



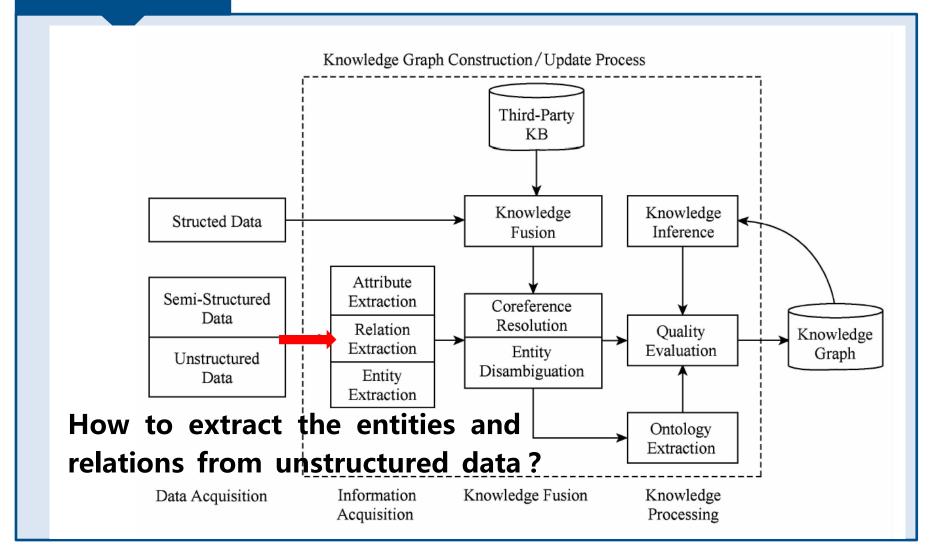
AAAI 2019

Jointly Extracting Multiple Triplets with Multilayer Translation Constraints

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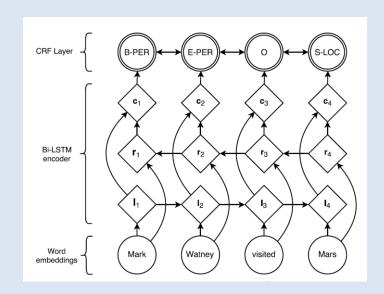
Framework





1.entity

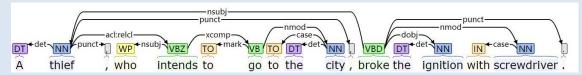
The rule, DNN and CRF are leveraged to extract the entities or attributes in the unstructured data.



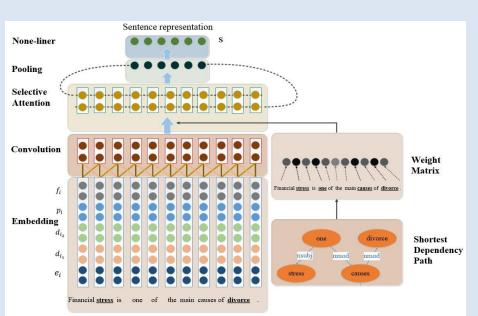
Bi-LSTM+CRF

Neural Architectures for Named Entity Recognition, NAACL2016

2.relation



- CNN or RNN
- +Dependency path
- +Attention Mechanism
- +variety Features



Error propagation!

NER+RC

- LSTM
- CNN
- Encode-Decode

too many candidate entities low joint extraction accuracy

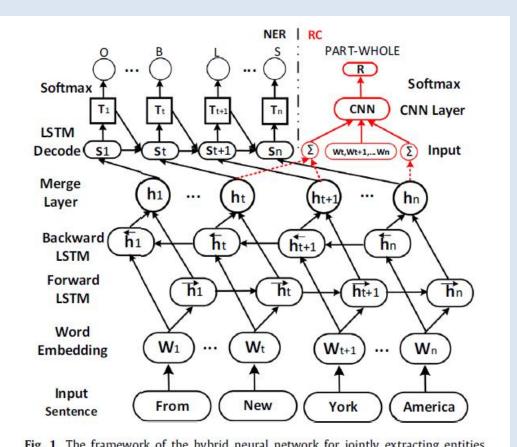
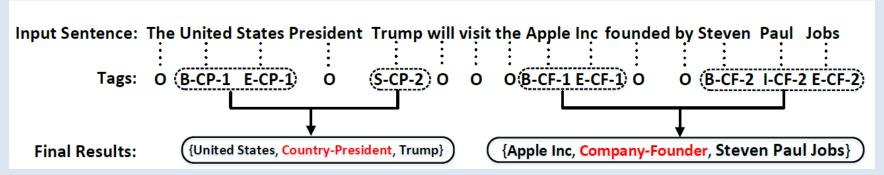


