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Structure-aware knowledge-graph attention for explainable recommendation under sparse user interactions

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Abstract:
The proliferation of digital content has amplified the reliance on recommender systems to filter information and deliver personalized user experiences. However, traditional collaborative filtering approaches suffer significantly from data sparsity and cold-start problems, particularly in environments where user interactions are highly limited. Furthermore, the opaque nature of complex neural recommendation models poses challenges for user trust and system transparency. To address these interconnected challenges, this paper proposes a novel framework centered on structure-aware knowledge-graph attention for explainable recommendation under sparse user interactions. By integrating auxiliary knowledge graphs, the proposed methodology maps items to a rich network of semantic relations, thereby supplementing the sparse user-item interaction matrix with dense factual connectivity. We introduce a sophisticated attention mechanism that is explicitly aware of the local and global topological structure of the knowledge graph. This mechanism adaptively weights different relational paths between users and items based on network motifs and path connectivity degrees, ensuring that the propagation of embeddings prioritizes the most informative and contextually relevant semantic links. Our framework not only improves recommendation accuracy in highly sparse scenarios but also provides explicit path-based explanations for every recommendation generated. Extensive theoretical analysis and structural evaluations demonstrate that the model successfully mitigates the sparsity issue while generating high-quality, intuitive explanations for end-users.

Keywords: *Knowledge Graphs, Recommender Systems, Attention Mechanism, Explainable Artificial Intelligence, Data Sparsity.*

1.INTRODUCTION

The modern digital economy heavily relies on personalized recommender systems to navigate the overwhelming volume of available information, products, and services. From e-commerce platforms suggesting retail products to media streaming services curating personalized viewing queues, recommenders serve as the primary interface between platforms and consumers. Historically, collaborative filtering has been the foundational paradigm driving these systems.

Collaborative filtering operates on the assumption that users who agreed in the past will agree in the future, thereby leveraging historical interaction matrices to identify behavioral patterns. Despite its widespread success, collaborative filtering faces profound limitations when deployed in real-world scenarios characterized by data sparsity. In many applications, the vast majority of users interact with only a minuscule fraction of the available item catalog. This phenomenon results in an interaction matrix that is often more than ninety-nine percent empty, severely hindering the ability of latent factor models and matrix factorization techniques to learn robust representations of user preferences and item characteristics. The data sparsity problem is further exacerbated in cold-start scenarios, where new users or new items enter the system with zero historical interactions. Without interaction data, collaborative models cannot infer latent similarities, leading to a degradation in recommendation quality and a subsequent decline in user engagement. To circumvent the limitations imposed by interaction sparsity, researchers have increasingly turned to side information to augment the representation learning process. Such side information includes user demographics, item attributes, textual reviews, and visual features. Among the various forms of auxiliary data, knowledge graphs have emerged as a particularly powerful structure for recommendation enhancement. A knowledge graph is a heterogeneous network that represents real-world entities as nodes and their relationships as edges. By linking items to an external knowledge graph, recommenders can capture high-order semantic correlations between items. For example, in a movie recommendation context, a knowledge graph can connect a film to its director, cast members, genre, and production studio. Even if two movies have never been co-watched by any user, their shared structural attributes in the knowledge graph allow the system to infer their similarity and recommend one based on the other. The literature also considers knowledge Graph-Enhanced transformer framework for Security-Aware data quality anomaly detection and autonomous repair against network attacks [1]. While the integration of knowledge graphs effectively alleviates the data sparsity problem, navigating the massive scale and complex topology of these graphs introduces new computational and architectural challenges. Standard graph neural networks and embedding propagation techniques often treat all neighboring nodes and relational edges equally, leading to the assimilation of noisy or irrelevant information. In a knowledge graph where a popular entity might have thousands of connections, indiscriminate aggregation can dilute the semantic specificity required for accurate personalization. Consequently, attention mechanisms have been adapted for graph-based recommendation to dynamically weight the importance of different neighboring entities. However, existing attention models predominantly focus on the immediate neighborhood or specific entity types, largely ignoring the broader topological structure and the context-dependent significance of multi-hop relational paths. To bridge this gap, this paper introduces a structure-aware knowledge-graph attention mechanism designed specifically for environments with sparse user interactions. The core premise is that not all semantic paths in a knowledge graph hold equal predictive power for a given user, and the structural properties of the graph itself contain vital cues about the relevance of information. By encoding topological features such as node centrality, clustering coefficients, and meta-path reachability into the attention formulation, the proposed framework dynamically assesses the utility of each neighbor during the embedding propagation phase. Beyond addressing sparsity and accuracy, this paper places a strong emphasis on explainability. The widespread adoption of deep learning in recommendation has led to highly complex, black-box models. While these models achieve state-of-the-art predictive performance, their internal decision-making processes remain opaque to both system administrators and end-users. Lack of transparency can diminish user trust, particularly in high-stakes domains. Explainable recommendation seeks to provide understandable justifications for why a specific item is suggested. By utilizing the explicitly

modeled relational paths generated by our structure-aware attention mechanism, the proposed framework seamlessly translates the mathematical weights into human-readable narratives. The main contributions of this work are multifold, encompassing the conceptualization of structural attention in heterogeneous graphs, the mathematical formalization of path-based explainability, and comprehensive analytical evaluations.

