GraphRel: Modeling Text as Relational Graphs for Joint Entity and Relation Extraction

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Background

- Entity-Relation extraction:

Taking into account the interaction between relations, especially for overlapping relations

- Three categories of relation tripets:
  - *Normal pair:*

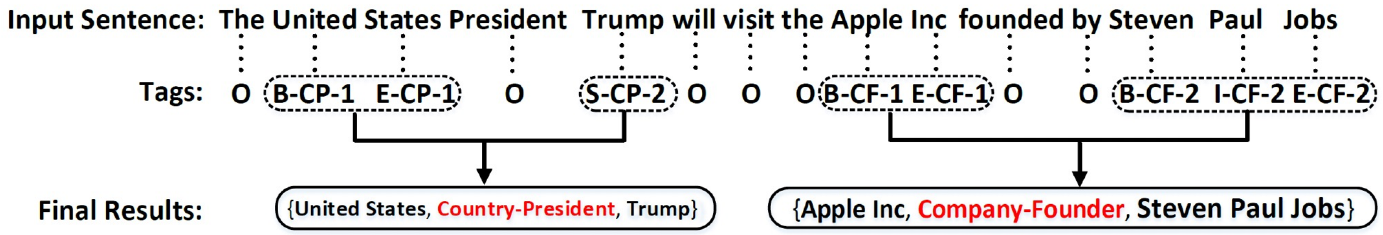
    (BarackObama, PresidentOf, UnitedStates)
  - *EntityPairOverlap(EPO):*

    (BarackObama, PresidentOf, UnitedStates)
    (BarackObama, Governance, UnitedStates)
  - *SingleEntityOverlap(SEO):*

    (BarackObama, LiveIn, WhiteHouse)
    (WhiteHouse, PresidentialPalace, UnitedStates)

Novel Tagging (Zheng et al., 2017)

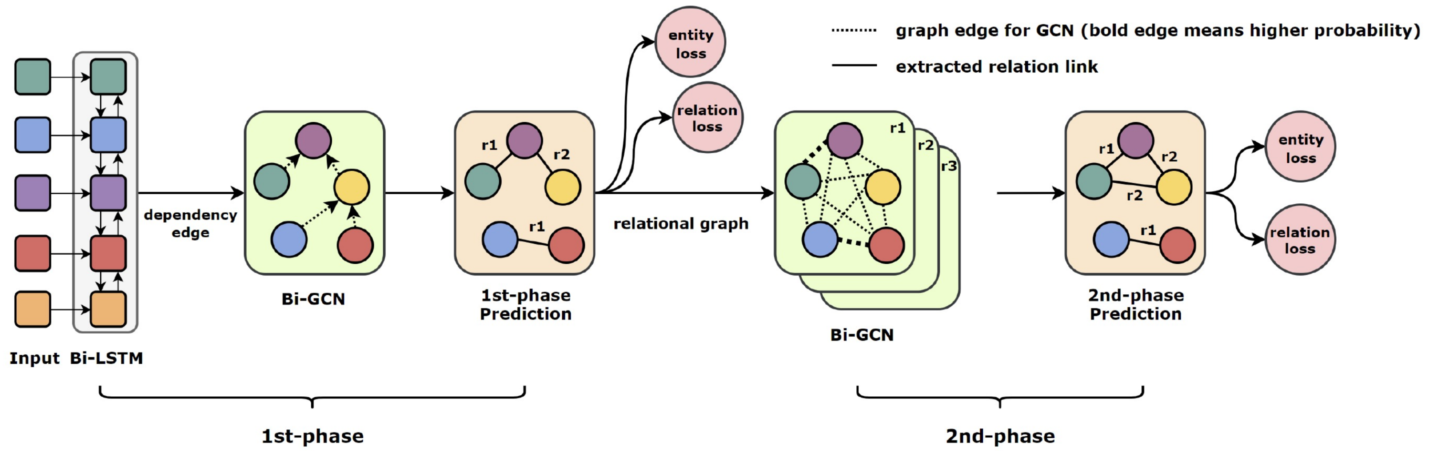
Proposed a strong neural end-to-end joint model of entities and relations based on an LSTM sequence tagger.


