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Yu Deng
University of Hunan Technology and Business
ShiWang Hou
houshiwang@hutb.edu.cn
Huaihua University
Mingyi Zhang
University of Hunan Technology and Business

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HSMGNN Hyperbolic $\mathbb{S}^2$ Rotation Group Multi-Channel Graph Neural Network for Cross-lingual Entity Alignment

Yu Deng[1], **Shiwang Hou**[2,*], **and Mingyi Zhang**[1]

[1]School of Computer Science and Frontier Interdisciplinary, University of Hunan Technology and Business, No. 569 YueLu Road, Changsha, 410205, Hunan Province, China
[2]School of Business, Huaihua University, No. 798 YingFeng East Road, Huaihua, 418000, Hunan Province, China
[*]houshiwang@hutb.edu.cn

ABSTRACT

Entity alignment—a crucial task in knowledge graph research—is often hampered by the inherent heterogeneity between the graphs being aligned. These differences pose serious challenges for existing alignment methods, highlighting the need for more innovative and adaptable solutions. To address this, we propose a novel framework that integrates with graph neural networks: the Hyperbolic $\mathbb{S}^2$ Rotation Group in Multi-Channel Graph Neural Network (HSMGNN). HSMGNN is designed to effectively capture the diverse and complex structures of heterogeneous knowledge graphs, offering a streamlined and powerful approach to entity alignment. HSMGNN operates across multiple channels, each equipped with a distinct relation-weighting strategy for encoding knowledge graphs. One channel uses self-attention mechanisms to complete the knowledge graph by filling in missing data within each graph. Simultaneously, another channel applies cross-graph attention to pinpoint and filter out entities that are irrelevant to the alignment task. These diverse features are then aggregated using pooling techniques to form a unified, high-quality representation. What distinguishes HSMGNN is its ability to infer and transfer rule-based knowledge between graphs, ensuring coherent and consistent completion on both sides. This end-to-end framework not only boosts performance in entity alignment tasks but also bridges structural differences between heterogeneous graphs in a principled way. In short, HSMGNN marks a meaningful step forward in entity alignment, offering a robust, efficient, and scalable solution for aligning knowledge graphs in complex real-world scenarios.

Introduction

The concept of knowledge graphs originated from Google's semantic network proposal[1] and has since undergone extensive development. Thanks to their well-structured representations, knowledge graphs—typically expressed in the form of triples (h,r,t)—have become a foundational component in data modeling for deep learning systems. With their growing adoption, knowledge graphs now play a vital role in tasks such as knowledge extraction, information representation, and recommendation systems. Traditionally, entity alignment in knowledge graphs has been approached through a variety of methods, many of which suffer from notable limitations. Early efforts primarily relied on embedding-based techniques, encompassing manifold learning methods, the TransE[2] family and its variants (e.g., TransH[3], TransR[4], TransD[5], RotatE[6], QuatE[7], HAKE[8], and DualE[9]), as well as matrix factorization models such as DistMult[10], RESCAL[11], ComplEx[12], and HolE[13]. In recent years, geometric deep learning has inspired the development of models like Hyper-KG[14] and LorentzE[15], which leverage hyperbolic and Lorentzian spaces to better represent the hierarchical structures of knowledge graphs. Graph neural network (GNN)-based approaches have also gained traction, including R-GCN[16] for relational graph encoding and GCN-Align[17] for cross-KG alignment. In addition, neural network-based embedding approaches—such as ConvKB[18], ConvE[19], ConvD[20], and the transformer-based KEPLER[21]—have been proposed to incorporate contextual information from text descriptions. However, many of these methods overly focus on vector-based embeddings, attempting to align entities either by projecting them into a shared latent space or using matrix-based quadratic formulations. This overreliance on vector space assumptions introduces several inherent limitations:

- **Uniform structural assumptions**: These methods typically assume that entities across different graphs share similar topological structures. In reality, knowledge graphs from diverse sources often exhibit substantial variations in topology, node connectivity, and edge density. Such assumptions significantly limit model performance when dealing with heterogeneous graph structures.
- **Neglect of relational semantics**: Many existing methods fail to account for the rich semantic properties embedded in

relations. Relations are more than mere connections—they encode essential semantic features such as directionality, strength, and transitivity. Traditional alignment techniques often treat all relations uniformly, overlooking these subtleties and thereby undermining alignment accuracy.

- **Inability to handle dynamic graphs**: Most alignment methods are designed for static knowledge graphs. In practice, knowledge graphs continuously evolve as new entities and relationships emerge. Existing models lack the adaptability to accommodate such changes, making them ineffective for real-time or incremental updates.

To address these challenges, we argue that solutions must move beyond conventional manifold learning, matrix factorization, or standard neural network approaches. Instead, they should directly confront the underlying structural inconsistencies of knowledge graphs. For instance, even semantically similar entities may exhibit vastly different local neighborhood structures—i.e., variations in the number and types of connected nodes and edges—making them difficult to align using traditional techniques. This issue is illustrated in Fig. 1., which shows two small knowledge graphs. On the left, we see entities like "Paris", "Eiffel Tower", "France", and "Wine", while on the right we encounter "Pairs", "Louvre", "French", and "Eiffel Two". Although the structures appear loosely aligned, the entity "Pairs" in another context Fig. 2., is linked to "Model", "T Management", and "Donald John Trump", suggesting that "Pairs" could also refer to a person. Despite the name similarity, these instances are semantically distinct, and traditional alignment models often fail to make this critical distinction. Furthermore, statistical analysis of entity clustering[22] has shown that entities in high-dimensional spaces tend to form hierarchical structures. Unlike Euclidean space, hyperbolic space—with its negative curvature—more naturally accommodates these hierarchies and allows for more efficient representation of tree-like structures.

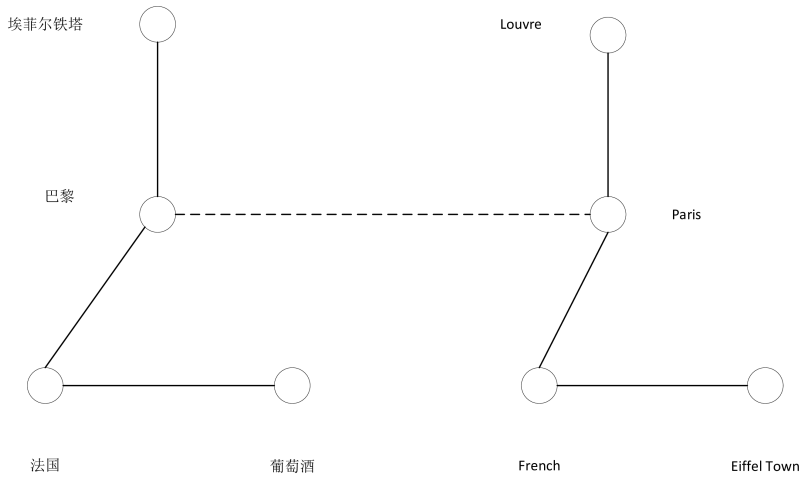


Figure 1. Visualization of Entity Alignment in Knowledge Graphs: The Paris Case.

In this paper, we propose a novel approach that integrates manifold geometry, hyperbolic embeddings, and graph neural networks to natively encode knowledge graphs from multiple perspectives. Our contributions are summarized as follows:

- **A graph neural network architecture with hyperbolic embeddings**: We introduce a GNN that leverages hyperbolic space to better capture hierarchical structures in knowledge graphs. This enhances the model's capacity to represent complex relationships and improves both entity representation and reasoning.

