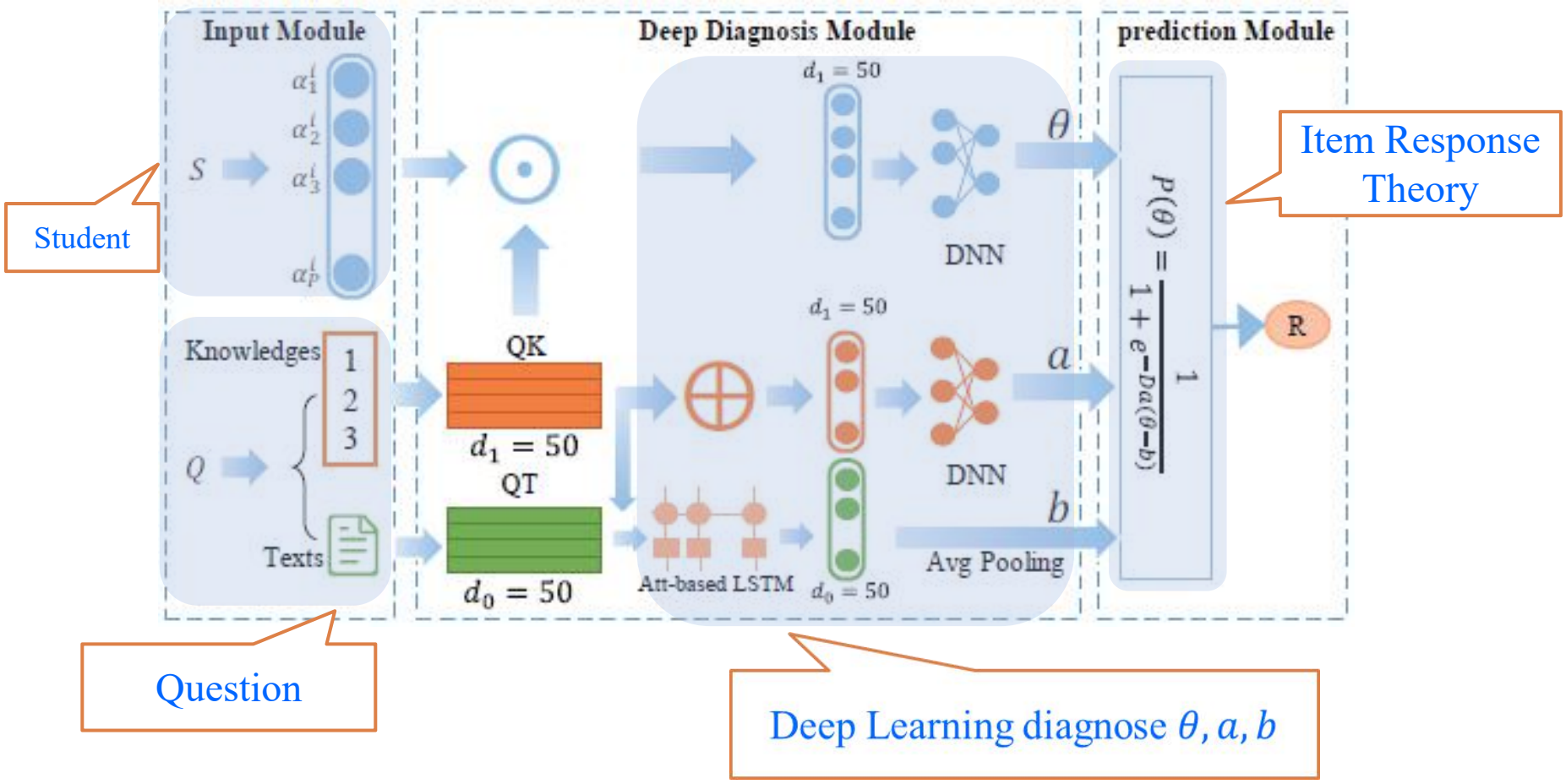
- **Deep Learning Enhanced Item Response Theory Framework**
  - Item Response Function $P(\theta) = \frac{1}{1+\exp(-Da(\theta-b))}$
  - Latent trait θ relates to students' knowledge concept proficiency.
  - Discrimination a can be reflected from knowledge concepts
  - Difficulty b relates to question texts, the width and depth of knowledge concepts.



Cheng S, Liu Q, Chen E, et al. DIRT: Deep Learning Enhanced Item Response Theory for Cognitive Diagnosis[C]//Proceedings of the 28th ACM International Conference on Information and Knowledge Management. ACM, 2019: 2397-2400.

Deep Learning Enhanced IRT

- **A Specific Implementation of DIRT Framework**



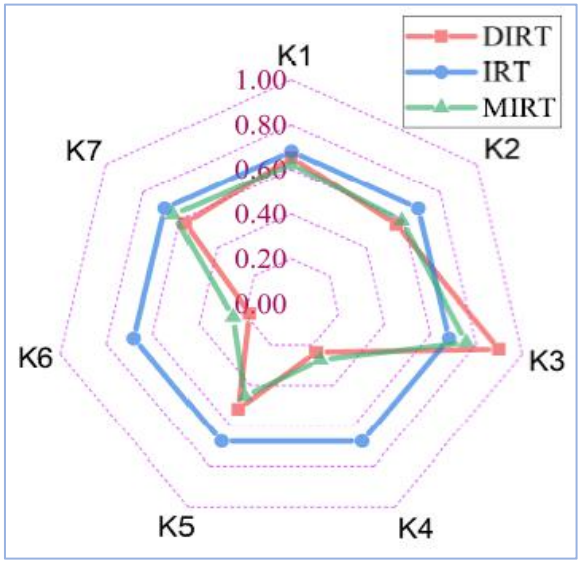
Song Cheng, Qi Liu, et al. DIRT: Deep Learning Enhanced Item Response Theory for Cognitive Diagnosis. ***CIKM 2019, Accepted.***

Deep Learning Enhanced IRT

- **Experiments on performance prediction task**
  - **IRT can only diagnose latent trait which has same value on all knowledge concepts.**
  - **MIRT is sensitive to knowledge, that is high proficiency knowledge can remedy low proficiency knowledge**

$$P(\boldsymbol{\theta}) = \frac{1}{1 + \exp(-1.7(\sum_i^k a_i \theta_i + d))}$$

Summation Sensitive to knowledge concepts



K1: Similar triangle properties

K2: Similar triangle judgement

K3: Proportional line segment

K4: Quadratic root operation

K5: Special trigonometric function

K6: Period

K7: Trigonometric

Song Cheng, Qi Liu, et al. DIRT: Deep Learning Enhanced Item Response Theory for Cognitive Diagnosis. ***CIKM 2019, Accepted.***

Neural Cognitive Diagnosis (NeuralCD)

- **Problems** in the interaction functions of traditional methods:
  - manually designed → labor intensive
  - mostly linear function

  → limited approximation ability



$$\text{IRT:} \quad P(\text{correct}) = \frac{1}{1 + e^{-a(\theta-\beta)}}$$

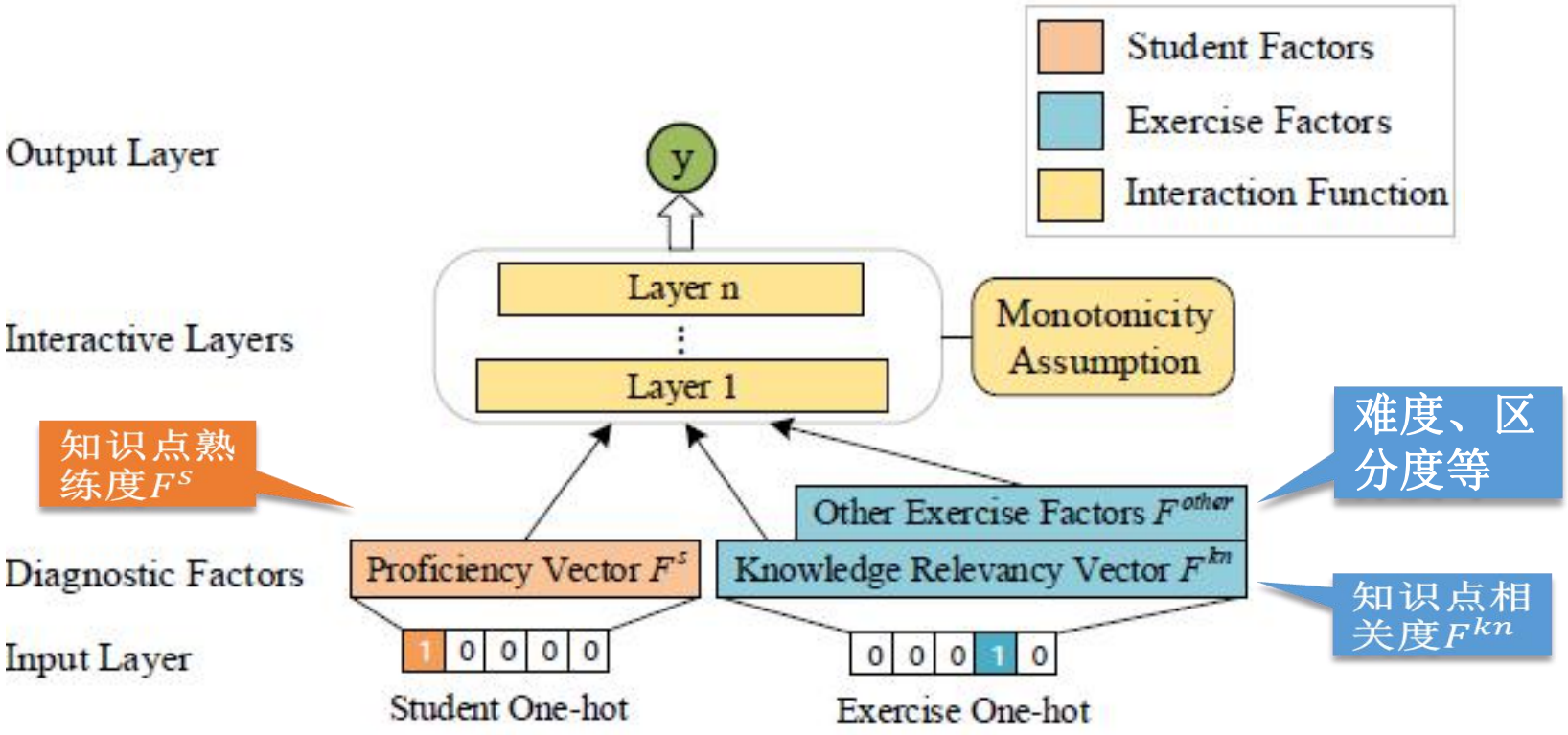
2 Learn interaction function automatically from data with deep learning

- Neural Cognitive Diagnosis (Wang et al. AAAI 2020)
  - general, explainable, extendible

