Research on High School Math Exercise Recommendation Based on Graph Neural Network

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Outline

Research Background

Objectives

- Knowledge State Monitoring
- Learning Resource Recommendation
- High School Math (Chinese)

Research Background

Existing Problems

Inappropriate Recommendation Exercise recommendation is not based on knowledge mastery

Disorganized exercise Labelling knowledge for exercises lacking knowledge tags

Knowledge evaluation The difficulty for obtaining knowledge mastery proficiency of the student

Exercise recommendation How to recommend appropriate exercises according to their knowledge status

Research Cores

Exercise knowledge labeling

A multi-knowledge point labeling algorithm for high school mathematics exercises based on bidirectional LSTM (Bi-LSTM) [1] and graph convolutional neural network (GCN) [2].

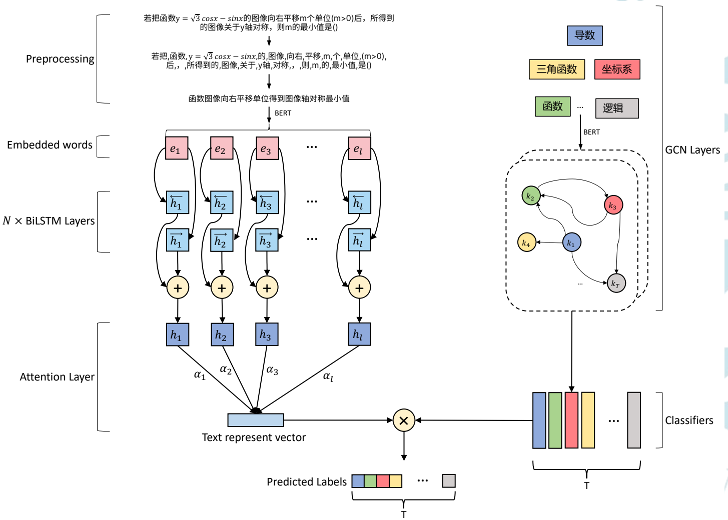
Knowledge tracing

An improved graph-based DKVMN [7] knowledge tracing model to evaluate the knowledge proficiency of students.

Exercise recommendation

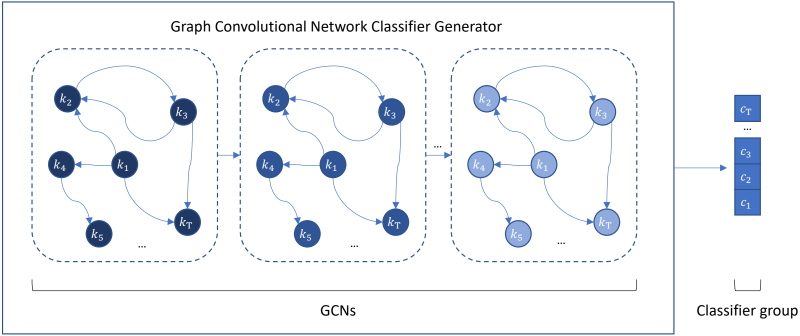
A mathematical exercise recommendation model based on Matching-Ranking [5].

