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Dynamic Knowledge Graph based Multi-Event Forecasting

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Challenge

- Structured and unstructured features

Event data is usually a mixture of structured records (time, actors, types, etc.) and unstructured textual information (e.g., the event summary shown on an edge). However, few studies have performed the fusion of heterogeneous data for concurrent event forecasting.

- Beyond link prediction

Knowledge graph completion models relational information by predicting links between entities. However, it is difficult in practice to apply this line of research to predict both relations (event types) and entities (actors). Most knowledge graph completion methods only model the inherent structure of relational data and fail to exploit global historical data for future event predictions.

- Beyond event forecasting

Prior research on event modeling mainly focuses on forecasting event occurrences or counts in the future using either pre-defined features or pre-trained embeddings. However, it is difficult to automatically extract event actors from graph-based text features.

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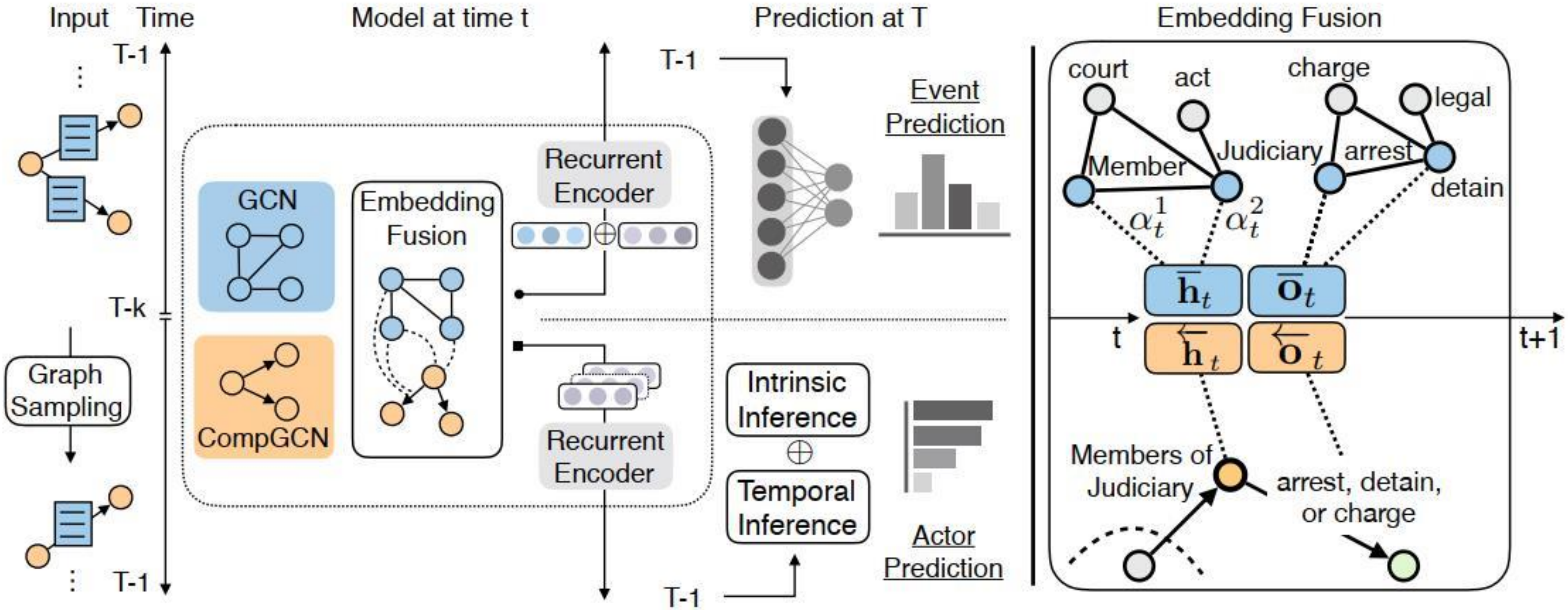
An overview of the model



