

A Hierarchical Framework for Relation Extraction with Reinforcement Learning

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AAAI 2019

Relation Extraction

Relation Extraction

Obama was **born in** the United States.



Relation Triple: ([Obama]_{es}, BornIn, [United States]_{et})

Source entity *Relation type* Target entity

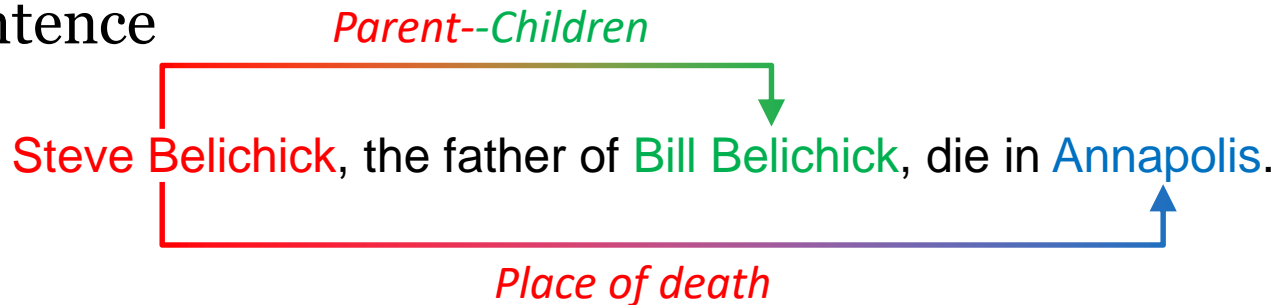
- Joint extraction of **entity mentions** and **relation types**.



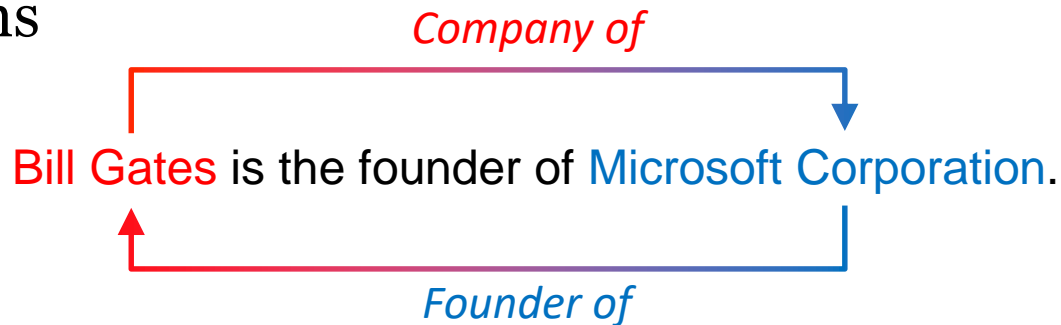
Motivation

◎ Deal with **overlapping relations**.

- ◆ one entity participate in multiple relations in the same sentence



- ◆ same entity pair in a sentence is associated with different relations



Motivation

- ◎ Capture the **interaction** between **relation type** and **entities**.
 - ◆ Previous methods: pipeline or Cartesian product.
- ◎ Novel end-to-end **hierarchical** paradigm with HRL method, which identify entity mentions and relation types **jointly**.



Framework

(Steve Belichick), the father of (New England Patriots) coach (Bill Belichick), died of heart failure in (Annapolis), at the age of 86 .

parent-children

Steve Belichick , the father of New England Patriots coach Bill Belichick ,

I

Figure 1: An example sentence which has two **overlapping relations** (*Steve Belichick*, parent-children, *Bill Belichick*), (*Steve Belichick*, place-of-death, *Annapolis*). The solid arrow indicates the high-level relation detection process, and the dashed arrow for low-level entity extraction. The dotted arrow marks a transition between the two processes. This example shows how overlapping relations are extracted (*Steve Belichick* is included in both triples).



