Pervasive Computing Lab
浙江大学普适计算实验室

NEURAL INFORMATION PROCESSING SYSTEMS

DECRL: A Deep Evolutionary Clustering Jointed Temporal Knowledge Graph Representation Learning Approach

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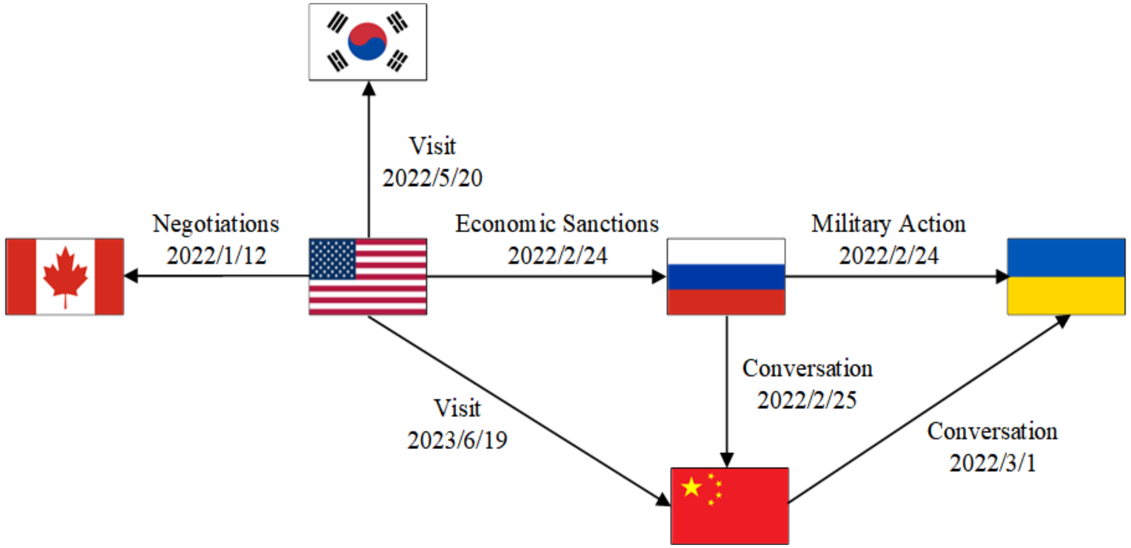
Background

A temporal knowledge graph (TKG) represents events in the form of quadruples (s, r, o, t), where s and o denote the subject and object entities, respectively, r denotes the relation between s and o, and t represents the timestamp.

TKG representation learning aims to map temporal evolving entities and relations to embedded representations in a continuous low-dimensional vector space.



Existing Methods: Leverage derived structures, e.g., communities, entity groups, and hypergraphs, to model high-order correlations among entities. However, existing approaches lack the capability to capture the temporal evolution of high-order correlations in TKGs.

Contributions

DECRL is the first work that integrates deep evolutionary clustering approaches into TKGs, which jointly optimizes TKG representation learning with evolutionary clustering to capture the temporal evolution of high-order correlations. Our main contributions are outlined as follows:

- We propose a **deep evolutionary clustering module** to capture the temporal evolution of high-order correlations among entities, where clusters represent the high-order correlations between multiple entities. Furthermore, a **cluster-aware unsupervised alignment mechanism** is introduced to ensure precise one-to-one alignment of soft overlapping clusters across timestamps, maintaining the temporal smoothness of clusters over successive timestamps.

- We propose an **implicit correlation encoder** to capture latent correlations between any pair of clusters, which defines the interaction intensities between clusters to form a cluster graph. In addition, a global graph, constructed from all events of training set, is introduced to guide the assignment of different interaction intensities to different cluster pairs.

