

Cross-Supervised Joint-Event-Extraction with Heterogeneous Information Networks

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Outline

- Introduction
- Preliminaries
- Our Proposed Model
- Experiments and Analysis



Named entities:

e.g. person, company, organization, geographic name...

Event triggers:

e.g. bankrupt, conflict, marry, dispatch...

Relations:

e.g. /location/location/contains, /people/person/place_of_birth, /people/person/place_lived The New York Times Annotated Corpus contains over 1.8 million articles written and published by the New York Times between January 1, 1987 and June 19, 2007 with article metadata provided by the New York Times Newsroom, the New York Times Indexing Service and the online production staff at nytimes.com. The corpus includes:

- · Over 1.8 million articles (excluding wire services articles that appeared during the covered period).
- · Over 650,000 article summaries written by library scientists.
- Over 1,500,000 articles manually tagged by library scientists with tags drawn from a normalized indexing vocabulary of people, organizations, locations and topic descriptors.
- Over 275,000 algorithmically-tagged articles that have been hand verified by the online production staff at nytimes.com.
- Java tools for parsing corpus documents from .xml into a memory resident object.

As part of the New York Times' indexing procedures, most articles are manually summarized and tagged by a staff of library scientists. This collection contains over 650,000 article-summary pairs which may prove to be useful in the development and evaluation of algorithms for automated document summarization. Also, over 1.5 million documents have at least one tag. Articles are tagged for persons, places, organizations, titles and topics using a controlled vocabulary that is applied consistently across articles. For instance if one article mentions "Bill Clinton" and another refers to "President William Jefferson Clinton", both articles will be tagged with "CLINTON, BILL".

The New York Times has established a community website for researchers working on the data set at http://groups.google.com/group/nytnlp and encourages feedback and discussion about the corpus.





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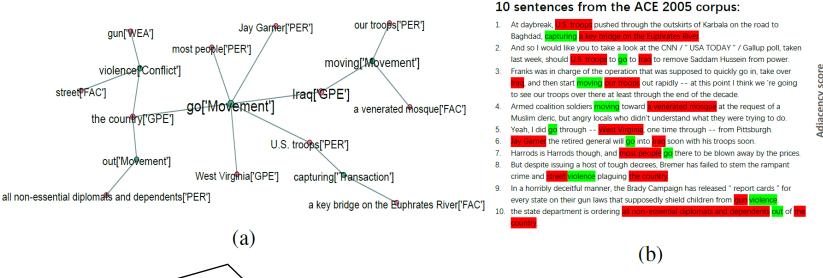
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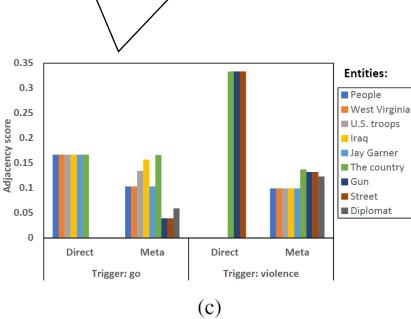


Problems of existing methods

The original positions for triggers (green) and entities (red).



Direct-adjacency-distribution for entities (Direct) v.s. meta-path-based distribution (Meta) based on a given trigger

