Improving Performance of Relation Extraction Algorithm via Leveled Adversarial PCNN and Database Expansion

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Improving Performance of Relation Extraction Algorithm via Leveled Adversarial PCNN and Database Expansion (1)

- Expanding database for better relation extraction by expanding data.
- PCNN + Database Expansion ----> to diminish wrong labels due to the incomplete/NA relation instances.
- We introduced the leveled adversarial attention neural networks (LATTADV-ATT).
- We introduce MDL-based database expansion to enlarge new instances using the most similar itemsets of the most common patterns of entity pairs.
- The attention of selective sentences in PCNN is to reduce noisy sentences.
- The use of adversarial perturbation training as a tool to improve the robustness of system performance.

Improving Performance of Relation Extraction Algorithm via Leveled Adversarial PCNN and Database Expansion (2)

- There are two issues:
- 1) rule generation in database expansion method; This is to find entity pair for generating instances,
- 2) advanced improvement of the classifier by using leveled strategy relation extraction.
- Experimental result has shown that the use of the database expansion is beneficial: P@100=0.842 (at no expansion), P@100=0.891 (at expansion factor k=7).

Contributions

- To demonstrate the use of database expansion through MDL based semantic identification as a novel preprocessing technique in relation extraction task;
- To propose LATTADV, a novel independent *deep learning framework for relation extraction classifier*.
- By independent means that the model also can be implemented on any classification tasks.

Methodology

- Given a dataset of text sentences with entity pair, $X = \{x1, x2, \ldots, xn\}$, and given R is relation labels, our model measures the probability of each relation r, where $r \in R$.

Hypotheses

- Our hypotheses are:

- 1) The MDL database expansion is beneficial to improve the classifier system performance.
- Preliminary Facts: the MDL can capture very well most frequent itemsets.
- The merged results must meet the grammatical/semantic rules.

- 2) The use of leveled sytrategy is beneficial to improve the performance of a classifier

Preprocessing:
The MDL Database Expansion Method

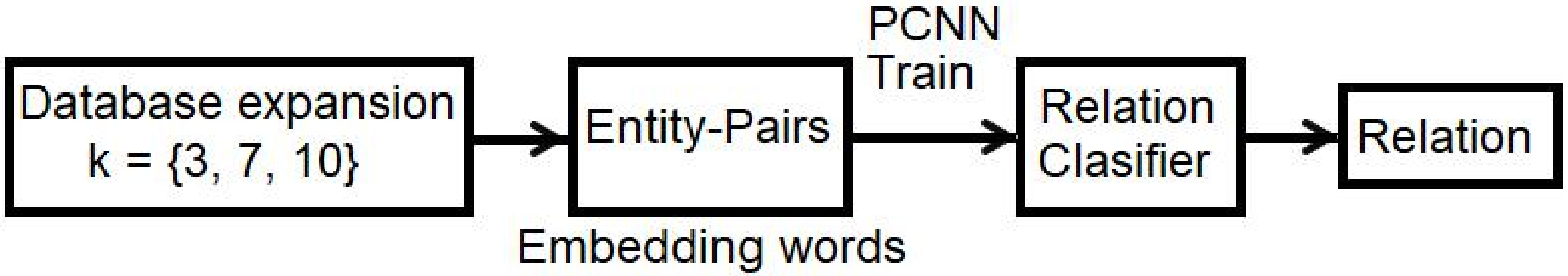


Fig. 1. Overview schema of the leveled adversarial PCNN relation extraction system with database expansion

- Pre-trained words learned from the New York Times (NYT) corpus 2005-2006.
- The entities of the dataset were annotated with Stanford NER (https://nlp.stanford.edu/software/CRF-NER.html) and linked to Freebase (www.freebase.com).
- As the initial embedding words were obtained using word2vec (https://code.google.com/archive/p/word2vec/).