- **A manifold-based representation incorporating the rotation group**: By integrating the mathematical structure of rotation groups from manifold theory, our model more effectively captures the geometric and topological properties of

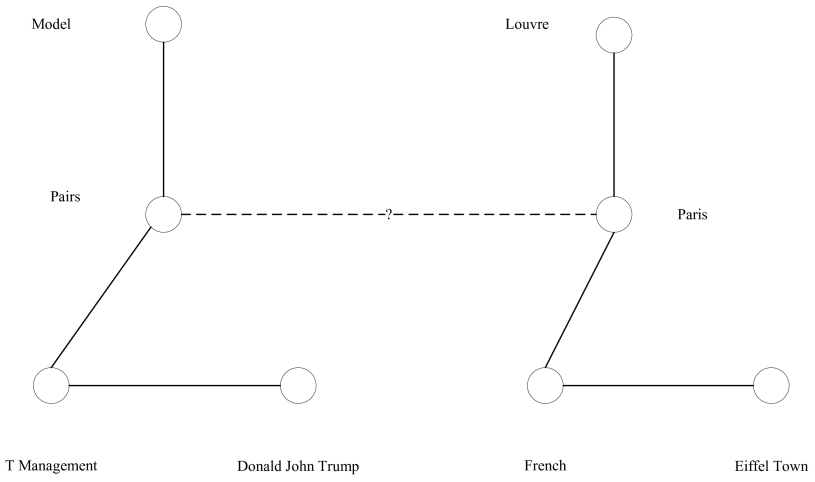


Figure 2. Structural Comparison of Knowledge Graphs Associated with "Paris".

entities. This leads to more expressive embeddings and more accurate entity alignment across heterogeneous knowledge graphs.

To further address the limitations of traditional Euclidean-based models in capturing hierarchical structures, we propose a hyperbolic embedding strategy inspired by the exponential distance property of non-Euclidean geometry. As shown in Fig. 3., hyperbolic space naturally encodes tree-like hierarchies with clear depth separation and consistent angular spacing, in stark contrast to the cluttered and ambiguous structures often produced by Euclidean and translation-based models.

This visualization reveals three key insights:

- **Exponential Depth Encoding**: In hyperbolic space, distances from the root node (e.g., “Life”) increase exponentially with depth, providing clear separation between levels of hierarchy (e.g., “Animal” vs. “Mammal”), consistent with the geometric efficiency of hyperbolic trees[14].
- **Uniform Angular Clustering**: Sibling nodes in the hierarchy maintain consistent angular spacing (e.g., 120° between “Mammal” and “Bird”), reflecting their semantic similarity. This consistency is often lost in Euclidean embeddings.
- **Structural Clarity**: Unlike traditional models such as TransE, which produce overlapping and tangled embeddings (e.g., "Flower" appearing near "Animal"), hyperbolic embeddings preserve parent-child relationships with radial clarity, reducing topological ambiguity.

1 Background and Framework Overview

1.1 Fundamental Concepts

- **Knowledge Graph (KG)**: A knowledge graph is modeled as a directed graph denoted by $G = (E, R, T)$, where E is the set of entities, R is the set of relation types, and T is the set of triplets. Each triplet $t = (e_i, r_{ij}, e_j) \in T$ indicates that the head entity e_i is related to the tail entity e_j via the relation $r_{ij} \in R$.
- **Rule Knowledge** $\mathscr{K} = \{K\}$: Logical rules can be derived from a knowledge graph, typically expressed in the form $\forall x, y \in E : (x, r_s, y) \Rightarrow (x, r_c, y)$. This indicates that if two entities are connected by relation r_s, they are likely also connected by relation r_c. A rule $k = (r_c \mid r_{s1}, \ldots, r_{sp})$ consists of a single conclusion and one or more premises.

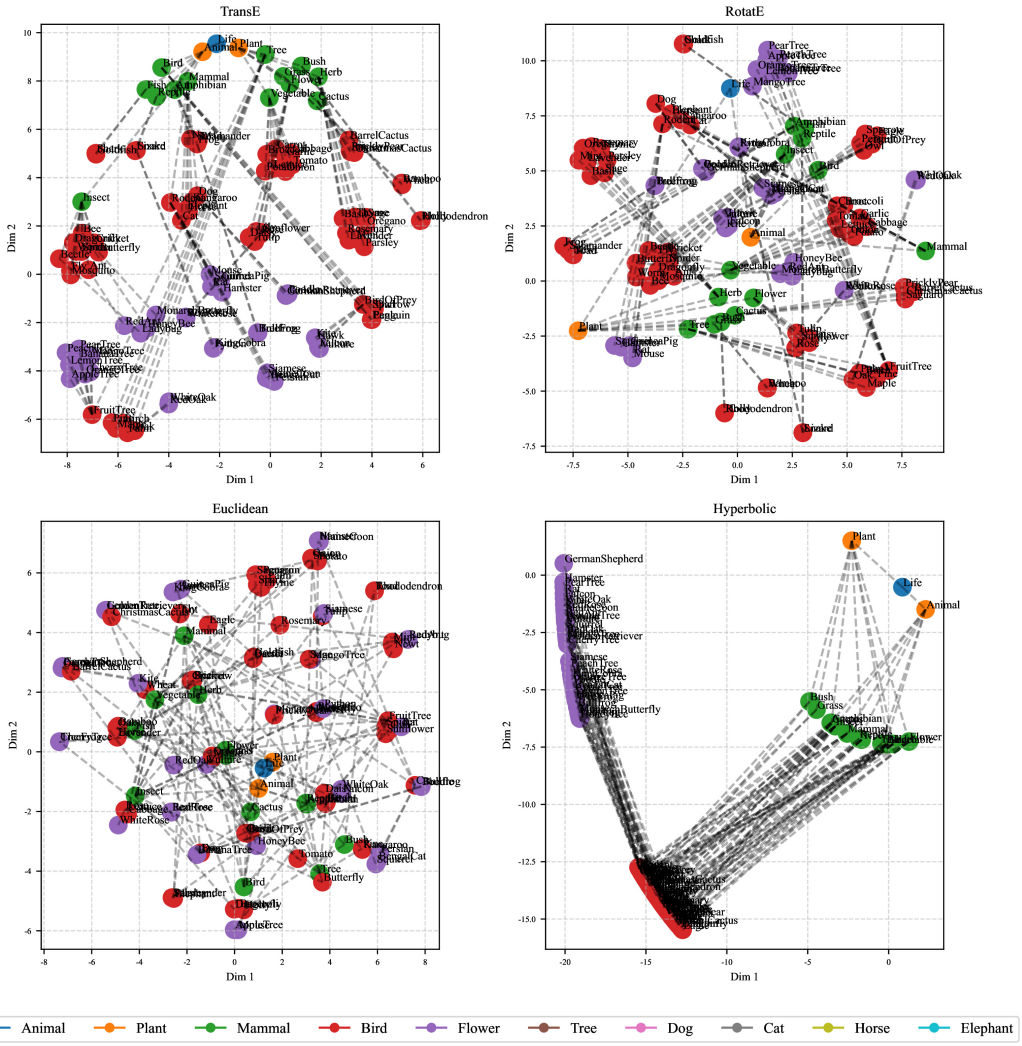


Figure 3. Visual comparison of embedding spaces for hierarchical knowledge graphs. Hyperbolic embedding (right) exhibits exponential distance growth between hierarchical levels (e.g., "Life" → "Animal" → "Mammal"), with sibling nodes (e.g., "Mammal", "Bird") uniformly spaced at ≈120° angles. Euclidean (middle) and spherical (left-middle) embeddings fail to distinguish depths, while TransE (left) shows overlapping edges and ambiguous clustering due to high-dimensional projection artifacts.

- **Rule Grounding**: Given a rule k, grounding refers to identifying specific triplets in the knowledge graph that satisfy the logical entailment. A grounded instance is denoted by $g(k) = (t_c \mid t_{s1}, \ldots, t_{sp})$, which includes $|p|+1$ triplets satisfying $(t_{s1} \wedge \cdots \wedge t_{sp}) \Rightarrow t_c$.

