# Double Graph Based Reasoning for Document-level Relation Extraction

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## Task

Relation extraction in document level

#### Elias Brown

[1] Elias Brown (May 9, 1793– July 7, 1857) was a U.S. Representative from Maryland. [2] Born near Baltimore, Maryland, Brown attended the common schools. ... [7] He died near Baltimore, Maryland, and is interred in a private cemetery near Eldersburg, Maryland.

Subject: Maryland

Object: *U.S.* relation: country

Subject: Baltimore; Eldersburg

Object: Maryland

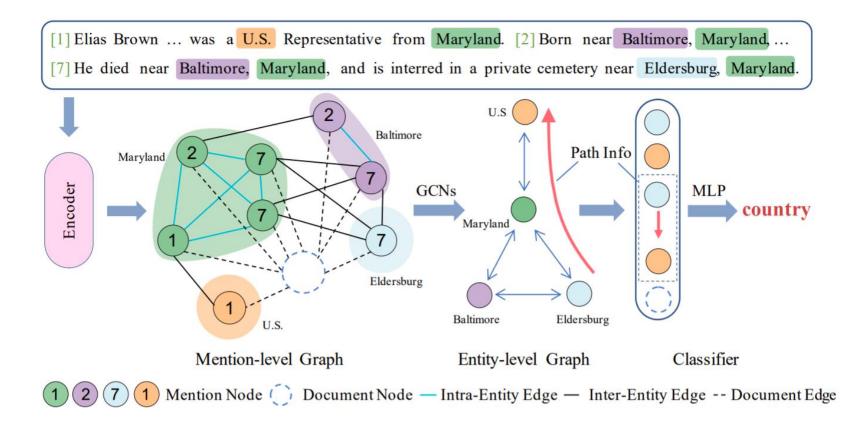
relation: located in the administrative territorial entity

Subject: Baltimore; Eldersburg

Object: *U.S.* relation: country

#### Motivation

- Infer document structure
  - Improve mention representation
  - Perform two-hop reasoning on entity graph



#### Encoder

• Encode words by word embedding, entity type and coreference embedding:

$$x_i = [E_w(w_i); E_t(t_i); E_c(c_i)]$$

• Encode the sequential order of the words:

$$[g_1, g_2, \dots, g_n] = Encoder([x_1, x_2, \dots, x_n])$$

## Mention-level Graph Aggregation Module

#### Nodes:

- Entity mentions
- Document node

#### • Edges:

- Intra-entity edge: All entity mentions are connected to each other
- Inter-entity edge: Entity mentions of two entities that cooccur in a sentence are connected to each other
- Document Edge: The document node is connected to all edges
- GCN is applied over the constructed graph

$$\mathbf{m}_u = [h_u^{(0)}; h_u^{(1)}; \dots; h_u^{(N)}]$$

## Entity-level Graph Inference Module

• Use entity mentions to represent the entity nodes:

$$\mathbf{e}_i = \frac{1}{N} \sum_n \mathbf{m}_n$$

Represent edges from entities:

$$\mathbf{e}_{ij} = \sigma \left( W_q[\mathbf{e}_i; \mathbf{e}_j] + b_q \right)$$

• Path reasoning:

$$\mathbf{p}_{h,t}^{i} = [\mathbf{e}_{ho}; \mathbf{e}_{ot}; \mathbf{e}_{to}; \mathbf{e}_{oh}]$$

$$s_{i} = \sigma([\mathbf{e}_{h}; \mathbf{e}_{t}] \cdot W_{l} \cdot \mathbf{p}_{h,t}^{i})$$

$$\alpha_i = \frac{e^{s_i}}{\sum_j e^{s_j}}$$

$$\mathbf{p}_{h,t} = \sum_i \alpha_i \mathbf{p}_{h,t}^i$$

## Classification

Prediction based on the vector:

$$I_{h,t} = [\mathbf{e}_h; \mathbf{e}_t; |\mathbf{e}_h - \mathbf{e}_t|; \mathbf{e}_h \odot \mathbf{e}_t; \mathbf{m}_{doc}; \mathbf{p}_{h,t}]$$

• Prediction:

$$P(r|\mathbf{e}_h, \mathbf{e}_t) = sigmoid\left(W_b\sigma(W_aI_{h,t} + b_a) + b_b\right)$$

• Loss:

$$\mathcal{L} = -\sum_{\mathcal{D} \in \mathcal{S}} \sum_{h \neq t} \sum_{r_i \in \mathcal{R}} \mathbb{I}(r_i = 1) \log P(r_i | \mathbf{e}_h, \mathbf{e}_t)$$
$$+ \mathbb{I}(r_i = 0) \log (1 - P(r_i | \mathbf{e}_h, \mathbf{e}_t))$$

