

Recursive Networks for NER

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Outline

- Named Entity Recognition
 - Task
 - Features
 - Related Work
- Leveraging Linguistic Structures for NER

Named Entities

- CoNLL-2003
 - PER, LOC, ORG, MISC

The defense secretary Donald Rumsfeld

ORG *PER*



- OntoNotes 5.0
 - person, NORP, facility, organization, GPE, location, product, event, work-of-art, law, language
 - date, time, percent, money, quantity, ordinal, cardinal

Gazetteer Features

- Senna
 - PER
 - LOC
 - ORG
 - MISC

Word Features

- Embedding
 - English -> 840B (common crawl)
 - Chinese -> CNA (gigaword) + ASBC (sinica)
- Uppercase
- Upper-initial
- Lowercase
- Mixed

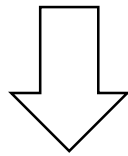
Character Features

- Embedding
 - English -> Random initialization
 - Chinese -> CNA (gigaword) + ASBC (sinica)
- Uppercase
- Lowercase
- Digit

Sequence Tagging

The defense secretary Donald Rumsfeld

ORG *PER*



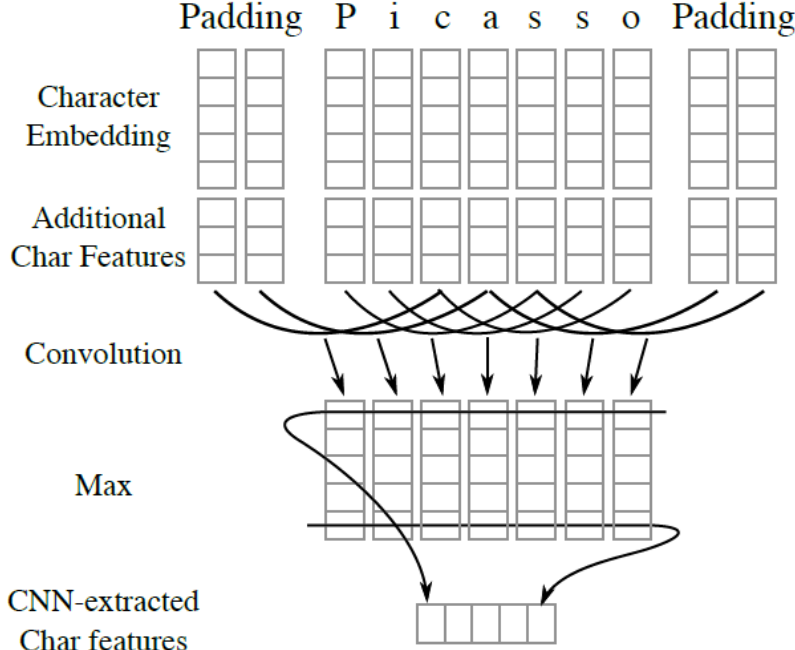
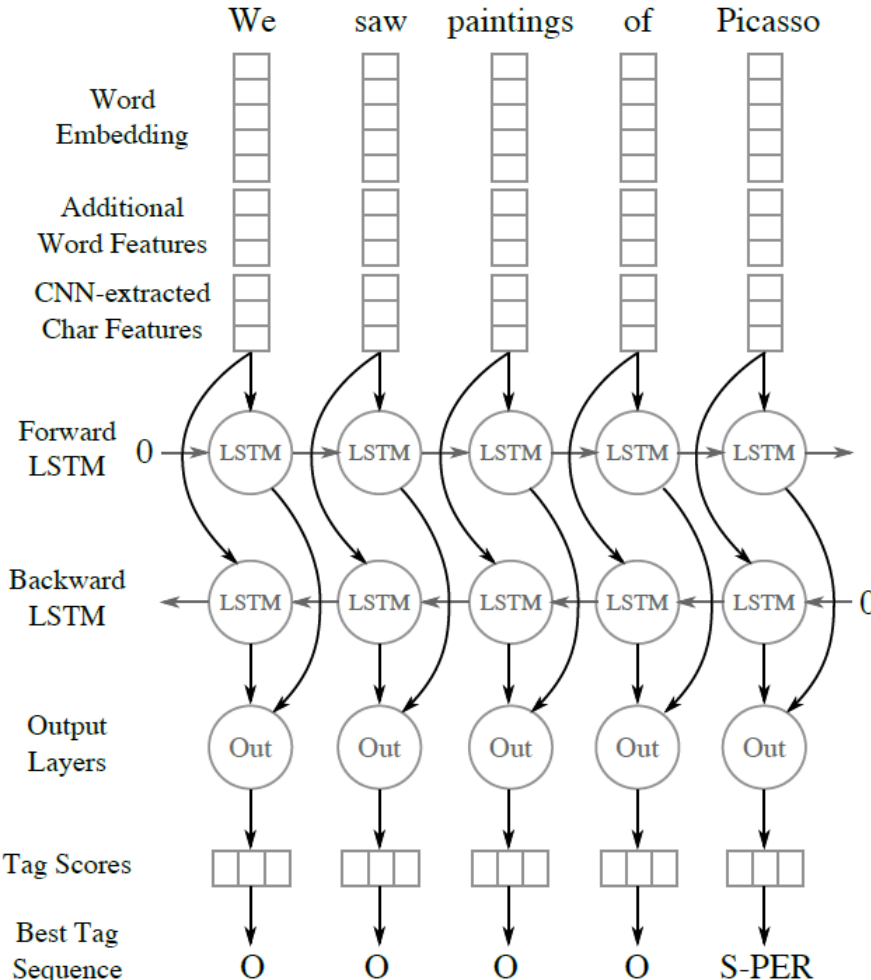
The → *defense* → *secretary* → *Donald* → *Rumsfeld*