Preprocessing: The MDL Database Expansion Method (2)

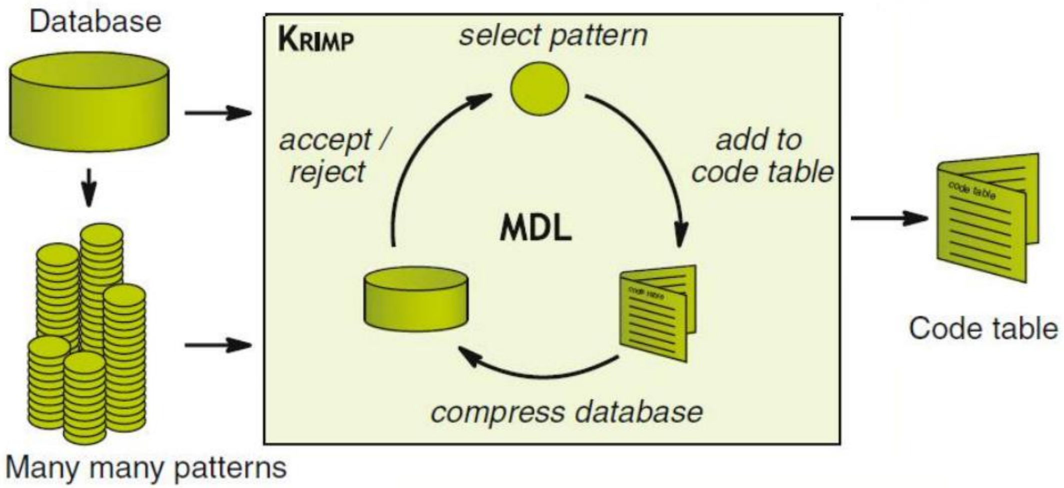


Fig. 2. How KRIMP works

The goal of MDL is to find CT that minimizes the compressed MDL size of the database:

$$L(D, CT) = L(D|CT) + L(CT|D) \qquad (1)$$

Preprocessing:
The MDL Database Expansion Method (3)

- Consider a set of patterns in CT, the expanded pattern generated from k-topmost similar itemsets defined by:
- $$F_i^* = \bigcup_{i=1}^{k} \min_{1 \le j \le l, i \ne j} \qquad (2)$$
- Where and Δ denotes text similarity technique, e.g., cosine similarity or Jaccard similarity. The l denotes the number of tuples in CT.

Preprocessing: The MDL Database Expansion Method (4)

- There are three kinds of situations about frequent itemsets that KRIMP generates from a sentence:
- **Ideal:** The ideal itemset of Fi* is a situation where an itemset (a collection of essential keywords of a sentence) has an entity pair inside. If the situation found, the itemset is appended to the database to expand the existing data.
- **Half ideal:** Another situation is the half ideal itemset. This kind of situation is when a pair of entities is found only a half in Fi*, thus creating an incomplete pair. This situation needs an expansion process of k-topmost similar pattern generation until Fi* has at least one entity pair inside. If there is no entity pair found in Fi* after the combination of k-topmost similar itemset, then Fi* is skipped away, and the base itemset is set up with the next item set.
- **Not ideal:** This is the situation when no entity found in the itemset. We skip this type of itemset since the expansion method never uses a not ideal code as a base itemset.

Preprocessing: The MDL Database Expansion Method (5)

(a). Ideal

0 1 2 3 : 0 is Entity (PERSON), 2 is Entity (LOCATION)
0 4 5 : 0 is Entity (PERSON), 4 is Entity (ORGANIZATION)

(b). Half ideal

0 5 6 : 0 is Entity (PERSON)
4 7 : 4 is Entity (ORGANIZATION)
1 2 : 2 is Entity (LOCATION)

(c). Not ideal

1 3 5 : No Entity is found

CT:

0	1	3	6	
0	3	5	6	(sim=0.75)
1	2	5	6	(sim=0.5)
2	5	6	7	(sim=0.25)
0	3	5		(sim=0.57735)
0	3	7		(sim=0.57735)
2	5	7		(sim=0)
4	5	7		(sim=0)

Base itemset = 0 1 3 6
k = 3 Extension itemsets:
0 1 3 6 U 0 3 5 6 U 0 3 5 U 1 2 5 6 = 0 1 2 3 5 6
0 1 3 6 U 0 3 5 6 U 0 3 7 U 1 2 5 6 = 0 1 2 3 5 6 7