Input Sentence: The United States President Trump will visit the Apple Inc founded by Steven Paul Jobs
Tags: O B-CP-1 E-CP-1 O S-CP-2 O O O B-CF-1 E-CF-1 O O B-CF-2 I-CF-2 E-CF-2
Final Results:
{United States, Country-President, Trump}
{Apple Inc, Company-Founder, Steven Paul Jobs}

Word Position
B: begin
S: single
E: end
I : inside
O: others

Not consider overlapping relations

GraphRel



- GraphRel learns to automatically extract hidden features for each word by stacking a Bi-LSTM sentence encoder and a GCN dependency tree encoder.
- Novel 2nd-phase relation-weighted GCN for further extraction

GraphRel 1st-phase

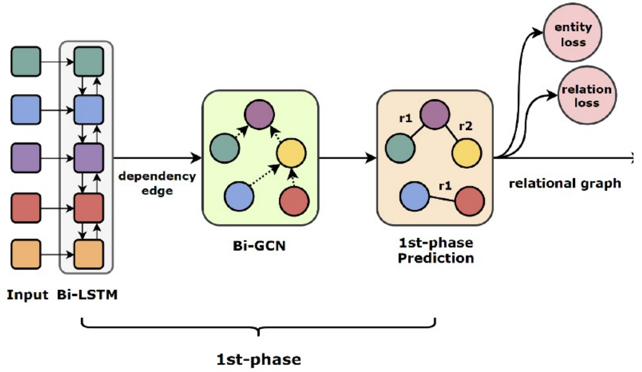
1st-phase Bi-LSTM +(usual) GCN:

- Bi-LSTM: extract sequential dependency word features

$$h_u^0 = \mathrm{Word}(u) \oplus POS(u)$$

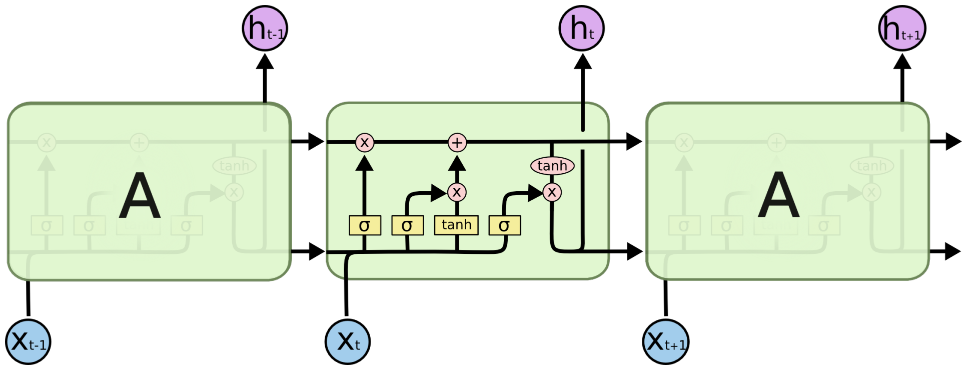
- GCN: extract regional dependency word features

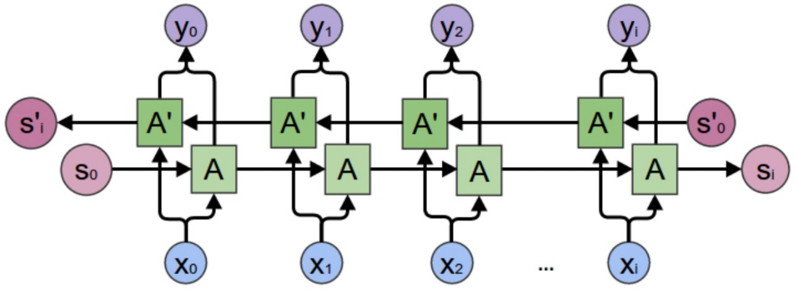
$$h_u^{l+1} = \mathrm{Re}\,LU\left(\sum_{v \in N(u)} \left(W^l h_v^l + b^l\right)\right)$$



- Given the word features, predict relations for each word pair and the entities for all words.

