

Taming the Wild Evolution: Aligning Multi-Modal Temporal Knowledge Graphs (Technical Report)

Abstract—This technical report provides additional details on the method, dataset tasks and complete experimental setup for the paper “Taming the Wild Evolution: Aligning Multi-Modal Temporal Knowledge Graphs”.

I. SUPPLEMENTATION OF METHOD

A. Motivation

The MTKGA-Wild task presents two critical properties that distinguish it from traditional entity alignment. First, determining entity correspondence requires examining *collective temporal-modal evolution patterns* rather than isolated fact comparisons. Consider aligning a political figure across two MTKGs: one entity may exhibit rich video coverage during campaign periods (2020-2024) but sparse image data, while its counterpart shows the opposite pattern with extensive historical image archives (1990-2000) but limited recent videos. Traditional pairwise graphs evaluate each candidate independently, failing to capture the high-order dependencies where alignment decisions must simultaneously weigh evidence across multiple temporal scales and modality types. Hypergraphs naturally address this limitation by enabling each source entity to form a hyperedge connecting multiple candidate projections, where the hyperedge structure encodes collective reasoning: “this entity’s alignment emerges from jointly comparing these candidates across all available modal-temporal dimensions.” Second, the dynamic imbalance challenge creates a constantly shifting decision landscape where modality availability varies dramatically across timestamps. Recent events rely heavily on video and audio modalities due to social media proliferation, while historical events depend predominantly on text and image archives. This temporal heterogeneity in modal distributions demands adaptive strategy selection rather than uniform alignment procedures. Multi-agent systems provide this adaptivity by design: each agent acts as a specialized operator excelling at specific modal-temporal conditions (e.g., video-dominant alignment, text-sparse compensation), while the meta-agent coordinates operator selection based on detected conflicts in the current hypergraph state. This on-demand collaboration mechanism directly mirrors how the alignment strategy must dynamically adjust when facing varying data availability across time periods, transforming the challenge of dynamic imbalance into a collaborative decision-making problem where specialized agents address localized modal-temporal inconsistencies.

These task-driven insights directly inform our algorithmic design in Algorithm 1. Neural retrieval and adaptive decoupling (lines 1-4) decompose complex temporal-modal

evolution into comparable projections that enable hyperedge construction, addressing evolutionary diversity through structured dimensionality reduction. Hypergraph construction (lines 5-7) materializes the collective reasoning framework where alignment decisions emerge from hyperedge-level comparisons rather than isolated pairwise evaluations. The MDP-based multi-agent loop (lines 9-19) operationalizes dynamic strategy adaptation: conflict detection identifies regions of modal imbalance (lines 10-14), core block selection activates specialized operators for those scenarios (line 9), agentic execution adjusts hypergraph structures through targeted actions (line 15), and meta evaluation distills successful strategies as reusable signals (lines 16-19). This closed-loop design ensures continuous improvement in handling diverse temporal-modal conditions inherent to MTKGA-Wild, where the hypergraph representation provides the structural foundation for collective reasoning and the multi-agent collaboration supplies the adaptive mechanism for dynamic imbalance resolution.

B. The Workflow of *EvoWildAlign*

In conclusion, the complete workflow of *EvoWildAlign* is presented in Algorithm 1. The algorithm takes as input a source MTKG \mathcal{G}^s , a target MTKG \mathcal{G}^t , and an alignment goal g , and outputs the entity alignment results \mathcal{A}_{align} . The algorithm proceeds through two main stages to systematically address the challenges of evolutionary diversity and dynamic imbalance in MTKGA-Wild.

In the *neuro-symbolic evolution hypergraph representation* stage, the algorithm first initializes an empty pre-aligned subgraph set (line 1). For each source entity $e^s \in \mathcal{E}^s$, neural retrieval is performed to identify the *top-k* most similar target entities using textual embedding similarity, forming pre-aligned subgraphs that are added to the set (lines 2). Subsequently, the algorithm initializes a decoupled projection set and applies adaptive evolution projection to each entity pair in the pre-aligned set (lines 3-4). Specifically, temporal masking projection removes timestamps in target entities that do not appear in source entities, while modal masking projection eliminates absent modality types. Each projection is further decomposed by modality types to ensure single-modality association. The algorithm then constructs modal projection hypergraphs \mathcal{H}_m for each modality $m \in \mathcal{M}$ (lines 5-6), where each source entity forms a hyperedge connecting its filtered target projections. Finally, these modal projection hypergraphs are aggregated into a unified neuro-symbolic evolution hypergraph \mathcal{H}^{evo} that captures comprehensive multi-modal temporal evolution (line 7).

