

Learning Representations of Bi-Level Knowledge Graphs for Reasoning beyond Link Prediction

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Main Contributions

- Define a **Bi-Level Knowledge Graph**, which represents the relationships between triplets as well as the relationships between entities.
- Create three real-world bi-level knowledge graphs: **FBH, FBHE, DBHE**
- Propose a random-walk-based **data augmentation** strategy on Bi-level KGs.
- BiVE** (embedding of Bi-level knowledge graphs): embedding model which takes into account **base-level**, **higher-level** and **augmented** triplets.
- Propose two new tasks: **Triplet Prediction** and **Conditional Link Prediction**

Bi-Level Knowledge Graph

- There can be meaningful relationships between triplets.
- T_1 : (Biden, HoldsPosition, Vice President), T_2 : (Obama, HoldsPosition, President)

Base-Level Knowledge Graph

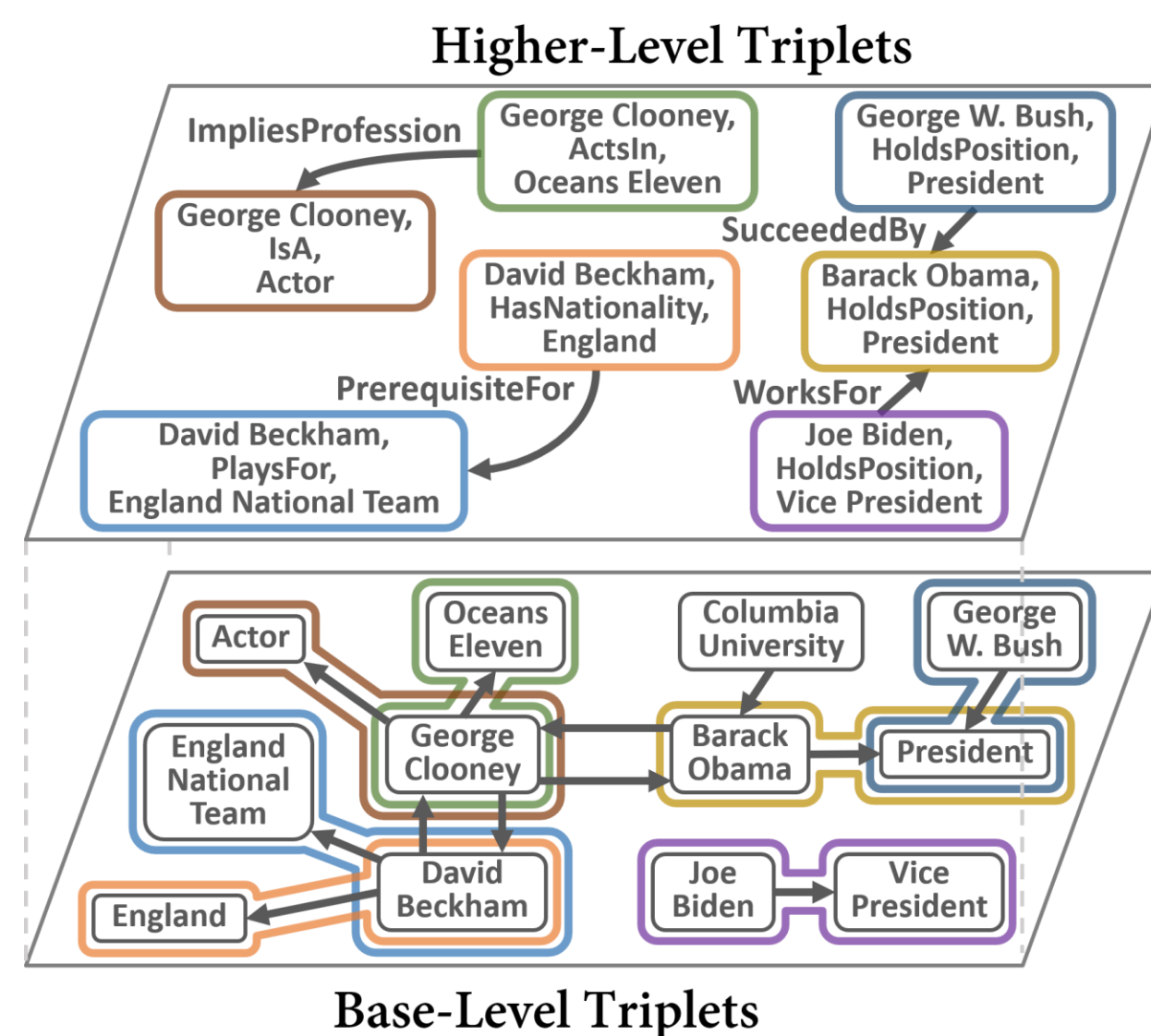
- $G = (\mathcal{V}, \mathcal{R}, \mathcal{E})$
- \mathcal{V} : a set of entities
- \mathcal{R} : a set of relations
- \mathcal{E} : a set of base-level triplets