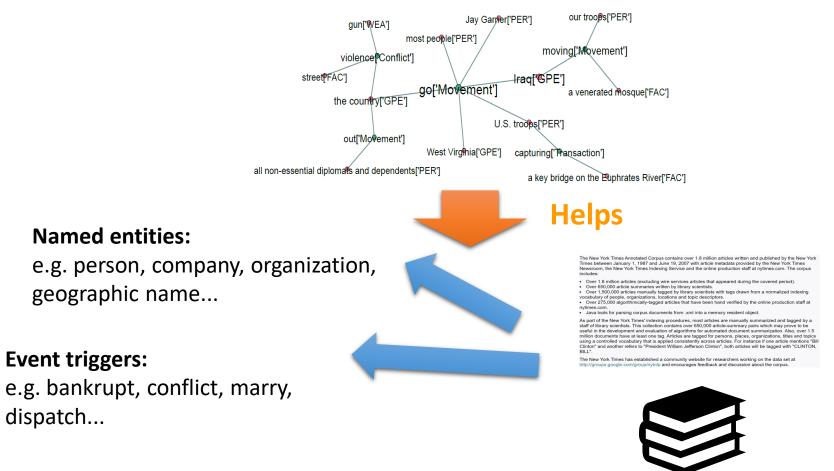


e.g. from "go" to "gun" along the metapath "Movement-GPE-Conflict-WEA"

An example of co-occurred relationships between triggers and entities.



Heterogeneous Information Network of entities and triggers





Comparison with different models without any pre-defined features

TABLE II: Comparison on real-world datasets

Model	Precision	ACE 2005 Recall	F1	Precision	NYT Recall	F1	Precision	CoNLL Recall	F1	Precision	WebNLG Recall	F1
Seq2Seq CRF GCN JEE JT CSM _{DA}	0.442±0.025 0.434±0.031 0.435±0.030 0.423±0.023 0.469±0.003 0.455±0.024	0.493±0.0272 0.478±0.033 0.487±0.032 0.468±0.030 0.426+0.005 0.494±0.022	0.466±0.026 0.455±0.032 0.459±0.031 0.443±0.026 0.447+0.004 0.474±0.023	0.818±0.012 0.813±0.011 0.804±0.013 0.717±0.009 0.725±0.012 0.835±0.012	0.832±0.012 0.828±0.011 0.819±0.013 0.645±0.014 0.691±0.006 0.847±0.012	0.825±0.012 0.821±0.01 0.811±0.013 0.679±0.012 0.708±0.009 0.841±0.012	0.709±0.015 0.718±0.016 0.706±0.015 0.713±0.019 0.738±0.025 0.730±0.017	0.852±0.011 0.867±0.013 0.871±0.014 0.814±0.013 0.837±0.006 0.856±0.021	0.774±0.013 0.785±0.014 0.780±0.013 0.76±0.015 0.784±0.021 0.788±0.019	0.851±0.009 0.864±0.005 0.884±0.008 0.775±0.015 0.818±0.011 0.908±0.005	0.910±0.007 0.921±0.005 0.931±0.008 0.818±0.012 0.829±0.007 0.941±0.004	0.880±0.008 0.892±0.005 0.907±0.008 0.796±0.013 0.823±0.008 0.924±0.004
$CSM_{ m HIN}$	0.477 ± 0.030	0.533 ± 0.033	0.503 ± 0.031	0.859 ± 0.007	0.870 ± 0.008	0.865 ± 0.008	0.754 ± 0.018	0.890 ± 0.020	0.816 ± 0.017	0.923 ± 0.004	0.953 ± 0.003	0.937 ± 0.003

Model		y extractio	n	Trigger extraction			
Wiodei	Precision	Recall	F1	Precision	Recall	F1	
Seq2Seq	0.494	0.489	0.49	0.383	0.426	0.403	
CRF	0.502	0.483	0.491	0.395	0.473	0.431	
GCN	0.508	0.491	0.499	0.381	0.443	0.410	
JEE	0.451	0.497	0.472	0.407	0.411	0.409	
JT	0.492	0.458	0.474	0.447	0.414	0.432	
CSM_{DA}	0.509	0.535	0.52	0.404	0.442	0.422	
CSM_{HIN}	0.512	0.552	0.532	0.464	0.484	0.474	

Our models



Main contributions of this paper.

- First to use the indirect "entity-trigger" cooccurrence relationships (encoded in HIN) to improve the performance of the joint-event-extraction task.
- Proposed Cross-Supervised-Mechanism.
- Verify the indirect "entity-trigger" cooccurrence relationships is helpful.