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

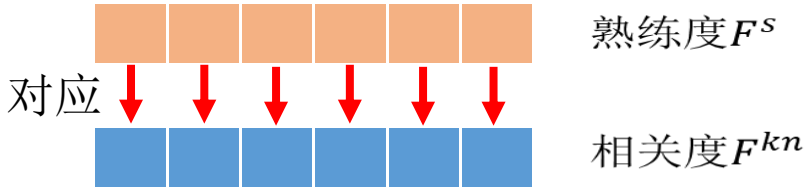
Neural Cognitive Diagnosis

- **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



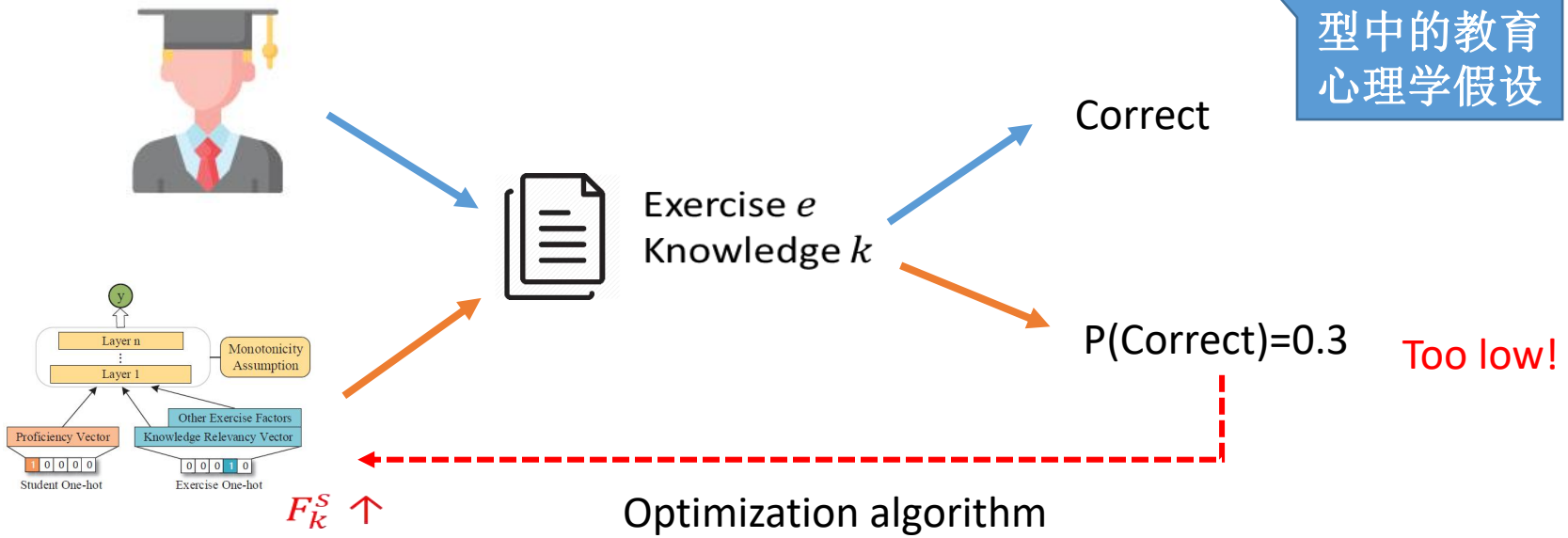
Neural Cognitive Diagnosis

- **Explainable**
  - $F^s \circ F^{kn}$: attach each entry of F^s to a specific knowledge concept



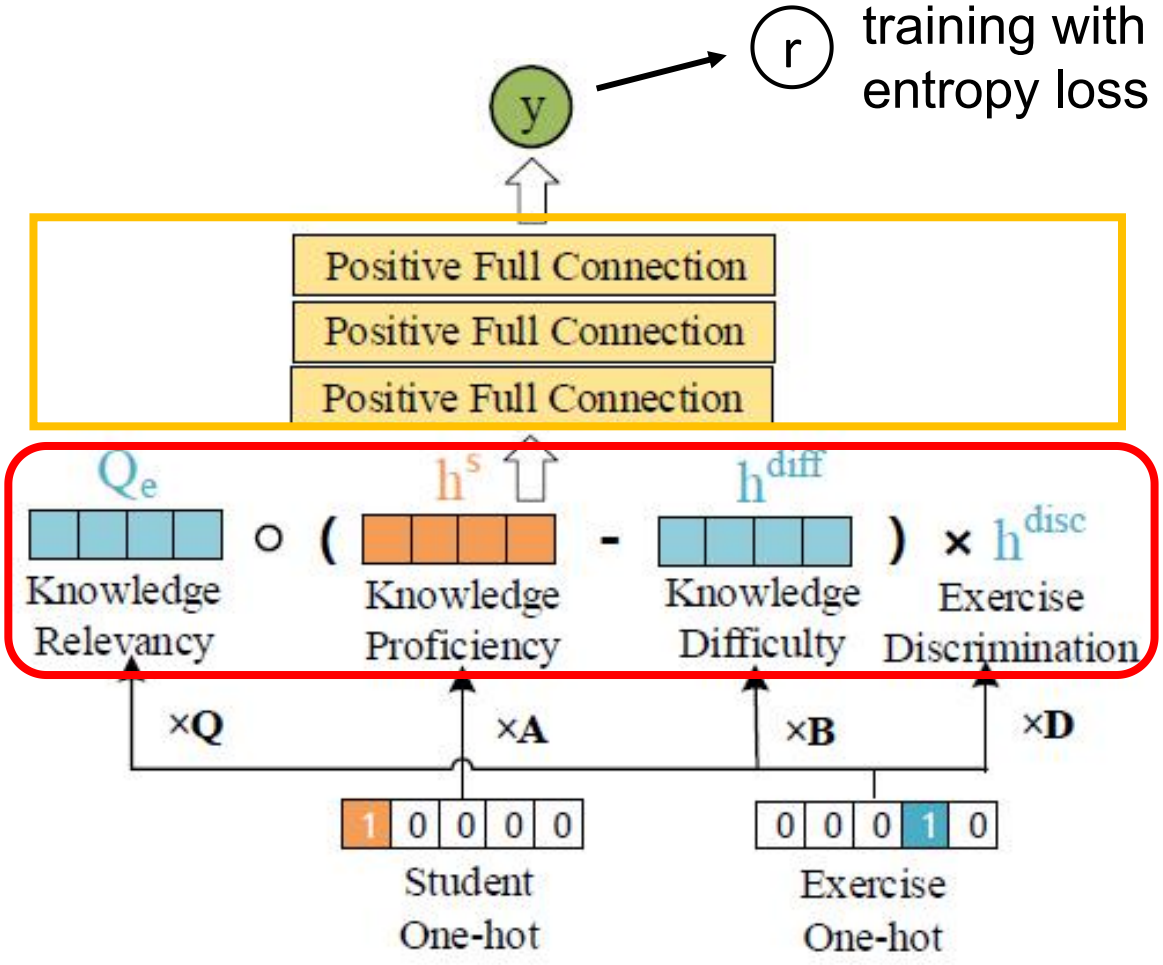
- **Monotonicity Assumption**: *The probability of correct response to the exercise is monotonically increasing at any dimension of the student's knowledge proficiency.* (widely applicable)

MIRT等模型中的教育心理学假设



Neural Cognitive Diagnosis

- **Feasible and effective** – basic implementation with Q-matrix



interaction layer:
- full connection
- positive weights

Monotonicity Assumption

input layer:

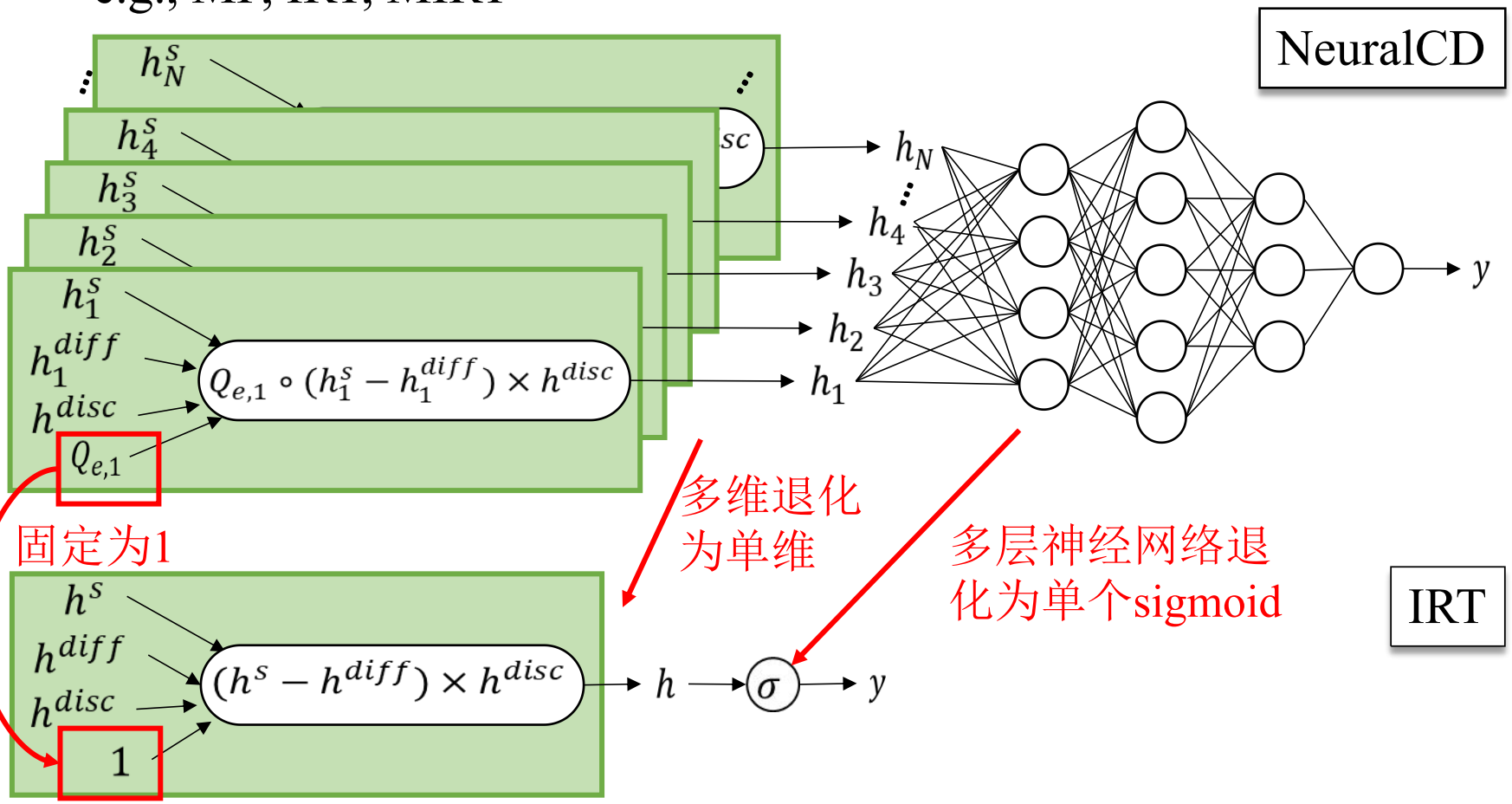
$$\boldsymbol{Q}_e \circ (\boldsymbol{h}^s - \boldsymbol{h}^{diff}) \times h^{disc}$$