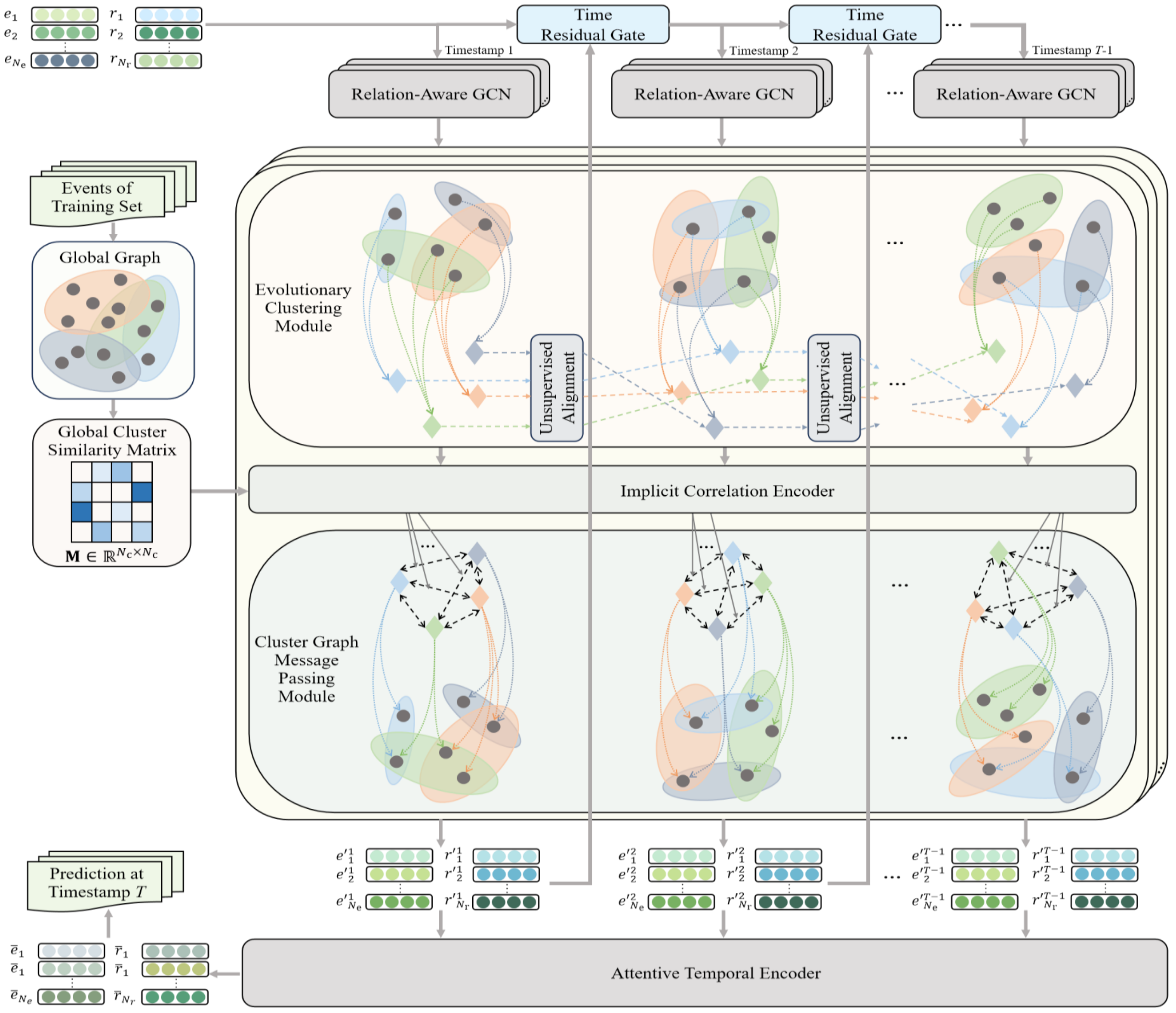
Approach

Evolutionary Clustering Module captures the temporal evolution of high-order correlations among entities by the fusion operation between clusters across timestamps, which contains a cluster-aware unsupervised alignment mechanism to ensure precise alignment of soft overlapping clusters across timestamps.

Implicit Correlation Encoder captures latent correlations between any pair of clusters.

Time Residual Gate combines updated representations with input representations through a weighted mechanism.

Attentive Temporal Encoder captures the temporal dependency among final updated representations across timestamps.