Bi-LSTM (Long Short-Term Memory)





LSTM has three gates

- forget gate layer

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

- input gate layer

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

- update the old cell state

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

- output gate layer

$$o_t = \sigma(W_o [h_{t-1}, x_t] + b_o)$$
$$h_t = o_t * \tanh(C_t)$$

Bi-GCN

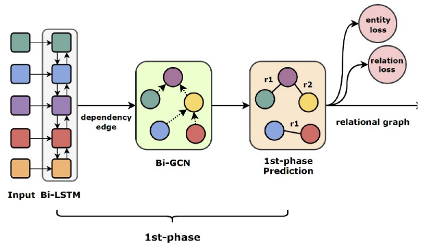
- use the dependency tree as the input sentence's adjacency matrix
- use GCN to extract regional dependency features

$$\overrightarrow{h}_u^{l+1} = ReLU\left(\sum_{v \in \overrightarrow{N}(u)} \left(\overrightarrow{W}^l h_v^l + \overrightarrow{b}^l\right)\right)$$

$$\overleftarrow{h}_u^{l+1} = ReLU\left(\sum_{v \in \overleftarrow{N}(u)} \left(\overleftarrow{W}^l h_v^l + \overleftarrow{b}^l\right)\right)$$

$$h_u^{l+1} = \overrightarrow{h}_u^{l+1} \oplus \overleftarrow{h}_u^{l+1},$$

GraphRel 1st-phase



Training:

- word entity categorical loss : eloss1p

$$-\Sigma_{c=1}^{M} y_{i,c} \log(p_{i,c})$$

Prediction:

- Predict word entity;
- remove the dependency edges and do relation prediction for all word pairs (w1, w2)

Calculate relation tendency score(including non-relation):

- for all word pairs (w1, w2) and relation r:

$$S_{(w1,r,w2)} = W_r^3 \operatorname{Re} LU\left(W_r^1 h_{w1} \oplus W_r^2 h_{w2}\right)$$

- apply softmax function to $S_{(w1,r,w2)}$
- get probability of each relation r for (w1, w2): $P_r(w1, w2)$
- calculate relation categorical loss: rloss1p

GraphRel 2nd-phase

1st-phase not consider interaction between named entities and relations.

- generate complete relation-weighted graph for each relation r
- edge of (w1, w2): Pr(w1,w2)

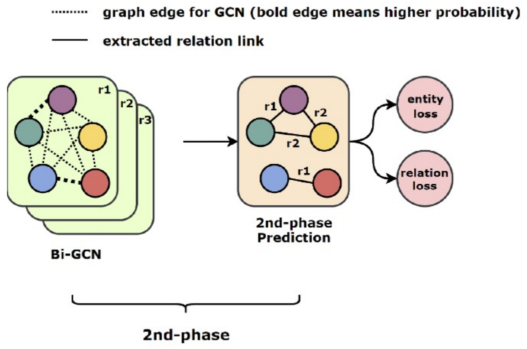
2nd-phase:
- adopts bi-GCN on each relation graph
- aggregate relations to generate comprehensive word feature

$$h_u^{l+1} = \mathrm{ReLU}\left(\sum_{v\in V}\sum_{r\in R} P_r(u,v) \times \left(W_r^l h_v^l + b_r^l\right)\right) + h_u^l$$

- the edge weight:

  $P_r(u,v)$,the probability of word u to word v under relation r

- Run named entity and relation classification



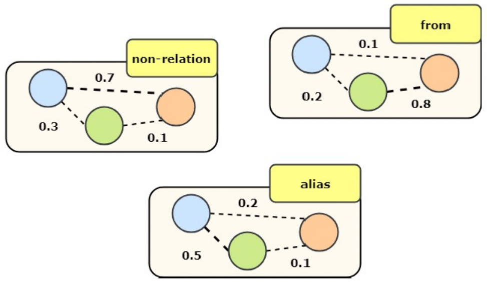


Figure 3: Relation-weighted graph for each relation.