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

Directly from Q-matrix

Neural Cognitive Diagnosis

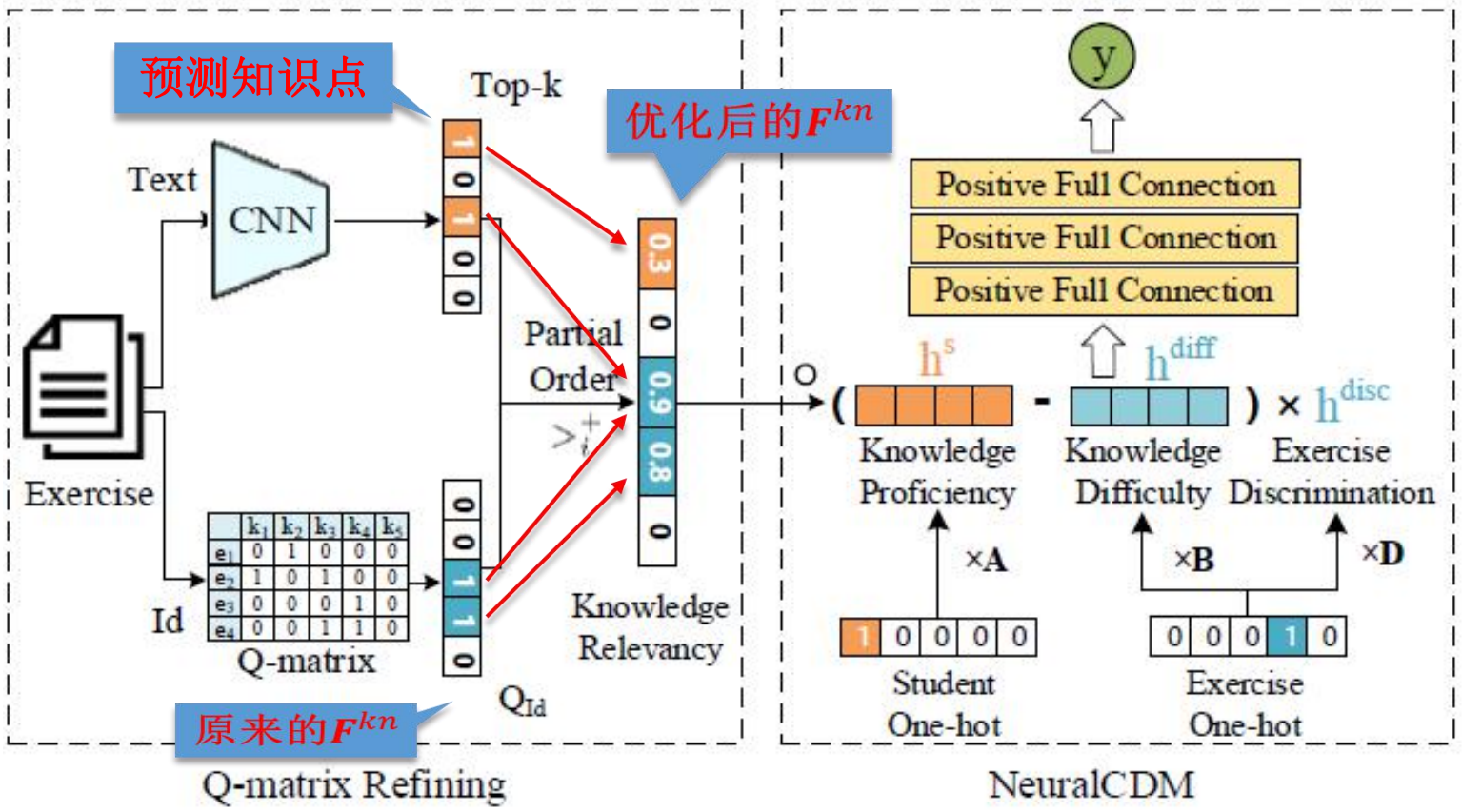
- **Generality**: NeuralCD framework is general and can cover some traditional models
  - e.g., MF, IRT, MIRT



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:

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



Neural Cognitive Diagnosis

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**: Zhixue[1], mathematical exercises (with texts) and logs
- **ASSIST**: Assistment[2], mathematical exercises (without texts) and logs

Student performance prediction

	Math			ASSIST		
Model	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

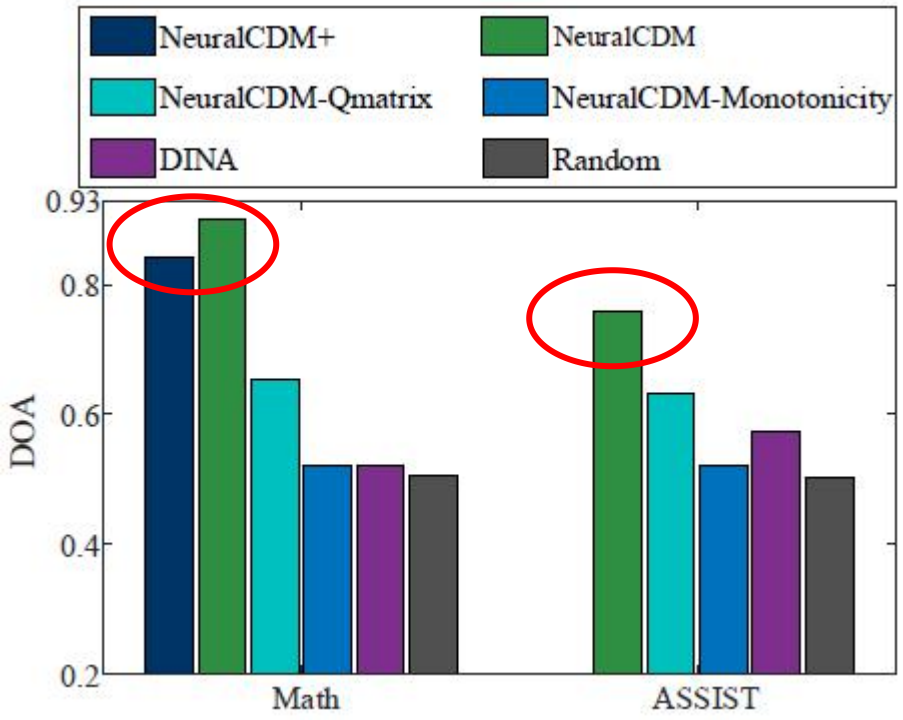
[1]Private dataset, provided by iFLYTEK Co., Ltd.

[2]https://sites.google.com/site/assistmentsdata/home/assistment-2009-2010-data/skill-builder-data-2009-2010

Neural Cognitive Diagnosis

- **Model interpretation**
  - If student a has a better mastery on knowledge concept k than student b, then a is more likely to answer exercises related to k correctly than b.

$$DOA(k) = \frac{1}{Z} \sum_{a=1}^{N} \sum_{b=1}^{N} \delta(F_{ak}^{s}, F_{bk}^{s}) \sum_{j=1}^{M} I_{jk} \frac{J(j,a,b) \wedge \delta(r_{aj}, r_{bj})}{J(j,a,b)}$$



Higher DOA: students who perform well on certain knowledge concept get higher diagnosed knowledge proficiency

Neural Cognitive Diagnosis

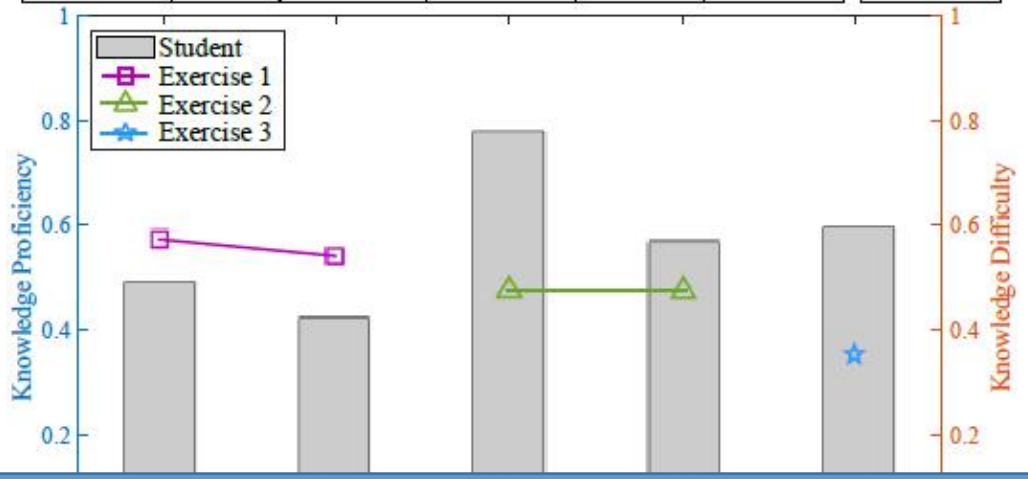
- **Case Study**
  - a student's performance on 3 exercise in ASSIST
  - and his/her diagnosed result

Q-Matrix

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

Response

Student Response
✗
✓
✓

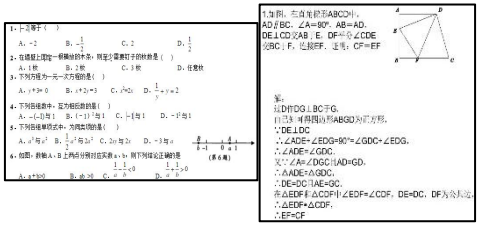


The student is more likely to answer correctly when his/her knowledge proficiency satisfy the requirement of the exercise.

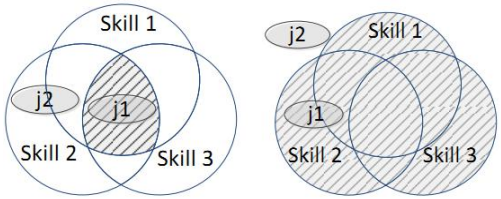
Code for NeuralCDM is available at https://github.com/bigdata-ustc/NeuralCD

Research Overview

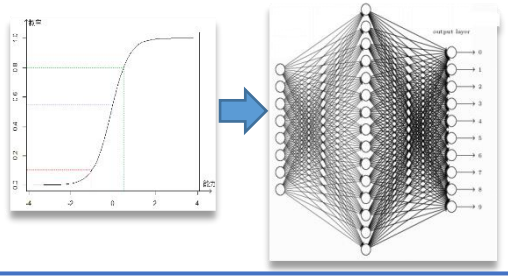
Model different response types of exercises



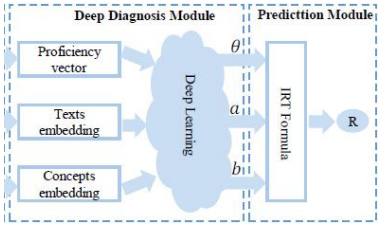
Fuzzy Cognitive Diagnosis (IJCAI 2015, TIST 2018)



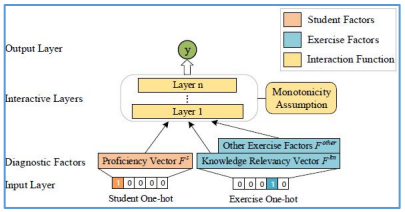
Model the complex relations



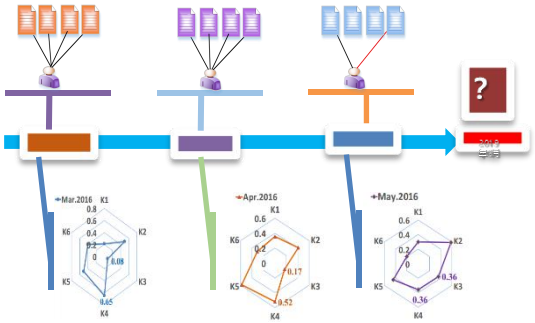
DIRT(CIKM2019)