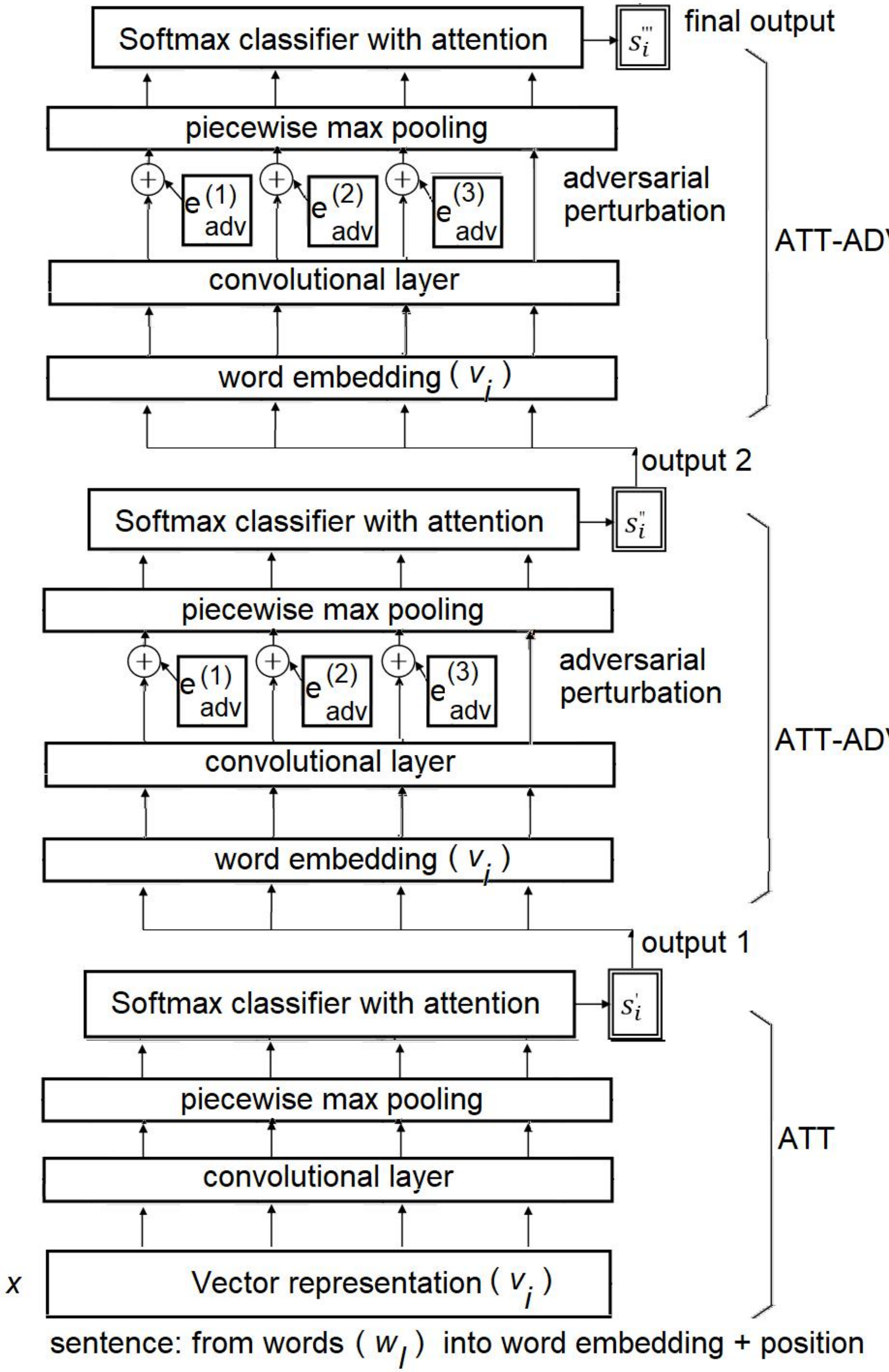
Preprocessing: The MDL Database Expansion Method (6)

- In our research, the expansion process focus on three entities: **PERSON**, **LOCATION**, and **ORGANIZATION**. After detecting the availability of the three entities in an itemset in CT (or in a sentence), the possible semantic relations are as follow:
- **• "/business/company/location":** when an entity of ORGANIZATION and entity of LOCATION found in the same sentence. The newly generated instance has a pattern of "X has location Y." Where X is an ORGANIZATION entity, Y is a LOCATION entity.
- **• "/people/person/place_lived":** when an entity of PERSON and entity of LOCATION found in the same sentence. The newly generated instance has a pattern of "X has location Y." Where X is a PERSON entity, Y is a LOCATION entity.
- **• "/business/person/company":** when an entity of PERSON and entity of ORGANIZATION found in the same sentence. The newly generated instance has a pattern of "X has organization Y." Where X is a PERSON entity, Y is an ORGANIZATION entity.