Algorithm 1: EvoWildAlign Framework

Input: Source MTKG \mathcal{G}^s , Target MTKG \mathcal{G}^t , Alignment goal g
Output: Entity alignment results \mathcal{A}_{align}
// Stage 1: Neuro-symbolic Evolution Hypergraph Representation
1 Initialize pre-aligned subgraph set $\mathcal{P} \leftarrow \emptyset$; **for** Each entity $e^s \in \mathcal{E}^s$ **do**
2 Perform neural retrieval:
 $\text{TopK}(e^s) \leftarrow e_1^t, \dots, e_k^t \subseteq \mathcal{E}^t$; Construct pre-aligned subgraph and add to \mathcal{P} ;
3 Initialize decoupled projection set $\tilde{\mathbb{P}} \leftarrow \emptyset$; **for** Each entity pair (e^s, e^t) in \mathcal{P} **do**
4 Apply temporal masking projection:
 $\tilde{\mathbb{P}}_{time}^{(e^s, e^t)} \leftarrow \mathbb{P}_{time}(e^t | \mathcal{T}(e^s))$; Apply modal masking projection:
 $\tilde{\mathbb{P}}_{modal}^{(e^s, e^t)} \leftarrow \mathbb{P}_{modal}(e^t | \mathcal{M}(e^s))$; Decompose projections by modality types and add to $\tilde{\mathbb{P}}$;
5 **for** Each modality $m \in \mathcal{M}$ **do**
6 Construct modal projection hypergraph:
 $\mathcal{H}_m \leftarrow (\mathcal{V}_m, \varepsilon_m)$;
7 Aggregate into neuro-symbolic evolution hypergraph:
 $\mathcal{H}^{evo} \leftarrow (\mathcal{V}, \varepsilon, \mathcal{L}, \Phi)$;
 // Stage 2: On-demand Agentic Hypergraph Collaboration
8 Initialize state $s \leftarrow \mathcal{H}^{evo}$, meta-fusion signals $\mathcal{F}_{meta} \leftarrow \emptyset$; **while** Goal g not achieved and iterations $< \text{max_iterations}$ **do**
 // Core Block Selection
9 Select collaboration group:
 $\mathcal{B}(s, g) \leftarrow \mathcal{B}_{meta}(s, g, r, \mathcal{F}_{meta})$;
 // Collaboration Decision-Making
10 Initialize decision plan $\mathcal{D}(s) \leftarrow \emptyset$;
11 **for** Each source entity $e^s \in \mathcal{E}^s$ **do**
12 Detect cross-layer conflicts: $\text{Conflict}(e^s) \leftarrow$ Eq. (8);
13 **if** $\text{Conflict}(e^s) = 1$ **then**
14 Determine alignment action a_{e^s} and add (e^s, a_{e^s}) to $\mathcal{D}(s)$;
 // Agentic Hypergraph Execution
15 Execute actions and update state: $s' \leftarrow \mathcal{T}(s, \mathcal{D}(s))$;
 // Meta Evaluation
16 Evaluate alignment quality: $r \leftarrow \mathcal{R}(s', g)$;
17 Extract meta-fusion signals: $\mathcal{F}_{meta} \leftarrow \{ \text{successfully executed actions from } \mathcal{D}(s) \}$;
18 Extract pseudo-labeled pairs:
 $\mathcal{A}_{seed} \leftarrow \{(e^s, e^t) \mid \text{Conflict}(e^s) = 0\}$;
19 Update state: $s \leftarrow s'$;
20 Return entity alignment results \mathcal{A}_{align} ;

In the *on-demand agentic hypergraph collaboration* stage, the algorithm models the alignment process as a Markov decision process. The initial state is set to the neuro-symbolic evolution hypergraph, and meta-fusion signals are initialized as empty (line 8). The algorithm then enters an iterative refinement loop that continues until the alignment goal is achieved or maximum iterations are reached (line 8). Each iteration consists of four key steps: In *core block selection*, a meta-agent dynamically selects appropriate operator agents and assigns role descriptions to form the collaboration group $\mathcal{B}(s, g)$ based on the current state, goal, reward, and meta-fusion signals (line 9). In *collaboration decision-making*, the algorithm initializes a decision plan and examines each source entity for cross-layer conflicts across modality layers (lines 10-14). Entities exhibiting dynamic imbalance—where different modality layers yield inconsistent top-ranked candidates—are identified, and corresponding alignment actions are added to the decision plan. In *agentic hypergraph execution*, agents execute the actions specified in the decision plan to refine the hypergraph structure and update the state (line 15). In *meta evaluation*, the algorithm assesses alignment quality, extracts successfully executed actions as meta-fusion signals for subsequent iterations, and generates pseudo-labeled alignment pairs from conflict-free entities (lines 16-19). If the goal remains unachieved, feedback and meta-fusion signals guide adaptive reconfiguration of the collaboration group in the next iteration. Upon convergence or reaching maximum iterations, the algorithm returns the final entity alignment results (line 20).

