

A Novel Cascade Binary Tagging Framework for Relational Triple Extraction

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Overview

- Most previous work addresses relation extraction (RE) by learning a mapping from a pair of entities (i.e., subject and object) to a relation:

$$f(s, o) \rightarrow r$$

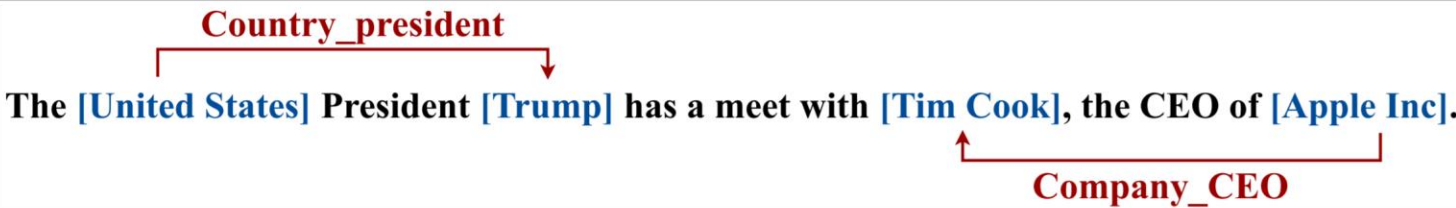
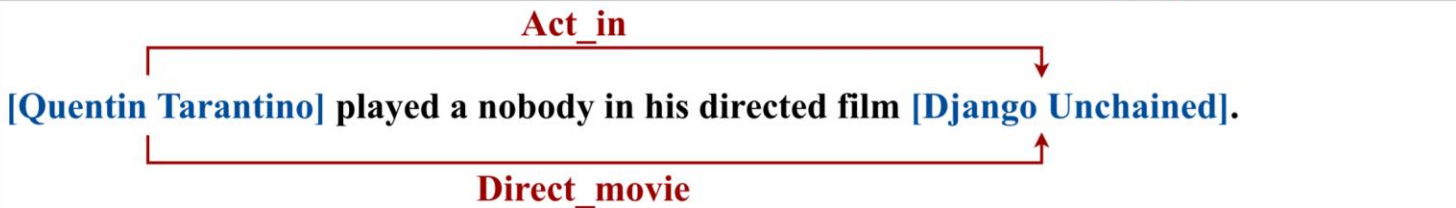
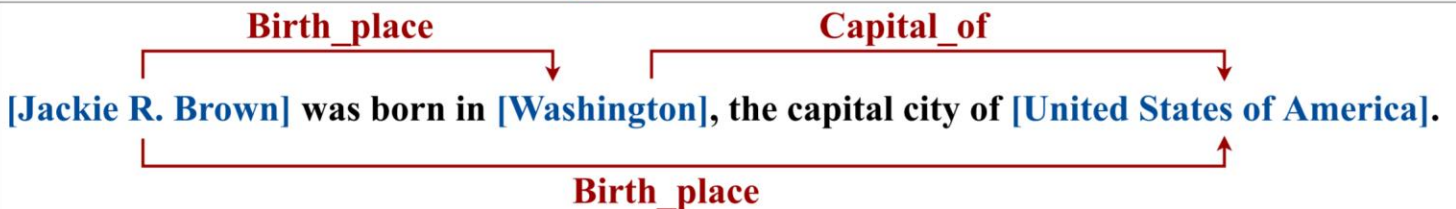
- This work treats RE as a learning problem of functions mapping subjects to objects:

$$f_r(s) \rightarrow o$$

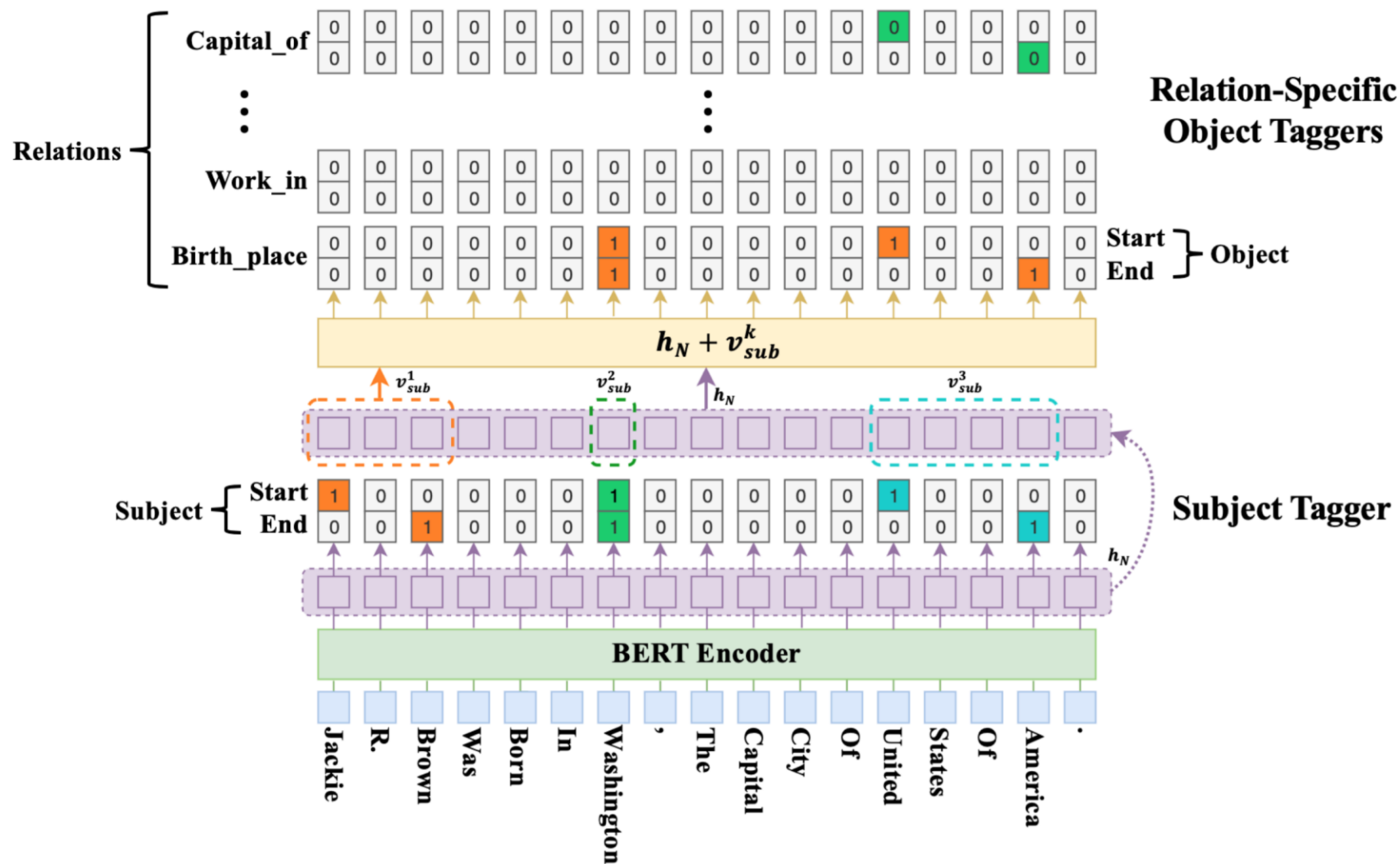
=> Naturally solve the problem of overlapping relations in RE.

