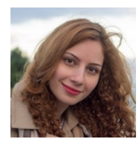
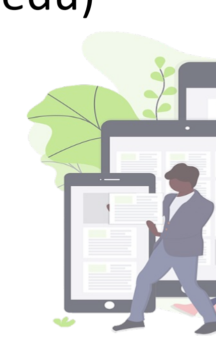
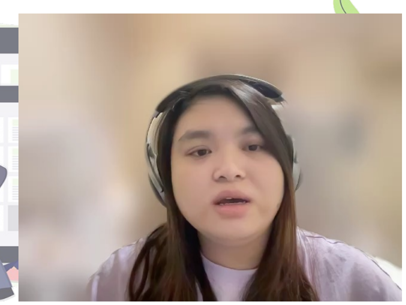
This paper is based upon work supported by the National Science Foundation under Grant No. 2047500.

Transition-Aware Multi-Activity Knowledge Tracing


Siqian Zhao

Chunpai Wang

Shaghayegh (Sherry) Sahebi

Presented By Siqian Zhao (szhao2@Albany.edu)

2022 IEEE International Conference on Big Data (Big Data)

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- Introduction
- Model
- Experiments
- Conclusions

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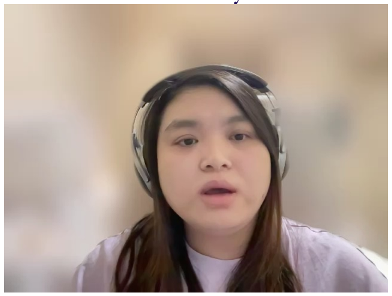
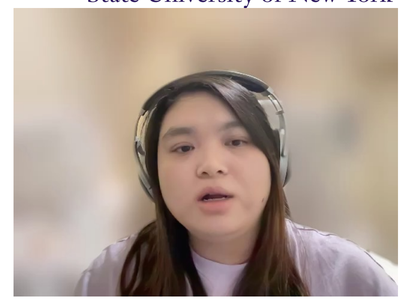


Introduction

- Online education systems
  - Enabling distance learning and abundant courses
  - Attracting more and more students
  - Promoting the development of Educational Data Mining (EDM)



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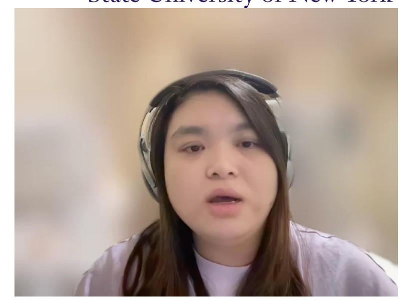
Introduction

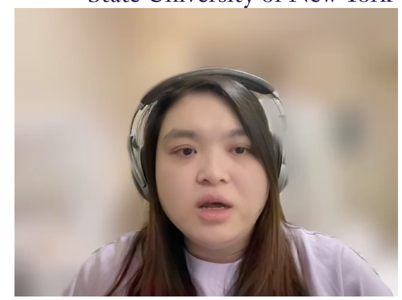


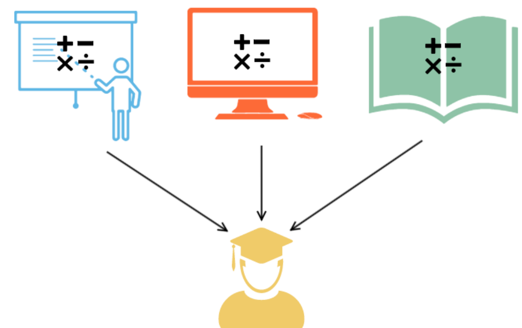
- Online education systems
  - Enabling distance learning and abundant courses
  - Attracting more and more students
  - Promoting the development of Educational Data Mining (EDM)

- Student knowledge tracing
  - Quantifying student knowledge state
    - Understanding student learning
    - Creating a study plan
    - Recommending learning materials
    - Analyzing knowledge gaps

Introduction

- Motivation and Limitation
  - Student learn by doing multiple types of activities
    - Solve questions (assessed), watch video lectures (non-assessed)





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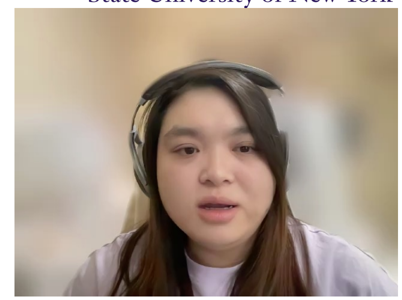
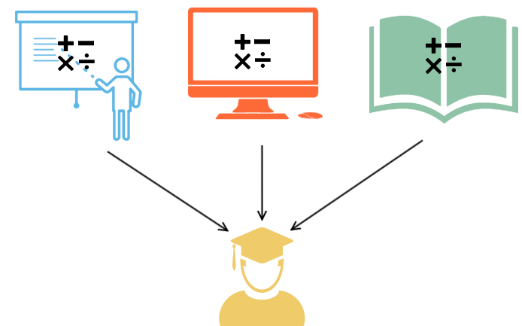
Introduction

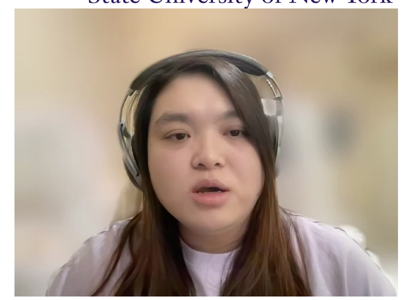


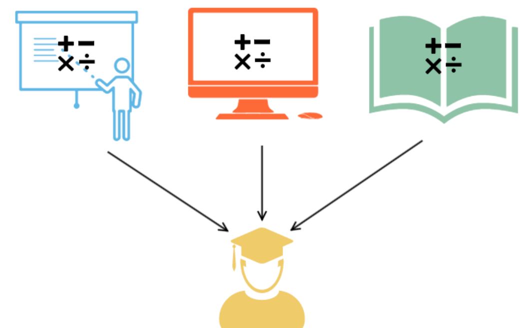
- Motivation and Limitation
  - Student learn by doing multiple types of activities
    - Solve questions (assessed), watch video lectures (non-assessed)
  - Most KT approaches rely on assessed activities (supervised sequence learning)
    - Linear and/or logistic regression, e.g. IRT [Frederic et al.], PFA [Philip et al.]
    - Hidden Markov model (HMM), e.g. BKT [Corbett et al.]
    - Recurrent Neural Networks, e.g. DKT [Piech et al.]



Introduction

- Motivation and Limitation
  - Few multi-activity KT approaches
    - Factorization machine, e.g. MA-FA [Abdi et al.]
    - Elo-based learner model, e.g. MAM-Elo[Abdi et al.]
    - Tensor factorization, e.g. MVKM [Zhao et al.]





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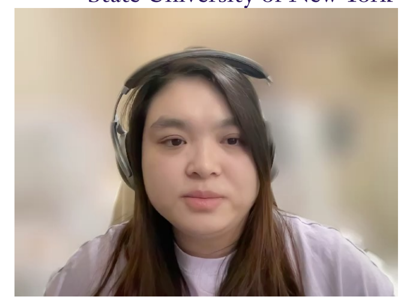
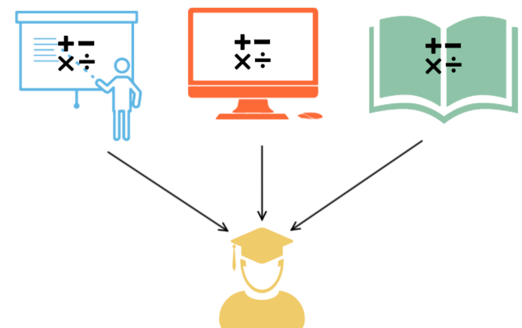
  - Knowledge transfer
    - Different activities more/less helpful for other types of activities
      - Example:

        practicing summation problems → multiplication lecture

        multiplication lecture ↛ practicing summation problems
    - Dynamics and realization of transfer depend on the transition order





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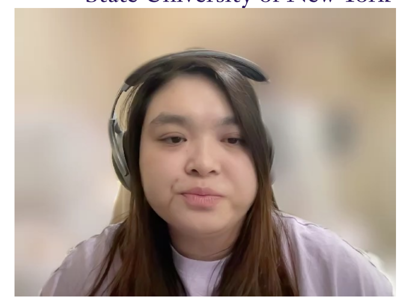
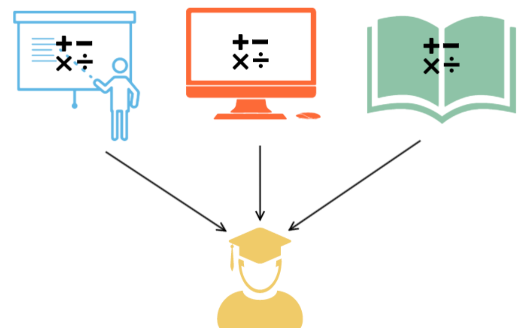
  - Knowledge transfer
    - Different activities more/less helpful for other types of activities
      - Example:

        practicing summation problems $\rightarrow$ multiplication lecture

        multiplication lecture $\not\rightarrow$ practicing summation problems
    - Dynamics and realization of transfer depend on the transition order
- Propose a transition-aware multi-activity component on top of LSTM (TAMKOT)





Model

- Problem formulation
- TAMKOT model

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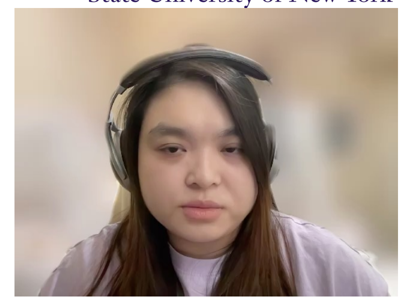