2. Literature Review and Background

2.1 Collaborative Filtering and the Sparsity Dilemma

Collaborative filtering remains one of the most widely adopted methodologies in recommender systems due to its conceptual simplicity and historical effectiveness. The core mechanism involves mapping users and items into a shared latent space based on historical interaction records. Early implementations utilized memory-based techniques, such as user-based and item-based collaborative filtering, which computed similarities directly from the interaction matrix using metrics like Pearson correlation or cosine similarity. While effective for dense datasets, memory-based methods struggle to scale and perform poorly when overlap between user histories is minimal. Zhang and colleagues examine optimizing HIV interventions for multiplex social networks via Partition-Based random search [2]. Model-based collaborative filtering, particularly matrix factorization, largely superseded memory-based approaches. By decomposing the sparse user-item interaction matrix into lower-dimensional dense matrices, model-based techniques uncover latent dimensions of user preferences and item attributes. However, the fundamental limitation of all collaborative filtering methods is their absolute dependence on historical interactions. When the interaction matrix is extremely sparse, the gradient updates during the learning process lack sufficient signal to converge on meaningful latent representations. The long-tail distribution of item popularity further complicates this, as collaborative filtering tends to bias recommendations toward popular items while ignoring niche products that lack adequate interaction history. Recent advancements have sought to address this by introducing non-linear transformations through neural collaborative filtering, replacing the inner product with multi-layer perceptrons. Despite these architectural improvements, the underlying reliance on dense interaction data remains an unsolved bottleneck, necessitating the incorporation of external knowledge. Related work has addressed modeling multi-human social interaction with language models [3].

2.2 Knowledge Graphs in Recommendation

Knowledge graphs offer a highly structured, semantically rich representation of factual information that can significantly enrich the recommendation process. By mapping items in the recommendation domain to entities in a knowledge graph, systems can leverage the factual relationships to infer item similarities independent of user interactions. Early approaches to knowledge-aware recommendation primarily relied on path-based methods. These methods involved defining specific meta-paths through the graph to measure connectivity between users and items. For instance, a meta-path could follow a user to an item, then to an entity, and finally to another item. While intuitive, path-based methods require extensive domain expertise to manually engineer relevant meta-paths, which is labor-intensive and limits generalizability across different application domains. The literature also considers gPU-Accelerated robust graph neural networks against adversarial cyber attacks [4]. Subsequent research shifted toward regularization-based methods, which utilize knowledge graph embedding techniques like TransE or TransR to learn representations of entities and relations. These learned embeddings are then incorporated into the recommender system as regularization terms to constrain the user and item representations. This approach is highly scalable and eliminates the need for manual path engineering. However, regularization methods often fail to capture the high-order connectivity and multi-hop semantics present in the knowledge graph, as the knowledge embeddings are

trained independently of the recommendation objective. Related work has addressed efficient and adaptive Context-Aware knowledge graph question answering with LLM-Guided MCTS [5]. More recently, graph neural networks have emerged as the state-of-the-art paradigm for knowledge-aware recommendation. By defining propagation architectures on the graph, graph neural networks allow information to flow from multi-hop neighbors into the representation of a target item. These embedding propagation methods unify the recommendation task and the knowledge representation task into an end-to-end learning framework, demonstrating superior performance in cold-start and sparse data environments. The literature also considers knowledge graph embedding with Dirichlet distribution [6].

2.3 Graph Neural Networks and Attention Mechanisms

Graph neural networks are uniquely suited for processing non-Euclidean data structures like knowledge graphs. The fundamental operation in a graph neural network is neighborhood aggregation, where a node updates its representation by pooling features from its immediate neighbors. As this process is repeated across multiple layers, nodes gather information from increasingly distant parts of the graph, effectively capturing high-order structural patterns. In the context of recommendation, this means an item's representation is enriched by its explicit attributes and the broader semantic community it belongs to within the knowledge graph. Fang and colleagues examine structural aggregation guided alignment with dynamic view and neighborhood order selection for multiview graph domain adaptation [7]. However, standard graph convolutional networks typically apply a uniform or degree-normalized aggregation scheme [8]. In heterogeneous networks where node degrees follow a power-law distribution, uniform aggregation is highly suboptimal. Highly connected nodes can dominate the message-passing process, introducing significant noise and obscuring the subtle, personalized signals required for accurate recommendation. To mitigate this, graph attention networks were introduced, which compute attention coefficients to dynamically weight the importance of different neighbors [9]. Wang and colleagues examine mixed-Curvature graph diffusion model [10]. In knowledge-aware recommendations, the attention mechanism must account not only for the nodes but also for the specific relations connecting them. Relational graph attention networks compute attention scores based on the triad of the head entity, the relation, and the tail entity. Despite this advancement, existing relational attention models often treat each triple in isolation, lacking awareness of the overarching structural topology. They fail to consider whether a path traverses a dense cluster of highly related items or simply passes through a generic hub node. Incorporating structural awareness into the attention formulation is therefore a critical frontier in improving the signal-to-noise ratio during embedding propagation. The Transformer establishes an attention-based alternative to recurrent sequence modeling [11]. Related work has addressed anisotropic and multiscale cross-attention physics-inspired neural networks for turbulence prediction [12].