↓ ↓ ↓ ↓ ↓

O *S-ORG* *O* *B-PER* *E-PER*

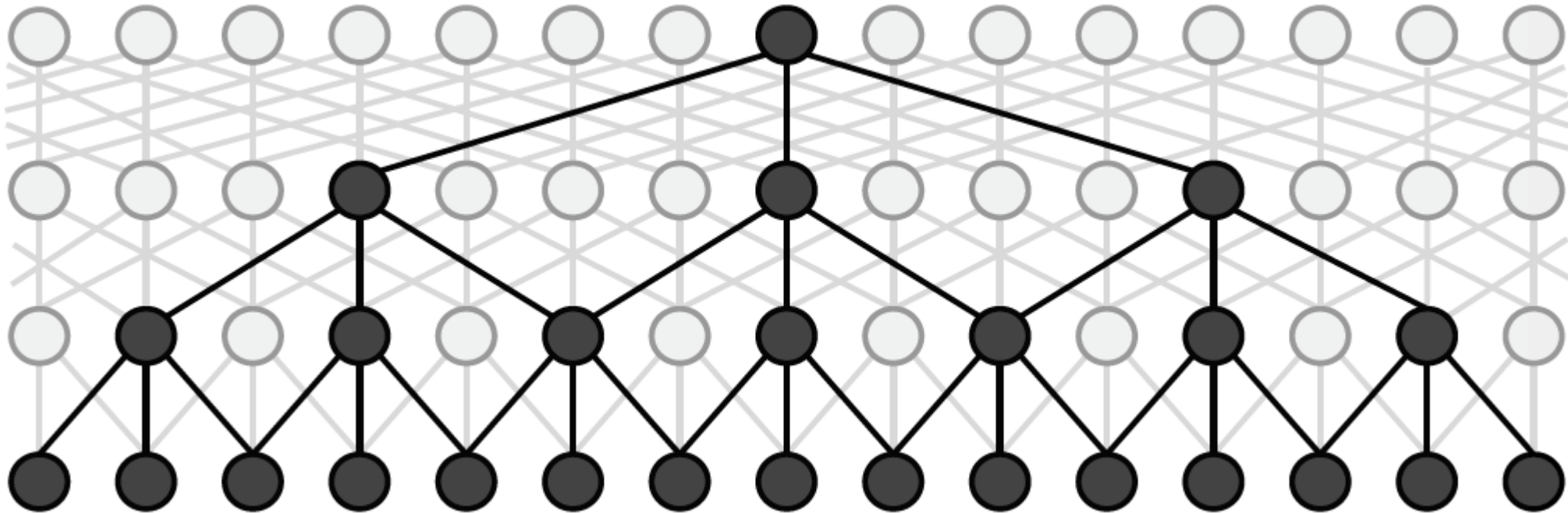
<u>Chunk Labels</u>
<i>B</i> (<i>begin</i>)
<i>I</i> (<i>inside</i>)
<i>O</i> (<i>outside</i>)
<i>E</i> (<i>end</i>)
<i>S</i> (<i>single</i>)