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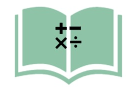
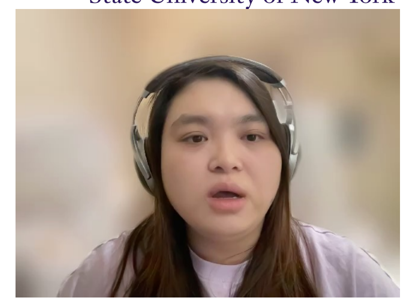
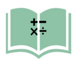
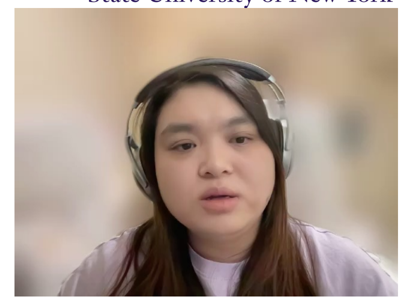
Problem formulation

- Suppose two materials types: Questions (Assessed), 
  Video lectures (Non-Assessed) 



Problem formulation

- Suppose two materials types: Questions (Assessed),
  Video lectures (Non-Assessed)
- Each activity at learning point t: $\langle (q_t, r_t), l_t, d_t \rangle$
  - q_t: question 
  - r_t: student performance: grades/correctness/ score ✓ ✗
  - l_t: video lecture 
  - d_t: material type: 1: assessed, 0: non-assessed



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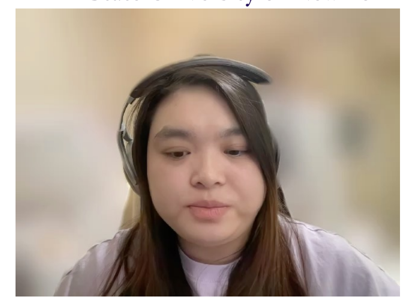
Problem formulation



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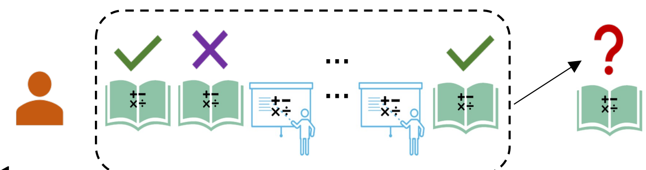
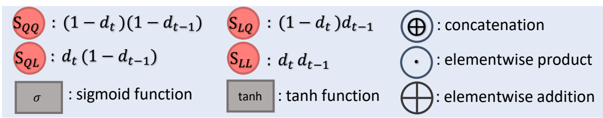
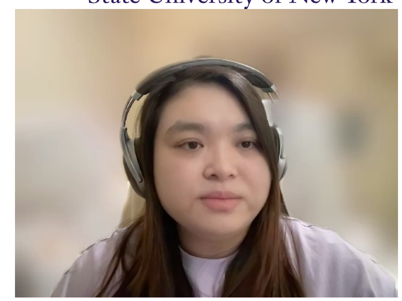
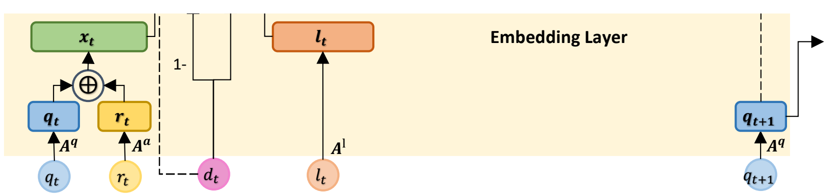


- Goal: predict every r_{t+1}
  - Given $\{\langle (q_1, r_1), l_1, d_1 \rangle, \ldots, \langle (q_t, r_t), l_t, d_t \rangle\}$ and q_{t+1}

TAMKOT Model

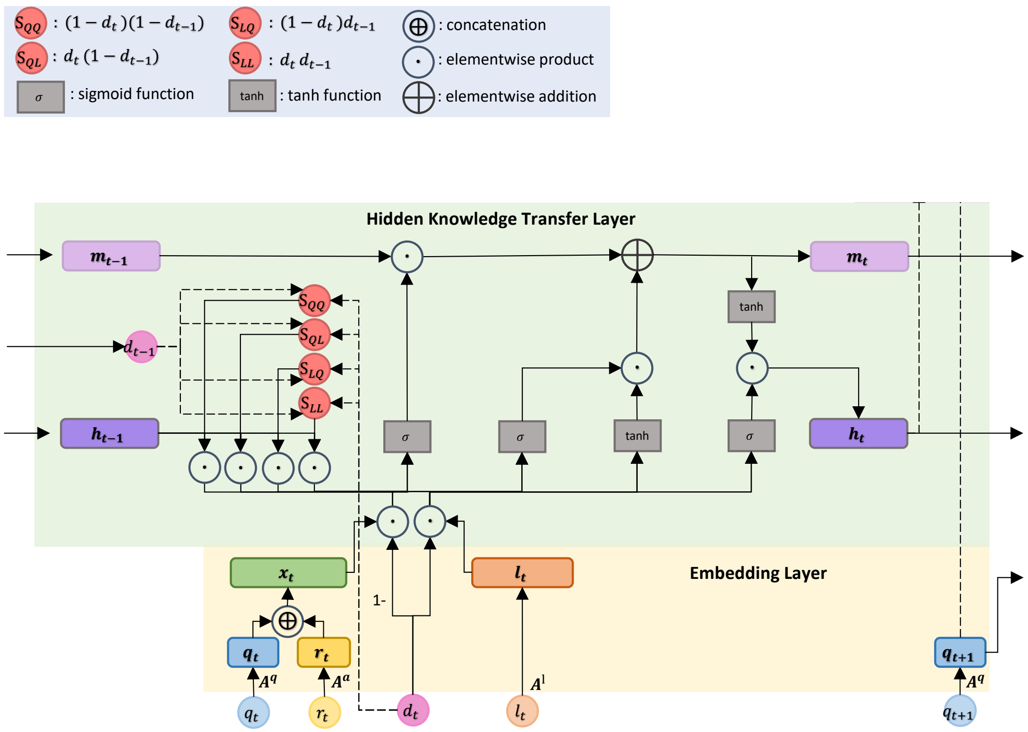


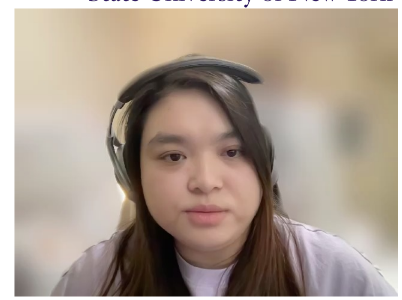




- Embedding layer
  - Map learning materials and student performance into latent concept space

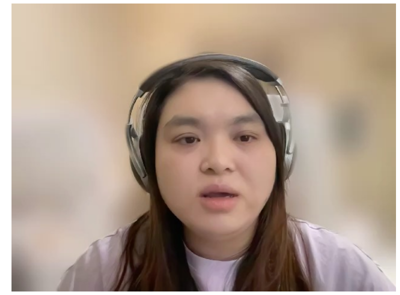
TAMKOT Model

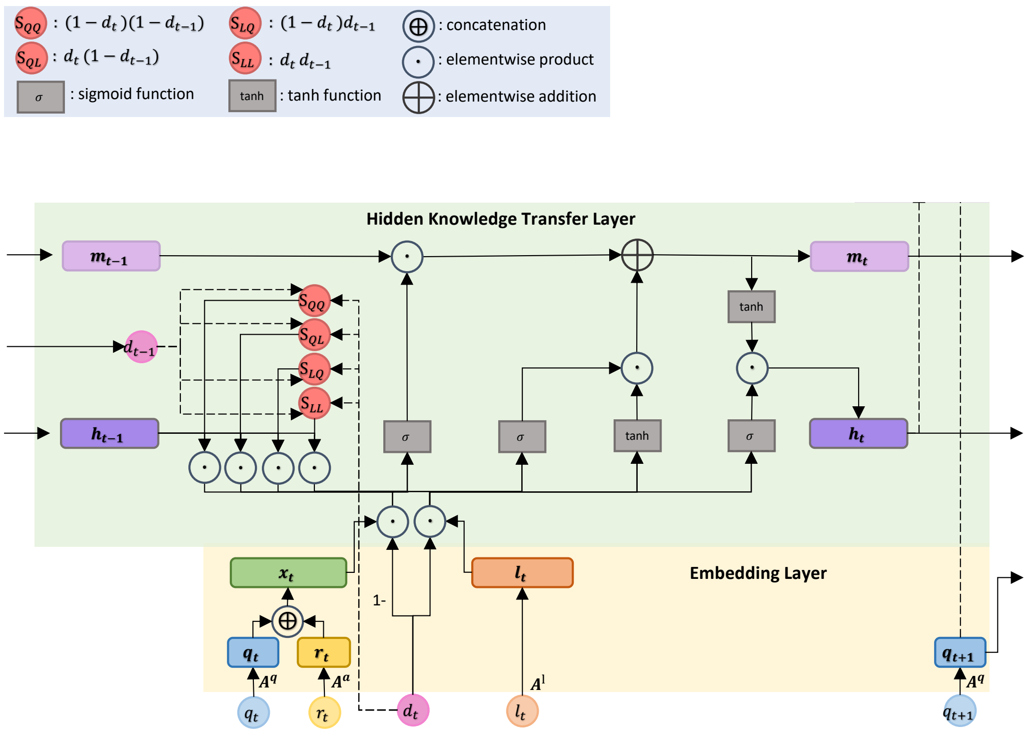




- Hidden Knowledge Transfer Layer
  - Represent student knowledge
- Embedding layer
  - Map learning materials and student performance into latent concept space

