Knowledge-based Graph Network with Semantic-Neighbor Items for Government Service Recommendation

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***Abstract*—Government service recommendation suffers from sparse user–item interactions. This data sparsity hinders the precise learning of embedding representation, leading to limited performance. Therefore, we construct a government service knowledge graph, which enriches the description of service items by introducing multi-dimensional entities. To enhance recommendation performance by semantically exploiting the auxiliary knowledge information, we propose a Relation-aware Knowledge-based graph network with Semantic-Neighbor Items (RKSNI). Firstly, semantic-neighbor items feature is proposed to directly capture valuable inter-item association. It guides the relation-attention graph convolution network in generating semantic-neighbor representation, while also serving as interpretable signal for contrastive learning. Secondly, holistic-structural representation is constructed through propagation over the collaborative knowledge graph, thereby capturing global information. To effectively integrate the two complementary representations, discriminative contrastive learning is designed to enrich the representation with interpretable difference, while alignment contrastive learning is applied to ensure fine-grained consistency between the two representations. Experiments on a real e-government service dataset and two common public datasets demonstrate that RKSNI outperforms state-of-the-art methods, verifying its effectiveness and generalization. These improvements arise from its focus on reducing noise in hidden relationship modeling and improving the semantic interpretation of contrastive learning signals. The implementations are available at: https://github.com/cczgsj/RKSNI.**

***Keywords*—E-government service recommendation, Graph Neural Network, Knowledge Graph, Contrastive Learning**

I. INTRODUCTION

With the continuous advancement of digital-government initiatives, effective government service is vital to sustain social operations and improve quality of life. [1]. Unlike mainstream recommendation domains such as e-commerce, multimedia, and news, government service exhibits strong domain specificity and rigid demand characteristics. Due to limited domain knowledge, citizens often struggle to accurately identify the services they need. Consequently, government-service recommendation systems play a crucial role in bridging public demands with governmental resources.

Although several studies—such as User-DTMF [2], SACF [3] and GCNSLIM [4] have attempted to apply recommendation techniques in the context of government-service, existing approaches still face fundamental challenge. Limited supervised signals hinder recommendation models from fully learning the attributes of each service, thus affecting the effectiveness of service recommendation for user. The knowledge graph (KG) stores entity relationships as structured triplets, providing rich attributes for target items. Integrating it eases data sparsity in recommendation systems and enriches user-item representations with auxiliary knowledge. However, current knowledge-based recommendation architectures still exhibit limitations in practical applications.

Most knowledge-based recommendation models employ multi-hop relation propagation to uncover potential associations between entities. However, in practice, exploring deeper and broader relational structures often introduces irrelevant or noisy information. As an illustrative case, some models infer user's preferences over different relation types and integrate them into user interest representation [5], [6]. This is effective in limited scenarios, most relations in KG encode semantic properties to items rather than user preferences. Incorporating such relations results in divergence from the user's true underlying characteristics.

Existing contrastive learning approaches construct positive and negative samples at the representation level. Negatives are typically obtained by randomly sampling items from the item set, while positives are generated through data augmentation [7], [8]. Although these strategies aid in representation learning and robustness, such transitional features cannot ensure semantic consistency. Lacking semantically grounded supervision, contrastive learning deviates from interpretation, ultimately degrading recommendation performance.

Complex network architectures may introduce noise and contrastive learning signals often lack semantic interpretation. To address these issues, we propose the relation-aware knowledge-based graph network with semantic-neighbor items (RKSNI). RKSNI is designed to make efficient use of KG by extracting semantically meaningful neighbor items. This design not only limits the inclusion of noisy information in representation learning, but also makes contrastive learning samples more interpretable. The main contributions of this work can be summarized as follows.

- We propose a semantic-neighbor items feature by exploiting the direct linkage between entities and items in the KG. To capture the varying influence of relations, a

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relation-attention graph convolution network is designed to learn semantic-neighbor representation.

- A multi-relational graph convolution network is designed to aggregate node features across different relations while preserving relation-specific characteristics. This process yields holistic-structural representation, which capture structural information from a global perspective.
- Dual-contrastive learning is proposed as an auxiliary constraint to improve representation quality. Using semantic-neighbor items, discriminative contrastive learning focuses on contrasting local positives with global negatives. Alignment contrastive learning focuses on fusing semantic and structural representation spaces.
- We conduct experiments on a real-world e-government service dataset and two widely used datasets. Experiment results show that RKSNI consistently outperforms state-of-the-art recommendation methods, demonstrating its effectiveness and broad applicability.

