An Empirical Study Towards Prompt-Tuning for Graph Contrastive Pre-training in Recommendations

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Haoran Yang[1], Xiangyu Zhao[2], Yicong Li[1], Hongxu Chen[3], Guandong Xu[1]

[1]University of Technology Sydney,

[2]City University of Hong Kong,

[3]University of Queensland

1 Introduction & Background

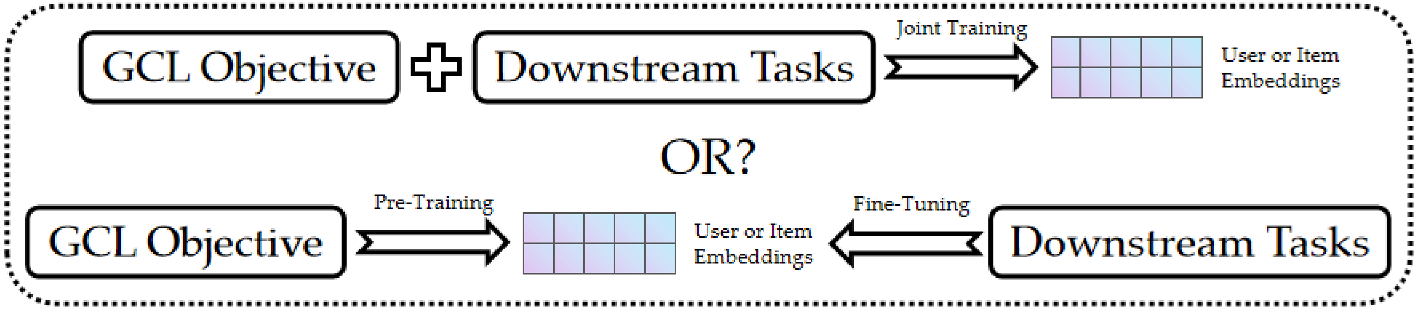
- Graph contrastive learning (GCL):
  - A powerful self-supervised graph pre-training paradigm.
  - The pipeline of GCL follows:

    GCL Pre-Train $\longrightarrow$ *Downstream Tasks* or *GCL Pre-Train* $\longrightarrow$ *Fine-Tune* $\longrightarrow$ *Downstream Tasks*

- GCL-based recommendation systems:
  - The contemporary GCL-based recommendation methods follow the pipeline:

    GCL Pre-Train + *Recommendation Tasks*
  - Why don't adopt the original pre-training pipeline?

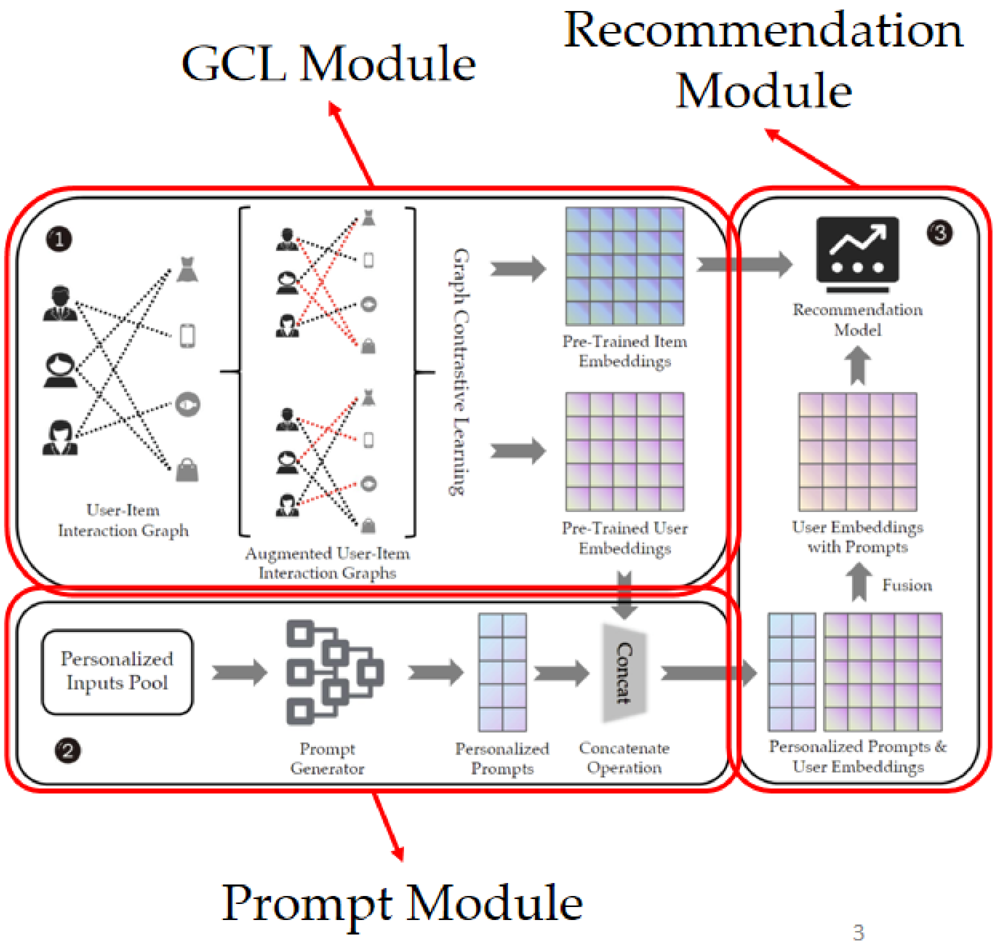
    GCL Pre-Train $\longrightarrow$ *Recommendation Tasks*