TAMKOT Model

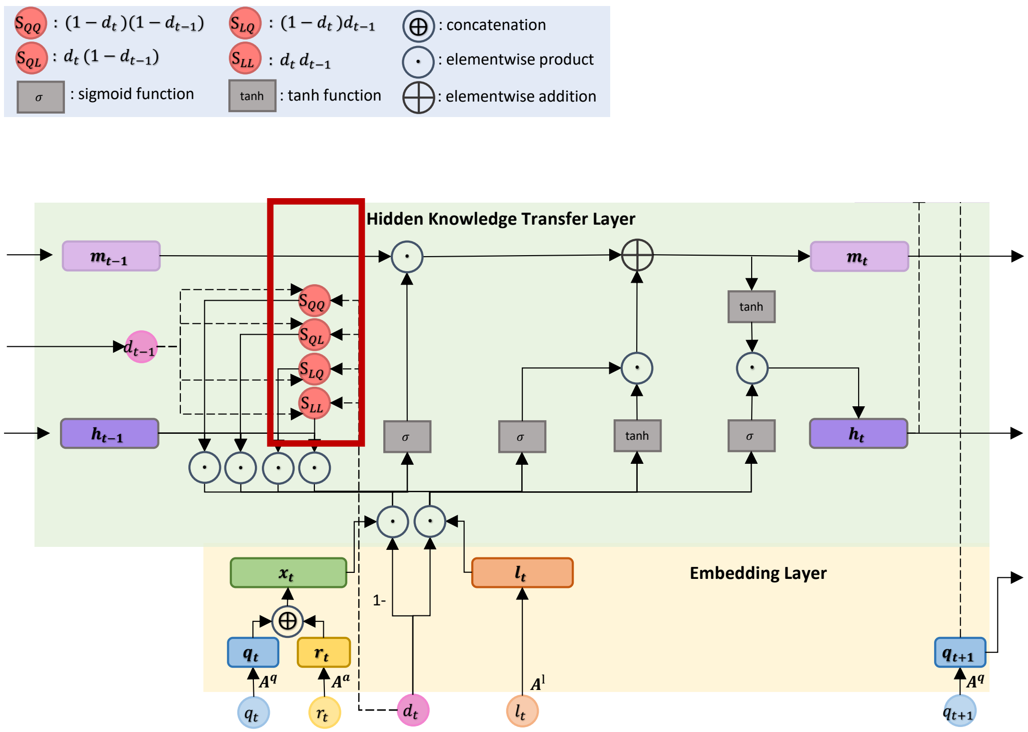




- Hidden Knowledge Transfer Layer
  - Memory cell
  - Input gate
  - Output gate
  - Forget gate

Different weight matrices for different transition permutations

TAMKOT Model



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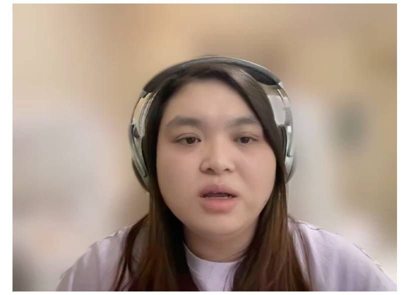
- Hidden Knowledge Transfer Layer

d_t: material type: 1: assessed, 0: non-assessed

$S_{QQ} = (1-d_t)(1-d_{t-1})$
$S_{QL} = d_t(1-d_{t-1})$
$S_{LQ} = (1-d_t)d_{t-1}$
$S_{LL} = d_t d_{t-1}$

TAMKOT Model



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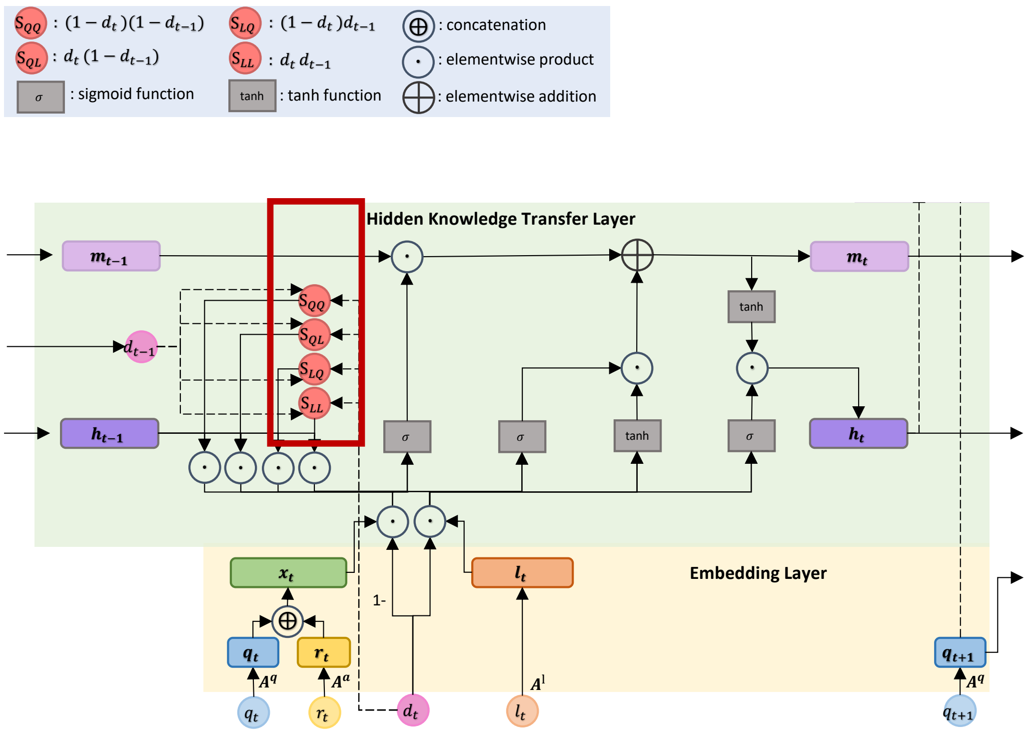

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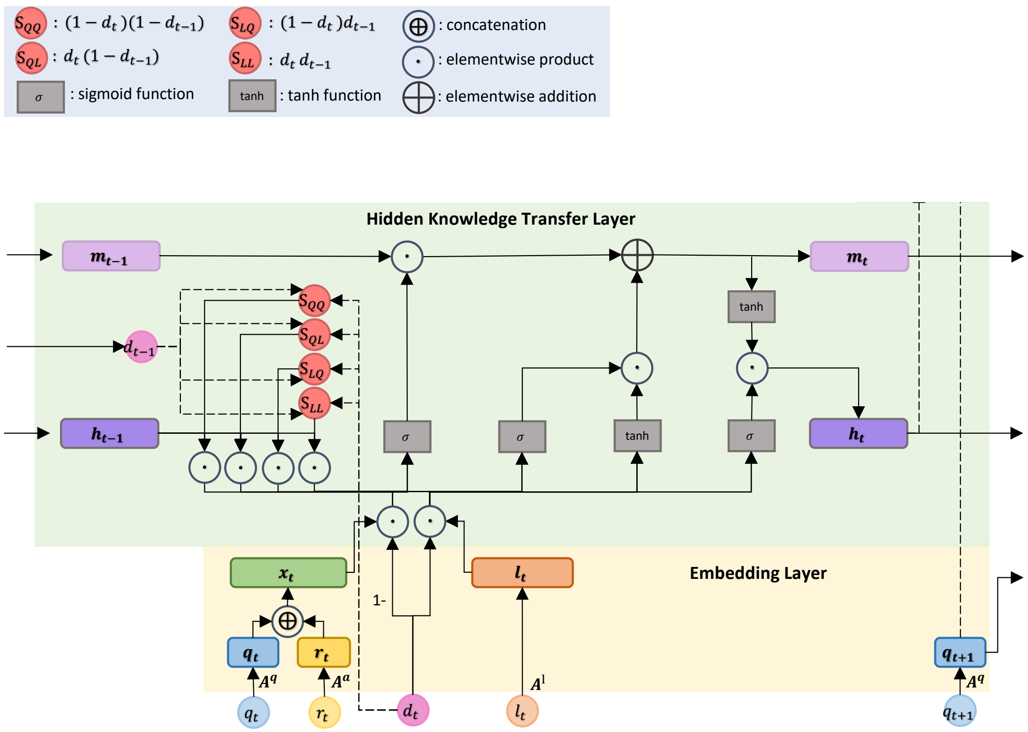
$S_{QL} = d_t(1 - d_{t-1})$
$S_{LQ} = (1 - d_t)d_{t-1}$
$S_{LL} = d_t d_{t-1}$

Only one of these four indicators equals to 1.

Example: $d_t = 1, d_{t-1} = 0,$
$S_{QL} = 1, S_{QQ} = S_{LQ} = S_{LL} = 0$

TAMKOT Model



- Hidden Knowledge Transfer Layer

$$i_t = \sigma\begin{pmatrix} (1-d_t)\cdot x_t V_{iQ} + d_t \cdot l_t V_{iL} + \\ S_{QQ} \cdot h_{t-1} W_{i_{QQ}} + S_{LL} \cdot h_{t-1} W_{i_{LL}} + \\ S_{QL} \cdot h_{t-1} W_{i_{QL}} + S_{LQ} \cdot h_{t-1} W_{i_{LQ}} \end{pmatrix}$$

$$g_t = tanh\begin{pmatrix} (1-d_t)\cdot x_t V_{gQ} + d_t \cdot l_t V_{gL} + \\ S_{QQ} \cdot h_{t-1} W_{g_{QQ}} + S_{LL} \cdot h_{t-1} W_{g_{LL}} + \\ S_{QL} \cdot h_{t-1} W_{g_{QL}} + S_{LQ} \cdot h_{t-1} W_{g_{LQ}} \end{pmatrix}$$

$$f_t = \sigma\begin{pmatrix} (1-d_t)\cdot x_t V_{fQ} + d_t \cdot l_t V_{fL} + \\ S_{QQ} \cdot h_{t-1} W_{f_{QQ}} + S_{LL} \cdot h_{t-1} W_{f_{LL}} + \\ S_{QL} \cdot h_{t-1} W_{f_{QL}} + S_{LQ} \cdot h_{t-1} W_{f_{LQ}} \end{pmatrix}$$

$$o_t = \sigma\begin{pmatrix} (1-d_t)\cdot x_t V_{oQ} + d_t \cdot l_t V_{oL} + \\ S_{QQ} \cdot h_{t-1} W_{o_{QQ}} + S_{LL} \cdot h_{t-1} W_{o_{LL}} + \\ S_{QL} \cdot h_{t-1} W_{o_{QL}} + S_{LQ} \cdot h_{t-1} W_{o_{LQ}} \end{pmatrix}$$

$$m_t = f_t\, m_{t-1} + i_t g_t$$

$$h_t = o_t \tanh(m_t)$$

Only one is activated.