  For example, consider the rule: $\text{bornIn}(x,y) \wedge \text{cityOf}(y,z) \Rightarrow \text{nationality}(x,z)$. A valid grounding would be: bornIn(Obama, Hawaii) $\wedge$ cityOf(Hawaii, United States) $\Rightarrow$ nationality(Obama, United States).

  The set of all groundings for rule k is denoted as $G(k) = \{g(k)\}$.

- **Entity Alignment**: Given two heterogeneous KGs, $G = (E, R, T)$ and $G' = (E', R', T')$, the goal is to find a set of entity alignments $\mathscr{A}_e = \{(e, e') \in E \times E' \mid e \longleftrightarrow e'\}$, where $\longleftrightarrow$ denotes an equivalence relation, indicating that e and e' refer to the same real-world entity despite being in different graphs. Throughout this paper, boldface symbols represent vector embeddings of entities and relations.

- **Manifold Theory**: Manifold-based modeling introduces geometric structures into KG embeddings. The special orthogonal group $SO(2)$, representing 2D rotations, is a Riemannian manifold suitable for capturing circular or periodic relational patterns. In the complex domain, rotations are naturally expressed via complex multiplication. Given a head embedding $\mathbf{h}$, a relation embedding $\mathbf{r}$, and a tail embedding $\mathbf{t}$, an $SO(2)$-based scoring function evaluates the similarity between $\mathbf{h} \otimes \mathbf{r}$ and $\mathbf{t}$, where $\otimes$ denotes complex multiplication.

- **Hyperbolic Geometry**: Hyperbolic space, characterized by negative curvature, is particularly effective for representing hierarchical or tree-like structures common in KGs. Unlike Euclidean space, hyperbolic space allows for exponential growth, enabling compact and semantically rich representations. Common models include the Poincaré ball and the hyperboloid. Entities and relations can be embedded as points or transformations in this space to better preserve semantic hierarchies.

1.2 System Architecture

HSMGNN is designed to learn knowledge graph embeddings with a focus on entity alignment. It combines knowledge graph reasoning with cross-KG rule transfer to explicitly fill in incomplete knowledge, while leveraging manifold-based relational weighting to robustly encode structural information through a multi-channel graph neural network.

As illustrated in Fig. 4, the framework consists of three primary stages:

Overview. Rectangles represent the two main stages: initial embedding and the application of the Hyperbolic $\mathbb{S}^2$ Rotation Group within a multi-channel GNN. Rounded rectangles denote the core components of each stage. After obtaining initial Euclidean embeddings, we apply a hyperbolic projection. Subsequently, rule-based inference and transfer generate new relational triples (e.g., $r3'$ shown as dashed lines). These enriched graphs are processed using manifold-aware attention mechanisms to form inputs for multi-channel GNN encoders. The final embeddings are then passed to an alignment model to perform entity alignment.

KG Completion: To address structural heterogeneity across KGs, HSMGNN performs KG completion through rule-based reasoning. It employs the AMIE+ rule mining system[23] to extract logical rules from each KG, and transfers them across graphs based on seed-aligned relations. This approach assumes that such rules are domain- and language-agnostic, making them suitable for cross-KG generalization.

Hyperbolic $\mathbb{S}^2$ Rotation Group in Multi-channel GNNs: Integrating the Hyperbolic $\mathbb{S}^2$ Rotation Group provides a geometric foundation for relational transformation and feature learning across GNN channels. Hyperbolic geometry effectively models hierarchical and complex relational structures, while the rotation group component enables flexible and expressive relation modeling. Embeddings are transformed through rotational operations in hyperbolic space, enabling different channels to capture distinct semantic perspectives. This design enhances the model's capability for entity alignment and KG completion by preserving semantic consistency and improving generalization

Fig. 5., titled "Angle Distribution Visualization Across Embedding Spaces," presents a series of polar plots illustrating the angular distribution of nodes under various embedding models. Each subplot corresponds to a different model or configuration, revealing how nodes are arranged in terms of angles. This angular information is crucial for understanding how well each model preserves structural and semantic relationships, especially in tasks such as entity alignment and KG completion. These visualizations complement insights drawn from embedding spaces shown in Fig. 3., further highlighting the advantages of HSMGNN's design in capturing complex relational patterns.

1.3 KG Completion

We propose a rule-guided hyperbolic embedding framework for multi-channel knowledge graphs (KGs), which includes three components: (1) hyperbolic initialization, (2) rule transfer, (3) rule grounding and (4) rule confidence weight. This framework enables efficient rule injection and migration across different KG views.

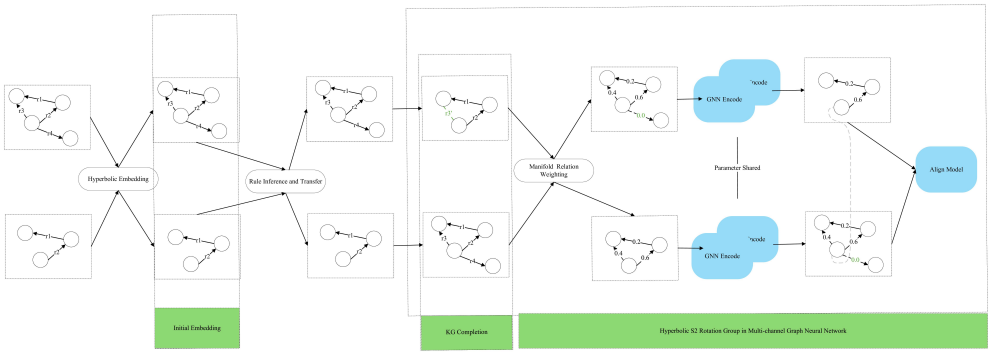


Figure 4. Overview of the HSMGNN Framework: Knowledge Graph Completion and Hyperbolic $\mathbb{S}^2$ Rotation Group in a Multi-Channel Graph Neural Network Architecture