2 Methodology

2.1 The Framework Overview

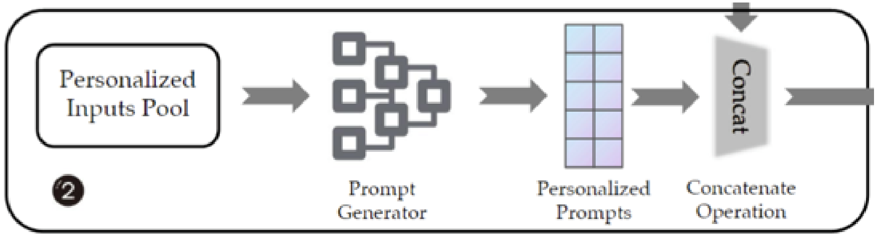
- The proposed CPTPP method:
  - A novel framework that follows the GCL's pre-training pipeline:
    GCL Pre-Train → Recommendation Tasks
- Three components:
  - **GCL module** conducts the pre-training task to generate pre-trained embeddings.
  - **Prompt module** generates personalized prompts to mitigate the inconsistency between the pre-trained embedding and the downstream recommendation tasks.
  - **Recommendation module** utilizes prompted embeddings to conduct the recommendation tasks.



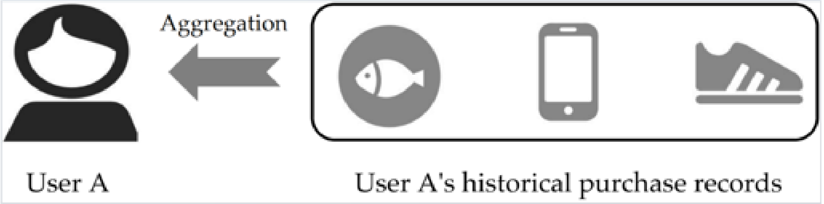
2 Methodology

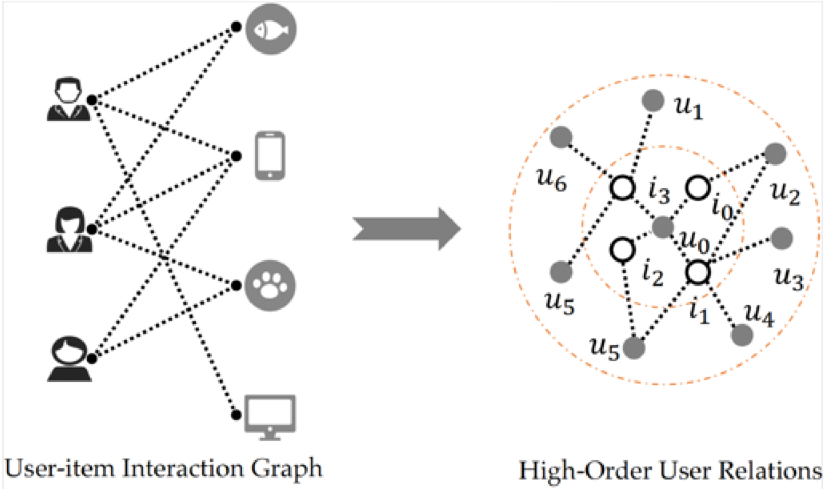
2.2 Personalized Prompts Generation

- Soft prompts generation:
  - Hard prompt design requires expert knowledge and resource-consuming.
  - Generate soft prompts based on the personalized profiles.



