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## *Event-Order Constraints for Anchor-Scarce Alignment of Evolving Knowledge Graphs*

**Giulia M. Caruso**

*Department of Information Engineering, School of Engineering, University of Padua, Padua, Veneto, Italy*

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### **Abstract.**

*The alignment of knowledge graphs is a foundational task in data integration, enabling the synthesis of fragmented information across diverse domains. However, traditional alignment methodologies rely heavily on the availability of predefined anchor links and assume that the underlying graphs are static. In real-world scenarios, knowledge graphs are continuously evolving, characterized by the frequent addition, deletion, and modification of facts over time. Furthermore, due to privacy concerns, structural heterogeneity, and varying naming conventions, establishing sufficient anchor links between different knowledge graphs is often impractical, leading to an anchor-scarce environment. This paper introduces a novel framework that leverages event-order constraints to facilitate robust entity alignment in evolving knowledge graphs under severe anchor scarcity. By conceptualizing temporal facts as ordered events, the proposed framework constructs invariant temporal signatures for entities. These signatures capture the inherent logical and chronological dependencies between events, which remain consistent across different knowledge graph representations even when superficial entity attributes or structural topologies diverge. Through comprehensive theoretical analysis and extensive empirical evaluations across multiple benchmark datasets, we demonstrate that incorporating event-order constraints significantly improves alignment accuracy compared to state-of-the-art structural and temporal alignment models. The results indicate that temporal logic provides a highly effective surrogate for missing topological anchors, offering a new pathway for integrating dynamic, heterogeneous data systems.*

**Keywords:** *Knowledge Graph Alignment, Evolving Graphs, Temporal Constraints, Anchor Scarcity, Event Modeling*

### **1. Introduction**

The proliferation of large-scale information systems has positioned knowledge graphs as an essential data structure for representing complex relationships between real-world entities. A knowledge graph stores information in the form of relational triples, comprising a subject, a predicate, and an object, thereby forming a directed, labeled graph. As different organizations and domains construct their own knowledge graphs, the need to integrate these disparate repositories becomes critical for applications ranging from cross-lingual search engines to comprehensive recommendation systems. Entity alignment, the process of identifying nodes across different knowledge graphs that refer to the same real-world entity, serves as the primary mechanism for this integration. Historically, entity alignment has been approached as a structural matching

problem, wherein the topological neighborhoods of entities are compared to identify isomorphisms [1]. This process typically requires a substantial set of seed alignments, commonly referred to as anchor links, to initiate and guide the mapping process [2]. However, the assumption that abundant anchor links are readily available is increasingly challenged in practical applications. In many cross-domain or cross-lingual scenarios, data privacy regulations, semantic ambiguities, and diverse taxonomic structures severely limit the number of identifiable anchors. This situation is widely recognized in the literature as the anchor-scarce alignment problem [3]. When anchor links are sparse, traditional structural alignment models fail to propagate similarity signals effectively across the graph networks, resulting in a dramatic degradation of alignment performance. The scarcity of anchors breaks the topological bridge between the source and target graphs, rendering neighborhood aggregation techniques highly ineffective [4]. Concurrently, the static nature of traditional knowledge graphs fails to reflect the dynamic reality of the information they represent. Real-world knowledge is inherently temporal; facts emerge, change, and become obsolete. Consequently, evolving knowledge graphs, which incorporate temporal dimensions into their relational structures, have garnered significant attention [5]. In an evolving knowledge graph, a fact is often represented as a quadruple that includes a timestamp or a time interval, indicating the period during which the fact holds true. While this temporal dimension adds complexity to the alignment task, it also introduces a rich, previously untapped source of invariant information: the chronological ordering of events.