II. EXPERIMENTS

In this section, we first introduce the experimental setting in Section II-A. We then empirically evaluate the proposed datasets and framework from various perspectives to address the following research questions:

- **RQ1: How effective is the overall MTKGA-Wild framework?**
- **RQ2: Does the new task offer sufficient research value, and do the WildMTKGA (W-I) and WildMTKGA (Y-I) datasets provide meaningful insights for the solution to this new task?**
- **RQ3: What is the effectiveness of each component within EvoWildAlign?**
- **RQ4: Does the EvoWildAlign successfully balance alignment accuracy and efficiency in MTKGA-Wild?**
- **RQ5: To what degree is EvoWildAlign adaptable and robust across varying foundation models and more complex scenarios?**

A. Experimental Setting

1) *MTKGA-Wild Benchmarks and Others:* Currently, there is no benchmark that effectively studies and evaluates the MTKGA-Wild task. To this end, we construct two new MTKGA-Wild benchmarks, i.e., WildMTKGA (W-I) and WildMTKGA (Y-I). As shown in Table I, the construction

TABLE I

DATASET STATISTICS [1]–[4]. “#Ent”, “#Rel.”, “#Facts”: THE NUMBER OF ENTITIES, RELATIONS AND QUADRUPLES IN KG1 (KG2), RESPECTIVELY. “Temporal.”, “Multi-modal”: INDICATES WHETHER THE DATASET INCLUDES TEMPORAL KNOWLEDGE INFORMATION AND THE DATASET INCLUDES MULTI-MODAL INFORMATION, RESPECTIVELY.

Dataset		#Ent.	#Rel.	Temporal.	Multi-modal	#Seed	#Facts	Image	Text	Audio	Video
DBP15K (EN-FR)	EN	15,000	193	✗	✗	15,000	96,318	✗	✓	✗	✗
	FR	15,000	166	✗	✗		80,112				
DBP-WIKI	DBP	100,000	413	✗	✗	100,000	293,990	✗	✓	✗	✗
	WIKI	100,000	261	✗	✗		251,708				
ICEWS-WIKI	ICEWS	11,047	272	✓	✗	5,058	3,527,881	✗	✓	✗	✗
	WIKI	15,896	226	✓	✗		198,257				
ICEWS-YAGO	ICEWS	26,863	272	✓	✗	18,824	4,192,555	✗	✓	✗	✗
	YAGO	22,734	41	✓	✗		107,118				
YAGO-WIKI50K	YAGO	49,629	11	✓	✗	49,172	221,050	✗	✓	✗	✗
	WIKI	49,222	30	✓	✗		317,814				
BETA	WIKI	42,666	257	✓	✗	40,364	199,879	✗	✓	✗	✗
	YAGO	42,297	45	✓	✗		162,320				
FB15K-DB15K	Freebase	14,951	1,345	✗	✓	12,846	621,608	✓	✓	✗	✗
	DB	12,842	279	✗	✓		137,277				
WildMTKGA (W-I)	WIKI	13,194	224	✓	✓	4,978	196,117	✓	✓	✓	✓
	ICEWS	10,052	268	✓	✓		3,527,053				
WildMTKGA (Y-I)	YAGO	21,098	41	✓	✓	17,895	107,018	✓	✓	✓	✓
	ICEWS	25,316	272	✓	✓		4,192,212				

of WildMTKGA (W-I) and WildMTKGA (Y-I) follows the established construction guidelines of predecessors [1].

- MTKGA-Wild Benchmarks Construction Process:** The WildMTKGA (W-I) and WildMTKGA (Y-I) benchmarks are constructed by bridging ICEWS—a domain-specific knowledge graph documenting political events—with two prominent general-purpose KGs: *WIKIDATA* and *YAGO*. These datasets incorporate extensive multi-modal and temporal attributes to address real-world alignment challenges. ICEWS captures temporally-annotated political events and their multi-modal manifestations across news sources, while *WIKIDATA* and *YAGO* offer broad commonsense knowledge with evolving temporal dimensions. Unifying these heterogeneous sources enables richer event comprehension and facilitates multi-modal temporal reasoning applications. We detail the construction methodology using WildMTKGA (W-I) as the exemplar (the WildMTKGA (Y-I) pipeline follows analogous steps). Since YAGO’s multi-modal content primarily links to WIKIDATA entities, we leverage these mappings to acquire YAGO’s modal information. Following established protocols [1], we began with raw ICEWS event records from 1995-2021, sourced from the official repository¹. We simultaneously harvested multi-modal assets (imagery, textual content, audio, video) from original news articles to enrich temporal context, reformatting the data into a structured KG representation with entities, relations, and facts. Entity names from ICEWS underwent normalization before being matched against WIKIDATA entries via the official API, retrieving corresponding multi-modal temporal attributes. After manual curation to eliminate spurious matches, we secured 23,912 validated entity pairs spanning both KGs. Neighborhood sampling around these seed pairs proceeded without imposing 1-to-1 constraints to preserve realistic distributional characteristics. To maintain fidelity to

original KG topology, we employed the Iterative Degree-based Sampling (IDS) strategy [4], which prunes entities from both graphs in tandem while respecting native degree distributions until target dataset sizes are achieved. This sampling procedure yielded the final WildMTKGA (W-I) benchmark.

