A Fine-grained and Noise-aware Method for Neural Relation Extraction

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OUTLINE

- Introduction
- Method
- Experiment
- Conclusion

INTRODUCTION

- **Relation Extraction（RE）**：Extracting semantic relations between two entities from the text corpus.

(Ex): Donald Trump is the 45th President of United States.

President of

INTRODUCTION

- **Supervised RE :**
  - Heavily relies on human-annotated data to achieve outstanding performance.
  - Limited in size and domain specific, preventing large-scale supervised relation extraction.

INTRODUCTION

- **Distant supervision RE：**
  - Automatically generates large-scale training data through knowledge base and plain texts.

Relations In KB	*President_of (Donald Trump, United States)*
Sentences in Plain texts	S1: Donald Trump is the 45th President of the United States. S2: Donald Trump was born in the United States. S3: Donald Trump believes the United States has incredible potential.

President of
(A training bag)

INTRODUCTION

- **Challenge in Distant supervision(1/2)：**
  - Multi-instance multi-label problem（MIML）.

Relations In KB	*Place_of_birth(Donald Trump, United States)* *President_of (Donald Trump, United States)*
Sentences in Plain texts	S1: Donald Trump is the 45th President of the United States. *(President_of)* S2: Donald Trump was born in the United States. *(Place_of_birth)*

Multi-label problem

Relations In KB	*Place_of_birth(Donald Trump, United States)* *President_of (Donald Trump, United States)*
Sentences in Plain texts	S3: Donald Trump believes the United States has incredible potential. (-)

Multi-instance problem

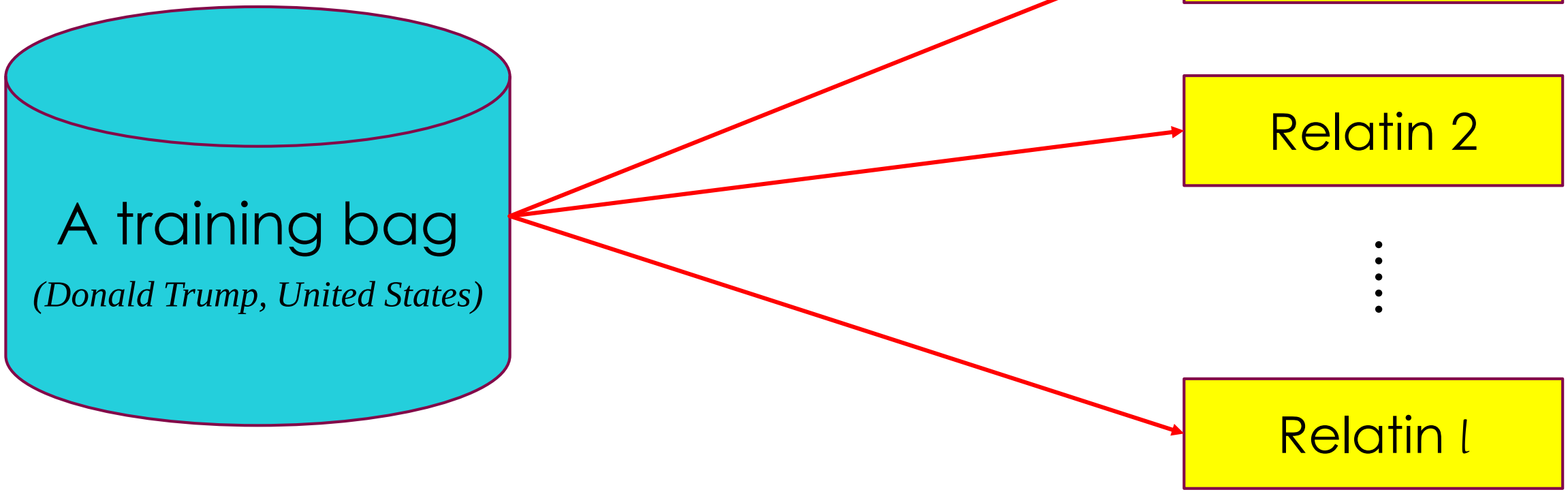
INTRODUCTION

- **Challenge in Distant supervision(2/2) :**
  - The assigned relation labels are annotated at bag-level (a set of sentences) instead of sentence-level.

Reinforcement Learning Model

INTRODUCTION

- **Goal :** The most informative sentence for each relation



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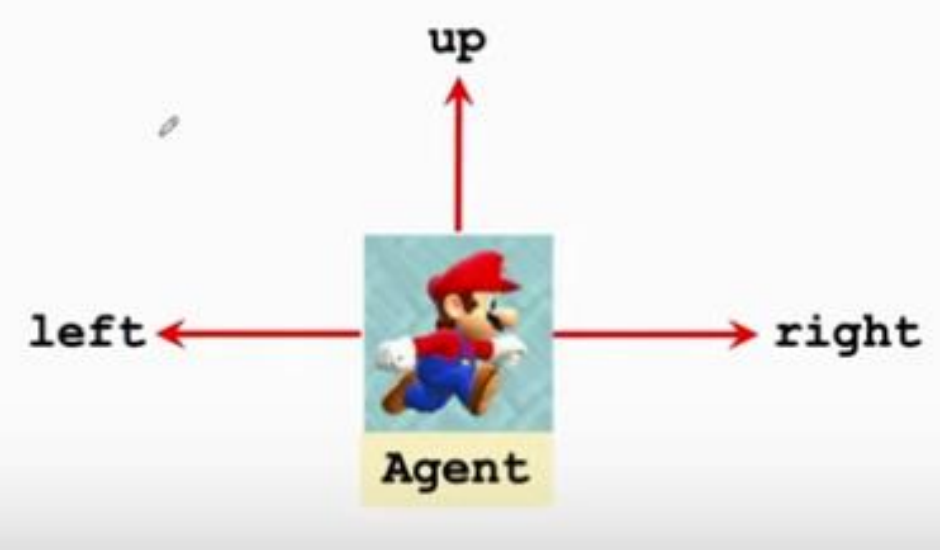
REINFORCEMENT LEARNING

