

Towards a Holistic Understanding of Mathematical Questions with Contrastive Pre-training

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Introduction

Background

- Online learning systems collect massive educational questions.
- Mathematical question understanding is a crucial but challenging issue in intelligent education field.
 - more difficult to understand with special components (e.g., formulas) and complex mathematical logic
 - require more domain knowledge for comprehensive understanding

Challenges

- Mathematical questions are more complex with special components (e.g., formulas), and require more mathematical knowledge and logic.
- > The holistic purposes of questions are more important than literal details.
- Related knowledge concepts play an important, since they reflect the purposes and mathematical domain of questions.





QuesCo Framework

Main Idea

learn comprehensive question representations by pulling questions with more similar purposes closer than those with less similar purposes



Question Augmentation

To learn latent purposes of mathematical questions, generate questions with similar holistic purposes but diverse literal details

	Trigonometric Function	Power Function	Application of Derivatives	Cuboid							
	$Q_1 Q_2$	Q ₃	Q_4	Q ₅							
similar	Knowledge Hierarchy										

Problem Definition

Mathematical Questions

- > consist of content and related knowledge concepts q = (x, k)
- Question content: x = {x₁, x₂, ..., x_T} a sequence of tokens, where each token is a word or symbol
- ➢ Related knowledge concepts: k = {k₁, k₂, ..., k_L} selected from a L-level knowledge hierarchy KH = {𝔅, 𝔅}

Question Representation Problem

- Given: mathematical question q = (x, k)
- ► Goal: a d-dimensional vector $\boldsymbol{v} \in \mathbb{R}^d$
 - be transferred to several downstream tasks and benefit their performances
 - capture latent purposes of questions
 - contain the rich information in question content and related knowledge concepts

- Two-level augmentation
 - Content-level
 - Text Augmentation + Formula Augmentation
 - Structure-level
 - Structure Augmentation

Knowledge Hierarchy-Aware Rank

- Exploit fine-grained similarities between questions based on the relationship of mathematical knowledge concepts
- Assign each question q_i in memory bank into one of L + 1 ranks

$$Q^{u} = \begin{cases} \{q^{+}\}, & u = 0\\ \{p|khd(q, p) = u\}, & u \in \{1, \cdots, L+1\} \end{cases}$$

Similarity ranking

 $h(q,q^0) > h(q,q^1) > \cdots > h(q,q^{L+1}), \forall q^u \in Q^u,$

Pre-training

Ranking Info Noise Contrastive Estimation loss (RINCE)

gradually decreasing similarity with increasing rank of samples

$$L_{rank} = \sum_{0}^{L} \ell_{i} \qquad \qquad \ell_{i} = -\log \frac{\sum_{p \in Q^{i}} \exp\left(\frac{h(q,p)}{\tau_{i}}\right)}{\sum_{p \in \bigcup_{j \ge i} Q^{j}} \exp\left(\frac{h(q,p)}{\tau_{j}}\right)}$$



# Knowledge in level-1	21	21
# Knowledge in level-2	81	54
# Knowledge in level-3	361	175
# Questions with difficulty label	7,056	/
# Questions with similarity label	/	6,873
Label sparsity	5.72%	27.18%

Overall Performance

Tasks	Similarit	y Prediction	Concept Prediction								Difficulty Estimation			
Datasets	SYSTEM2		SYSTEM1				SYSTEM2				SYSTEM1			
Metrics	Pearson	Spearman	level-1		leve	level-2		level-1		level-2		PMSE	DCC	
			ACC	F1	ACC	F1	ACC	F1	ACC	F1		RNDL	rcc	DOA
BERT	0.2957	0.3655	0.7309	0.5213	0.4472	0.1833	0.4822	0.2374	0.2984	0.0945	0.1987	0.2463	0.3974	0.6318
DAPT-BERT	0.4856	0.5313	0.8032	0.6288	0.5597	0.2727	0.6522	0.3855	0.4960	0.1836	0.1880	0.2313	0.5087	0.6589
ConSERT	0.5060	0.4760	0.8064	0.6655	0.5933	0.3135	0.6987	0.4952	0.5020	0.2076	0.1873	0.2308	0.5115	0.6621
SCL	0.6901	0.7101	0.8985	0.8011	0.7492	0.4683	0.8083	0.6498	0.6225	0.3071	0.1996	0.2460	0.4002	0.6340
QuesNet	0.5370	0.5549	0.7881	0.6930	0.5693	0.3604	0.7194	0.6213	0.5810	0.3118	0.1865	0.2305	0.3959	0.6539
DisenQNet	0.6922	0.6955	0.8210	0.7064	0.6404	0.4332	0.7945	0.6805	0.2431	0.1023	0.1970	0.2424	0.4293	0.6338
QuesCo	0.7385	0.7245	0.9176	0.8938	0.7857	0.5550	0.8340	0.7018	0.6719	0.3756	0.1778	0.2219	0.5623	0.6765

Performance comparisons on three typical downstream tasks.

Ablation Study

	Tasks	Similarit	y Prediction			(Concept I	Predictio	rediction				Difficulty Estimation			
Γ	Datasets	SYS	STEM2	SYSTEM1			SYSTEM2				SYSTEM1					
Metrics	Pearson	Spearman	leve	level-1 level-2		level-1		level-2		MAE	PMSE	PCC				
			ACC	F1	ACC	F1	ACC	F1	ACC	F1						
(QuesCo	0.7385	0.7245	0.9176	0.8938	0.7857	0.5550	0.8340	0.7018	0.6719	0.3756	0.1778	0.2219	0.5623	0.6765	
w	/o AUG	0.7028	0.7213	0.9079	0.8770	0.7305	0.4497	0.8320	0.6972	0.6443	0.3412	0.2007	0.2482	0.3797	0.6204	
w/	o KHAR	0.5481	0.5057	0.8202	0.7160	0.6181	0.3416	0.7332	0.5996	0.5613	0.2746	0.1810	0.2248	0.5475	0.6655	

Effectiveness of each module.

KH-distance khd

The relationship between *khd* and labeled similarity between questions in SYSTEM2.



Case Study: A case of questions with different similarities.