Framework

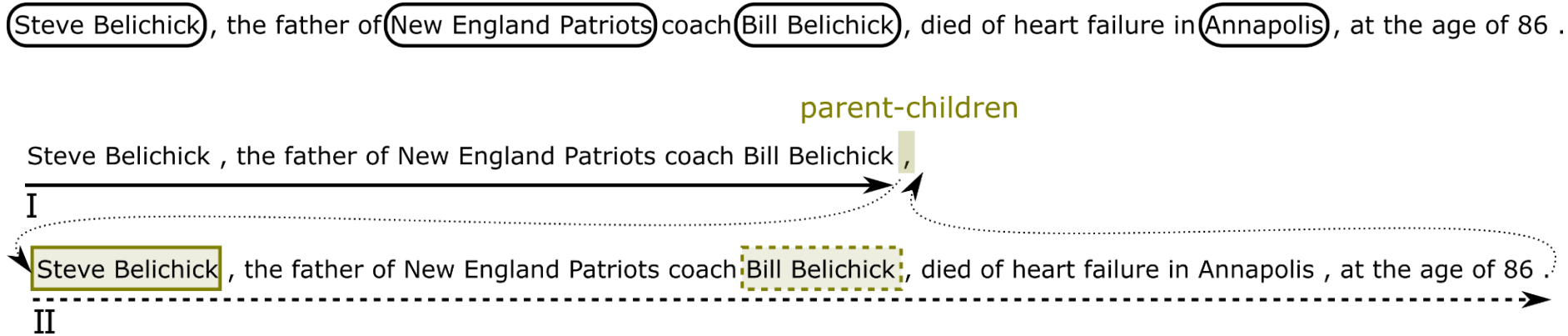


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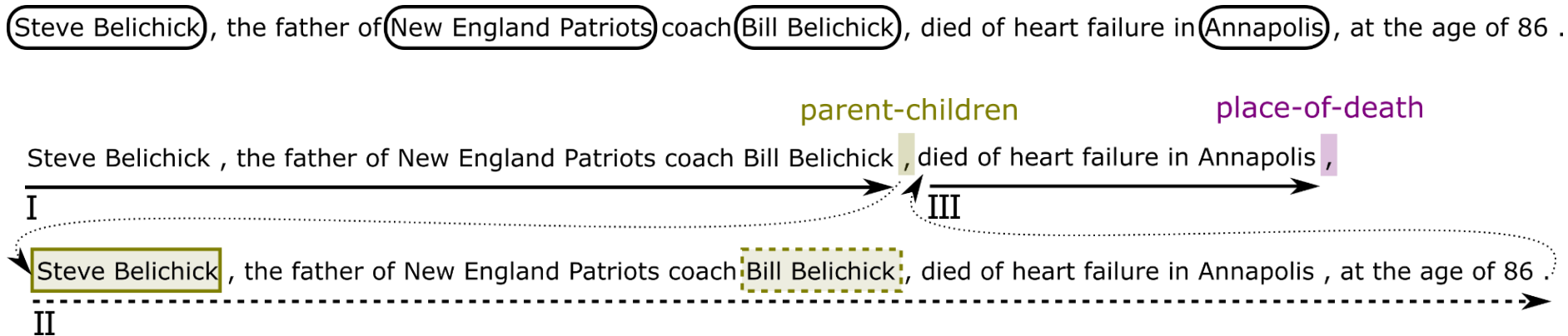