- Personalized profiles:
  - Historical interaction records.
  - High-order user relations.
  - Adjacency matrix factorization.





3 Experiments

3.1 Comparison Experiments

Datasets	Metrics	Methods							
		BPR-MF	BUIR	SelfCF	NCL	SimGCL	CPTPP-H	CPTPP-M	CPTPP-R
Douban	Hit Ratio@5	0.0134	0.0156	0.0161	0.0161	0.0161	0.0164	**0.0165***	0.0164
	Hit Ratio@20	0.0446	0.0492	0.0502	0.0507	0.0489	0.0521	**0.0528***	0.0523
	Precision@5	0.1812	0.2113	0.2185	0.2187	0.2182	0.2221	**0.2235***	0.2224
	Precision@20	0.1512	0.1667	0.1699	0.1717	0.1657	0.1766	**0.1790***	0.1772
	NDCG@5	0.1904	0.2209	0.2264	0.2313	0.2370	0.2359	**0.2378***	0.2355
	NDCG@20	0.1749	0.2019	0.2058	0.1958	0.2020	0.2065	**0.2098***	0.2070
ML-1M	Hit Ratio@5	0.0469	0.0617	0.0624	0.0655	0.0631	**0.0676***	0.0674	0.0672
	Hit Ratio@20	0.1454	0.1519	0.1643	0.1796	0.1698	0.1851	**0.1861***	0.1845
	Precision@5	0.1800	0.2368	0.2396	0.2513	0.2420	**0.2592***	0.2585	0.2577
	Precision@20	0.1395	0.1457	0.1576	0.1723	0.1629	0.1776	**0.1785***	0.1770
	NDCG@5	0.1968	0.2722	0.2689	0.2818	0.2767	**0.2919***	0.2895	0.2878
	NDCG@20	0.2103	0.2367	0.2508	0.2683	0.2670	0.2781	**0.2782***	0.2756
Gowalla	Hit Ratio@5	0.0429	0.0479	0.0497	0.0488	0.0513	0.0518	0.0512	**0.0519***
	Hit Ratio@20	0.1039	0.0993	0.1042	0.1040	0.1065	0.1115	0.1103	**0.1120***
	Precision@5	0.0624	0.0698	0.0723	0.0711	0.0746	0.0754	0.0745	**0.0755***
	Precision@20	0.0378	0.0361	0.0379	0.0378	0.0387	0.0406	0.0401	**0.0407***
	NDCG@5	0.0770	0.0911	0.0939	0.0894	0.0963	**0.0963**	0.0953	0.0961
	NDCG@20	0.0939	0.0990	0.1036	0.1005	0.1126	**0.1092**	0.1083	**0.1092**

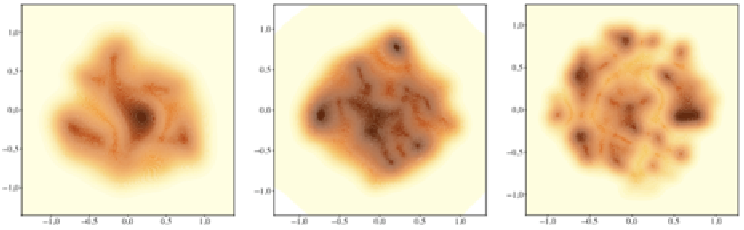
"*" indicates that CPTPP outperforms the best baseline significantly (i.e., two-sided t-test with $p < 0.05$).

- GCL-based recommendation significantly outperforms the conventional self-supervised ones, like SelfCF and BUIR.
- All versions of the proposed method achieve competitive results. Some of them have SOTA performance.
- BPR is outperformed by all the baselines, verifying the effectiveness of the self-supervised training signal of GCL.

3 Experiments

3.2 Hyper-Parameter Study & Embedding Visualizations

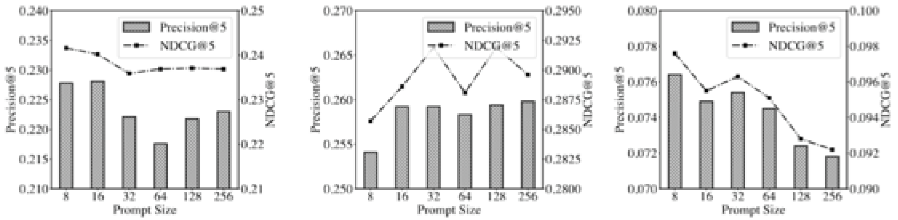
➢ Embedding visualizations:



(a) CPTPP - Douban (b) CPTPP - ML-1M (c) CPTPP - Gowalla

- To further evaluate the quality of the user embeddings used in downstream tasks, we visualize them by t-SNE and KDE.
- The proposed CPTPP method has more uniform distributions, indicating the powerful capability to model the diverse preferences of users.