https://www.youtube.com/watch?v=vmkRMvhCW5c&t=1557s

State

Action; Agent



Reward

Collect a coin: $R = +1$

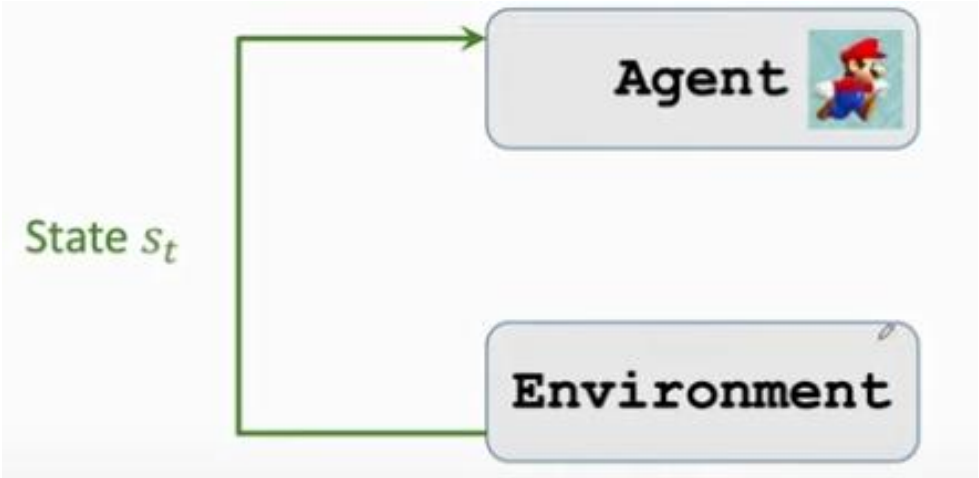
Win the game: $R = +10000$

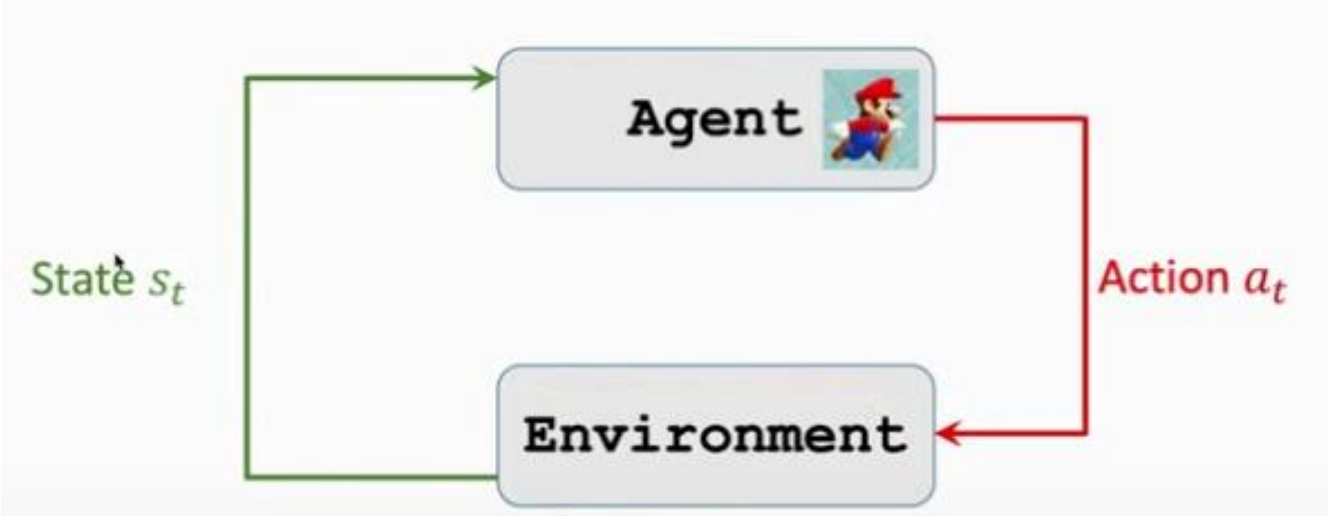
Touch a Goomba: $R = -10000$ (game over).