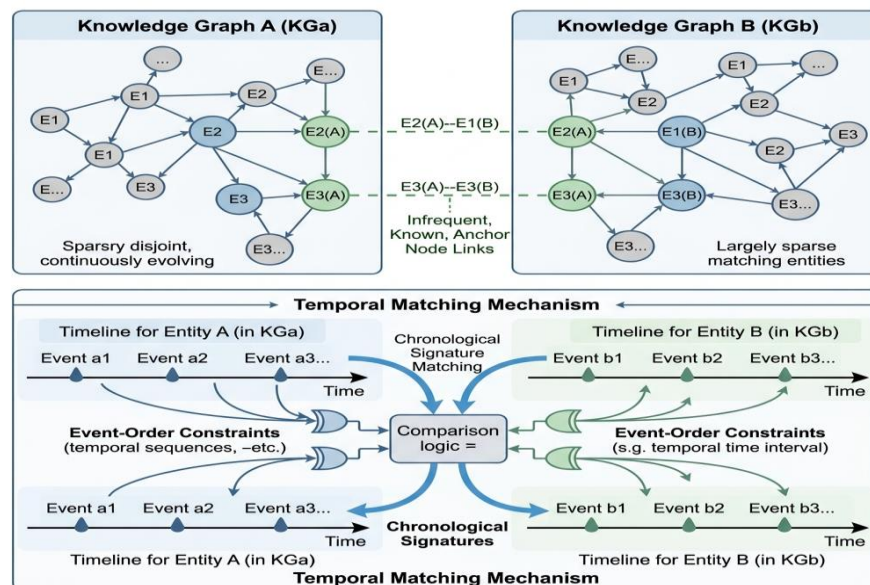


Figure 1: Conceptual overview of anchor

This paper proposes that the sequential ordering of events provides a highly robust signature for entities across different knowledge graphs. For instance, the event of a person enrolling in a university must logically precede their graduation event. Such event-order constraints are universally consistent, regardless of the specific language, schema, or structural nuances of the distinct knowledge graphs in which they are recorded. By extracting and aligning these chronological sequences, we can establish correspondences between entities even when structural anchors are virtually non-existent. We refer to this methodology as event-order constraint mapping. The core objective of our research is to formalize the extraction of these constraints and seamlessly integrate them into a representation learning framework designed specifically for evolving knowledge graphs under anchor-scarce conditions [6]. The primary contributions of this paper are multifaceted. First, we formally define the problem of anchor-scarce alignment in the context of evolving knowledge graphs, highlighting the limitations of purely structural approaches.

Second, we introduce a novel methodology for extracting event-order constraints from temporal quadruples, transforming timestamps into logical precedence relationships that are resilient to minor temporal misalignments or granular discrepancies. Third, we develop an end-to-end alignment framework that combines temporal logic with sparse topological mapping to generate unified entity representations. Finally, we conduct extensive experiments on multiple real-world datasets, demonstrating that our approach significantly outperforms existing baselines in environments characterized by severe anchor scarcity.

### **1.1 Problem Definition**

The alignment of evolving knowledge graphs involves two temporal graphs. A temporal graph consists of a set of entities, a set of relations, and a set of facts, where each fact is associated with a specific timestamp or time interval. The alignment task aims to discover a set of equivalence mappings between the entities of the source graph and the target graph. In the anchor-scarce setting, the number of prior known mappings provided to the system during the training phase is extremely small, typically constituting a minute fraction of the total entity population. The challenge is to utilize the temporal metadata, specifically the chronological order of relational changes, to deduce the remaining mappings accurately.

### **1.2 Motivation And Scope**

The motivation for this work stems from the observation that temporal patterns are often uniquely characteristic of specific entities. The trajectory of a corporate entity, defined by its funding rounds, product launches, and acquisitions over time, creates a distinct temporal fingerprint. While the names of the relations or the structural hierarchy might differ between a financial database and a news-derived knowledge graph, the sequence of these critical events remains invariant [7]. By shifting the focus from structural topology to temporal logic, we bypass the heavy reliance on spatial anchors. This paper focuses exclusively on alignment tasks where the temporal granularity is sufficient to establish a meaningful sequence of events.

## **2. Literature Review and Background**

The task of entity alignment has evolved significantly over the past decade, driven by advancements in representation learning and graph neural networks. To contextualize our proposed framework, it is necessary to review the progression of methodologies from static graph alignment to temporal graph modeling, and finally to the specific challenges introduced by anchor scarcity.