Multi-Event Forecasting

- Graph Aggregation
- Context-aware Embedding Fusion
- Recurrent Encoder

一、Graph Aggregation

- We employ graph convolution network to learn the representations of temporal event graphs and word graphs

1)Relational Embedding

The node embedding: $\overleftarrow{\mathbf{h}}_v^{(l+1)} = f(\sum_{(\boldsymbol{r},\boldsymbol{u})\exists(v,r,u)\in\mathcal{G}_t} \boldsymbol{W}_q^{(l)} \phi(\overleftarrow{\mathbf{h}}_u^{(l)}, \overleftarrow{\mathbf{o}}_r^{(l)}))$

The edge embedding: $\overleftarrow{\mathbf{o}}_r^{(l+1)} = \boldsymbol{W}_{edge}^{(l)} \overleftarrow{\mathbf{o}}_r^{(l)}$

2)Semantic Embedding

The semantic embedding: $\overline{\mathbf{h}}_\omega^{(l+1)} = f(\sum_{(\omega,\varphi)\epsilon\mathcal{D}_t} \boldsymbol{W}_g^{(l)} \overline{\mathbf{h}}_\varphi^{(l)})$

二、Context-aware Embedding Fusion

——enhance representations of entities and event types by blending contextual features from words.

For instance, in the introduction example, (Citizen, Criticizes, Government, 02/26/15) with description “A Politician attacked the state government on various fronts such as fertilizer crunch and land acquisition act.”.

三、Recurrent Encoder

——learn temporal global embeddings across all historical times

Given a sequence of fused embeddings of entities and event types, we employ a recurrent neural network to model temporal information.

Multi-Actor Forecasting

- Graph Sampling
- Intrinsic Inference
- Temporal Inference

we model the multi-actor forecasting problem $\mathbb{P}(a_t|y_t = r)$ in the following way:

$$\mathbb{P}\left(a_t \middle| y_t, \mathcal{G}_{t-m:t-1}^{y_t}, \mathcal{D}_{t-m:t-1}^{y_t}\right) = \sigma(\tilde{\mathbf{z}} + \boldsymbol{z}) \in \mathbb{R}^{|\varepsilon|}$$

Intrinsic Inference

We model the inherent correlation for entities and each given event type in a modified way as in RESCAL.

Given an event, a shared bilinear layer for all entities is applied:

$$\boldsymbol{z} = \mathbf{H} \cdot \mathbf{W}_{\beta} \cdot \boldsymbol{o}_{r} \ \in \mathbb{R}^{|\varepsilon|}$$

Temporal Inference

We then model the temporal features at time t by using the latent embedding of the event type r and all entities at time t − 1:

$$\tilde{\mathbf{z}} = \widetilde{\boldsymbol{H}}_{t-1} \cdot \widetilde{\boldsymbol{o}}_{t-1,(r)} \in \mathbb{R}^{|\varepsilon|}$$

Experimental results

- Datasets:The experimental evaluation was conducted on event datasets of five countries from Integrated Conflict Early Warning System (ICEWS). It contains political events designed to assess national and international crisis events. These events are coded using 20 main categories and their subcategories. Each event is encoded with geolocation, time (day, month, year), category, entity (subject, object) and its associated text, etc. In this paper, we focus on all categories of events and select country-level datasets from five countries, India, Russia, Nigeria, Afghanistan and Iran. The main event types include make public statement, appeal, express intent to cooperate, protest, etc.

Table 3: Prediction results of the proposed method vs. baselines for the multi-event forecasting task over all datasets (%).