Example: $S_{QL} = 1, S_{QQ} = S_{LQ} = S_{LL} = 0$

$$f_t = d_t \cdot l_t V_{fL} + S_{QL} \cdot h_{t-1} W_{f_{QL}}$$

TAMKOT Model

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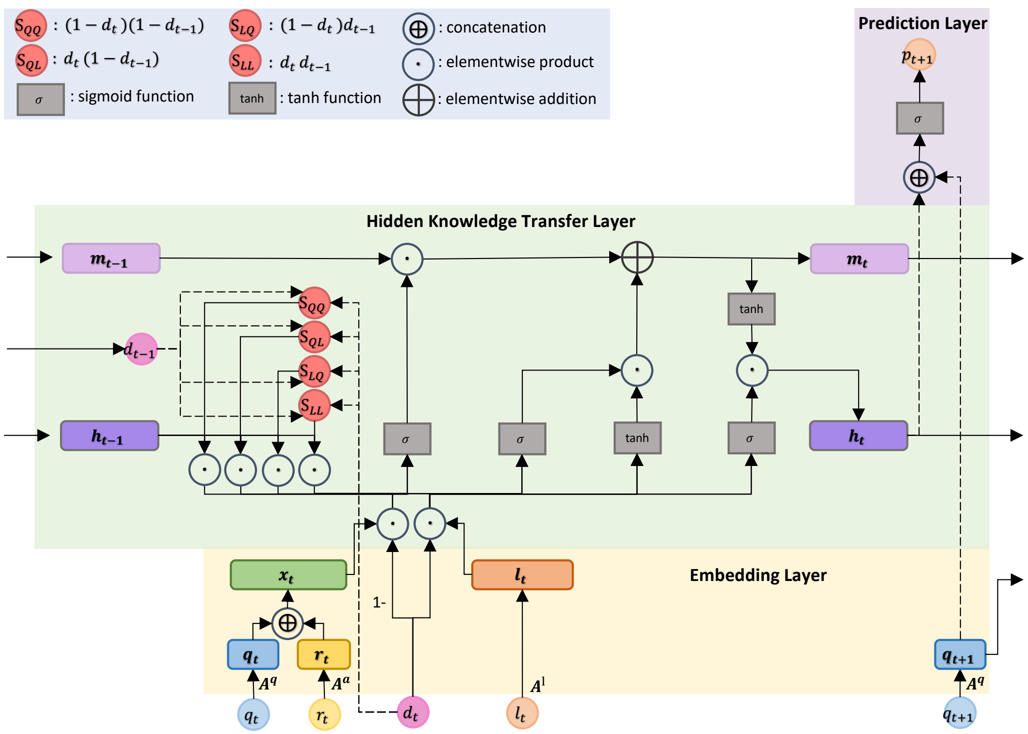

- Prediction Layer
  - Predict student performance of q_{t+1}
- Hidden Knowledge Transfer Layer
  - Represent student knowledge
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  - Map learning materials and student performance into latent concept space

TAMKOT Model

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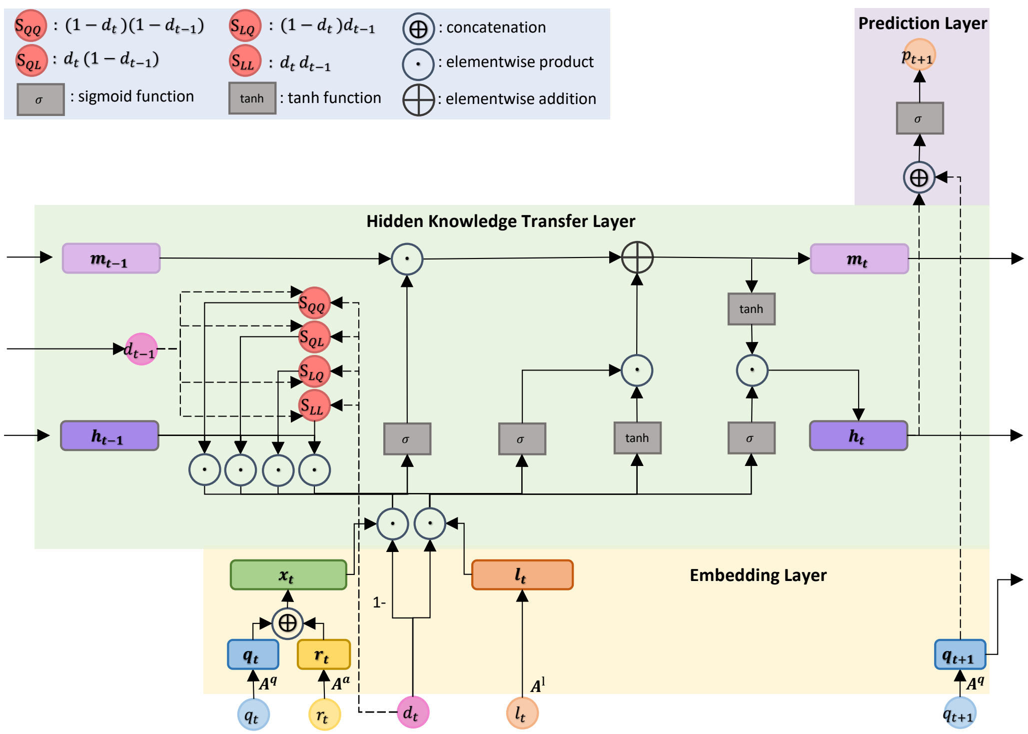

- Prediction Layer
  - Predict student performance of q_{t+1}

$$p_{t+1} = \sigma(\boldsymbol{W}_P^T[\boldsymbol{h}_t \oplus \boldsymbol{q}_{t+1}] + b_p)$$

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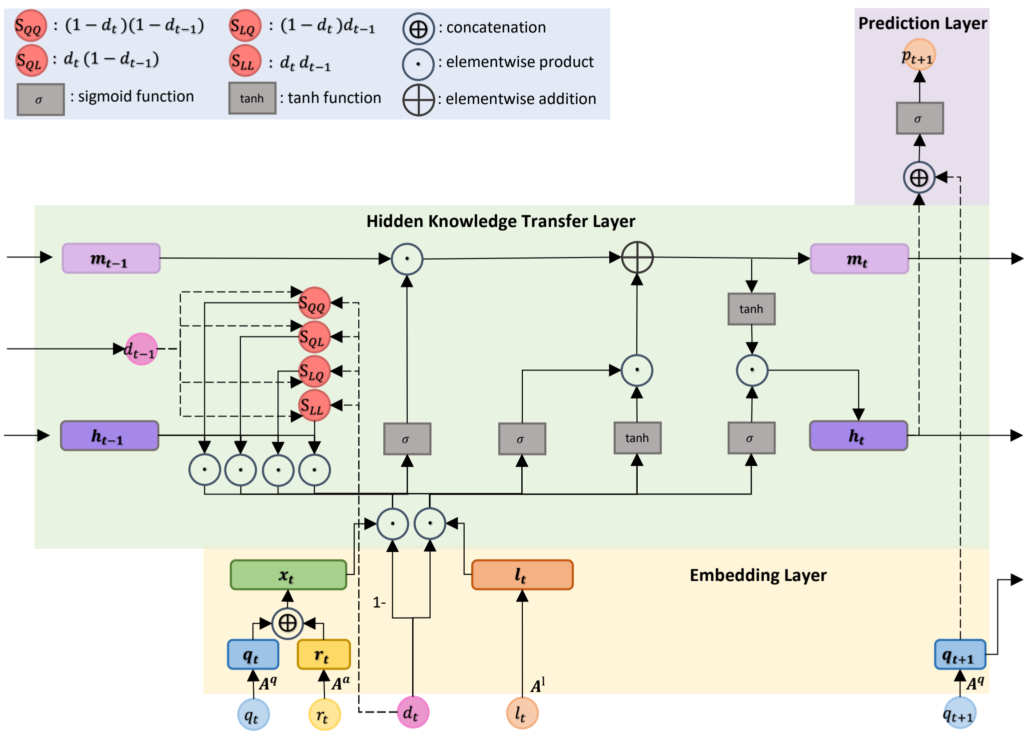
TAMKOT Model



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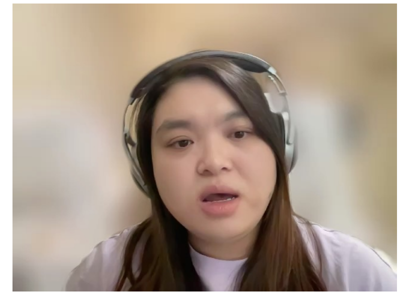
Objective function:

$$\mathcal{L} = \sum_t (r_t log p_t + (1 - r_t) log(1 - p_t)) + \overbrace{\lambda_\theta ||\theta||^2}^{\text{regularization}}$$

Experiments



- We evaluate our model with three sets of experiments:
  - **Student Performance Prediction -** to validate if the model captures the variability of student performance
  - **Knowledge Transfer Analysis -** to analyze the knowledge transfer between assessed and non-assessed learning material types
  - **Student Knowledge State Visualization -** to check if our model represents student knowledge state

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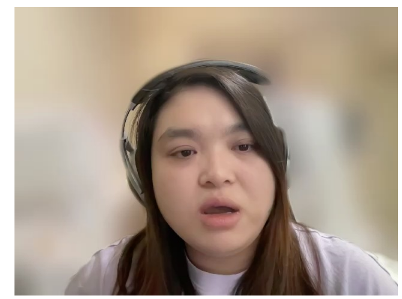
Datasets & Experiment Setup

- Datasets
  - MORF: Assignments and lecture
  - EdNet: Questions and question explanations
  - Junyi: Problems and hints

Dataset	#Users	#Questions	Question Records	Question Responses Mean	Question Responses STD	#Correct Question Responses	#Incorrect Question Responses	#Non-assessed materials	#Non-assessed Records
MORF	686	10	12031	0.7763	0.2507	N/A	N/A	52	41980
EdNet	1000	11249	200931	0.5910	0.2417	118747	82184	8324	150821
Junyi	2063	3760	290754	0.6660	0.2224	193664	97090	1432	69050