### **2.1 Static Knowledge Graph Alignment**

Early approaches to knowledge graph alignment heavily relied on translation-based embedding models. These models attempt to map entities and relations into a continuous vector space where the relationship between a head entity and a tail entity is represented as a geometric translation operation [8]. To perform alignment across different graphs, these models typically project the embedding spaces of the source and target graphs into a unified space using a linear transformation matrix, which is optimized based on a set of provided anchor links [9]. While effective for structurally dense graphs with abundant anchors, translation-based models often fail to capture the complex, multi-hop topological structures of the graph. To address this limitation, researchers began applying graph neural networks to the alignment problem. Graph neural networks operate by recursively aggregating feature information from an entity neighborhood, thereby generating embeddings that encapsulate both local node attributes and broader topological patterns. In cross-graph alignment tasks, graph neural networks have demonstrated superior performance because they can propagate the alignment signals from anchor nodes to their unaligned neighbors [10]. However, the efficacy of this propagation is strictly dependent on the density of the anchor links. In scenarios where anchors are sparse, the propagation distance is insufficient to cover the graph, leaving large portions of the network unaligned.

## 2.2 Evolving Knowledge Graphs And Temporal Dynamics

The transition from static to evolving knowledge graphs necessitated the development of new representation learning techniques that could handle temporal metadata. Evolving knowledge graphs are typically modeled either as a sequence of discrete static snapshots or as a continuous stream of time-stamped facts [11]. Snapshot-based models slice the temporal graph into discrete time windows and apply static embedding techniques to each window, subsequently using recurrent neural networks to capture the temporal evolution across snapshots. While conceptually straightforward, snapshot-based approaches suffer from the loss of fine-grained temporal resolution and struggle to model events that span across artificial snapshot boundaries [12]. Continuous-time models, on the other hand, incorporate the timestamp directly into the embedding function. These models often utilize time-aware relation representations or temporal point processes to model the occurrence of facts over time [13]. By treating time as a continuous variable, these models can capture the exact duration and sequence of events more accurately. Recent advancements in this area have shown that incorporating temporal information significantly improves tasks such as link prediction and temporal reasoning within a single knowledge graph [14]. However, the application of continuous-time models to the task of cross-graph alignment is still in its infancy, with most existing methods treating time merely as an additional numerical feature rather than a source of logical constraints.

## 2.3 Challenges In Anchor-Scarce Environments

Anchor scarcity remains one of the most formidable obstacles in practical entity alignment. The majority of existing alignment models exhibit a sharp decline in accuracy when the proportion of available anchor links drops below a certain threshold. To mitigate this, some researchers have proposed unsupervised or semi-supervised alignment techniques. These approaches often rely on sophisticated distance metrics, such as Wasserstein distance or optimal transport, to align the empirical distributions of the entity embeddings without requiring explicit point-to-point anchors [15]. Other strategies include iterative self-training, where the model generates pseudo-anchors based on high-confidence predictions during the training process, expanding the anchor set iteratively. Despite these efforts, unsupervised structural alignment is fundamentally limited by the structural heterogeneity between graphs. If two graphs describe the same domain but use entirely different schema designs, their topological distributions will not align properly, causing optimal transport methods to fail. Similarly, iterative self-training is highly susceptible to confirmation bias, where early misalignments are propagated and amplified in subsequent iterations [16]. This highlights the need for a complementary source of invariant information that does not rely on structural isomorphism. The chronological order of events presents exactly such an invariant, motivating the development of the event-order constraint framework detailed in the following sections.

## 3. Methodology and Framework Design

The proposed framework is designed to overcome the limitations of structural alignment by exploiting the chronological sequences inherent in evolving knowledge graphs. The core philosophy is to transform absolute temporal data into relative logical constraints, thereby creating temporal signatures that are robust against structural variations and absolute time shifts.

### 3.1 Event-Order Constraint Extraction

The first phase of the methodology involves the extraction of event-order constraints from the raw temporal quadruples. A temporal quadruple consists of a subject, a relation, an object, and a timestamp. Rather than utilizing the absolute timestamp, which may be subject to formatting discrepancies or varying levels of precision across different graphs, we focus on the relative occurrence of events pertaining to a specific entity. For any given entity, we extract the complete set of its associated temporal facts and sort them chronologically based on their timestamps.