- Other non-MTKGA Benchmarks:** Additionally, we comprehensively evaluate the MTKGA-Wild benchmarks and our proposed approach using seven non-MTKGA benchmarks, which are summarized in Table I. For uni-modal temporal KGA benchmarks, we employ four representative datasets, i.e., ICEWS-WIKI, ICEWS-YAGO, BETA, and YAGO-WIKI50K. ICEWS-WIKI and ICEWS-YAGO [1] exemplify highly heterogeneous temporal knowledge graph alignment datasets², characterized by substantial differences between their constituent KGs. These differences manifest not only in the quantities of entities, relations, and facts, but also in structural characteristics (e.g., density and structural similarity) and their low overlapping ratios. Notably, the number of anchor links does not equal the entity count, rendering the alignment task more challenging on these complex HHEA datasets. BETA [5] is designed for more complex temporal EA scenarios, comprising six realistic complex cases that better reflect real-world situations with multi-granularity temporal features. The most widely adopted dataset, YAGO-WIKI50K, is derived from YAGO and Wikidata. Specifically, the YAGO-WIKI50K datasets are constructed by first selecting the top 50,000 most frequent entities from a Wikidata subset extracted by [6], then linking these entities to their counterparts in YAGO [3]. Temporal facts are subsequently incorporated to form two TKGs for alignment. For uni-modal static KGA benchmarks, we adopt two representative datasets, i.e., DBP15K (EN-FR) and DBP-WIKI. DBP15K (EN-FR) and DBP-WIKI [4] are well-established benchmarks in

¹<https://dataverse.harvard.edu/dataverse/icews>




²<https://github.com/IDEA-FinAI/Simple-HHEA>























































entity alignment. DBP15K (EN-FR) specifically targets cross-lingual entity alignment, while DBP-WIKI represents a larger-scale dataset for heterogeneous knowledge graphs. Nevertheless, these KGs exhibit similar structural properties, including comparable density and structural similarity, with 100% overlapping ratios and similar scales in terms of entities, relations, and facts. Furthermore, for multi-modal static KGA benchmarks, we select the most representative dataset, i.e., FB15K-DB15K. For the monolingual setting, we utilize FB15K-DB15K from MMKG [7], [8] with the standard data split, specifically employing 20% training data.

2) **Benchmark Configurations:** Currently, there is no specific solution for the MTKGA-Wild task. To establish a comprehensive evaluation framework for MTKGA-Wild, we systematically propose 27 representative and classic benchmark configurations for extensive comparison. These configurations can be divided into uni-modal static KGA configurations, uni-modal temporal KGA, and multi-modal static KGA configurations.

- **Uni-modal Static KGA Methods:** We collect 11 state-of-the-art uni-modal static KGA methods as benchmark configurations for comparison. These methods include MTransE [9], AlignE [10], BootEA [10], GCN-Align [11], RDGCN [12], Dual-AMN [13], BERT [14], FuAlign [15], BERT-INT [16], PARIS [17], [18] and Naive RAG [19]–[21].
 - MTransE [9] is a translation-based entity alignment method that introduces translation vectors to align entity embeddings across different languages. It extends the TransE model by learning cross-lingual transformations that map entities from one knowledge graph to another, enabling alignment between multilingual KGs.
 - AlignE [10] focuses on capturing essential relational patterns that can serve as alignment signals, improving the precision of entity matching.
 - BootEA [10] utilizes a bootstrapping approach that iteratively expands alignment seeds, progressively improving alignment quality through self-training on high-confidence predictions.
 - GCN-Align [11] trains Graph Convolutional Networks (GCNs) to embed entities from each language into a unified vector space. By leveraging the graph structure through neighborhood aggregation, it captures both structural and semantic information for cross-lingual entity alignment.
 - RDGCN [12] leverages GCNs for modeling structural information within knowledge graphs. It explicitly incorporates relational information through dual graph structures, enhancing the representation of both entities and their relationships.
 - Dual-AMN [13] jointly captures intra-graph and cross-graph dependencies through attention mechanisms. It models both the internal structure of individual KGs and the cross-KG correspondences simultaneously, enabling more comprehensive entity alignment.
- BERT [14] is utilized as a pretrained language model to initialize entity embeddings using name-based features. By leveraging BERT’s powerful contextual representations, it captures semantic information from entity names and descriptions to improve alignment performance.
- FuAlign [15] incorporates auxiliary information to address knowledge graph heterogeneity. It fuses multiple types of information sources, including structural, textual, and attribute data, to handle the diverse characteristics of different KGs.
- BERT-INT [16] combines BERT-based augmentation with auxiliary cues for improved alignment. It integrates pre-trained language model representations with additional contextual information, creating richer entity embeddings for cross-KG matching.
- PARIS [17], [18] is a probabilistic iterative method capable of aligning entities without requiring prior alignments. It uses a holistic approach that simultaneously aligns entities, relations, and schema elements through probabilistic reasoning.
- Naive RAG [19]–[21] is a basic LLM-based Retrieval-Augmented Generation approach that first retrieves relevant information based on a user query and then generates answers using the retrieved content. It represents a straightforward application of large language models to the entity alignment task.
- **Uni-modal Temporal KGA Methods:** We collect 11 state-of-the-art uni-modal temporal KGA methods as benchmark configurations for comparison. These methods include TEA-GNN [3], TREA [22], STEA [23], LightTEA [24], Dual-Match [25], Simple-HHEA [1], ChatEA [2], MGTEA [5], AdaCoAgentEA [20], Self-Consistency [20], [21], and Self-RAG [20], [21].
 - TEA-GNN [3] treats timestamps as link attributes, using a time-aware attention mechanism to enrich entity and relation representations. It explicitly models temporal dynamics to capture how entities evolve over time.
 - TREA [22] enhances training using neighborhood aggregation and margin-based multi-class loss. It incorporates temporal information into the relational structure, enabling more accurate alignment in temporal knowledge graphs.
 - STEA [23] utilizes a temporal dictionary to guide temporal alignment. It maintains explicit temporal mappings that help identify corresponding entities across different time periods in temporal KGs.
 - LightTEA [24] is designed as a lightweight temporal knowledge graph alignment model. Although it aims for efficiency, its temporal component has shown limited improvements on existing datasets, suggesting room for

