Extracting Knowledge from Web Text with Monte Carlo Tree Search

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Problem

Open Information Extraction (**OIE**):

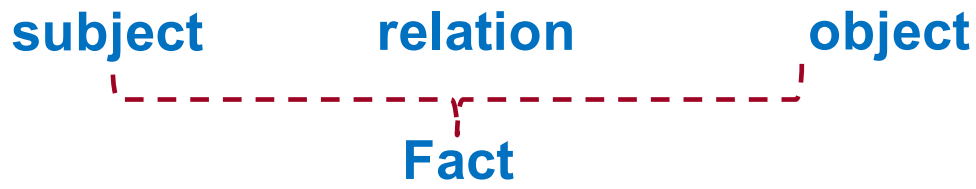
- Three main property: 1) **unlexicalized**, 2) **domain-independent** 3) scales to the **diversity and size of** the web corpus [1], for example:

Source Sentence:

Mencius has followed the example of Confucius, and led disciples to lobby the nations.

Target Sequence (contains three facts):

(Mencius $ follow the example of $ Confucius) (Mencius $ lead $ disciples) (Mencius $ lobby $ nations)



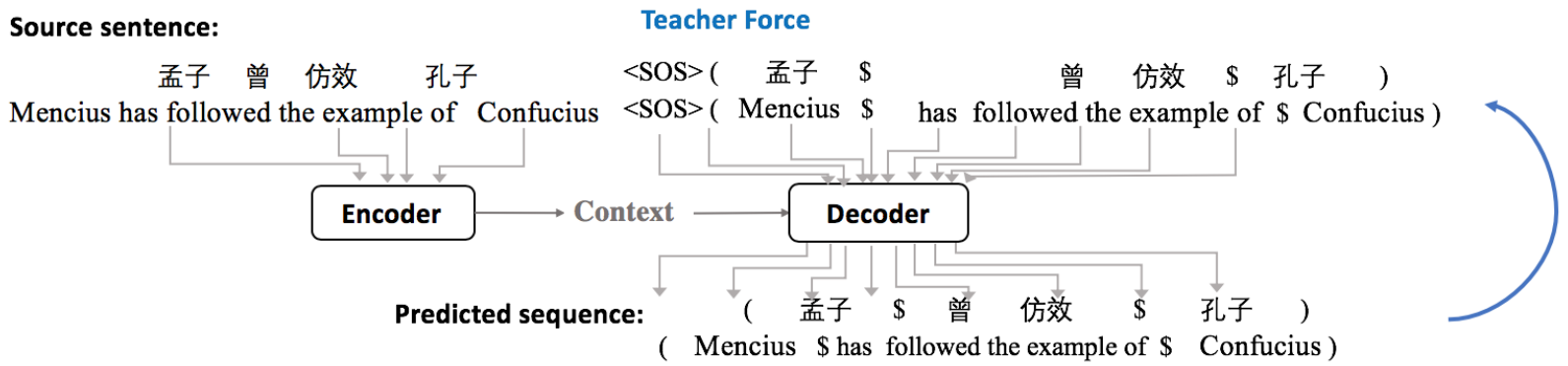
- In this work, we solve OIE as a task of **sequence prediction:** source sentence -> target sequence.

[1] Michele Banko, et,al. Open Information Extraction from the Web. In Proceedings of IJCAI. 2007

