Zero-shot Relation Classification from Side Information

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Code: https://github.com/gjiaying/zslrc

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Reported by Yang Peng





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Introduction

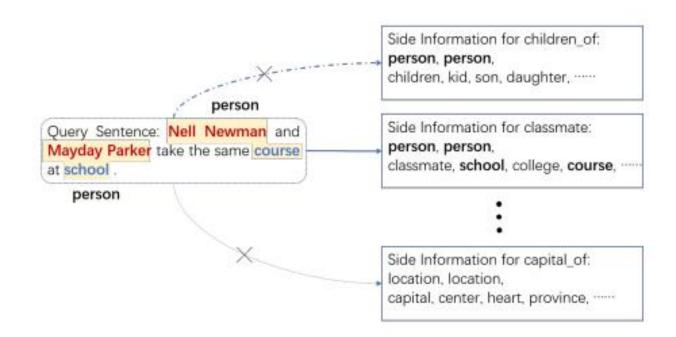


Figure 1: Example of relation classification based on side information.

Introduction

- We propose the first approach (ZSLRC) to enable zero-shot learning on relation classification without relying on other complex models that need to be learned and assumed to be 100% accurate.
- ZSLRC uses side information including labels, keywords, and hypernyms of name entities, and it has been shown that our model can perform competitively using the weighted side information.
- We modify prototypical networks to recognize new relations in addition to recognized previously known relations.

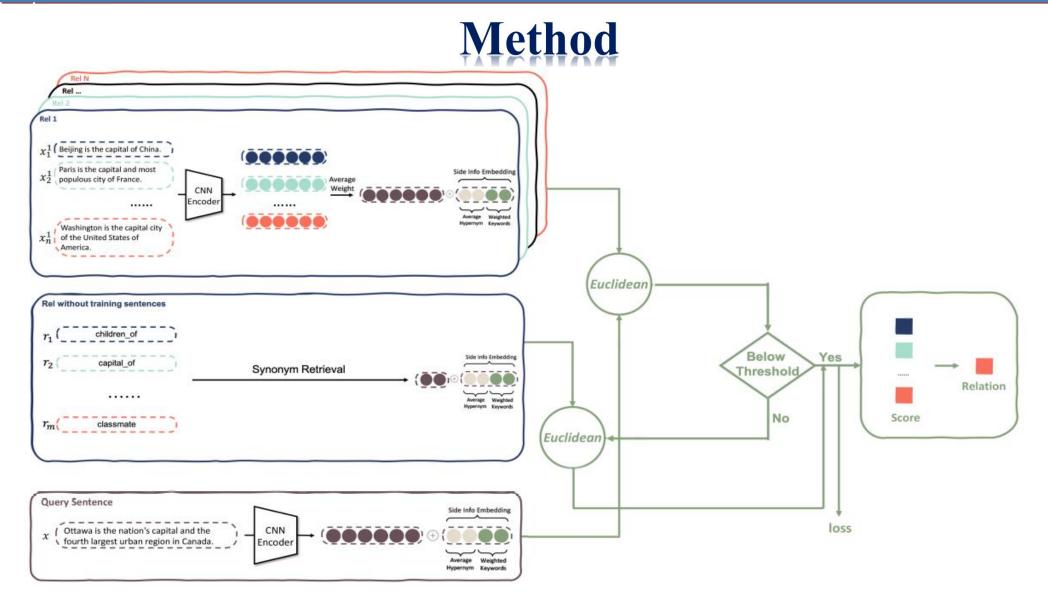


Figure 2: Model of Zero-shot Learning for Relation Classification (ZSLRC)