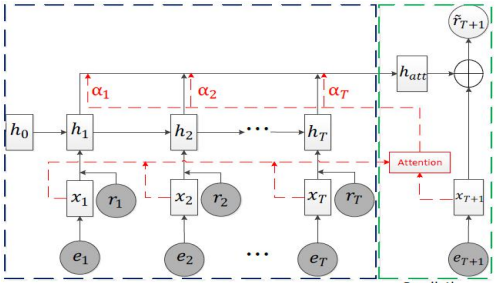
Neural Cognitive Diagnosis (AAAI2020)



Model the evolving proficiencies

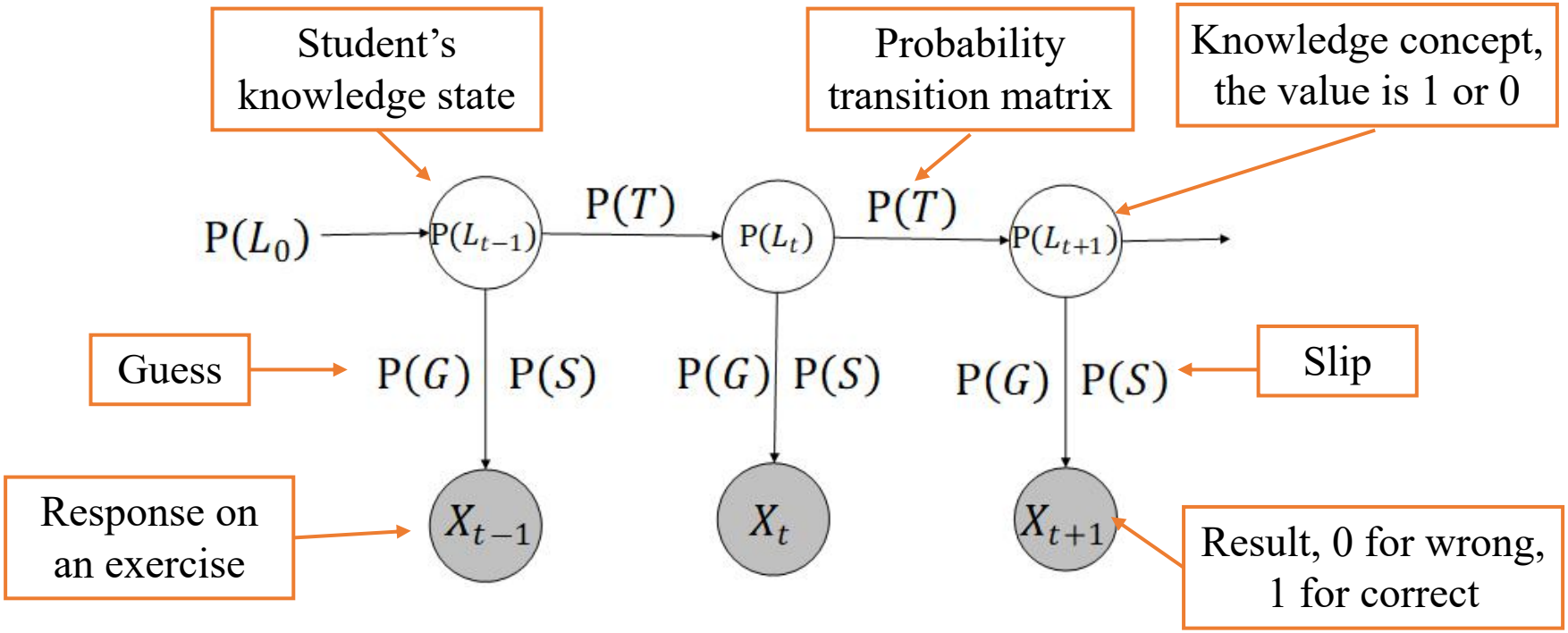


Knowledge Tracing (AAAI 2018, TKDE 2019)



Dynamic cognitive diagnosis

- **Bayesian knowledge tracing (BKT)**
  - model a learning process by a hidden Markov model
  - Single skill tracing
  - Diagnostic results are discrete (mastered or non-mastered)

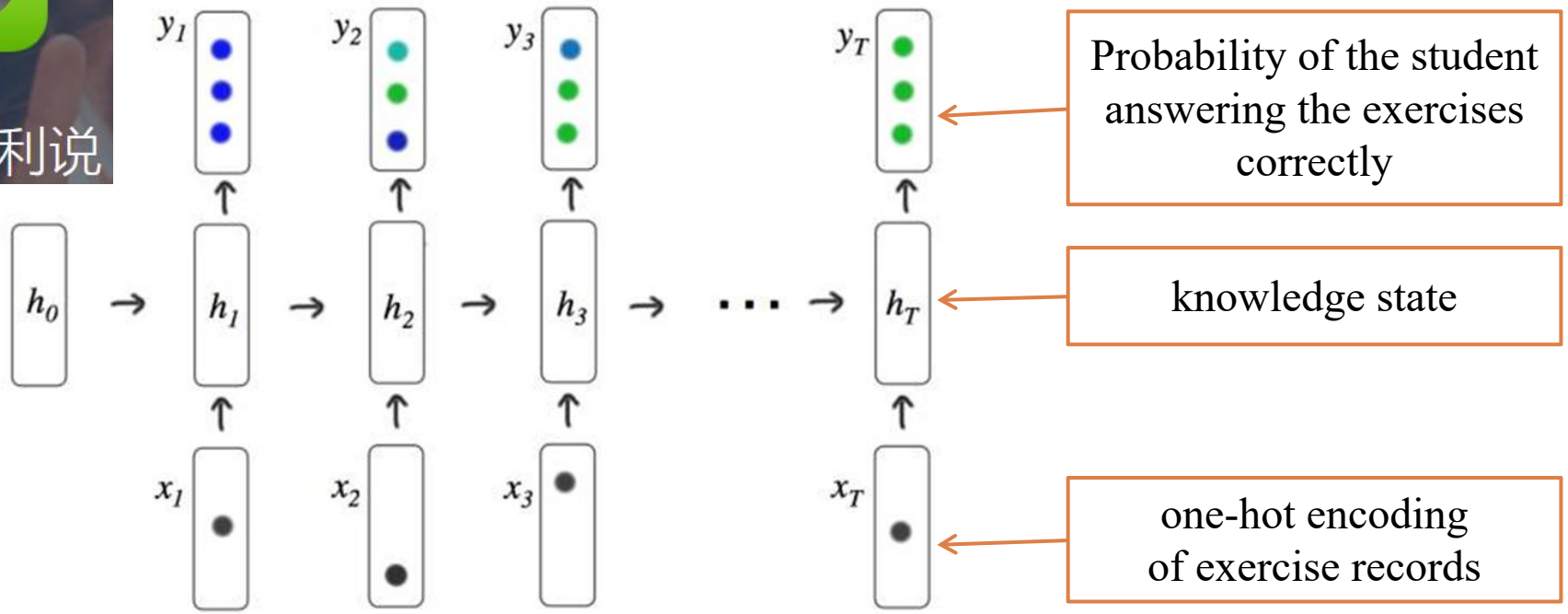


Corbett A T, Anderson J R. Knowledge tracing: Modeling the acquisition of procedural knowledge[J]. User modeling and user-adapted interaction, 1994, 4(4): 253-278.

Dynamic cognitive diagnosis

- **Deep Knowledge Tracing (DKT)**
  - Apply RNNs (LSTM) to model student knowledge over time
  - Hidden states represent the latent knowledge state