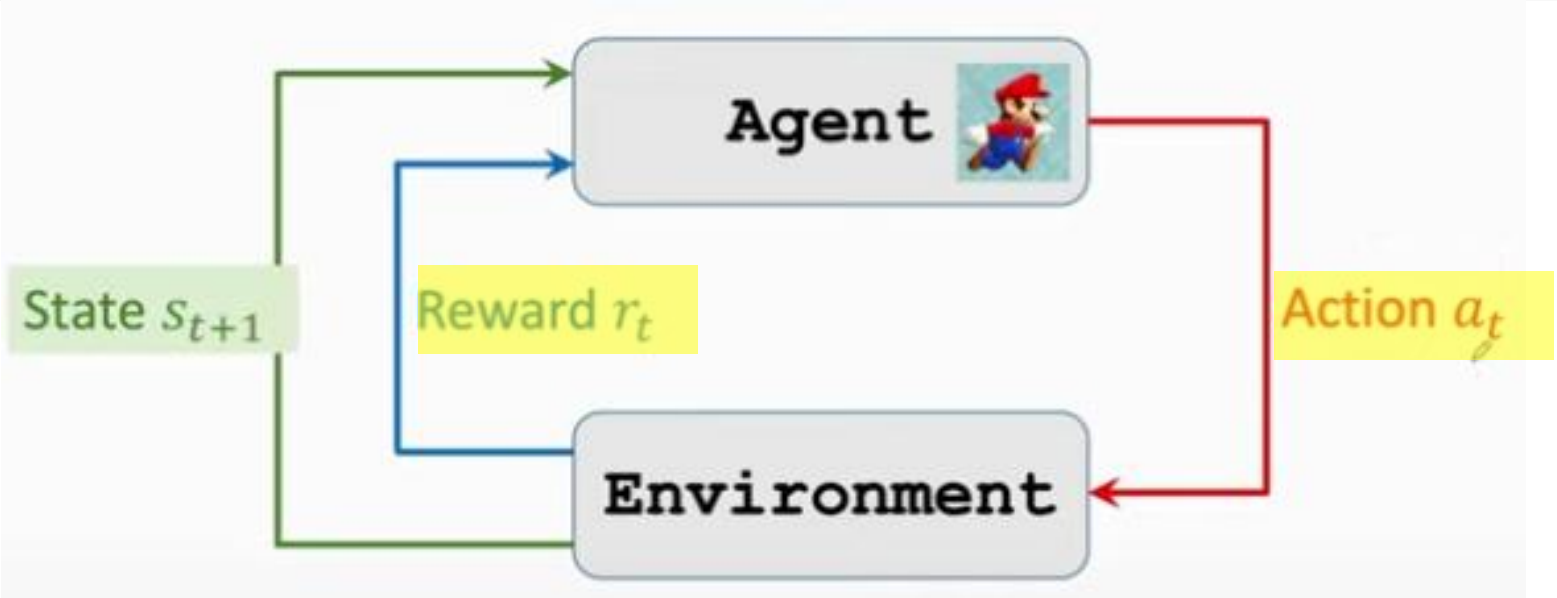
Nothing happens: $R = 0$

REINFORCEMENT LEARNING

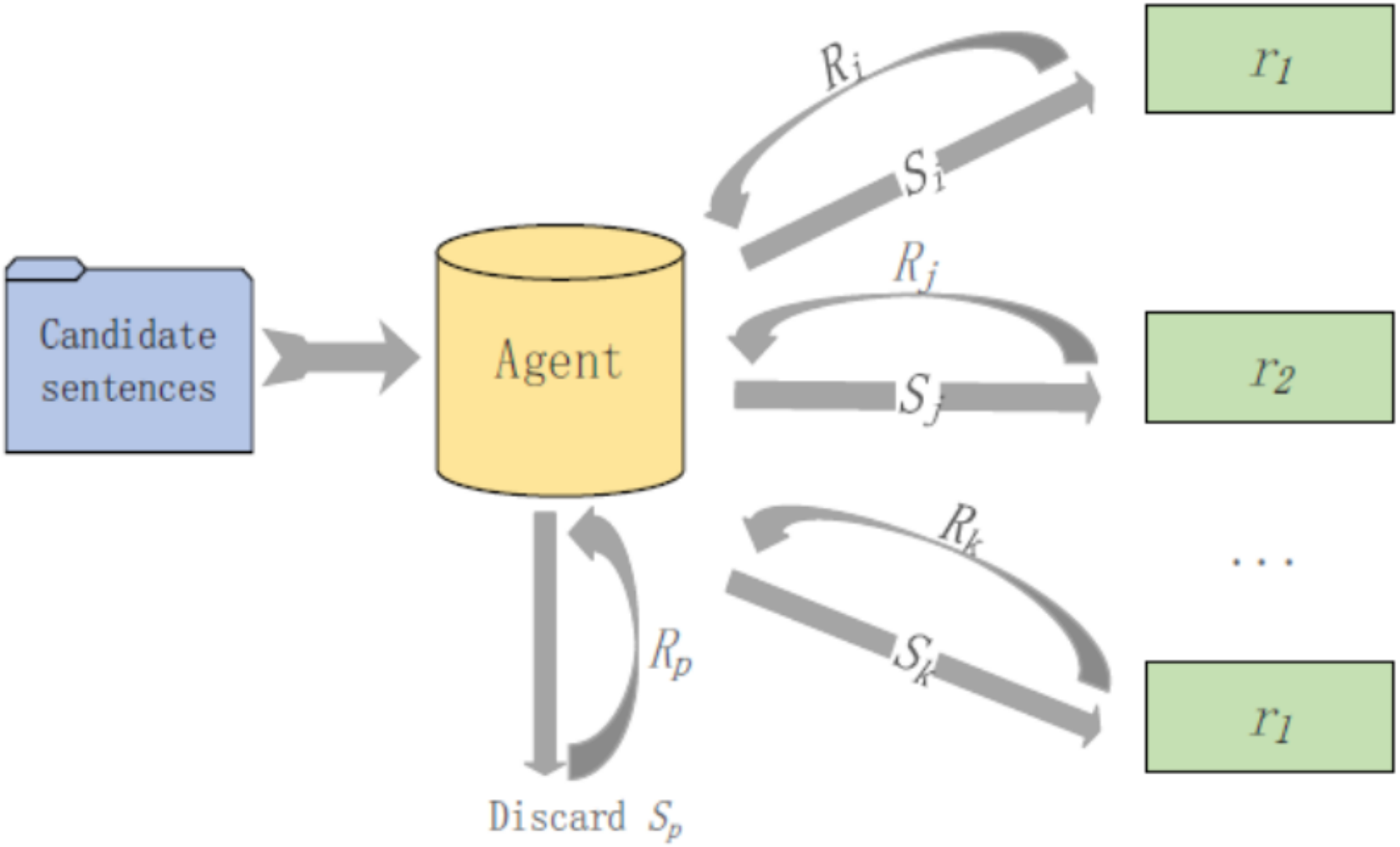
https://www.youtube.com/watch?v=vmkRMvhCW5c&t=1557s







FRAMEWORK


Candidate sentences
Agent
R_i
S_i
R_j
S_j
R_k
S_k
R_p
Discard S_p
r_1
r_2
...
r_1

METHOD Notation and Problen definition

- Let B ={⟨ e_1, e_2 ⟩, (r_1, · · · , r_l), {S_1, · · · , S_n }} be a training bag.

An entity pair

The relations that link the entity pair in KB

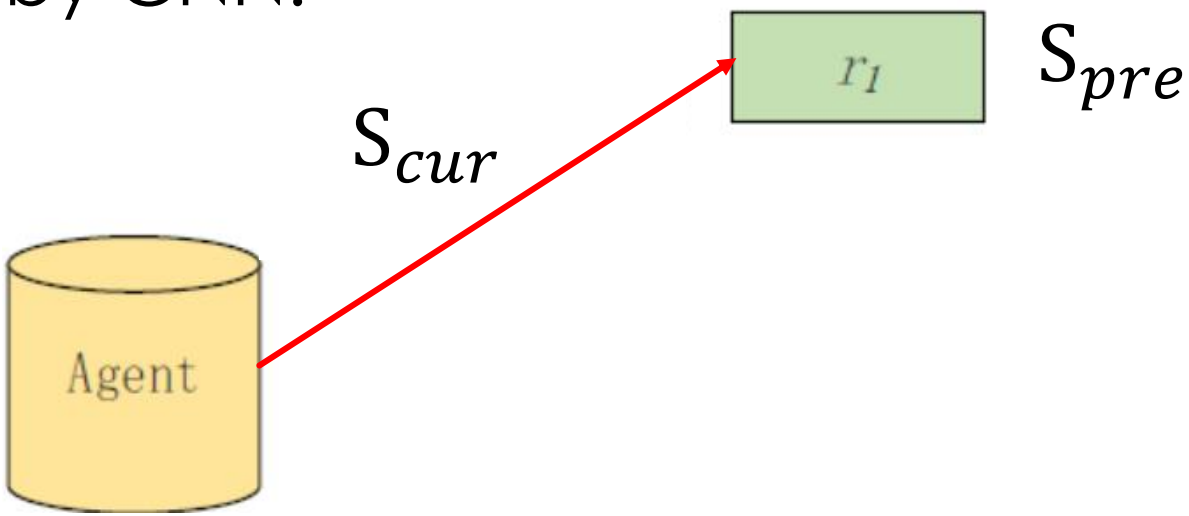
The sentences from corpus which mention this entity pair

- **Problem definition**：Figuring out the most expressive sentence for each relation in B.

