HyDRA: Temporal Knowledge Graph Alignment in the Wild
Technical Report

Abstract—**This technical report contains the full experimental setup of the paper "HyDRA: Temporal Knowledge Graph Alignment in the Wild".**

I. Experiments

In this section, we first introduce the experimental setting[1] in Section I-A.

A. Experimental Setting

Datasets. In our experiments, we conducted comprehensive evaluations on **eight datasets**, including `BETA`, `WildBETA`, and 6 current datasets (as detailed in Table I).

Among these, `DICEWS` and `YAGO-WIKI50K` are the most frequently used datasets for Temporal Knowledge Graph Alignment (TKGA), derived from `ICEWS05-15`, `YAGO`, and `Wikidata`. Specifically, `ICEWS05-15` is constructed from the `ICEWS` dataset [4], which comprises political events annotated with specific dates, using a daily temporal resolution and covering the period from 2005 to 2015. Xu et al. [3] randomly partitioned the quadruples in `ICEWS05-15` into two equally sized subsets with a 50% entity overlap, yielding the datasets `DICEWS-200` (`D200`) and `DICEWS-1K` (`D1K`). These subsets differ in the number of seed alignments: 200 for `D200` and 1000 for `D1K`. The `YAGO-WIKI50K` datasets are similarly constructed by Xu et al. [3], who first selected the top 50,000 most frequent entities from a Wikidata subset (as extracted in [5]) and linked them to corresponding entities in YAGO. Temporal facts were then added to form two temporally enriched knowledge graphs. The resulting datasets, `YAGO-WIKI50K-1K` (`YW1K`) and `YAGO-WIKI50K-5K` (`YW5K`), contain 1000 and 5000 seed entity pairs, respectively.

In contrast, `ICEWS-WIKI` and `ICEWS-YAGO` [1] represent new heterogeneous and temporal datasets, posing more realistic and challenging alignment scenarios. These datasets are characterized by significant discrepancies not only in the number of entities, relations, and triples. Furthermore, the number of seeds is not directly proportional to the total entity count, adding complexity to the temporal alignment task.

In addition, two standard non-temporal KGA datasets, `DBP15K(EN-FR)` and `DBP-WIKI` [6], are also included. `DBP15K(EN-FR)` focuses on cross-lingual alignment, while `DBP-WIKI` offers a large-scale benchmark for aligning heterogeneous KGs. Both datasets exhibit similar structural properties and high overlap (100%) in aligned entities, relations, and facts.

[1]The source codes and datasets of the previous work are available at https://github.com/DexterZeng/BETA. The source codes and datasets for this extended work will be released upon acceptance

Baselines. Currently, no specific solutions exist for TKGA-Wild. To establish a comprehensive baseline, we introduced 23 SOTA and classic baseline methods for extensive comparison:

- MTransE [7], which introduces translation vectors to align entity embeddings across languages; and
- AlignE [8], which employs neural relation extraction to identify key relationships; and
- BootEA [8], which is one of the most competitive translation-based EA methods; and
- GCN-Align [9], which trains GCNs to embed entities of each language into a unified vector space; and
- MRAEA [10], which applies attention over local neighborhoods and relation-level meta-information; and
- RREA [11], which implements relational reflection transformations to generate relation-aware embeddings; and
- RDGCN [12], which leverages GCNs for modeling structural information within knowledge graphs.
- Dual-AMN [13], which iointly captures intra-graph and cross-graph dependencies; and
- TEA-GNN [3], which treats timestamps as link attributes, using a time-aware attention mechanism to enrich entity and relation representations; and
- TREA [14], which enhances training using neighborhood aggregation and margin-based multi-class loss; and
- STEA [15], which utilizes a temporal dictionary to guide temporal alignment; and
- Dual-Match [16], which employs a temporal encoder for unsupervised layer-wise propagation; and
- MGTEA [17], which proposes a simple yet effective multi-granularity approach for temporal alignment; and
- LightTEA [18], which is a lightweight TKGA model, though its temporal component yields limited improvements on existing datasets; and
- BERT [19], utilized as a pretrained language model to initialize entity embeddings using name-based features; and
- FuAlign [20], which incorporates auxiliary information to address KG heterogeneity; and
- BERT-INT [21], which combines BERT-based augmentation with auxiliary cues for improved alignment; and

TABLE I: Dataset statistics [1]–[3]. "*#Ent*", "*#Rel.*", "*#Facts*", "*#T.Facts*": The number of entities, relations, quadruples and quadruples with valid time interval in KG1 (KG2), respectively. "*Temp.*", "*Multi-Granularity*": Indicates whether the dataset includes temporal knowledge information and the dataset includes multi-granularity temporal knowledge information. "*Multi-Source*", "*MTE.%*": Refers to whether both TKGs in the dataset are temporal incompleteness, and the average proportion of valid temporal facts in the two TKGs, respectively. "Δ F.%", "Δ D.%": Relative difference in facts/density values between two KGs, using the KG with the smaller facts/lower density as the base.