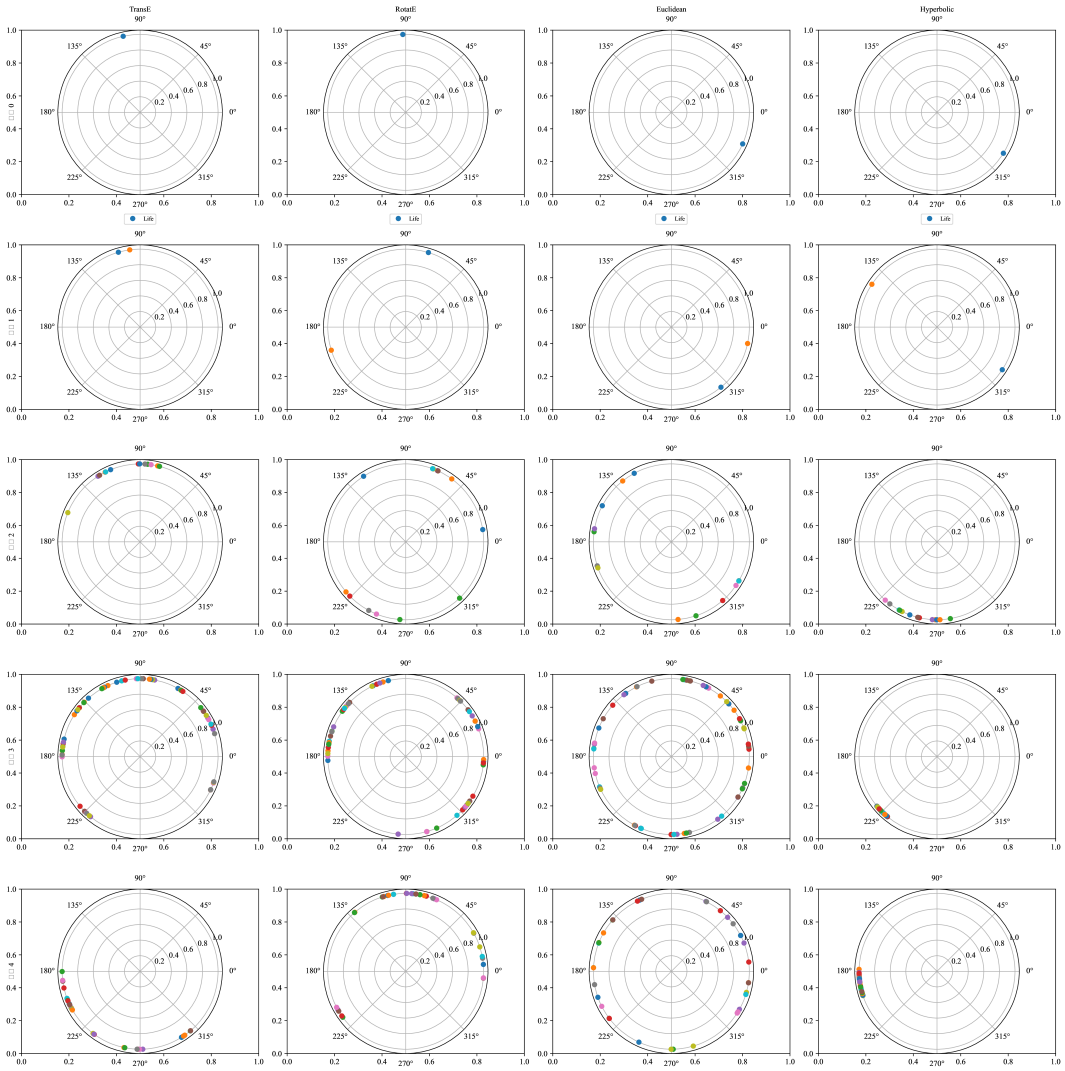


Figure 5. Angle Distribution Visualization Across Embedding Spaces. Each polar plot shows the angular relationships among nodes in a particular embedding space, highlighting how different models capture structural and semantic properties through angular distribution.

1.4 Hyperbolic Initialization

To capture hierarchical structures in KGs, we adopt the Poincaré ball model with curvature $c < 0$. Given an origin $\mathbf{o}$, any tail entity $\mathbf{t}$ is first projected into the tangent space $\mathscr{T}_{\mathbf{o}}\mathbb{D}_c^n$ via the logarithmic map:

$$\mathbf{t}_{\log} = \log_{\mathbf{o}}^c(\mathbf{t}). \tag{1}$$

Next, a relation-specific transformation is applied in the tangent space:

$$\mathbf{t}'_{\log} = \mathbf{R}_r(\mathbf{h}) = \mathbf{t}_{\log} + \mathbf{r}, \tag{2}$$

where $\mathbf{r}$ is the relation embedding and $\mathbf{h}$ is the head entity. The transformed vector is then mapped back to the hyperbolic space via the exponential map:

$$\mathbf{t}' = \exp_{\mathbf{o}}^c(\mathbf{t}'_{\log}). \tag{3}$$

1.5 Rule Transfer

We exploit high-confidence rules mined from a primary channel (e.g., a textual KG view) and transfer them to auxiliary channels (e.g., structural or semantic views) based on the assumption of knowledge consistency across views. The alignment of embeddings across different channels is achieved using shared entities and relation names, which guide the rule transfer process effectively.

1.6 Rule Grounding

Once transferred, the rules are injected into the auxiliary channels to impose logical constraints on the embeddings. Let $\mathscr{G}$ denote the KG and $\mathscr{R}$ the rule set. Each rule $r_i \in \mathscr{R}$ with confidence α_i incurs a grounding loss defined as:

$$\mathscr{L}_{\text{rule}} = \sum_{r_i \in \mathscr{R}} \alpha_i \cdot \mathscr{L}_{r_i}(\mathscr{G}), \tag{4}$$

where $\mathscr{L}_{r_i}(\mathscr{G})$ denotes the grounding loss of rule r_i in graph $\mathscr{G}$.

To further enhance representation learning across heterogeneous channels, we optionally integrate the MuGNN[24], which aggregates channel-specific features via attention mechanisms. This improves robustness, especially when certain channels are sparse or noisy.

1.7 Rule Confidence Weighting

In this work, we assign fixed confidence scores to rules. Learning rule confidences dynamically during training is a promising direction and is left for future exploration.

2 Hyperbolic $\mathbb{S}^2$ Rotation Group in Multi-Channel Graph Neural Network

This section presents the architecture of the HSMGNN framework, which consists of five primary components designed for alignment-oriented representation learning across knowledge graphs (KGs):

2.1 Hyperbolic Embedding

Hyperbolic spaces excel in modeling hierarchical structures common in real-world graphs. In HSMGNN, we embed graph nodes into a hyperbolic space $\mathbb{H}^d$ using the Poincaré ball model. For a graph $G = (V, E)$, the embedding function $\mathbf{h} : V \to \mathbb{H}^d$ maps each node into hyperbolic space, preserving the graph's hierarchical topology.

The hyperbolic distance between two points $\mathbf{u}, \mathbf{v} \in \mathbb{H}^d$ is:

$$d_{\mathbb{H}}(\mathbf{u}, \mathbf{v}) = \cosh^{-1}\left(1 + 2\frac{\|\mathbf{u} - \mathbf{v}\|^2}{(1 - \|\mathbf{u}\|^2)(1 - \|\mathbf{v}\|^2)}\right)$$

To learn embeddings, we use the following contrastive loss:

$$L_{emb} = \sum_{(i,j) \in E} d_{\mathbb{H}}(\mathbf{h}(i), \mathbf{h}(j)) + \sum_{(i,j) \notin E} \max(0, \gamma - d_{\mathbb{H}}(\mathbf{h}(i), \mathbf{h}(j)))$$

where γ is a margin hyperparameter.

2.2 Manifold Relation Weighting

To account for relation-specific semantics, we learn relation weights via a neural network. Given a multi-relational graph $G = (V, E, R)$, we compute a weight w_r for each relation type $r \in R$.

Each relation instance (i, r, j) is represented by a feature vector $\mathbf{x}_{ij}^r$ and passed through a two-layer MLP:

$$w_r = \sigma\left(\mathbf{W}_2\sigma(\mathbf{W}_1\mathbf{x}_{ij}^r + \mathbf{b}_1) + \mathbf{b}_2\right)$$

where σ denotes a non-linear activation such as ReLU. These learned weights are used during message passing to scale the contribution of each relation.

2.3 KG Self-Attention

We incorporate two types of attention to enhance structural learning:

(1) Intra-KG Attention: Inspired by GAT[25], it highlights important neighbors:

$$a_{ij} = \text{softmax}(c_{ij}) = \frac{\exp(c_{ij})}{\sum_{e_k \in N_{e_i} \cup \{e_i\}} \exp(c_{ik})}$$

$$c_{ij} = \text{LeakyReLU}\left(\vec{p}^\top [\vec{W}_{e_i} \parallel \vec{W}_{e_j}]\right)$$

(2) Cross-KG Attention: Promotes structural consistency across KGs:

$$a_{ij} = \max_{r \in R, r' \in R'} 1((e_i, r, e_j) \in T) \cdot \text{sim}(r, r')$$

with $\text{sim}(r, r') = r^\top r'$.

2.4 Hyperbolic $\mathbb{S}^2$ Rotation Group in Multi-channel GNN Encoder

We define a multi-channel GNN on a hyperbolic spherical manifold $\mathbb{S}^2$, ideal for capturing the curved hierarchical structure of KGs. Each node embedding lies on the unit 2-sphere.

Each GNN channel applies a rotation in tangent space:

$$\vec{H}_i^{l+1} = \sigma\left(\text{Rot}_{\mathbb{S}^2}(\vec{A}_i, \vec{H}^l; \vec{W}_i)\right)$$

where $\vec{A}_i$ is the i-th channel's adjacency matrix, and $\vec{W}_i$ defines the rotation axis and angle.