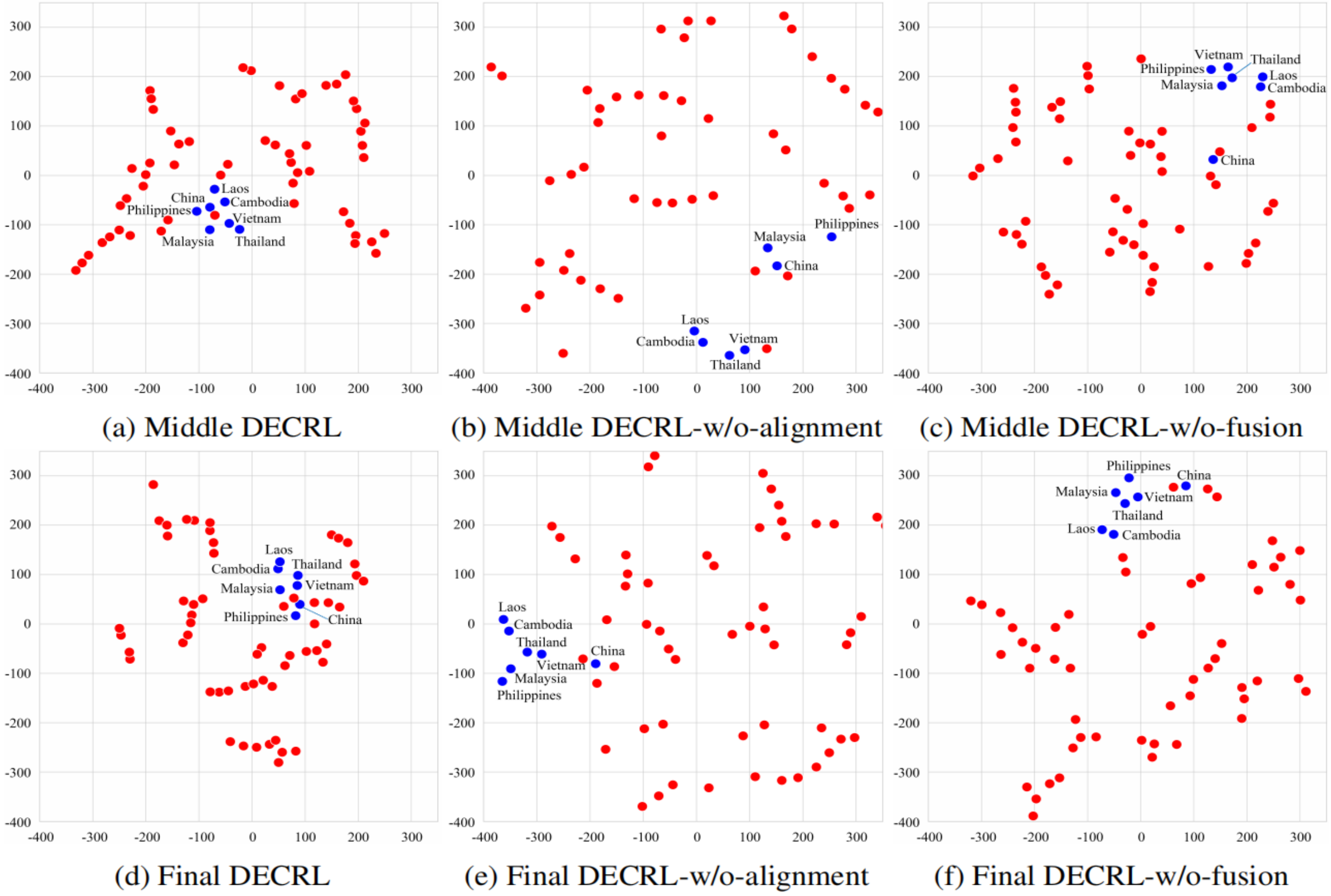
Evaluation

Approach	ICEWS14				ICEWS14C			
	MRR	Hits@1	Hits@3	Hits@10	MRR	Hits@1	Hits@3	Hits@10
TTransE (WWW 2018)	23.79*	14.24*	29.17*	34.56*	11.79*	13.24*	19.97*	24.88*
HyTE (EMNLP 2018)	25.12*	18.15*	30.15*	45.37*	22.17*	18.15*	27.28*	35.37*
RE-NET (EMNLP 2020)	45.77*	37.98*	49.07*	58.87*	43.27*	36.97*	47.08*	55.19*
Glean (KDD 2020)	42.20*	36.86*	47.68*	52.39*	40.24*	34.62*	45.48*	50.09*
TeMP (EMNLP 2020)	46.04*	39.07*	49.84*	59.74*	44.17*	37.37*	47.78*	55.66*
RE-GCN (SIGIR 2021)	45.56*	38.09*	50.37*	62.44*	41.76*	36.67*	45.37*	51.74*
DACHA (TKDD 2022)	45.44*	37.88*	49.47*	58.69*	44.26*	37.59*	44.18*	53.19*
TiRGN (IJCAI 2022)	46.07*	39.83*	52.17*	63.95*	44.73*	38.13*	49.77*	60.91*
TITer (EMNLP 2021)	46.12*	39.08*	50.76*	60.39*	44.86*	39.37*	48.84*	55.79*
EvoExplore (KBS 2022)	47.71*	40.68*	52.37*	65.94*	49.77*	40.12*	54.37*	65.83*
GTRL (TKDE 2023)	46.25*	40.11*	51.09*	65.79*	50.95*	40.31*	52.09*	64.89*
DHyper (TOIS 2024)	56.15*	43.76*	65.46*	85.89*	54.16*	41.45*	62.03*	75.35*
DECRL	**62.61**	**48.73**	**70.57**	**93.03**	**58.55**	**44.62**	**66.52**	**82.06**
Improvement	**11.50%**	**11.36%**	**7.81%**	**8.31%**	**8.11%**	**7.65%**	**7.24%**	**8.91%**

