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SARLR: Self-adaptive Recommendation of Learning Resources

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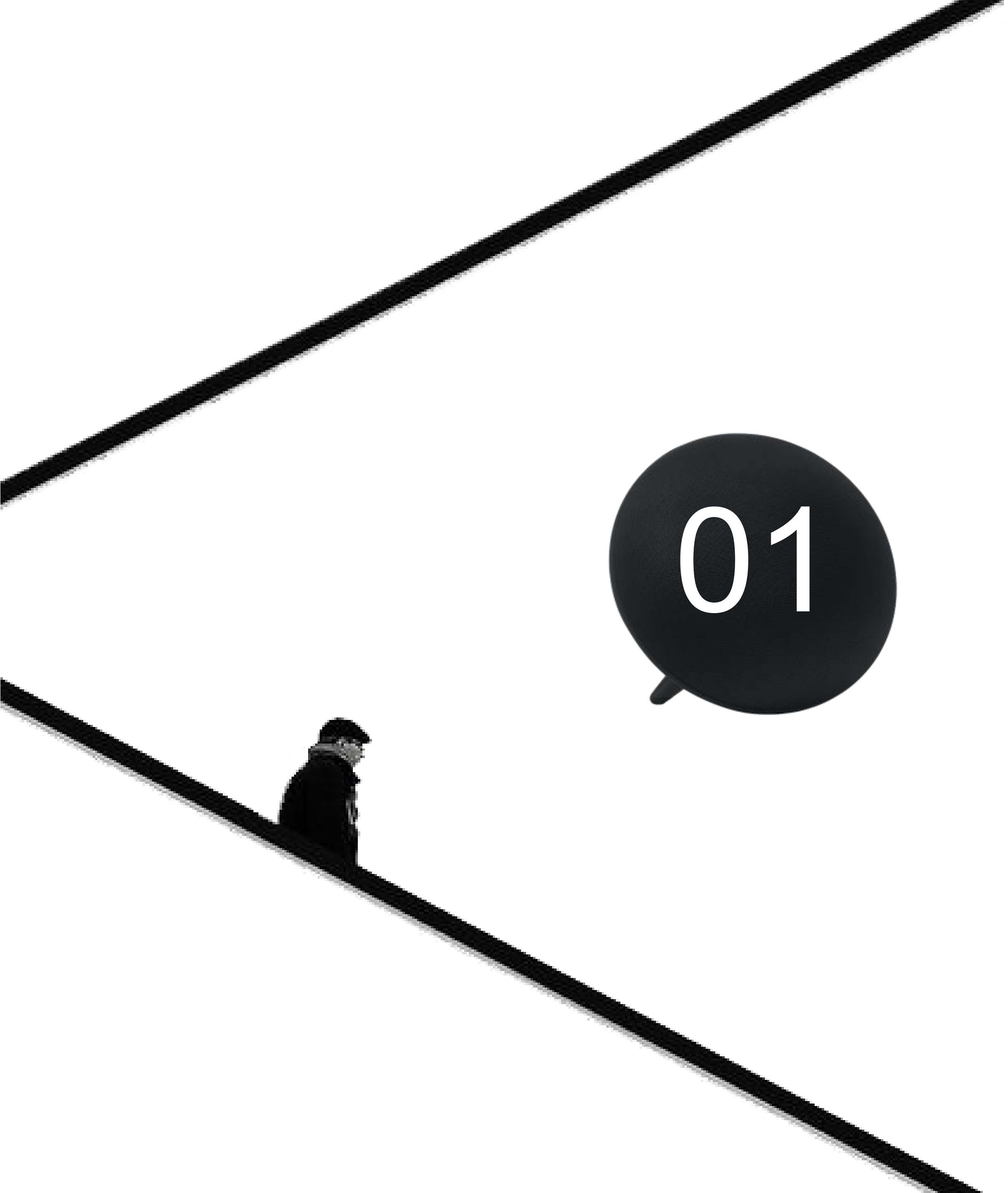
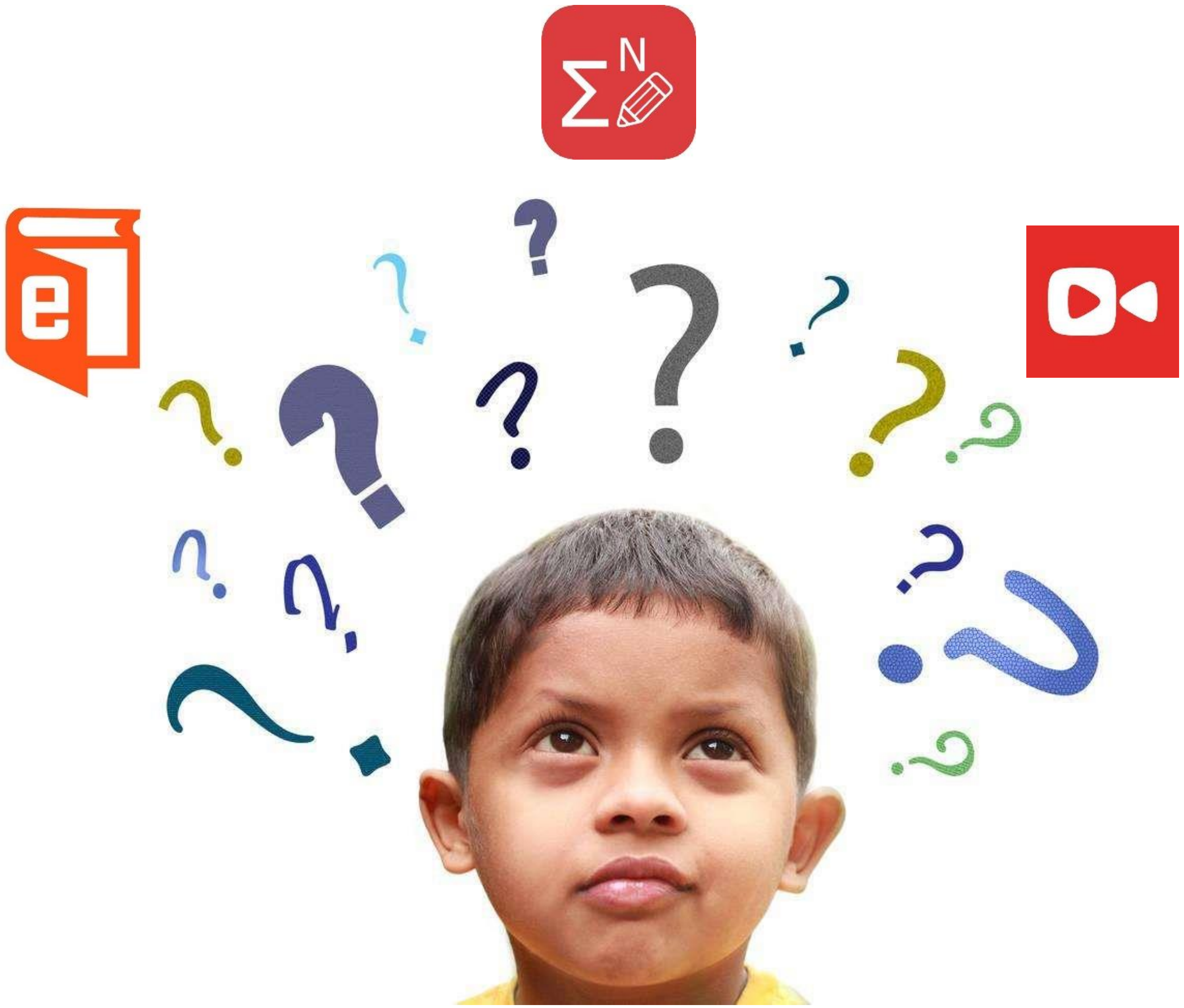
Content