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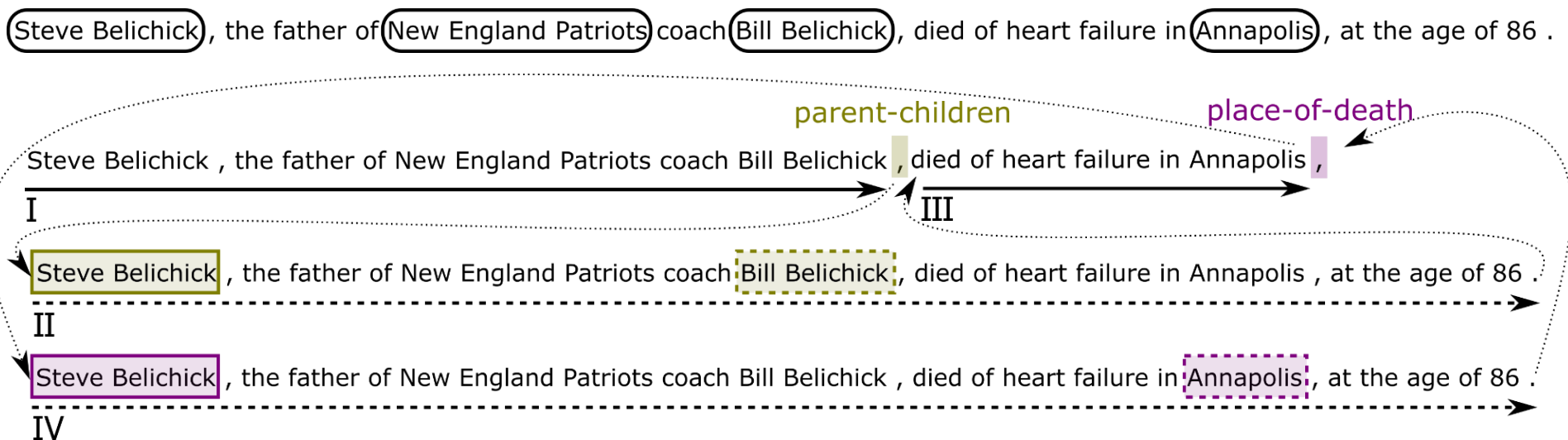


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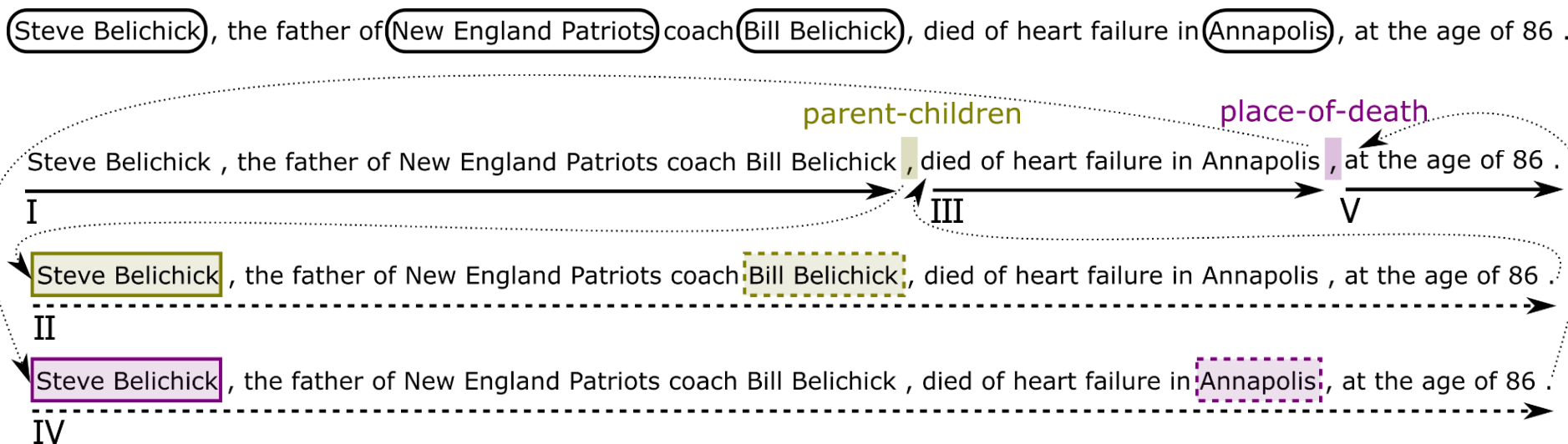
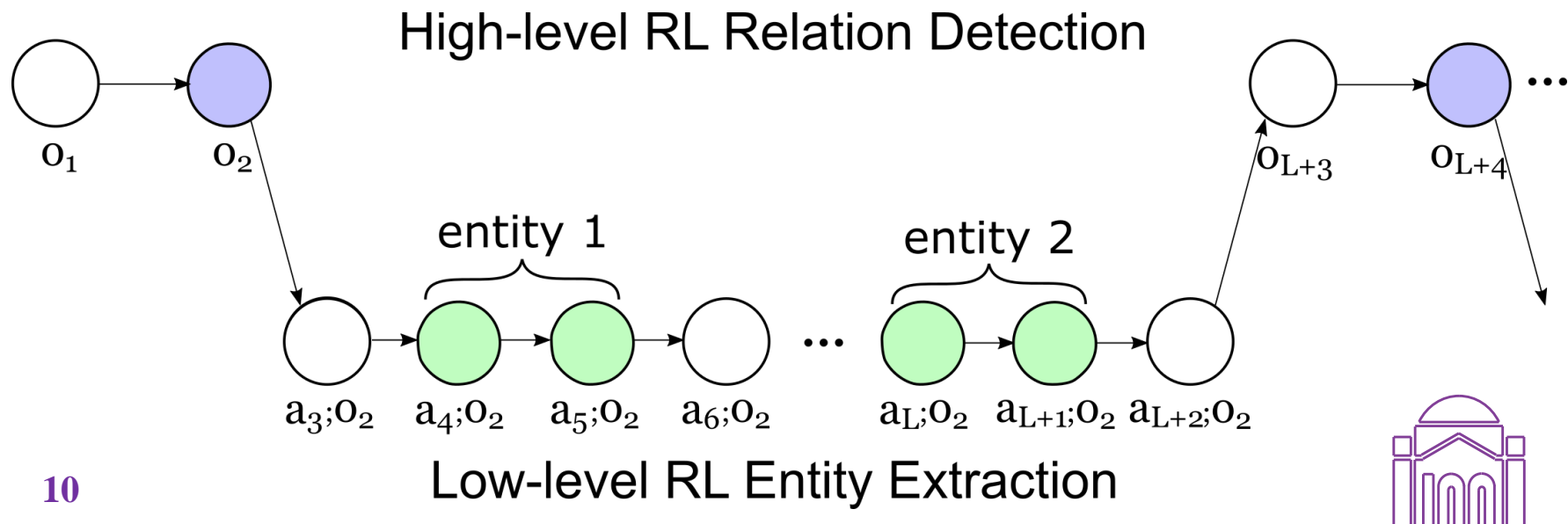