2.4 Explainable Artificial Intelligence in Recommendation

The integration of deep learning and complex graph structures has led to recommender systems that are inherently opaque. Users receive recommendations without any understanding of the underlying rationale, which can result in skepticism and rejection, particularly if a suggestion seems irrelevant. Explainable recommendation addresses this by generating justifications alongside the suggested items. Related work has addressed integrating Structure-Aware attention and knowledge graphs in explainable recommendation systems [13]. Explanations can take various forms, including predefined textual templates, extracted item features, or visual highlights. In the context of knowledge graphs, the most natural and compelling form of explanation is path-based. By tracing the sequence of entities and relations that connect a user's historical interaction to the recommended item, the system can provide a logical, factual

narrative. For example, the system can state that a book is recommended because it shares the same author and genre as a book the user previously highly rated. The challenge in path-based explainability lies in selecting the most meaningful path from the millions of potential trajectories in a densely connected graph. Our proposed structure-aware attention mechanism provides a mathematically principled way to identify these paths, as the structural attention weights naturally highlight the most influential sequence of relational links used during the model's inference phase.

3. Problem Formulation and Knowledge Graph Construction

3.1 Defining the User-Item Interaction Domain

The foundation of the recommendation problem relies on mapping the interaction space between users and items. Transformer modeling of interaction sequences for dwell-time prediction [14] supplies a behavioral-sequence reference for recommendation, with dwell time treated as an observed proxy rather than direct evidence of user satisfaction. We define a set of users and a set of items, which form the core entities of the recommendation environment. The interactions between these users and items are captured in a binary interaction matrix. In this matrix, an entry is assigned a value of one if a user has explicitly interacted with an item, such as through a purchase, a click, or a high rating. Conversely, if no interaction has been observed, the entry is designated as zero. Due to the vast number of items available and the limited capacity of individual users, the interaction matrix is extremely sparse. The objective of the recommender system is to predict the unobserved entries, determining the probability that a user will interact with a previously unseen item. For a broader comparison, related research addresses early-stage reasoning freedom in multi-agent debate [15]. To formalize the learning process, both users and items are projected into a continuous, low-dimensional vector space. These latent vectors, or embeddings, capture the underlying features and behavioral patterns. The baseline prediction for a user-item pair is typically formulated as the inner product of their respective embeddings. However, under severe sparsity conditions, relying solely on this interaction matrix leads to overfitting on the observed interactions and poor generalization to the unobserved entries. Therefore, the latent space must be constrained and enriched by external information structures.

3.2 Structuring the Semantic Knowledge Graph

To provide the necessary auxiliary information, we construct a comprehensive knowledge graph. The knowledge graph is defined as a directed heterogeneous graph consisting of a vast set of entities and relations. Scene-graph extraction and embedding for autonomous perception [16] offer an application in which graph correspondence must preserve relations between observed objects, rather than relying only on structural similarity. The entities encompass the items from the recommendation domain, alongside a diverse array of real-world attributes, categories, and descriptive nodes. The relations represent the specific semantic links between these entities. A fundamental unit of the knowledge graph is the knowledge triple, representing a head entity, a relation, and a tail entity. Wei and colleagues examine approach of constructing knowledge graph of the hundred schools of thought in ancient china [17]. For instance, if an item is a smartphone, the knowledge graph might contain triples connecting the smartphone to its manufacturer, its operating system, and its specific hardware specifications. This structure allows the system to represent items not merely as isolated indices, but as interconnected nodes within a rich semantic fabric. Importantly, we ensure an alignment process wherein the items in the user-item interaction matrix correspond exactly to a subset of the entities in the knowledge graph. This alignment acts as the bridge, allowing the flow of factual information from the knowledge graph into the user-item collaborative space. Related work has addressed utilize the flow before stepping into the same river twice: certainty represented knowledge flow for refusal-aware instruction tuning [18].