An Example of Database Expansion

Relation	/business/person/company
entity1.id	m.0dan05
entity1.name	danay
entity2.id	m.0ele14
entity2.name	eleftherotypia
*F**	steijn danay eleftherotypia
TP	danay has organization eleftherotypia

The Proposed Classifier (PCNN LATTADV-ATT) Model



The Proposed Classifier (PCNN LATTADV-ATT) Model (2)

- Selective attention (ATT): When distributed vector representations of X learned, ATT only gives attention to sentence sr that sincerely express relation r through computing the weighted average of sentences s1, s2, ..., sn, with sr defined as:

$$s_r = \sum_i \alpha_i^r s_i \qquad (3)$$

- The softmax function is used to compute the embedding vector of the query vector qr. The αr denotes the attention weights with relation r, αr=softmax(tanh(si)⊤ qr)), see [4]. ATT de-emphasizes noisy sentence. ATT helps to avoid massive false labeling during training ⊤ q(r) and testing. Final loss function for ATT[15]:

$$L_{ATT}(X,\theta) = -\sum_{i=1}^{K} \log P(r \mid x, \theta) \qquad (4)$$

- The θ denotes parameters, and the K denotes the total number of predefined relation labels r. The conditional probability of relation:

P(r|x,θ)=softmax(Asr + b) (5)

- Where A denotes a weighted diagonal representation matrix of relations, sr denotes attended sentence, and b denotes a bias vector.

The Proposed Classifier (PCNN LATTADV-ATT) Model (3)

- Adversarial training (ADV): Adversarial training first introduced in [2]. In ADV, a small amount of perturbation, eadv, is added on word embedding after that adversarial training computes the gradient direction of a loss function with aims to maintain closeness and linearity to input data (viz. by linearizing loss function near the input X). Given word embedding of all the words in X called as V, V = {v1, v2, ..., vn}, ADV adds eadv to V. The final loss function for ATT-ADV is defined as follows [15]:

$$LATT\text{-}ADV(X,\theta)=LATT(X+eadv,\theta) \qquad (6)$$

where:

$$eadv=\epsilon g/||g|| \qquad (7)$$

and

$$g = \nabla_v L_{ATT}(X, \hat{\theta}) \qquad (8)$$

The θ denotes all parameters. The ||g|| denotes the norm of gradients over all the words from all the sentences in X.

Experiments

Parameter settings:

- sentence embedding size 230,
- position embedding dimension 5,
- word embedding size 50,
- sliding window size 3,
- maximum of training epochs 60,
- learning rate 0.5,
- batch size 160,
- dropout rate 0.5,
- weight decay 0.00001, and
- maximum of relations 53.

Experiments (2)

Training set	k	#Rel	#Ent-Pair	#Mention	#Sentence
base	0	53	172399	293162	570088
cos	3	53	172499	293170	570388
jac	3	53	172499	293170	570388
cos	7	53	173099	293187	572990
jac	7	53	173099	293185	572988
cos	10	53	173299	293185	573649
jac	10	53	173299	293185	573649

Testing set	k	#Rel	#Mention	#Sentence
base	0	53	1950	172448
cos	3	53	1950	172525
jac	3	53	1950	172525
cos	7	53	1950	173175
jac	7	53	1950	173175
cos	10	53	1950	173341
jac	10	53	1950	173341