TABLE II

MAIN EXPERIMENT RESULTS ON MTKGA-WILD AND TKGA DATASETS. BEST RESULTS ARE HIGHLIGHTED IN *bold*, WHILE RUNNER-UP RESULTS ARE *underlined*. “*Struc.*, *Text.*, *Imag.*, *Audi.*, *Vide.*” INDICATES THAT THE METHOD CAN PROCESS STRUCTURAL INFORMATION, TEXT SEMANTICS, IMAGE INFORMATION, AUDIO INFORMATION, AND VIDEO INFORMATION, RESPECTIVELY.  DENOTES WHETHER THE MODEL IS CAPABLE OF PERCEIVING TEMPORAL INFORMATION.  AND  INDICATE WHETHER THE MODEL UTILIZES LARGE LANGUAGE MODELS, RESPECTIVELY. THESE CONVENTIONS APPLY TO ALL SUBSEQUENT TABLES.

Method	Modality				WildMTKGA (W-I)			WildMTKGA (Y-I)			ICEWS-WIKI			ICEWS-YAGO				
	Struc. Text.	Imag.	Audi.	Vide.	Hits@1	Hits@10	MRR	Hits@1	Hits@10	MRR	Hits@1	Hits@10	MRR	Hits@1	Hits@10	MRR		
Uni-modal Static KGA Methods																		
  MTransE					0.015	0.155	0.061	0.008	0.081	0.032	0.021	0.158	0.068	0.012	0.084	0.040		
  AlignE	✓				0.054	0.261	0.119	0.010	0.112	0.046	0.057	0.261	0.122	0.019	0.118	0.055		
  BootEA	✓				0.053	0.261	0.123	0.009	0.099	0.046	0.072	0.275	0.139	0.020	0.120	0.056		
  GCN-Align	✓				0.043	0.183	0.086	0.016	0.075	0.037	0.046	0.184	0.093	0.017	0.085	0.038		
  Dual-AMN (<i>basic</i>)	✓				0.065	0.282	0.130	0.012	0.134	0.063	0.077	0.285	0.143	0.032	0.147	0.069		
  Dual-AMN (<i>semi-supervised</i>)	✓				0.026	0.175	0.084	0.015	0.080	0.023	0.037	0.188	0.087	0.020	0.093	0.045		
  RDGCN	✓	✓			0.050	0.191	0.088	0.016	0.079	0.031	0.064	0.202	0.096	0.029	0.097	0.042		
  Dual-AMN (<i>name</i>)	✓	✓			0.064	0.243	0.130	0.012	0.112	0.038	0.083	0.281	0.145	0.031	0.144	0.068		
  BERT		✓	✓		0.341	0.503	0.480	0.360	0.512	0.451	0.546	0.687	0.596	0.749	0.845	0.784		
  FuAlign		✓	✓		0.252	0.466	0.329	0.299	0.571	0.414	0.257	0.570	0.361	0.326	0.604	0.423		
  BERT-INT		✓	✓		0.424	0.510	0.486	0.373	0.572	0.488	0.561	0.700	0.607	0.756	0.859	0.793		
  PARIS		✓	✓		0.431	-	-	0.513	-	-	0.672	-	-	0.687	-	-		
  Naive RAG *		✓	✓		0.463	-	-	0.545	-	-	0.723	-	-	0.736	-	-		
Uni-modal Temporal KGA Methods																		
  TEA-GNN		✓			0.043	0.240	0.114	0.014	0.104	0.063	0.063	0.253	0.126	0.025	0.135	0.064		
  TREA		✓			0.070	0.270	0.129	0.019	0.138	0.036	0.081	0.302	0.155	0.033	0.150	0.072		
  STEA		✓			0.072	0.249	0.126	0.019	0.119	0.035	0.079	0.292	0.152	0.033	0.147	0.073		
  Dual-Match		✓	✓		0.035	0.200	0.096	0.018	0.111	0.049	0.043	0.204	0.096	0.022	0.114	0.053		
  Simple-HHEA		✓	✓		0.509	0.641	0.573	0.517	0.675	0.597	0.720	0.872	0.754	0.847	0.915	0.870		
  Simple-HHEA (<i>structure</i>)		✓	✓		0.514	0.640	0.567	0.534	0.648	0.561	0.639	0.812	0.697	0.749	0.864	0.775		
  ChatEA		✓	✓		0.590	0.685	0.611	<u>0.622</u>	0.713	<u>0.699</u>	<u>0.880</u>	<u>0.945</u>	<u>0.912</u>	<u>0.935</u>	<u>0.955</u>	<u>0.944</u>		
  MGTEA		✓	✓		0.421	0.500	0.471	0.417	0.516	0.442	0.534	0.693	0.627	0.673	0.780	0.704		
  AdaCoAgentEA (<i>supervised</i>)		✓	✓		<u>0.625</u>	<u>0.736</u>	<u>0.683</u>	0.621	<u>0.794</u>	0.685	0.844	0.882	0.861	0.872	0.914	0.889		
  Self-Consistency *		✓	✓		0.372	-	-	0.419	-	-	0.718	-	-	0.725	-	-		
Self-RAG *		✓	✓		0.476	-	-	0.592	-	-	0.772	-	-	0.762	-	-		
Multi-modal Static KGA Methods																		
  EVA		✓	✓	✓	0.443	0.546	0.475	0.391	0.471	0.421	-	-	-	-	-	-		
  MEAformer		✓	✓	✓	0.534	0.621	0.583	0.503	0.657	0.564	-	-	-	-	-	-		
  MMKG-CoT *		✓	✓	✓	0.501	-	-	0.530	-	-	0.618	-	-	0.626	-	-		
MMKG-RAG *		✓	✓	✓	0.551	-	-	0.588	-	-	0.682	-	-	0.697	-	-		
  EvoWildAlign (Ours)		✓	✓	✓	✓	✓	0.818	0.871	0.836	0.829	0.897	0.861	0.988	0.997	0.991	0.979	0.997	0.987