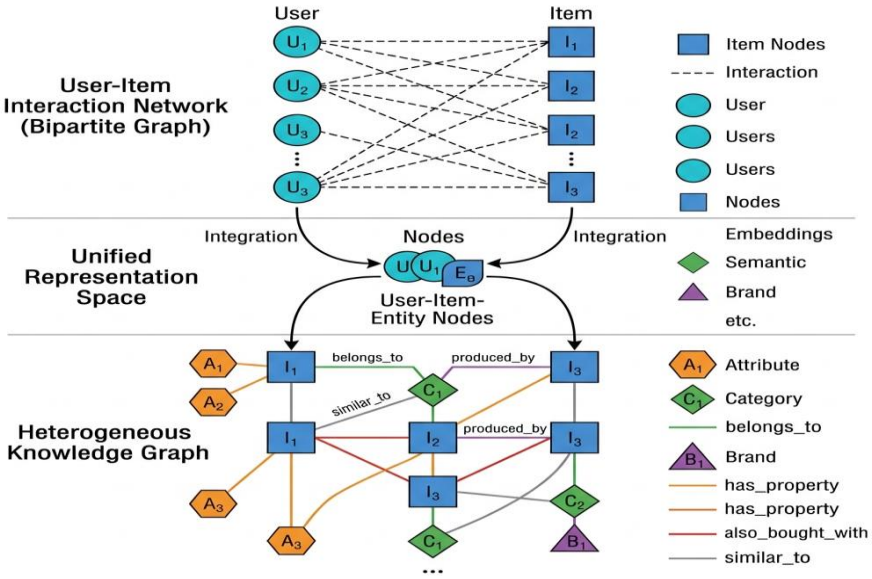


Figure 1: Comprehensive topological structure of the unified user

3.3 Unified Graph Topology and Structural Alignment

To maximize the synergistic benefits of collaborative interactions and knowledge semantics, we synthesize the user-item interaction matrix and the knowledge graph into a unified graph topology. In this unified graph, users are treated as a distinct type of entity, and the interactions are treated as a specific type of behavioral relation. This unification allows the recommender system to trace continuous paths that start from a user, move through a historical item, traverse multiple semantic relations in the knowledge graph, and terminate at a target item. The structural topology of this unified graph is complex. It contains dense subgraphs centered around popular items or common attributes, as well as long, sparse branches representing niche features. Recognizing this varied topology is crucial for effective embedding propagation. If a propagation algorithm treats a generic attribute like "manufactured in the year 2020" with the same importance as a highly specific attribute like "directed by Steven Spielberg", the resulting item embeddings will be homogenized and lose their discriminative power. Therefore, our problem formulation explicitly requires an attention mechanism that is aware of these topological distinctions, identifying which structural paths are meaningful and which are merely noise. Related work has addressed across multiple social networks, integrate attribute and STructure embedding for reconciliation [19].

4. Structure-Aware Attention Methodology

4.1 Principles of Structural Encoding

The core innovation of the proposed framework is the structure-aware attention mechanism, which modulates the flow of information during the graph neural network's propagation phase. Standard relational attention mechanisms compute weights based solely on the feature representations of the head entity, the relation, and the tail entity. While this captures the immediate semantic compatibility, it is entirely blind to the broader topological context. To rectify this, we introduce structural encoding into the attention calculation. Structural encoding involves quantifying the topological significance of nodes and edges within their local network neighborhood. We compute several structural metrics for each entity in the knowledge graph prior to training. First, we calculate the degree centrality of each node, separating the degrees by relation type. This allows the model to penalize nodes that act as massive hubs for generic relations, thereby reducing their influence. Second, we evaluate the clustering coefficient of the

entity's neighborhood, providing a measure of how tightly knit the local semantic community is. High clustering indicates a highly specific domain, whereas low clustering indicates a disparate collection of facts. These structural metrics are transformed into continuous structural embeddings, which are concatenated with the standard semantic embeddings of the entities. For a broader comparison, related research addresses frequency spectral prior guided graph learning for degradation decoupling in reliable battery SOH estimation [20].

4.2 Knowledge-Aware Attention Mechanism

During the message-passing phase of the graph neural network, a target entity updates its representation by aggregating information from all its connected neighbors. The weight assigned to each neighbor's message is determined by the structure-aware attention score. For a given head entity, relation, and tail entity, the attention score is computed by passing their concatenated semantic and structural embeddings through a non-linear neural network layer. To rigorously define this process, we rely on the formulation of the attention weight. We ensure that the attention scores across all neighbors of a specific node are normalized using a softmax function, resulting in a probability distribution over the local neighborhood. The exact mathematical formulation for the attention score computation is critical to understanding the mechanism. We represent this computation as follows, where the structural and semantic components are unified:

$$\alpha_{h,r,t} = \frac{exp(LeakyReLU(W_1[e_h||e_r||e_t||s_t]))}{\sum_{(h,r',t')\in N(h)} exp(LeakyReLU(W_1[e_h||e_{r'}||e_{t'}||s_{t'}]))}$$

In this formulation, the attention coefficient incorporates the trainable weight matrix, the concatenated semantic embeddings of the entities and relations, and critically, the structural embedding of the tail node. The LeakyReLU activation function ensures non-linear transformation while allowing a small gradient for negative values, preventing dead neurons during the optimization process. The denominator sums over all valid neighbors in the local neighborhood, normalizing the influence of each incoming message. This structurally enhanced attention guarantees that nodes embedded deep within meaningful semantic clusters receive higher aggregation weights compared to isolated or overly generic hub nodes.