## Results

Model	Dev				Test	
	Ign F1	Ign AUC	F1	AUC	Ign F1	F1
CNN* (Yao et al., 2019)	41.58	36.85	43.45	39.39	40.33	42.26
LSTM* (Yao et al., 2019)	48.44	46.62	50.68	49.48	47.71	50.07
BiLSTM* (Yao et al., 2019)	48.87	47.61	50.94	50.26	48.78	51.06
Context-Aware* (Yao et al., 2019)	48.94	47.22	51.09	50.17	48.40	50.70
HIN-GloVe* (Tang et al., 2020)	51.06	-	52.95	-	51.15	53.30
GAT <sup>‡</sup> (Velickovic et al., 2017)	45.17	-	51.44	-	47.36	49.51
GCNN <sup>‡</sup> (Sahu et al., 2019)	46.22	-	51.52	-	49.59	51.62
EoG <sup>‡</sup> (Christopoulou et al., 2019)	45.94	-	52.15	_	49.48	51.82
AGGCN <sup>‡</sup> (Guo et al., 2019)	46.29	-	52.47	-	48.89	51.45
LSR-GloVe* (Nan et al., 2020)	48.82	-	55.17	-	52.15	54.18
GAIN-GloVe	53.05	52.57	55.29	55.44	52.66	55.08
BERT-RE* <sub>base</sub> (Wang et al., 2019a)	-	-	54.16	1.#.j	-	53.20
RoBERTa-RE $_{base}^{\dagger}$	53.85	48.27	56.05	51.35	53.52	55.77
BERT-Two-Step** (Wang et al., 2019a)	-	-	54.42	-	-	53.92
HIN-BERT* (Tang et al., 2020)	54.29	-	56.31	-	53.70	55.60
CorefBERT-RE* (Ye et al., 2020)	55.32	-	57.51	-	54.54	56.96
LSR-BERT $_{base}^*$ (Nan et al., 2020)	52.43	-	59.00	-	56.97	59.05
GAIN-BERT <sub>base</sub>	59.14	57.76	61.22	60.96	59.00	61.24
BERT-RE* (Ye et al., 2020)	56.67	-	58.83	-	56.47	58.69
CorefBERT-RE <sub>large</sub> (Ye et al., 2020)	56.73	-	58.88	0.00	56.48	58.70
RoBERTa-RE** (Ye et al., 2020)	57.14	-	59.22	-	57.51	59.62
CorefRoBERTa-RE* <sub>large</sub> (Ye et al., 2020)	57.84	-	59.93	-	57.68	59.91
GAIN-BERT <sub>large</sub>	60.87	61.79	63.09	64.75	60.31	62.76

## Ablation Study

Model	Dev				Test	
Wiodei	Ign F1	Ign AUC	F1	AUC	Ign F1	F1
GAIN-GloVe	53.05	52.57	55.29	55.44	52.66	55.08
- hMG	50.97	48.84	53.10	51.73	50.76	53.06
- Inference Module	50.84	48.68	53.02	51.58	50.32	52.66
- Document Node	50.86	48.68	53.01	52.46	50.32	52.67
GAIN-BERT <sub>base</sub>	59.14	57.76	61.22	60.96	59.00	61.24
- hMG	57.12	51.54	59.17	54.61	57.31	59.56
- Inference Module	56.97	54.29	59.28	57.25	57.01	59.34
- Document Node	57.26	52.07	59.62	55.51	57.01	59.63

## Inter and Intra-relations

Model	Intra-F1	Inter-F1
CNN*	51.87	37.58
LSTM*	56.57	41.47
BiLSTM*	57.05	43.49
Context-Aware*	56.74	42.26
LSR-GloVe*	60.83	48.35
GAIN-GloVe	61.67	48.77
- hMG	59.72	46.49
$BERT ext{-}RE^*_{base}$	61.61	47.15
$RoBERTa$ - $RE_{base}$	65.65	50.09
BERT-Two-Step*	61.80	47.28
$LSR ext{-}BERT^*_{base}$	65.26	52.05
$GAIN ext{-}BERT_{base}$	67.10	53.90
- hMG	66.15	51.42

## Inference Relations

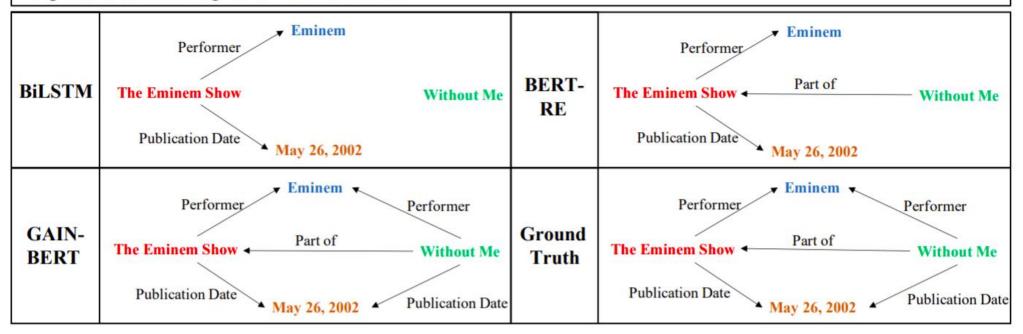
Relations that need inference

$$e_h \xrightarrow{r_1} e_o \xrightarrow{r_2} e_t \qquad e_h \xrightarrow{r_3} e_t$$

Model	Infer-F1	P	R
CNN	37.11	32.81	42.72
LSTM	39.03	33.16	47.44
BiLSTM	38.73	31.60	50.01
Context-Aware	39.73	33.97	47.85
GAIN-GloVe	40.82	32.76	54.14
- Inference Module	39.76	32.26	51.80
BERT-RE <sub>base</sub>	39.62	34.12	47.23
$RoBERTa$ - $RE_{base}$	41.78	37.97	46.45
GAIN-BERT <sub>base</sub>	46.89	38.71	59.45
- Inference Module	45.11	36.91	57.99

## Case Study

- [1] *The Eminem Show* is the fourth studio album by American rapper *Eminem*, released on *May 26, 2002* by Aftermath Entertainment, Shady Records, and Interscope Records.
- [2] *The Eminem Show* includes the commercially successful singles "*Without Me*", "Cleanin' Out My Closet", "Superman", and "Sing for the Moment"....



## Thanks