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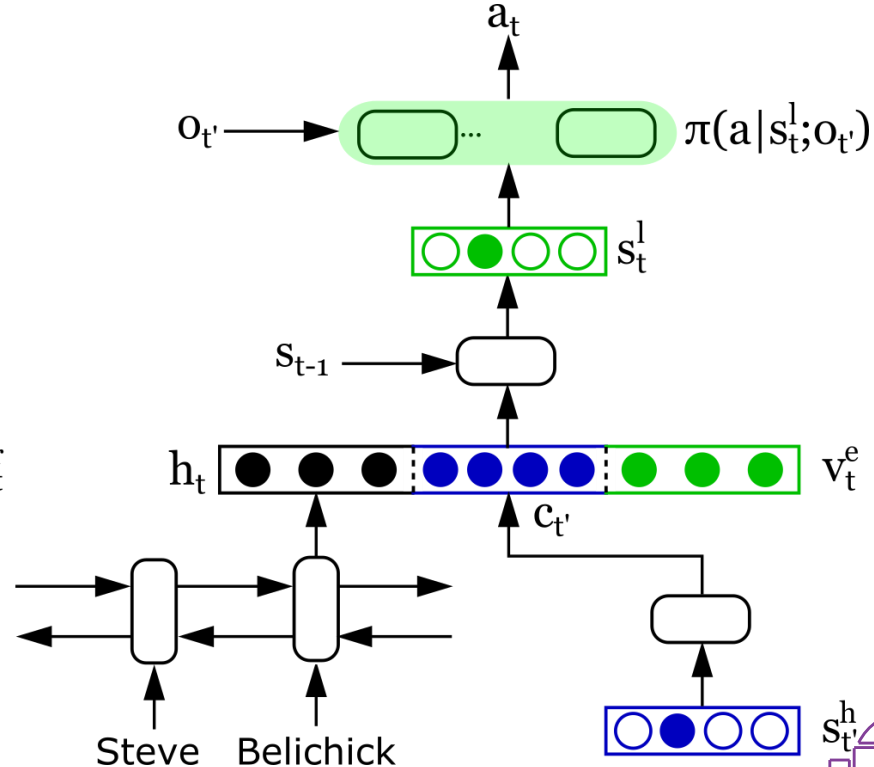
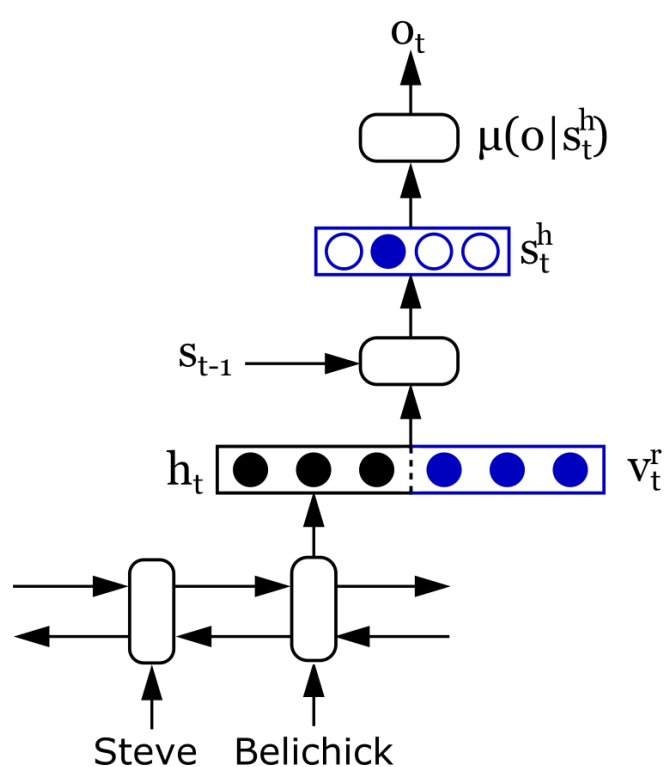
- Relation Indicator: the position in a sentence when sufficient information has been mentioned to identify a semantic relation.
- Treats entities as the **arguments** of a relation