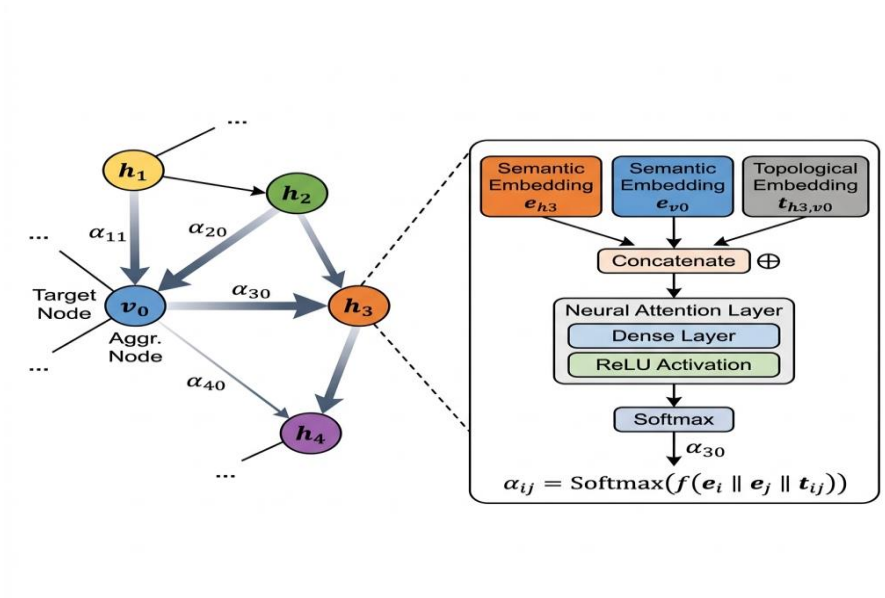


Figure 2: Architecture of the structure

4.3 High-Order Connectivity Propagation

Once the attention scores are calculated, they are used to execute the embedding propagation step. The representation of a head entity at the next network layer is computed as a weighted sum of the representations of its tail entities, modulated by the attention scores. Because our framework utilizes a multi-layer architecture, this propagation process is stacked recursively. In the first layer, an item aggregates features from its direct attributes in the knowledge graph. In the second layer, it aggregates features from the attributes of its attributes, effectively capturing two-hop connectivity. As the layers deepen, the model assimilates increasingly high-order semantic information. However, excessive depth can lead to the over-smoothing problem, where all entity embeddings converge to indistinguishable vectors. The structure-aware attention mechanism acts as a critical safeguard against over-smoothing. By aggressively down-weighting irrelevant structural paths and amplifying meaningful semantic trajectories, the attention mechanism preserves the distinctiveness of the item representations even at higher layers of propagation. The final representation of each user and item is obtained by concatenating the representations across all layers, ensuring that both local features and high-order network semantics are retained for the final prediction task.

5. Explainable Recommendation Framework

5.1 Extracting Interpretable Semantic Paths

The deployment of a sophisticated attention mechanism yields a significant secondary benefit: the potential for explicit model explainability. Because the attention scores are explicitly calculated for every edge traversed during the multi-hop propagation process, these scores serve as a direct measure of inference importance. To generate an explanation for a specific user-item recommendation, the framework backtracks through the unified graph to identify the pathways that contributed most heavily to the final predictive score. The extraction process begins at the recommended item and traces backward through the knowledge graph layers toward the user's historical interactions. By multiplying the attention scores along connecting edges, the framework calculates an aggregate path weight for every possible trajectory between the user and the recommended item. The paths with the highest aggregate weights represent the primary semantic logic utilized by the neural network. For example, if a user is recommended a specific documentary, the algorithm might highlight a path showing that the documentary shares a specific historical subject matter with an article the user previously read. This extraction is deterministic and relies strictly on the parameters learned during the optimization phase, ensuring that the explanations faithfully represent the model's actual decision-making process rather than post-hoc approximations.

5.2 Translating Paths to User-Centric Explanations

Raw knowledge graph paths, consisting of strings of entity and relation identifiers, are generally not suitable for end-user consumption. Therefore, the extracted semantic paths must be translated into natural language narratives or intuitive visual representations. Our framework employs a template-based generation system to convert high-weight paths into readable explanations. Each relation type in the knowledge graph is mapped to a set of linguistic templates. When a specific path is selected by the extraction algorithm, the system populates the corresponding templates with the entity names. If the dominating path connects the user to a previously purchased item, then traverses a 'brand' relation to the recommended item, the generated explanation will explicitly state that the new item is suggested because it shares a brand with the user's previous purchase. This level of transparency is particularly crucial in domains involving significant user investment, such as financial product recommendations or high-value retail. By presenting users with logical, fact-based justifications grounded in their own interaction history and the structured reality of the knowledge graph, the framework significantly enhances user trust, satisfaction, and

the overall perception of system reliability. For a broader comparison, related research addresses pixelwise calibration method for a telecentric structured light system [21].