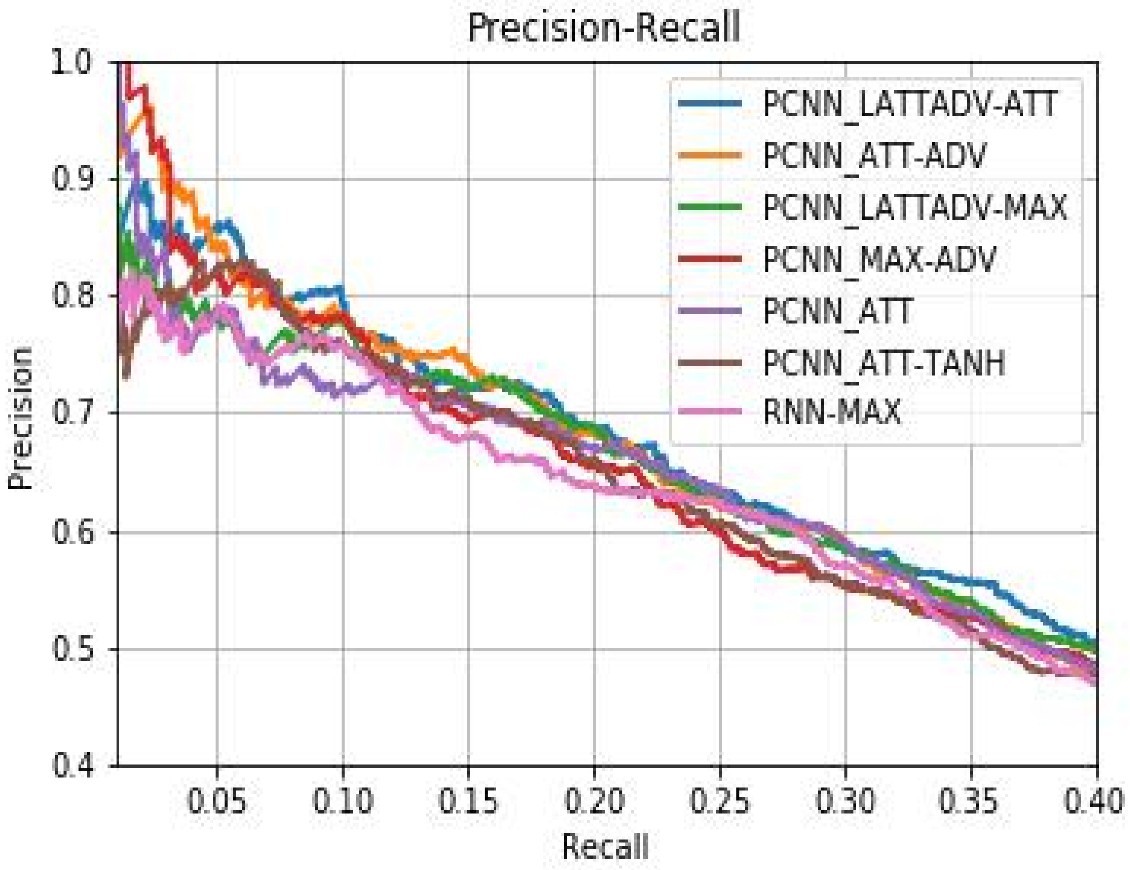
Word size=50, position size=5, hidden size=230.
#Rel: number of relation.
#Ent-Pair: number of entity pair.
cos: NYT dataset+expansion with k topmost similar itemsets by Cosine similarity.

Experiments (3)

Method	k	AUC	Max F1	P@100	P@200	P@300	Mean
LATTADV-ATT	0	0.418	0.456	0.842	0.801	0.761	0.801
ATT-ADV	0	0.412	0.441	0.861	0.786	0.754	0.801
LATTADV-MAX	0	0.409	0.452	0.782	0.761	0.741	0.761
MAX-ADV	0	0.402	0.447	0.802	0.776	0.741	0.773
ATT	0	0.399	0.448	0.752	0.726	0.724	0.734
ATT_tanh	0	0.395	0.443	0.822	0.781	0.741	0.781
RNN-MAX	0	0.395	0.441	0.762	0.756	0.734	0.751

LATTADV-ATT: PCNN + leveled attention and adversarial attention
ATT-ADV: PCNN + attention + adversarial
LATTADV-MAX: PCNN + leveled attention and adversarial + maximum function
MAX-ADV: PCNN + maximum function + adversarial
ATT: PCNN with attention
ATT_tanh: PCNN with attention + tanh activation function
RNN-MAX: recurrent neural network + maximum function

Experiments (4)