The rotation operation is:

- Map embeddings from $\mathbb{S}^2$ to the tangent space via the logarithmic map.
- Apply channel-specific rotation in the tangent space.
- Project the result back to $\mathbb{S}^2$ via the exponential map.

The outputs of all channels are pooled:

$$\text{HSMGNN}(\vec{H}^l; A_1, \ldots, A_c) = \text{Pooling}\left(\vec{H}_1^{l+1}, \ldots, \vec{H}_c^{l+1}\right)$$

We use average pooling. The final output after L layers is $\vec{H}^L$ (and $\vec{H'}^L$ for the other KG), with parameters shared across graphs, i.e., $W_i = W_i'$.

2.5 Alignment Model

The alignment model embeds entities from different KGs into a shared hyperbolic space, ensuring that semantically equivalent entities are geometrically close.

Let E and E' be entity sets of two knowledge graphs with seed alignment pairs $\mathscr{S} = \{(e_i, e_i')\}$. The alignment loss minimizes the hyperbolic distance between aligned entities:

$$L_{align} = \sum_{(e_i, e_i') \in \mathscr{S}} d_{\mathbb{H}}(\mathbf{h}(e_i), \mathbf{h}'(e_i'))$$

The overall training objective integrates the embedding loss, relation weighting loss, and alignment loss:

$$L = L_{emb} + \lambda_1 L_{align} + \lambda_2 L_{rw}$$

where λ_1 and λ_2 are hyperparameters balancing the objectives.

3 Rule Knowledge Constraints

To enhance the original knowledge graphs, we incorporate grounded rules (i.e., additional triplets derived from first-order logic) and introduce a rule constraint loss to ensure that these rules are respected in the manifold embedding space. Taking the knowledge graph G as an example, and following the general framework of[26], we define the loss as:

$$\mathscr{L}r = \sum g^+ \in \mathscr{G}(\mathscr{K}) \sum_{g^- \in \mathscr{G}^-(\mathscr{K})} \left[\gamma_r - I(g^+) + I(g^-)\right] + + \sum t^+ \in T \sum_{t^- \in T^-} \left[\gamma_r - I(t^+) + I(t^-)\right]_+ \tag{5}$$

Here, g denotes a grounded rule, $\mathscr{G}(\mathscr{K})$ is the set of valid grounded rules, and $\mathscr{G}^-(\mathscr{K})$ is the corresponding set of negative samples generated by entity corruption (e.g., using nearest neighbor sampling[27]). T and T^- denote the sets of valid and corrupted triplets, respectively. The truth value function $I(\cdot)$ evaluates the plausibility of a triplet or rule grounding based on spherical geometry.

For a triplet $t = (e_i, r_{ij}, e_j)$ embedded on the spherical manifold $\mathbb{S}^2$, we define the truth value as:

$$I(t) = 1 - \frac{1}{\pi} \cdot d_{\mathbb{S}^2}(e_i \circ r_{ij}, e_j) \tag{6}$$

where $\circ$ denotes a manifold-aware transformation (e.g., rotation) of e_i by r_{ij} on $\mathbb{S}^2$, and $d_{\mathbb{S}^2}(x,y) = \arccos(\langle x,y \rangle)$ is the geodesic distance on the unit sphere. The value is normalized to $[0,1]$ by dividing by π.

For a rule grounding $g = (t_c \mid t_{s1}, \ldots, t_{sp})$, we define the recursive truth value function as:

$$I(t_s) = I(t_{s1}) \cdot I(t_{s2}) \cdots I(t_{sp})\, I(t_s \Rightarrow t_c) \qquad = I(t_s) \cdot I(t_c) - I(t_s) + 1 \tag{7}$$

where t_s is the premise and t_c is the conclusion. This formulation follows fuzzy logic implication semantics.

We similarly define a loss term $\mathscr{L}_r'$ for the other knowledge graph G'. The final objective for training our multi-channel GNN model is given by:

$$\mathscr{L} = \mathscr{L}_a + \mathscr{L}_r + \mathscr{L}_r' \tag{8}$$

4 Experiment

We conduct comprehensive experiments on five publicly available datasets encompassing diverse language pairs and data sources. Furthermore, we investigate the key components of the HSMGNN framework, focusing on the effectiveness of knowledge inference and transfer mechanisms in knowledge graph alignment.

4.1 Experimental Settings

Following the protocol of Sun et al.[28], we perform evaluations on two benchmark datasets: DBP15K and DWY100K.

The **DBP15K** dataset consists of three cross-lingual sub-datasets: DBPZH-EN (Chinese–English), DBPJA-EN (Japanese–English), and DBPFR-EN (French–English). Each subset contains 15,000 aligned entity pairs extracted from the multilingual DBpedia.

The **DWY100K** dataset comprises two large-scale cross-resource sub-datasets: DWY-DB and DWY-WD, aligning DBpedia with Wikidata. Each sub-dataset provides 100,000 pre-aligned entities. For relation alignment, we utilize the official alignment list released by DBpedia.

The statistics of these datasets are summarized in Table 1.

Table 1. Statistics of the DBP15K and DWY100K datasets.

Dataset	#Relations	$\lvert\mathscr{A}^s\rvert$	#Entities	#Triples
DBP_{ZH}	–	2,830	66,469	153,929
DBP_{EN}	819	2,317	98,125	237,674
DBP_{JA}	–	2,043	65,744	164,373
DBP_{EN}	2,096	582	95,680	233,319
DBP_{FR}	–	1,379	66,858	192,191
DBP_{EN}	2,209	75	105,889	278,590
DWY_{DB}	–	330	100,000	463,294
DWY_{WD}	62	220	100,000	448,774

For rule mining, we use AMIE+ with a maximum of two premises ($p = 2$) and a minimum PCA confidence threshold of 0.8. Table 2 shows the number of mined rules, transferred rules (Tr.Rule), grounded triples, and grounded triples derived from transferred rules (Tr.Ground).

Table 2. Statistics of knowledge graph inference and rule transfer.

Dataset	#Rules	#Tr.Rule	#Grounded	#Tr.Ground
DBP_{ZH}	2,279	1,058	46,959	19,278
DBP_{EN}	1,906	578	78,450	24,018
DBP_{JA}	1,440	651	61,733	25,337
DBP_{EN}	1,316	259	77,614	17,838
DBP_{FR}	1,263	25	77,342	1,527
DBP_{EN}	1,252	12	75,338	1,364
DWY_{DB}	843	40	281,271	13,136
DWY_{WD}	630	51	184,010	56,373

- **Baselines:** To evaluate the performance of HSMGNN, we compare it against four strong baselines: three translation-based models and one graph-based model.
  - **MTransE**[29]: Employs TransE to learn separate embeddings for each knowledge graph and minimizes the Euclidean distance between aligned entities.
  - **JAPE**[28]: Learns a joint embedding space for entities and relations across KGs, incorporating attribute triples to enhance alignment.
  - **GCN-Align**[17]: Uses Graph Convolutional Networks (GCNs) to propagate information from neighbors for entity representation.
  - **AlignEA**[27]: A non-iterative method that exchanges aligned entities in triples to create a unified embedding space.

  We also compare with **MuGNN**[24], which serves as the reference for parameter settings.
- **Training Details:** Following Sun et al.[28], we use 30% of the entity alignment seeds for training and the remaining 70% for testing. We report two standard metrics: Hits@N and Mean Reciprocal Rank (MRR). Hits@N reflects the proportion of correct alignments ranked within the top N, while MRR is the average reciprocal rank of correct alignments. Higher values indicate better performance.

