A Hierarchical Framework for Relation Extraction with Reinforcement Learning

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AAAI19

Characteristics:

1. Jointly extract relation and entity pair.
2. Higher performance in extraction of overlapping relations

Open test-reading-friendly.json ~/projects/OpenNRE-PyTorch/raw_data Save


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        "head": {
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            "type": "/user/narphorium/people/nndb_person,/music/artist,/base/moscratch/topic,/award/award_winner,/music/composer,/music/producer,/broadcast/artist,/people/person,/common/topic,/internet/social_network_user,/base/moscratch/shce021709,/user/narphorium/people/topic",
            "word": "Johnny Rivers"
        },
        "relation": "/people/person/place_lived",
        "sentence": "There were also performers who were born in Louisiana , including Lucinda Williams , Jerry Lee Lewis and Johnny Rivers , whose '' Secret Agent Man '' had a touch of bayou-country swamp-pop .",
        "tail": {
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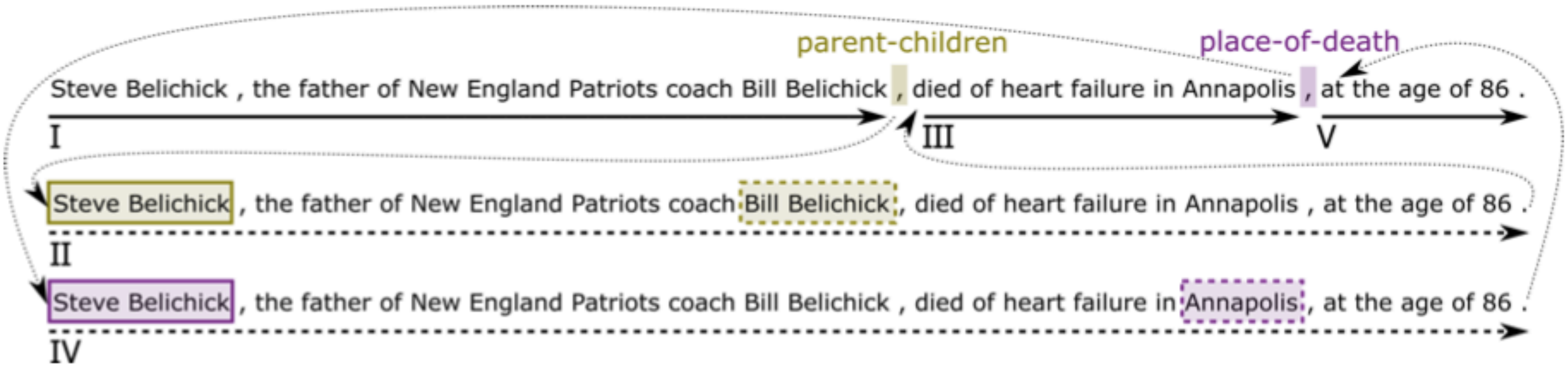
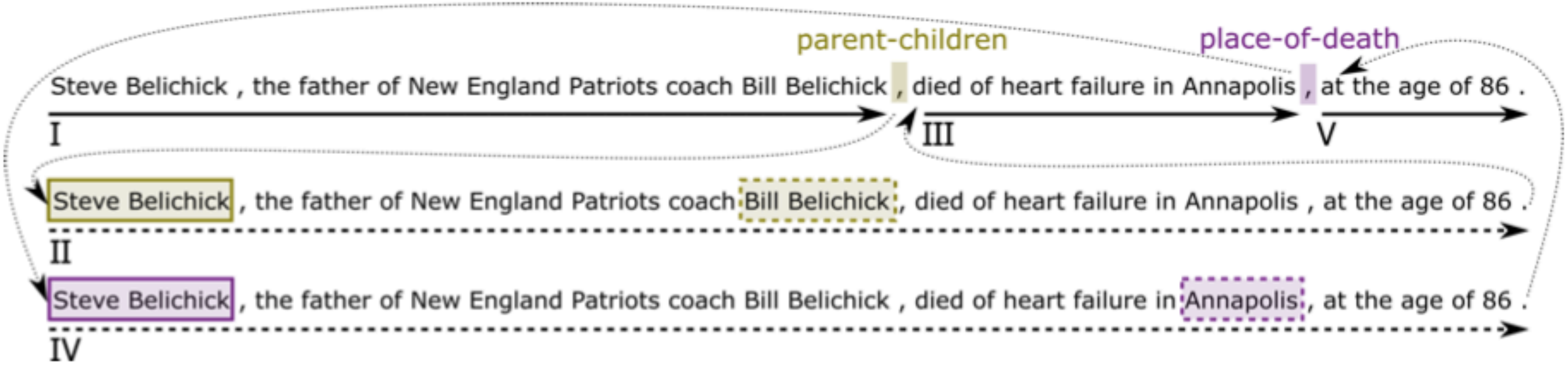