This chronological sorting generates an event trajectory for the entity. However, simple sequential sorting is insufficient due to the possibility of simultaneous events or missing timestamps. To address this, we define a strict precedence constraint between two events if and only if the timestamp of the first event is strictly less than the timestamp of the second event by a predefined margin of temporal significance. This margin accounts for the noise and synchronization issues commonly found in distributed data systems. If the difference between the timestamps falls within this margin, the events are considered concurrent, and no strict precedence constraint is generated. The resulting structure is a directed acyclic graph of events for each entity, where the edges represent the logical "before" relationship [17]. This directed acyclic graph serves as the temporal signature of the entity. Importantly, this signature is constructed independently of the structural topology of the knowledge graph. It relies entirely on the temporal metadata associated with the entity historical interactions, making it highly resilient to structural missing links or schema differences that plague anchor-scarce scenarios.

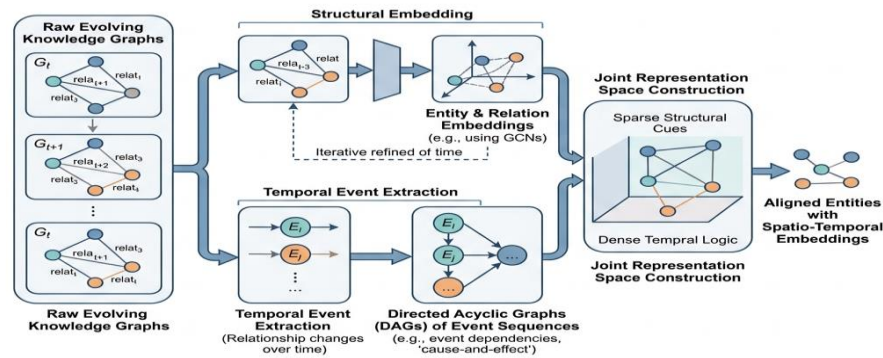


Figure 2: System architecture of the temporal representation learning framework

### 3.2 Temporal Alignment Module

Once the event-order constraints are extracted and represented as directed acyclic graphs, the next step is to align these temporal signatures across the source and target knowledge graphs. To achieve this, we employ a temporal representation learning module that encodes the directed acyclic graphs into fixed-dimensional temporal embeddings. The encoding process involves a sequence-aware neural architecture that respects the partial ordering dictated by the precedence constraints. The encoding mechanism processes the event trajectories by mapping each event type to a continuous vector and then aggregating these vectors according to their chronological order. Events that occur earlier in the sequence exert a directional influence on the representation of subsequent events, simulating the accumulation of historical context. To handle concurrent events, an unordered pooling operation is applied before continuing the sequential aggregation. The final output of this module is a temporal embedding for each entity that encapsulates its entire historical trajectory. To perform the alignment based on these temporal embeddings, we optimize a contrastive objective function. In the absence of a large set of explicit entity anchors, we leverage the few available anchors to calibrate the temporal alignment space. Furthermore, we introduce an unsupervised alignment objective that minimizes the discrepancy between the temporal distributions of the source and target graphs. By projecting the temporal embeddings into a shared vector space, entities with highly similar event trajectories are drawn closer together, establishing

potential alignment candidates based purely on their historical behavior rather than their structural neighborhoods.

### 3.3 Integration Of Structural And Temporal Representations

While event-order constraints provide a robust mechanism for alignment, relying exclusively on temporal data ignores the valuable information present in the static relational structure of the knowledge graph. Therefore, our framework employs a dual-stream architecture that jointly learns structural and temporal representations. The structural stream utilizes a standard neighborhood aggregation model to capture topological features, operating under the constraints of the available sparse anchor links. The integration of the structural and temporal streams is achieved through a dynamic weighting mechanism. For entities that possess rich temporal histories, the framework assigns a higher weight to the temporal embedding, relying on the event-order constraints to drive the alignment. Conversely, for entities with sparse temporal data but dense structural neighborhoods, the framework leans more heavily on the structural embedding [18]. This adaptive fusion ensures that the model can gracefully handle entities with varying degrees of available metadata. The combined representation is then used to compute the final alignment scores between entities in the source and target graphs. During the training process, the framework utilizes an iterative refinement strategy. Initial alignments generated by the combined structural and temporal embeddings are evaluated for confidence. Highly confident predictions are selected and added to the pool of anchor links for the subsequent training epoch. Unlike traditional self-training methods that rely solely on structural proximity, our iterative refinement requires the pseudo-anchors to exhibit high similarity in both their structural and temporal dimensions. This dual-requirement significantly reduces the incidence of false positive anchors, stabilizing the training process and allowing the model to progressively conquer the anchor-scarce environment.