Exercise Knowledge Labelling
Architecture



Exercise Knowledge Labelling

GCN-based Classifier Generator



Knowledge Tracing

Problem Description

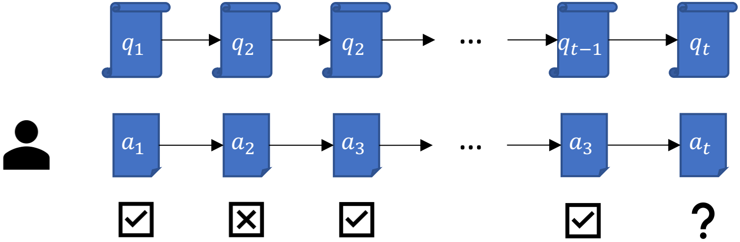
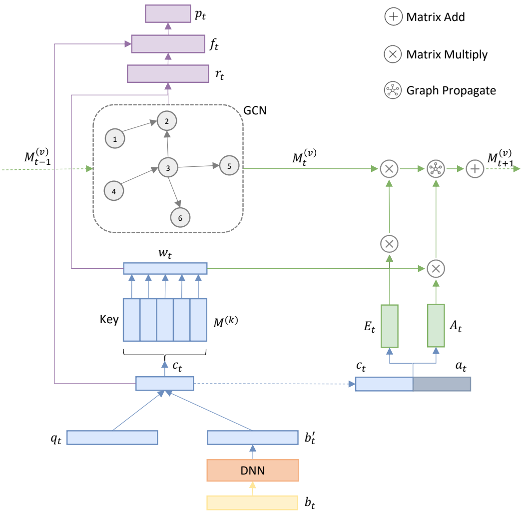


Figure: Knowledge tracing modeling

Knowledge Tracing

Architecture



Knowledge Tracing
Question-Knowledge Relation Modelling

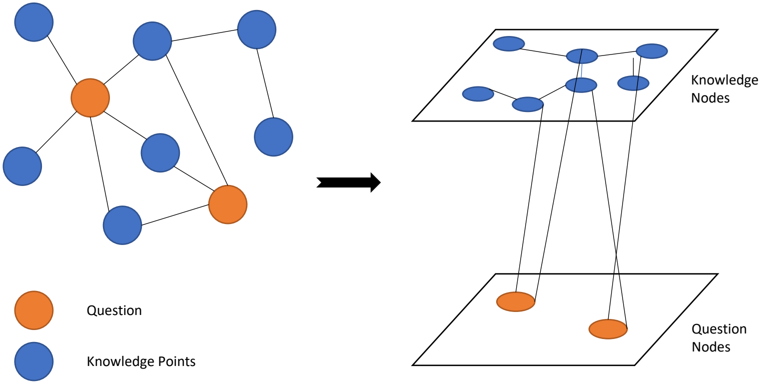


Figure: Relation modeling of exercise question and knowledge points

Exercise Recommendation

Architecture

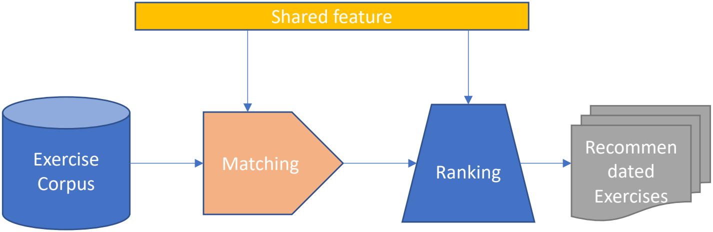
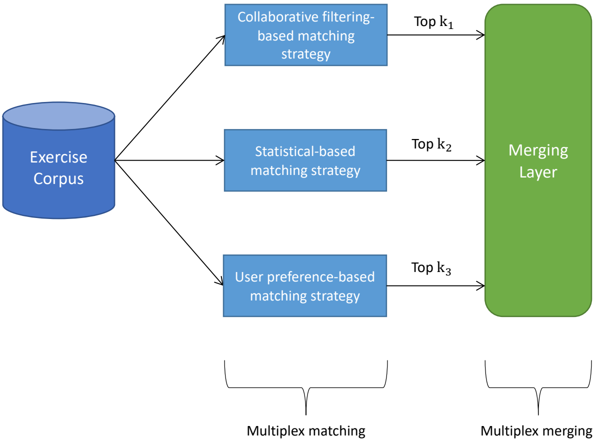