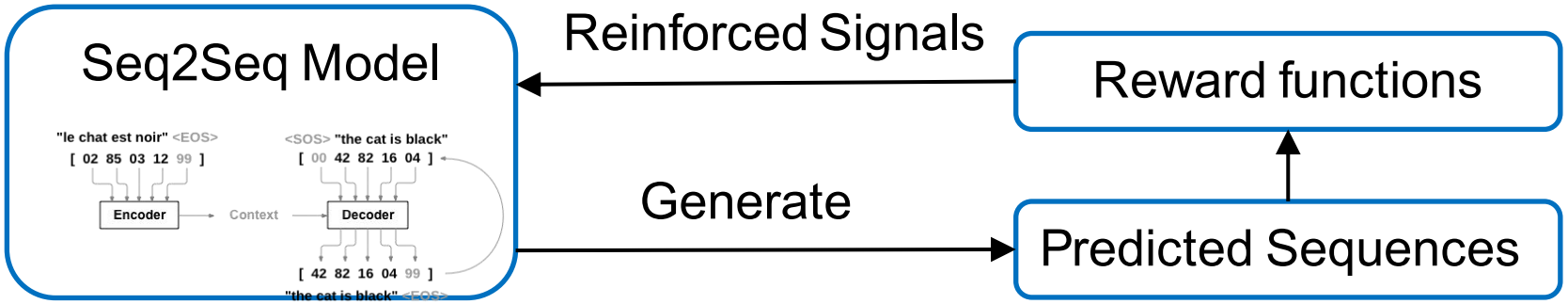
Motivation

Previous works on OIE:

- Sequence-to-Sequence (**Seq2Seq**) model: Supervised Learning.



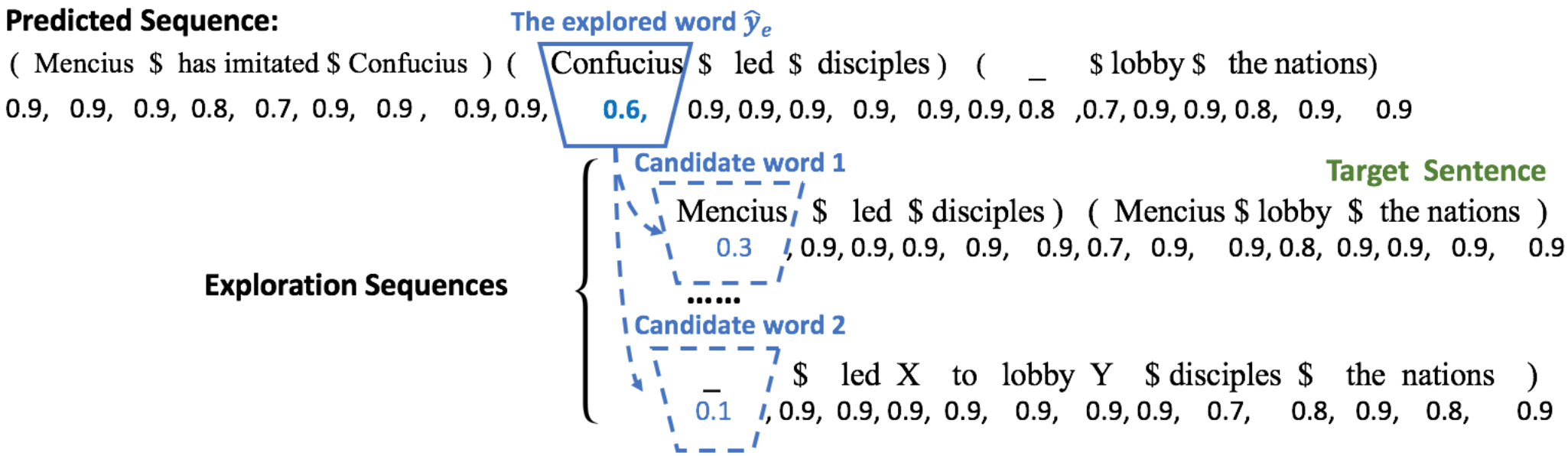
- **Reinforced** Algorithm: Semi-supervised Learning.



Motivation

Common Issues of previous works:

- **1) No look ahead** and **2) limited exploration** during prediction.
- Why so important? *A previously predicted word (sub-optimal) will significantly influence the following predictions*, for example:



Model

Monte Carlo Tree Search (MCTS):

- Run Monte Carlo simulations on a Upper Confidence Tree (UCT). At each node (state s_t:source sentence + predictions until t-1), we select an edge (action a_t: word at t) by:

$$a_t = \arg\max_a \left[Q(s_t, a) + c_{puct} Pr_0(s_t, a) \frac{\sqrt{\sum_b N(s, b)}}{1 + N(s_t, a)} \right]$$

  a) Q function $Q(s_t, a_t)$ learns expected rewards (provides **look ahead**).

  b) c_{puct} controls the scale of exploration. It encourages selecting the unvisited nodes (provides **exploration**).