Higher-Level Triplets \mathcal{H}

- Relationships between triplets
- e.g., $\langle T_1, \text{WorksFor}, T_2 \rangle$

Bi-Level Knowledge Graph

- $\hat{G} = (\mathcal{V}, \mathcal{R}, \mathcal{E}, \hat{\mathcal{R}}, \mathcal{H})$
- $\hat{\mathcal{R}}$: a set of **higher-level relations**
- e.g., WorksFor



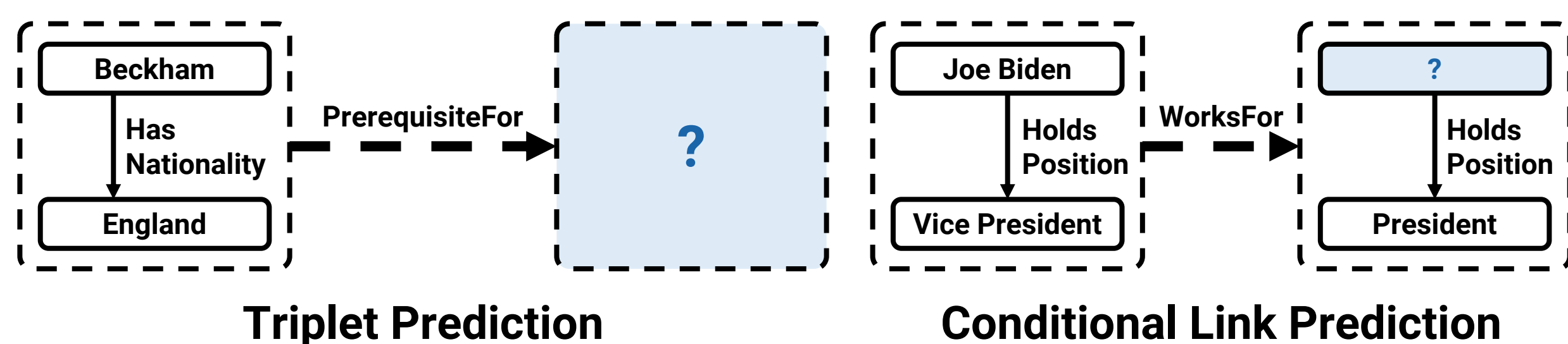
Real-World Bi-Level Knowledge Graphs

- Create three real-world bi-level knowledge graphs: **FBH, FBHE, DBHE**
- FBH and FBHE are based on **FB15K237** and DBHE is based on **DB15K**.