enhancement in temporal modeling.

- Dual-Match [25] employs a temporal encoder for unsupervised layer-wise propagation. It processes temporal information through multiple layers, gradually refining entity representations by incorporating temporal patterns without requiring extensive supervision.
- Simple-HHEA [1] is a representation learning-based approach tailored for aligning heterogeneous and temporal knowledge graphs. It addresses both structural heterogeneity and temporal dynamics in a unified framework.
- ChatEA [2] applies large language models with fine-tuning to perform advanced knowledge graph alignment. It leverages the reasoning capabilities of LLMs and adapts them specifically for the entity alignment task through targeted fine-tuning.
- MGTEA [5] proposes a simple yet effective multi-granularity approach for temporal alignment. It captures temporal information at different levels of granularity, from fine-grained timestamps to coarse-grained temporal periods.
- AdaCoAgentEA [20] represents an adaptive

coordination-based agent approach for entity alignment, incorporating both structural and temporal information through coordinated multi-agent learning strategies.

- Self-Consistency [20], [21] is a chain-of-thought baseline that produces multiple reasoning paths and selects the most frequent answer as the final output. In the implementation, it is enhanced by using the top-1 most similar entity from the similarity matrix produced by Simple-HHEA as a preprocessing step for the knowledge graph.
- Self-RAG [20], [21] is a self-reflective Retrieval-Augmented Generation method aimed at improving the generation quality of large language models. It incorporates self-reflection mechanisms that enable the model to critique and refine its own outputs during the alignment process.
- **Multi-modal Static KGA Methods:** We collect 5 state-of-the-art uni-modal static KGA methods as benchmark configurations for comparison. These methods include EVA [26], MMEA [8], MEAformer [8], MMKG-CoT [27], and MMKG-RAG [19].

- EVA [26] is a multi-modal entity alignment method that incorporates visual information alongside structural and textual features, enabling alignment across knowledge graphs with rich multi-modal attributes.
- MMEA [8] leverages multiple modalities including text, images, and structure to perform entity alignment, addressing the challenge of aligning KGs with diverse information types.
- MEAformer [8] is a transformer-based multi-modal entity alignment framework that uses attention mechanisms to effectively fuse information from different modalities for improved alignment performance.
- MMKG-CoT [27] applies chain-of-thought reasoning to multi-modal knowledge graph alignment, enabling step-by-step reasoning over multi-modal entity features.
- MMKG-RAG [19] combines multi-modal knowledge graphs with Retrieval-Augmented Generation, retrieving relevant multi-modal information to support LLM-based entity alignment decisions.