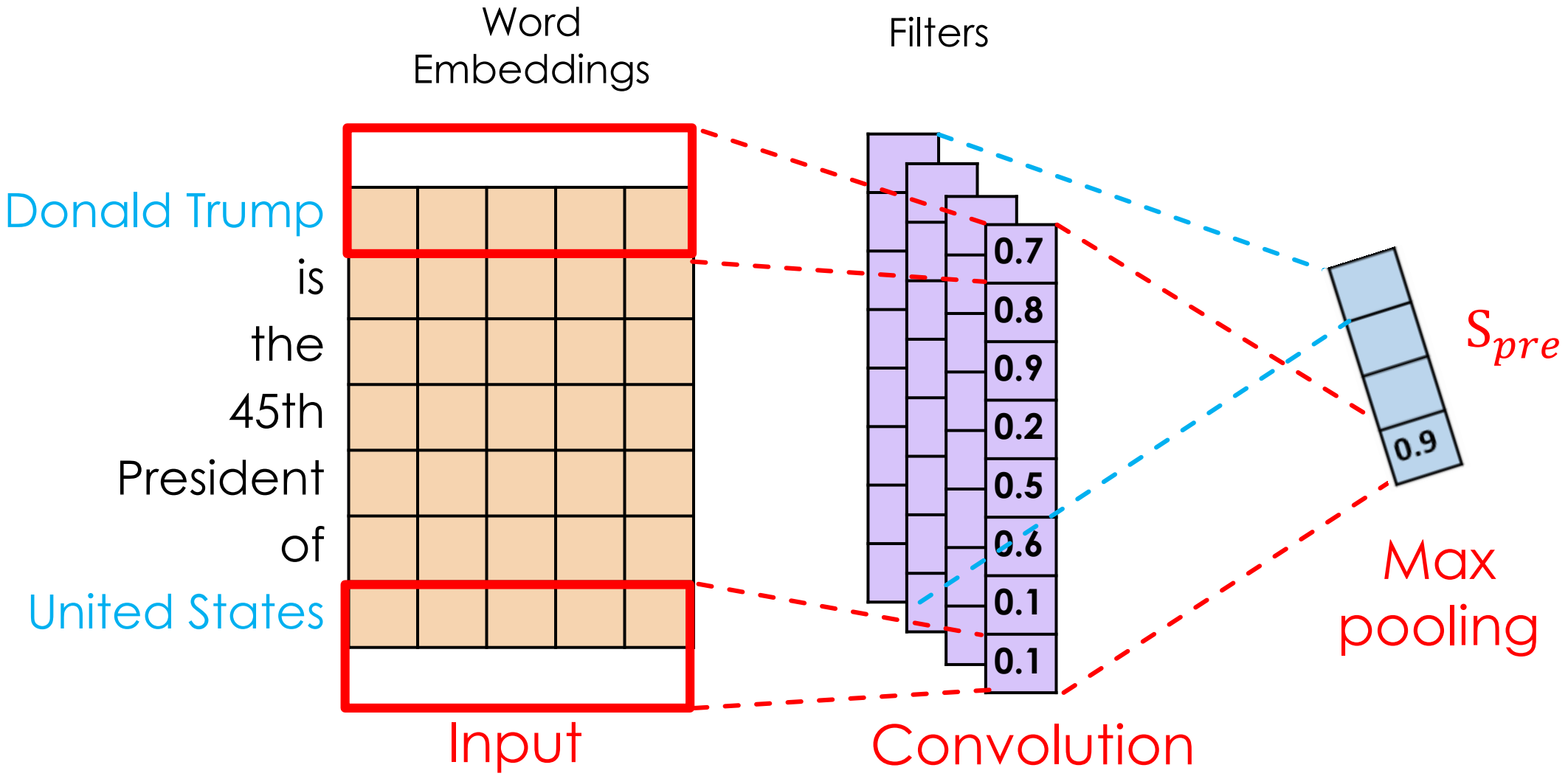
（in order to promote the extractor's performance）

METHOD State

- **Embedding of target entity pair**：$[e_1, ; e_2]$
- **Encoding for previously chosen sentence**：S_{pre}, encoded by CNN.

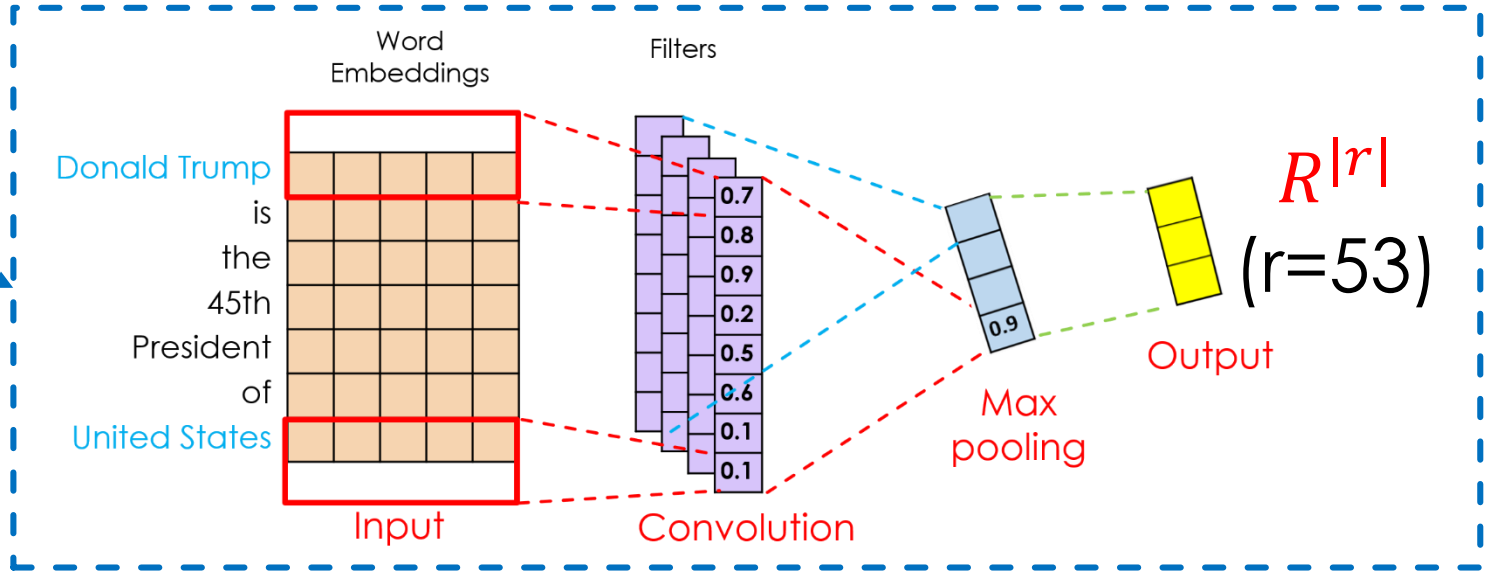


METHOD State



METHOD State

- **Confidence score for** S_{pre} : $p(\mathrm{r} \mid S_{pre}; \theta)$, calculated by relation extractor.



