Context-aware Event Forecasting via Graph Disentanglement

https://github.com/yecchen/SeCoGD

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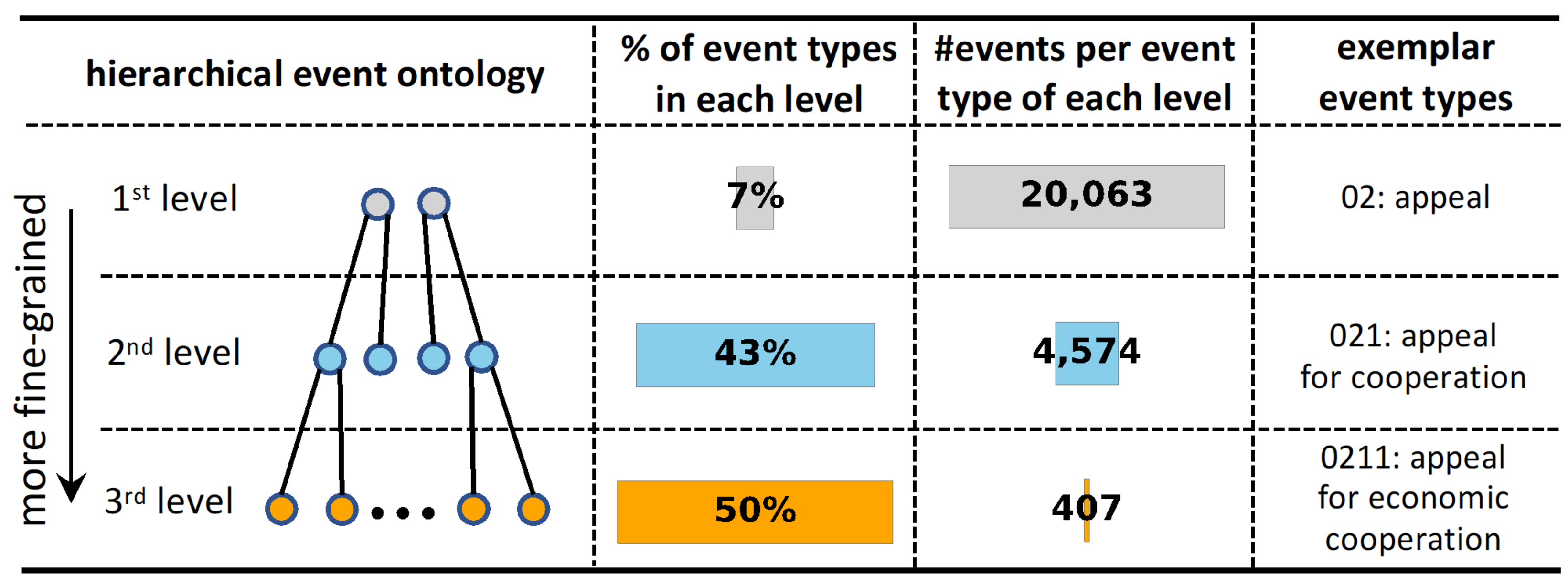
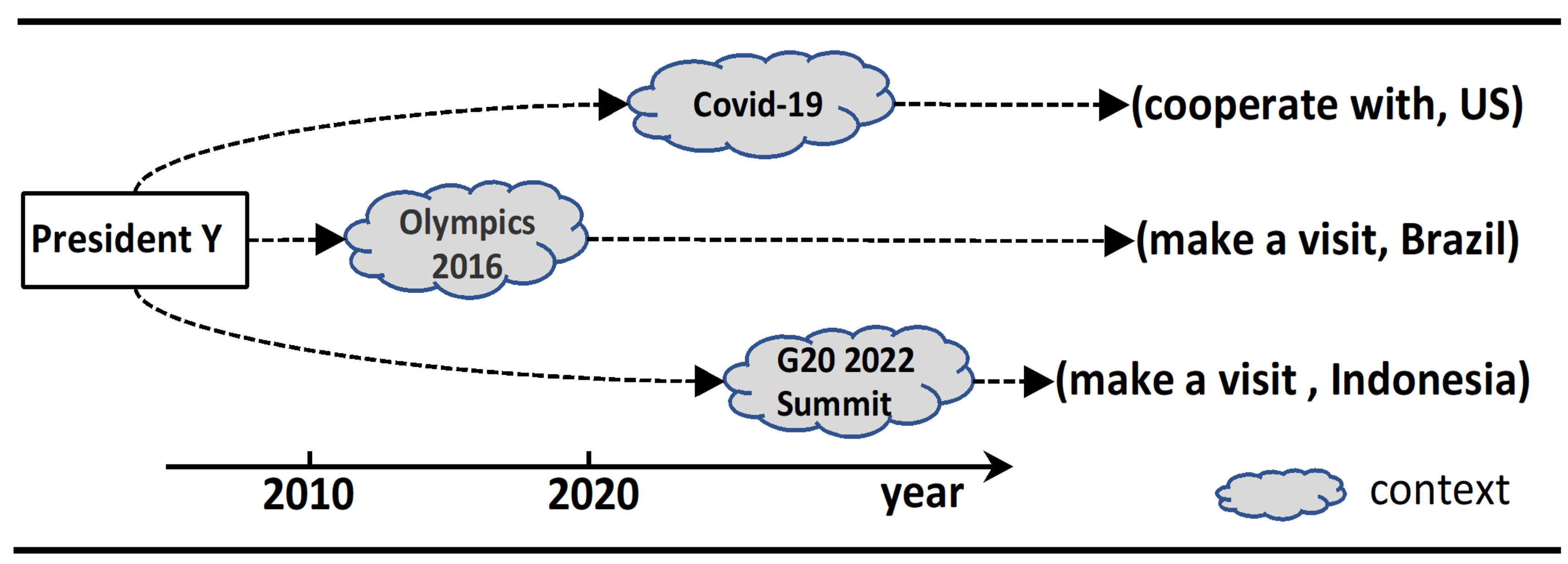
Motivation