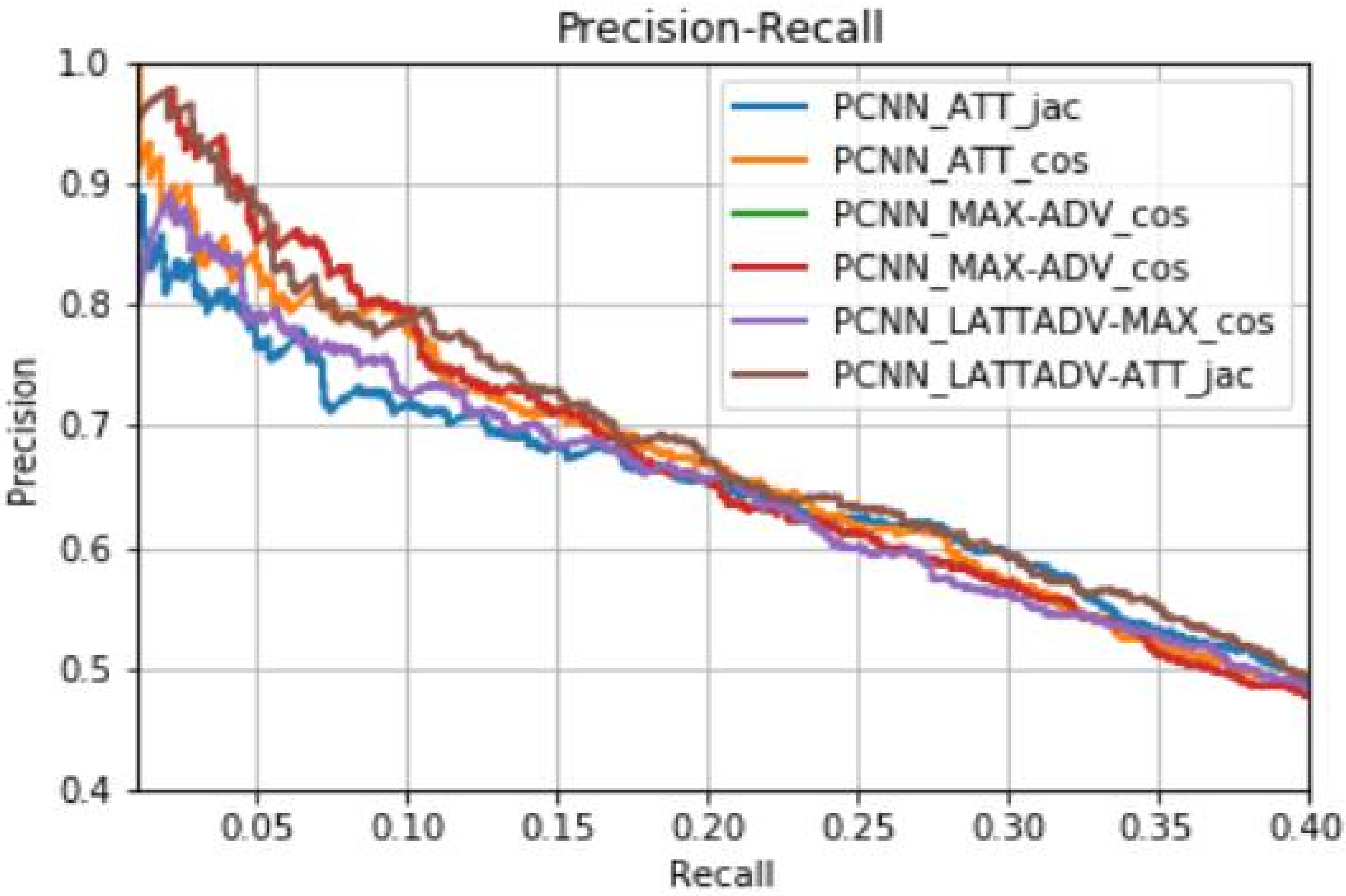
LATTADV-ATT: PCNN + leveled attention and adversarial attention
ATT-ADV: PCNN + attention + adversarial
LATTADV-MAX: PCNN + leveled attention and adversarial + maximum function
MAX-ADV: PCNN + maximum function + adversarial
ATT: PCNN with attention
ATT_tanh: PCNN with attention + tanh activation function
RNN-MAX: recurrent neural network + maximum function