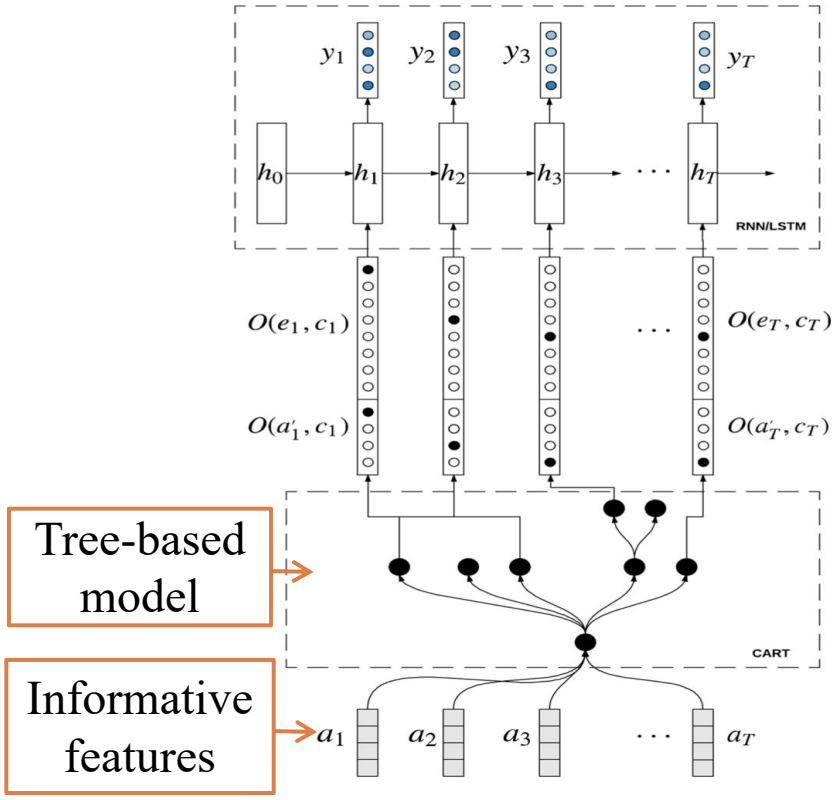


Piech C, Bassen J, Huang J, et al. Deep knowledge tracing. NIPS 2015: 505-513

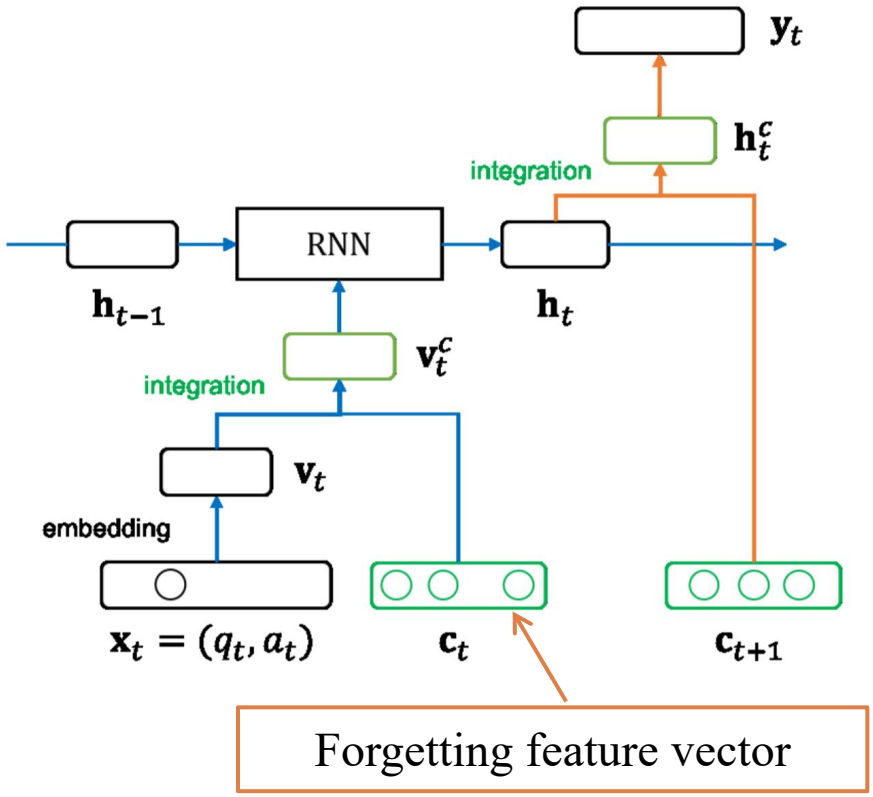
Dynamic cognitive diagnosis

- **Extensions of Deep Knowledge Tracing**

DKT-Trees



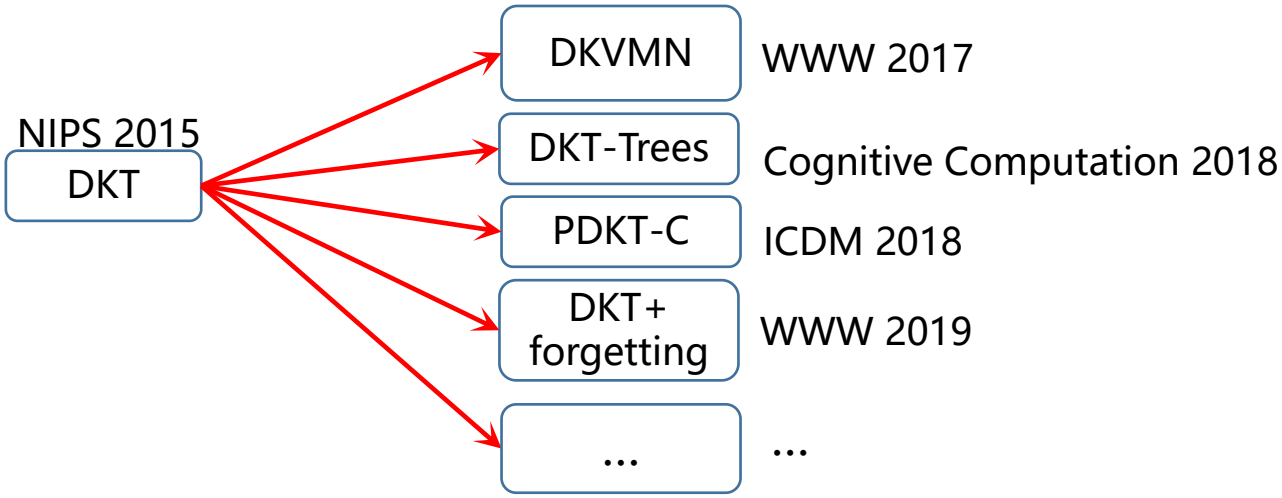
DKT + forgetting



- Yang H, Cheung L P. Implicit heterogeneous features embedding in deep knowledge tracing[J]. Cognitive Computation, 2018, 10(1): 3-14.
- Nagatani K, Zhang Q, Sato M, et al. Augmenting Knowledge Tracing by Considering Forgetting Behavior. WWW 2019.

Existing Problem

- **Summary of existing studies**



- **The information contained in the exercise text is underexplored.**
  - Same Concept, but diverse text expressions of exercises

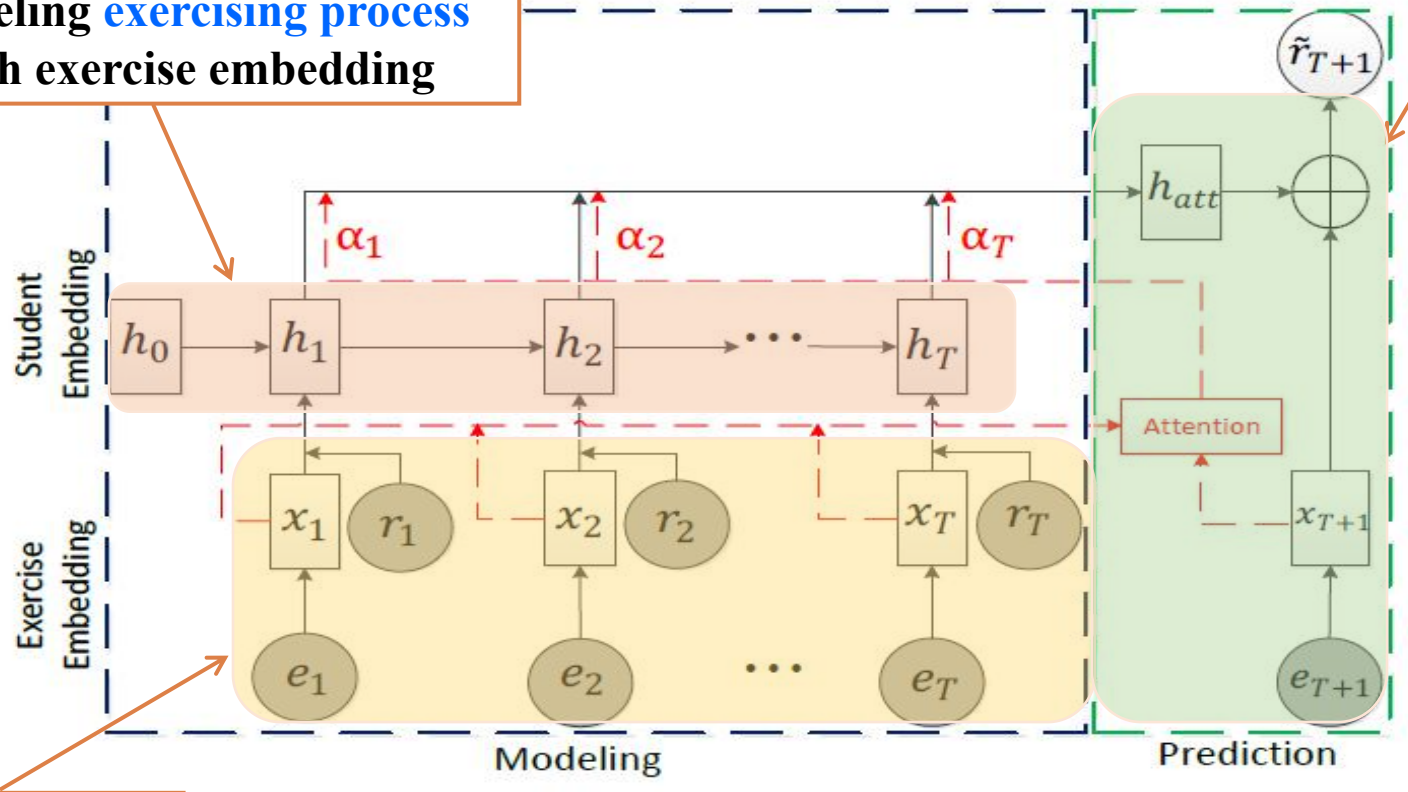
	Exercise Texts	Knowledge Concept
1	Can you guess the texts of the 3 exercises?	Function
2		Function
3		Function

Exercise-aware Knowledge Tracing

- **EERNNA Framework with Attention**

Track the focused states for students in the process

Modeling exercising process with exercise embedding



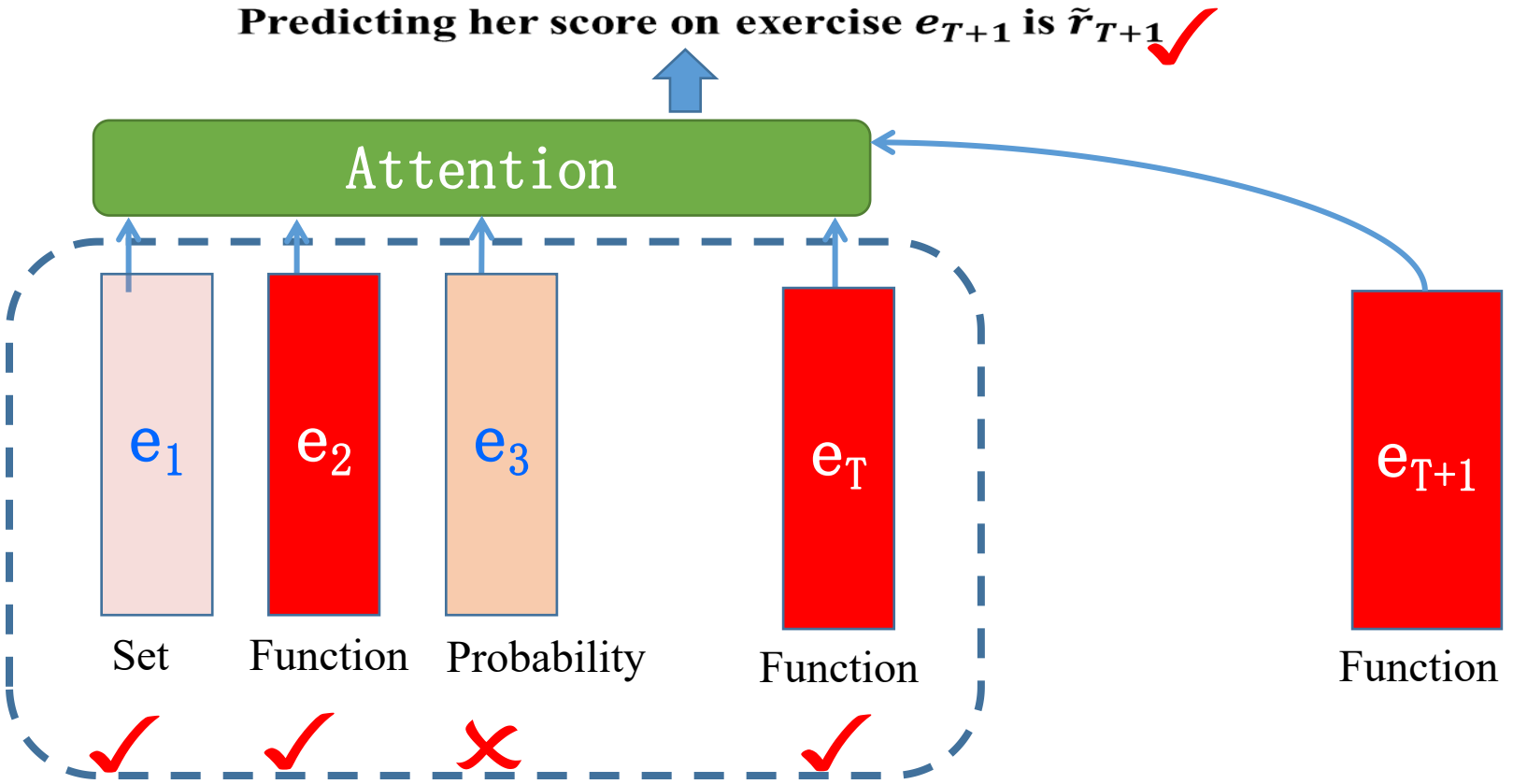
(b) EERNNA with Attention mechanism

Modeling for exercise texts

- Su Y, Liu Q, Liu Q, et al. Exercise-enhanced sequential modeling for student performance prediction[C]//Thirty-Second AAAI Conference on Artificial Intelligence. 2018.