  We fix the embedding size of HSMGNN to 128. The model is implemented in PyTorch 2.0 with CUDA 11.8 and trained on a server equipped with dual 44-core Intel Xeon Platinum 8457C CPUs (supporting 176 threads) and NVIDIA H20 GPUs (96 GB VRAM). Each model is trained for 500 epochs.

4.2 Results Analysis

Table 3. Performance comparison on four cross-lingual datasets

Method	DBP(zh-en)			DBP(ja-en)			DBP(fr-en)			DBP(wd)		
	H@1	H@10	MRR	H@1	H@10	MRR	H@1	H@10	MRR	H@1	H@10	MRR
MTransE	.308	.614	.364	.279	.575	.349	.224	.556	.335	.281	.520	.363
JAPE	.412	.745	.490	.363	.685	.476	.324	.667	.430	.318	.589	.411
AlignEA	.472	.792	.581	.448	.789	.563	.481	.824	.599	.566	.827	.655
GCN-Align	.413	.744	.549	.399	.745	.546	.399	.745	.546	.506	.772	.600
MuGNN	.494	.844	.611	.501	.857	.621	.501	.857	.621	.616	.897	.714
HSMGNN	**.533**	**.841**	**.641**	**.626**	**.927**	**.731**	**.626**	**.927**	**.731**	**.625**	**.912**	**.725**

Table 3 presents the performance comparison of various models on four cross-lingual entity alignment datasets: DBP(zh-en), DBP(ja-en), DBP(fr-en), and DBP(wd), evaluated using Hits@1, Hits@10, and MRR metrics. Overall, all the advanced models

outperform the baseline MTransE by a substantial margin, highlighting the importance of incorporating structural and semantic information for improving alignment performance.

Among the competitive baselines, models such as **JAPE**, **AlignEA**, and **GCN-Align** employ different strategies to enhance entity representations via structural similarity and semantic embeddings. **AlignEA** in particular shows consistently strong results across datasets, especially in terms of Hits@10 and MRR, demonstrating the advantage of enforcing global alignment consistency.

Our proposed HSMGNN achieves the best overall performance on all datasets, significantly surpassing not only traditional methods but also the strong GNN-based baseline **MuGNN**. For example, on DBP(ja-en), HSMGNN achieves a Hits@1 of 0.626 and an MRR of 0.731, the highest across all methods. These results demonstrate that our hierarchical semantic modeling approach effectively captures deeper multi-level correlations between cross-lingual entities, leading to superior alignment accuracy.

4.3 Loss Analysis

As shown in Figure 6, the "Relation Align Loss" exhibits a distinct downward trend as the number of training steps increases.

Initial Phase: At the beginning of training (i.e., when the horizontal axis values are small), the loss is relatively high. Notably, the orange curve starts with a loss value exceeding 1.5, indicating poor initial performance in the relation alignment task and a large discrepancy between predicted and true values.

Rapid Descent Phase: As training progresses, the loss rapidly decreases. Before approximately 100 steps, the orange curve shows a substantial drop, suggesting that the model quickly learns effective parameter adjustments to reduce the alignment loss.

Slow Descent Phase: With further increases in training steps, the rate of decline slows down. The orange curve continues to decrease gradually, indicating the model is approaching convergence and fine-tuning its parameters.

Low-Level Stabilization Phase: In the later training stages, the loss values of the brown and green curves plateau at very low levels. This suggests the model has achieved good performance in the relation alignment task, and parameter updates have largely stabilized.

4.4 Validation Hyperbolic Analysis

In this section, we analyze a subset of DBP15K with a hierarchical structure, such as the "biological classification" subgraph. This subset includes 1000 entities and has a three-level hierarchy with depth $d \leq 3$. We compare the following embedding methods: TransE (a Euclidean-based embedding), RotatE (a complex-valued embedding), Euclidean Embedding (another classical embedding), and Hyperbolic Embedding.

- HSMGNN consistently surpasses strong baselines, including translation-based methods like MTransE and graph-based models such as GCNAlign and MuGNN. For example, on the DBP ZH-EN dataset, HSMGNN achieves a Hits@1 of 0.533, significantly outperforming MuGNN's 0.494. On the DBP JA-EN dataset, HSMGNN reaches a Hits@1 of 0.626, well above the 0.501 achieved by the second-best model.

- The training loss curves further highlight HSMGNN's efficiency and stability. A rapid early decrease in loss indicates swift parameter adaptation and effective learning, while the steady downward trend in later stages confirms continued optimization towards a highly accurate alignment.

- In summary, HSMGNN not only addresses the key challenges of structural heterogeneity and seed scarcity but does so with greater efficiency and accuracy than prior methods. Our approach sets a new benchmark for knowledge graph alignment and provides a promising foundation for future research in this area.

Figure 7 presents a visual comparison of four models: TransE, RotatE, Euclidean, and Hyperbolic. The x-axis lists the models, while the left y-axis represents parameter count (indicating model complexity), and the right y-axis shows performance metrics, specifically Depth Variance and Angular STD.

The purple bars indicate the parameter count. RotatE has the most parameters, followed by TransE and Euclidean, with Hyperbolic having the fewest. The blue line with dots corresponds to the Depth Variance metric, where RotatE shows the highest value, followed by Euclidean, TransE, and finally Hyperbolic. The red line with squares represents the Angular STD, which increases from TransE to RotatE and Euclidean, but drops sharply for Hyperbolic.

This figure allows researchers to assess the trade-off between model complexity and performance. It highlights how different models utilize parameters to capture hierarchical structures, aiding in informed model selection.

Figure 8 explores the relationship between **Hierarchical Depth** (x-axis) and **Distance from Root** (y-axis) in a hierarchical structure.