01

Introduction

Introduction



1. Introduction

Rule-based Recommendation	Data-driven Recommendation

Rule-based Recommendation

- Require domain experts to evaluate learning scenarios
- Define extensive recommendation rules
- Only be applied in specific learning domains

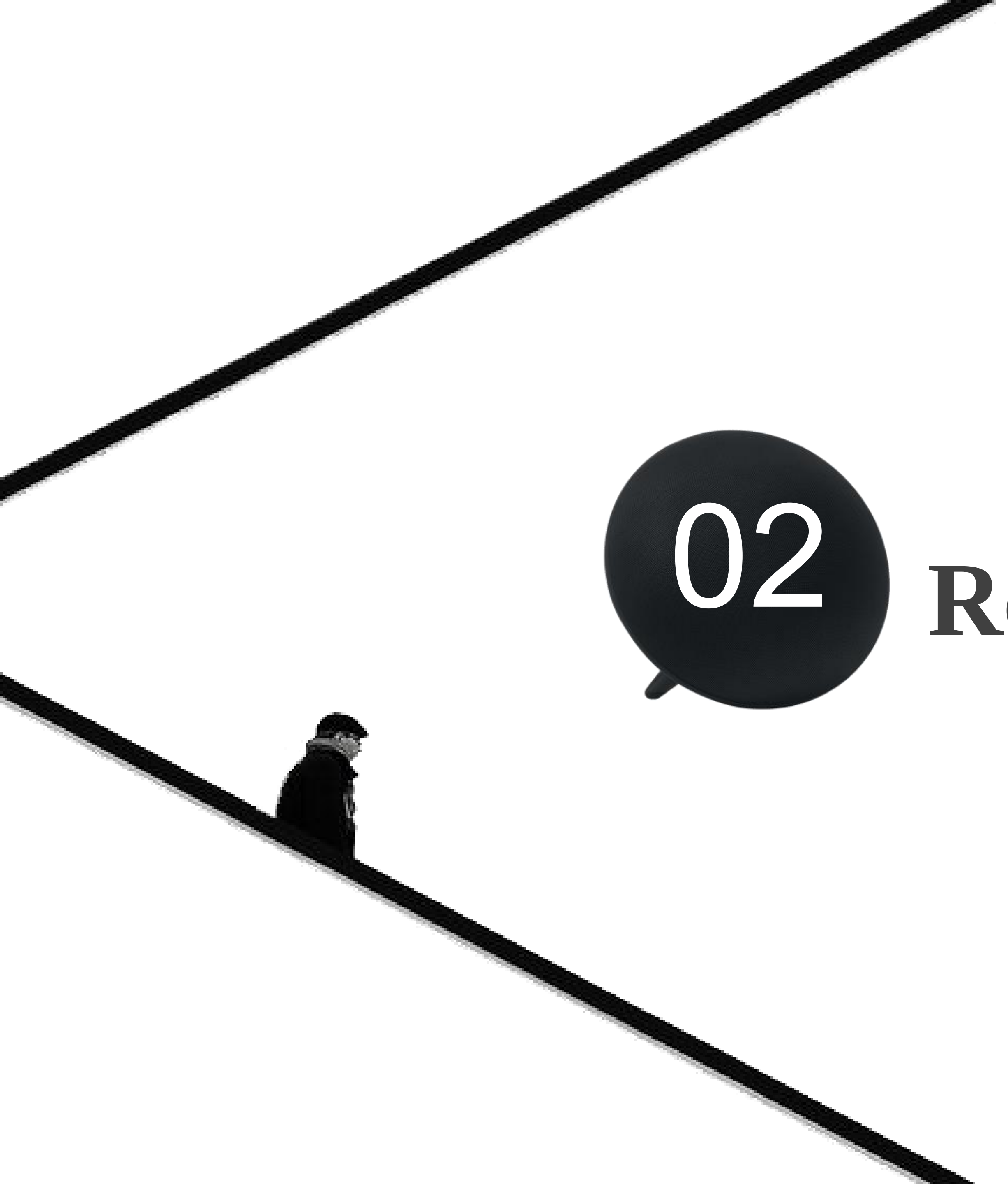
Data-driven Recommendation

- Compare similarity among students and learning objects
- Be more scalable and general
- Fail to consider the impact of difficulty of learning objects and dynamic change

1. Introduction

Contributions

- SARLR, a novel learning recommendation algorithm
- T-BMIRT, a temporal, multidimensional IRT-based model, incorporates the parameter of video learning
- An evaluation strategy for recommendation algorithms in terms of rationality and effectiveness



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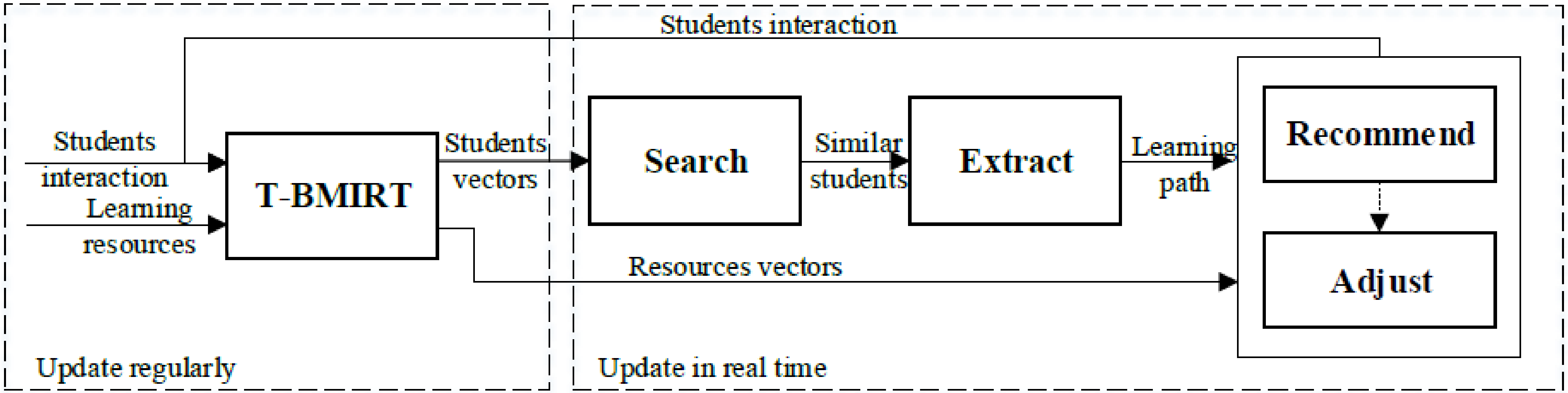
Self-Adaptive Recommendation

