

Artificial

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EIDER: Empowering Document-level Relation Extraction with Efficient Evidence Extraction and Inference-stage Fusion

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Code: https://github.com/Veronicium/Eider

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Reported by ChangJiang Hu





Introduction

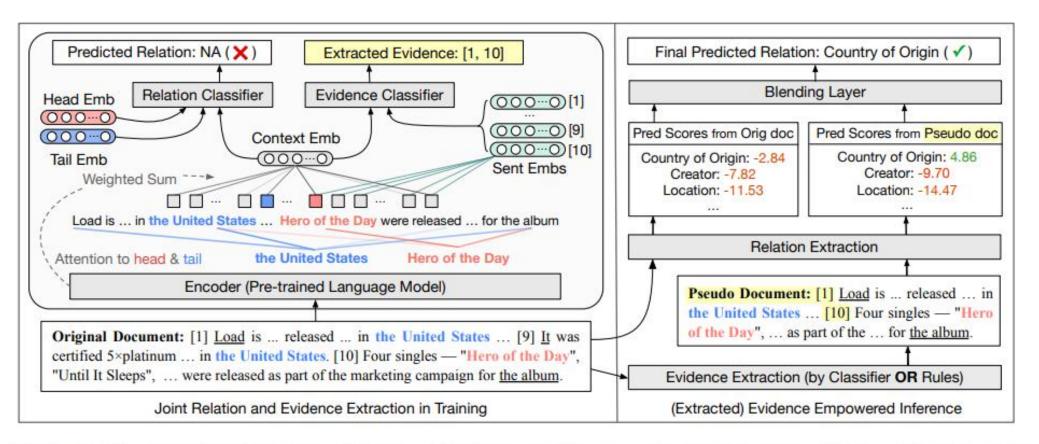
GT evidence sentences: [1,10]	
Original document as input: <u>album</u> by the American heavy me June 4, 1996 by Elektra Records was certified 5×platinum for the United States. [10] Four "Until It Sleeps", "Mama Said", released as part of the marketing Prediction scores: NA: 17.6	etal band Metallica, released on in the United States [9] <u>It</u> shipping five million copies in singles—"Hero of the Day", and "King Nothing" — were campaign for <u>the album</u> .
Extracted evidence as input: album released in the Uni — "Hero of the Day", were re Prediction scores: country	ted States [10] Four singles eleased for the album.
Final prediction of our model:	country of origin (✔)

Head: Hero of the Day Tail: the United States Rel: [country of origin]

Figure 1: A test sample in the DocRED dataset (Yao et al., 2019), where the i^{th} sentence in the document is marked with [i] at the start. Our model correctly predicts [1,10] as evidence, and if we only use the extracted evidence as input, the model can predict the relation "country of origin" correctly.