II. RELATED WORK

A. Government Service Recommendation

To address the information overload on government service platforms, existing studies have explored recommendation models tailored to government service scenarios. Time-decayed BPR [9] models sequence-dependent user preferences by introducing temporal decay into the Bayesian Personalized Ranking framework. NMCF [10] focuses on enhancing collaborative filtering by leveraging both negative item information and original embedding features under implicit feedback. User-DTMF [2] exploits user historical service interaction to construct dynamic topology information and applies convolution neural network to model complex behavioral patterns. SACF [3] revisits collaborative filtering by factorizing similarity matrix into the product of two low-rank feature matrices.

B. GNN-based Knowledge-aware Recommendation

Existing GNN-based recommendation models typically propagate messages over the collaborative knowledge graph(CKG). MCCLK [11] performs GNN propagation across multiple KG-based graph views, learning node representations by aggregating collaborative, semantic and unified structural neighborhood information. KGIE [5] constructs user–relations and item-users interactive embeddings, allowing user and item embeddings to absorb interaction contexts during messages passing on the KG. VRKG [12] constructs virtual relational graphs by clustering semantically related relations in the KG. It performs message passing over these virtual graphs to enable more effective neighborhood aggregation.

C. Contrastive Learning

Contrastive learning is widely used as an effective self-supervised paradigm that generates auxiliary training signals directly from data. ADGCL [8] adds minimal noise to generate distinct views without damaging core information. It adopts cross-layer contrastive learning: positives are formed by the same node's final-layer output and pre-defined layer embedding, while negatives are sampled from other nodes. FACLK [13] employs cross-view contrastive learning to align the final representation with its counterpart from the interaction view. At the same time, it contrasts this representation with the knowledge-view counterpart, aiming to suppress irrelevant knowledge. KMMCL [14] produces two node representations via separate forward passes, treating different-dropout views of the same node as positives and different nodes as negatives.

III. METHODOLOGY

In this section, we present the overall architecture of RKSNI, as illustrated in Figure 1. Firstly, semantic-neighbor items are constructed, based on which relation specific positives and global negatives are established. Subsequently, by leveraging the semantic-neighbor items' connection within specific relation contexts, a relation-attention graph convolution network(RA-GCN) integrated with Light-GCN is designed to learn semantic-neighbor representation. Furthermore, the construction of holistic-structural representation involves two key components. On one hand, relation-specific information from the CKG is aggregated through a multi-relation graph convolution network (MR-GCN). On the other hand, discriminative contrastive learning incorporates the feature of semantic-neighbor items using positives and negatives. Both processes are coordinated by a shared relation weight, derived from relation representation in the RA-GCN network. Finally, alignment contrastive learning mechanism is utilized to integrate both types of representations, and recommendation prediction is generated based on the final representation.

A. Semantic-Neighbor Items Adjacency Matrix Construction

The knowledge graph G is partitioned into multiple relation-specific subgraphs. Each subgraph $G_{\mathcal{R}} = (\mathcal{V}_{\mathcal{R}}, \mathcal{E}_{\mathcal{R}})$ is defined by retaining all edges of a specific relation type $\mathcal{R}$ and their connected nodes-including both item nodes p and entity nodes q. For a given entity node q_i, all directly connected item nodes are collected in its neighbor set $\mathcal{N}_i$. All items within $\mathcal{N}_i$ are mutually considered as semantic-neighbor items. Any pairwise combination of these items constitutes positives (p_x, p_y).

$$\begin{gathered}\mathcal{E}_{\mathcal{R}} = \{(p,q) \mid relation(p,q) = \mathcal{R}\} \\ \mathcal{V}_{\mathcal{R}} = \{p,q \mid (p,q) \in \mathcal{E}_{\mathcal{R}}\} \quad \mathcal{N}_i = \{p \mid (p,q_i) \in \mathcal{E}_{\mathcal{R}}\}\end{gathered} \tag{1}$$

We collect all positives derived from each entity node in $\mathcal{V}_{\mathcal{R}}$ to form the positive set $\mathcal{S}_{\mathcal{R}}$ for relation $\mathcal{R}$. However, simply treating all non-positives as negatives for each relation is a naive construction strategy. This results in a critical label conflict: a positive under relation $\mathcal{R}_1$ might be incorrectly treated as a negative under relation $\mathcal{R}_2$. To avoid such conflicts, a unified set of global negatives $\mathcal{D}$ is constructed instead of multiple relation-specific negative sets. Specifically, a negative consists of two items that do not share any common neighboring entity across the entire KG. To maintain a balanced contrastive learning setup, the negative set is constrained to a size comparable to that of the positive set. This is achieved