Exercise-aware Knowledge Tracing

- **EERNNA Framework with Attention**
  - Problem: Vanish problem, ignoring the effects of historical states
  - Intuition: Students may get similar scores on similar exercises



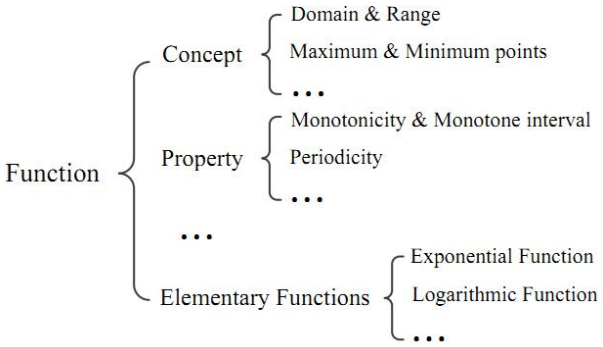
Exercise-aware Knowledge Tracing

Experiments dataset

- Mathematical records of high school students

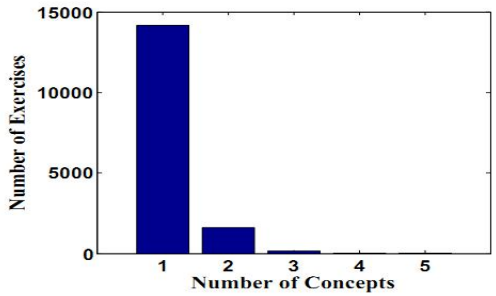
TABLE 1
The statistics of mathematics dataset.

Statistics	Original	Pruned
# of records	68,337,149	5,596,075
# of students	1,100,726	84,909
# of exercises	1,825,767	15,045
# of knowledge concepts	37	37
# of knowledge features	550	447
Avg. exercising records per student	\	65.9
Avg. content length per exercise	\	27.3
Avg. knowledge concepts per exercise	\	1.12
Avg. knowledge features per exercise	\	1.8
Avg. exercises per knowledge concept	\	406.6

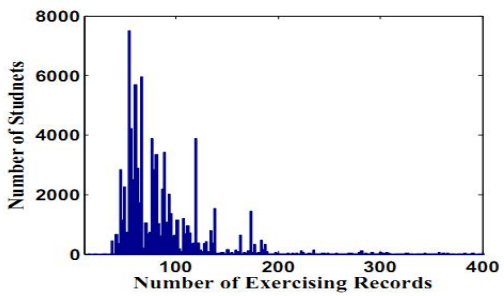


Dataset analysis

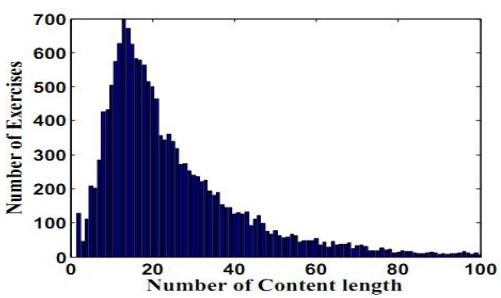
- Most exercises contain less than 2 knowledge concepts and features
- One specific knowledge concept is related to 406 exercises on average
- The average content length of each exercise is about 27



(a) Distribution of concepts



(b) Distribution of exercising records



(c) Distribution of content length

Exercise-aware Knowledge Tracing

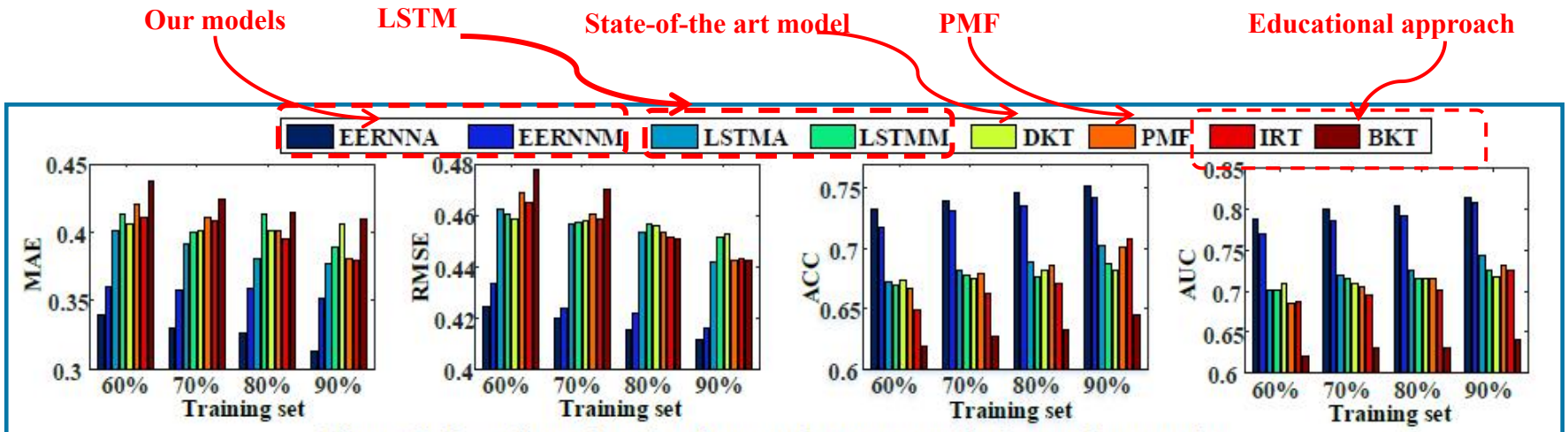


Figure 5: Overall results of student performance prediction on four metrics.

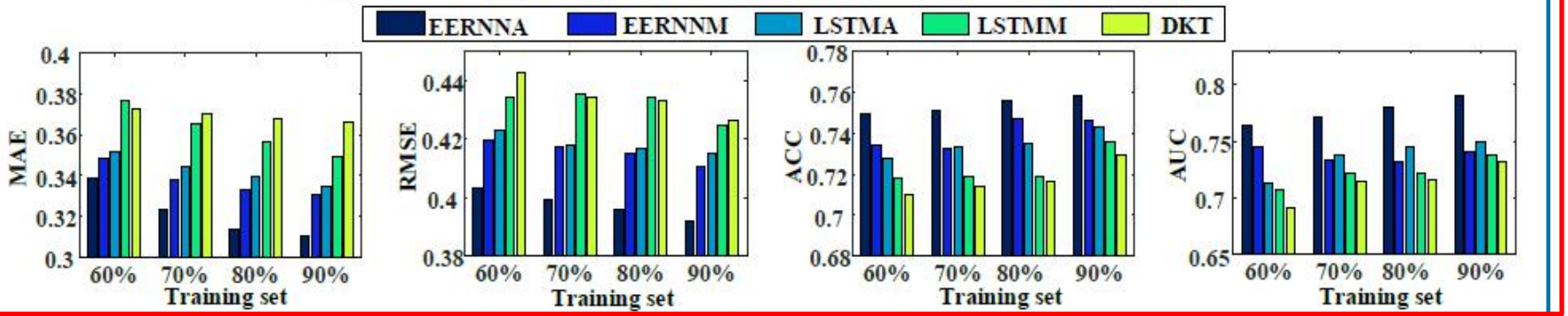
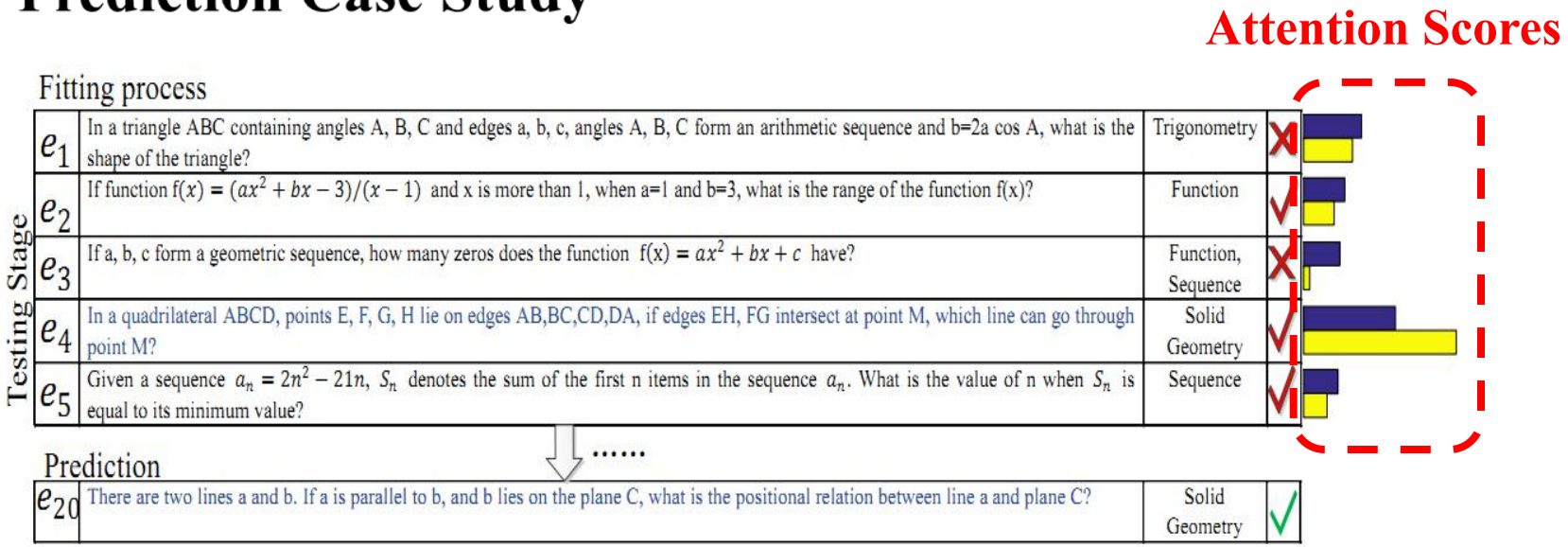


Figure 6: Results of student performance prediction on cold start new exercises on four metrics.