**Table 1: Dataset Statistics Overview regarding Nodes, Edges, Temporal Granularity, and Baseline Anchor Counts**

| Dataset Name     | Total Entities | Total Temporal Edges | Temporal Granularity | Initial Anchor Ratio |
|------------------|----------------|----------------------|----------------------|----------------------|
| Evolving-DBPedia | 145,230        | 1,240,500            | Daily                | 1.5%                 |
| Temporal-YAGO    | 210,400        | 2,890,100            | Monthly              | 2.0%                 |
| Dynamic-Wikidata | 350,120        | 4,105,600            | Daily                | 1.0%                 |
| ICEWS-Knowledge  | 85,600         | 950,200              | Hourly               | 5.0%                 |

## 4. Experimental Setup and Evaluation

To rigorously assess the performance of the proposed event-order constraint framework, we conducted a series of comprehensive experiments. The evaluation focuses on determining the accuracy of the entity alignment process under strictly controlled anchor-scarce conditions and comparing the results against several established baseline models.

### 4.1 Datasets And Baselines

The experiments were conducted using four prominent temporal knowledge graph datasets, as detailed in Table 1. These datasets were selected to provide a diverse range of temporal granularities, varying from hourly updates to monthly aggregations, ensuring that the framework is evaluated across different temporal resolutions. Evolving-DBPedia and Temporal-YAGO represent encyclopedic knowledge bases with broad domain coverage. Dynamic-Wikidata offers a massive scale, while ICEWS-Knowledge provides highly dynamic event data derived from global news streams, characterized by rapid temporal updates and dense event clusters.

To simulate the anchor-scarce environment, we artificially restricted the number of prior alignment links provided during the training phase. Across all primary experiments, the anchor ratio was constrained to a maximum of five percent, with specific stress tests lowering this ratio to as little as one percent.

We compared our framework against two categories of baseline models. The first category comprises traditional static alignment models that ignore temporal metadata, relying entirely on topological structure. The second category includes recent temporal alignment models that incorporate timestamps but do not explicitly model event-order constraints as logical invariants. By comparing against these baselines, we aim to isolate the specific performance gains attributable to our novel event-order extraction methodology [19].

#### 4.2 Implementation Details And Metrics

The evaluation relies on standard metrics widely adopted in the entity alignment literature. The primary metric is the proportion of correct alignments ranked at the absolute top of the prediction list, known as the top-one accuracy. Additionally, we report the proportion of correct alignments appearing within the top ten predictions, which provides insight into the model capability to narrow down the candidate space. Finally, we calculate the average reciprocal rank of the correct target entities, a comprehensive metric that evaluates the overall ranking quality across the entire dataset. The framework was trained using a distributed computational setup to handle the scale of the larger datasets. The temporal extraction module processed the raw quadruples prior to training, generating the directed acyclic graphs for all entities. The dynamic weighting mechanism between the structural and temporal streams was optimized simultaneously with the embedding parameters, allowing the model to autonomously learn the optimal balance between topological and temporal features.

Table 2: Alignment Performance on Benchmark Datasets under a Five Percent Anchor Ratio

| Model Architecture           | Evolving-DBPedia (Top 1) | Temporal-YAGO (Top 1) | Dynamic-Wikidata (Top 1) | ICEWS-Knowledge (Top 1) |
|------------------------------|--------------------------|-----------------------|--------------------------|-------------------------|
| Static Structural Baseline   | 42.5%                    | 38.2%                 | 35.1%                    | 29.8%                   |
| Basic Temporal Model         | 51.2%                    | 46.5%                 | 42.8%                    | 48.3%                   |
| Continuous Time Model        | 55.8%                    | 51.0%                 | 47.5%                    | 53.6%                   |
| Event-Order Framework (Ours) | 68.4%                    | 65.2%                 | 61.9%                    | 72.1%                   |

