

Arbitrary Time Information Modeling via Polynomial Approximation for Temporal Knowledge Graph Embedding

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≻ Knowledge Graph VS. Temporal Knowledge Graph



➢ Formalization

• A temporal knowledge graph is a *multi-relational graph* representation of a collection \mathcal{F} of facts in quadruple form $(e_h, r, e_t, \tau) \in \mathcal{E} \times \mathcal{R} \times \mathcal{E} \times \mathcal{T}$. If $(e_h, r, e_t, \tau) \in \mathcal{F}$, then head entity e_h is related to tail entity e_t by relation r on timestamp τ .

- Background
- ➤ Main Challenges
- The limited capability to model arbitrary timestamps continuously.
- The lack of rich inference patterns under temporal constraints.



Inference Pattern

Symmetry: $r_1(e_1, e_2 | \tau) \Rightarrow r_1(e_2, e_1 | \tau)$ Antisymmetry: $r_1(e_1, e_2 | \tau) \Rightarrow \neg r_1(e_2, e_1 | \tau)$ Inversion: $r_1(e_1, e_2 | \tau) \Leftrightarrow r_2(e_2, e_1 | \tau)$ Composition: $r_1(e_1, e_2 | \tau) \land r_2(e_2, e_3 | \tau) \Rightarrow r_3(e_1, e_3 | \tau)$ Hierarchy: $r_1(e_1, e_2 | \tau) \Rightarrow r_2(e_1, e_2 | \tau)$ Intersection: $r_1(e_1, e_2 | \tau) \land r_2(e_1, e_2 | \tau) \Rightarrow r_3(e_1, e_2 | \tau)$ Mutual exclusion: $r_1(e_1, e_2 | \tau) \land r_2(e_1, e_2 | \tau) \Rightarrow \bot$

- Methodology
- ➢ Motivation
- Polynomial decomposition-based temporal representation: flexibly represent arbitrary timestamp.
- Box embedding-based entity representation: learn rigid inference patterns.



- Methodology
- Polynomial Decomposition based Temporal Representation
- Modeling the timestamp via polynomial decomposition-based representation (PTR).
- Weierstrass approximation theorem:

$$f \in C[a,b], \forall \epsilon > 0, \exists P_n \Rightarrow \forall x \in [a,b], |f - P_n| < \epsilon$$
⁽¹⁾

• Temporal representation function of any given timestamp.

$$P_n(f_{\tau}, x) = \sum_{k=0}^n f(\frac{k}{n}) \binom{n}{k} x^k (1-x)^{n-k}$$
(2)

$$\mathcal{P}_{\tau} = P_n(f_{\tau}, x) = \boldsymbol{\alpha}_{\tau} \cdot \boldsymbol{X}$$
(3)

- Methodology
- Box Embedding based Entity Representation
- Modeling the entities via box embedding based entity representations (BER).
- The maximum and minimum coordinates of *Gumbel boxes* follow the Gumbel distribution, then the boxes can be formulated as:

$$Box(e) = \prod_{i=1}^{d} [e_i^m, e_i^M],$$

$$e_i^m \sim \text{MaxGumbel}(\mu_i^m, \beta),$$

$$e_i^M \sim \text{MinGumbel}(\mu_i^M, \beta).$$
(4)

• The approximation of *volume in Gumbel boxes* can be formulated as:

$$\mathbb{E}[Vol(Box(e))] \approx \prod_{i=1}^{d} \beta \log(1 + \exp(\frac{\mu_i^M - \mu_i^m}{\beta} - 2\gamma))$$
(5)

- Methodology
- ➢ Modeling and Evaluation of Quadruples
- The *evolutionary dynamics* of entities and relations over time:

$$e'_{h} = \mathcal{P}_{\tau}(e_{h};W) = Box(e_{h}) + (W^{T}Box(e_{h}))W,$$

$$e'_{t} = \mathcal{P}_{\tau}(e_{t};W) = Box(e_{t}) + (W^{T}Box(e_{t}))W,$$

$$r'_{t} = \mathcal{P}_{\tau}(r_{t};W) = r_{t} + (W^{T}r_{t})W.$$
(6)

• Relation transformation $T_r \subseteq \mathbb{R}^{2 \times d}$ for entity *e*:

$$e^{t} = f_{r}^{t}(e|T_{r}) = Box(e) + T_{r}[0],$$

$$e^{s} = f_{r}^{s}(e|T_{r}) = Box(e) \odot T_{r}[1].$$
(7)

• Scoring function:

$$\mathcal{S}(h,r,t,\tau) = \frac{\mathbb{E}[Vol\left(f_r^s \circ f_r^t(\mathcal{P}_\tau(e_h;W)) \cap f_r^s \circ f_r^t(\mathcal{P}_\tau(e_t;W))\right)]}{\mathbb{E}[Vol\left(f_r^s \circ f_r^t(\mathcal{P}_\tau(e_t;W))\right)]}$$
(8)

- Methodology
- > Analysis of Model Properties
- Local Identifiability:

Assuming a set of parameters Ω is local identifiable if, for all $\theta \in \Omega$, there exists $N(\theta)$, a neighborhood of θ , such that for all $\theta' \in N(\theta)$, $L(x|\theta') \neq L(x|\theta)$.

• Inference Patterns.