For cold start scenario, our models also have accurate and stable results

Exercise-aware Knowledge Tracing

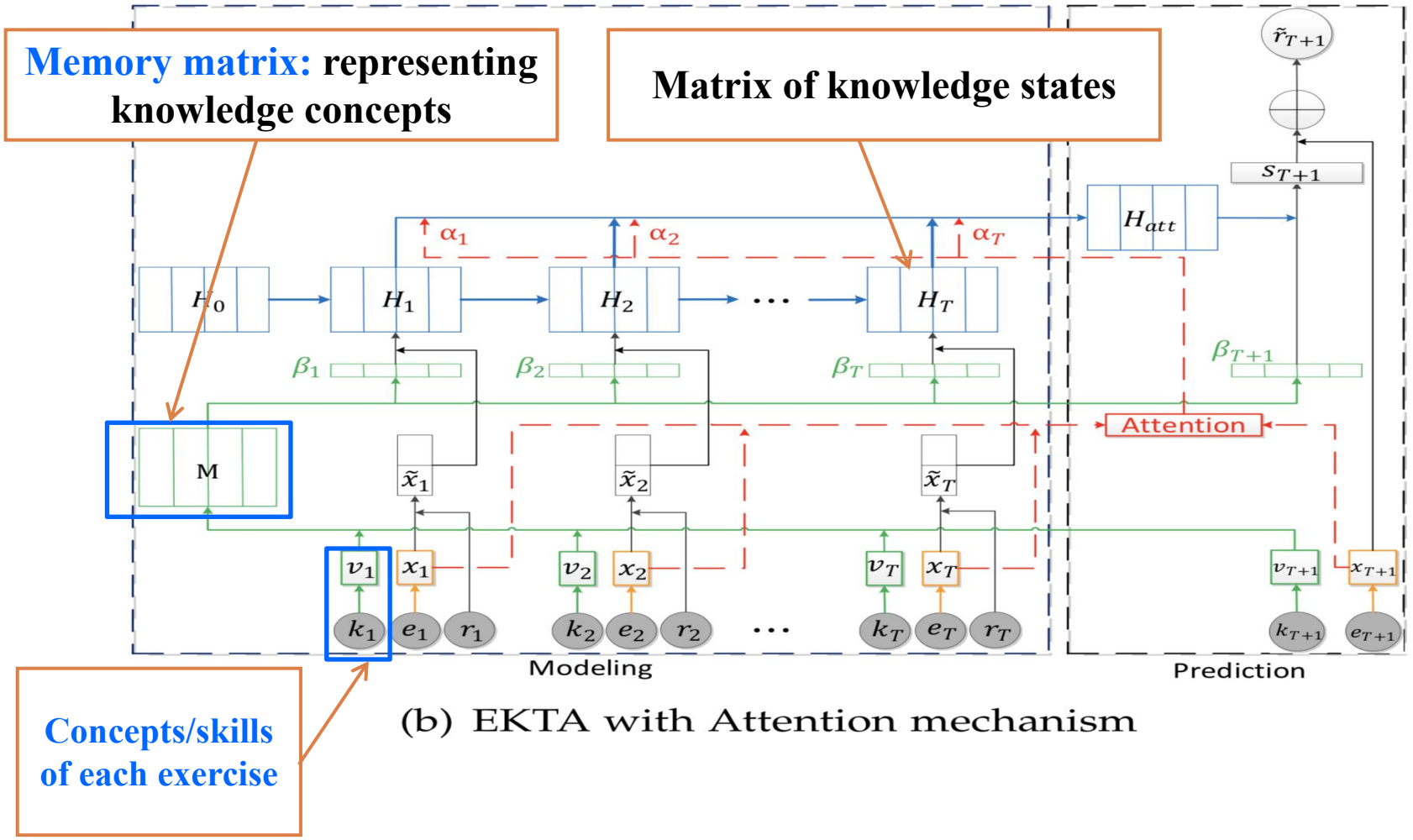
Prediction Case Study



- e_4 is actually much more difficult than e_{20}
- Both e_4 and e_{20} contain the same knowledge concept "Solid Geometry"
- EKTA endows a larger attention weight on e_4

Exercise-aware Knowledge Tracing

EKT Framework with Attention

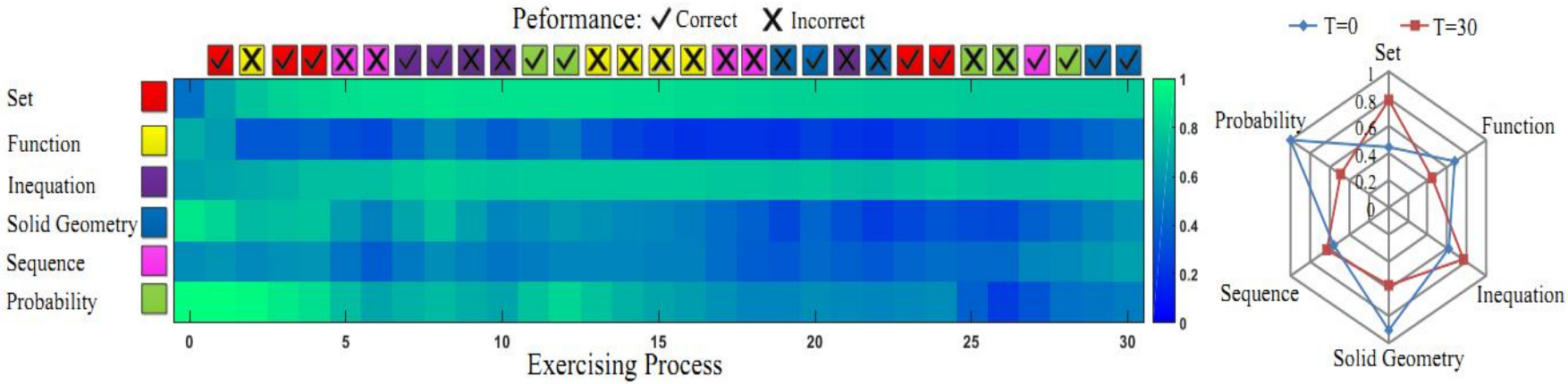


(b) EKTA with Attention mechanism

Huang Z, et al. EKT: Exercise-aware Knowledge Tracing for Student Performance Prediction[J]. IEEE Transactions on Knowledge and Data Engineering, 2019.

Exercise-aware Knowledge Tracing

Knowledge Acquisition Tracking



- The mastery levels on concepts change gradually during the process
- When she answers an exercise right (wrong), her knowledge state on the corresponding concept increases (decreases)

Outline

1 Background

2 Cognitive Diagnosis

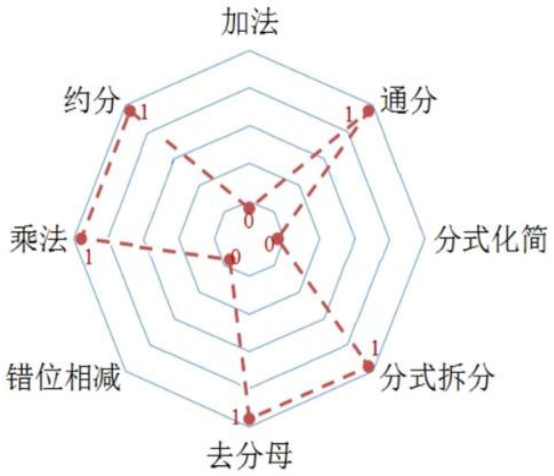
3 Issues of Cognitive Diagnosis

4 Application

5 Conclusion and Discussion

Application

- **How to exploit cognitive diagnosis for personalized learning**



Knowledge States

Too hard

Suitable

Too easy

Personalized Learning

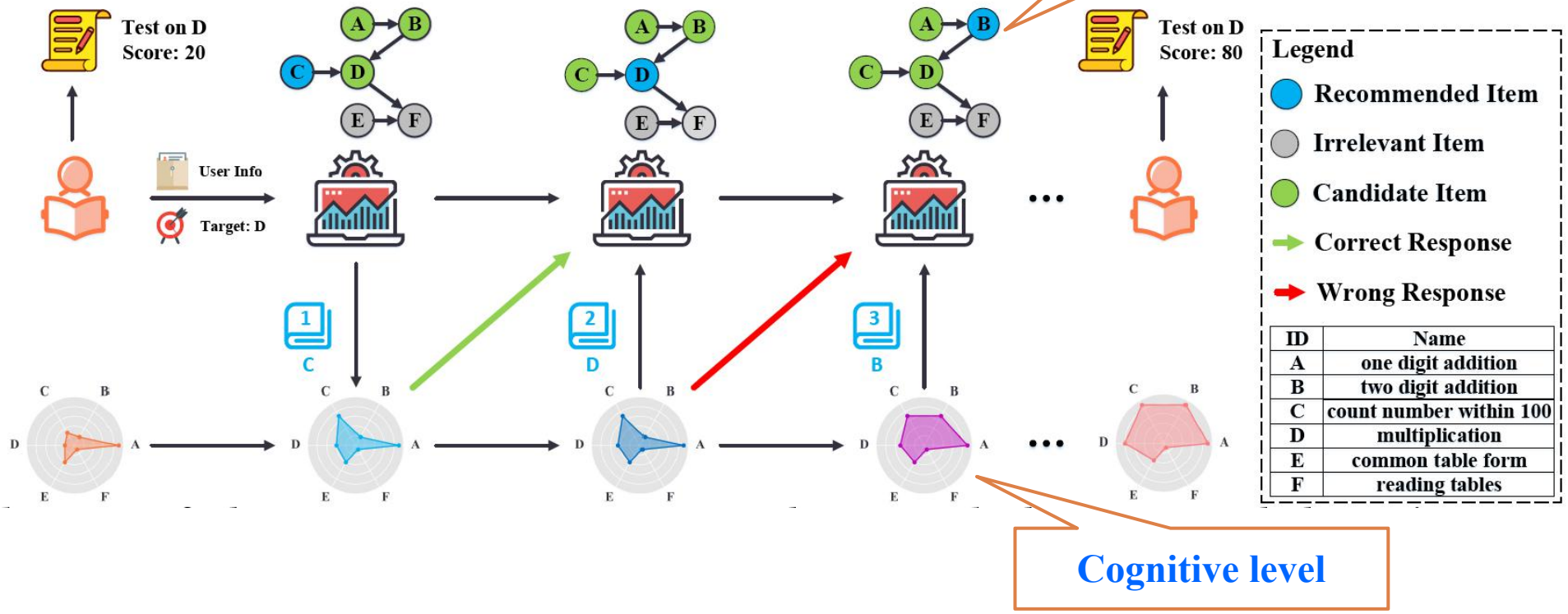
Learning Resources

I reach it just right!



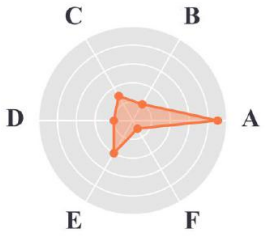
Learning Path Recommendation

- **Learning path recommendation: key to adaptive learning**
  - Important factors to be adaptive:
  - Adapt to learners' knowledge level
  - Follow knowledge structure (e.g. prerequisites)

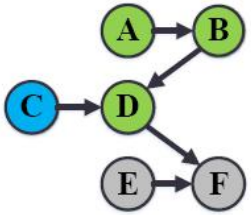


Learning Path Recommendation

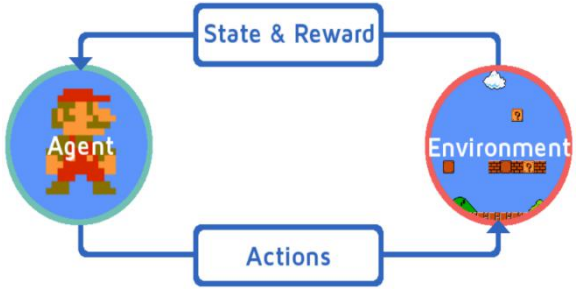
- **Three key challenges in Adaptive learning**
  - How to model the implicitly evolving knowledge level of the learner?
    - E.g., with the poor mastery of two digit addition, it is difficult to learn multiplication.
  - The learning path should be in accordance with the logicality determined by the 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