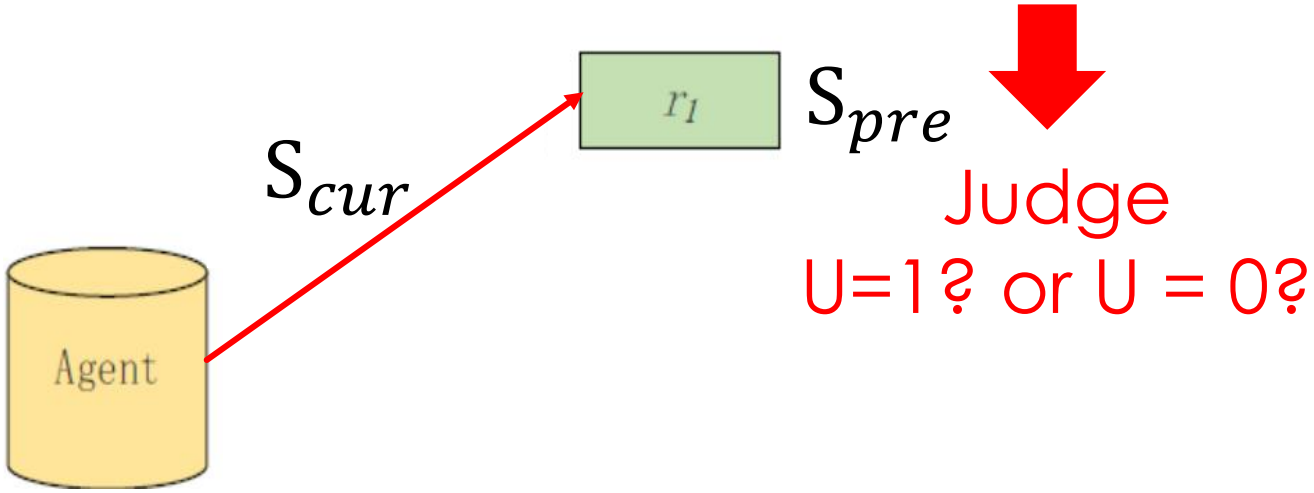
- **Encoding for current sentence** : S_{cur}
- **Confidence score for** S_{cur} : $p(\mathrm{r} \mid S_{cur}; \theta)$
- **St** : $[e_1 ; e_2 ; S_{pre} ; p(\mathrm{r} \mid S_{pre}; \theta) ; S_{cur} ; p(\mathrm{r} \mid S_{cur}; \theta)]$

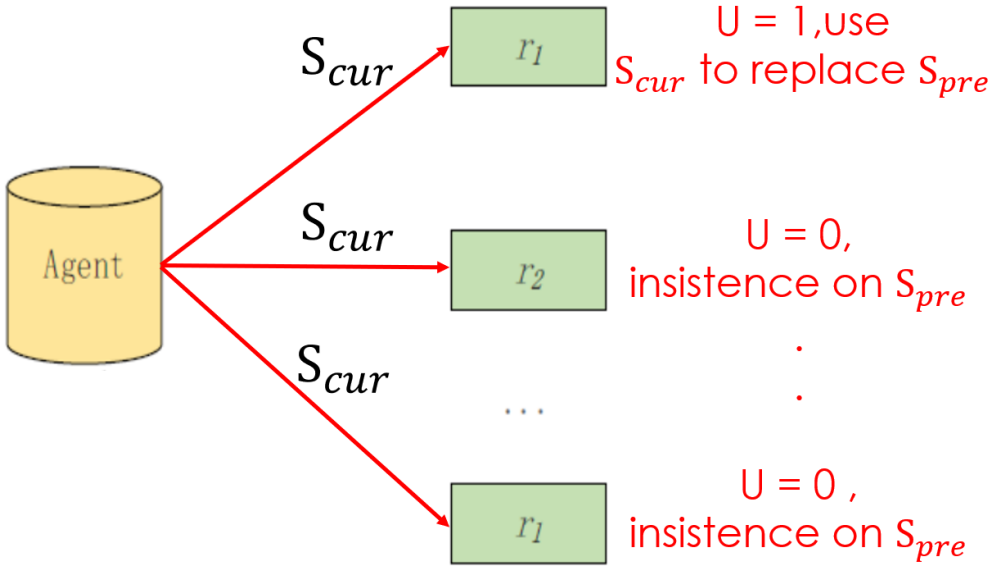
METHOD Action

➢ **First part of action**：U, decide whether to adopt the current sentence to replace the previously chosen.

- U =1 → Yes.
- U = 0 → No.

$$Q(St, U) = f(\boldsymbol{W_u}(f(\boldsymbol{W} \cdot St)) + \boldsymbol{b_u})$$





METHOD Action

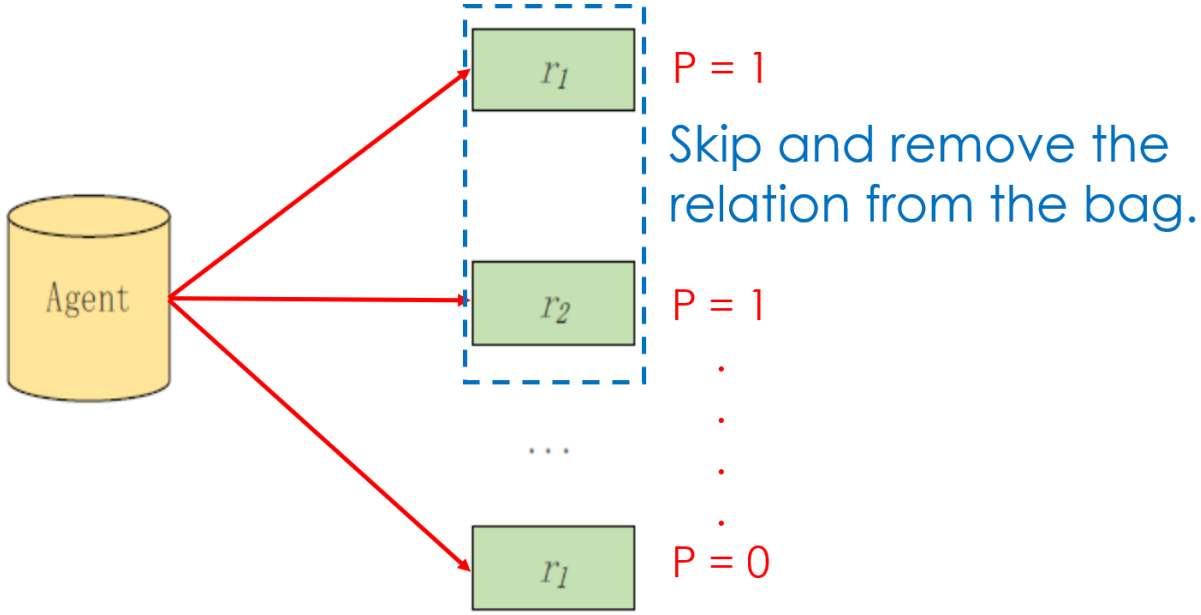
- **Reasonable assumptions for each bag：**
  - Expressed-at-least-once
  - Express-at-most-one
- **Compete mechanism：**
  - When more relations simultaneously intend to update the S_{pre} with the S_{cur}.
  - Only update the relation which has highest $Q(S_t, U=1)$.