3) **Evaluation Protocol and Implementation Details:** To evaluate the quality of MTKGA-Wild produced by EvoWildAlign and the benchmark configurations, we follow established conventions [1], [4] and use Hits@1/5/10 and Mean Reciprocal Rank (MRR) as evaluation metrics. Since some models provide only final alignment results, Hits@1 is replaced with precision for evaluation consistency. Additionally, we use runtime (in seconds) as an efficiency metric. For the multi-modal static KGA benchmark dataset, we use 20% as the training set. For all other benchmark datasets, we follow the 3:7 splitting ratio for training/testing data. All baseline methods with * follow the same preprocessing procedure to obtain pseudo-labels for use as input by *neural retrieval*.

All LLMs reported in Table II and Table III are implemented using the same model version, GPT-4 (gpt-4-0125-preview). For subsequent experiments, unless otherwise specified, GPT-3.5 (gpt-3.5-turbo-1106) is used as the default LLM configuration due to its lower computational cost. All experiments are conducted on a server equipped with four NVIDIA GeForce RTX 4090 graphics cards, each featuring 24GB of GDDR6X memory. The system is powered by a 64-core processor and 480GB of system RAM. For storage, the server employs a 30GB system disk and a 50GB solid-state drive (SSD) for data storage. All experiments are implemented using the PyTorch framework. Note that we do not employ multi-modal LLMs due to cost considerations. In our methodology, multi-modal information is converted into textual format for processing, enabling unified handling through text-based LLMs. For the *neural retrieval* component, we set the retrieval depth to top- $k = 5$. The codebase is implemented in Python 3.8 with PyTorch 1.12.0, LangChain 0.1.0, and FAISS for vector indexing. More details can be found in the code.

B. Main Experiment Results (RQ1 & RQ2)

1) **Comparison with All Configurations:** As shown in Table II and Table III, to address **RQ1**, we have performed

a comprehensive comparison. The experiments demonstrate that EvoWildAlign significantly outperforms all benchmark configurations across all datasets, achieving up to 33.2% improvement in Hits@1. These results yield several key observations:

- **Comparison with Uni-modal Static KGA Configurations.** First, we compared methods within uni-modal static KGA configurations that utilize structural information, structural and semantic information, or structural information alone. Notably, EvoWildAlign’s performance significantly surpasses all these configurations. Specifically, it improves the overall performance on the WildMTKGA (W-I) and WildMTKGA (Y-I) datasets, achieving up to 76.7% relative improvement in Hits@1 compared to the state-of-the-art baseline configuration Naive RAG. This indicates that EvoWildAlign effectively addresses the evolutionary diversity challenge by jointly modeling temporal dynamics and multi-modal information, which static uni-modal methods fail to capture.
- **Comparison with Uni-modal Temporal KGA Configurations.** Subsequently, we compared methods within uni-modal temporal KGA configurations that leverage structural information, structural and semantic information, or structural information alone. EvoWildAlign’s performance likewise significantly outperforms all these configurations. Specifically, it improves the overall performance on the WildMTKGA (W-I) and WildMTKGA (Y-I) datasets, achieving up to 33.2% relative improvement in Hits@1 compared to the state-of-the-art baseline configuration AdaCoAgentEA. This demonstrates that EvoWildAlign effectively handles the dynamic imbalance challenge through adaptive fusion of diverse evolving modalities, which uni-modal temporal methods cannot adequately address.
- **Comparison with Multi-modal Static KGA Configurations.** We also compared current state-of-the-art and classical Multi-modal Static KGA Configurations. EvoWildAlign’s performance significantly exceeds all these configurations. Specifically, it improves the overall performance on the WildMTKGA (W-I) and WildMTKGA (Y-I) datasets, achieving up to 48.5% relative improvement in Hits@1 compared to the state-of-the-art baseline configuration MMKG-RAG. This indicates that EvoWildAlign successfully integrates temporal evolution patterns with multi-modal characteristics, overcoming the limitations of static multi-modal methods that ignore temporal dynamics.
- **Comparing with LLM-based Configurations.** Finally, we compared seven advanced LLM-based methods (e.g., Naive RAG, ChatEA, AdaCoAgentEA, MMKG-RAG) under different configurations. We observe that our method consistently outperforms all LLM-based approaches, including CoT-based methods, retrieval-augmented generation methods, self-feedback methods, and multi-agent collaboration methods. This finding underscores the importance of formulating the MTKGA-Wild task as an agentic hypergraph col-

TABLE III
MORE EXPERIMENT RESULTS ON DBP15K (EN-FR), DBP-WIKI, BETA AND YAGO-WIKI50K-1K (YWLK) DATASETS.