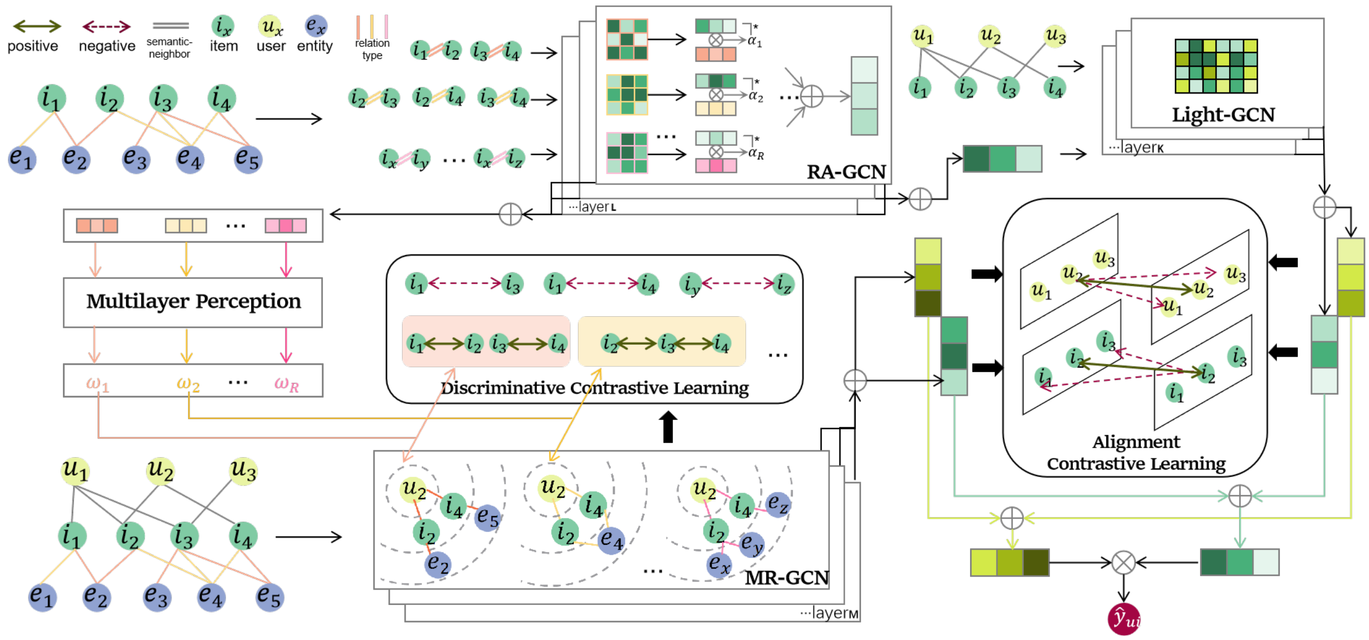

Fig. 1. The overall architecture of the RKSNI, the semantic-neighbor representation and the holistic-structural representation are constructed on the top and bottom of the graph respectively, with the discriminative and alignment contrastive learning processes bridging the middle.

through random sampling: down-sampling when global negatives are more numerous than all relational positives combined, and up-sampling with repetition otherwise.

$$\begin{aligned} \mathcal{S}_{\mathcal{R}} &= \{(v_x, v_y) \mid v_x, v_y \in N_i, v_x \neq v_y, \forall e_i \in \mathcal{V}_{\mathcal{R}}\} \\ \mathcal{D} &= \{(v_x, v_z) \mid v_x \in N_i, v_z \notin N_i, \forall e_i \in \mathcal{V}\} \end{aligned} \tag{2}$$

For each relation, an adjacency matrix of semantic-neighbor items $A^{\mathcal{R}}$, is constructed based on its corresponding positive set $\mathcal{S}_{\mathcal{R}}$. Each element $A^{\mathcal{R}}_{x,y}$ in the matrix records the occurrence count of the positive (p_x, p_y). It is important to note that (p_x, p_y) may be generated from multiple entity nodes $q_i, q_j, \ldots$ within the same relation subgraph. Therefore, $A^{\mathcal{R}}_{x,y}$ is defined as the total number of entity nodes that simultaneously connect to both p_x and p_y, reflecting the strength of their similarity under relation $\mathcal{R}$. Formally, this can be expressed as: $A^{\mathcal{R}}_{x,y} = \text{mult}_{\mathcal{S}_{\mathcal{R}}}\left((p_x, p_y)\right)$

Following the construction of the relation-specific adjacency matrix $A^{\mathcal{R}}$, self-loop augmentation and symmetric normalization are applied to obtain the normalized adjacency matrix $\hat{A}^{\mathcal{R}}$ used in subsequent graph convolution:

$$\hat{A}^{\mathcal{R}} = \tilde{D}^{-\frac{1}{2}}\left(A^{\mathcal{R}} + I\right)\tilde{D}^{-\frac{1}{2}} \tag{3}$$

where I is the identity matrix of the same dimension as $A^{\mathcal{R}}$, and $\tilde{D}$ is the degree matrix of $A^{\mathcal{R}} + I$, defined as a diagonal matrix with $\tilde{D}_{ii} = \sum_j (A^{\mathcal{R}} + I)_{ij}$. This combined operation simultaneously introduces self-connection to preserve node identity and applies symmetric normalization to balance feature aggregation across nodes with varying degrees. Unlike models that collapse multiple relations into a unified adjacency matrix, our framework retains all $\hat{A}^{\mathcal{R}}$ as separate inputs to the subsequent relation-attention graph convolution network.