2. Self-Adaptive Recommendation

- **The Overall architecture of the SARLR algorithm**

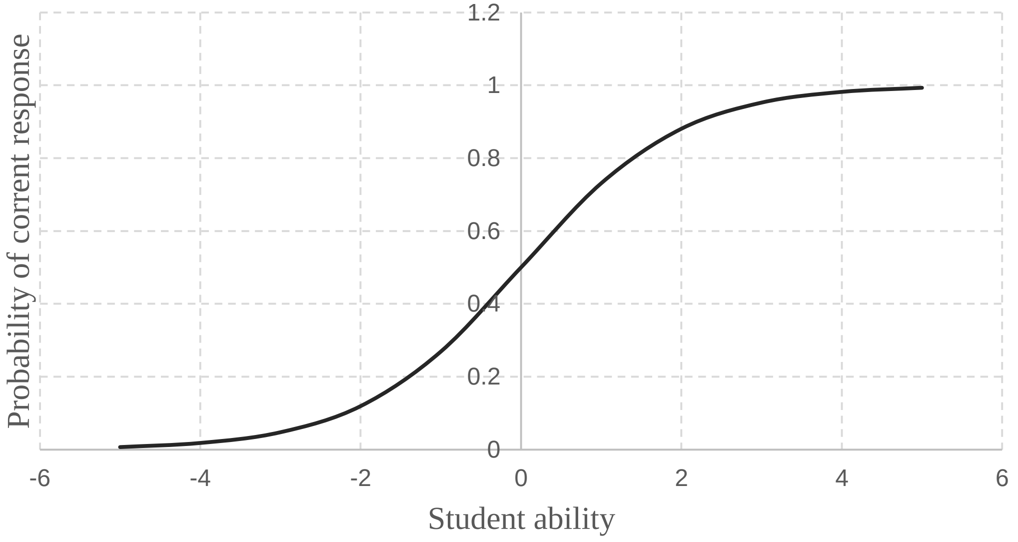


2. Self-Adaptive Recommendation

IRT

$$p_{sq} = \frac{1}{1 + exp[-(\alpha_q(\theta_s - \beta_q))]}$$

- α: question discrimination
- β: question difficulty
- θ: student's ability



Item Characteristic Curve(ICC)

T-IRT

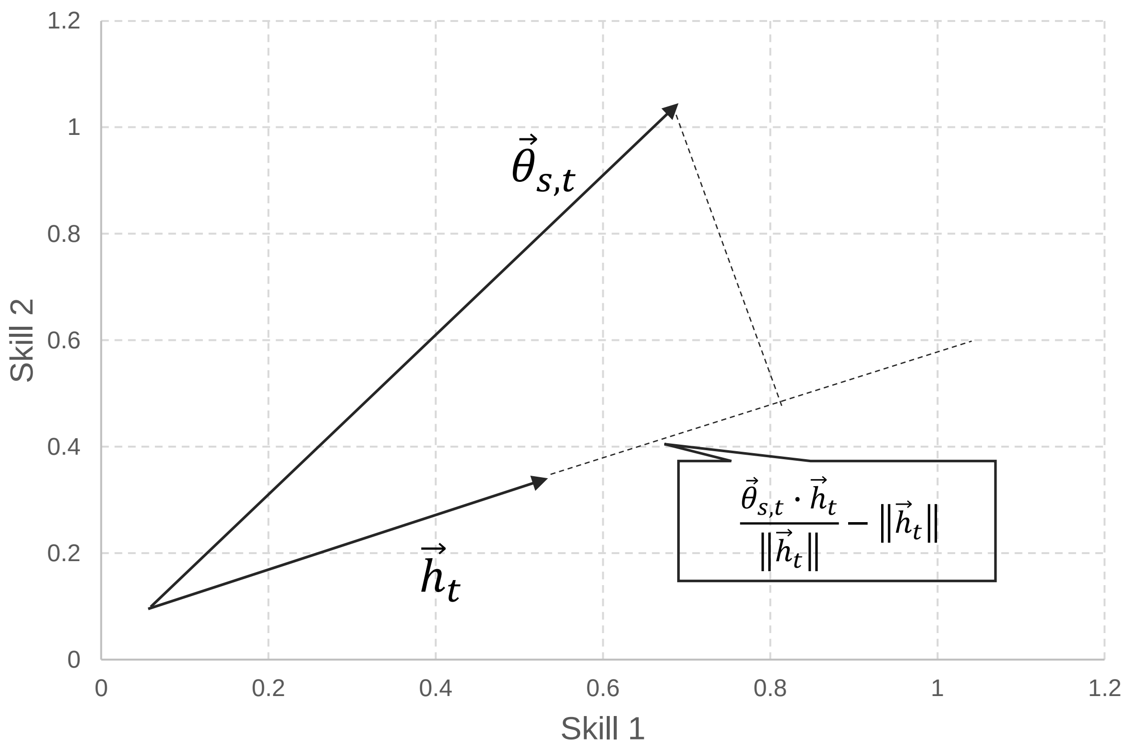
The Temporal IRT extend IRT model by modeling the student's knowledge state over time as a Wiener process