Training

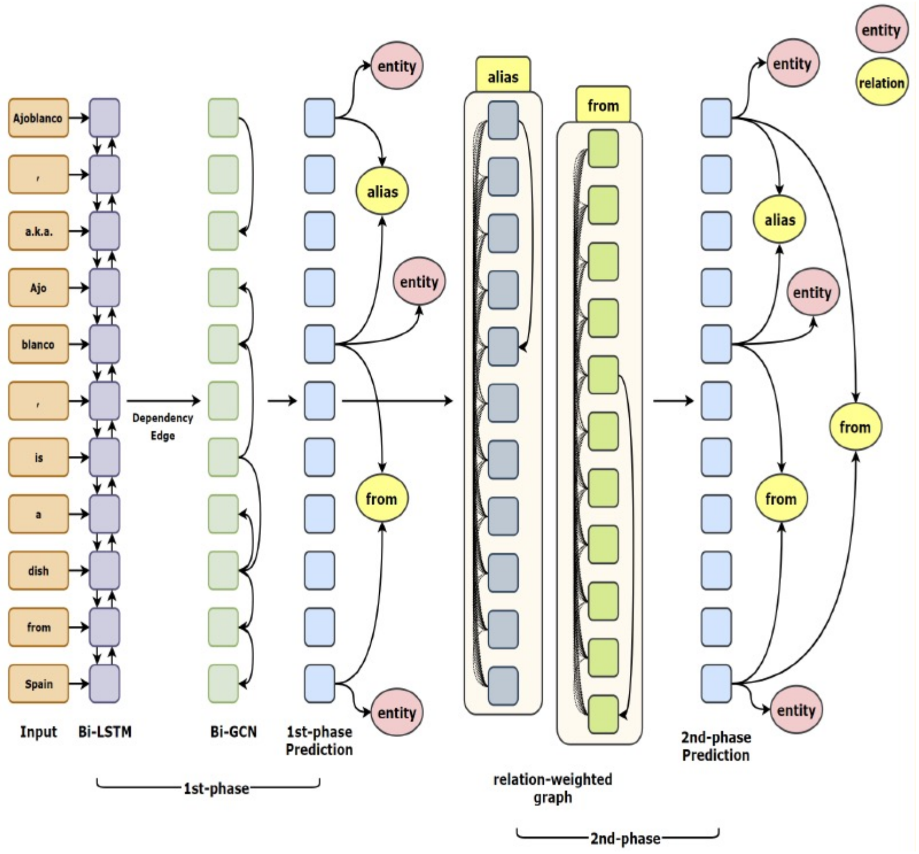
Ground-truth label:

- entity loss: conventional (Begin, Inside, End, Single, Out) tagging
- relation loss: a one-hot relation vector of Pr(w1,w2) for each word pair (w1, w2).

- Calculate categorical cross entropy loss

$$\text{loss}_{all} = (e\,\text{loss}_{1p} + \text{rloss}_{1p}) + \alpha(e\,\text{loss}_{2p} + r\,\text{loss}_{2p})$$

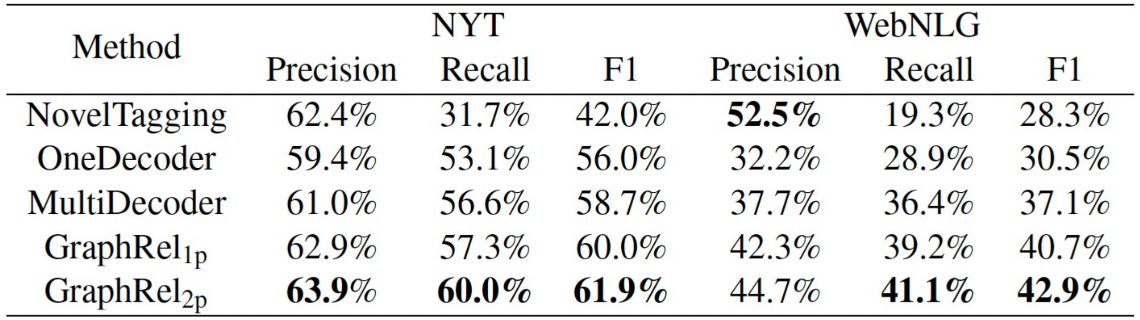
GraphRel



entity
relation
Ajoblanco
,
a.k.a.
Ajo
blanco
,
is
a
dish
from
Spain
Dependency Edge
entity
alias
entity
from
entity
alias
from
entity
alias
entity
from
from
entity
Input
Bi-LSTM
Bi-GCN
1st-phase Prediction
relation-weighted graph
2nd-phase Prediction
1st-phase
2nd-phase