B. *Semantic-Neighbor Representation Learning*

Building upon the relation-specific adjacency matrices $\hat{A}^{\mathcal{R}}$, a relation-attention graph convolution network (RA-GCN) is designed to diffuse semantic-neighbor items feature.

Each item i is initialized with a learnable embedding vector $s_i^{(0)}$. The propagated messages are computed by aggregating features from its semantic neighbors as defined by $\hat{A}_{\mathcal{R}}$:

$$h_{i,\mathcal{R}}^{(l)} = \sum\nolimits_j \hat{A}^{\mathcal{R}}_{ij} \cdot f_{\mathcal{R}}\left(s_j^{(l)}\right) \tag{4}$$

where $f_{\mathcal{R}}(s) = \tanh\left(W_{\mathcal{R},2} \cdot \text{relu}\left(W_{\mathcal{R},1} \cdot s\right)\right)$ is a relation-specific transformation implemented as multi-layer perceptron.

To characterize fine-grained relation dependence between the target item and its neighboring items, the relation $\mathcal{R}$ is parameterized with independent embedding at each convolution layer $\mathbf{r}_{\mathcal{R}}^{(l)}$. The embedding $\mathbf{r}_{\mathcal{R}}^{(l)}$ is employed to compute relation weight that is specific to the layer l and the target item i. This weight dynamically adapts during neighbor aggregation, thereby capturing layer-specific and relation-aware interactions between the target item and its neighbors. The embedding $\mathbf{r}_{\mathcal{R}}^{(l)}$ is first projected into the same embedding space as the transformed item representation. The attention score between the item $h_{i,\mathcal{R}}^{(l)}$ and relation $r_{\mathcal{R}}^{(l)}$ is then computed as their inner product. And the attention weight $\alpha_{i,\mathcal{R}}^{(l)}$ is obtained via softmax normalization over all relations.

$$\begin{aligned} a_{i,\mathcal{R}}^{(l)} &= h_{i,\mathcal{R}}^{(l)} \cdot f_{\mathcal{R}}\left(\mathbf{r}_{\mathcal{R}}^{(l)}\right)^{\top} \\ \alpha_{i,\mathcal{R}}^{(l)} &= \frac{\exp(a_{i,\mathcal{R}}^{(l)})}{\sum_{\mathcal{R}' \in R} \exp(a_{i,\mathcal{R}'}^{(l)})} \end{aligned} \tag{5}$$

For each item i, the model integrates information from all relations through an attention-weighted combination:

$$h_i^{(l)} = \sum\nolimits_{\mathcal{R} \in R} \alpha_{i,\mathcal{R}}^{(l)} \cdot h_{i,\mathcal{R}}^{(l)} \tag{6}$$

To mitigate potential over-smoothing and preserve original item characteristics, a residual smoothing mechanism is introduced for layer-wise update:

$$s_i^{(l+1)} = \frac{1}{2}\left(s_i^{(l)} + h_i^{(l)}\right) \tag{7}$$

The temporal semantic-neighbor representation of item i and the relation representation $\mathbf{r}_{\mathcal{R}}$ are obtained by a decay-weighted combination of their layer-wise outputs:

$$s_i = \sum_{l=0}^{L} \gamma^{(l)} \cdot s_i^{(l)}, \quad \mathbf{r}_{\mathcal{R}} = \sum_{l=0}^{L} \gamma^{(l)} \cdot \mathbf{r}_{\mathcal{R}}^{(l)}, \quad \gamma^{(l)} = \frac{e^{\delta^l}}{\sum_{j=0}^{L} e^{\delta j}} \tag{8}$$

where $\delta \in (0, 1)$ is a decay factor that prioritizes representations from shallower layers. This design enables the model not only to capture high-order patterns through multi-layer propagation based on $\hat{A}_{\mathcal{R}}$ but also to suppress potential noise introduced by over-smooth in deeper layers.

Based on the representation of the item s_i, user–item interaction information is integrated using the Light-GCN network. The item embedding is initialized as $z_i^{(0)} = s_i$, while user embedding is randomly initialized as $z_u^{(0)}$.

$$z_u^{(k+1)} = \sum_{i \in \mathcal{N}_u} \frac{z_i^{(k)}}{\sqrt{|\mathcal{N}_u||\mathcal{N}_i|}} \qquad z_i^{(k+1)} = \sum_{u \in \mathcal{N}_i} \frac{z_u^{(k)}}{\sqrt{|\mathcal{N}_u||\mathcal{N}_i|}} \tag{9}$$

where $\mathcal{N}_u$ and $\mathcal{N}_i$ denote the sets of neighbors of user u and item i in the interaction graph.