$$\theta_{t+\tau} - \theta_t \sim N(\theta_t, v_2\tau)$$

$$P(\theta_{t+\tau}|\theta_t) = \phi_{\theta_t, v^2\tau}(\theta_{t+\tau})$$

2. Self-Adaptive Recommendation

- **T-BMIRT**



We use vector projection method to get the value that student's ability exceed the video requirements.

$$P\left(\vec{\theta}_{s,t+\tau} \middle| \vec{\theta}_{s,t}, \vec{l}_{s,t}\right) = \phi_{\vec{\theta}_{s,t}+\vec{l}_{s,t}, \upsilon^2\tau}\left(\vec{\theta}_{s,t+\tau}\right)$$

$$\vec{l}_{s,t} = \frac{d_{s_t}}{d_t} \cdot \vec{g}_t \cdot \frac{1}{1 + exp\left(-\left(\frac{\vec{\theta}_{s,t} \cdot \vec{h}_t}{\|\vec{h}_t\|} - \|\vec{h}_t\|\right)\right)}$$

$\vec{l}_{s,t}$: the knowledge that student s gains from the video t

$\vec{g}_t$: the knowledge of the video t

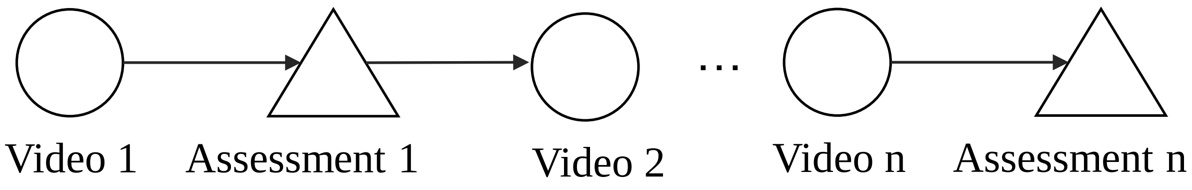
$\vec{h}_t$: is the prerequisites of video t

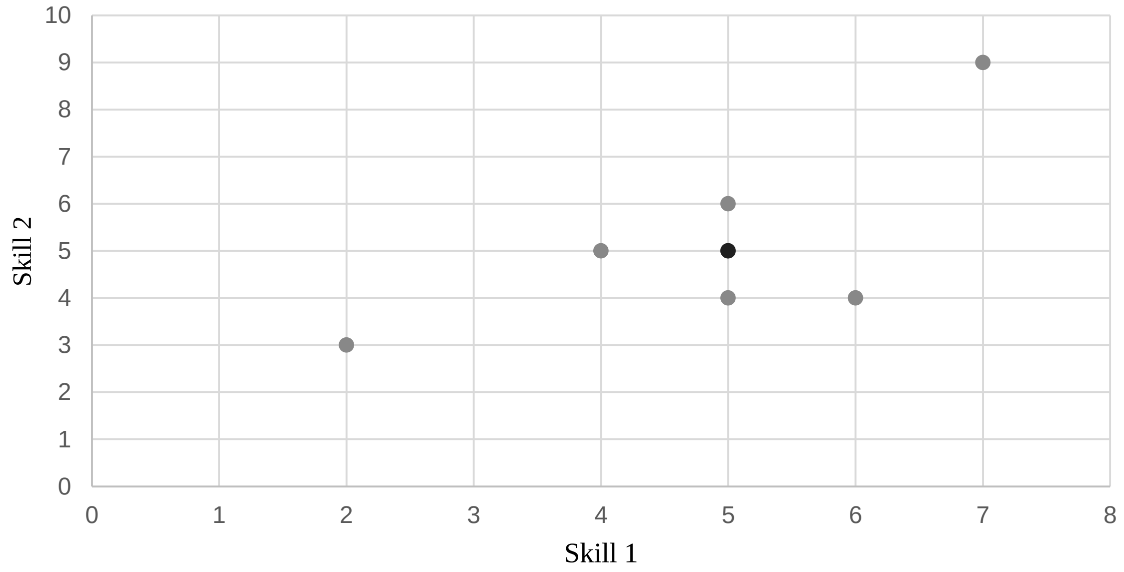
d_{s_t} is the duration in which student s watches video t