Overlapping problem in RE

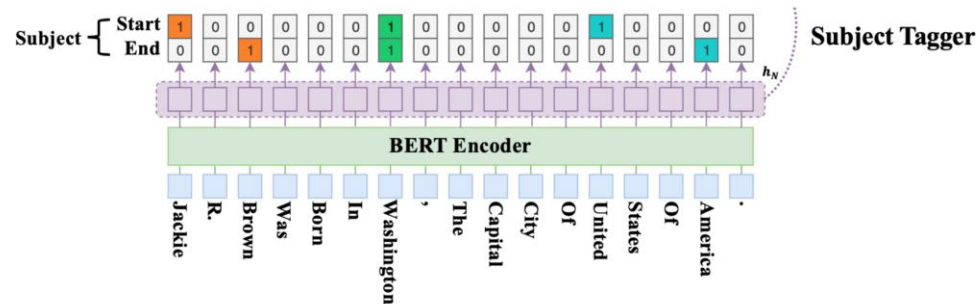
- There are two types of overlapping in RE:
 - Entity Pair Overlap (EPO).
 - Single Entity Overlap (SEO).

Normal	<p>The [United States] President [Trump] has a meet with [Tim Cook], the CEO of [Apple Inc].</p> 
EPO	<p>[Quentin Tarantino] played a nobody in his directed film [Django Unchained].</p> 
SEO	<p>[Jackie R. Brown] was born in [Washington], the capital city of [United States of America].</p> 

Model: Overview



Model: Subject Tagger



- Given a sentence j , it uses BERT as the encoder to obtain \mathbf{x}_j
- Employs two classifiers for identifying "start"s and "end"s of subjects.

$$p_i^{start-s} = \sigma(\mathbf{W}_{start}\mathbf{x}_i + \mathbf{b}_{start})$$

$$p_i^{end-s} = \sigma(\mathbf{W}_{end}\mathbf{x}_i + \mathbf{b}_{end})$$

- Training objective: maximizes the log likelihood of the groundtruth subject spans:

$$\sum_{s \in T_j} \log p_{\theta}(s | \mathbf{x}_j)$$

where: $p_{\theta}(s | \mathbf{x})$

$$= \prod_{t \in \{start-s, end-s\}} \prod_{i=1}^L (p_i^t)^{\mathbf{I}\{y_i^t=1\}} (1 - p_i^t)^{\mathbf{I}\{y_i^t=0\}}$$

Model: Relation-specific Object Taggers

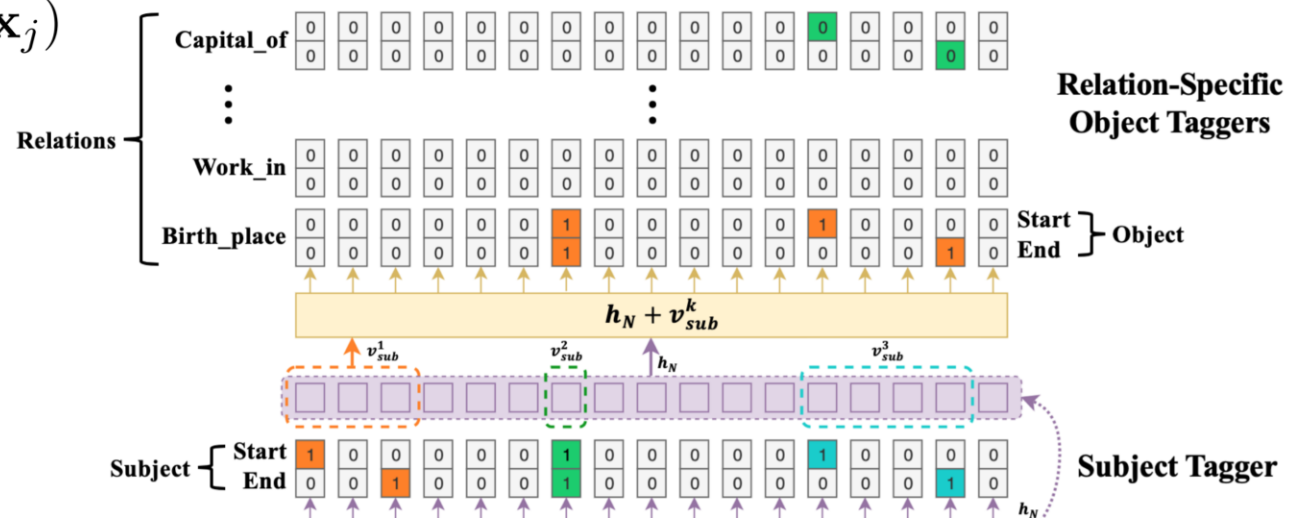
- For each relation, takes the representation \mathbf{v}_{sub}^k of the detected subject into account.