METHOD Action

➢**Second part of action**：P, decide the relation whether to stop the search action.

- P =1 → Yes（believe has picked out the expressive sentence for this relation）.
- P = 0 → No.

$$Q(St, P) = f(\boldsymbol{W_p}(f(\boldsymbol{W} \cdot St)) + \boldsymbol{b_p})$$



METHOD Action

- **Takes the action A^* that equals $argmax_A$ Q(S_t ,A) :**

- $$Q(St, A; \eta) = \begin{cases} Q(St, U) = f(\boldsymbol{W_u}(f(\boldsymbol{W} \cdot St)) + \boldsymbol{b_u}) \\ \\ Q(St, P) = f(\boldsymbol{W_p}(f(\boldsymbol{W} \cdot St)) + \boldsymbol{b_p}) \end{cases}$$

METHOD Reward

➢**Reward :**

- When execute a action → Get a reward.
- The objective of reinforcement learning : By maximize total reward to learn Q function.

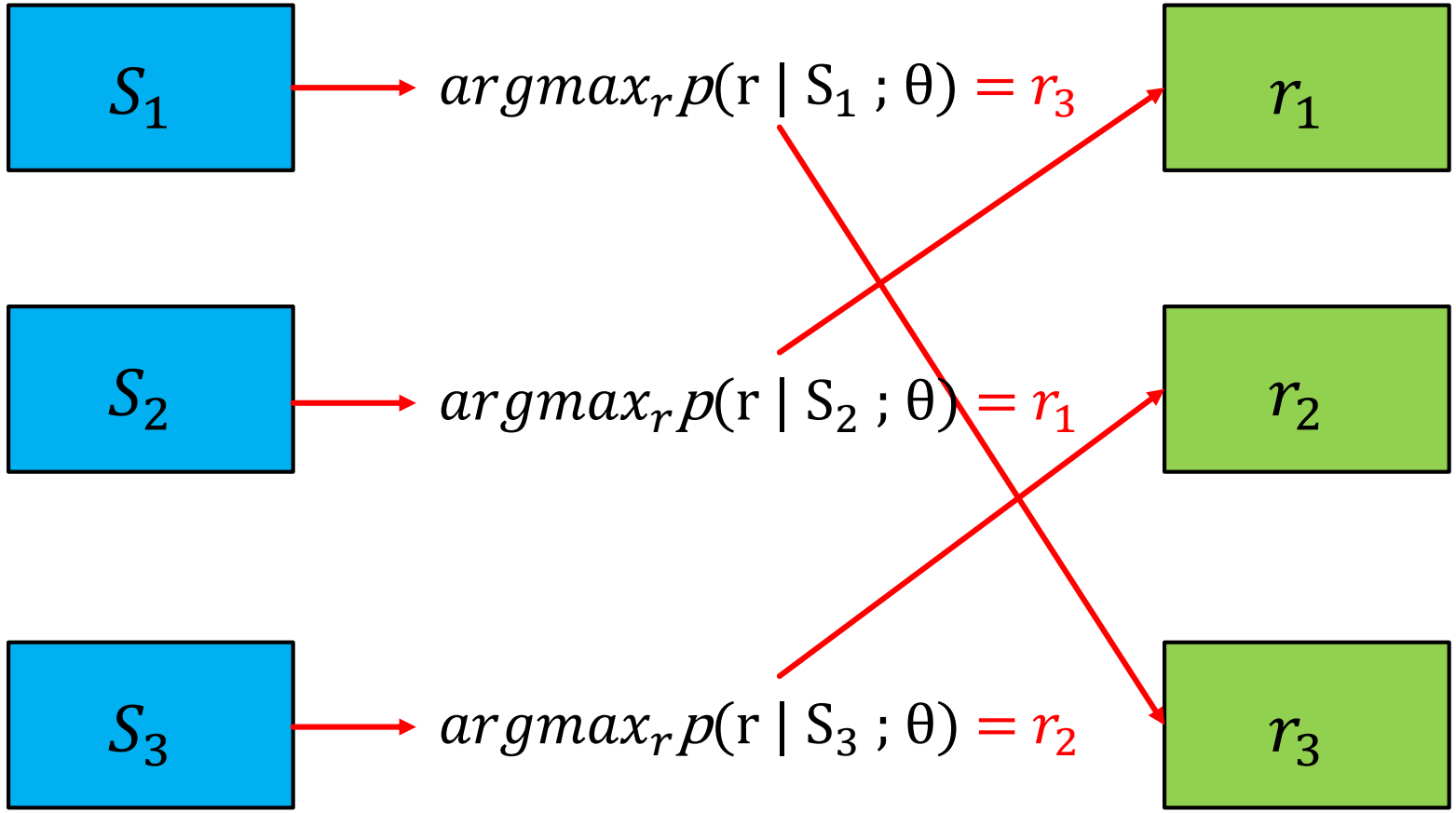
$$Re(St, A) = \begin{cases} p(r_t|S_{cur};\theta) - p(r_t|S_{pre};\theta) & (\neg T) \wedge (U = 1) \quad (+)/(-) \\ p(r_t|S_{pre};\theta) - p(r_t|S_{cur};\theta) & (\neg T) \wedge (U = 0) \wedge (\arg\max_r p(r|S_{cur};\theta) = r_t) \quad (+)/(-) \\ 0 & (\neg T) \wedge (U = 0) \wedge (\arg\max_r p(r|S_{cur};\theta) \neq rt) \\ p(r_t|S_{cur};\theta) & (T) \wedge (U = 1) \wedge (\arg\max_r p(r|S_{cur};\theta) = rt) \quad (+) \\ p(r_t|S_{cur};\theta) - \max(p(r|S_{cur};\theta)) & (T) \wedge (U = 1) \wedge (\arg\max_r p(r|S_{cur};\theta) \neq r_t) \quad (-) \\ p(r_t|S_{pre};\theta) & (T) \wedge (U = 0) \wedge (\arg\max_r p(r|S_{pre};\theta) = rt) \quad (+) \\ p(r_t|S_{pre};\theta) - \max(p(r|S_{pre};\theta)) & (T) \wedge (U = 0) \wedge (\arg\max_r p(r|S_{pre};\theta) \neq r_t) \quad (-) \end{cases}$$