            "type": "/location/administrative_division,/common/topic,/base/locations/states_and_provences,/base/locations/topic,/location/location,/base/ontologies/ontology_instance,/organization/organization_scope,/location/statistical_region,/base/coloniesandempire/topic,/base/coloniesandempire/former_french_colonies,/base/localfood/food_producing_region,/freebase/apps/hosts/com/acre/juggle/juggle,/base/seafood/topic,/government/political_district,/base/seafood/fishery_location,/government/governmental_jurisdiction,/user/robert/default_domain/states_i_ve_been_to,/user/skud/names/namesake,/user/tsegaran/random/taxonomy_subject,/location/dated_location,/location/us_state,/base/localfood/topic,/book/book_subject,/user/skud/names/topic,/meteorology/cyclone_affected_area",
            "word": "Louisiana"
        }
    },
    {
```


NYT10



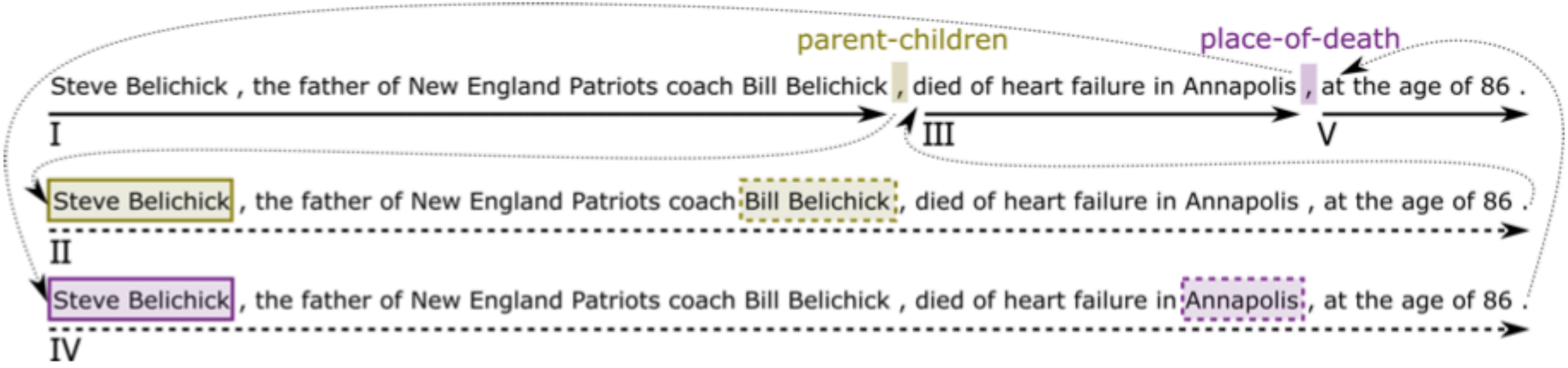
Overlapping relation case



High-Level policy:

Scan sequentially until find a **Relation indicator.**

Relation indicator: is the ***position*** *in a sentence when sufficient information has been mentioned to identify a semantic relation*

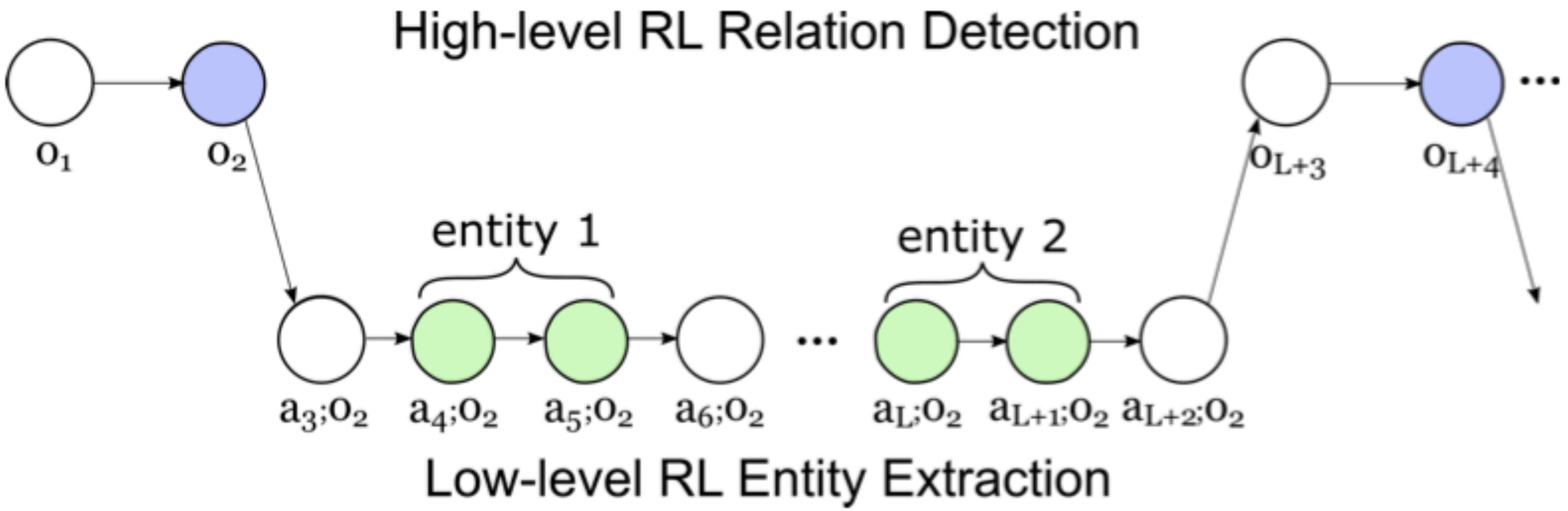


Low-Level policy:

Scan from the beginning, and tag corresponding **entity pair**.

Motivation:

1. Treating entities as the arguments of a relation, therefore the model can connect classification and tagging process.
2. Hierarchical structures to solve overlapping problem.

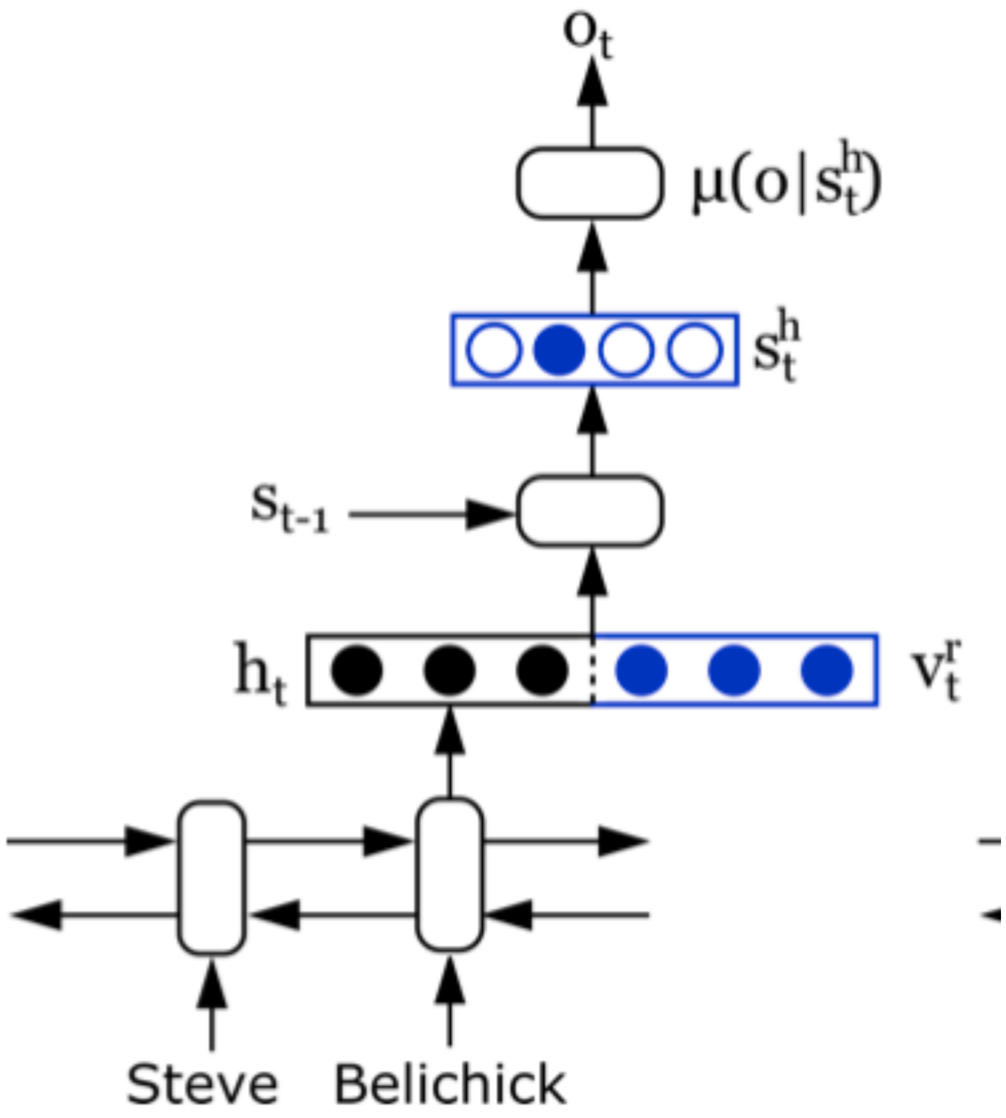


Hierarchical Reinforcement Learning:

Task:

Agent: High-Level policy: Drive…

Low-Level policy: object detection, muscle-control



High-Level policy

Option:

Selected from $\{NR\} \cup \mathcal{R}$

State:

$$s_t^h = f^h(W_s^h[h_t; v_t^r; s_{\{t-1\}}])$$

Policy:

$$o_t \sim \mu(o_t | s_t^h) = softmax(W_\mu s_t^h)$$

Reward:

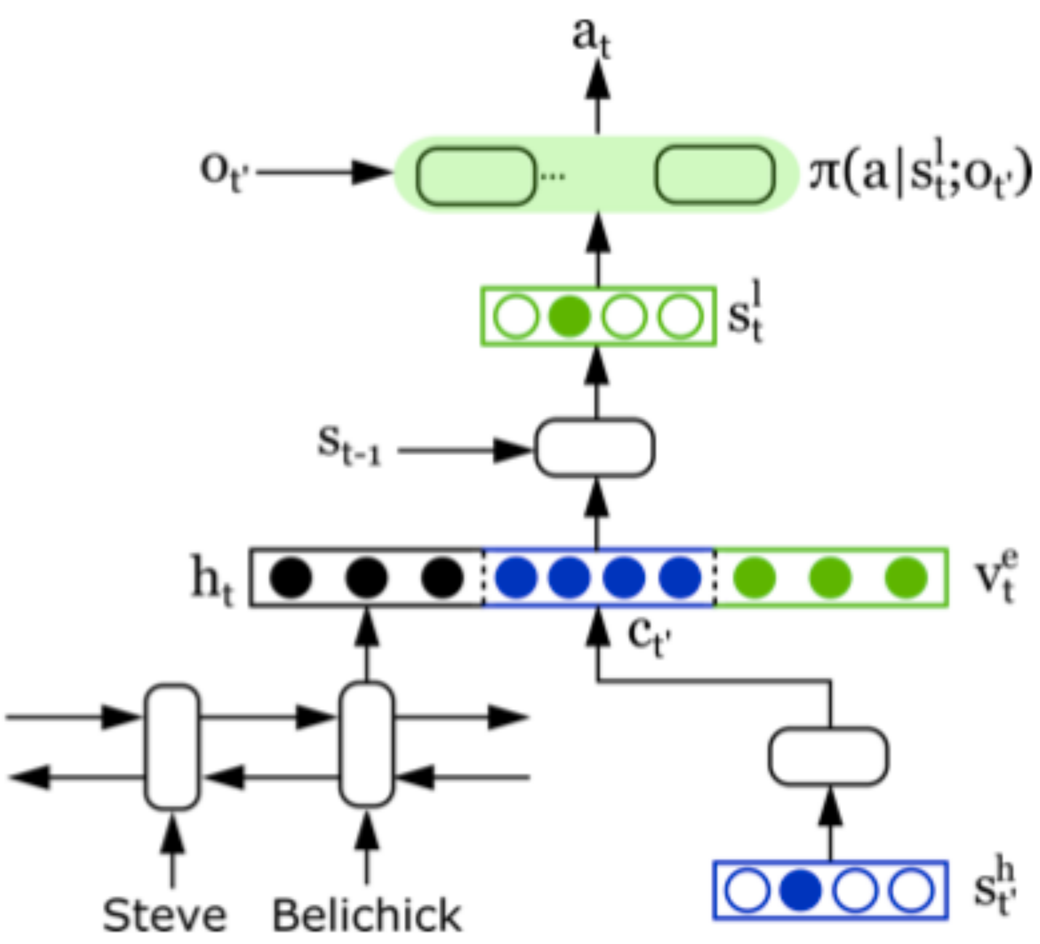
$$r_t^h = \begin{cases} -1, & if\ o_t\ not\ in\ S \\ 0, & if\ o_t = \mathrm{NR} \\ 1, & if\ o_t\ in\ S. \end{cases}$$

$$r_{fin}^h = F_\beta(S) = \frac{(1+\beta^2)Prec \cdot Rec}{\beta^2 Prec + Rec},$$

	Steve	Belichick	,	the	father	of	New	England	Patriots	coach	Bill	Belichick	,	died	of	heart	failure	in	Annapolis	,	…
Entity Tag	*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*	

Action:

A=({S,T,O}*{B,I})



State:

$$c_{t'} = g\left(W_h^l s_{t'}^h\right)$$
$$s_t^l = f^l\left(W_s^l[h_t; v_t^e; s_{t-1}; c_{t'}]\right)$$