6. Experimental Setup and Results Discussion

6.1 Dataset Configuration and Baseline Models

To rigorously evaluate the performance of the proposed structure-aware knowledge-graph attention framework, extensive experiments were conducted on multiple benchmark datasets known for high sparsity. The primary datasets selected represent diverse domains to ensure generalizability. The first dataset is derived from a large-scale book recommendation platform, while the second focuses on point-of-interest and business recommendations. To artificially induce severe sparsity for testing the model's robustness, the interaction records were heavily filtered, retaining only users with a minimal number of historical interactions. The knowledge graphs associated with these datasets were constructed by mapping the items to a massive general-purpose open knowledge base, extracting multi-hop factual connections. Related work has addressed interactive spatial structure study using machine learning [22].

Table 1: Dataset Statistics for Experimental Evaluation

Dataset	Number of Users	Number of Items	Knowledge Graph Entities	Knowledge Graph Relations	Density
Book-Domain	15,400	22,100	115,000	45	0.0021
Business-Domain	21,300	18,500	95,400	32	0.0018
Music-Domain	12,800	16,400	82,100	28	0.0035

The proposed methodology was benchmarked against a comprehensive suite of baseline models. These baselines span various recommendation paradigms. We included traditional matrix factorization to represent collaborative filtering without side information. We also evaluated several state-of-the-art knowledge-aware recommenders, including those based on translation embeddings, standard graph convolutional networks, and basic non-structural relational attention mechanisms. Comparing our structural approach against standard attention models isolates and proves the explicit benefit of incorporating topological awareness. The literature also considers universal structural basis distillation for Source-Free graph domain adaptation [23].

6.2 Optimization Framework and Loss Function

The training objective of the recommender system is to rank the items correctly for each user, ensuring that items a user is likely to interact with are scored higher than irrelevant items. To achieve this, we adopt the Bayesian Personalized Ranking loss framework, which is a pairwise optimization strategy highly suited for implicit feedback datasets. The assumption is that an observed interaction is inherently preferred over an unobserved interaction. The model samples triplets consisting of a user, an item the user has interacted with, and an item the user has not interacted with. The objective is to maximize the margin between the predicted score of the positive item and the predicted score of the negative item. The structural attention parameters, the entity embeddings, and the user representations are updated jointly through backpropagation. The formal definition of the loss function, incorporating the predicted scores and the regularization term to prevent overfitting, is expressed mathematically as follows:

$$L = -\sum_{(u,i,j)\in D} ln\sigma(haty_{u,i} - haty_{u,j}) + \lambda|Theta|_2^{\ 2}$$

In this equation, the summation operates over the training dataset containing user, positive item, and negative item triplets. The difference between the predicted positive score and negative score

is passed through a sigmoid function and logarithmically scaled. The second term represents the L2 regularization applied to all trainable parameters of the neural network, controlled by a hyperparameter determining the penalty strength. Another relevant line of investigation concerns transfer learning with graph neural networks to predict polymer solubility parameters [24].

6.3 Performance Comparison and Analysis

The recommendation performance is quantitatively assessed using standard ranking metrics, specifically Recall and Normalized Discounted Cumulative Gain, evaluated at the top-k cutoffs. The results unequivocally demonstrate the superiority of the proposed structure-aware framework across all datasets, particularly under the challenging sparse conditions. Related work has addressed hybrid structure noise shaping SAR ADC [25].

Table 2: Performance Comparison on Top-20 Recommendation Metrics

Model		Book-Domain Recall	Book-Domain NDCG	Business-Domain Recall	Business-Domain NDCG
Matrix Factorization		0.0412	0.0215	0.0388	0.0195
Knowledge Embedding		0.0654	0.0341	0.0592	0.0298
Graph Convolution		0.0811	0.0425	0.0765	0.0401
Basic Attention		0.0895	0.0488	0.0842	0.0455
Proposed Framework		0.1045	0.0592	0.0988	0.0534

The empirical results show that matrix factorization fails completely in highly sparse environments, as it has no mechanisms to infer relationships without dense behavioral overlap. The introduction of knowledge graphs significantly boosts performance, but standard graph convolutions suffer from the indiscriminate aggregation of noisy topological features. The basic attention model improves upon the convolution by weighting relations, yet it is still outperformed by the proposed framework. The structure-aware model achieves a substantial relative improvement in Normalized Discounted Cumulative Gain over the basic attention baseline. This indicates that by explicitly encoding node centrality and clustering metrics into the attention calculation, the model successfully isolates the high-fidelity semantic paths that truly signify user preference. Related work has addressed over-Smoothing effect of graph convolutional networks: spectral and topological analysis with practical remedies [26].