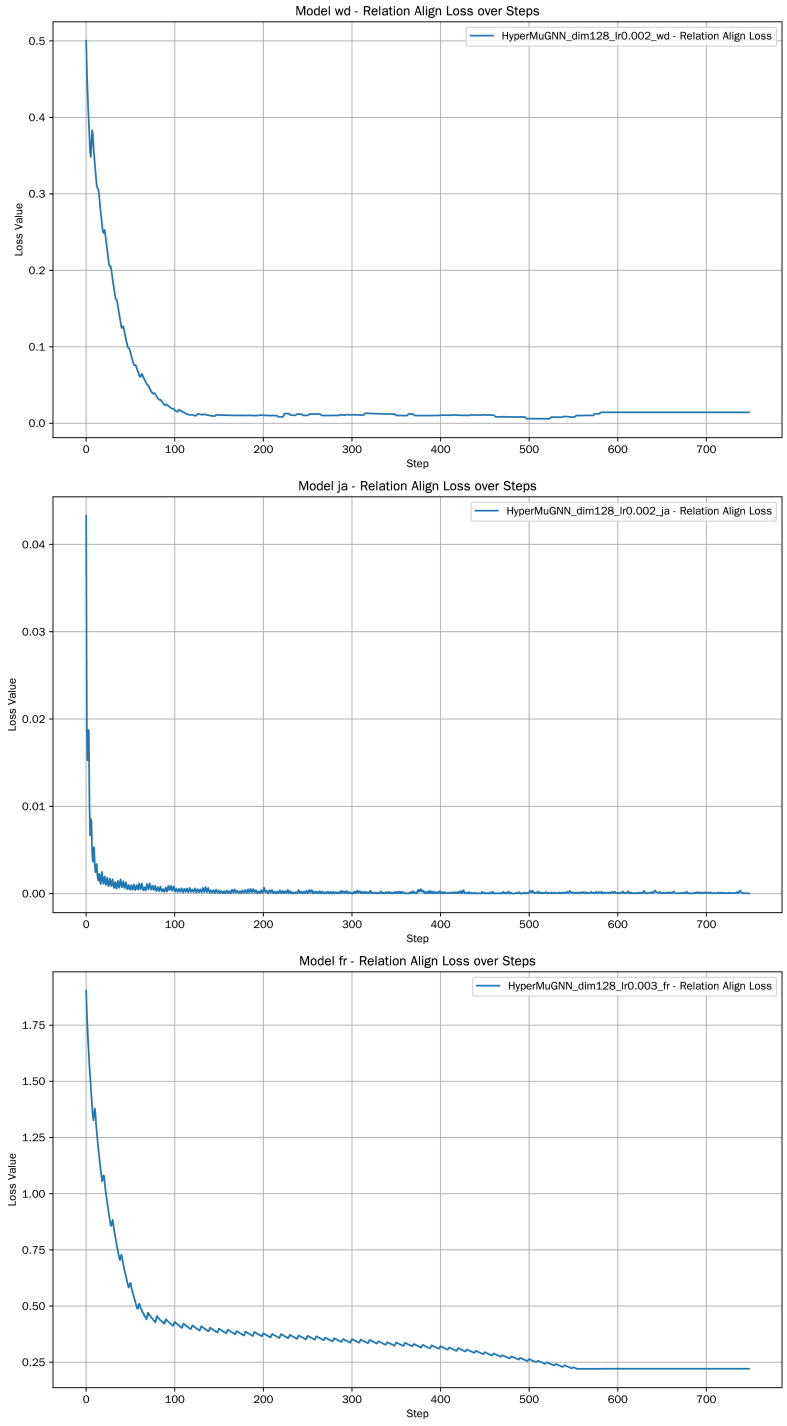


Figure 6. Trend of Relation Align Loss with Training Steps

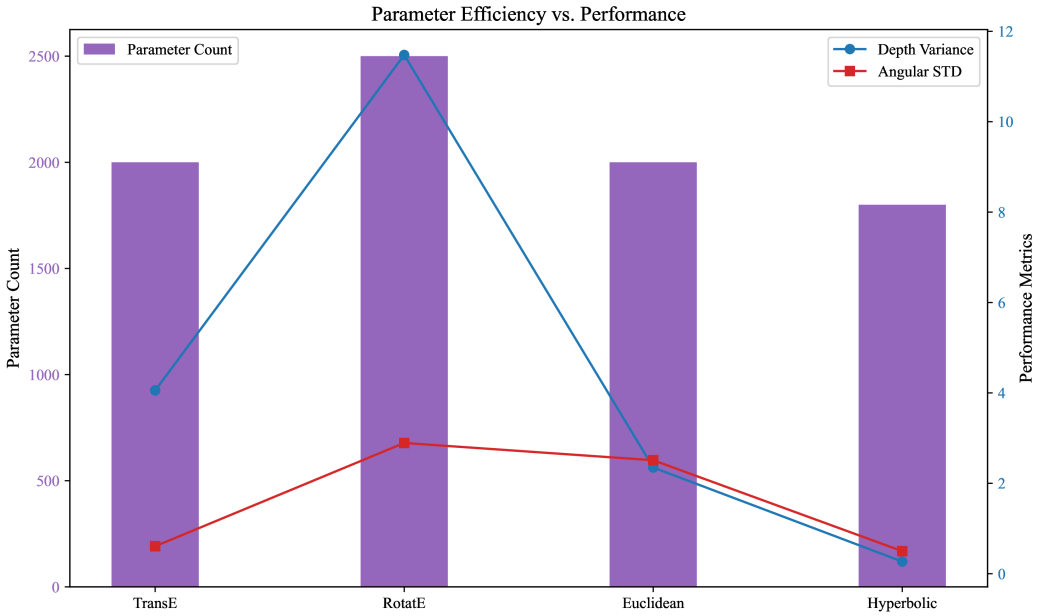


Figure 7. Parameter Efficiency vs. Performance for Different Knowledge Graph Embedding Models. This figure illustrates the relationships between parameter count and performance metrics (Depth Variance and Angular STD) for four models: TransE, RotatE, Euclidean, and Hyperbolic. It provides insight into the efficiency of parameter utilization and model performance, aiding model selection in knowledge graph-related tasks.

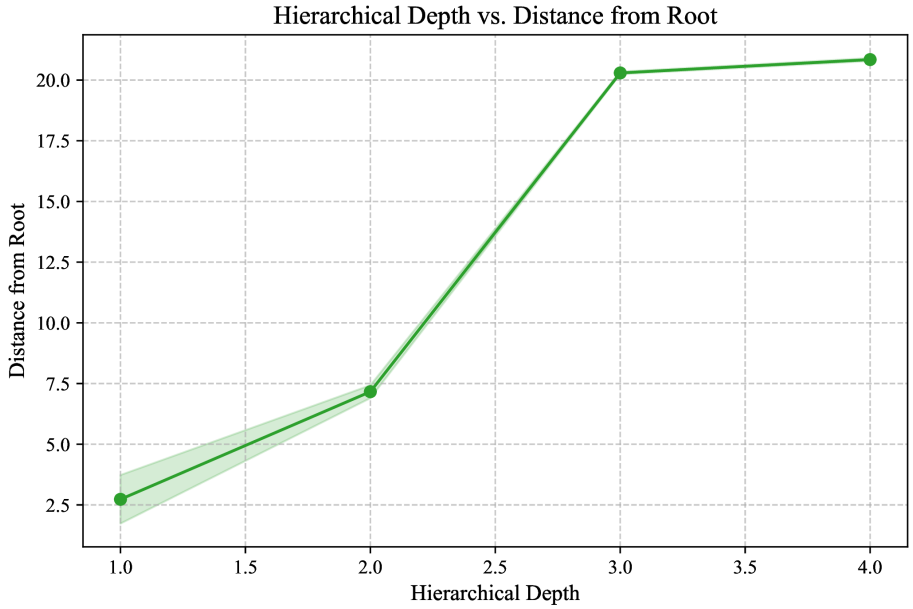


Figure 8. Relationship between Hierarchical Depth and Distance from Root. This plot illustrates how the distance from the root node varies with hierarchical depth. The green line shows the trend, and the shaded area indicates a confidence interval or value range, helping to visualize the distance growth pattern as hierarchy deepens.

Initially, as the depth increases from 1.0 to 2.0, the distance from the root increases gradually. Between depths 2.0 and 3.0, a significant increase in distance is observed. Beyond depth 3.0, the distance stabilizes and remains relatively constant up to depth 4.0.

The shaded area around the green line likely represents a confidence interval or range of possible values, illustrating variability in the distance-depth relationship. This visualization helps understand geometric patterns in hierarchical knowledge graphs, such as semantic depth and structural organization.