Preliminaries

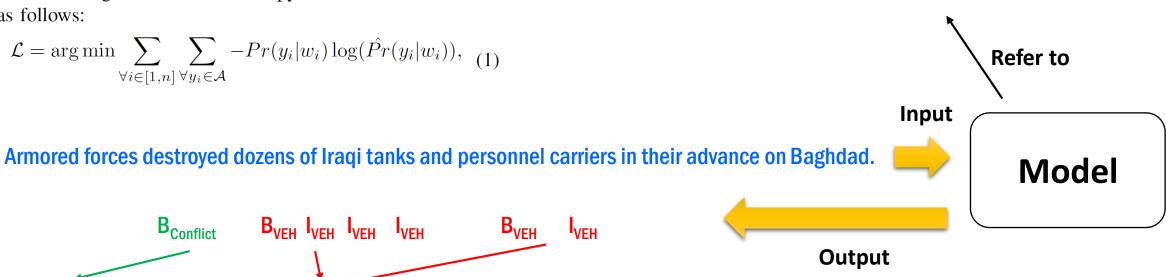
The Joint-Event-Extraction Task

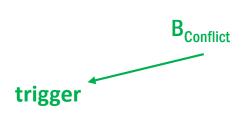
Sequence-to-Sequence Labeling. The goal of joint-eventextraction is to train a machine learning model under the supervision of a pre-annotated corpus. Minimizing the crossentropy loss function [15] has always been introduced to achieve this goal. The cross-entropy loss function is defined as follows:

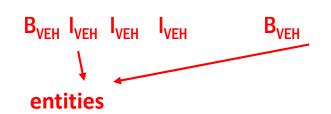
$$\mathcal{L} = \arg\min \sum_{\forall i \in [1, n]} \sum_{\forall y_i \in \mathcal{A}} -Pr(y_i|w_i) \log(\hat{Pr}(y_i|w_i)), \quad (1)$$

Combined tag-set (example)

BORG, IORG, BPER, IPER, BATTACK, O,...



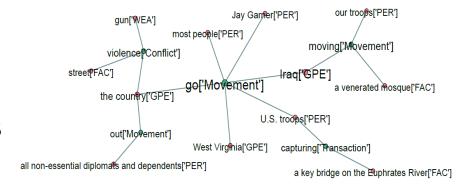






Preliminaries

- "Entity-Trigger" Heterogeneous Information Network
 - It is defined as a weighted graph
 - G = <V, E, W>
 - V is a node set of entities and triggers
 - E is the co-occurred relationships between nodes



Two maps

$$\phi: V \to \mathcal{A}$$

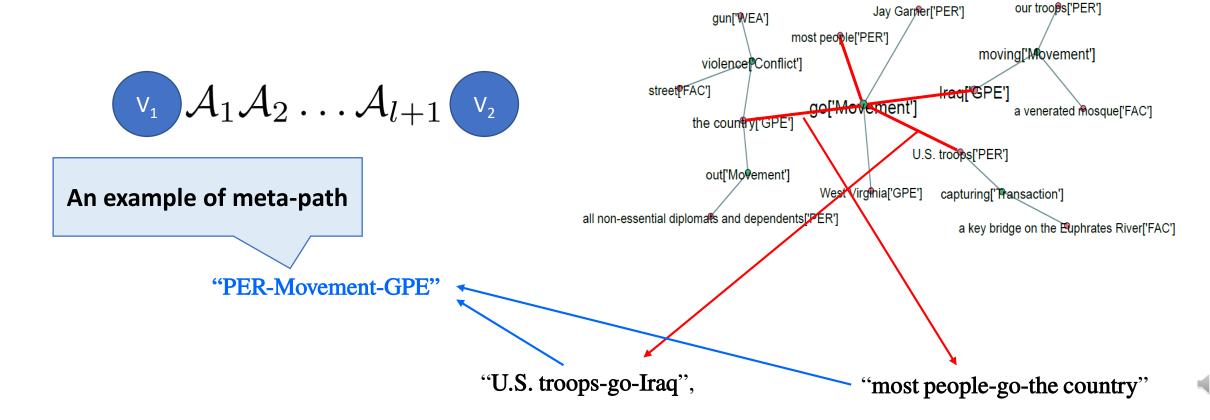
$$\psi: E \to \mathcal{R}$$

$$\psi : E \to \mathcal{R}$$



Preliminaries

"Entity-Trigger" Heterogeneous Information Network
 Meta-path between two nodes (entities or triggers)