The final semantic-neighbor representation z_u and z_i is obtained by decay-weighted combination:

$$z_u = \sum\nolimits_{k=0}^{K} \gamma^{(k)} \cdot z_u^{(k)}, \quad z_i = \sum\nolimits_{k=0}^{K} \gamma^{(k)} \cdot z_i^{(k)} \tag{10}$$

C. Holistic-Structural Representation Learning

We perform multi-relational graph convolution(MR-GCN) over the unified CKG to learn holistic-structural representation. In this graph, all nodes—including users, items and knowledge entities—are treated uniformly. For each relation type $\mathcal{R}$, the representation of node t update at the m-th layer aggregates information from its neighbors under relation $\mathcal{R}$:

$$e_{t,\mathcal{R}}^{(m+1)} = \frac{1}{|\mathcal{N}_{t,\mathcal{R}}|} \sum\nolimits_{j \in \mathcal{N}_{t,\mathcal{R}}} e_{j,\mathcal{R}}^{(m)} \tag{11}$$

where $\mathcal{N}_{t,\mathcal{R}}$ denotes the set of neighbors of node t under relation $\mathcal{R}$, and the initial embedding $e_{t,\mathcal{R}}^{(0)}$ is initialized randomly. After M propagation layers, the relation-specific embedding $e_{t,\mathcal{R}}$ is obtained by a decay-weighted combination of the layer-wise outputs:

$$e_{t,\mathcal{R}} = \sum\nolimits_{m=0}^{M} \gamma^{(m)} \cdot e_{t,\mathcal{R}}^{(m)} \tag{12}$$

To fuse information across different relations, a relation-specific weight $\omega_{\mathcal{R}}$ is computed based on the relation representation $\mathbf{r}_{\mathcal{R}}$ obtained from the semantic-neighbor representation learning stage. The weight is produced from Multilayer Perception (MLP). The holistic-structural representation for each node t is obtained by weighted aggregation across relations:

$$\omega_{\mathcal{R}} = \text{MLP}(\mathbf{r}_{\mathcal{R}}), \quad e_t = \sum\nolimits_{\mathcal{R} \in R} \omega_{\mathcal{R}} \cdot e_{t,\mathcal{R}} \tag{13}$$

This representation e_t fully integrates structural information from the entire CKG. By sharing the relation representation $\mathbf{r}_{\mathcal{R}}$ across stages, the model maintains a unified relation semantics throughout the representation learning stage.

D. Discriminative Contrastive Learning

To effectively incorporate the semantic-neighbor items feature into the holistic-structural representation, discriminative contrastive learning is proposed based on the previously constructed sets $\mathcal{S}_{\mathcal{R}}$ and $\mathcal{D}$.

For a pair of items (v_x, v_y), their similarity is measured using cosine similarity between e_x and e_y:

$$\text{sim}(x, y) = \frac{e_x \cdot e_y}{|e_x| \cdot |e_y| \cdot \tau} \tag{14}$$

where $\tau > 0$ is a temperature hyperparameter. For each relation $\mathcal{R}$, the discriminative contrastive loss for positive pairs component is defined as follows:

$$\mathcal{L}_{\text{dis}}^{\mathcal{R}} = -\sum\nolimits_{(v_x, v_y) \in \mathcal{S}_{\mathcal{R}}} \text{sim}(x, y) \tag{15}$$

To integrate positive signals from different relations in a semantically consistent manner, relation weight $\omega_{\mathcal{R}}$ is introduced to aggregate $\mathcal{L}_{\text{dis}}^{\mathcal{R}}$. Based on this weighted formulation, the overall discriminative contrastive loss is then constructed by further incorporating the similarity over global negative pairs, which is defined as:

$$\mathcal{L}_{\text{dis}} = \sum\nolimits_{\mathcal{R} \in R} \omega_{\mathcal{R}} \cdot \mathcal{L}_{\text{dis}}^{\mathcal{R}} + \sum\nolimits_{(v_x, v_z) \in \mathcal{D}} \text{sim}(x, z) \tag{16}$$

E. Alignment Contrastive Learning

To align the semantic-neighbor representation z_t and the holistic-structural representation e_t for the same user or item t, an alignment contrastive loss is introduced, which encourages consistency between the two complementary representation spaces.The loss of aligning z_t to e_t is:

$$\ell_t^{(z \to e)} = -\log \frac{\text{sim}(z_t, e_t)}{\sum_{j=1}^{N} \text{sim}(z_t, z_j) + \text{sim}(z_t, e_j) - \text{sim}(z_t, z_t)} \tag{17}$$

where N is the set of users or items in the current batch. Symmetrically, the loss for aligning e_t to z_t, denoted $\ell_t^{(e \to z)}$, is defined in an analogous manner by swapping the roles of z_t and e_t in the above formula.