Statistics for each datasets



Datasets & Experiment Setup

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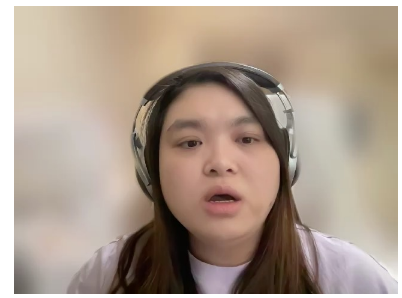
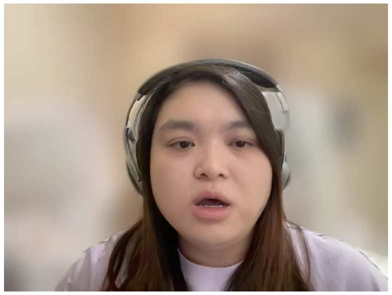


- Experiment Setup
  - 5-fold student stratified cross-validation
    - Training set: 80% student sequences (20% sequences of training)
    - Testing set: 20% student sequences

Baselines & Metrics



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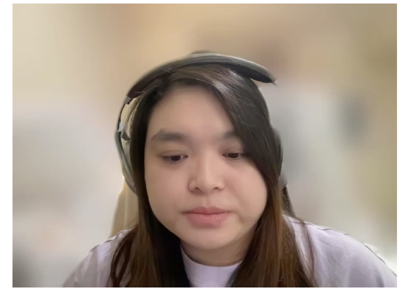
- Baselines
  - Single-activity: **DKT** [Piech et al.], **DKVMN** [Zhang et al.], **SAINT** [Choi et al.], **SAKT** [Pandey et al.], **AKT** [Ghosh et al.], **DeepIRT** [Yeung et al.]
  - Multi-activity**: MVKM** [Zhao et al.], **DMKT** [Wang et al.]**,**
  - **[method name]+MV**: Baselines 'Multi-activity' setting
  - **MLP+M:** simple multi-layer perceptron consider three recent assessed and three non-assessed activities as input

Baselines & Metrics



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- Metrics
  - Area Under Curve (AUC)
  - Root Mean Squared Error (RMSE)

Performance Prediction

Methods	MORF	EdNet	Junyi
	RMSE	AUC	AUC
DKT	0.1938*	0.6393**	0.8623**
DKVMN	0.2043**	0.6296**	0.8558**
SAKT	0.2113**	0.6334**	0.8053**
SAINT	0.2019**	0.5205**	0.7951**
AKT	0.2420**	0.6393**	0.8093**
DeepIRT	0.1946**	0.6290**	0.8498**
DKT+M	0.1928	0.6372**	0.8652*
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AKT+M	0.2240**	0.6404**	0.8099**
MLP+M	0.2433**	0.6102**	0.7290**
MVKM	0.1936*	–	–
DMKT	**0.1754****	0.6394**	0.8561**
TAMKOT	0.1871	**0.6786**	**0.8745**

Performance Prediction results, ** and * indicate t-test p − value < 0.05 and p − value < 0.1

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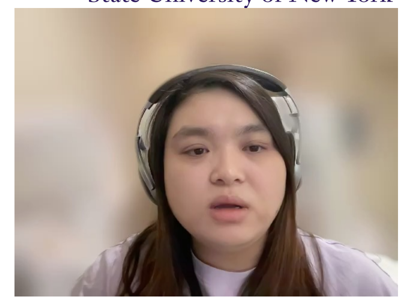

Does Multi-Activity help improve prediction performance?

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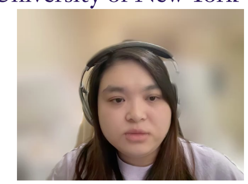

Methods	MORF	EdNet	Junyi
	RMSE	AUC	AUC
DKT	0.1938*	0.6393**	0.8623**
DKVMN	0.2043**	0.6296**	0.8558**
SAKT	0.2113**	0.6334**	0.8053**
SAINT	0.2019**	0.5205**	0.7951**
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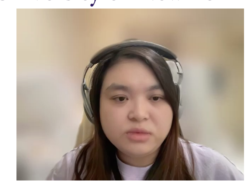
- Findings:
  - TAMKOT significantly outperforms all the single activity models

Does Multi-Activity help improve prediction performance? Yes!



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- Findings:
  - TAMKOT significantly outperforms all the single activity models
  - TAMKOT significantly outperforms all the 'Multi-activity' setting models

Does TAMKOT outperform Multi-Activity baselines?

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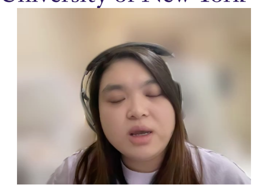

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Performance Prediction results, $**$ and $*$ indicate t-test $p - \text{value} < 0.05$ and $p - \text{value} < 0.1$

- Findings:
  - TAMKOT significantly outperforms all the single activity models
  - TAMKOT significantly outperforms all the 'Multi-activity' setting models
  - TAMKOT significantly outperforms all the multi-activity baseline methods, except DMKT on MORF

Does TAMKOT outperform Multi-Activity baselines? Mostly!

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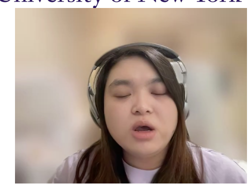

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    - DMKT's complexity with MORF's learning material complexity

Does the knowledge transfer from question to lecture is similar as from lecture to question?

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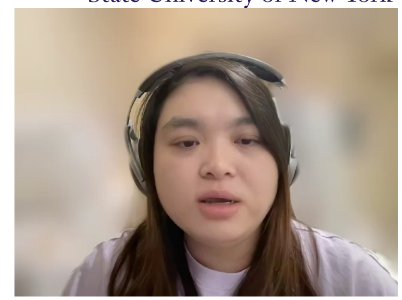

- Compared weight matrices $W_{f_{QL}}$ and $W_{f_{LQ}}$ of forget gate
  - Spearman correlation
  - Visualization

	MORF	EdNet	Junyi
Correlation	-0.03686	0.33680	0.38443
p-value	0.55714	3.30e-08	2.09e-37

Spearman correlation coefficients with p-values

Does the knowledge transfer from question to lecture is similar as from lecture to question?

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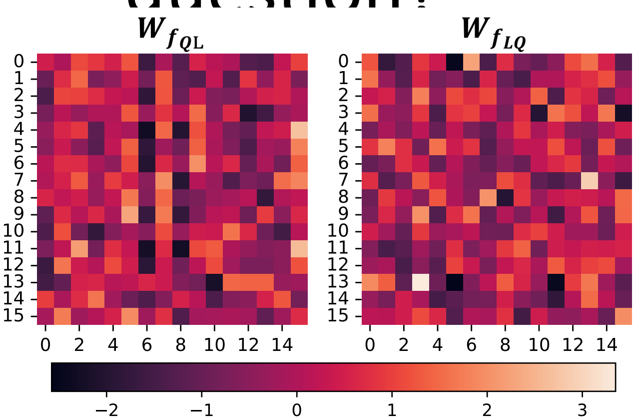
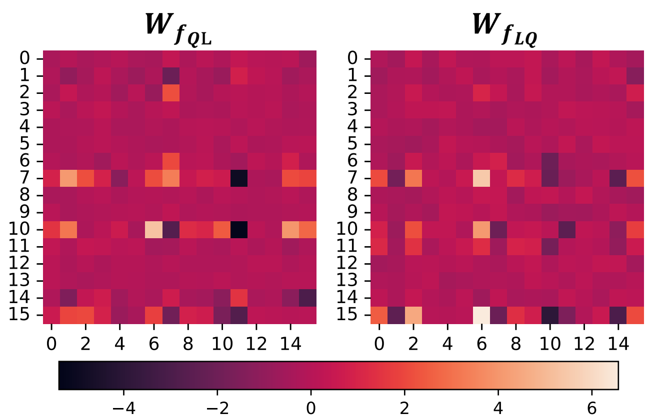
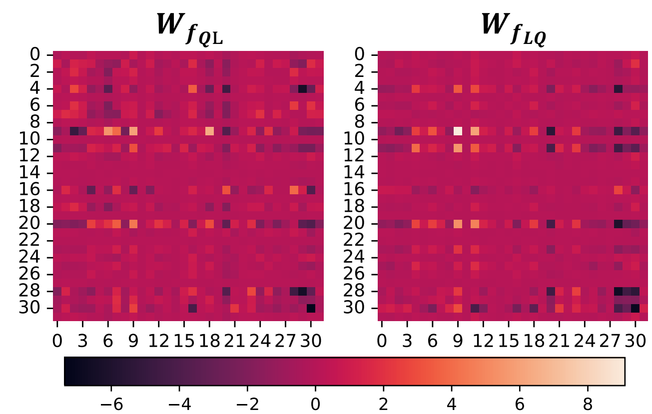


Forget gate weight matrices for MORF

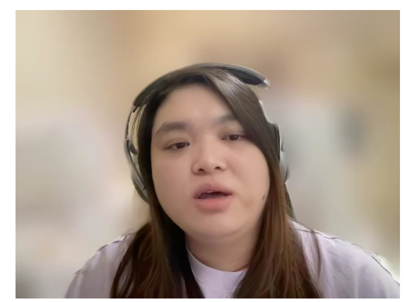


Forget gate weight matrices for EdNet



Forget gate weight matrices for Junyi

- Findings:
  - MORF: knowledge transfer is generally different with some are the same



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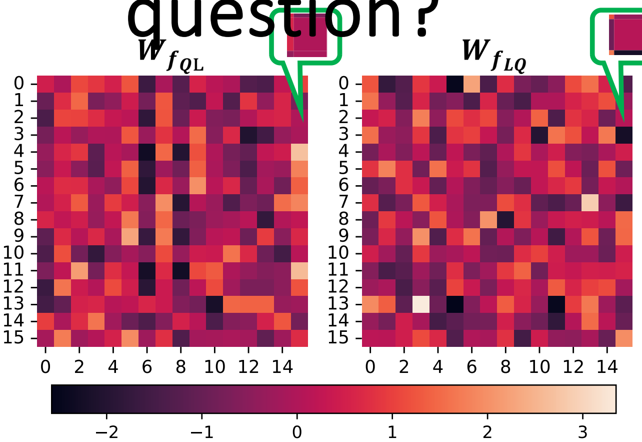