Knowledge Tracing



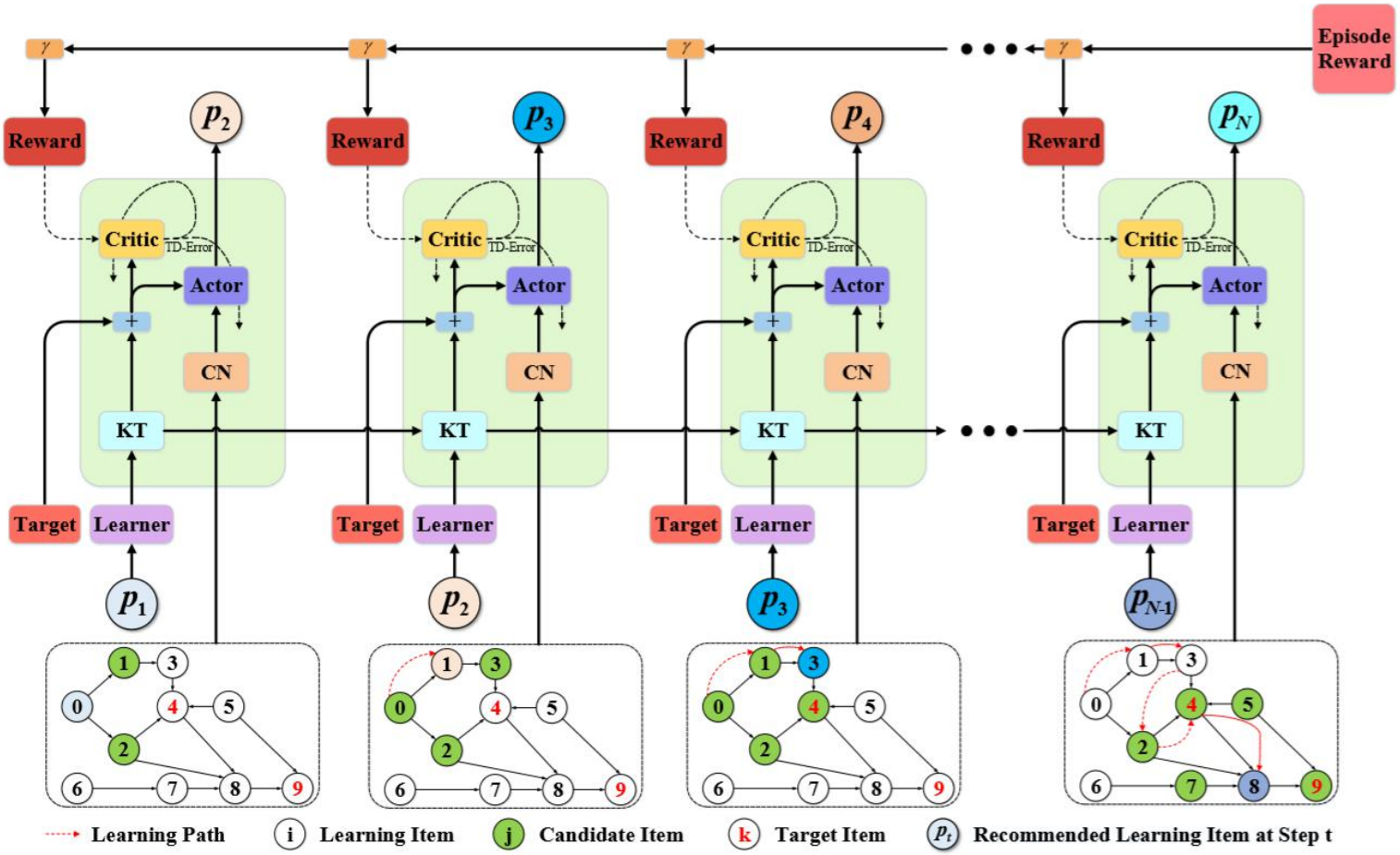
Cognitive Navigation algorithm



Actor-critic recommender

Learning Path Recommendation

- **CSEAL: Cognitive Structure Enhanced framework for Adaptive Learning**



- Q. Liu, S. Tong, C. Liu, H. Zhao, E. Chen, H. Ma and S. Wang. Exploiting Cognitive Structure for Adaptive Learning. ***KDD 2019 accepted.***

Learning Path Recommendation

- **CSEAL: Cognitive Structure Enhanced framework for Adaptive Learning**

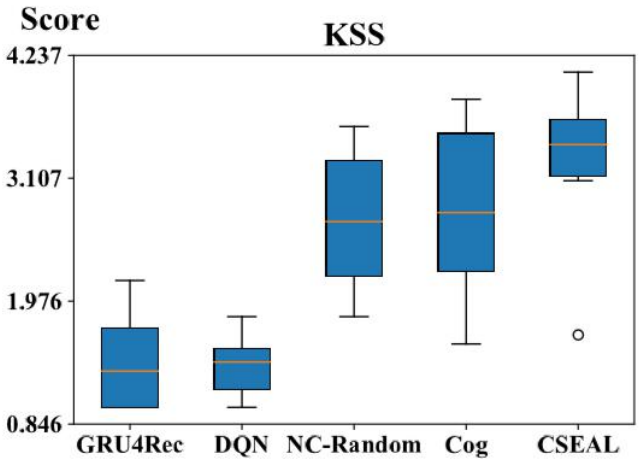
Table 3: Overall results of $E_{\mathcal{P}}$.

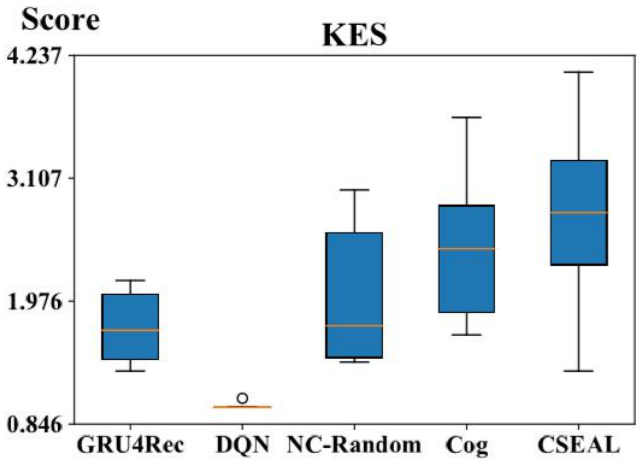
	KSS	KES
KNN	0.000700	0.257919
GRU4Rec	0.007727	0.201219
MC-10	0.110577	0.002236
MC-50	0.108636	-0.005103
DQN	0.100610	0.002688
CSEAL-NCN	0.222363	0.003354
CN-Random	0.272784	0.138526
Cog	0.164128	0.166560
CSEAL	**0.346883**	**0.405823**

- KSS: IRT simulation
- KES: DKT simulation

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

Student performance improves in simulated environments.





Better evaluation results given by experts

Learning Path Recommendation

- **CSEAL: Cognitive Structure Enhanced framework for Adaptive Learning**

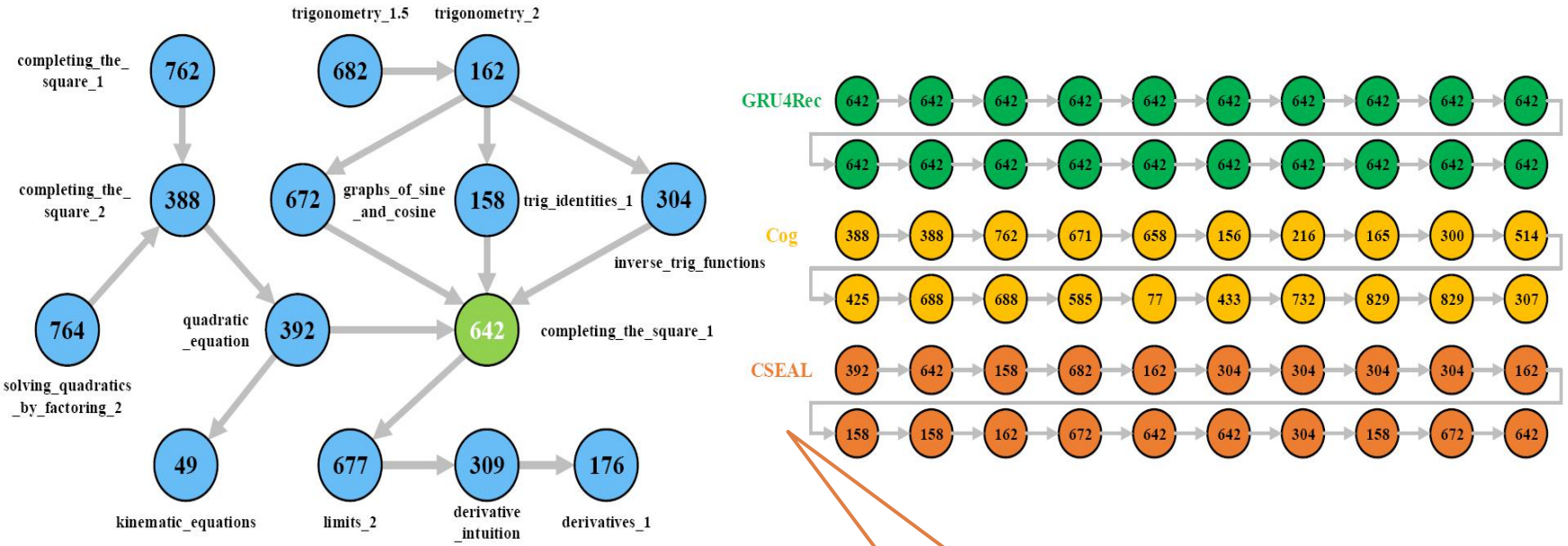


Figure 9: Visualization of different recommended learning paths for the learning item 642, i.e., *completing_the_square_1*.

More efficient and logical learning path

Adaptive Learning

- **Adaptive Learning**
  - Student online exercising
  - Cognitive diagnosis for students
  - Exercise recommendations for students



Outline

1 Background

2 Cognitive Diagnosis

3 Issues of Cognitive Diagnosis

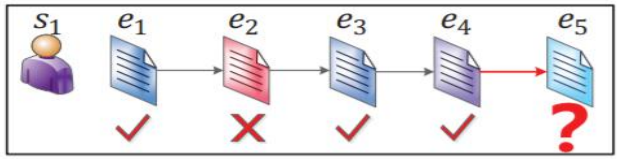
4 Application

5 Conclusion and Discussion

Study Overview

3

Exercise-aware Knowledge Tracing



Dynamic cognitive diagnosis

A

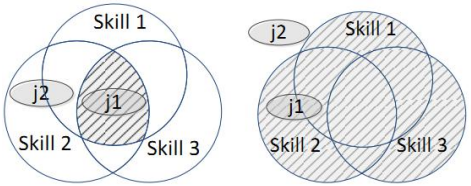
Learning Path Recommendation



Application of cognitive diagnosis

1

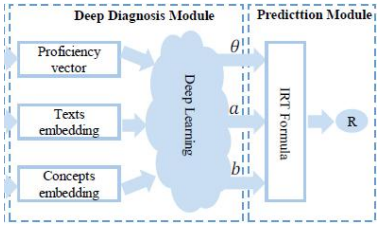
Fuzzy Cognitive Diagnosis



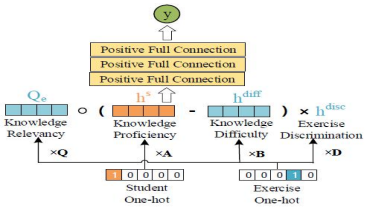
Heterogeneous exercise modality

2

Deep Learning Enhanced IRT



Neural Cognitive Diagnosis



Cognitive diagnosis with deep learning

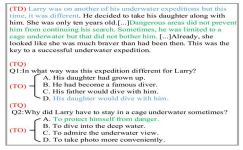
Q-matrix

	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
……			

Response matrix R

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

Exercise Text



Materials

Discussion

- Knowledge transfer for cognitive diagnosis
  - subject-specific knowledge
  - knowledge structure
  - students' social relations
- Cognitive diagnosis for groups
  - class analysis
  - assist with offline teaching
- Cognitive diagnosis in more areas
  - games
  - sports
  - …







Reference

- .Qi Liu, Shiwei Tong, Chuanren Liu, Hongke Zhao, Enhong Chen, Haiping Ma and Shijin Wang. Exploiting Cognitive Structure for Adaptive Learning. KDD 2019 accepted.
- 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



Thanks!

Personal website: http://staff.ustc.edu.cn/~cheneh/

BASE： http://base.ustc.edu.cn/