Fig. 1. The framework of the hybrid neural network for jointly extracting entities and relations.

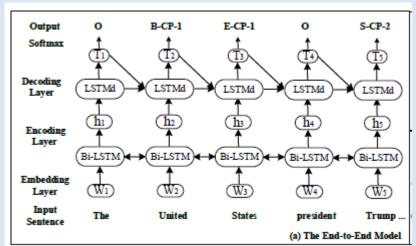
Joint entity and relation extraction based on a hybrid neural network, Neurocomputing

NTS



- Encode-Decode
- Tagging Scheme

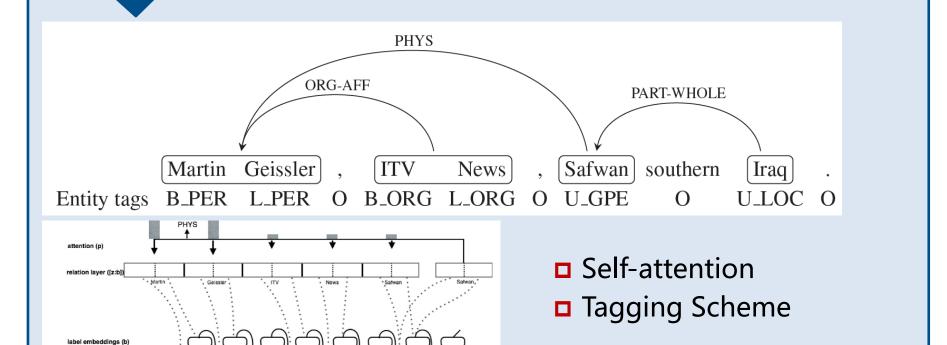
Each entity pair can only have a relationship



Joint Extraction of Entities and Relations Based on a Novel Tagging Scheme, ACL 2017



softmax (y)



top-hidden layer (z)
multi-layer Bi-LSTM (h)
word embeddings (x)

multi-layer Bi-LSTM (h)

Each entity can only be

Going out on a limb: Joint Extraction of Entity Mentions and Relations without Dependency Trees, ACL 2017

shortcoming

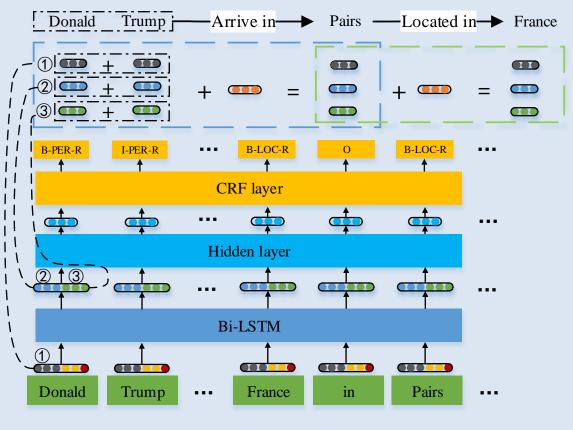
How to extract multiple triplets (entities and relations) from unstructured data?