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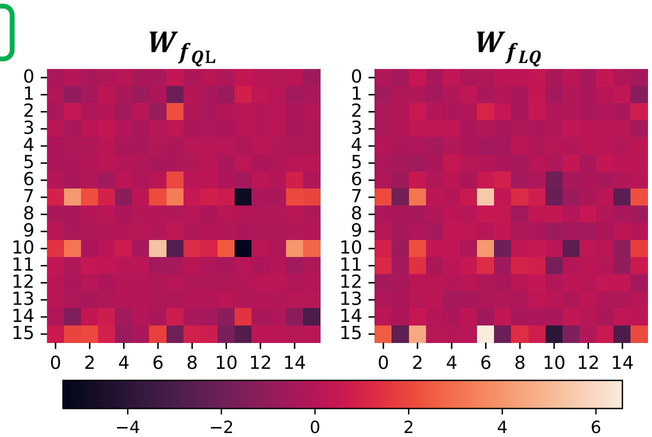
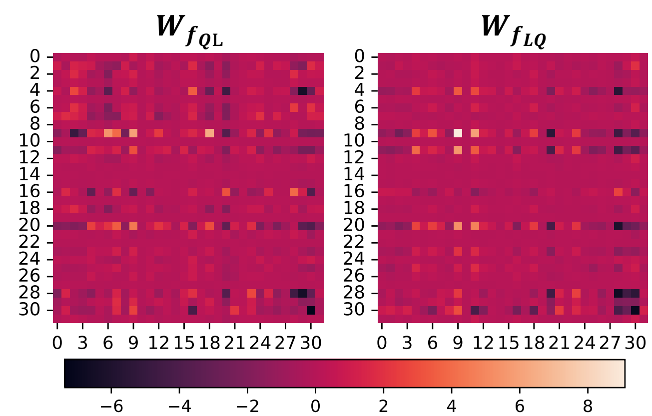


Forget gate weight matrices for EdNet



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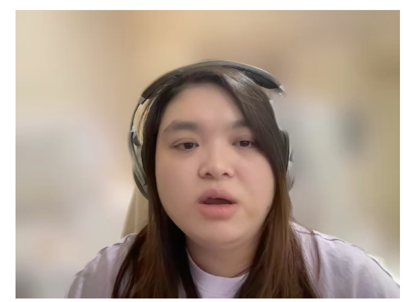

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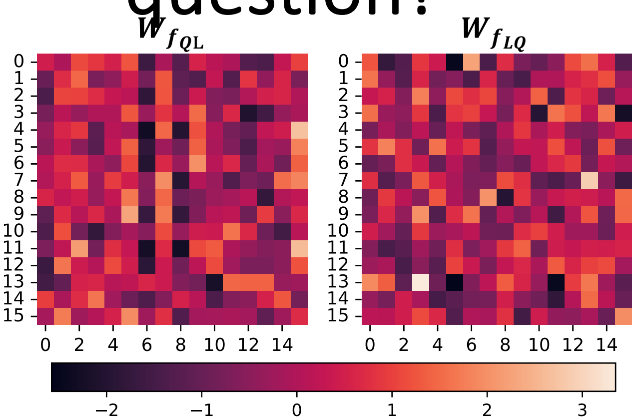
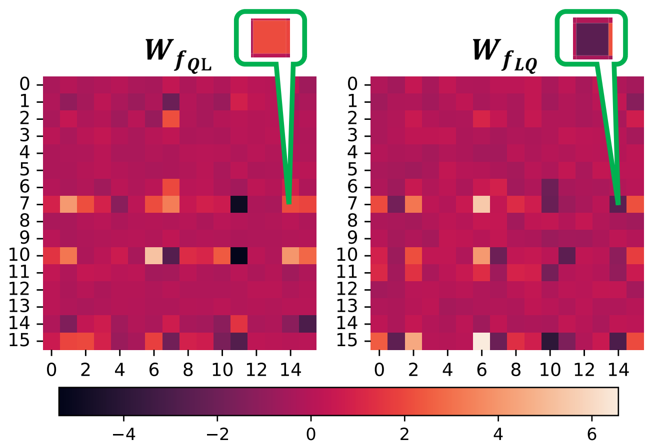
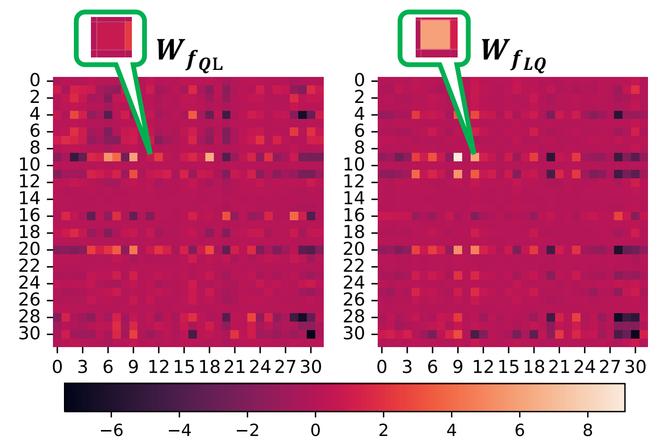


Forget gate weight matrices for MORF

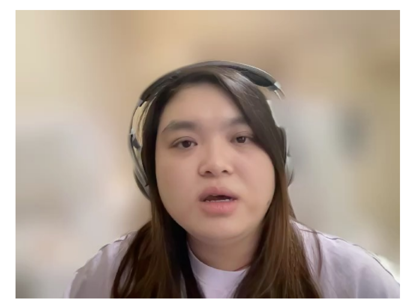


Forget gate weight matrices for EdNet



Forget gate weight matrices for Junyi

- Findings:
  - MORF: knowledge transfer is generally different with some are the same
  - Ednet and Junyi: Knowledge transfer is similar with exist difference



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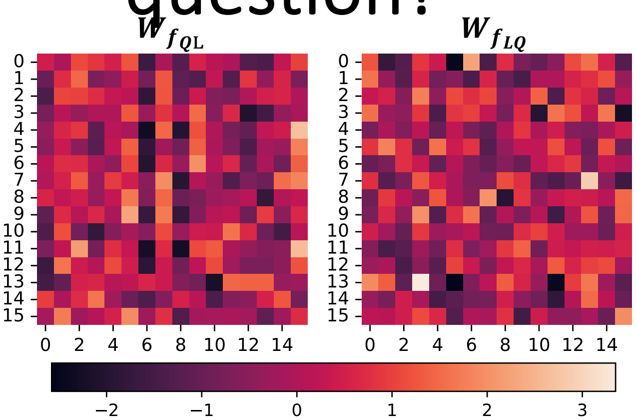
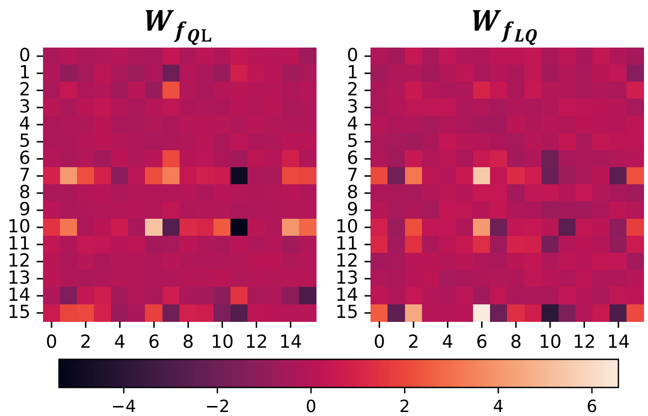
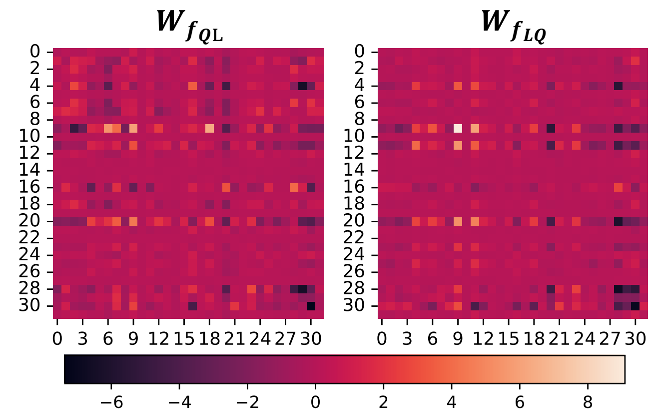