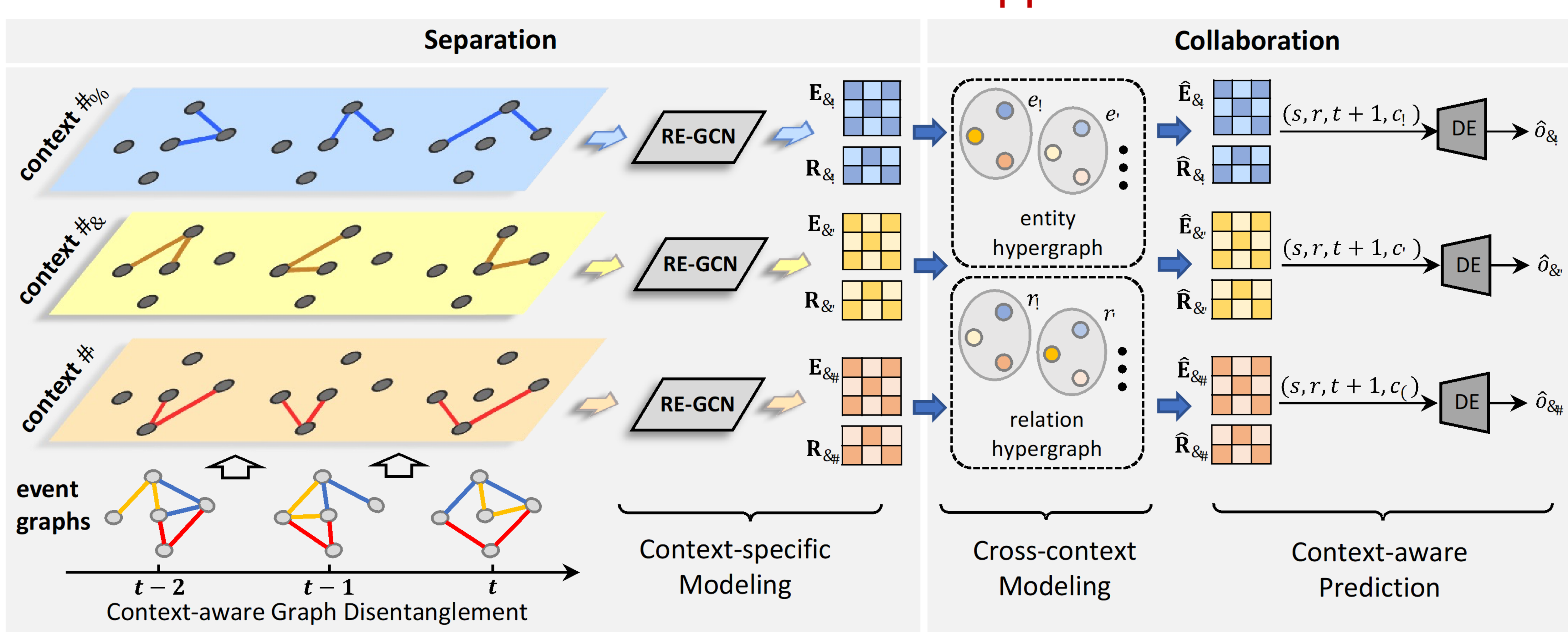


Motivation 1: Most current events fall in the coarse-grained and higher level types of the ontology, while more informative fine- grained events are fewer.



Motivation 2: Out-of-ontology and diverse contexts affect events. Context can provide more fine-grained information to enhance the event forecasting performance.

Approach



We introduce context into existing event representation as supplementary information and define a novel task named context-aware event forecasting. We associate each event with a categorical context, elaborating the event's occurrence situation or condition. Then each event is extended from a quadruple to a quintuple, i.e., (s, r, o, t, c), where c denotes the context.

We borrow the idea from graph disentanglement representation learning and propose a general framework SeCoGD (Separation and Collaboration Graph Disentanglement), for context-aware event forecasting. It consists of two stages: separation and collaboration. The separation stage includes the context-aware graph disentanglement and context-specific modeling modules, and the collaboration stage comprises the cross-context modeling and context-aware prediction modules.

Experiments

Model	EG				IR				IS			
	MRR	HIT@1	HIT@3	HIT@10	MRR	HIT@1	HIT@3	HIT@10	MRR	HIT@1	HIT@3	HIT@10
DistMult [49]	0.1164	0.0344	0.1214	0.2927	0.1349	0.0392	0.1468	0.3379	0.1031	0.0223	0.0929	0.2950
ConvE [12]	0.1151	0.0312	0.1272	0.2882	0.1365	0.0409	0.1485	0.3400	0.1060	0.0251	0.0984	0.2935