Experiment

Datasets: NYT (Riedel et al., 2010),WebNLG (Gardent et al., 2017)
Setting: word embedding(Glove 300d), POS embedding(15d)
The POS tag and the dependency tree were retrieved from spaCy

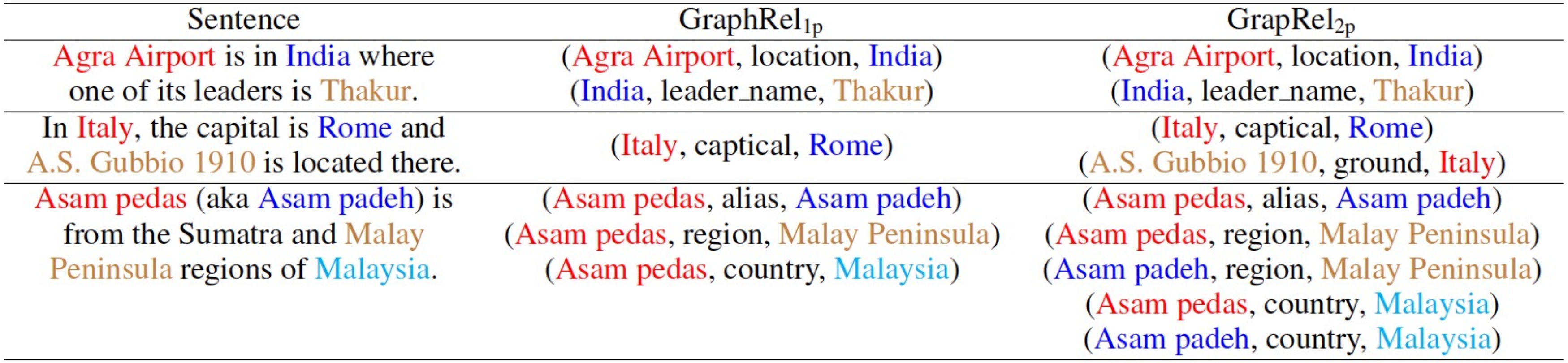


Method	NYT			WebNLG		
	Precision	Recall	F1	Precision	Recall	F1
NovelTagging	62.4%	31.7%	42.0%	**52.5%**	19.3%	28.3%
OneDecoder	59.4%	53.1%	56.0%	32.2%	28.9%	30.5%
MultiDecoder	61.0%	56.6%	58.7%	37.7%	36.4%	37.1%
GraphRel_{1p}	62.9%	57.3%	60.0%	42.3%	39.2%	40.7%
GraphRel_{2p}	**63.9%**	**60.0%**	**61.9%**	44.7%	**41.1%**	**42.9%**

Table 1: Results for both NYT and WebNLG datasets.

GraphRel maintains both high precision and high recall

Experiment



Sentence	GraphRel$_{1p}$	GrapRel$_{2p}$
Agra Airport is in India where one of its leaders is Thakur.	(Agra Airport, location, India) (India, leader_name, Thakur)	(Agra Airport, location, India) (India, leader_name, Thakur)
In Italy, the capital is Rome and A.S. Gubbio 1910 is located there.	(Italy, captical, Rome)	(Italy, captical, Rome) (A.S. Gubbio 1910, ground, Italy)
Asam pedas (aka Asam padeh) is from the Sumatra and Malay Peninsula regions of Malaysia.	(Asam pedas, alias, Asam padeh) (Asam pedas, region, Malay Peninsula) (Asam pedas, country, Malaysia)	(Asam pedas, alias, Asam padeh) (Asam pedas, region, Malay Peninsula) (Asam padeh, region, Malay Peninsula) (Asam pedas, country, Malaysia) (Asam padeh, country, Malaysia)

Table 3: Case Study for Graph$_{1p}$ and GraphRel$_{2p}$.

Thank you

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