Forget gate weight matrices for MORF

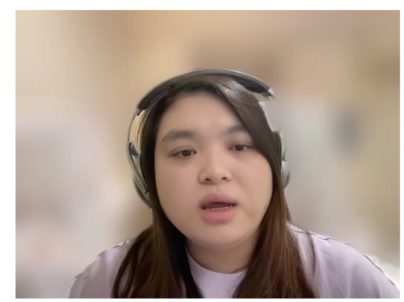


Forget gate weight matrices for EdNet



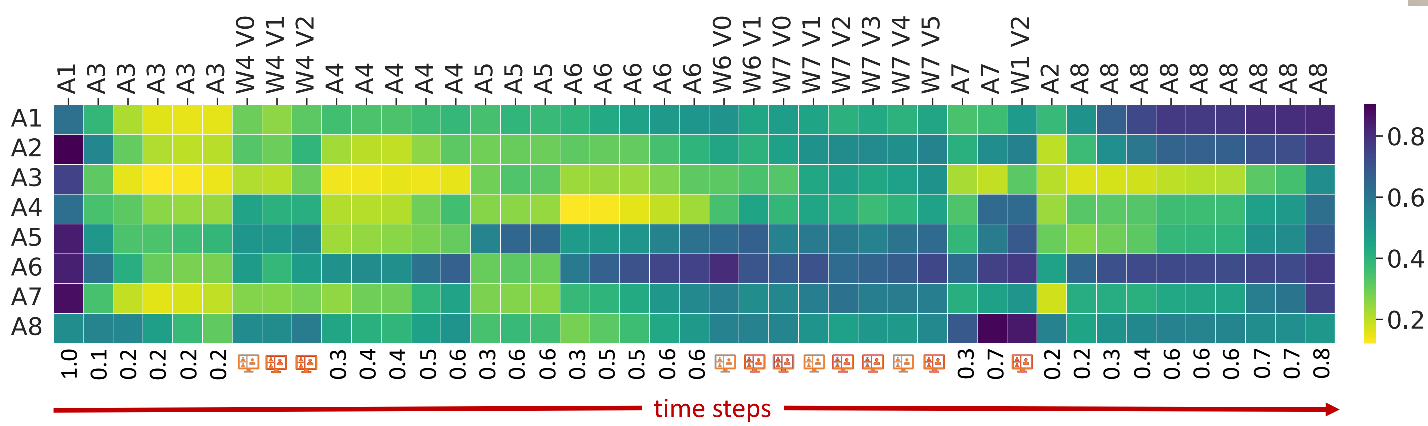
Forget gate weight matrices for Junyi

- Findings :
  - MORF: knowledge transfer is generally different with some are the same
  - Ednet and Junyi: Knowledge transfer is similar with exist difference
- Reason:
  - Close-knit associations between material types in Junyi and EdNet
  - Each assignment includes multiple problems in MORF

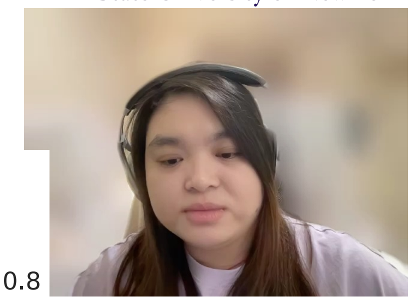


Student Knowledge State Visualization

- Predicted performance in each assignment



Student's knowledge (estimated performance) visualization of a sample student in MORF



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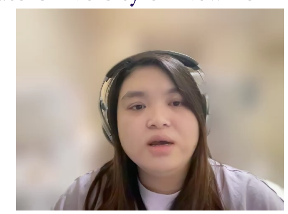

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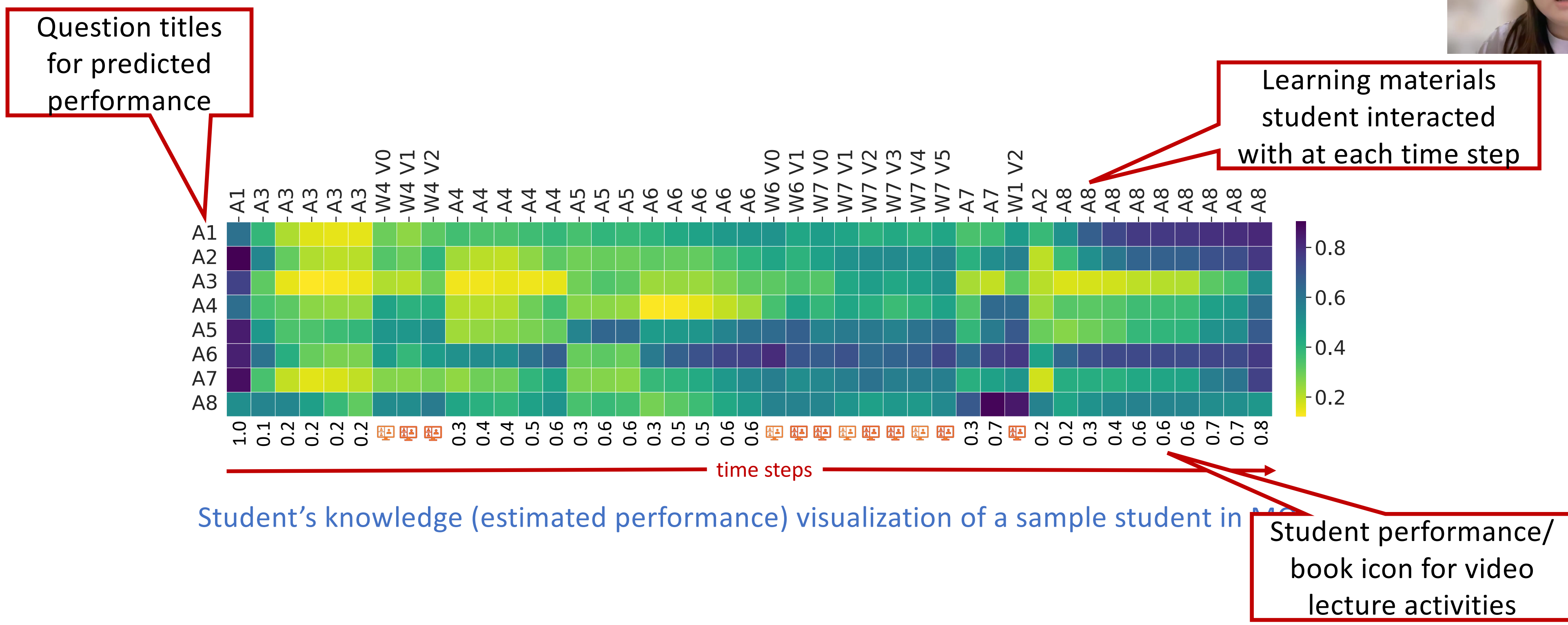

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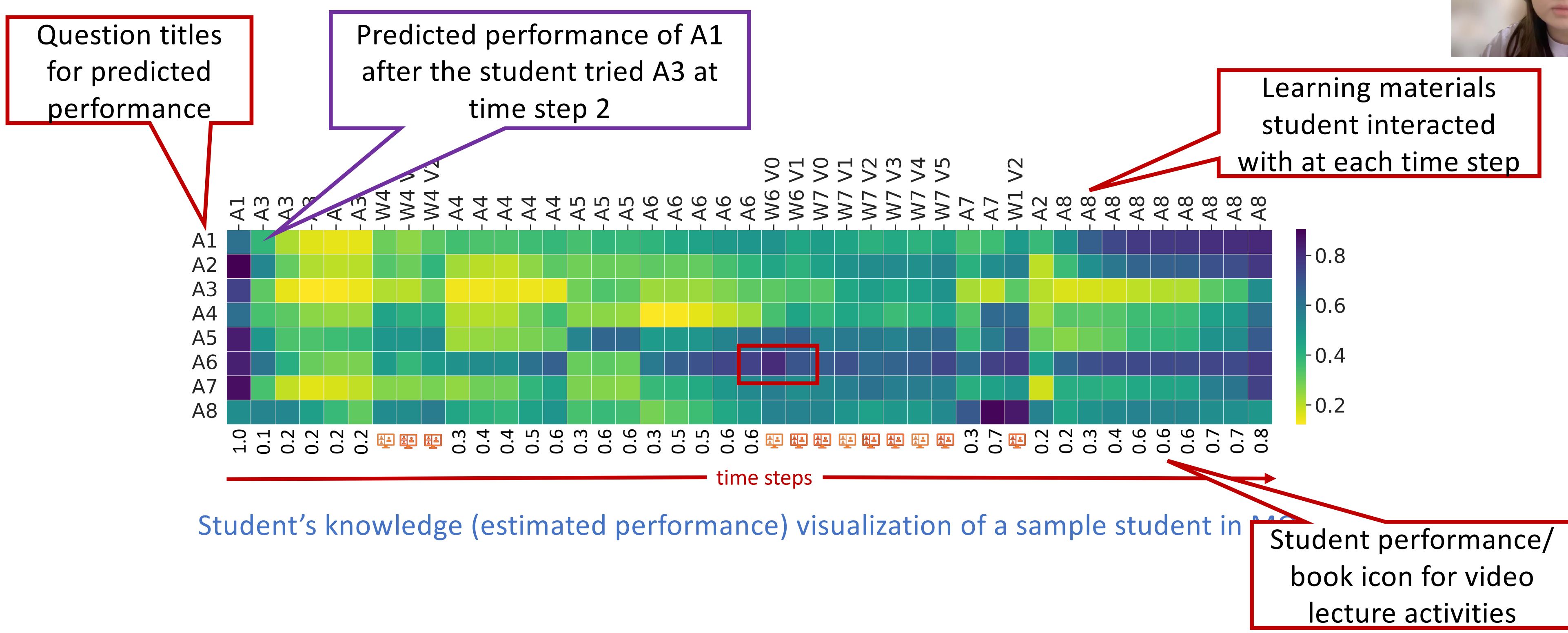

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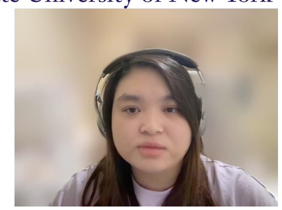