The overall alignment contrastive loss is the average over all nodes and both directions:

$$\mathcal{L}_{\text{align}} = \frac{1}{2N} \sum_{t=1}^{N} \left(\ell_t^{(z \to e)} + \ell_t^{(e \to z)}\right) \tag{18}$$

By minimizing $\mathcal{L}_{\text{align}}$, the model learns to harmonize the neighbor-aware semantics encoded in z_t with the holistic structure captured in e_t. After alignment contrastive learning, z_t and e_t are updated to $\tilde{z}_t$ and $\tilde{e}_t$, which enhance the robustness and consistency of the final representation.

F. Model Prediction and Optimization

To obtain the final representation for prediction, the two complementary representations— $\tilde{z}_t$ and $\tilde{e}_t$ are combined by element-wise addition:

$$g_t = \tilde{z}_t + \tilde{e}_t \tag{19}$$

where t denotes a user or an item node. Let g_u and g_i be the final representations of user u and item i respectively. The predicted preference score of user u for item i is computed using the inner product:

$$\hat{y}_{ui} = g_u^\top g_i \tag{20}$$

The model is optimized with a Bayesian Personalized Ranking (BPR) loss, which encourages the predicted score of an observed interaction (u, i) to be higher than that of an unobserved pair (u, j):

$$\mathcal{L}_{\text{BPR}} = \sum\nolimits_{(u,i,j)\in\mathcal{O}} - \ln \sigma\big(\hat{y}_{ui} - \hat{y}_{uj}\big) \tag{21}$$

where $\{\mathcal{O} = (u, i, j) \mid (u, i) \in \mathcal{E}^+, (u, j) \in \mathcal{E}^-\}$ denotes the set of training triplets, $\mathcal{E}^+$ is the set of observed interactions, $\mathcal{E}^-$ is the set of sampled unobserved interactions, σ is the sigmoid function.

The overall training loss integrates the BPR loss with the previously defined discriminative contrastive loss $\mathcal{L}_{\text{dis}}$ and the alignment loss $\mathcal{L}_{\text{align}}$, along with a regularization term:

$$\mathcal{L} = \mathcal{L}_{\text{BPR}} + \lambda_1[\lambda_2\mathcal{L}_{\text{dis}} + (1 - \lambda_2)\mathcal{L}_{\text{align}}] + \lambda_3\big(|\Theta|_2^2\big) \tag{22}$$

where λ_2 is a hyper parameter to determine the dis-align contrastive loss ratio, λ_1 and λ_3 are hyper parameters that control the contrastive loss and L_2 regularization term respectively. Θ denotes all trainable model parameters.

IV. EXPERIMENTS

In this section, we conduct extensive experiments on three datasets to evaluate the performance of RKSNI, aiming to answer the following research questions:

- How does our RKSNI model perform compared to advanced recommendation methods?
- How does each component contribute to performance?
- How do different hyperparameters affect performance?
- Is the constructed KG beneficial to the recommendation?

A. Experiment Settings

Datasets. The e-government service dataset Wuhou comes from the data available upon application of the Wuhou District Administrative Approval Bureau in Chengdu [1], which is consistent with the literature [2]–[4]. The service types, executing agencies and required materials for government services are all collected from the Sichuan Government Service Website [2] for the purpose of constructing a KG of government services. The MovieLens-1M and Last.FM datasets, representing movie and music recommendation respectively, are sourced from RecBole [15] and are publicly available. Table I shows the statistical information of the experimental datasets. The Wuhou and ML-1M are preprocessed as similar as GCNSLIM [4].

TABLE I
STATISTICS OF DATASETS

		Wuhou	MovieLens-1M	Last.FM
User-Item Interaction	User	16,216	6,033	1,872
	Item	437	3,123	3,846
	Interactions	540,557	834,449	21,173
Knowledge Graph	Relations	5	12	60
	Entities	1,232	182,011	9,366
	Triples	3,221	1241,996	15,518

Evaluation Methods. Top-K recommendation ranks and selects the K most preferred items for each user from a candidate set. The candidate set consists of all items except those already observed in the training data. We employ two widely adopted metrics: Recall@K focuses on the proportion of preferred items retrieved within the top-K results, while NDCG@K additionally considers the ranking order of preferred items to measure ranking quality. By default, we set K=10.