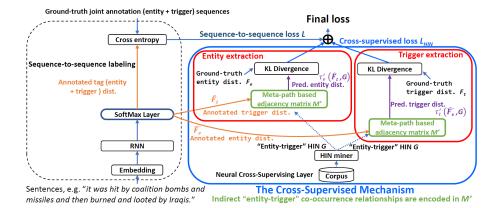


Our Proposed Model

Entity DistributionTrigger Distribution

Frequencies for diff. named entities

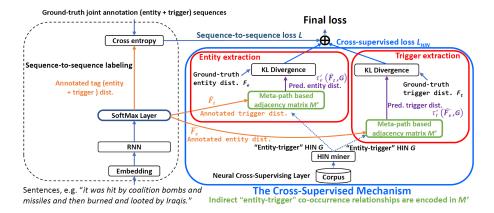
Frequencies for diff. event triggers





Our Proposed Model

Entity DistributionTrigger Distribution

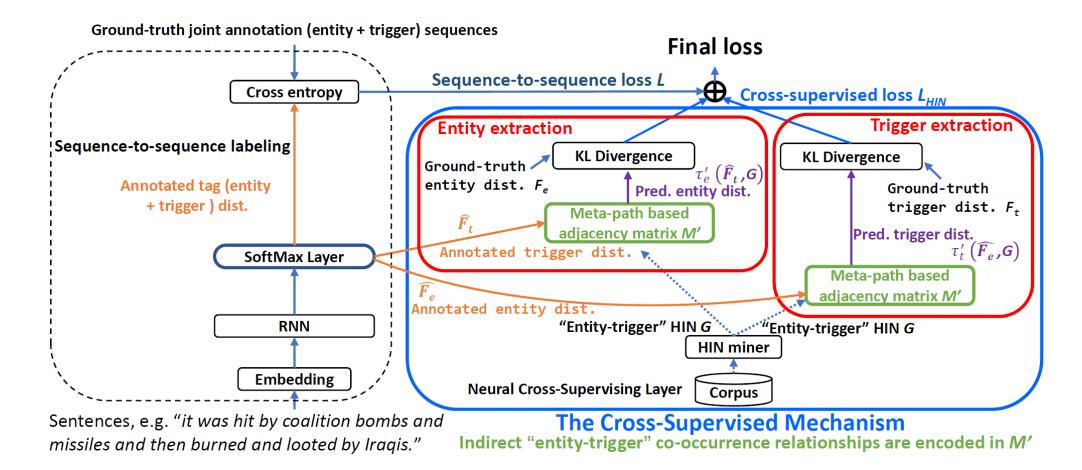


Cross-Supervised Mechanism

$$\mathcal{L}_{HIN} = F_t \log \frac{F_t}{\tau_t'(\hat{F}_e, G)} + F_e \log \frac{F_e}{\tau_e'(\hat{F}_t, G)},$$



Our Proposed Model



Datasets

From Linguistic Data Consortium (LDC)

New York Times
Newsroom

A Spanish corpus made available by the Spanish EFE News Agency

LE I: Da

et statistics

	ACE2005	NYT	CoNLL	WebNLG	
sentences entities triggers entity types event types meta-paths (1=3)	2,107 4,590 1,921 11 8 4,459	6,304 12,643 6,355 17 4 18,035	3,932 13,511 3,903 4 11 22,399	$\angle \cdot \angle 1$	nallenge of natural guage generation



A basic model in seq2seq framework with a combined tag-set

- Sequence-to-Sequence Joint Extraction (Seq2Seq)
- Conditional Random Field Joint Extraction (CRF)

An improved seq2seq method with CRF constraints

- GCN
- Joint Event Extraction (JEE)
- Joint Transition (JT)
- CSM_{DA}
- CSM_{HIN}

The proposed model with ADJ. matrix

A state-of –the-art method, based on GCN

A classic joint method for extracting entities and triggers together.