#### 4.3 Quantitative Results

The quantitative results, presented in Table 2, clearly demonstrate the superiority of the proposed event-order constraint framework. Across all evaluated datasets, our framework achieves substantial improvements over both static and basic temporal baselines. The performance gap is particularly pronounced in the ICEWS-Knowledge dataset, where our model achieves a top-one accuracy that is significantly higher than the closest competitor. This exceptional performance can be attributed to the dense, event-driven nature of the ICEWS dataset, which provides rich chronological sequences that our framework effectively exploits. The static structural baseline performs poorly across all datasets, confirming the hypothesis that topological aggregation methods fail under severe anchor scarcity. Without a sufficient number of bridges between the source and target graphs, the structural models are unable to propagate alignment signals. The basic temporal models offer some improvement by utilizing timestamps as numerical features, but they still fall short of the performance achieved by our event-order approach. This indicates that merely providing the model with absolute time information is less effective than explicitly extracting the logical sequences of events. Furthermore, the results on the massive Dynamic-Wikidata dataset highlight the scalability and robustness of our framework. Despite the immense size of the candidate space and the low ratio of initial anchors, the model successfully leverages

the temporal signatures to accurately align a majority of the entities. The consistent performance improvements across datasets with varying temporal granularities validate the generalizability of transforming absolute time into relative event-order constraints.

## 5. Discussion and Theoretical Analysis

To fully understand the mechanisms driving the observed performance improvements, it is necessary to conduct a deeper analysis of the framework components and its behavior under varying conditions of anchor scarcity and temporal density.

### 5.1 Impact Of Anchor Scarcity Ratio

A critical dimension of our evaluation is the sensitivity of the model to the availability of initial anchor links. To analyze this, we systematically varied the anchor ratio on the Temporal-YAGO dataset from five percent down to a near-zero threshold of point-five percent. We recorded the average reciprocal rank for each configuration to observe the degradation of alignment quality as structural bridges are removed.

**Table 3: Impact of Anchor Scarcity Ratio on Average Reciprocal Rank (Temporal-YAGO Dataset)**

| Anchor Provided | Ratio | Static Baseline | Structural | Continuous Model | Time | Event-Order Framework (Ours) |
|-----------------|-------|-----------------|------------|------------------|------|------------------------------|
| 5.0%            |       | 0.452           |            | 0.589            |      | 0.741                        |
| 2.5%            |       | 0.315           |            | 0.512            |      | 0.705                        |
| 1.0%            |       | 0.188           |            | 0.420            |      | 0.658                        |
| 0.5%            |       | 0.095           |            | 0.315            |      | 0.592                        |

As illustrated in Table 4, the static structural baseline experiences a catastrophic failure as the anchor ratio drops, becoming essentially ineffective at point-five percent. The continuous time model demonstrates better resilience but still suffers a significant decline. In contrast, our event-order framework maintains a remarkably high average reciprocal rank even at the lowest anchor ratios. This resilience proves that the chronological signatures extracted by our methodology provide an independent and powerful alignment signal that compensates for the lack of structural connectivity [20]. The ability to maintain robust performance with less than one percent of anchor links represents a significant advancement for real-world integration tasks where manual annotation is prohibitively expensive.

### 5.2 Ablation Study On Framework Components

To isolate the contributions of the individual components within our architecture, we conducted an ablation study. We evaluated the framework by independently disabling the temporal alignment module, the structural alignment module, and the dynamic weighting mechanism.