METHOD Initial states St_i^0 for all episodes

- **Initial states St_i^0 for all relations of a bag are the same：**
  - B $=\{\langle e_1, e_2 \rangle, (r_1, \cdots, r_l), \{S_1, \cdots, S_n\}\}$, $i \in \{1, 2, \cdots, l\}$
  - $St_i^0 = [e_1 ; e_2 ; 0 ; 0 ; S_1 ; p(r \mid S_1; \theta)]$, for all i.
  - The output values of Q-function are the same too.

METHOD Initial states St_i^0 for all episodes

➢ **heuristic initialization :**



$St_1^0 = [e_1 ;\ e_2 ; \mathrm{S}_2; p(\mathrm{r} \mid \mathrm{S}_2; \theta); \mathrm{S}_{3+1} ; p(\mathrm{r} \mid \mathrm{S}_{3+1}; \theta)]$

$St_2^0 = [e_1 ;\ e_2 ; \mathrm{S}_3; p(\mathrm{r} \mid \mathrm{S}_3; \theta); \mathrm{S}_{3+1} ; p(\mathrm{r} \mid \mathrm{S}_{3+1}; \theta)]$

$St_3^0 = [e_1 ;\ e_2 ; \mathrm{S}_1; p(\mathrm{r} \mid \mathrm{S}_1; \theta); \mathrm{S}_{3+1} ; p(\mathrm{r} \mid \mathrm{S}_{3+1}; \theta)]$

METHOD

- **Reinforcement learning algorithm for MIML：**
  - In paper Algorithm 1.

METHOD Joint training

https://morvanzhou.github.io/tutorials/machine-learning/ML-intro/4-03-q-learning/

- **Optimization of the extractor：**

- **Maximize** $J(\theta) = \sum_{i=1}^{|TS|} \log p(y_i | x_i; \theta)$

x_i is a sentence in TS with relation y_i

- **Optimization of the reinforcement learning：**

- **minimize** $Loss = \sum_{i=1}^{|Z|} (\boxed{z_i} - Q(St_i, A_i; \eta))^2$

Regarded as accurate value of $Q(St_i, A_i)$

- $z_i = \begin{cases} Reward & St^{i+1} \in terminal \\ Reward + \alpha \max_{A'} Q(St^{\boxed{i+1}}, A') & St^{i+1} \notin terminal \end{cases}$

METHOD

- **Joint training for extractor and reforcement learning :**
  - In paper Algorithm 2.

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EXPERIMENT

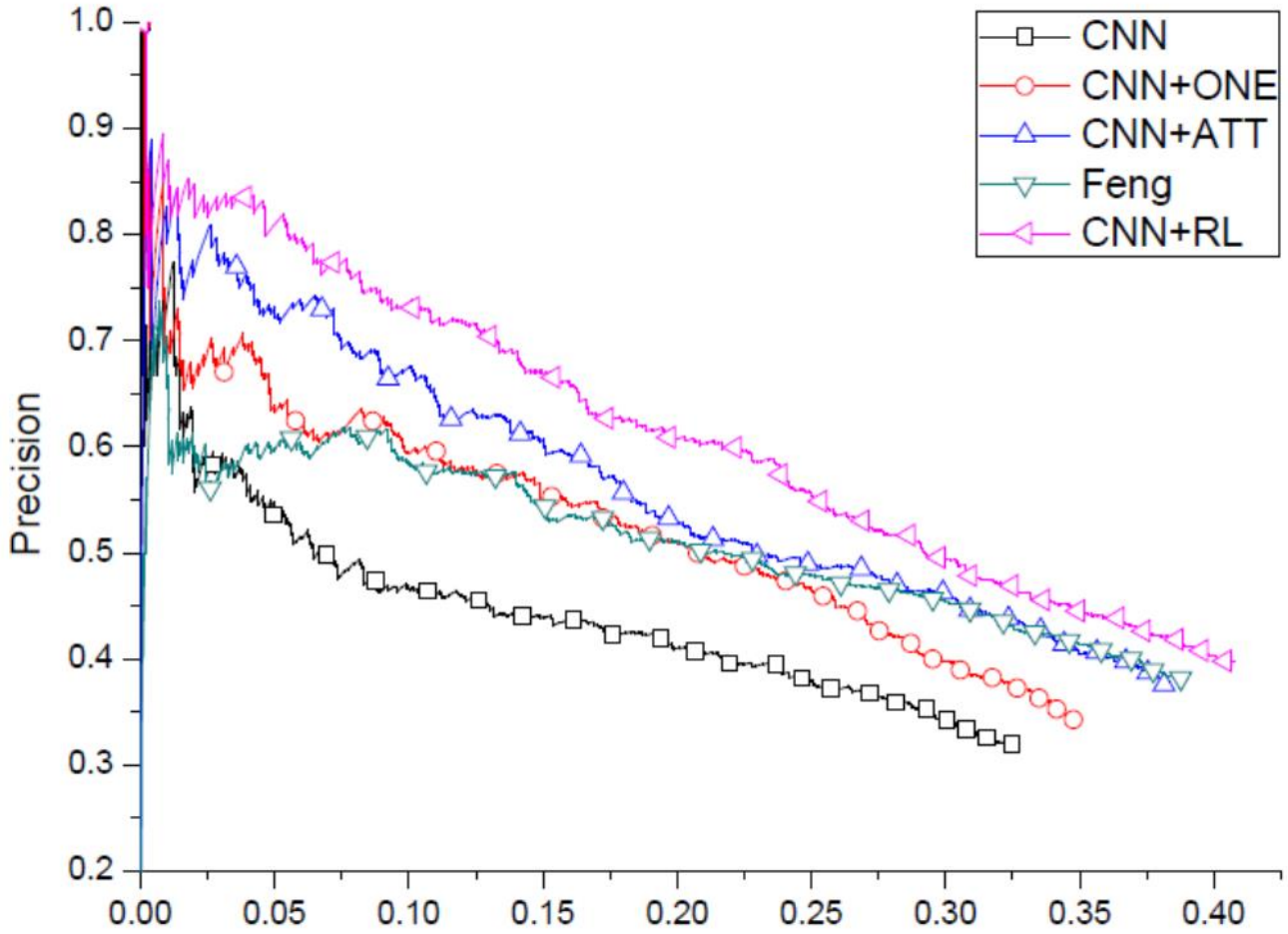
Dataset

- **NYT+Freebase**：Aligning entities and relations in Freebase with the corpus of New York Times.
  - NYT in 2005-2006 → Training data
  - NYT in 2007 → Testing data