Method

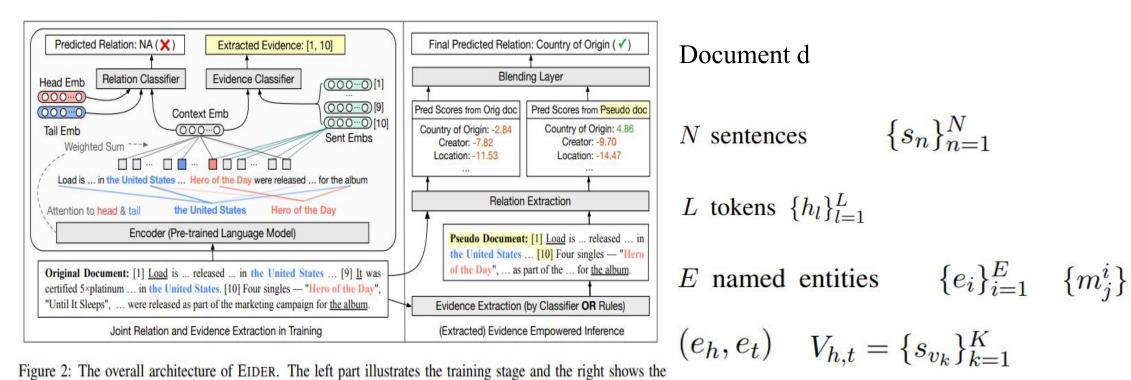




Method

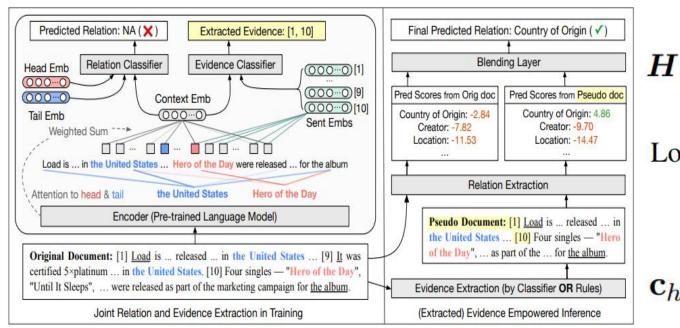
inference stages of EIDER. We highlight head entities, tail entities and extracted evidences.







Method



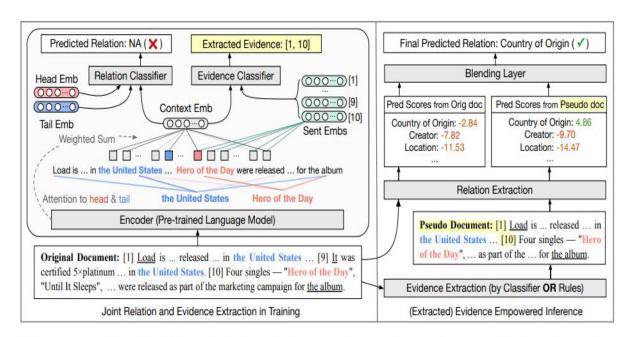
$$\boldsymbol{H}, \boldsymbol{A} = \text{Encoder}([h_1, ..., h_L]), \quad (1)$$

LogSumExp pooling
$$\mathbf{e}_i = \log \sum_j \exp(\mathbf{m}_j^i)$$
.

$$\mathbf{c}_{h,t} = \boldsymbol{H}^T \frac{\boldsymbol{A}_h \circ \boldsymbol{A}_t}{\boldsymbol{A}_h^T \boldsymbol{A}_t},$$
 (2)



Relation Classifier



$$z_{h} = \tanh \left(W_{h} \mathbf{e}_{h} + W_{c_{h}} \mathbf{c}_{h,t} \right),$$

$$z_{t} = \tanh \left(W_{t} \mathbf{e}_{t} + W_{c_{t}} \mathbf{c}_{h,t} \right),$$
 (3)

$$\mathbf{y}_{r} = z_{h} W_{r} z_{t} + \boldsymbol{b}_{r},$$

$$\mathbf{y}_{\mathrm{TH}} = \boldsymbol{z}_h \boldsymbol{W}_{\mathrm{TH}} \boldsymbol{z}_t + \boldsymbol{b}_r. \tag{4}$$

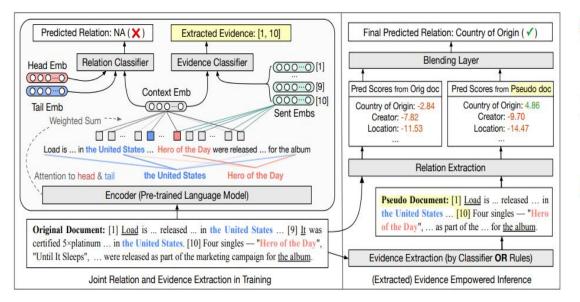
$$S_{h,t,r}^{(O)} = \mathbf{y}_r - \mathbf{y}_{TH}.$$

$$\mathcal{L}_{RE} = -\sum_{h \neq t} \sum_{r \in \mathcal{P}_{h,t}^{T}} \log \left(\frac{\exp\left(\mathbf{y}_{r}\right)}{\sum_{r' \in \mathcal{P}_{h,t}^{T} \cup \{\text{TH}\}} \exp\left(\mathbf{y}_{r'}\right)} \right) - \log \left(\frac{\exp\left(\mathbf{y}_{\text{TH}}\right)}{\sum_{r' \in \mathcal{N}_{h,t}^{T} \cup \{\text{TH}\}} \exp\left(\mathbf{y}_{r'}\right)} \right).$$
(5)





Evidence Classifier



$$s_{n}: \mathbf{s}_{n} = \log \sum_{h_{l} \in s_{n}} \exp(\mathbf{h}_{l}).$$

$$P(s_{n}|e_{h}, e_{t}) = \sigma(\mathbf{s}_{n} \mathbf{W}_{v} \mathbf{c}_{h,t} + \mathbf{b}_{v}), \quad (6)$$