Method

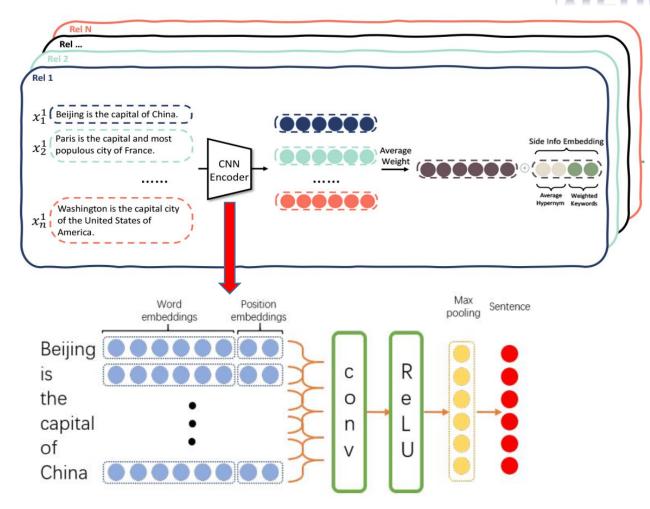


Figure 3: CNN Encoder

inputs sentences $\{x_1, x_2, x_3, \dots x_n\}$

For each word $w \in S = \{w_1, w_2, \dots w_n\}$ $S \in \mathbb{R}^{s \times d}$,

$$\hat{w}_i = w_i \oplus p_{i1} \oplus p_{i2} \tag{1}$$

s is the sentence length and $d = d_w + d_p \times 2$

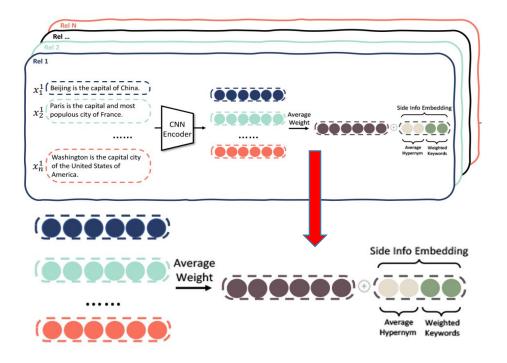
Instance embedding as follows:

$$x_i = CNN(w_{i-\frac{n-1}{2}}, \cdots, w_{i+\frac{n-1}{2}})$$
 (2)

$$\hat{x_i} = \max(0, x_i) \tag{3}$$

$$[s]_j = max\{[\hat{x_1}]_j, \cdots, [\hat{x_n}]_j\}$$
 (4)

 $[\cdot]_j$ is the j-th value of a vector.



Method

final prototype including side information for each relation can be expressed as follows:

$$c_{i}' = \begin{cases} r \oplus si_{h} \oplus si_{r} \oplus si_{k} & r \neq 0 \\ si_{h} \oplus si_{r} \oplus si_{s} & r = 0 \end{cases}$$
 (5)

Each prototype is the mean vector of embedded sentences

$$c_{i} = \frac{1}{N} \sum_{i=1}^{N} f_{\phi}(x_{i}) \tag{6}$$

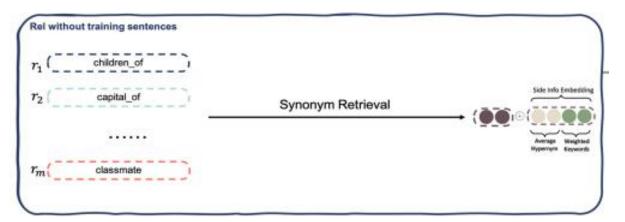
The equation of side information embedding si is as follows:

$$si = f(\frac{h_1 + h_2}{2}) \oplus f(k_1) \oplus \cdots \oplus f(k_n) \oplus K$$
 (7)

$$K = \sum_{m=n}^{m} \left(\frac{\alpha_i}{\sum_{i=m-n}^{m} \alpha_i} f(k_i) \right)$$
 (8)

$$\alpha_i = \frac{count(k, s)}{size(s)} \cdot log(\frac{N}{sentence(k, S)})$$
 (9)

$$ps_i = c_i \oplus si_i \tag{10}$$

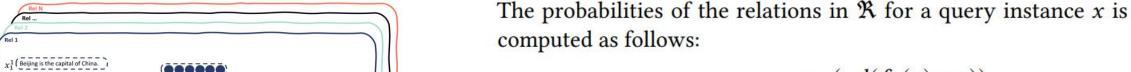


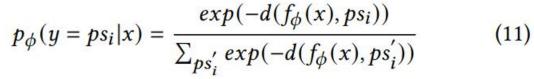
 x_2^1 Paris is the capital and most populous city of France.