d_t is the total length of the video t

2. Self-Adaptive Recommendation

➢ Search and Extraction





SARLR Phase 1: Search and Extraction

- **INPUT**:
  - Set of students $S = \{s_1, s_2, \dots, s_n\}$, target student $s_X \in S$
  - Matrix of abilities $A = [\theta_{s,t}]$, where $\theta_{s,t}$ is the ability value of student s at time t
  - Set of learning resources $E = \{e_1, e_2, \dots, e_m\}$
- **OUTPUT**: learning path p

1: search for similar students MS, where $s_k \in MS$ and θ_{s_k,t_0} is similar to θ_{s_X,t_0}

2: for each $s_i \in MS$ do

3: find $s_b = argmax(distance(\theta_{s_i,T_{s_i}} - \theta_{s_i,t_0}))$, where T_{s_i} is the time of s_i completing learning

4: end for

5: extract the learning path $p = (e_{i_1}, e_{i_2}, \dots e_{i_T})$ of s_b

6: return p

2. Self-Adaptive Recommendation

➢ Adaptive Adjustment

SARLR Phase 2: Adaptive Re-planning

- **INPUT:**
  - Target student s_X, recommended learning path $p = (e_{i_1}, e_{i_2}, \dots e_{i_T})$
  - Result of s_X interacted with learning resources in p
- **OUTPUT: new learning path**

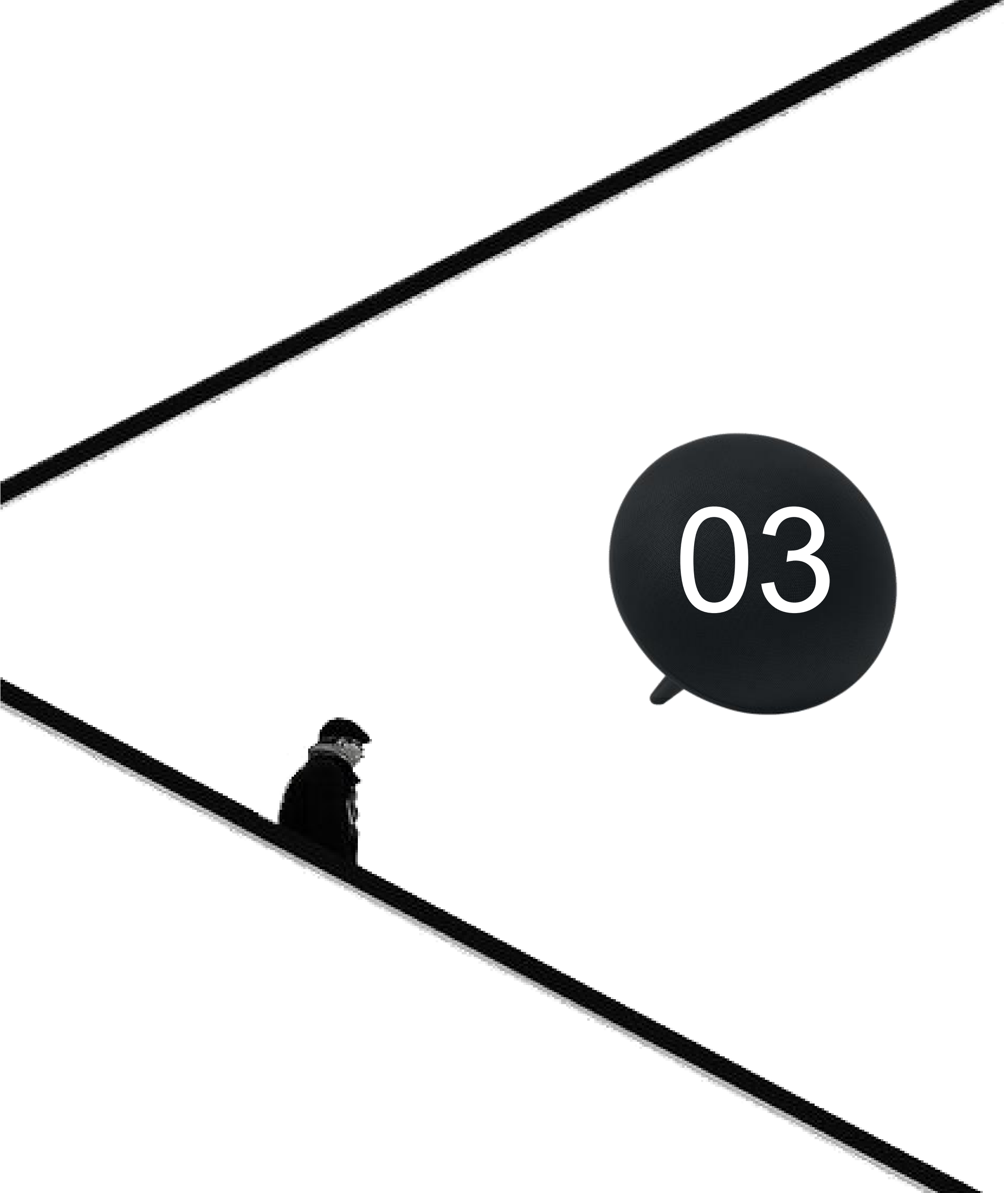
1: **for each** $e \in p$ **do**
2: **if** e is a video **and** $p_{se} < C_{se}$ **do**
3: **return** *SARLR Phase 1* to re-plan path p
4: **else if** e is an exercise **and** s_X failed it **and** $p_{sq} < C_{sq}$ **do**
5: **return** *SARLR Phase 1* to re-plan path p
6: **end if**
7: **end for**