A latest joint method for extracting entities and triggers together.

The full proposed model with HIN



• Results.

Model	ACE 2005			NYT			CoNLL			WebNLG		
	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
Seq2Seq	0.442 ± 0.025	0.493 ± 0.0272	0.466 ± 0.026	0.818 ± 0.012	0.832 ± 0.012	0.825 ± 0.012	0.709 ± 0.015	0.852 ± 0.011	0.774 ± 0.013	0.851 ± 0.009	0.910 ± 0.007	0.880 ± 0.008
CRF	0.434 ± 0.031	0.478 ± 0.033	0.455 ± 0.032	0.813 ± 0.011	0.828 ± 0.011	0.821 ± 0.01	0.718 ± 0.016	0.867 ± 0.013	0.785 ± 0.014	0.864 ± 0.005	0.921 ± 0.005	0.892 ± 0.005
GCN	0.435 ± 0.030	0.487 ± 0.032	0.459 ± 0.031	0.804 ± 0.013	0.819 ± 0.013	0.811 ± 0.013	0.706 ± 0.015	0.871 ± 0.014	0.780 ± 0.013	0.884 ± 0.008	0.931 ± 0.008	0.907 ± 0.008
JEE	0.423 ± 0.023	0.468 ± 0.030	0.443 ± 0.026	0.717 ± 0.009	0.645 ± 0.014	0.679 ± 0.012	0.713 ± 0.019	0.814 ± 0.013	0.76 ± 0.015	0.775 ± 0.015	0.818 ± 0.012	0.796 ± 0.013
IT	0.469 ± 0.003	0.426 ± 0.005	0.447 ± 0.004	0.725 ± 0.012	0.691 ± 0.006	0.708 ± 0.009	0.738 ± 0.025	0.837 ± 0.006	0.784 ± 0.021	0.818 ± 0.011	0.829 ± 0.007	0.823 ± 0.008
CSM_{DA}	0.455 ± 0.024	0.494 ± 0.022	0.474 ± 0.023	0.835 ± 0.012	0.847 ± 0.012	0.841 ± 0.012	0.730 ± 0.017	0.856 ± 0.021	0.788 ± 0.019	0.908 ± 0.005	0.941 ± 0.004	0.924 ± 0.004
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Our method excels other alternatives significantly



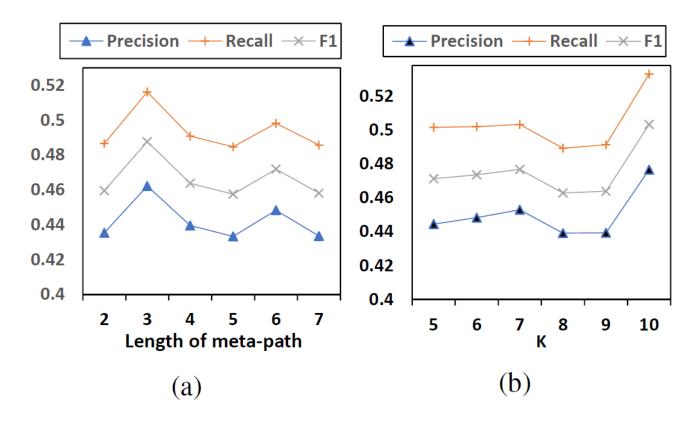


Fig. 3: Sensitivity in different parameters



Conclusion

- This is the first test to leverage this kind of information to the joint models.
- We verify the indirect entity-trigger co-occurred relationships are important to the joint-event-extraction task.
- Different from the distant supervision or other methods, this method tries to maximize the utilization of the currently available training data.





Any questions?

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