- Pipeline extraction leads to error propagation and low accuracy
- Existing joint extraction models are not suited for extracting multiple triples in sentences

Our work

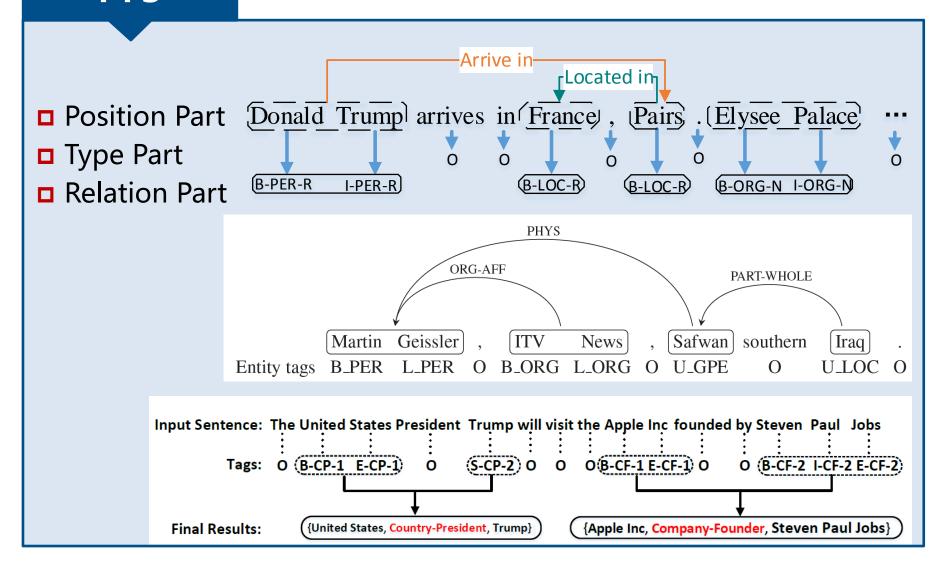
joint extraction model for multi-triplets TME

- □ Bi-LSTM
- □ TTS
- Multi-layer translationbased constrains





TTS



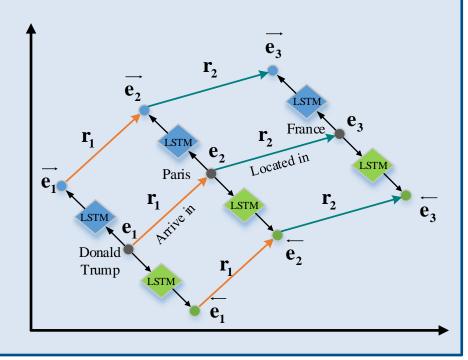


$$\mathbf{e} = \sum_{k=i}^{i+e_l} \mathbf{w}_k, \overrightarrow{\mathbf{e}} = \sum_{k=i}^{i+e_l} \overrightarrow{\mathbf{h}}_k, \overleftarrow{\mathbf{e}} = \sum_{k=i}^{i+e_l} \overleftarrow{\mathbf{h}}_k,$$

$$f(\tau) = -\|\mathbf{e}_1 + \mathbf{r} - \mathbf{e}_2\|_2^2.$$

$$\overrightarrow{f}(\tau) = - \left\| \overrightarrow{\mathbf{e}_1} + \mathbf{r} - \overrightarrow{\mathbf{e}_2} \right\|_2^2,$$

$$\overleftarrow{f}(\tau) = - \left\| \overleftarrow{\mathbf{e}_1} + \mathbf{r} - \overleftarrow{\mathbf{e}_2} \right\|_2^2.$$





Training

Entity loss function

$$\mathcal{L}_e = \log(p(\mathbf{y}|\mathbf{X})) = f(\mathbf{X}, \mathbf{y}) - \log(\sum_{\mathbf{y} \in Y} e^{f(\mathbf{X}, \tilde{\mathbf{y}})}).$$

Relation loss function

$$\mathcal{L}_{em} = \sum_{\tau \in \mathcal{T}} \sum_{\tau' \in \mathcal{T}'} \text{ReLu}(f(\tau) + \gamma - f(\tau')),$$

$$\overrightarrow{\mathcal{L}} = \sum_{\tau \in \mathcal{T}} \sum_{\tau' \in \mathcal{T}'} \text{ReLu}(\overrightarrow{f}(\tau) + \gamma - \overrightarrow{f}(\tau')),$$

$$\overleftarrow{\mathcal{L}} = \sum_{\tau \in \mathcal{T}} \sum_{\tau' \in \mathcal{T}'} \text{ReLu}(\overleftarrow{f}(\tau) + \gamma - \overleftarrow{f}(\tau')).$$

$$\mathcal{L}_{r} = \mathcal{L}_{em} + \overrightarrow{\mathcal{L}} + \overleftarrow{\mathcal{L}}.$$

$$\mathcal{L}_r = \mathcal{L}_{em} + \overrightarrow{\mathcal{L}} + \overleftarrow{\mathcal{L}}$$