Framework

Left: high-level policy for **relation detection** (as option)

Right: low-level policy for **entity extraction** (as primitive action)



Relation Detection

◎ **Option:** $\mathcal{O} = \{NR\} \cup R$, Relation type set.

◎ **State:** $s_t^h = f^h(W_s^h[\mathbf{h}_t; \mathbf{v}_t^r; \mathbf{s}_{t-1}])$

◆ \mathbf{v}_t^r : The embedding of the **latest** option.

◆ \mathbf{h}_t : LSTM output.

◎ **Policy:** $o_t \sim \mu(o_t | s_t^h) = \text{softmax}(W_\mu s_t^h)$

◎ **Reward:**

$$\text{◆ } r_t^h = \begin{cases} -1, & \text{if } o_t \text{ not in } S \\ 0, & \text{if } o_t = NR \\ 1, & \text{if } o_t \text{ in } S \end{cases} \quad r_{fin}^h = F_\beta(S)$$



Entity Extraction

- ⊙ **Action:** $A = (\{S, T, O\} \times \{B, I\}) \cup \{N\}$
- ⊙ **State:** $s_t^l = f^l(W_s^l[h_t; v_t^e; s_{t-1}; c_{t'}])$
 - ◆ v_t^e : a learnable embedding of a_{t-1}
 - ◆ $c_{t'}$: relational state representation assigned to the latest option $s_{t'}^h$, $c_{t'} = g(W_h^l s_{t'}^h)$
- ⊙ **Policy:** $a_t \sim \pi(a_t | s_t^l; o_{t'}) = \text{softmax}(W_\pi[o_{t'}] s_t^l)$
- ⊙ **Reward:**
 - ◆ $r_t^l = \begin{cases} \text{sgn}(a_t = y_t(o_{t'})), & \text{if } y \neq N \\ \alpha \times \text{sgn}(a_t = y_t(o_{t'})), & \text{if } y = N \end{cases}$