	\hat{r}	$\langle T_i, \hat{r}, T_j \rangle$	
FBHE	PrerequisiteFor	T_i : (Beckham, HasNationality, England)	Externally-sourced Knowledge
		T_j : (Beckham, PlaysFor, England National Team)	
	WorksFor	T_i : (Joe Biden, HoldsPosition, Vice President)	
		T_j : (Barack Obama, HoldsPosition, President)	

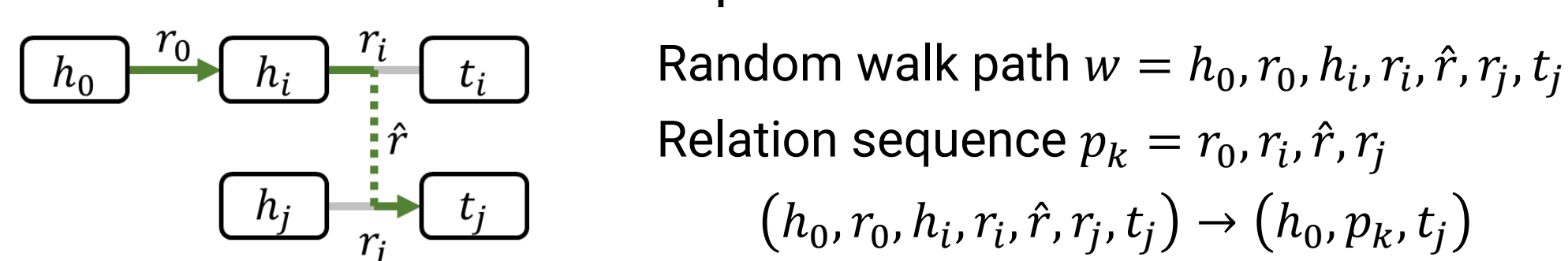
Triplet Prediction and Conditional Link Prediction

- Triplet Prediction**
 - Predicts a **triplet** connected to a given triplet by a higher-level relation.
 - $\langle (\text{Beckham, HasNationality, England}), \text{PrerequisiteFor}, (?) \rangle$
 - Answer: **(Beckham, PlaysFor, England National Team)**
- Conditional Link Prediction**
 - Predicts a **missing entity in a triplet** conditioned by another triplet.
 - $\langle (\text{Joe Biden, HoldsPosition, Vice President}), \text{WorksFor}, (?, \text{HoldsPosition, President}) \rangle$
 - Answer: **Barack Obama**