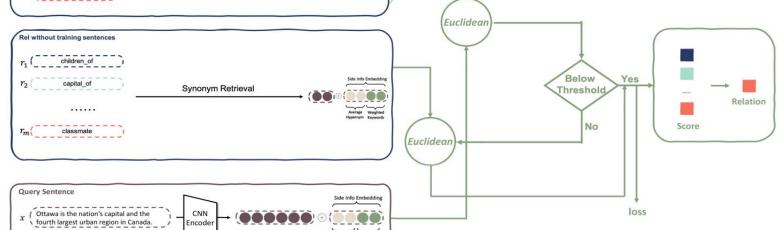
Washington is the capital city χ_n^1 of the United States of

Encoder

Method







Average Weighted Hypernym Keywords

where d(.) is Euclidean distance function as below:

$$d(f_{\phi}(x), ps_i) = \sqrt{\sum_{i=1}^{n} (ps_i - f_{\phi}(x))^2}$$
 (12)

Table 1: Parameter Settings

Parameter	Value
Word Embedding Dimension d_w	50
Position Embedding Dimension d_p	5
Side Information Embedding Dimension d_{si}	300
Hidden Layer Dimension d_h	800
Convolutional Window Size n	3
Batch Size	1
Initial Learning Rate α	0.01
Weight Decay	10^{-5}
Threshold t	2e-08

Table 2: Results of different models on NYT (%). Our reimplementation is marked by *.

Model	Precision	Recall	F1	
CDNN* [43]	46.4	52.7	45.8	
REDN [19]	95.1	94.0	94.6	
ZSLRC	98.1	97.9	97.6	

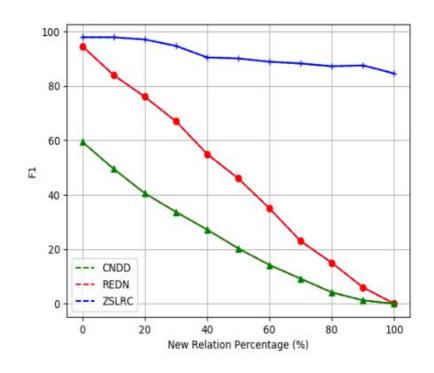


Figure 5: F1-score of ZSLRC when different proportions of new relations appear in NYT dataset.

Table 3: Ablation Results on NYT dataset (Accuracy%)

	10%	30%	50%	70%	90%
ZSLRC(HE)	88.94	70.57	52.12	33.87	15.48
ZSLRC(KE)	93.12	82.22	71.00	60.47	49.07
ZSLRC(SIE)	93.86	85.14	81.91	78.79	72.57
ZSLRC(WSIE)	96.64	94.46	92.14	91.82	89.3

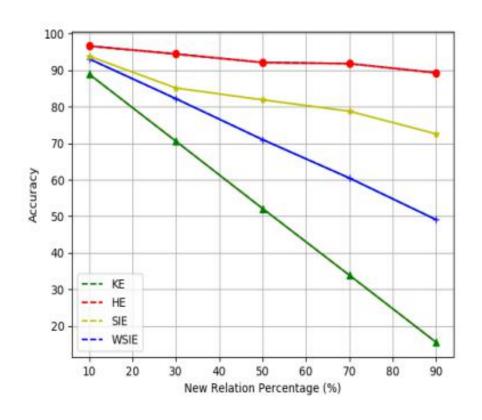


Figure 6: Ablation study of ZSLRC on NYT dataset.