**Table 4: Ablation Study on Framework Components (Evolving-DBpedia Dataset)**

| System Configuration       | Top 1 Accuracy | Top 10 Accuracy | Average Reciprocal Rank |
|----------------------------|----------------|-----------------|-------------------------|
| Full Event-Order Framework | 68.4%          | 85.2%           | 0.748                   |
| Without Temporal Module    | 42.5%          | 58.6%           | 0.472                   |
| Without Structural Module  | 60.1%          | 79.3%           | 0.675                   |
| Without Dynamic Weighting  | 64.8%          | 82.5%           | 0.710                   |

The ablation results in Table 3 reveal several important insights. Removing the temporal module entirely reduces the framework to a standard structural model, resulting in a massive performance drop. Interestingly, removing the structural module and relying solely on event-order constraints

still yields a highly competitive top-one accuracy of over sixty percent. This confirms that temporal logic alone is a stronger predictor of entity identity in anchor-scarce scenarios than structural topology. However, the full framework achieves the highest performance, demonstrating that structural and temporal features are complementary. The dynamic weighting mechanism is also shown to be beneficial, as removing it and forcing a fixed combination of features leads to a noticeable degradation in accuracy.

### 5.3 Limitations And Edge Cases

Despite the significant advantages of the proposed methodology, there are inherent limitations. The primary dependency of the event-order framework is the presence of sufficient temporal variation. For entities that represent immutable concepts or possess highly static relational histories, the extracted directed acyclic graphs will be sparse or non-existent. In such cases, the framework must fall back on structural alignment, which is inherently weak under anchor scarcity. Additionally, the framework assumes a reasonable degree of temporal synchronization between the source and target graphs. While the margin of temporal significance handles minor discrepancies, massive structural delays in data recording across different systems can distort the apparent chronological order of events. For instance, if an event is recorded in real-time in the source graph but batch-processed months later in the target graph, the resulting logical sequence may be fundamentally altered, leading to incorrect alignments. Addressing these severe synchronization issues requires more advanced temporal warping techniques that are beyond the scope of the current framework.

### 6. Conclusion and Future Directions

This paper presented a novel framework for the alignment of evolving knowledge graphs in environments characterized by severe anchor scarcity. By conceptualizing temporal metadata as a series of logical event-order constraints, we developed a methodology for extracting invariant temporal signatures that uniquely identify entities across disparate graph structures. The integration of these chronological sequences with sparse structural topology through a dynamic weighting mechanism resulted in a highly robust alignment system. Extensive empirical evaluations confirmed that shifting the alignment paradigm from spatial topology to temporal logic significantly mitigates the detrimental effects of missing anchor links. The proposed framework demonstrated exceptional resilience, maintaining high accuracy even when less than one percent of reference anchors were available. Future research directions will focus on enhancing the robustness of the event-order extraction process against extreme temporal asynchrony. Investigating dynamic time warping algorithms adapted for graph-structured event sequences could provide a solution for aligning systems with vastly different data ingestion latencies. Furthermore, exploring the application of large language models to infer implicit temporal constraints from the textual descriptions of unstructured entities presents an exciting opportunity to expand the applicability of this framework [21]. Ultimately, integrating chronological reasoning into knowledge graph alignment paves the way for building more cohesive, accurate, and dynamic global information networks.

### References

- Zhao, R., Zeng, W., Tang, J., Li, Y., Ye, G., Du, J., & Zhao, X. (2025, May). Towards unsupervised entity alignment for highly heterogeneous knowledge graphs. In 2025 IEEE 41st international conference on data engineering (ICDE) (pp. 3792-3806). IEEE.
- Lee, Y., Xu, Y., Gao, P., & Chen, J. (2024). Tenet: triple-enhancement based graph neural network for cell-cell interaction network reconstruction from spatial transcriptomics. *Journal of Molecular Biology*, 436 (9), 168543.
- Lee, Y., Gao, P., Xu, Y., Wang, Z., Li, S., & Chen, J. (2025). MEGA-GO: functions prediction of diverse protein sequence length using Multi-scale Graph Adaptive neural network. *Bioinformatics*, 41 (2), btaf032.