Dataset		#Ent.	#Rel.	Temp.	Multi-Granularity	#Seed	Overlapping ⇓	Inter. Consis. ⇓	#Facts	#T.Facts	Multi-Source	MTF.% ⇓	Δ F.% ⇑	#Density	Δ D.% ⇑
DBP15K(EN-FR)	EN FR	15,000 15,000	193 166	✗ ✗	✗ ✗	15,000	100% 100%	✗	96,318 80,112	0 0	✗	✗	20.2%	6.421 5.341	20.2%
DBP-WIKI	DBP WIKI	100,000 100,000	413 261	✗ ✗	✗ ✗	100,000	100% 100%	✗	293,990 251,708	0 0	✗	✗	16.8%	2.940 2.517	16.8%
ICEWS-WIKI	ICEWS WIKI	11,047 15,896	272 226	✓ ✓	✗ ✗	5,058	45.79% 31.82%	1.3%	3,527,881 198,257	3,527,881 51,002	✗	96.05%	1,679.4%	319.352 12.472	2,460.6%
ICEWS-YAGO	ICEWS YAGO	26,863 22,734	272 41	✓ ✓	✗ ✗	18,824	70.07% 82.80%	0.9%	4,192,555 107,118	4,192,555 30,240	✗	98.21%	3,814.0%	156.072 4.712	3,212.2%
DICEWS	ICEWS ICEWS	9,517 9,537	247 246	✓ ✓	✗ ✗	8,566	90.01% 89.82%	70.6%	307,552 307,553	307,552 307,553	✗	100%	0%	64.632 64.497	0.2%
YAGO-WIKI50K	YAGO WIKI	49,629 49,222	11 30	✓ ✓	✗ ✗	49,172	99.08% 99.90%	50.3%	221,050 317,814	221,050 317,814	✗	100%	43.8%	8.908 12.913	45.0%
BETA	WIKI YAGO	42,666 42,297	257 45	✓ ✓	✓ ✓	40,364	94.60% 95.43%	0.2%	199,879 162,320	104,774 69,896	✓	48.22%	23.1%	9.369 7.675	22.1%
WildBETA	WIKI YAGO	20,234 21,148	290 35	✓ ✓	✓ ✓	5,304	**26.21%** **25.08%**	**0.1%**	386,758 3,038	102,064 1,587	✓	**26.59%**	**12,630.7%**	38.124 1.132	**3,267.8%**

- PARIS [22], which is a probabilistic iterative method capable of aligning entities without prior alignments; and
- Simple-HHEA [1], which is a representation learning-based approach tailored for aligning heterogeneous and temporal KGs; and
- ChatEA [2], which applies large language models with fine-tuning to perform advanced KG alignment; and
- Naive RAG [23], [24], a basic LLM-based RAG approach that first retrieves relevant information based on a user query and then generates answers using the retrieved content; and
- Self-Consistency [25], a chain-of-thought baseline that produces multiple reasoning paths and selects the most frequent answer as the final output. In our implementation, we further enhance it by using the top-1 most similar entity from the similarity matrix produced by Simple-HHEA as a preprocessing step for the knowledge graph; and
- Self-RAG [26], a self-reflective RAG method aimed at improving the generation quality of LLMs.

Implementation details. All experiments were conducted on a server equipped with four NVIDIA GeForce RTX 4090 graphics cards, each with 24 GB of GDDR6X memory. The system features a 64-core processor and 480 GB of RAM. For storage, the server utilizes a 30 GB system disk alongside a 50 GB solid-state drive (SSD) for data storage. All implementations were carried out using the PyTorch framework.

The large language models (LLMs) reported in Table III and Table IV were evaluated under identical settings, employing GPT-4[2], except for ChatEA, which directly follows the results reported in its original paper. For subsequent experiments, unless otherwise specified, GPT-3.5[3] was adopted as the default LLM owing to its cost-effectiveness.

The multi-granular information encoders and the integrated training were configured with a learning rate of 0.01, a weight decay of 0.001, gamma set to 1.0, and were trained for 500 epochs.

Evaluation metrics. Consistent with prior benchmark studies [1], [6], we adopt two widely recognized evaluation metrics to assess the effectiveness of entity alignment models: Hits@k and Mean Reciprocal Rank (MRR).

1) Hits@k evaluates the proportion of correctly aligned entity pairs that appear among the top-k ranked candidates. Formally, let N denote the total number of reference (ground truth) alignments, and for each reference entity e_i, let rank_i denote the rank position of its correct counterpart in the candidate list. The Hits@k is defined as:

$$\text{Hits@}k = \frac{1}{N}\sum_{i=1}^{N}\mathbb{I}(\text{rank}_i \leq k), \tag{1}$$

where $\mathbb{I}(\cdot)$ is the indicator function, which returns 1 if the condition is true and 0 otherwise. In practice, Hits@1 reflects the strict accuracy of top-1 predictions, while Hits@10 provides insight into broader top-k retrieval performance.

2) Mean Reciprocal Rank (MRR) measures the average of the reciprocal ranks of the correct entities in the prediction lists. It is computed as:

$$\text{MRR} = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{\text{rank}_i}. \tag{2}$$

MRR captures both the presence and position of correct alignments, thereby emphasizing early correct retrieval.

Both metrics are positively oriented, meaning higher values indicate better alignment quality. Notably, in cases where models yield only the final alignment predictions (i.e., without ranked candidate lists), the Hits@1 score is substituted with standard precision.

[2] gpt-4-0125-preview from the OpenAI API, https://openai.com/api/
[3] gpt-3.5-turbo-1106 from the OpenAI API, https://openai.com/api/

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