Table 4: Results of Accuracy Comparison Among Models (%)

Model	5 way 1 shot	5 way 5 shot	5 way 10 shot	10 way 1 shot	10 way 5 shot	10 way 10 shot
Meta Network*	64.46 ± 0.54	80.57 ± 0.48	5,	53.96 ± 0.56	69.23 ± 0.52	5
GNN*	66.23 ± 0.75	81.28 ± 0.62	-	46.27 ± 0.80	64.02 ± 0.77	-
SNAIL*	67.29 ± 0.26	79.40 ± 0.22	-	53.28 ± 0.27	68.33 ± 0.25	-
Proto(CNN)	73.62 ± 0.20	85.78 ± 0.16	88.45 ± 0.10	60.96 ± 0.22	75.38 ± 0.19	78.71 ± 0.11
Proto-HATT(CNN)	74.68 ± 0.18	86.73 ± 0.12	89.64 ± 0.12	61.61 ± 0.16	77.04 ± 0.12	79.99 ± 0.11
Proto-CATT(CNN)	=	87.48 ± 0.12	89.28 ± 0.08	1000	77.46 ± 0.13	80.39 ± 0.14
ZSLRC(CNN)	75.83±0.17	87.84±0.12	89.67±0.12	63.54±0.14	77.64 ± 0.11	80.69±0.10

Note that to fairly compare the performance of each model, we only compare the models with the same 50-dimension GloVe embedding and CNN encoders of the same parameters. Better results can be achieved through the BERT encoder.

Table 5: Ablation Results on FewRel dataset (%).

Model	5 way 1 shot	5 way 5 shot	5 way 10 shot	10 way 1 shot	10 way 5 shot	10 way 10 shot
Proto(CNN)	73.62 ± 0.20	85.57 ± 0.14	88.17 ± 0.10	62.22 ± 0.32	75.01 ± 0.16	78.50 ± 0.11
ZSLRC(HE)	75.66 ± 0.14	86.55 ± 0.13	88.98 ± 0.10	63.28 ± 0.20	76.58 ± 0.06	79.93 ± 0.05
ZSLRC(KE)	74.57 ± 0.08	86.70 ± 0.17	89.09 ± 0.11	62.39 ± 0.12	76.99 ± 0.20	80.06 ± 0.09
ZSLRC(SIE)	75.56 ± 0.12	87.34 ± 0.14	89.17 ± 0.13	63.02 ± 0.15	77.16 ± 0.12	80.34 ± 0.10
ZSLRC(WSIE)	75.83 ± 0.17	87.84 ± 0.12	89.67 ± 0.12	63.54 ± 0.14	77.64 ± 0.11	80.69 ± 0.10
ZSLRC(WSIEA)	75.58 ± 0.15	87.16 ± 0.16	89.17 ± 0.15	62.85 ± 0.18	76.71 ± 0.14	80.18 ± 0.11

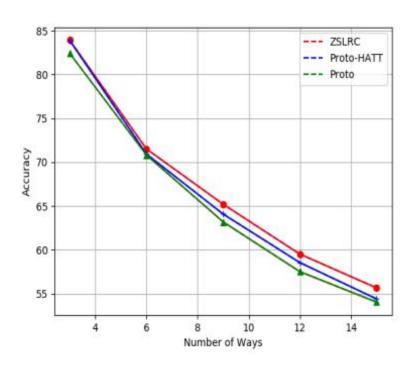


Figure 7: Accuracy of our proposed model in different N-way One-shot tasks.

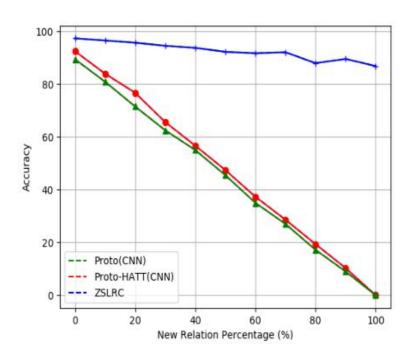


Figure 8: Accuracy of ZSLRC when different proportions of new relations appear in re-splitted FewRel dataset.

Thank you!