$$p_i^{start-o} = \sigma(\mathbf{W}_{start}^r(\mathbf{x}_i + \mathbf{v}_{sub}^k) + \mathbf{b}_{start}^r)$$

$$p_i^{end-o} = \sigma(\mathbf{W}_{end}^r(\mathbf{x}_i + \mathbf{v}_{sub}^k) + \mathbf{b}_{end}^r)$$

- Training objective: maximizes the following log likelihood:

$$\sum_{r \in T_j | s} \log p_{\phi_r}(o | s, \mathbf{x}_j) + \sum_{r \in R \setminus T_j | s} \log p_{\phi_r}(o_{\emptyset} | s, \mathbf{x}_j)$$



Results

- Datasets:
 - Highly-overlapping RE datasets: NYT and WebNLG.

Category	NYT		WebNLG	
	Train	Test	Train	Test
<i>Normal</i>	37013	3266	1596	246
<i>EPO</i>	9782	978	227	26
<i>SEO</i>	14735	1297	3406	457
ALL	56195	5000	5019	703

- Also on ACE04, NYT10-HRL, NYT11-HRL, WikiKBP.

Results

- Achieves 17.5% and 30.2% improvements in F1-score over the best state-of-the-art method (Zeng et al., 2019).

Method	NYT			WebNLG		
	<i>Prec.</i>	<i>Rec.</i>	<i>F1</i>	<i>Prec.</i>	<i>Rec.</i>	<i>F1</i>
NovelTagging (Zheng et al., 2017)	62.4	31.7	42.0	52.5	19.3	28.3
CopyR _{OneDecoder} (Zeng et al., 2018)	59.4	53.1	56.0	32.2	28.9	30.5
CopyR _{MultiDecoder} (Zeng et al., 2018)	61.0	56.6	58.7	37.7	36.4	37.1
GraphRel _{1p} (Fu et al., 2019)	62.9	57.3	60.0	42.3	39.2	40.7
GraphRel _{2p} (Fu et al., 2019)	63.9	60.0	61.9	44.7	41.1	42.9
CopyR _{RL} (Zeng et al., 2019)	77.9	67.2	72.1	63.3	59.9	61.6
CopyR _{RL} [*]	72.8	69.4	71.1	60.9	61.1	61.0
CASREL _{random}	81.5	75.7	78.5	84.7	79.5	82.0
CASREL _{LSTM}	84.2	83.0	83.6	86.9	80.6	83.7
CASREL	89.7	89.5	89.6	93.4	90.1	91.8

Results

- Performance comparison in different types of overlapping.