Baseline. To demonstrate the effectiveness, our proposed method is compared with the baseline model as follows:

- **CFKG** [16]: An explainable framework that embeds heterogeneous entities via a soft matching algorithm.
- **KGCN** [17]: A graph convolution network that captures multi-hop item relationship and semantic context.
- **MCCLK** [11]: Three-view complementary multi-level contrastive model captures item relation from kNN graph.
- **KGIC** [18]: Intra and inter contrastive model that contrasts collaborative-knowledge and local-nonlocal graph.
- **CMGAN** [19]: Two level contrastive model selectively emphasizes relations and entities to capture user interests.
- **GCNSLIM** [4]: A sparse linear network combined with graph convolution alleviates user-item imbalance.
- **RAFRCE** [20]: A fine-grained model that mines implicit relations and adopts an adaptive fusion mechanism.
- **FACLK** [13]: An adaptive contrastive model mitigates feature-correlation and reduces irrelevant noise.

Parameter Settings. All models are implemented based on the PyTorch framework, with a unified embedding size of 64, L2 regularization term of $1e^{-5}$, and batch size of 4096; the Adam optimizer is adopted for model optimization. The parameters λ_1 and λ_2 are tuned within the range of [0, 1]. The K,L,M are chosen in the range of {2, 3, 4}. The dropout ratio, τ and δ are adjusted to 0.3, 0.2 and 0.8, respectively.

B. Performance Comparison (RQ1)

As shown in Table II, RKSNI achieves superior performance over all baseline models on both Recall@10 and NDCG@10. These results indicate that the proposed semantic-neighbor items feature extracts highly interpretable item relationships from the KG while suppressing irrelevant noise in representation learning. In addition, the structural representation complements local neighbor semantics from a global perspective, and

[1]https://www.chengdu.gov.cn/data/oportal/
[2]https://www.sczwfw.gov.cn/

the two contrastive learning strategies further promote fusion between semantic and structural representations.

Unlike RAFRCE [20], which constructs semantic similarity graph of items by computing embeddings' similarity, RKSNI directly leverages explicit connectivity information from the KG to construct relation-aware semantic-neighbor items. This knowledge-driven sample construction strategy is highly interpretable, which can be jointly applied to semantic-neighbor representation design and discriminative contrastive learning. Thus, RKSNI improves the Recall and NDCG metrics by 21.21% and 9.99% on Wuhou, respectively.

CMGAN [19] enhances model generalization by constructing positive and negative pairs through random data augmentation. RKSNI introduces discriminative contrastive learning that contrasts relation-aware local positives with randomly sampled global negatives. While preserving the generalization ability by random sampling, this design further enables the model to differentiate the importance of various relations in positive samples, leading to an improvement of 3.94% and 2.72% in the Recall and NDCG metrics on Wuhou, respectively.

TABLE II
PERFORMANCE COMPARISON ON DIFFERENT DATASETS

Dataset	Wuhou		Last.FM		ML-1M	
Metric	Recall	NDCG	Recall	NDCG	Recall	NDCG
RAFRCE	0.538	0.3801	0.0887	0.0549	0.1031	0.2457
KGCN	0.591	0.3614	0.119	<u>0.069</u>	0.0994	0.2283
GCNSLIM	0.6548	0.4188	<u>0.1225</u>	0.046	0.0858	0.2351
CFKG	0.6562	0.4172	0.1056	0.0583	<u>0.1082</u>	0.2085
FACLK	0.6685	0.405	0.0775	0.0485	0.1066	<u>0.3052</u>
KGIC	0.6957	0.4261	0.1142	0.0617	0.1011	0.2569
CMGAN	0.7107	0.4528	0.0524	0.0302	0.0999	0.2784
MCCLK	<u>0.7443</u>	<u>0.4664</u>	0.1172	0.0597	0.097	0.2695
RKSNI	**0.7501**	**0.48**	**0.1312**	**0.0767**	**0.1212**	**0.3233**

C. Ablation Study of RKSNI Framework (RQ2)

The results of ablation studies are shown in Table III. Specifically, we analyze the impact of the semantic-neighbor module, the discriminative and alignment contrastive learning by selectively removing each component while keeping other settings unchanged. The experiment results indicate how different components contribute to the overall performance and validate the effectiveness of the proposed model design.

The ablation results reveal that the effects of removing the discriminative and alignment contrastive learning vary across datasets, which is mainly attributed to differences in the scale of knowledge graphs. On Wuhou, w/o-Dis leads to a more pronounced performance degradation than w/o-Align , whereas the opposite trend is observed on other datasets. This observation indicates that the joint use of the two contrastive learning enables the model to better capture similarities and differences under diverse data characteristics.

Furthermore, when all components related to semantic-neighbor items are completely removed, the performance (w/o-SNI) consistently drops across all datasets. This result clearly demonstrates that the semantic-neighbor items feature plays a critical role in improving recommendation performance.