- Zhao, R., Tang, J., Zeng, W., Guo, Y., & Zhao, X. (2025). Towards human-like questioning: Knowledge base question generation with bias-corrected reinforcement learning from human feedback. *Information Processing & Management*, 62(3), 104044.
- Li, B., Zhang, R., Liang, H., Zhang, J., Zhang, J., Chen, X., ... & Wang, J. (2026). Interagent: Physics-based multi-agent command execution via diffusion on interaction graphs. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 15253-15265).
- Zhang, W., Huang, M., Zhou, Y., Zhang, J., Yu, J., Wang, J., & Xu, L. (2024). Both2hands: Inferring 3d hands from both text prompts and body dynamics. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 2393-2404).
- Yao, Y., Xiao, W., Miao, P., Chen, G., Yang, H., Chae, C. B., & Wong, K. K. (2026). UAV-RHS-enabled full-duplex ISAC covert system: Robust beamforming and trajectory optimization. *IEEE Transactions on Communications*.
- Yao, Y., Xiao, W., Miao, P., Chen, G., Yang, H., Chae, C. B., & Wong, K. K. (2025). UAV-relay-aided secure maritime networks coexisting with satellite networks: robust beamforming and trajectory optimization. *IEEE Transactions on Wireless Communications*.
- Yao, Y., Zhang, J., Miao, P., Zhang, L., Chen, G., Shu, F., & Wong, K. K. (2025). Hybrid RIS-enhanced ISAC secure systems: Joint optimization in the presence of an extended target. *IEEE Transactions on Communications*.
- Wang, F., Sun, L., & Zhang, Z. (2020, December). Hyperbolic user identity linkage across social networks. In *GLOBECOM 2020-2020 IEEE Global Communications Conference* (pp. 1-6). IEEE.
- Mo, Z. (2025). Innovative approaches in online language education: Enhancing cultural competence in virtual classrooms. *Business and Social Sciences Proceedings*, 1, 84-91.
- Wang, Y., Wang, Y., Yue, Z., Zeng, H., Wang, Y., Lourentzou, I., ... & McAuley, J. (2026). Fasa: Frequency-aware sparse attention. *arXiv preprint arXiv:2602.03152*.
- Li, Q., Ye, Q., Zhang, N., Zhang, W., & Hu, F. (2025). Digital-twin-enabled industrial IoT: Vision, framework, and future directions. *IEEE Wireless Communications*, 32(6), 173-181.
- Li, Y. Z., Zhang, J. P., Chen, Z. Y., Wang, H. C., Zhang, K. X., Hu, S. S., ... & Dudley, M. (2026, September). Growth and Characterization of High-Quality Thick Epitaxial 4H-SiC Wafers for High Voltage Devices. In *Defect and Diffusion Forum* (Vol. 452, pp. 79-85). Trans Tech Publications Ltd.
- Wang, S., Zhang, X., Wang, P., & Li, X. (2026). Design of Magnetic Sensor Array-Based PUFs for IoT Security. *IEEE Transactions on Instrumentation and Measurement*, 75, 1-9.
- Liang, R., Xu, S., Xie, C., Chen, J., Ren, F., Yang, S., & Yabe, T. (2026). Abstain Mask Retain Core: Time Series Prediction by Adaptive Masking Loss with Representation Consistency. *Advances in Neural Information Processing Systems*, 38, 99445-99471.
- Hu, H., Yang, Y., Zhao, Q., & Zhang, C. (2022, June). On the role of discount factor in offline reinforcement learning. In *International conference on machine learning* (pp. 9072-9098). PMLR.
- Yang, Z., Liang, B., & Ji, W. (2021). An intelligent end-edge-cloud architecture for visual IoT-assisted healthcare systems. *IEEE internet of things journal*, 8(23), 16779-16786.
- Peng, Y., Li, H., BouDagher-Fadel, M., Wang, L., Zhang, D., Zheng, T., & Yang, K. (2022). Benthic foraminifera distribution and sedimentary environmental evolution of a carbonate platform: A case study of the Guadalupian (middle Permian) in eastern Sichuan Basin. *Marine Micropaleontology*, 170, 102079.
- Meng, L., Jia, Z., Hu, X., Zhang, B., & Cao, L. (2026). Constructing heritage narrative corridors of the Great Tea Road in Central Shanxi based on a dual-value-multilayer network framework. *npj Heritage Science*.

Emani, M., Xie, Z., Raskar, S., Sastry, V., Arnold, W., Wilson, B., ... & Boyd, M. (2022, November). A comprehensive evaluation of novel AI accelerators for deep learning workloads. In 2022 IEEE/ACM international workshop on performance modeling, benchmarking and simulation of high performance computer systems (PMBS) (pp. 13-25). IEEE.