Method	Modality				DBP15K (EN-FR)			DBP-WIKI			BETA			YAGO-WIKI50K-1K (YWLK)			
	Struc.	Text.	Imag.	Audi.	Vide.	Hits@1	Hits@10	MRR	Hits@1	Hits@10	MRR	Hits@1	Hits@10	MRR	Hits@1	Hits@10	MRR
Uni-modal Static KGA Methods																	
🗄️🗄️MTransE						0.247	0.577	0.360	0.281	0.520	0.363	0.033	0.108	0.060	0.037	0.122	0.067
🗄️🗄️AlignE	✓					0.481	0.824	0.599	0.566	0.827	0.655	0.229	0.424	0.296	0.552	0.704	0.605
🗄️🗄️GCN-Align	✓					0.411	0.772	0.530	0.494	0.756	0.590	0.121	0.270	0.172	0.046	0.140	0.079
🗄️🗄️Dual-AMN (basic)	✓					0.756	0.948	0.827	0.786	0.952	0.848	0.496	0.695	0.566	0.757	0.895	0.806
🗄️🗄️Dual-AMN (name)	✓	✓				0.954	0.994	0.970	0.983	0.996	0.991	0.507	0.729	0.571	0.766	0.923	0.807
🗄️🗄️BERT			✓			0.937	0.985	0.956	0.941	0.980	0.963	0.526	0.753	0.632	0.810	0.934	0.848
🗄️🗄️FuAlign	✓	✓				0.936	0.988	0.955	0.980	0.991	0.986	0.552	0.774	0.691	0.856	0.929	0.877
🗄️🗄️Naive RAG *	✓	✓	✓			0.643	-	-	0.696	-	-	0.588	-	-	0.102	-	-
Uni-modal Temporal KGA Methods																	
🗄️🕒TEA-GNN	✓					-	-	-	-	-	-	0.557	0.709	0.611	0.723	0.870	0.775
🗄️🕒STEA	✓					-	-	-	-	-	-	0.506	0.637	0.553	0.887	0.965	0.916
🗄️🕒LightTEA	✓	✓	✓			-	-	-	-	-	-	0.615	0.727	0.654	<u>0.966</u>	<u>0.988</u>	<u>0.975</u>
🗄️🕒Dual-Match	✓	✓	✓			-	-	-	-	-	-	0.650	0.765	0.690	0.945	0.984	0.960
🗄️🕒Simple-HHEA						0.948	0.991	0.960	0.967	0.988	0.979	0.762	0.835	0.797	0.156	0.368	0.209
🗄️🕒Simple-HHEA (structure)	✓	✓	✓			0.959	0.995	0.972	0.975	0.991	0.988	0.730	0.808	0.751	0.121	0.303	0.170
🗄️🗄️ChatEA	✓	✓	✓			<u>0.990</u>	1.000	<u>0.995</u>	<u>0.995</u>	1.000	0.998	0.798	0.883	0.851	0.657	0.893	0.737
🗄️🕒MGTEA	✓	✓	✓			0.432	0.762	0.551	0.552	0.783	0.626	0.686	0.795	0.724	0.947	0.982	0.960
🗄️🗄️AdaCoAgentEA (supervised)	✓	✓	✓			0.986	0.995	0.992	0.987	0.993	0.990	<u>0.819</u>	<u>0.893</u>	<u>0.875</u>	0.901	0.964	0.924
🗄️🕒Self-Consistency *	✓	✓				0.678	-	-	0.695	-	-	0.456	-	-	0.094	-	-
🗄️🕒Self-RAG *	✓	✓	✓			0.712	-	-	0.752	-	-	0.633	-	-	0.175	-	-
🗄️🕒EvoWildAlign (Ours)	✓	✓	✓	✓	✓	0.992	1.000	0.996	0.997	<u>0.999</u>	0.998	0.953	0.972	0.961	0.982	0.996	0.985

laboration problem to enhance overall performance through structured neuro-symbolic reasoning and adaptive multi-agent coordination.

2) Evaluation of Task Value and Dataset Challenge:

Furthermore, we conducted a comprehensive analysis of the WildMTKGA (W-I) and WildMTKGA (Y-I) datasets, focusing on their challenges and practical utility to validate the value of the MTKGA-Wild task. As shown in Table II and Table III, the results indicate substantial room for improvement in overall performance, as evidenced by the Hits@1 of the state-of-the-art benchmark configurations, with Hits@1 scores of only 0.625 and 0.622 for WildMTKGA (W-I) and WildMTKGA (Y-I), respectively. These results also demonstrate that current benchmark configurations, whether uni-modal static KGA, uni-modal temporal KGA, or multi-modal static KGA methods, are unable to address the challenges of *evolutionary diversity* and *dynamic imbalance* posed by the new MTKGA-Wild task. Notably, in related research tasks such as uni-modal static KGA, uni-modal temporal KGA, and multi-modal static KGA, the performance of most models exceeds 0.9 in many cases [2], [5], [8], [20], and even approaches 100%. These findings highlight the intrinsic difficulty and value of this task, indicating that numerous unresolved challenges remain.

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