XINA: Explainable Instance Alignment using Dominance Relationship (Extended abstract)

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***Abstract*—In this extended abstract, we present an instance alignment framework, namely XINA, for KB integration. We then show its effectiveness and efficiency on real-world KBs.**

***Index Terms*—Instance alignment, Explainable AI**

I. Introduction

Large-scale Knowledge bases (KBs) such as DBpedia [1], Freebase [2], and YAGO [3] are very useful resources for not only providing structured information to human users but also data-intelligent tasks (*e.g.*, question answering [4]) for machine systems. However, despite their size, a single KB is often incomplete for certain entities as reported in [5], *e.g.*, 71% of the roughly 3 million people in Freebase have no known place of birth, 94% have no known parents, and 99% have no known ethnicity. Such drawback motivates the integration of multiple KBs with complementary information, but requires finding instances of the same entity across different KBs, called *instance alignment problem*. For example, in Fig. 1, an instance pair (two round nodes connected by dotted line) can be aligned across two KBs S and T as many of their common properties (text labeled on directed edge) have the same literal values (textual node). This is challenging, however, due to the heterogeneous representation of properties (*e.g.*, `bornDate` and `birthDate`) and literals (*e.g.*, "10/28/1955" and "Oct. 28, 1955") between S and T.

The standard way [6]–[8] to align instances despite this heterogeneity is (1) to find the property matching pairs, *e.g.*, ⟨`bornDate`, `birthDate`⟩, then (2) to manually assign a literal similarity per property pair, *e.g.*, edit distance for ⟨`LastName`, `FamilyName`⟩, and (3) finally compute the pairwise instance similarities as scalar alignment scores by summing the literal similarities in an *aggregation function*. We call this a "user-explain" system, since users must explain the functions required for the purpose of alignment. In contrast, in this paper, we focus on a "machine-explain" system, wherein alignment decisions are explained in an interpretable and faithful manner to users, even without "user-explain" efforts.

Specifically, in this work, we propose a fundamentally different approach, called eXplainable INstance Alignment (XINA), based on the distributed representation, *i.e.*, vectors, for instance similarities. As illustrated in Fig. 1, existing scalar approach quantifies the instance similarity by aggregating proper literal similarities into one scalar value. On the other hand, the vector representation preserves all possible literal similarities and delays alignment scoring and eliminates the need of aggregation function. Instead, to generate both alignment results and their explanation, XINA leverages the skyline-based dominance relationship. For example, (s_1, t_1) dominates (s_1, t_2) and (s_2, t_1) because none of its vector dimensions has a lower value. Therefore, each dominant dimension, characterized by a property pair (and a certain literal similarity function), can explain the alignment decision.

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II. Technical Challenges

Despite "explainability", realizing XINA as a practical KB integration tool is non-trivial due to "unalignability". For example, in Fig. 1, (s_2, t_1) and (s_2, t_2) do not dominate each other and thus s_2 is unalignable with either t_1 or t_2. Such unalignability exponentially increases as the vector size gets bigger. A quick fix is thus dimensionality reduction– For example, we can select the first and second dimensions as "decision space" which makes an alignment decision for s_2, such that (s_2, t_1) dominates (s_2, t_2). Our problem is more complex than classic feature selection problem, as such decision is **dependent** on that of all other pairs.

- **Dependence by similarity:** How do we decide the cardinality of decision space? Even assuming the optimal cardinality is known as two, how do we argue the first and second dimensions are better than the first and the third, given both choices successfully eliminate unalignability of s_2 in Fig. 1. For example, when given an alignment decision for s_2, we can decide by similarity with other alignment decisions, some of which are labeled with ground truth feature selection. To compare with other decisions and propagate their feature selections, we mathematically define the ideal cardinality of decision space globally maximizing the alignability.
- **Dependence by competition:** In 1-1 alignment constraint, an alignment decision may compete with another alignment decision. In our example, if (s_1, t_1) dominates (s_1, t_2) and (s_2, t_1) dominates (s_2, t_2) on their decision spaces, the two alignment decisions for s_1 and s_2 compete with each other to align with t_1. In this case, some alignment decision can be revised to the second best alignment, *e.g.*, aligning t_2 instead t_1, which is a global optimization problem. After this optimization, its "decision space" can no longer explain the revised alignment, for which we need to identify localized "explanation space". For example, in Fig. 1, the explanation space of an alignment result (s_2, t_2) is a dominant fourth dimension with 0.5, where (s_2, t_2) dominates another