Approach	ICEWS18				ICEWS18C			
	MRR	Hits@1	Hits@3	Hits@10	MRR	Hits@1	Hits@3	Hits@10
TTransE (WWW 2018)	11.96*	13.97*	12.79*	24.33*	9.84*	10.29*	11.04*	18.89*
HyTE (EMNLP 2018)	21.85*	16.86*	25.64*	41.86*	22.23*	16.27*	25.68*	33.39*
RE-NET (EMNLP 2020)	42.25*	33.81*	44.98*	52.72*	41.05*	32.87*	42.78*	50.43*
Glean (KDD 2020)	37.11*	34.15*	42.56*	47.35*	35.58*	32.26*	40.44*	46.49*
TeMP (EMNLP 2020)	43.24*	38.77*	45.04*	55.94*	43.08*	36.07*	43.18*	53.03*
RE-GCN (SIGIR 2021)	41.56*	37.59*	44.34*	57.42*	40.27*	36.35*	41.75*	49.25*
DACHA (TKDD 2022)	43.87*	37.11*	47.47*	57.69*	40.11*	36.11*	46.17*	52.37*
TiRGN (IJCAI 2022)	44.27*	38.13*	50.66*	62.90*	43.57*	37.23*	47.67*	54.44*
TITer (EMNLP 2021)	45.44*	39.78*	48.77*	58.73*	44.07*	38.85*	46.44*	49.79*
EvoExplore (KBS 2022)	46.65*	40.05*	50.07*	58.35*	47.33*	38.96*	49.37*	56.15*
GTRL (TKDE 2023)	46.35*	40.95*	51.19*	60.18*	49.33*	40.15*	53.39*	60.74*
DHyper (TOIS 2024)	54.22*	42.16*	63.26*	75.38*	52.11*	41.04*	60.03*	73.22*
DECRL	**63.30**	**50.13**	**70.72**	**90.82**	**61.37**	**46.28**	**67.01**	**86.79**
Improvement	**16.75%**	**18.90%**	**11.79%**	**20.48%**	**17.77%**	**12.76%**	**11.63%**	**18.53%**

Approach	MRR	Hits@1	Hits@3	Hits@10
TTransE (WWW 2018)	8.62*	7.73*	11.03*	23.34*
HyTE (EMNLP 2018)	10.63*	8.39*	14.23*	28.79*
RE-NET (EMNLP 2020)	17.55*	11.73*	18.14*	35.52*
Glean (KDD 2020)	15.60*	10.35*	17.61*	37.40*
TeMP (EMNLP 2020)	19.19*	11.07*	19.84*	40.52*
RE-GCN (SIGIR 2021)	20.84*	10.80*	21.09*	43.65*
DACHA (TKDD 2022)	21.91*	11.27*	17.49*	47.13*
TiRGN (IJCAI 2022)	24.61*	13.78*	25.66*	49.02*
TITer (EMNLP 2021)	TLE	TLE	TLE	TLE
EvoExplore (KBS 2022)	18.53*	10.74*	19.45*	42.07*
GTRL (TKDE 2023)	22.44*	12.48*	18.03*	50.82*
DHyper (TOIS 2024)	OOM	OOM	OOM	OOM
DECRL	**27.58**	**15.74**	**29.16**	**59.54**
Improvement	**12.07%**	**14.22%**	**13.64%**	**17.16%**

Visualization



(a) Middle DECRL (b) Middle DECRL-w/o-alignment (c) Middle DECRL-w/o-fusion

(d) Final DECRL (e) Final DECRL-w/o-alignment (f) Final DECRL-w/o-fusion

The visualization of entity representations on ICEWS14C. “Middle” and “Final” denote entity representations obtained after training at the penultimate epoch and the final epoch, respectively. DECRL-w/o-alignment denotes removing unsupervised alignment mechanism. DECRL-w/o-fusion denotes removing fusion operation between clusters across timestamps.

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Thank you for your lisenting!

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