Policy:

$$a_t \sim \pi(a_t|\mathbf{s}_t^l; o_{t'}) = softmax(\mathbf{W}_\pi[o_{t'}]\mathbf{s}_t^l),$$

Reward:

$$r_t^l = \lambda(y_t) \cdot sgn(a_t^l = y_t(o_{t'})),$$

$$\lambda(y) = \begin{cases} 1, & if\ y \neq \mathrm{N} \\ \alpha, & if\ y = \mathrm{N}. \end{cases}$$

The smaller α leads to less reward on words that are not entities. In this manner, the model avoids to learn a trivial policy that predicts all words as N (non-entity words). When

Maximize total reward

High-level policy reward function

$$J(\theta_{\mu,t}) = \mathbb{E}_{\mathbf{s}^h, o, r^h \sim \mu(o|\mathbf{s}^h)}[\sum_{k=t}^{T} \gamma^{k-t} r_k^h], \qquad (10)$$

High-level policy reward function

$$J(\theta_{\pi,t}; o_{t'}) = \mathbb{E}_{\mathbf{s}^l, a, r^l \sim \pi(a|\mathbf{s}^l; o_{t'})}[\sum_{k=t}^{T'} \gamma^{k-t} r_k^l], \qquad (11)$$

Main Results

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**

CopyR:
Treat Relation Extraction as a triple generation process.

Two types of overlapping

- Type I: *two triples share only one entity within a sentence*
- Type II: *two triples share two entities (both head and tail entities) within a sentence*

To test performance of extracting overlapping relations

NYT11-plus: manually annotated overlapping sentences, mainly of type I.
NYT11-sub: without manually annotated, overlapping percent: 90/2082, mainly of type II.

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**

To test the interaction between high-level policy and low-level policy:

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**

Option: The option o_t is selected from $\mathcal{O} = \{\text{NR}\} \cup \mathcal{R}$ where NR indicates no relation, and $\mathcal{R}$ is the relation type set. When a low-level RL process enters a terminal state, the control of the agent will be taken over to the high-level RL process to execute the next options.

Reward: Then, the environment provides intermediate reward r_t^h to estimate the future return when executing o_t. The reward is computed as below:

$$r_t^h = \begin{cases} -1, & if\ o_t\ not\ in\ S \\ 0, & if\ o_t = \text{NR} \\ 1, & if\ o_t\ in\ S. \end{cases} \tag{4}$$

If $o_t = \text{NR}$ at certain time step, the agent transfers to a new high-level inter-option state at the next time step. Otherwise the low-level policy will execute the entity extraction process. The inter-option state will not transfer until the subtask