$$p_{sq} = \frac{1}{1 + exp\left(-\left(\vec{\theta}_{s,i} \cdot \vec{\alpha}_q - b_q\right)\right)}$$

$$p_{se} = \frac{1}{1 + exp\left(-\left(\frac{\vec{\theta}_{s,i} \cdot \vec{h}_e}{\|\vec{h}_e\|} - \|\vec{h}_e\|\right)\right)}$$

p_{sq} : the probability of student s correctly answering exercise q

p_{se} : the degree of knowledge that student s can acquire from the video e



03 Experiments

3. Experiments

➢ Datasets

- A publicly accessible data set
  - Assistments Math 2004-2005
    - From *Assistment* online platform
    - Including 224,076 interactions, 860 students, 1,427 assessments and 106 skills
- A proprietary data set
  - blended learning data
    - From our blending learning analysis platform
    - Including 14,037,146 learning behavior data from 140 schools and 9 online educational companies

3. Experiments

➢ Experiments for T-BMIRT

Models	Assistments				Blended learning data			
	One-dimensional		Multidimensional		One-dimensional		Multidimensional	
	ACC	AUC	ACC	AUC	ACC	AUC	ACC	AUC
Frequency method	0.694	N/A	0.683	N/A	0.702	N/A	0.688	N/A
IRT	0.716	0.779	0.701	0.758	0.721	0.784	0.706	0.752
MIRT	0.714	0.771	0.721	0.786	0.718	0.775	0.722	0.783
T-IRT	0.738	0.805	0.712	0.769	0.744	0.801	0.717	0.764
T-BMIRT	0.743	0.815	0.738	0.803	0.757	0.820	0.748	0.816

- **Frequency method**: predict the student correctly answer the assessment when his history correct rate is greater than 50%.
- **IRT**: two-parameter ogive model.
- **MIRT**: multidimensional item response.
- **T-IRT**: temporal IRT with $\upsilon = 0.5$, which were selected in exploratory experiments.
- **T-BMIRT**: temporal blended multidimensional IRT with $\upsilon = 0.15$ and $\alpha = 10^{-4}$.

3. Experiments

Rationality Evaluation

$$\mathrm{RC}_{s_x} = \frac{\sum_{e_i}^{p} similarity(h_{e_i}, KC_{s_x})}{m}$$

$$\mathrm{DC}_{s_x} = \frac{\sum_{e_i}^{p} similarity(h_{e_i}, \theta_{s_{x,i}})}{m}$$

- $e_i \in p$: the learning resources in a recommended path, m is the length of the path
- KC_{s_x} : the knowledge components which s_x is learning in the current chapter
- *similarity()* : the adjusted cosine similarity of the two vectors in the parentheses.