ConvTransE [38]	0.1205	<u>0.0377</u>	0.1305	0.2921	0.1405	0.0462	0.1529	0.3412	0.1079	0.0287	0.0994	0.2930
RotatE [40]	0.0892	0.0125	0.0772	0.2748	0.1055	0.0125	0.1074	0.3152	0.0879	0.0132	0.0714	0.2638
RGCN [37]	0.0974	0.0279	0.1046	0.2377	0.1185	0.0366	0.1301	0.2860	0.0861	0.0242	0.0652	0.2307
TANGO [16]	0.1043	0.0240	0.1106	0.2761	0.1249	0.0281	0.1367	0.3314	0.0972	0.0171	0.0852	0.2889
RE-NET [22]	0.1212	0.0413	0.1224	0.2932	0.1401	0.0451	0.1501	0.3452	0.1064	0.0263	0.1016	0.2894
RE-GCN [30]	<u>0.1245</u>	0.0352	<u>0.1366</u>	<u>0.3101</u>	<u>0.1647</u>	<u>0.0622</u>	<u>0.1796</u>	<u>0.3838</u>	<u>0.1301</u>	0.0408	<u>0.1281</u>	<u>0.3346</u>
EvoKG [36]	0.0797	0.0012	0.0775	0.2529	0.0892	0.0011	0.0767	0.3120	0.0779	0.0008	0.0518	0.2789
HiSMatch [29]	0.1126	0.0275	0.1279	0.2906	0.1469	0.0496	0.1599	0.3572	0.1283	<u>0.0434</u>	0.1248	0.3017
CMF$_{ont}$ [10]	0.1206	0.0348	0.1298	0.3015	0.1527	0.0529	0.1643	0.3673	0.1248	0.0368	0.1224	0.3256
CMF$_{art}$ [10]	0.1202	0.0345	0.1293	0.3027	0.1510	0.0496	0.1636	0.3716	0.1263	0.0382	0.1236	0.3261
DisenGCN [32]	0.0849	0.0196	0.0805	0.2198	0.1084	0.0275	0.1096	0.2793	0.0833	0.0162	0.0633	0.2427
DisenKGAT [48]	0.0801	0.0083	0.0822	0.2382	0.0895	0.0059	0.0977	0.2744	0.0724	0.0106	0.0429	0.2322
SeCoGD(ours)	**0.1464**	**0.0593**	**0.1605**	**0.3236**	**0.1757**	**0.0724**	**0.1902**	**0.3975**	**0.1552**	**0.0595**	**0.1588**	**0.3693**
%Improv.	17.59	57.29	17.50	4.35	6.68	16.40	5.90	3.57	19.29	37.10	23.97	10.37