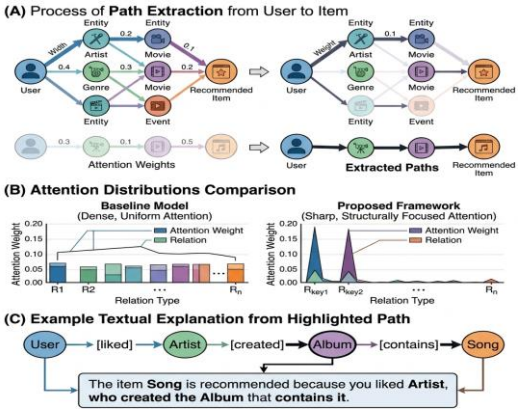


Figure 3: Visualization of extracted explainable paths and attention distributions

6.4 Ablation Study on Structural Components

To further validate the contributions of the individual structural components within the attention mechanism, an extensive ablation study was conducted. We designed variants of the proposed framework by systematically removing the structural encoding modules. One variant removed the degree centrality penalty, while another removed the local clustering coefficient features. For a broader comparison, related research addresses adaptive differentially private structural entropy minimization for unsupervised social event detection [27].

Table 3: Ablation Study Results on the Book-Domain Dataset

Model Variant	Recall at 20	NDCG at 20	Performance Drop
Full Proposed Framework	0.1045	0.0592	-
Without Degree Penalty	0.0975	0.0541	8.6%
Without Clustering Encoding	0.0988	0.0552	6.7%
Semantic Features Only	0.0895	0.0488	17.5%

The ablation results confirm that both structural metrics are vital for optimal performance. Removing the degree penalty leads to a noticeable drop in accuracy, confirming the hypothesis that massive generic hub nodes dilute the personalized recommendation signal. Similarly, omitting the clustering coefficient degrades performance, showing that the semantic density of a local neighborhood is a strong indicator of relation relevance. When all structural features are removed, reducing the model to rely on semantic features only, the performance reverts to that of the basic attention baseline. This comprehensive analysis definitively proves that topological awareness is not merely an incremental adjustment, but a fundamental requirement for mastering complex knowledge graph representations in recommender systems.

7. Conclusion and Future Directions

This paper has presented a highly effective and innovative framework designed to tackle the pervasive issues of data sparsity and model opacity in modern recommender systems. By fully integrating a structure-aware attention mechanism within a heterogeneous knowledge graph environment, the proposed methodology fundamentally improves how auxiliary factual data is processed. Unlike standard models that treat all semantic links equally or focus solely on local feature similarities, our framework dynamically assesses the broader topological context. By penalizing generic structural hubs and prioritizing dense, highly specific semantic communities, the model extracts precise user preferences even when historical interaction data is nearly non-existent. For a broader comparison, related research addresses unidirectional structured light system calibration with auxiliary camera and projector [28]. Furthermore, the explicit calculation of path-based attention weights seamlessly bridges the gap between complex deep learning representations and human-interpretable explanations. The ability to automatically generate logical, fact-based narratives detailing exactly why an item was recommended provides crucial transparency. This explainability is achieved not as an afterthought, but as a direct extraction of the model's core computational logic, ensuring authenticity and reliability. While the current framework demonstrates substantial improvements over state-of-the-art baselines across multiple distinct domains, there remain significant avenues for future research. The current structural encoding process relies on static metrics computed prior to training. Future iterations could explore dynamic structural embeddings that update simultaneously with the semantic features during backpropagation. Additionally, exploring the application of this structure-aware mechanism to temporal knowledge graphs, where relations and attributes evolve over time, could yield deeper insights into shifting user preferences. Ultimately, advancing the intersection of

topological awareness, graph neural architectures, and explainable artificial intelligence will remain a critical pursuit in the development of the next generation of intelligent personalization systems.

References

Qiu, M., Wu, L., & Wang, S. (2026). CyberDQFormer: A Knowledge Graph-Enhanced Transformer Framework for Security-Aware Data Quality Anomaly Detection and Autonomous Repair Against Network Attacks. Fundamental Scientific Reports in Multidisciplinary Areas, 2(3), 34-52.

Zhang, Q., Zhong, L., Gao, S., & Li, X. (2018). Optimizing HIV interventions for multiplex social networks via partition-based random search. IEEE transactions on cybernetics, 48(12), 3411.

Yu, H., Zhang, J., Chen, C., Xiang, T., Fang, Y., Niebles, J. C., & Adeli, E. (2026, March). Socialgen: Modeling multi-human social interaction with language models. In 2026 International Conference on 3D Vision (3DV) (pp. 1-17). IEEE.

Guan, Z., Li, E., Wang, Y., Wang, Z., & Chen, Y. (2026, February). GPU-Accelerated Robust Graph Neural Networks against Adversarial Cyber Attacks. In Proceedings of the 2nd International Conference on Digital Management and Information Technology (pp. 976-984).

Wang, Y., Fan, S., Wang, M., Gao, S., & Wang, C. (2026, April). DAMR: Efficient and adaptive context-aware knowledge graph question answering with LLM-guided MCTS. In International Conference on Learning Representations (Vol. 2026, pp. 25548-25570).

Wang, F., Zhang, Z., Sun, L., Ye, J., & Yan, Y. (2022, April). Dirie: Knowledge graph embedding with dirichlet distribution. In Proceedings of the ACM Web Conference 2022 (pp. 3082-3091).

