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G-TRAC: Graph-textual Representations Alignment for Cold-start Recommendations

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1.Introduction

Introduction

The cold-start problem remains a persistent and significant challenge in modern recommendation systems, particularly for new users or unseen items with little to no historical interaction data. While Graph Neural Networks (GNNs) have become a standard for modeling complex user-item relationships by capturing higher-order structural signals and collaborative filtering (CF) signals, their effectiveness is inherently tied to the existence of an interaction graph. Consequently, when new entities enter a system without prior connections, these existing graph structures become ineffective, leading traditional models to falter. To mitigate this issue, researchers have explored various alternatives though these often suffer from data sparsity or limited adaptability in data-scarce environments. Concurrently, the advent of Transformers has revolutionized recommendation tasks through discriminative models like P5 and generative approaches that improve interpretability by verbalizing outputs. However, off-the-shelf Large Language Models (LLMs) often underperform in recommendation contexts without specific fine-tuning. To bridge this gap, we introduce G-TRAC, a novel framework that rethinks the cold-start problem by leveraging textual data as a bridge to the graph neural network.

Key Contributions

- **Deep Semantic Fusion:** Utilizing a transformer-based encoder, the framework extracts deep semantic features and fuses them with heterogeneous user-item graphs, surpassing the limitations of traditional content-based methods.
- **Multi-granularity Alignment:** We introduce a three-level alignment strategy—spanning instance, neighborhood, and summary levels—to unify textual and graph representations within a shared latent space. This allows cold-start entities to inherit structural knowledge while maintaining semantic richness.
- **Cross-Scenario Consistency:** G-TRAC maintains competitive performance in warm-start settings, matching state-of-the-art models like LightGCN, while simultaneously providing superior cold-start capabilities.

2.Methodology: Graph-textual Representations Alignment

Dual-Encoder Architecture

The framework employs two specialized modules to process different data modalities:

- Graph Model (ϕ_G): Uses a Graph Neural Network (GNN) with layer-wise fusion to extract collaborative filtering (CF) signals from the user-item interaction graph.
- Text Model (ϕ_T): Utilizes a naive transformer-based encoder to generate comprehensive embeddings from user reviews and item descriptions, capturing deep semantic features.

Three level granularity for alignment graph & text signal

To unify these modalities in a shared latent space, G-TRAC implements three levels of contrastive alignment:

- Instance-level Alignment: Directly synchronizes a specific node's graph representation with its own text embedding to ensure consistency across modalities.
- Text-neighborhood Context Matching: Aligns a node's text embedding with a summary embedding aggregated from the text of its neighbors, such as matching user preferences to item descriptions.
- Summary-level Alignment: Aligns graph embeddings with neighborhood summary embeddings to ensure global structural consistency and allow cold-start entities to inherit structural knowledge.