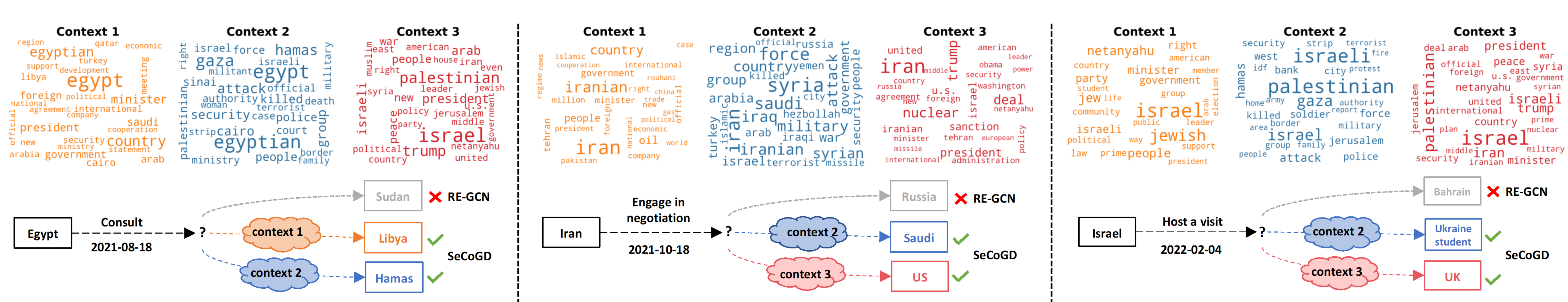
The overall performance comparison between SeCoGD and three types of baselines, including 1) static KG completion methods, 2) temporal KG forecasting methods, and 3) temporal event forecasting methods with texts. Our method outperforms all the baselines on all three datasets.

Model	EG		IR		IS	
	MRR	H@10	MRR	H@10	MRR	H@10
SeCoGD	0.146	0.324	0.176	0.397	0.155	0.369
w/o Ent HG	0.139	0.315	0.168	0.391	0.147	0.359
w/o Rel HG	0.143	0.331	0.170	0.400	0.147	0.362
w/o Ent or Rel HG	0.138	0.315	0.163	0.386	0.144	0.355
Avr. Context	0.130	0.309	0.163	0.373	0.129	0.331

Study of the cross-context modeling and context-aware prediction. From the results, we can see that the results of removing either relation or entity hypergraph are worse than SeCoGD but better than that of removing both, demonstrating the efficacy of both hypergraphs.

Model	EG		IR		IS	
	MRR	H@10	MRR	H@10	MRR	H@10
RE-GCN	0.125	0.310	0.165	0.384	0.130	0.335
K-means	0.139	0.314	0.169	0.388	0.145	0.352
GMM	0.139	0.316	0.165	0.375	0.134	0.339
LDA(SeCoGD)	0.146	0.324	0.176	0.397	0.155	0.369

Study of using alternative context generation methods. We find that alternative automatic approaches are also workable for our framework



(a) Dataset EG (b) Dataset IR (c) Dataset IS

Case study on three datasets. In each sub-figure, the context number K is set as three, the top shows the word cloud of each context, and the bottom illustrates several exemplar forecasting results by SeCoGD and RE-GCN. From word clouds, we observe rich information within each context and clear content differences among contexts. For example, each context in the EG dataset covers background information such as popular actors, important cities, and critical actions; meanwhile, they are about economic, military, and political events respectively.

Please contact the authors to access the code and data via email (Yunshan Ma: yunshan.ma@u.nus.edu, Chenchen Ye: ccye@cs.ucla.edu) https://github.com/yecchen/SeCoGD