Inference Pattern	Setting
Symmetry: $r_1(e_1, e_2 \tau) \Rightarrow r_1(e_2, e_1 \tau)$	$P_{r_1}(e_1 e_2) = P_{r_1}(e_2 e_1) \neq 0$
Antisymmetry: $r_1(e_1, e_2 \tau) \Rightarrow \neg r_1(e_2, e_1 \tau)$	$P_{r_1}(e_1 e_2) \neq 0, P_{r_1}(e_2 e_1) = 0$
Inversion: $r_1(e_1, e_2 \tau) \Leftrightarrow r_2(e_2, e_1 \tau)$	$P_{r_1}(e_1 e_2) = P_{r_2}(e_2 e_1) \neq 0$
Composition: $r_1(e_1, e_2 \tau) \wedge r_2(e_2, e_3 \tau) \Rightarrow r_3(e_1, e_3 \tau)$	$P_{r_3}(e_1, e_2, e_3) \neq 0$
Hierarchy: $r_1(e_1, e_2 \tau) \Rightarrow r_2(e_1, e_2 \tau)$	$P_{r_1,r_2}(e_1 e_2) \ge P_{r_1}(e_1 e_2)P_{r_2}(e_1 e_2) \ne 0$
Intersection: $r_1(e_1, e_2 \tau) \wedge r_2(e_1, e_2 \tau) \Rightarrow r_3(e_1, e_2 \tau)$	$P_{r_3}(e_1 e_2) \ge P_{r_1,r_2}(e_1 e_2) \ne 0$
Mutual exclusion: $r_1(e_1, e_2 \tau) \land r_2(e_1, e_2 \tau) \Rightarrow \bot$	$P(\mathcal{B}(e_1^{r_1}) \cap \mathcal{B}(e_2^{r_1}), \mathcal{B}(e_1^{r_2}) \cap \mathcal{B}(e_2^{r_2})) = 0$

Runtime and Space Complexity.
 time O(d) and space O((|E| + |R| + K)d)

• Experiments

➤ Comparing with SOTA

Madal	YAGO11k			WikiData						
Model	MRR	Hits@3	Hits@10	MRR	Hits@3	Hits@10				
TransE	0.100	0.138	0.244	0.178	0.192	0.339	Model	YA	YAGO11k	YAGO11k Wil
DistMult	0.158	0.161	0.268	0.222	0.238	0.460	MODEI	MR	MR Hits@1	MR Hits@1 MR
RotatE	0.167	0.167	0.305	0.116	0.236	0.461	TransE	1 70	1 70 0 784	1 70 0 784 1 35
QuatE	0.164	0.148	0.270	0.125	0.243	0.416	TransH	1.70	1.70 0.704	1.70 0.704 1.00 1.53 0.761 1.40
TTransE	0.108	0.150	0.251	0.172	0.184	0.329		2.55	2.57 0.602	
HyTE	0.105	0.143	0.272	0.180	0.197	0.333		2.57	2.57 0.695	2.37 0.093 2.23
TA-DistMult	0.161	0.171	0.292	0.218	0.232	0.447	t-IransE	1.66	1.66 0.755	1.66 0.755 1.97
ATiSE	0.170	0.171	0.288	0.280	0.317	0.481	HyTE	1.23	1.23 0.812	1.23 0.812 1.13
TeRo	<u>0.187</u>	0.197	0.319	0.299	0.329	0.507	PTBox	1.12	1.12 0.896	1.12 0.896 1.12
RotateQVS	0.189	<u>0.199</u>	<u>0.323</u>	-	-	-				
PTBox	0.162	0.222	0.347	0.290	0.331	0.527				

Link prediction

Relation prediction

• Experiments

► Ablation Study

DTD	BER		YAGO11	k	WikiData			
FIN		MRR	Hits@3	Hits@10	MRR	Hits@3	Hits@10	
		0.105	0.143	0.272	0.180	0.197	0.333	
\checkmark		0.137	0.174	0.313	0.259	0.278	0.478	
	\checkmark	0.127	0.180	0.280	0.253	0.281	0.426	
\checkmark	\checkmark	0.162	0.222	0.347	0.290	0.331	0.527	

About proposed two modules

Mada	YAC	GO11k	WikiData			
Mode	MRR	Hits@10	MRR	Hits@10		
$\mathcal{P}_{ au}(e)$	0.127	0.289	0.267	0.485		
$\mathcal{P}_{ au}(r)$	0.162	0.347	0.290	0.527		
$\mathcal{P}_{ au}(e,r)$	0.135	0.311	0.277	0.503		

About different evolutionary patterns

- Experiments
- ≻ Case Study

Case study of qualitative analysis on relation prediction. The order of prediction is in descending order. Correct one is in **bold**.

Test quadruples	HyTE	Ours
Katie_Holmes, ?, Tom_Cruise, [2006, 2012]	isMarriedTo , hasWonPrize	isMarriedTo, created
Tricia_Devereaux, ?, Illinois, [1975, 1975]	diedIn, wasBornIn	wasBornIn, diedIn
Jeremy_Lloyd, ?, London, [2014, 2014]	wasBornIn, diedIn	diedIn, wasBornIn
Will_Haining, ?, Fleetwood_Town_F.C., [2011, -]	isMarriedTo, playsFor	playsFor, isMarriedTo
Bob_Hope, ?, Toluca_Lake,_Los_Angeles, [2003, 2003]	isMarriedTo, hasWonPrize	isMarriedTo, diedIn

- Experiments
- ➢ Visualization

Visualization of polynomial decomposition based temporal representations on YAGO11k.



• Conclusion

- We propose an innovative temporal knowledge graph embedding method, namely PTBox.
 Experimental results verify the state-of-the-art performance of our method on two publicly available datasets.
- Proposing an interpretable time representation method that decomposes time information by polynomial approximation theory to flexibly represent arbitrary timestamp.
- Proposing a box-embedding-based entity representation method that effectively represents calibrated probability distributions and learns rigid inference patterns.

THANK YOU FOR LISTENING!