Entity Tag

- ◎ **S:** the source entity
- ◎ **T:** the target entity
- ◎ **O:** the entities that are not associated with the predicted relation
- ◎ **B:** beginning of an entity
- ◎ **I:** inside of an entity
- ◎ **N:** non-entity words

Steve Belichick , the father of New England Patriots coach Bill Belichick , died of heart failure in Annapolis , ...

S_B S_I N N N N O_B O_I O_I N T_B T_I N N N N N N O_B N



Experiment

Model	NYT10			NYT11		
	Prec	Rec	F_1	Prec	Rec	F_1
FCM	–	–	–	.432	.294	.350
MultiR	–	–	–	.328	.306	.317
CoType	–	–	–	.486	.386	.430
SPTree	.492	.557	.522	.522	.541	.531
Tagging	.593	.381	.464	.469	.489	.479
CopyR	.569	.452	.504	.347	.534	.421
HRL	.714	.586	.644	.538	.538	.538

Table 2: Main results on relation extraction.

Model	NYT10-sub			NYT11-plus		
	Prec	Rec	F_1	Prec	Rec	F_1
FCM	–	–	–	.234	.199	.219
MultiR	–	–	–	.241	.214	.227
CoType	–	–	–	.291	.254	.271
SPTree	.272	.315	.292	.466	.229	.307
Tagging	.256	.237	.246	.292	.220	.250
CopyR	.392	.263	.315	.329	.224	.264
HRL	.815	.475	.600	.441	.321	.372

Table 3: Performance comparison on extracting overlapping relations.

Model	NYT11			NYT11-plus		
	Prec	Rec	F_1	Prec	Rec	F_1
FCM	.502	.479	.490	.447	.327	.378
MultiR	.465	.439	.451	.423	.336	.375
CoType	.558	.558	.558	.491	.413	.449
SPTree	.650	.614	.631	.700	.343	.460
CopyR	.480	.714	.574	.626	.426	.507
HRL-Ent	.676	.676	.676	.577	.321	.413
HRL	.654	.654	.654	.626	.456	.527

Table 5: Performance comparison on relation detection.



Case Study

The lawsuit contended that the chairman of the [[News Corporation]_{Et-Company}]_{Es-Founder} , [[[Rupert Murdoch]_{Es-Company}]_{Et-Founder}]_{Es-Nationality} , promised certain rights to shareholders , including the vote on the poison pill , in return for their approval of the company 's plan to reincorporate in the United States from [Australia]_{Et-Nationality} .

Both [Steven A. Ballmer]_{Es-Company} , [[Microsoft]_{Et-Company}]_{Et-Company}]_{Es-Founder} 's chief executive , and [[Bill Gates]_{Es-Company}]_{Et-Founder} , the chairman , have been involved in that debate inside the company , according to that person .

Table 4: Extraction examples by our model. The words in a bracket represents an entity extracted by the model. *Es* stands for source entity and *Et* for target entity. A predicted relation indicator is marked in background color (e.g. “Murdoch” in the first instance). The entities which form a triple are bracketed in the same color.

- Two triples (**Red** & **Brown**) share two entities (both head and tail entities) within a sentence



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- Two triples (Red & Blue) share only one entity within a sentence



Summary

- ◎ A **hierarchical extraction** paradigm to approach relation extraction via **hierarchical reinforcement learning**.
 - ◆ Treats entities as the arguments of a relation.
 - ◆ Decomposes the relation extraction task into a hierarchy of two subtasks
- ◎ Good at modeling the **interactions** between the two subtasks.
- ◎ Particularly excels at extracting **overlapping relations**.
- ◎ **May be generalized to other pairwise tasks. (e.g. aspect-opinion mining)**