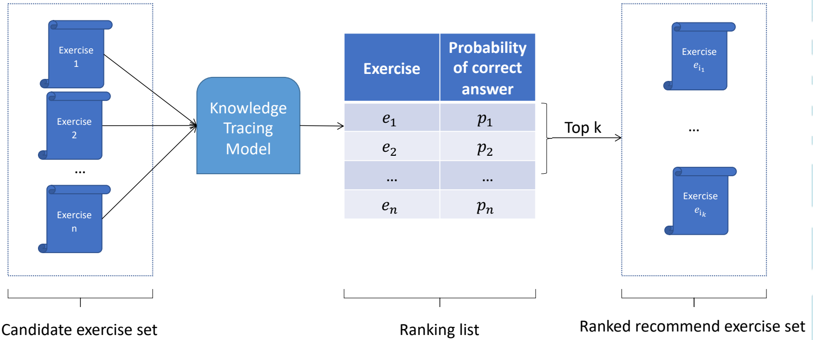
Figure: The architecture of recommendation model

Exercise Recommendation
Matching Phase



Exercise Recommendation

Ranking Phase



Exercise	Probability of correct answer
e_1	p_1
e_2	p_2
...	...
e_n	p_n

Experiment Design

Exercise Knowledge Labelling

- Compare with several baseline models
- Evaluate the multi-label classification performance

Experiment Design

Knowledge Tracing

Basic Method

Compare with other KT baseline models BKT [6]、DKT [4]、DKVMN [1] and GKT [3]

Table: Dataset Statistics

Dataset	#students	#exercises	#knowledge points	#interactions
ASSIST15	19,917	102,396	100	709K
ASSIST17	1,709	4,117	102	943K
STATICS11	333	1,223	156	189K

Experiment Design

Exercise Recommendation

- Compared with conventional Collaborative Filtering and Random Recommendation
- Using adapted KT dataset for testing
- Check if the selected exercise is in the final recommendation list

Result

Exercise Knowledge Labeling

Table: The performance comparison between baseline and proposed knowledge labelling models.

Metrics	$\mathrm{F1}_{macro}$	$\mathrm{F1}_{micro}$	Acc_{ML}	$\mathrm{F1}_{ML}$
BiLSTM+Attention	0.824	0.924	0.874	0.926
fastText	0.846	0.922	0.854	0.916
TextCNN	0.761	0.923	0.857	0.917
Proposed	**0.912**	**0.932**	**0.888**	**0.937**

Result

Exercise Knowledge Labeling

Table: The multi-label classification performance of proposed model.

Class	Precision	Recall	F1 Score	Support
三角函数	0.957	0.710	0.815	31
函数奇偶性	0.946	0.930	0.938	187
导数	0.918	0.866	0.892	247
平面向量	0.942	0.961	0.951	204
数列	0.996	0.971	0.983	243
逻辑与命题关系	0.958	0.883	0.919	180
集合	0.907	0.867	0.886	45
Micro avg	0.951	0.915	0.932	1137
Macro avg	0.946	0.884	0.912	1137
Weighted avg	0.951	0.915	0.932	1137
Samples avg	0.951	0.935	0.937	1137

Result
Knowledge Tracing

Table: The performance comparison between baseline and proposed knowledge tracing models.

Model	ACC (%)	AUC (%)	Training time (sec)
DKT	76.99 ± 0.08	81.79 ± 0.09	$2,731$
DKVMN	75.63 ± 0.19	79.58 ± 0.27	$3,378$
NPA	77.09 ± 0.08	81.81 ± 0.13	$3,872$
SAKT	76.37 ± 0.15	80.77 ± 0.09	$4,367$
Proposed	$\mathbf{81.34} \pm \mathbf{0.25}$	$\mathbf{83.20} \pm \mathbf{0.25}$	$4,597$

Result and Analysis

Exercise Recommendation

Table: The performance comparison between baseline and proposed recommendation models.

Model	ACC	AUC
CF	0.6329	0.6627
DKT	0.7741	0.7906
Proposed	**0.7997**	**0.7923**

Conclusion

- The three modules of the proposed model satisfy the requirements of the design
- The proposed model achieves better performance compared with baseline models.

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