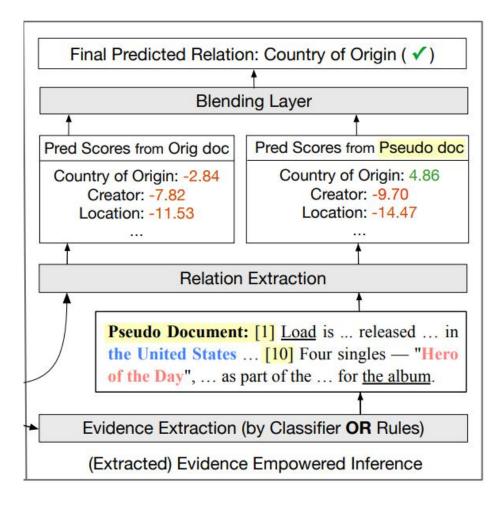
$$\mathcal{L}_{Evi} = -\sum_{h \neq t, \mathsf{NA} \notin \mathcal{P}_{h,t}^{T}} \sum_{s_{n} \in \mathcal{D}} y_{n} \cdot P(s_{n}|e_{h}, e_{t}) + (1 - y_{n}) \cdot \log(1 - P(s_{n}|e_{h}, e_{t})), \quad (7)$$

$$\mathcal{L} = \mathcal{L}_{RE} + \mathcal{L}_{Evi}.$$
 (8)





Fusion of Evidence in Inference



$$P_{Fuse}(r|e_h, e_t) = \sigma(S_{h,t,r}^{(O)} + S_{h,t,r}^{(E)} - \tau). \quad (9)$$

$$\mathcal{L}_{Fuse} = -\sum_{d \in \mathcal{D}} \sum_{h \neq t} \sum_{r \in \mathcal{R}} y_r \cdot \mathcal{P}_{Fuse} \left(r | e_h, e_t \right) + (1 - y_r) \cdot \log(1 - \mathcal{P}_{Fuse} \left(r | e_h, e_t \right)), \quad (10)$$



Heuristic Evidence Label Construction

Co-occur

Coref

Original Document: [1] <u>Load</u> is ... released ... in the United States ... [9] <u>It</u> was certified 5×platinum ... in the United States. [10] Four singles — "Hero of the Day", "Until It Sleeps", ... were released as part of the marketing campaign for <u>the album</u>.

Bridge



Model	Dev				Test	
Model	Ign F1	F1	Intra F1	Inter F1	Ign F1	F1
LSR-BERT _{base} (Nan et al., 2020)	52.43	59.00	65.26	52.05	56.97	59.05
GLRE-BERT _{base} (Wang et al., 2020)	-		2	-	55.40	57.40
Reconstruct-BERT _{base} (Xu et al., 2021)	58.13	60.18	-	-	57.12	59.45
GAIN-BERT _{base} (Zeng et al., 2020)	59.14	61.22	67.10	53.90	59.00	61.24
BERT _{base} (Wang et al., 2019)	-	54.16	61.61	47.15	-	53.20
BERT-Two-Step (Wang et al., 2019)	-	54.42	61.80	47.28	-	53.92
HIN-BERT _{base} (Tang et al., 2020)	54.29	56.31	-	-	53.70	55.60
E2GRE-BERT _{base} (Huang et al., 2021a)	55.22	58.72	7:	0.70	-	-
CorefBERT _{base} (Ye et al., 2020)	55.32	57.51	2	-	54.54	56.96
ATLOP-BERT _{base} (Zhou et al., 2021)	$59.11 \pm 0.14^\dagger$	$61.01\pm0.10^{\dagger}$	$67.26\pm0.15^{\dagger}$	$53.20\pm0.19^\dagger$	59.31	61.30
EIDER (Rule)-BERT _{base}	60.36 ± 0.13	62.34 ± 0.08	68.40 ± 0.14	54.79 ± 0.13	60.23	62.21
EIDER-BERT _{base}	$\textbf{60.51} \pm \textbf{0.11}$	$\textbf{62.48} \pm \textbf{0.13}$	$\textbf{68.47} \pm \textbf{0.08}$	$\textbf{55.21} \pm \textbf{0.21}$	60.42	62.47
RoBERTa _{large} (Ye et al., 2020)	57.14	59.22	÷	2 -	57.51	59.62
CorefRoBERTalarge (Ye et al., 2020)	57.35	59.43	Ξ.	2. 	57.90	60.25
E2GRE-RoBERTalarge (Huang et al., 2021a)	59.55	62.91	-	-	60.29	62.51
GAIN-BERT _{large} (Zeng et al., 2020)	60.87	63.09	The second s	-	60.31	62.76
ATLOP-RoBERTalarge (Zhou et al., 2021)	$61.30\pm0.22^{\dagger}$	$63.15 \pm 0.21^\dagger$	$69.61\pm0.25^\dagger$	$55.01\pm0.18^\dagger$	61.39	63.40
EIDER (Rule)-RoBERTa _{large}	61.73 ± 0.07	63.91 ± 0.07	69.99 ± 0.09	56.27 ± 0.11	61.93	64.12
EIDER-RoBERTalarge	$\textbf{62.34} \pm \textbf{0.14}$	$\textbf{64.27} \pm \textbf{0.10}$	$\textbf{70.36} \pm \textbf{0.07}$	$\textbf{56.53} \pm \textbf{0.15}$	62.85	64.79