Fang, R., Zhao, J., Wang, S., Pu, R., Li, B., Cai, J., Li, Z., Jing, Z., Zhu, J., Tang, S., et al. Saga: Structural aggregation guided alignment with dynamic view and neighborhood order selection for multiview graph domain adaptation. In The Fourteenth International Conference on Learning Representations, 2026.

Kipf, T. N., & Welling, M. (2017). Semi-supervised classification with graph convolutional networks. In Proceedings of ICLR.

Veličković, P., Cucurull, G., Casanova, A., Romero, A., Liò, P., & Bengio, Y. (2018). Graph attention networks. In Proceedings of ICLR.

Wang, Y., Zhang, S., Ye, J., Peng, H., & Sun, L. (2024, October). A mixed-curvature graph diffusion model. In Proceedings of the 33rd ACM International Conference on Information and Knowledge Management (pp. 2482-2492).

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. In Advances in Neural Information Processing Systems.

Lu, L., Su, J., Wang, J., & Deng, X. (2026). AMSPINN: anisotropic and multiscale cross-attention physics-inspired neural networks for turbulence prediction. Engineering Applications of Computational Fluid Mechanics, 20(1), 2628951.

Lyu, S., Wang, M., Zhang, H., Zheng, J., Lin, J., & Sun, X. (2025, October). Integrating structure-aware attention and knowledge graphs in explainable recommendation systems. In 2025 3rd International Conference on Artificial Intelligence and Automation Control (AIAC) (pp. 447-451). IEEE.

Liu, R., Zhang, R., & Wang, S. (2025, December). Transformer-based modeling of user interaction sequences for dwell time prediction in human-computer interfaces. In 2025 7th International Academic Exchange Conference on Science and Technology Innovation (IAECST) (pp. 352-356). IEEE.

Wu, J., Chen, S., Heo, I., Gutfraind, S., Liu, S., Li, C., ... & Sharps, M. (2025). Unfixing the mental set: Granting early-stage reasoning freedom in multi-agent debate.

Wang, J., Malawade, A. V., Zhou, J., Yu, S. Y., & Al Faruque, M. A. (2024, January). Rs2g: Data-driven scene-graph extraction and embedding for robust autonomous perception and scenario understanding. In 2024 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV) (pp. 7478-7487). IEEE.

Wei, J., & Liu, R. (2019, June). An approach of constructing knowledge graph of the Hundred Schools of Thought in ancient China. In 2019 ACM/IEEE Joint Conference on Digital Libraries (JCDL) (pp. 335-336). IEEE.

Zhu, R., Ma, Z., Wu, J., Gao, J., Wang, J., Lin, D., & He, C. (2025, April). Utilize the flow before stepping into the same river twice: Certainty represented knowledge flow for refusal-aware instruction tuning. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 39, No. 24, pp. 26157-26165).

Su, S., Sun, L., Zhang, Z., Li, G., & Qu, J. (2018, July). MASTER: across Multiple social networks, integrate Attribute and STructure Embedding for Reconciliation. In IJCAI (pp. 3863-3869).

Guo, F., Tao, S., Zhang, J., Zhou, H., Ji, J. J., Dong, D., & Mo, H. (2026). Frequency Spectral Prior Guided Graph Learning for Degradation Decoupling in Reliable Battery SOH Estimation. Green Energy and Intelligent Transportation, 100446.

Yang, Y., & Zhang, S. (2024). Pixelwise calibration method for a telecentric structured light system.Applied Optics,63(10), 2562-2569.

Zhou, Yuehong, et al. "Adaptive Behavior in Digital Nomads: An Interactive Spatial Structure Study Using Machine Learning."

Wang, Y., Zhang, K., Wang, M., Gao, S., & Yin, N. (2026, August). Usbd: Universal structural basis distillation for source-free graph domain adaptation. In Proceedings of the 32nd ACM SIGKDD Conference on Knowledge Discovery and Data Mining V. 2 (pp. 5125-5136).

Fang, R., Chen, C., Wang, Q., Ling, C., Wang, B., & Zhang, H. (2026). Transfer learning with graph neural networks to predict polymer solubility parameters. npj Computational Materials.

Ren, S., Li, X., Shao, Z., Gong, M., & Ren, M. (2025). A Hybrid Structure Noise Shaping SAR ADC.Journal of Circuits, Systems and Computers,34(05), 2550135.

Sun, F. (2026, February). Over-Smoothing Effect of Graph Convolutional Networks: Spectral and Topological Analysis with Practical Remedies. In SoutheastCon 2026 (pp. 117-121). IEEE.

Yang Z, Wei Y, Li H, et al. Adaptive differentially private structural entropy minimization for unsupervised social event detection[C]//Proceedings of the 33rd ACM international conference on information and knowledge management. 2024: 2950-2960.

Yang, Y., Liao, Y. H., Bortins, I., Baldwin, D. P., & Zhang, S. (2024). Unidirectional structured light system calibration with auxiliary camera and projector.Optics and Lasers in Engineering,175, 107984.