EXPERIMENT

https://blog.csdn.net/u013249853/article/details/96132766

Performance with NN methods



EXPERIMENT

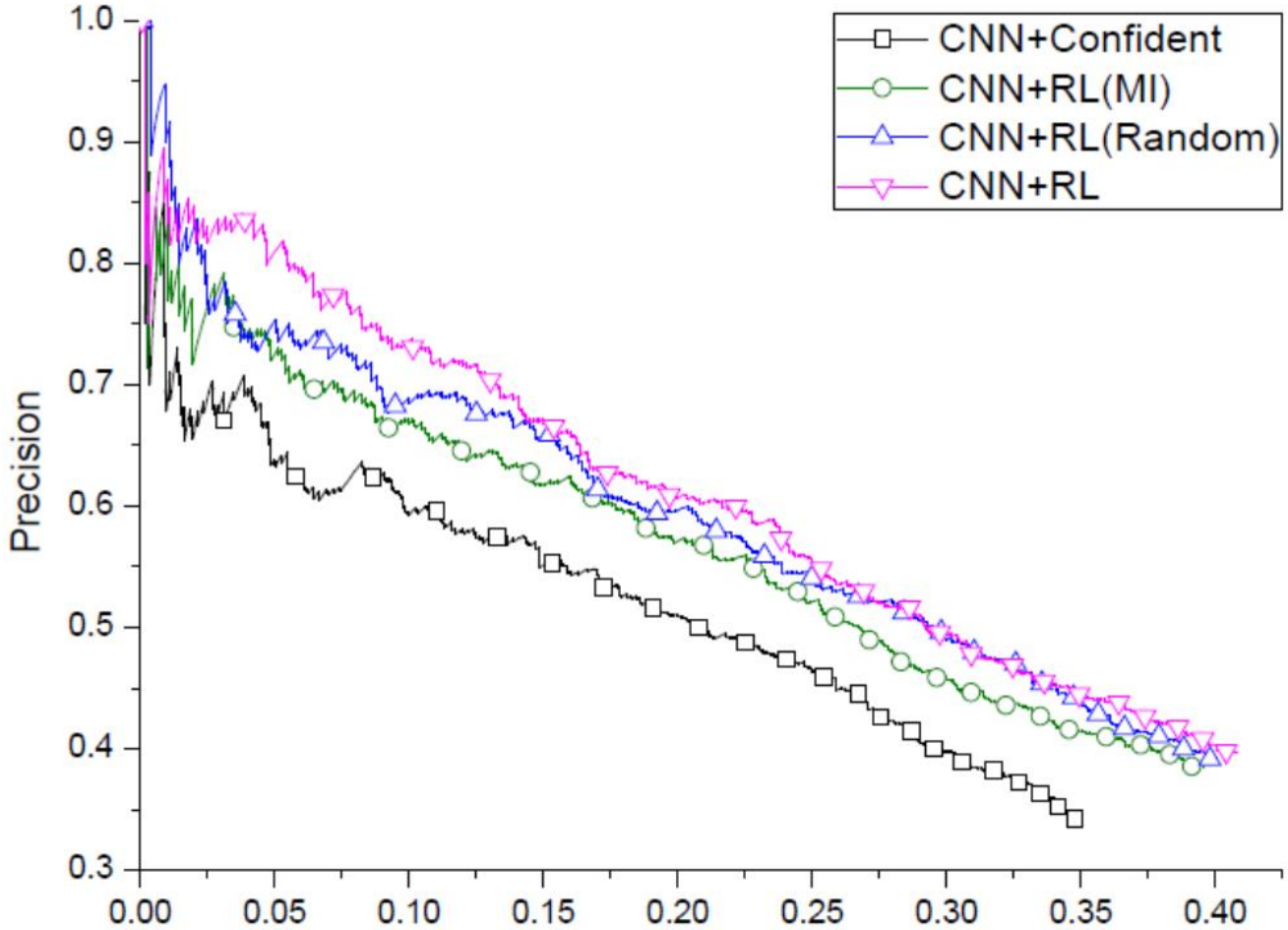
Performance with NN methods

P@N(%)	100	200	300	500	mean
CNN	59.00	53.00	47.67	46.20	51.47
CNN+ONE	69.00	61.00	61.33	56.80	62.03
CNN+ATT	76.00	70.50	66.67	59.40	68.14
Feng	57.00	59.50	60.67	56.00	58.29
CNN+RL	**82.00**	**76.50**	**72.00**	**64.40**	**73.73**

EXPERIMENT

https://blog.csdn.net/u013249853/article/details/96132766

Reasonability of model design



EXPERIMENT

Case study

Method	Sentences	/location/contains	/country/capital
Feng	*S1:* according to local legend , recounted by the Africa scholar Stephen Ellis in his book " the mask of anarchy , " a baby born in **Monrovia** , **Liberia** 's capital , miraculously spoke english straight from the womb	choose	choose
CNN+RL		not choose	choose
Feng	*S2:* my sister was living in the **Monrovia** suburb of Paynesville , **Liberia** , with her family and a handful of orphans and other refugees from the liberian civil war.	choose	choose
CNN+RL		choose	not choose

EXPERIMENT

Case study

		/person/place_lived	/deceased_person /place_of_death
Feng	*S3:* **Jane Jacobs** , the activist who took him on , now lives in **Toronto** .	choose	choose
CNN+RL		choose	not choose
Feng	*S4:* **Jane Jacobs** , the writer and thinker who brought penetrating eyes and ingenious insight to the sidewalk ballet of her own greenwich village street and came up with a book that challenged and changed the way people view cities , died yesterday in **Toronto** , where she moved in 1968 .	not choose	not choose
CNN+RL		not choose	choose

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CONCLUSION

- Craft reinforcement learning to solve MIML problem,and generate the sentence-level annotated signal in distantlysupervised relation extraction.
- Then these chosen expressive sentences serve as training instances to feed the extractor.
- We conduct extensive experiments and the experimental results demonstrate that our model can effectively alleviate MIML problem and achieve the new state-of-the-art performance.