Table 1: Relation extraction results on DocRED. We report the mean and standard deviation on the development set by conducting 5 runs with different random seeds. We report the official test score of the best checkpoint on the development set. Results with † are based on our implementation. Others are reported in their original papers. We separate graph-based and transformer-based methods into two groups.



Model	CDR	GDA
LSR-BERT _{base} (Nan et al., 2020)	64.8	82.2
SciBERT _{base} (Zhou et al., 2021)	65.1 ± 0.6	82.5 ± 0.3
DHG-BERT _{base} (Zhang et al., 2020b)	65.9	83.1
GLRE-SciBERT _{base} (Wang et al., 2020)	68.5	3723
ATLOP-SciBERT _{base} (Zhou et al., 2021)	69.4 ± 1.1	83.9 ± 0.2
EIDER (Rule)-SciBERTbase	70.63 ± 0.49	84.54 ± 0.22

Table 2: Relation extraction results on CDR and GDA.





Model	Dev Evi F1	Test Evi F1
E2GRE-BERT _{base}	47.14	48.35
EIDER-BERT _{base}	50.71	51.27
E2GRE-RoBERTalarge	51.11	50.50
EIDER-RoBERTalarge	52.54	53.01

Table 3: Evidence extraction results on DocRED. We compare EIDER with E2GRE (Huang et al., 2021a).



	Rules (ours)	EIDER-BERT _{base}	NoJoint
PosEvi F1	77.43	80.33	51.13

Table 4: Ablation study for evidence extraction.

Ablation	Ign F1	F1	Intra F1	Inter F1
EIDER-BERT _{base}	60.51	62.48	68.47	55.21
NoJoint	59.98	62.03	68.51	54.10
NoPseudo	59.70	61.53	67.55	54.01
NoOrigDoc	58.47	60.44	66.24	53.23
NoBlending	58.93	61.46	67.33	54.37
FinetuneOnEvi	60.11	62.29	68.13	54.84
EIDER (Rule)-BERT _{base}	60.36	62.34	68.40	54.79
NoJoint	60.01	62.09	68.21	54.34

Table 5: Ablation study of EIDER on DocRED.



	Co-occur	Coref	Bridge	Total
Count	6711	984	3212	10,907
Percent	54.46%	7.99%	26.07%	88.52%

Table 6: Statistics of the 12,323 relations in the DocRED development set.

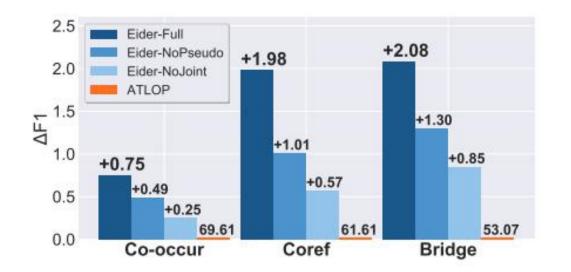


Figure 3: Performance gains in F1 by relation categories. The gains are relative to the second best baseline (ATLOP-RoBERTa_{large}).



Thank you!