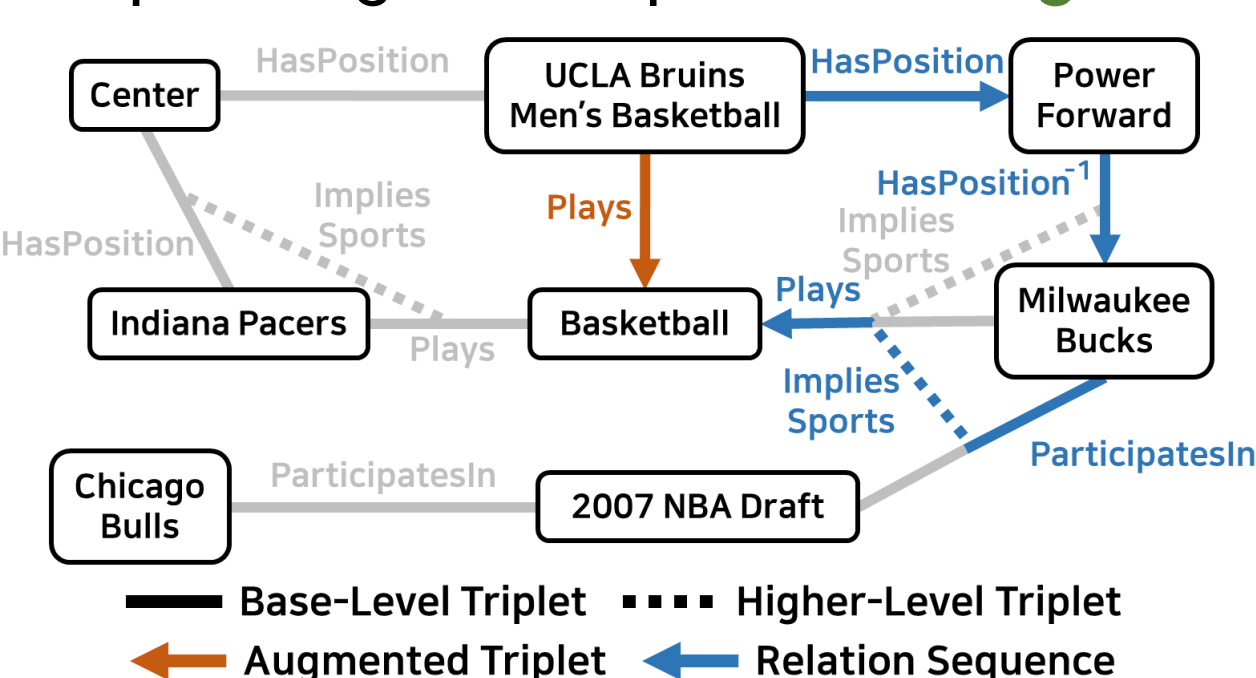


Data Augmentation Strategy based on Random Walks

- Step 1. Perform **Random Walks** by following base-level/higher-level triplets.
- Random Walk Path**: Sequence of entities, relations, higher-level relations
- Relation Sequence p_k** : Sequence of relations and higher-level relations extracted from a random walk path



- Step 2. Calculate the **Confidence Score** $c(p_k, r)$.
- Probability that the entity pair connected by p_k is also connected by r
- Step 3. Augment triplets with **high confidence scores**.



Relation sequence p_k :
(HasPosition, HasPosition¹, ParticipatesIn, ImpliesSports, Plays)

Relation r : Plays

Augmented triplet:
(UCLA Bruins Men's Basketball, Plays, Basketball)

BiVE: embedding of Bi-level knowledge graphs

- Loss incurred by the **base-level triplets** (L_{base})
 - $L_{base} = \sum_{(h,r,t) \in \mathcal{E}_{train}} g(-f(\mathbf{h}, \mathbf{r}, \mathbf{t})) + \sum_{(h',r',t') \in \mathcal{E}'_{train}} g(f(\mathbf{h}', \mathbf{r}', \mathbf{t}'))$
 - $g(x) = \log(1 + \exp(x))$
 - We can use any knowledge graph embedding scoring function for $f(\cdot)$.
 - BiVE-Q**: uses the scoring function of QuatE
 - BiVE-B**: uses the scoring function of BiQUE
- Loss incurred by the **higher-level triplets** (L_{high})
 - $L_{high} = \sum_{(T_i, \hat{r}, T_j) \in \mathcal{H}_{train}} g(-f(\mathbf{T}_i, \hat{\mathbf{r}}, \mathbf{T}_j)) + \sum_{(T'_i, \hat{\mathbf{r}}', \mathbf{T}'_j) \in \mathcal{H}'_{train}} g(f(\mathbf{T}'_i, \hat{\mathbf{r}}', \mathbf{T}'_j))$
 - $\mathbf{T}_i = W[\mathbf{h}_i; \mathbf{r}_i; \mathbf{t}_i]$ is the embedding vector of $T_i = (h_i, r_i, t_i)$.
- Loss incurred by the **augmented triplets** (L_{aug})
 - $L_{aug} = \sum_{(h,r,t) \in \mathcal{S}} g(-f(\mathbf{h}, \mathbf{r}, \mathbf{t})) + \sum_{(h',r',t') \in \mathcal{S}'} g(f(\mathbf{h}', \mathbf{r}', \mathbf{t}'))$
 - \mathcal{S} is the set of augmented triplets.
- Loss Function of BiVE:** $L_{BiVE} = L_{base} + \lambda_1 \cdot L_{high} + \lambda_2 \cdot L_{aug}$
- To solve a **triplet prediction problem** $\langle T_i, \hat{r}, ? \rangle$, compute $F_{tp} = f(\mathbf{T}_i, \hat{\mathbf{r}}, \mathbf{X})$ for every base-level triplet $X \in \mathcal{E}_{train}$.
- To solve a **conditional link prediction problem** $\langle T_i, \hat{r}, (h_j, r_j, ?) \rangle$, compute $F_{clp} = f(\mathbf{h}_j, \mathbf{r}_j, \mathbf{x}) + \lambda_1 \cdot f(\mathbf{T}_i, \hat{\mathbf{r}}, W[\mathbf{h}_j; \mathbf{r}_j; \mathbf{x}])$ for every $x \in \mathcal{V}$.