Final loss function

$$\mathcal{L} = \mathcal{L}_e + \lambda \mathcal{L}_r$$

Extraction

- Get the label of each word
- Generate candidate entities
- Generate candidate entity pairs
- Calculate the score for each candidate entity pair
- Select one triple for each entity pair
- Sort the candidate triples and select the triplet with the highest score as the correct triple.

$$\hat{y} = \arg \max_{\tilde{y} \in Y} f(\mathbf{X}, \tilde{y}).$$

$$\hat{\mathcal{E}} = \{\hat{e}_1, \dots, \hat{e}_i, \dots, \hat{e}_m\},$$

$$\tilde{\mathcal{T}} = \{\tilde{\tau} = (\hat{e}_i, \hat{e}_j, r) | r \in \mathcal{R}\},$$

$$f_c(\tilde{\tau}) = f(\tilde{\tau}) + \overrightarrow{\tau}(\tilde{\tau}) + \overleftarrow{f}(\tilde{\tau}),$$

$$\hat{\tau} = \arg \max_{\tilde{\tau} \in \tilde{\mathcal{T}}} f_c(\tilde{\tau}).$$

results

表 4.1 数据集统计信息

数据集	#Train	#Test	#Triplet	#Ent	#Rel
NYT-single	235,983	395	17,663	67,148	24
NYT-multi	63,602	1,000	17,494	25,894	24

表 4.2 在数据集 NYT-single 上的三元组抽取效果

Methods	Prec	Rec	F1
FCM	0.553	0.154	0.240
DS+logistic	0.258	0.393	0.311
LINE	0.335	0.329	0.332
MultiR	0.338	0.327	0.333
DS-Joint	0.574	0.256	0.354
СоТуре	0.423	0.511	0.463
NTS-Joint	0.615	0.414	0.495
TME (Top-1)	0.583	0.485	0.530
TME (Top-2)	0.515	0.508	0.511
TME (Top-3)	0.458	0.522	0.489

表 4.3 在数据集 NYT-multi 上的三元组抽取效果

Methods	Prec	Rec	Fl
СоТуре	0.385	0.340	0.361
NTS-Joint	0.533	0.336	0.412
TME-MR	0.638	0.421	0.507
TME-RR	0.423	0.452	0.437
TME-NS	0.558	0.496	0.525
TME (Top-1)	0.749	0.436	0.551
TME (Top-2)	0.696	0.478	0.567
TME (Top-3)	0.631	0.500	0.558