Experiments (5)

M1: PCNN ATT; M2: PCNN ATT-ADV; M3: PCNN MAX-ADV;
M4: PCNN LATTADV-MAX; M5: PCNN LATTADV-ATT
Jac: Jaccard similarity; Cos: Cosine similarity

Alg	k	AUC	Max F1	P@100	P@200	P@300	Mean	Borda
M1	k=0	0.399	0.448	0.753	0.726	0.724	0.734	28
M1	Jac, k=3	0.398	0.44	0.782	0.761	0.728	0.757	33
M1	Jac, k=7	0.397	0.45	0.802	0.716	0.711	0.743	35
M1	Jac, k=10	0.404	0.438	0.822	0.796	0.734	0.784	95
M1	k=0	0.399	0.448	0.753	0.726	0.724	0.734	28
M1	Cos, k=3	0.408	0.45	0.782	0.781	0.764	0.776	109
M1	Cos, k=7	0.406	0.442	0.822	0.791	0.738	0.784	100
M1	Cos, k=10	0.4	0.44	0.822	0.751	0.73	0.767	45
M2	k=0	0.412	0.442	0.861	0.786	0.754	0.801	149
M3	k=0	0.402	0.447	0.802	0.776	0.741	0.773	74
M3	Cos, k=3	0.406	0.446	0.881	0.796	0.761	0.813	109
M3	Cos, k=7	0.407	0.445	0.891	0.811	0.744	0.815	100
M3	Cos, k=10	0.399	0.438	0.861	0.781	0.728	0.79	45
M4	k=0	0.41	0.452	0.782	0.761	0.741	0.761	79
M4	Cos, k=3	0.405	0.44	0.852	0.766	0.734	0.784	80
M4	Cos, k=7	0.406	0.454	0.842	0.761	0.731	0.778	88
M4	Cos, k=10	0.405	0.44	0.852	0.766	0.734	0.784	73
M5	k=0	0.418	0.456	0.842	0.801	0.761	0.801	187
M5	Jac, k=3	0.415	0.449	0.852	0.791	0.764	0.802	169
M5	Jac, k=7	0.422	0.455	0.891	0.791	0.771	0.818	207
M5	Jac, k=10	0.416	0.451	0.861	0.796	0.751	0.803	179

Experiments (6)



- Fig. 7.Precision-Recall of LATTADV-ATT with expansion factor (k=7)

Effect of Number of Relations in Database Expansion

- A careful step of expansion factor k can have a significant effect on the improvement of the relation extraction system.
- Larger *k* means a more quantity of relations generated in the expanded database (Table I).
- Test carefully. To obtain better performance, we must test first the appropriate *k* value carefully because the generated merging itemsets of CT (the F*) may too far away in meaning from the original sentences meaning if the *k* is too big.
- The best improvement is achieved using LATTADV-ATT with Jaccard similarity expansion at *k*=7 (Table III and Fig. 7).

Effect of The Deep Learning Strategy Setup and The Similarity Metric Used

- Compared to PCNN ATT-ADV as the best baseline of state-of-the-art methods used, the percentages of the LATTADV-ATT Jaccard k=7 improvement are as follows: AUC=2.43%, maximum of F1=2.94%, P@100=3.48%, P@200=0.64%, P@300=2.25%, mean of precisions=2.12%.
- Also, when compared to the attention network without expansion (PCNN ATT k=0), the percentages of the LATTADV-ATT Jaccard k=7 improvement are as follows: AUC=5.76%, maximum of F1=1.56%, P@100=18.33%, P@200=8.95%, P@300=6.49%, mean of precisions=11.44%.
- **The use of the database expansion can improve the relation extraction system's performance.**
- **Cosine or Jaccard similarity can be used substitutive.**

Conclusions

- 1) The MDL database expansion is beneficial to improve the performance of the classifier model.

This ability is because the minimum description length-based algorithm can sharply capture associations, and the semantic understanding of entity pair helps in generate new expansion sentences.

- 2) The leveled network with attention and adversarial training strategy in the proposed strategy is beneficial to improve the performance of the PCNN-based relation extraction classifier.

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