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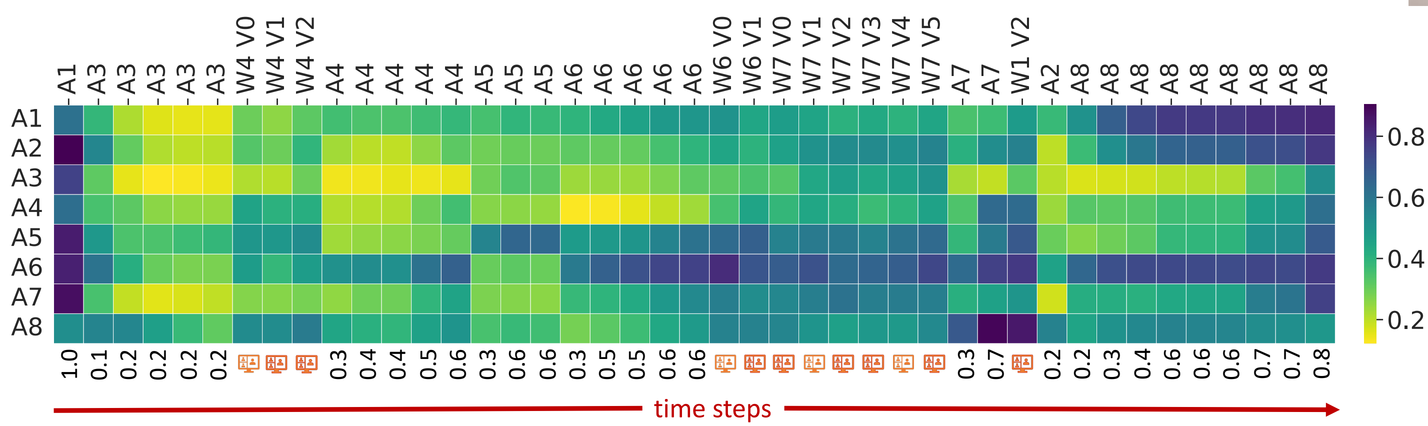
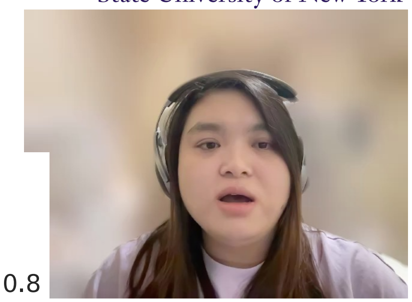


Student's knowledge (estimated performance) visualization of a sample student in MORF

- Findings
  - Videos produce knowledge improvement for corresponding assignment



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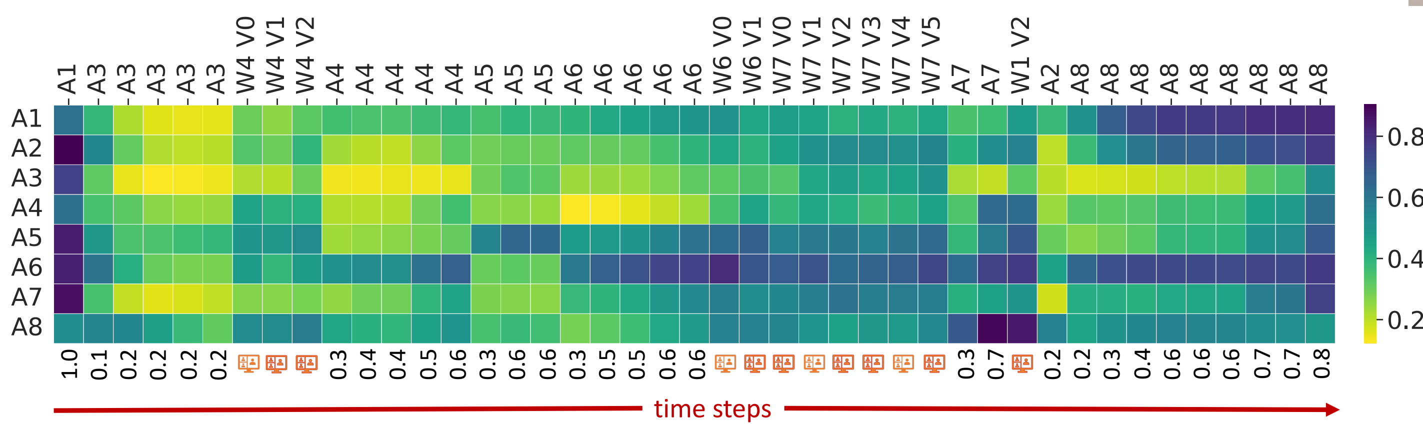

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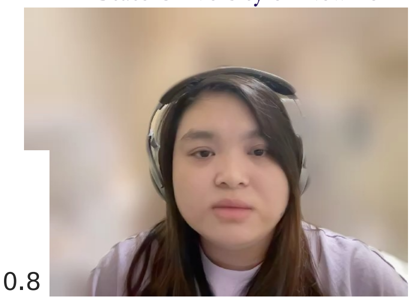

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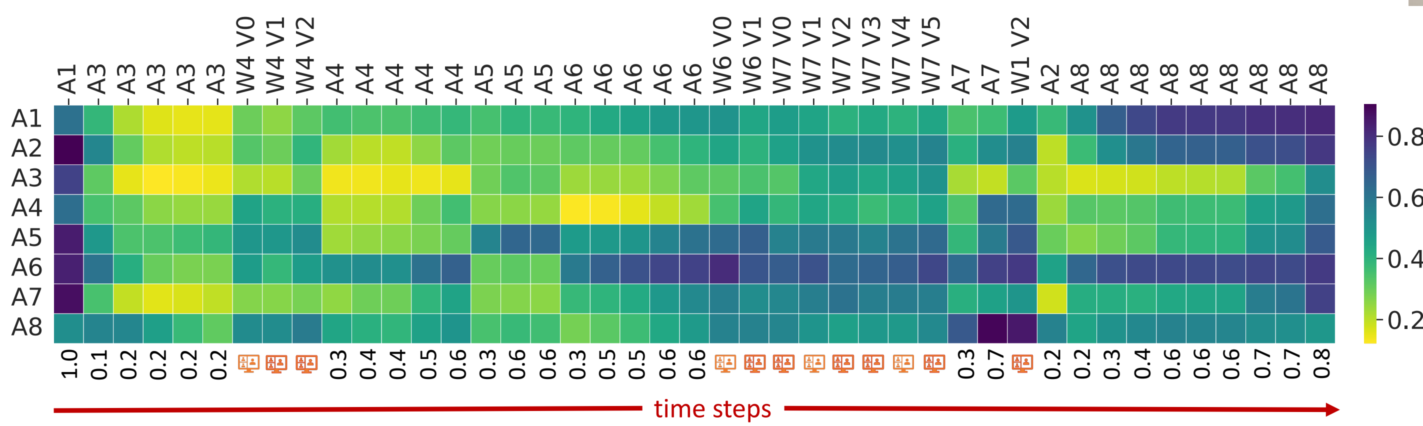
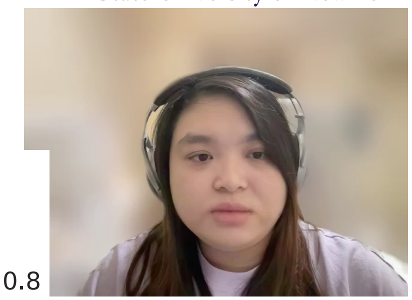


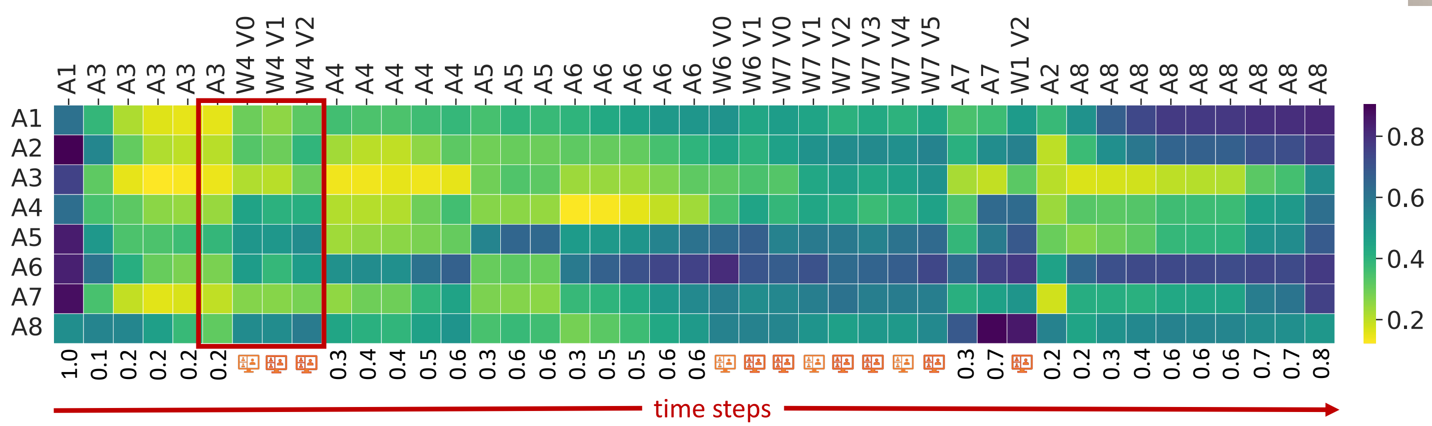
Student's knowledge (estimated performance) visualization of a sample student in MORF

- Findings
  - Videos produce knowledge improvement for corresponding assignment
  - First attempt of video lecture has the largest improvement



Student Knowledge State Visualization

- Predicted performance in each assignment



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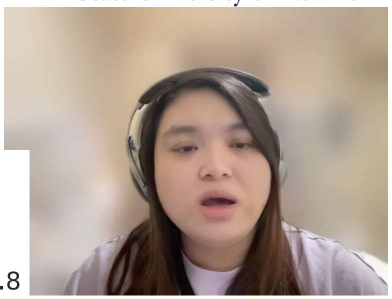

Conclusions

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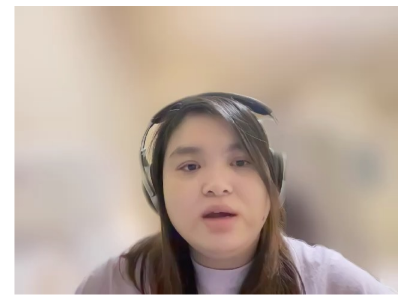
- We proposed a Transition-Aware Multi-Activity Knowledge Tracing Model (TAMKOT)
  - Can accurately represent student knowledge and predict their performance
  - Can explicitly learn the knowledge transfer between different learning activity types.
- The knowledge transfer amount depend on the transition order
- For some students, the assessed activities were more helpful

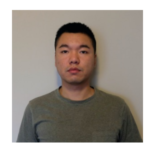
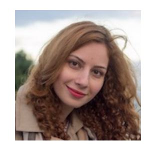
This paper is based upon work supported by the National Science Foundation under Grant No. 2047500.

Thank you!

Q & A



Our code are available at GitHub:
https://github.com/persai-lab/BigData2022-TAMKOT

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