Ablation

表 4.4 NYT-multi 数据集上 TME 模型的成分分析

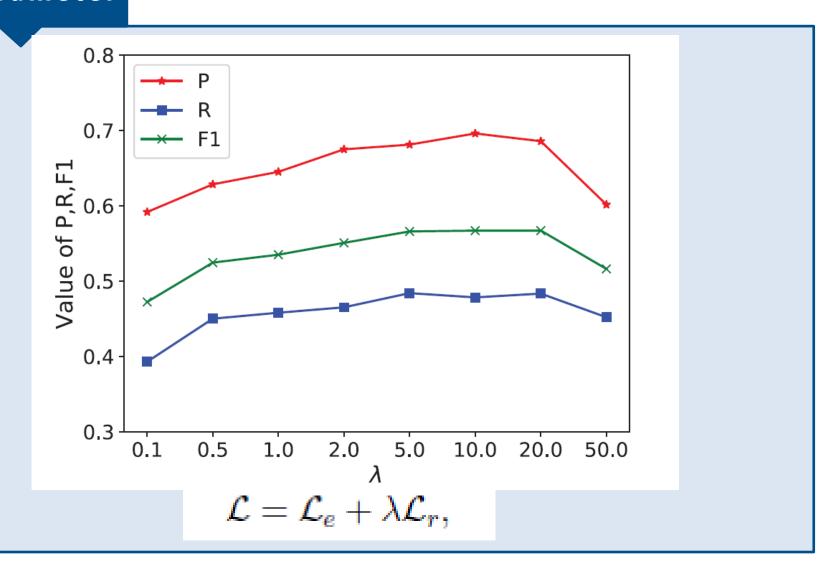
Model	Top-1		Top-2			Тор-3			
Model	Prec	Rec	Fl	Prec	Rec	Fl	Prec	Rec	Fl
TME-MR	0.692	0.385	0.495	0.638	0.421	0.507	0.575	0.438	0.498
TME-RR	0.478	0.417	0.445	0.423	0.452	0.437	0.365	0.462	0.408
TME-NS	0.687	0.419	0.520	0.558	0.496	0.525	0.448	0.523	0.483
TME	0.749	0.436	0.551	0.696	0.478	0.567	0.631	0.500	0.558
-TTS (-TP)	0.741	0.436	0.549	0.680	0.478	0.561	0.610	0.498	0.548
-TTS (-RP)	0.610	0.376	0.465	0.488	0.484	0.486	0.400	0.547	0.462
-TTS (-TP-RP)	0.575	0.353	0.438	0.474	0.468	0.470	0.391	0.531	0.450
-Character	0.723	0.428	0.538	0.663	0.472	0.552	0.597	0.497	0.542
-CRF	0.690	0.414	0.517	0.608	0.470	0.530	0.522	0.495	0.509
- 7 - 7	0.552	0.310	0.398	0.521	0.368	0.431	0.468	0.399	0.431
-f	0.569	0.332	0.419	0.518	0.372	0.433	0.465	0.395	0.428
-Dropout	0.723	0.424	0.535	0.666	0.478	0.556	0.593	0.503	0.544
-Pretrain	0.686	0.411	0.514	0.613	0.466	0.530	0.539	0.495	0.516

Case Study

表 4.5 TME (Top-3) 模型在 NYT-multi 数据集上的样例分析				
Sentence I	President Jacques $Chirac_{[PER]}$ of $France_{[LOC]}$ and $Chancellor$ Angela $Merkel_{[PER]}$ of $Germany_{[LOC]}$ to press for agreement on a Security Council resolution demanding that $Iran_{[LOC]}$ stop			
(Jacques C	ecques Chirac, nationality, France) (Jacques Chirac, nationality, France)			
(Angela Me	rkel, nationality, Germany)	(Angela Merkel, nationality, Germany)		
		(Jacques Chirac, nationality, Germany)		
	grasping the critical	need for the $United\ States_{[LOC]}$ to get		
Sentence II	$Afghanistan_{[LOC]}$ right, she moved to $Kandahar_{[LOC]}$ to help $Afghanistan_{[LOC]}$			
	for Civil Society, founded by the brother of Hamid Karzai $[PER]$.			
(Afghanis	tan, contains, Kandahar)	(Kandahar, contains, Hamid Karzai)		
(Hamid Karza	i, place_of_birth, Kandahar)	(Afghanistan, contains, Kandahar)		
(Hamid Karz	ai, nationality, Afghanistan)	(Hamid Karzai, nationality, Afghanistan)		
	Across $Iraq_{[LOC]}$, from $Mosul_{[LOC]}$ and $Ramadi_{[LOC]}$ to $Basra_{[LOC]}$			
Sentence III	and Kirkuk _[LOC] , the li	nes of votes hummed with excitement,		
	and with the hope that a permanent Iraqi government			
(Irac	q, contains, Mosul)	(Iraq, contains, Mosul)		
(Iraq, contains, Ramadi)		(Iraq, contains, Basra)		
(Iraq, contains, Basra)		(Iraq, contains, Ramadi)		
(Iraq	l, contains, Kirkuk)			
<u> </u>				



H-Parameter





Future

- Unable to resolve the same entity pair containing two different relationships (Located in and Capital)
- Unable to automatically recognize the number of entities in a sentence





Thanks! Q84A!