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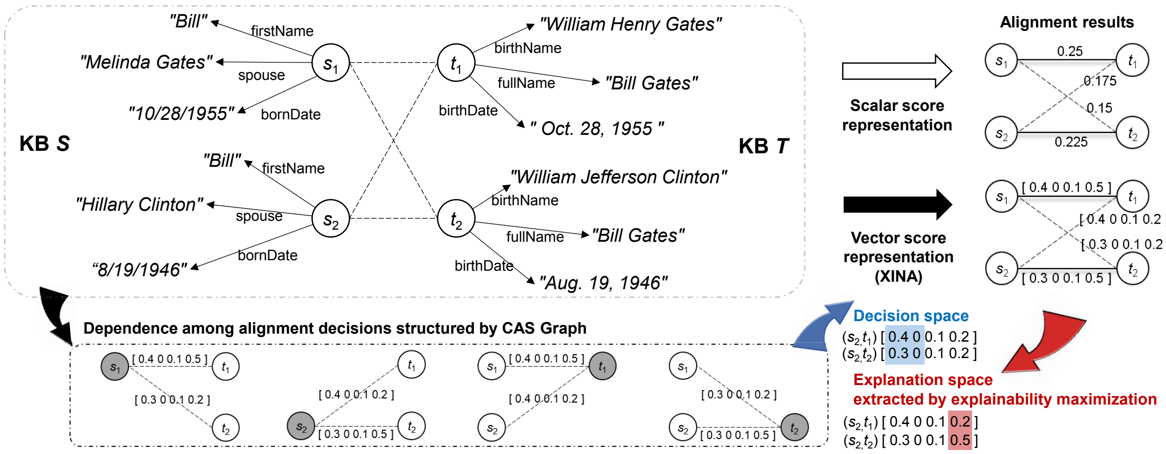

Fig. 1. An illustration of instance alignment problem. XINA adopts the vector representation of instance similarity for alignment scoring.

competitor (s_2, t_1). Our goal is to globally minimize the disagreements between decision and explanation spaces.

III. Method

Our technical contribution is (1) leveraging similarity dependence for effective feature selection while (2) minimizing the disagreement with more intuitive yet localized explanation. For these two goals, we present novel methodologies as:

For (1), we first invent a graph model, called Collective Alignment Scoring (CAS) model, that represents the similarity/competition dependence of the given global problem. For example, in Fig. 1, a CAS graph connects four alignment decisions, each of which is of a (grey) target instance node. Then, this graph gradually activates neighbor alignment decisions by propagating decision spaces in the manner of alleviating the competitive nature. In CAS model, we mathematically define the globally optimal cardinality of decision space for the desirable propagation considering all dependences.

For (2), building on the alignment scoring on CAS model, we formalize the instance alignment problem as Explainability Maximization (EM) problem, where we define "explainability" as the degree of agreement between the decision and explanation spaces when given certain alignment results. For example, in Fig. 1, an alignment results (s_2, t_2) can be mapped to decision and explanation space, shaded in blue and red respectively. When all decision are independent, both spaces are identical. However, dependency may cause discrepancy, to make a better global optimal decision, with the expensive of lower explainability. We thus aim to reduce such discrepancy, by designing a greedy approach that exploits the dependency information in CAS graph.

IV. Experiment

To evaluate, we test the KB integration tasks among three real-world public KBs: DBpedia (D), Freebase (F), and YAGO (Y). As baselines, we adopt state-of-the-arts in graph- and embedding-based instance alignment, ARIA [6] and JEIA [9], respectively. Such extensive experiments show that, despite far less user-explain efforts, XINA outperforms all baselines on all KB integration scenarios.

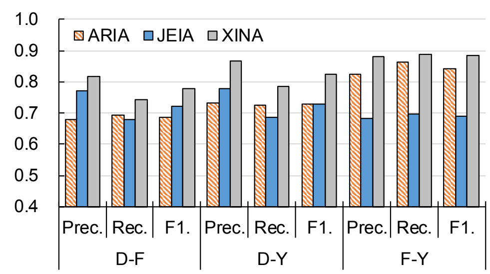

Fig. 2. Performance of the overall instance alignment

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