Method	India			Russia			Nigeria			Afghanistan			Iran		
	F1	F2	Recall	F1	F2	Recall	F1	F2	Recall	F1	F2	Recall	F1	F2	Recall
DNN	52.49	54.65	56.38	53.81	58.44	62.61	53.54	60.64	67.70	55.77	61.80	68.14	57.54	61.85	66.19
MLkNN	52.33	54.27	55.77	51.38	55.29	58.62	26.92	28.10	28.97	45.43	48.10	50.35	53.86	56.68	59.01
BRkNN	50.36	53.05	56.00	47.46	51.53	56.64	42.48	47.28	52.45	49.89	54.98	61.52	48.56	52.24	56.77
MLARAM	33.68	33.93	34.10	25.67	26.27	26.71	41.78	45.56	48.80	33.84	34.66	35.26	27.46	27.71	27.88
DynGCN	41.80	42.57	43.19	52.81	56.77	60.14	46.27	54.65	54.65	50.05	53.97	57.75	54.22	56.93	59.21
T-GCN	60.73	64.14	67.20	56.36	61.86	67.66	56.06	63.88	72.19	60.04	67.82	76.93	61.65	67.35	73.77
RENET[1]	55.10	57.26	58.99	54.47	58.98	63.02	53.47	60.07	66.54	55.07	60.60	66.32	58.89	63.41	68.09
RENET[2]	58.44	61.46	64.18	55.85	60.86	65.66	56.44	64.37	72.82	60.58	68.47	77.75	61.66	67.24	73.52
Glean$_{-fusion}$	65.91	70.87	75.80	**58.92**	65.60	73.47	58.13	66.95	77.07	62.28	71.14	82.36	63.84	70.78	79.60
Glean	**66.69**	**71.95**	**77.31**	**58.92**	**65.64**	**73.57**	**58.76**	**68.13**	**79.49**	**62.48**	**71.43**	**82.84**	**64.12**	**71.25**	**80.46**
% relative gain	9.8%	10.9%	15.0%	4.5%	6.1%	8.7%	4.8%	5.8%	10.1%	3.1%	4.3%	6.5%	4.0%	5.8%	9.1%

Table 4: Performance results of the proposed method vs. baselines for the multi-actor forecasting task over all datasets (%).

Method	India			Russia			Nigeria			Afghanistan			Iran		
	H @ 1	3	10	1	3	10	1	3	10	1	3	10	1	3	10
DNN	2.09	11.01	33.87	1.46	9.72	36.40	5.10	17.06	**43.35**	8.55	17.42	35.32	10.71	19.48	26.50
RENET[3]	8.87	21.57	39.85	16.52	22.31	40.21	4.02	11.53	26.95	7.28	18.65	37.44	12.81	18.36	37.44
tRGCN	9.74	22.74	41.04	18.83	30.79	44.62	6.73	15.17	31.69	9.58	24.14	49.17	12.93	22.26	34.98
tCompGCN	9.62	21.91	40.53	18.27	30.20	44.79	6.50	14.95	31.06	9.64	23.67	49.04	12.79	21.43	34.88
$\text{Glean}_{-\text{temp}}$	13.39	24.50	43.68	18.24	31.15	43.27	6.16	14.41	26.98	9.21	22.27	47.03	11.01	17.96	29.87
$\text{Glean}_{-\text{fusion}}$	13.95	27.03	**45.73**	20.25	**34.64**	**48.10**	7.63	**18.06**	35.84	12.28	29.82	**56.89**	14.27	**24.41**	39.74
Glean	**14.01**	**27.17**	**45.73**	**20.49**	34.36	**48.10**	**7.66**	18.03	35.85	**12.29**	**30.04**	56.74	**14.31**	24.27	**39.75**
% relative gain	4.6%	10.9%	4.7%	8.8%	11.2%	7.4%	13.8%	5.9%	-	27.5%	24.4%	15.7%	10.7%	9.7%	6.2%

Conclusion

- We design a novel multi-event multi-actor forecasting framework that utilizes global event information from entities, event types, and event descriptions, to predict concurrent events of multiple types; and predicts potential participants (actors/entities) in these events with temporal and intrinsic inference modules based on historical events and the inherent association between entities and event types.
- We introduce a new encoding method for integrating both dynamic graph data (event graphs) and text data (documents and summaries) into graph-based relational features. We also provide a graph sampling method to obtain specific features in history for a given event-type, thereby eliminating the unwanted noise. Given the entities and event types in event graphs, we identify related words from event summaries and propose a context-aware embedding fusion method. We incorporate an attention mechanism to learn the importance of each identified word and capture local contextual semantics.

谢谢！