TABLE III
PERFORMANCE COMPARISON OF REMOVING KEY COMPONENT

Dataset	Wuhou		Last.FM		ML-1M	
Metric	Recall	NDCG	Recall	NDCG	Recall	NDCG
w/o-SNI	0.5992	0.4013	0.1074	0.0593	0.1024	0.2855
w/o-Dis	0.7406	0.4774	0.0969	0.0591	0.111	0.2994
w/o-Align	0.7314	0.479	0.1259	0.0711	0.1206	0.3211
RKSNI	**0.7501**	**0.48**	**0.1312**	**0.0767**	**0.1212**	**0.3233**

D. Hyperparameter Influence Analysis (RQ3)

We further investigate the sensitivity of RKSNI to key hyper-parameters related to graph convolution depth and contrastive learning weights. Specifically, the numbers of convolution layers for MR-GCN and Light-GCN, denoted as M and K, are selected from $\{2,\ 3,\ 4\}$. The convolution depth of RA-GCN L is configured as 2, as the experiments indicate that this value yields the best performance. The corresponding Recall and NDCG results of Wuhou dataset under different combinations are illustrated in Figure 2 (a) and (b). A consistent observation is that model performance with M set to 3 is inferior to that with 2 or 4 layers. This can be attributed to the fact that during message propagation over the KG, odd-layer convolutions aggregate heterogeneous node representation, whereas even-layer convolutions update target nodes using homogeneous neighbor information. In addition, increasing K generally leads to improving performance, suggesting that deeper propagation in the user-item graph benefits representation learning in RKSNI.

We also analyze the influence of contrastive learning weights, where λ_1 controls the overall contribution of contrastive learning and λ_2 balances the two contrastive loss. We select λ_1 from $0.01, 0.1, 0.4, 0.7$ and λ_2 from $0.2, 0.5, 0.8$, with the results shown in Figure 2 (c) and (d). The experimental results demonstrate that the setting $\lambda_2 = 0.5$ yields the best overall performance, while $\lambda_1 = 0.1$ achieves a favorable balance between Recall and NDCG, leading to consistently strong performance in all evaluation metrics.

E. Knowledge Graph Contribution Analysis (RQ4)

To validate the effectiveness of the KG constructed based on the Wuhou dataset, we generate three variants of the original KG, namely KG-Removal, KG-Decrease, and KG-False, as proposed in [21]. Specifically, KG-Removal and KG-Decrease are obtained by removing 100% and 50% of the (h, r, t) triples from the original KG respectively. KG-False is constructed by introducing random perturbations to the partial KG, such as replacing (h, r, t) with (h, r, t'), thereby producing a corrupted

KG with semantic conflicts. We conduct experiments on these three variant datasets under the same experimental settings. As shown in Figure 3, the recommendation performance (NDCG and Recall) consistently improves with the increase of auxiliary information in the KG. This result demonstrates that integrating the KG effectively enhances recommendation performance. The superior performance on the KG-False over KG-Decrease is attributed to the random sampling of global negatives, which reduces the impact of partial noisy data.

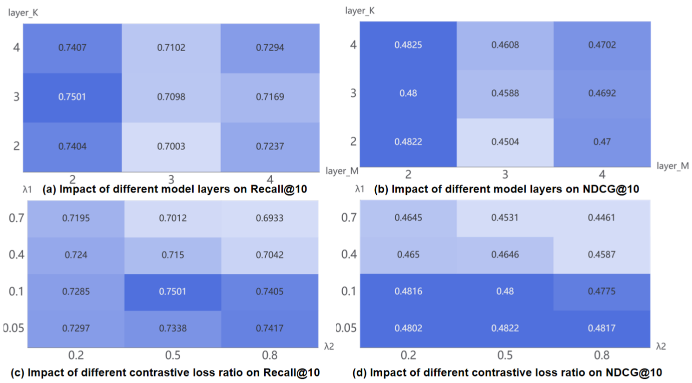

Fig. 2. Hyperparameter analysis of RKSNI

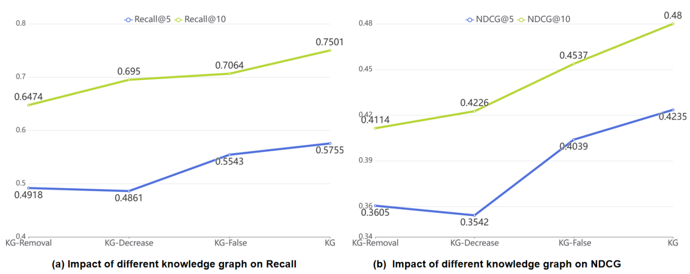

Fig. 3. Knowledge graph contribution analysis

V. CONCLUSION

In this work, we propose a graph convolution network recommendation framework for the government service domain. It is augmented by a relation attention mechanism and a multi-relation module, which inject relation-aware features at neighbor and holistic levels. A key innovation is the proposal of semantic-neighbor items. This feature efficiently and directly exploits graph connection information to learn semantic representation, and simultaneously provides an interpretable space based on structural representation for contrastive learning. This work is supported by the National Natural Science Foundation of China (No.62372176).

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