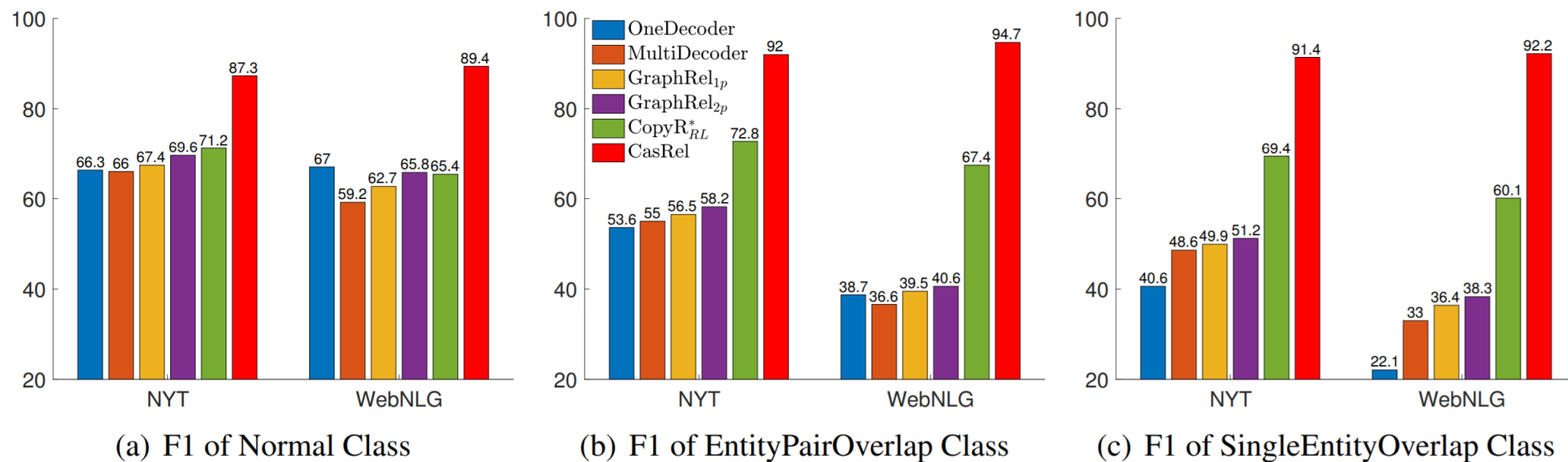


Figure 3: F1-score of extracting relational triples from sentences with different overlapping pattern.

Results

- Results on low-overlapping RE datasets:

Method	<i>Partial Match</i>									<i>Exact Match</i>		
	ACE04			NYT10-HRL			NYT11-HRL			Wiki-KBP		
	<i>Prec.</i>	<i>Rec.</i>	<i>F1</i>	<i>Prec.</i>	<i>Rec.</i>	<i>F1</i>	<i>Prec.</i>	<i>Rec.</i>	<i>F1</i>	<i>Prec.</i>	<i>Rec.</i>	<i>F1</i>
Chan and Roth (2011)	42.9	38.9	40.8	–	–	–	–	–	–	–	–	–
MultiR (Hoffmann et al., 2011)	–	–	–	–	–	–	32.8	30.6	31.7	30.1	53.0	38.0
DS-Joint (Li and Ji, 2014)	64.7	38.5	48.3	–	–	–	–	–	–	–	–	–
FCM (Gormley et al., 2015)	–	–	–	–	–	–	43.2	29.4	35.0	–	–	–
SPTree (Miwa and Bansal, 2016)	–	–	–	49.2	55.7	52.2	52.2	54.1	53.1	–	–	–
CoType (Ren et al., 2017)	–	–	–	–	–	–	48.6	38.6	43.0	31.1	53.7	38.8
Katiyar and Cardie (2017)	50.2	48.8	49.3	–	–	–	–	–	–	–	–	–
NovelTagging (Zheng et al., 2017)	–	–	–	59.3	38.1	46.4	46.9	48.9	47.9	53.6	30.3	38.7
ReHession (Liu et al., 2017)	–	–	–	–	–	–	–	–	–	36.7	49.3	42.1
CopyR (Zeng et al., 2018)	–	–	–	56.9	45.2	50.4	34.7	53.4	42.1	–	–	–
HRL (Takanobu et al., 2019)	–	–	–	71.4	58.6	64.4	53.8	53.8	53.8	–	–	–
PA-LSTM-CRF (Dai et al., 2019)	–	–	–	–	–	–	–	–	–	51.1	39.3	44.4
CASREL	57.2	47.6	52.0	77.7	68.8	73.0	50.1	58.4	53.9	49.8	42.7	45.9