Experimental Settings

- Statistics of the datasets used in the experiments

	$ \mathcal{V} $	$ \mathcal{R} $	$ \mathcal{E} $	$ \hat{\mathcal{R}} $	$ \mathcal{H} $	$ \hat{\mathcal{E}} $	
FBH	14,541	237	310,117	6	27,062	33,157	No. of base-level triplets involved in the higher-level triplets
FBHE	14,541	237	310,117	10	34,941	33,719	
DBHE	12,440	87	68,296	8	6,717	8,206	

- 12 baseline methods:** ASER, MINERVA, Multi-Hop, AnyBURL, Neural-LP, DRUM, PTransE, RPJE, TransD, ANALOGY, QuatE, BiQUE

Experimental Results

Results of Triplet Prediction (TP)

	FBH		FBHE		DBHE	
	MR	Hit@10	MR	Hit@10	MR	Hit@10
Best-baseline	74277.3	0.117	52159.4	0.318	16698.1	0.230
BiVE-Q	18.7	0.853	33.1	0.683	56.6	0.523
BiVE-B	19.7	0.837	27.9	0.718	4.7	0.914

Results of Conditional Link Prediction (CLP)

	FBH		FBHE		DBHE	
	MR	Hit@10	MR	Hit@10	MR	Hit@10
Best-baseline	111.0	0.686	90.1	0.753	19.3	0.780
BiVE-Q	7.0	0.906	11.0	0.839	12.5	0.828
BiVE-B	6.6	0.911	12.8	0.834	3.2	0.958

- BiVE outperforms 12 different baseline methods on both **TP** and **CLP**.
- BiVE shows comparable base-level link prediction results to baselines.

Examples of Conditional Link Prediction

- $\langle (\text{Joe Jonas, IsA, ?}), \text{ImpliesProfession}, (\text{Joe Jonas, IsA, Actor}) \rangle$
- Prediction made by BiVE-Q: **Voice Actor**
- $\langle (\text{Joe Jonas, IsA, ?}), \text{ImpliesProfession}, (\text{Joe Jonas, IsA, Musician}) \rangle$
- Prediction made by BiVE-Q: **Singer-songwriter**

Analysis on the Augmented Triplets

- Examples of the augmented triplets in **FBHE** and **DBHE**

Relation Sequence p_k	Relation r	$c(p_k, r)$	Examples of the Augmented Triplets
Plays, Plays ⁻¹ , ImpliesSports, HasPosition	HasPosition	0.78	(Bayer 04 Leverkusen, HasPosition, Forward)
Program ⁻¹ , Program, Language	Language	0.70	(David Copperfield, Language, English)
IsPartOf, IsPartOf, ImpliesLocation, IsPartOf	IsPartOf	0.76	(San Pedro, IsPartOf, California)
IsProducedBy ⁻¹ , IsProducedBy, ImpliesProfession, IsA	IsA	0.73	(Jim Wilson, IsA, Film Producer)

- Statistics of the Augmented Triplets

	FBH	FBHE	DBHE
No. of augmented triplets	16,601	17,463	2,026
$ \mathcal{S} \cap \mathcal{E}_{valid} + \mathcal{S} \cap \mathcal{E}_{test} $	5,237	5,380	316

No. of the augmented triplets contained in either \mathcal{E}_{valid} or \mathcal{E}_{test}

- Our augmented triplets include many **ground-truth** triplets that are missing.

Conclusion & Future Work

- We define a **bi-level knowledge graph** by introducing the higher-level relations between triplets, and **BiVE** successfully incorporates the structures of the **base-level**, the **higher-level** and the **augmented** triplets.
- Our method can contribute to advancing many knowledge-based applications, including **Conditional QA** and **Multi-Hop QA**.