Model	Relevance accuracy	Difficulty accuracy
UCF	0.86	0.77
ICF	0.71	0.83
LFM	0.87	0.84
SARLR	0.97	0.92

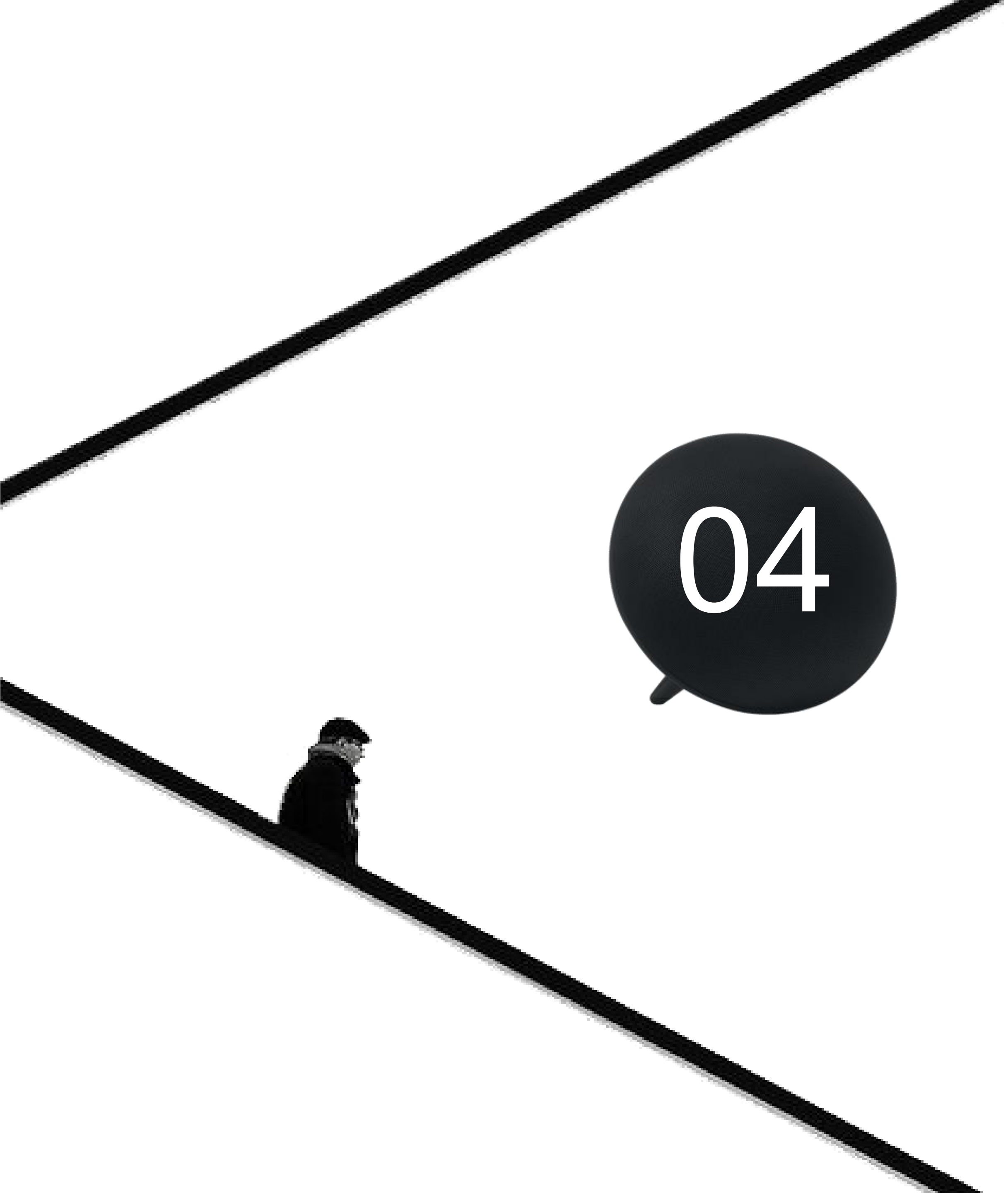
3. Experiments

Effectiveness Evaluation

$$G = \frac{E(R_{S'}) - E(R_S)}{E(R_S)}$$

- S' : the students whose learning paths are strictly recommended
- S the students whose learning path are randomly selected
- $E(R_{S'})$ and $E(R_S)$: the students' average score in the last online assessment.

Model	Expected gain					
	1	2	3	4	5	6
UCF	-0.04	-0.06	0.07	-0.03	0.08	0.01
ICF	0.05	0.04	-0.03	0.07	-0.02	0.05
LFM	0.04	0.12	0.09	0.10	0.03	-0.05
SARLR	0.11	0.27	0.24	0.23	0.17	0.06



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Conclusions

4. Conclusions

Establishes conditions to adaptively adjust recommendations towards the dynamic needs of the students

T-BMIRT

Adaptively Strategy

Evaluation criteria

Performs well on the prediction task of multi-dimensional skills assessments

For personalized learning recommendation in terms of rationality and effectiveness

THANKS