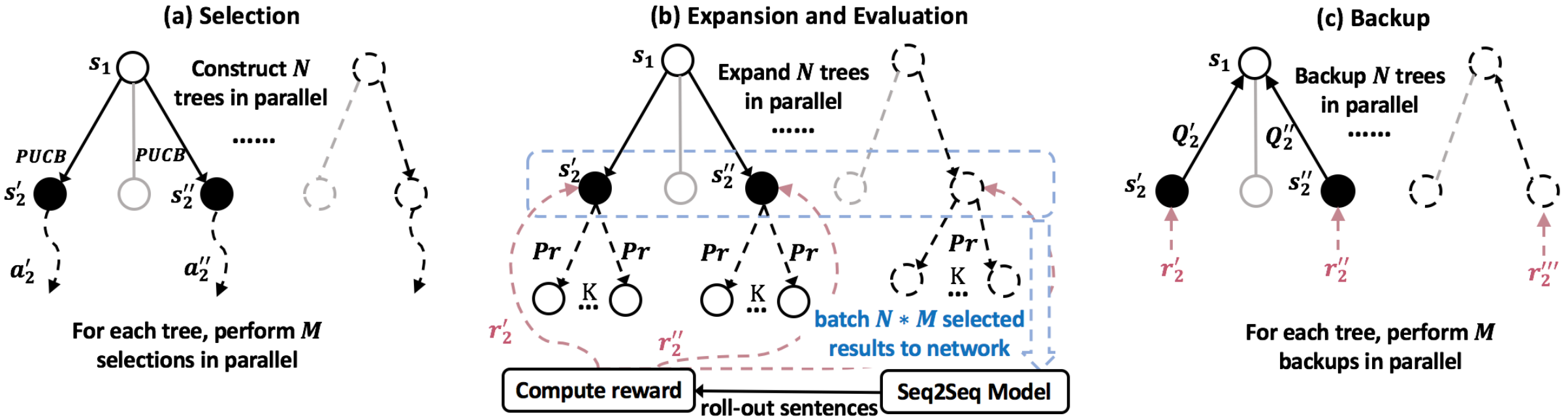
- Run MCTS by:

  a) Implementing a play (simulation) recording four phases: selection, expansion, evaluation and backup (parallelization for acceleration).

  b) Determine the predicted words from the distribution of visited number.

Model

Monte Carlo Tree Search (MCTS):



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Model

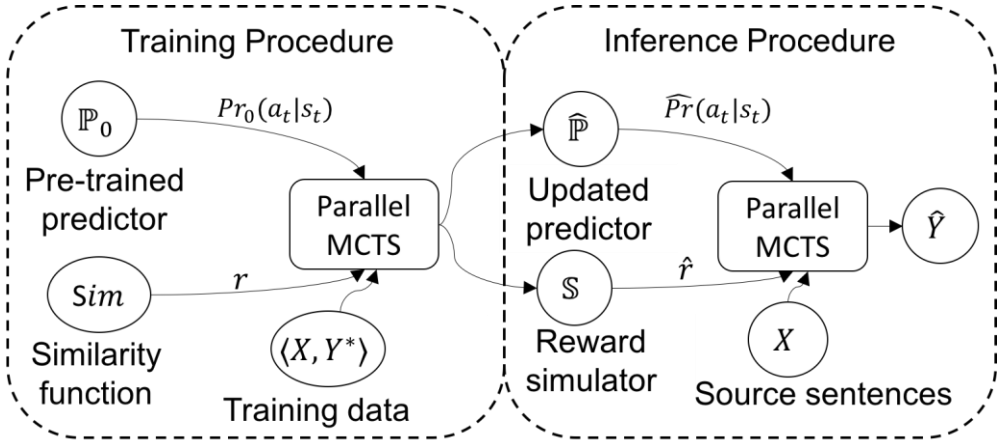
Reward Simulator:

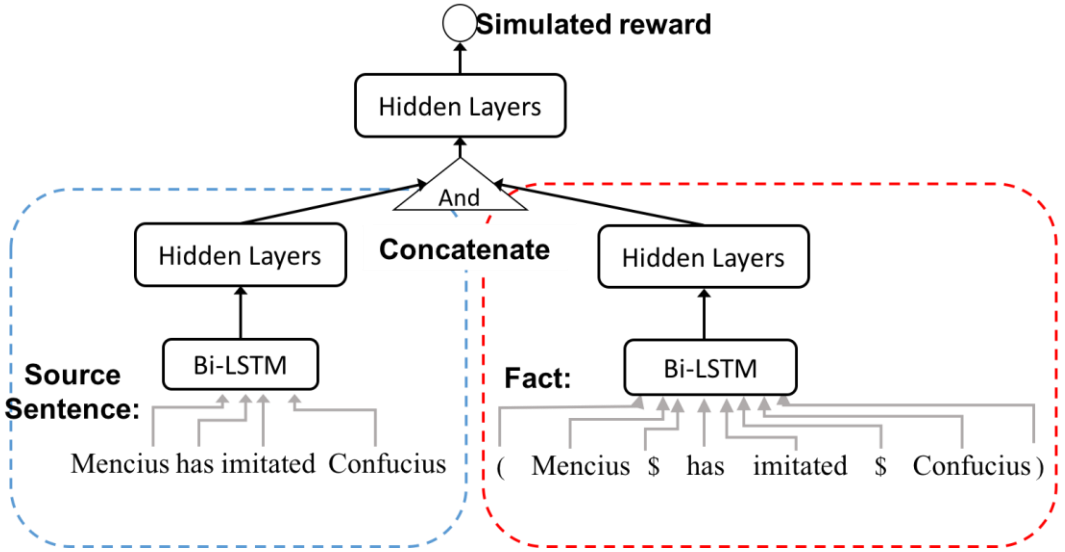
- Learn (Mimic) the reward signals.
  a) Training rewards: similarity between predicted facts and target facts.

$$Sim(\hat{Y}_{1..t}, Y^*) = \sum_{l=1}^{\min(N_p, N_G)} \eth((\hat{F}_i, F_j^*)_l)$$

  b) During testing, target facts are unavailable and requires a reward simulator:

- Defines a complete RL environment





Experiment

Running Setting:

- Dataset: SAOKE[1] contains over 47,000 source-target sequences. (manually labeled by crowdsourcing)
- Comparison Methods:
  a) DSNF and CORE (pattern matching)
  b) Logician (Seq2Seq model for OIE.)
  c) Reinforced algorithm.
  d) Dual structured reinforced learning.
  e) Search method: (greedy and beam)

[1] http://ai.baidu.com/broad/subordinate?dataset=saoke

Results:

- Label a extracted fact as 1 if it is correct (sim>0.85, ≈target fact) and 0 otherwise.
- Compute Precision, Recall and F1

	Training Data			Testing Data		
	P	R	F1	P	R	F1
DSNF	0.126	0.100	0.170	0.220	0.112	0.148
CORE	0.348	0.183	0.240	0.400	0.1760	0.232
Logician(B=3)	0.560	0.478	0.515	0.469	0.400	0.432
Reinforce(B=3)	0.580	0.460	0.513	0.487	0.410	0.445
Dual(B=3)	0.594	0.499	0.543	0.494	0.426	0.457
Logician(B=50)	0.555	0.491	0.521	0.466	0.407	0.435
Reinforce(B=50)	0.583	0.460	0.514	0.485	0.416	0.448
Dual(B=50)	0.594	0.501	0.544	0.498	0.422	0.457
MCTS@Train + Beam@Infer(B=3)	0.573	0.475	0.519	0.518	0.425	0.467
MCTS@Train + Beam@Infer(B=50)	0.586	0.473	0.523	0.519	0.422	0.465
MCTS@Train + MCTS@Infer(**Ours**)	**0.690**	**0.582**	**0.632**	**0.611**	**0.506**	**0.554**

Table 1: Evaluation results for the predicted facts.

Conclusion

Take home messages from presenter:

- If no explore, add exploration.
- If don't know how to explore, try Monte-Carlo Method (e.g. UCT model).
- If MC gives you huge time complexity, remember it is often parallelizable.
- If it is still unaffordable (inputs are images), check our future work.

Future Work:

- Representation Learning, for example:
  a) Data disentangling, map input (images under the curse of dimensionality) to independent factors of variation by Variational methods (VAE).

THANK YOU!