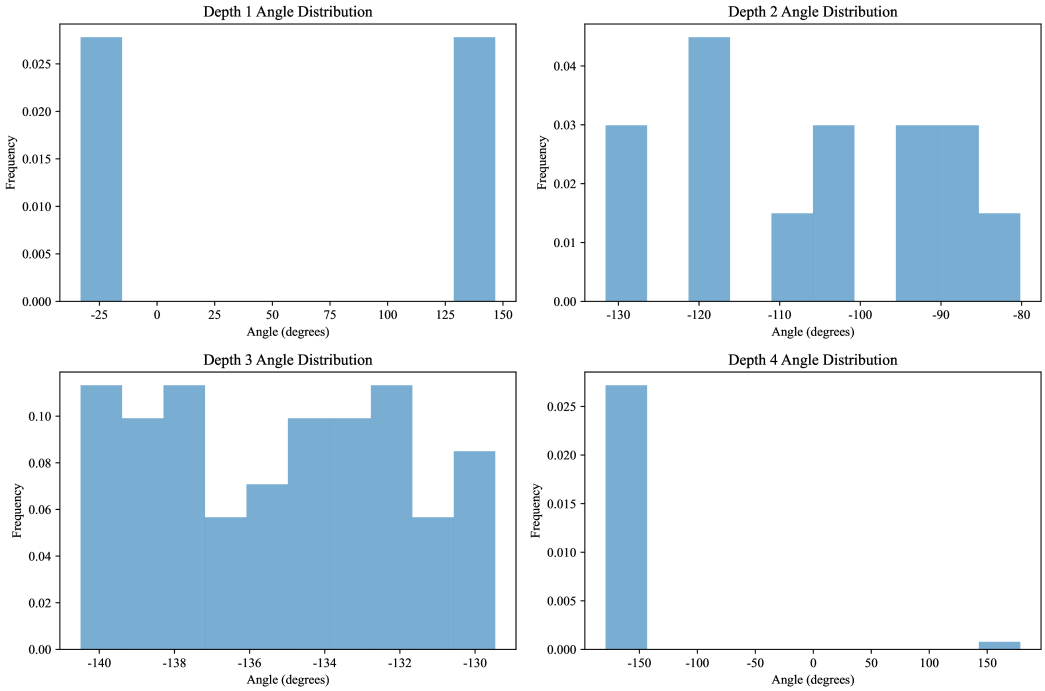


Figure 9. Angle Distribution Histograms at Different Hierarchical Depths. These histograms show the frequency of angles at Depths 1 to 4 within a hierarchical structure, visualizing how angular relationships vary across levels.

Figure 9 includes four histograms, each depicting the angle distribution at a different hierarchical depth:

- **Depth 1**: Angles range from -25° to 150°, with two prominent peaks. This suggests a preference for specific angular relationships at this level.
- **Depth 2**: Angles range from -130° to -80°, showing a more dispersed but still somewhat clustered distribution.
- **Depth 3**: Angles range from -140° to -130°, with a complex distribution pattern and varying frequencies.
- **Depth 4**: Angles span from -150° to 150°, with low frequencies across most bins and a small peak toward the negative angle side, indicating different angular characteristics due to deeper structural layering.

These histograms help understand how angular relationships evolve with hierarchical depth, offering insights into structural and semantic properties of hierarchical knowledge graphs.

Evaluation Criteria:

- **Hierarchical Distinguishability**: Measured by the standard deviation of angles among nodes at the same layer (lower values indicate tighter clustering).
- **Depth Separability**: Measured by the variance of distances between nodes at different layers and the root node (higher values indicate clearer hierarchical separation).

Table 4 highlights significant differences among embedding methods in terms of geometric representation and parameter efficiency. Specifically, the Euclidean model exhibits the highest standard deviation of same-layer angles (2.3492), indicating stronger angular discriminability within hierarchical levels. The RotatE model follows closely with a standard deviation

Table 4. Experimental Results Analysis for Hierarchical Structure Representation

Method	Std. Dev. of Same-layer Angles	Variance of Depth-Distance	Parameter Count
TransE	1.3026	1.7283	2000
RotatE	2.0262	8.5174	2500
Euclidean	2.3492	2.5109	2000
Hyperbolic	**0.4993**	**0.2690**	**1800**

of 2.0262 and shows the largest variance in depth-distance (8.5174), suggesting it effectively captures hierarchical depth separability.

In contrast, the Hyperbolic Embedding model shows the lowest values for both the standard deviation of same-layer angles (0.4993) and variance of depth-distance (0.2690), reflecting its tendency to embed entities more compactly in a continuous geometric space. This compression aligns well with the nature of hierarchical data, enabling clearer semantic clustering and better parameter efficiency, as it achieves these results with the fewest parameters (1800). Thus, hyperbolic embeddings demonstrate superior suitability for representing hierarchical structures with lower complexity.

The experimental results indicate that hyperbolic embedding excels in representing hierarchical structures:

Hierarchical Distinguishability: The lowest same-layer angular standard deviation (0.4993) suggests that hyperbolic embeddings produce tighter, more semantically consistent clusters.

Depth Separability: Although the depth-distance variance (0.2690) appears small, the exponential nature of hyperbolic space allows it to effectively separate hierarchical levels.

Parameter Efficiency: With only 1800 parameters, the hyperbolic model achieves superior performance, validating its suitability for representing tree-like hierarchical structures.

In summary, hyperbolic geometry naturally supports low-dimensional, high-efficiency hierarchical representation, as evidenced by its compact clustering, clear hierarchical separation, and minimal parameter use.

5 Related Work

The integration of heterogeneous Knowledge Graphs (KGs) has become a crucial research direction, driving significant progress in knowledge-driven applications such as information extraction[31], question answering[32], and recommendation systems[34]. Early entity alignment methods mainly depended on handcrafted features, leveraging machine translation and external lexicons to bridge semantic gaps between KGs[23]. However, these methods struggled to scale effectively with the increasing complexity and size of modern KGs.

The emergence of KG representation learning marked a paradigm shift by embedding entities into low-dimensional vector spaces, often guided by seed alignments[29]. Translation-based approaches such as MTransE[29] and graph-based models like GCN-Align[17] demonstrated promising results. Nevertheless, these methods still face two critical challenges: (1) the scarcity of high-quality seed alignments and (2) structural heterogeneity across KGs, both of which limit embedding quality and alignment accuracy.

To overcome these challenges, subsequent works incorporated additional signals. Models like JAPE[28] and KDCoE[33] enhanced embeddings by leveraging attribute triples and textual descriptions, while IPTransE[36] and BootEA[37] iteratively expanded seed alignments using self-training. Although effective to some extent, these strategies either depend on external resources or require computationally expensive iterative procedures.

In contrast, our proposed Heterogeneous Structure-aware Multi-channel Graph Neural Network (HSMGNN) introduces a fundamentally different and more effective paradigm for KG alignment. Drawing inspiration from GCN-based encoding frameworks[24,38], HSMGNN advances the state-of-the-art by:

- **Explicitly Modeling Structural Heterogeneity:** By applying graph completion and pruning techniques, HSMGNN effectively reconciles topological discrepancies between heterogeneous KGs, without relying on external knowledge sources.
- **Multi-channel Feature Extraction:** Through parallel GNN channels integrating node embeddings, relation paths, and semantic context, HSMGNN comprehensively captures diverse and complementary structural features.
- **Non-iterative Alignment Optimization:** HSMGNN achieves alignment-oriented embedding learning in a single training pass, eliminating the need for costly iterative training while maintaining or exceeding previous accuracy levels.

These innovations enable HSMGNN to consistently outperform existing state-of-the-art baselines across multiple benchmark datasets, demonstrating its superior capacity for aligning heterogeneous knowledge graphs.

6 Conclusions

In this work, we presented HSMGNN, a novel and effective framework for knowledge graph alignment. Our extensive experiments on four challenging datasets—DBP ZH-EN, DBP JA-EN, DBP FR-EN, and DBP-WD—covering multiple language pairs and sources, comprehensively validate the robustness and superiority of our approach.

HSMGNN consistently surpasses strong baselines, including translation-based methods like MTransE and graph-based models such as GCNAlign and MuGNN. For example, on the DBP ZH-EN dataset, HSMGNN achieves a Hits@1 of 0.533, significantly outperforming MuGNN's 0.494. On the DBP JA-EN dataset, HSMGNN reaches a Hits@1 of 0.626, well above the 0.501 achieved by the second-best model.

The training loss curves further highlight HSMGNN's efficiency and stability. A rapid early decrease in loss indicates swift parameter adaptation and effective learning, while the steady downward trend in later stages confirms continued optimization towards a highly accurate alignment. In summary, HSMGNN not only addresses the key challenges of structural heterogeneity and seed scarcity but does so with greater efficiency and accuracy than prior methods. Our approach sets a new benchmark for knowledge graph alignment and provides a promising foundation for future research in this area.

7 Data Availability

The data that support the findings of this study are available in https://github.com/nju-websoft/JAPE.

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Author contributions statement

Yu Deng. wrote the main manuscript text. All authors reviewed the manuscript.

Additional information

Correspondence should be addressed to Shiwang Hou.