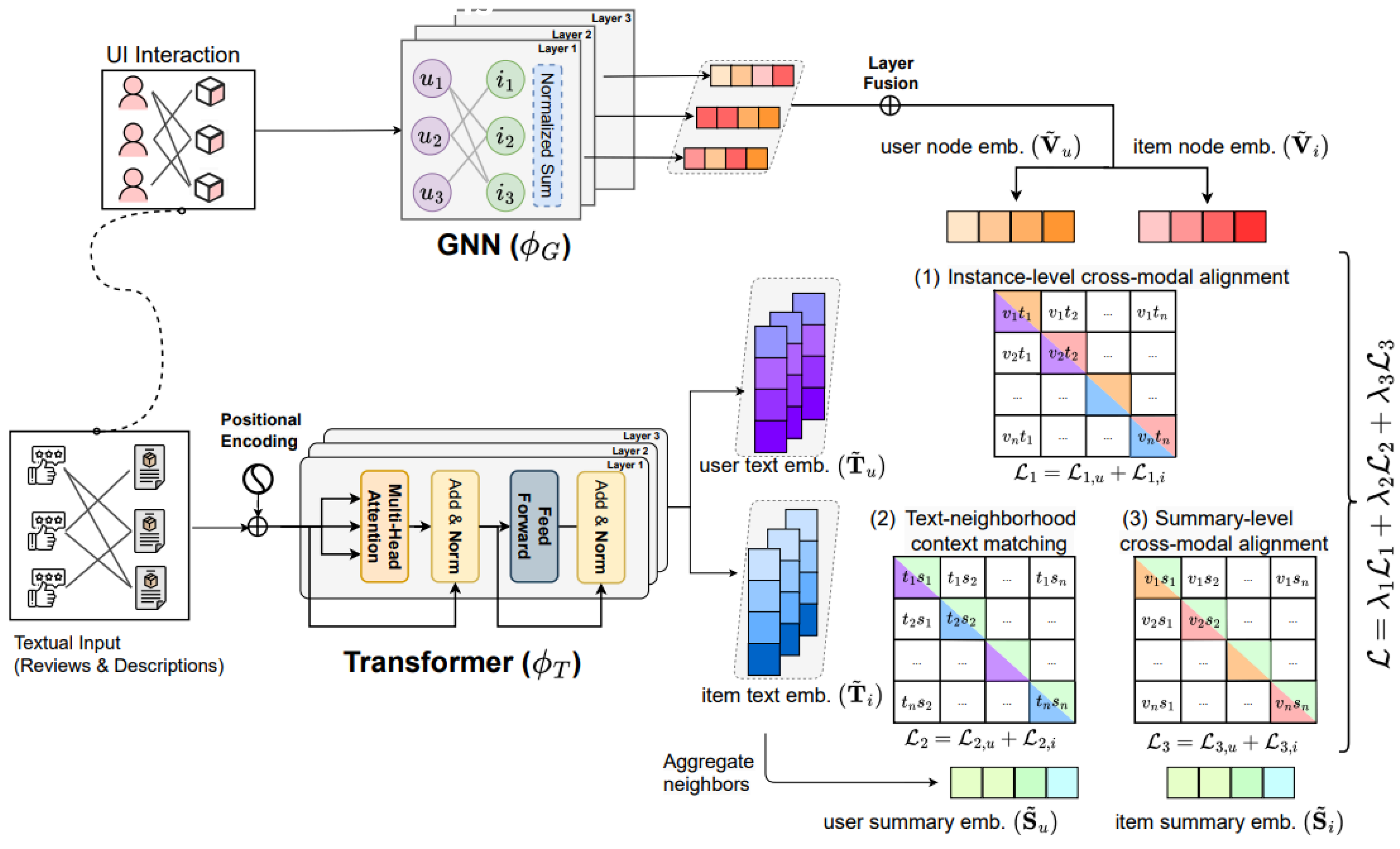

Figure 1: Overall framework of G-TRAC for heterogeneous user-item graphs.

3.Experiments and Conclusion

Experiment Setup

- We evaluate G-TRAC across 2 Amazon datasets
- experiment on 3 scenarios
  - User Cold-start case
  - Item Cold-start case
  - Warm start use case

Key Findings

- **Superior Cold-Start Performance:** G-TRAC consistently outperforms state-of-the-art baselines, including meta-learning and LLM-based methods (e.g., MetaHIN, TIGER, and P5), across multiple datasets.
- **Significant Metrics Gains:** In user cold-start scenarios, the model surpasses the best baseline by 16% on the All Beauty dataset and 34% on Musical Instruments. For item cold-start, it achieves improvements of 25% and 61%, respectively.
- **Generative vs. Alignment Strategy:** While recent generative approaches (LLMs) improve interpretability by verbalizing outputs, they often underperform in recommendation contexts without specific fine-tuning. G-TRAC addresses this by using textual data as a semantic bridge to align with graph structures.
- **Effective Representation Alignment:** The framework successfully unifies textual and graph modalities through a three-level alignment strategy: instance-level, neighborhood-level, and summary-level.
- **Robustness in Warm-Start Scenarios:** Unlike many cold-start specialized methods that perform poorly when data is abundant, G-TRAC maintains competitive performance in warm-start settings, matching standard collaborative filtering models like LightGCN.

Concluson

- G-TRAC effectively addresses the cold-start problem by bridging the gap between textual semantics and structural graph data. By aligning transformer-based encoders with graph neural networks across three hierarchical levels, the framework enables new users and items to inherit structural knowledge through their textual descriptions

	Model	All Beauty		Musical Instruments	
		nDCG@10↑	HR@10↑	nDCG@10↑	HR@10↑
User Cold-start	DropoutNet	0.0096	0.0110	0.0091	0.0103
	MeLU	0.0348	0.0383	0.0337	0.0372
	MetaHIN	0.0371	0.0410	0.0383	0.0423
	HERec	0.0353	0.0395	0.0292	0.0324
	P5	0.0236	0.0223	0.0296	0.0312
	TIGER	0.0261	0.0292	0.0352	0.0385
	G-TRAC	**0.0433**	**0.0480**	**0.0513**	**0.0567**
		nDCG@10↑	HR@10↑	nDCG@10↑	HR@10↑
Item Cold-start	DropoutNet	0.0070	0.0078	0.0085	0.0093
	CLCRec	0.0270	0.0301	0.0215	0.0238
	CCFCRec	0.0250	0.0277	0.0260	0.0290
	MetaHIN	0.0260	0.0290	0.0280	0.0312
	HERec	0.0230	0.0257	0.0250	0.0278
	P5	0.0211	0.0210	0.0204	0.0231
	TIGER	0.0265	0.0295	0.0360	0.0397
	G-TRAC	**0.0338**	**0.0375**	**0.0420**	**0.0468**

Table 1: Performance for cold-start recommendation.

Model	All Beauty		Musical Instruments	
	nDCG@10↑	HR@10↑	nDCG@10↑	HR@10↑
MF-BPR	0.6523	0.7251	0.6731	0.7498
LightGCN	**0.7825**	**0.8673**	**0.7984**	**0.8856**
P5	0.3721	0.3373	0.3931	0.4196
TIGER	0.4821	0.5370	0.4953	0.5539
CLCRec	0.2005	0.2221	0.2143	0.2374
CCFCRec	0.2207	0.2452	0.2351	0.2617
G-TRAC (ϕ_T)	0.3654	0.4072	0.3748	0.4158
G-TRAC (ϕ_G)	0.7312	0.8115	0.7496	0.8328

Table 2: Performance for warm-start recommendation.