➢ Hyper-parameter study :



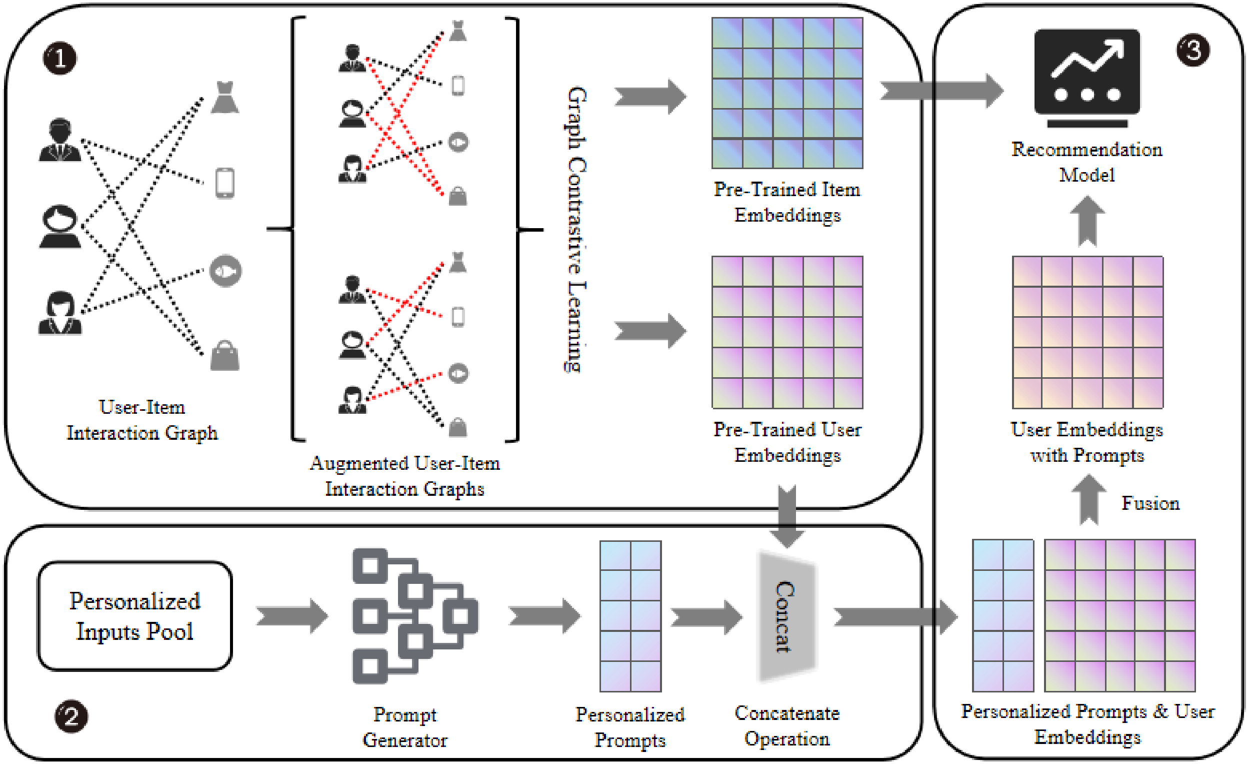
(a) CPTPP-H - Douban (b) CPTPP-H - ML-1M (c) CPTPP-H - Gowalla

- A hyper-parameter study about prompt size.
- In most cases, CPTPP has the best performance size when the prompt size is not larger than the dimensionality of user embeddings.
- A relatively small prompt size is a better option in practices, balancing the recommendation quality and the training efficiency.

More experiment results can be found in the appendix of the paper.

THANKS FOR LISTENING!

Contact: haoran.yang-2@student.uts.edu.au



User-Item
Interaction Graph
Augmented User-Item
Interaction Graphs
Graph Contrastive Learning
Pre-Trained Item
Embeddings
Pre-Trained User
Embeddings
Recommendation
Model
User Embeddings
with Prompts
Fusion
Personalized
Inputs Pool
Prompt
Generator
Personalized
Prompts
Concat
Concatenate
Operation
Personalized Prompts & User
Embeddings