Bi-LSTM for Sequence Tagging



Jason Chiu and Eric Nichols. 2016. Named Entity Recognition with Bidirectional LSTM-CNNs. Transactions of ACL.

Dilated CNN for Sequence Tagging



Emma Strubell, Patrick Verga, David Belanger, and Andrew McCallum. 2017. Fast and Accurate Entity Recognition with Iterated Dilated Convolutions. In Proceedings of EMNLP.

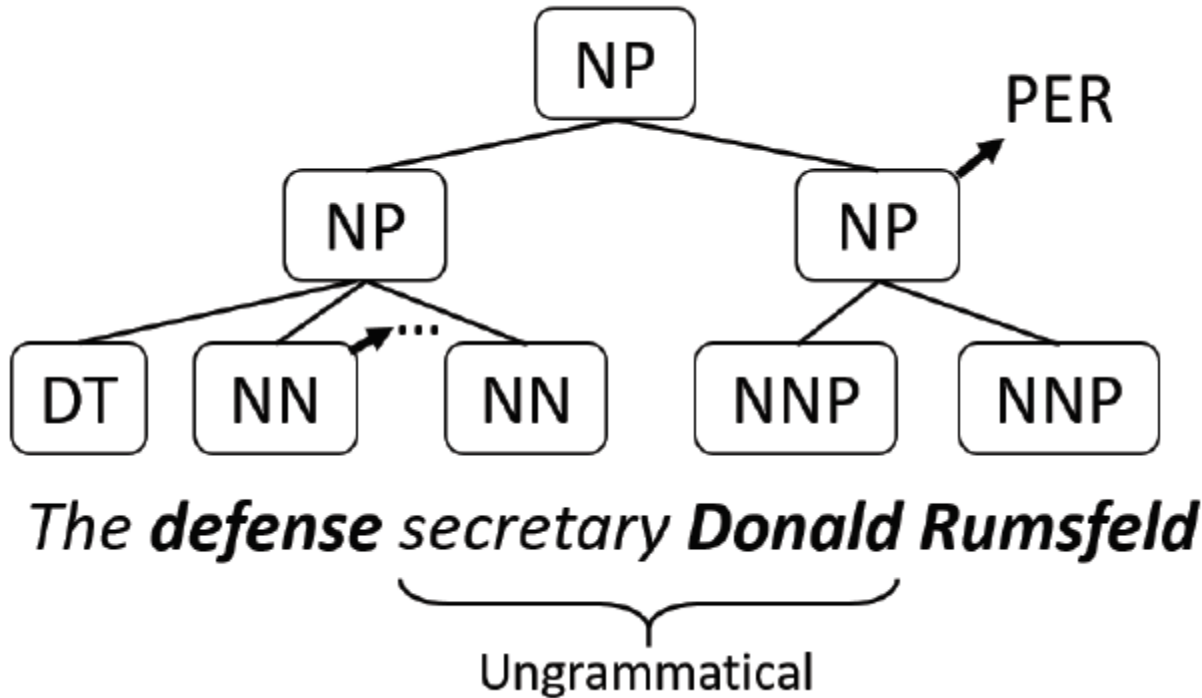
Results of Sequence Tagging

Model	Sources	CoNLL-2003	OntoNotes 5.0
BLSTM		90.67	83.76
BLSTM-CRF	Huang et al., 2015	90.94	86.99
BLSTM-CNN	Chiu and Nichols, 2016	90.98	-
BLSTM-CNN-CRF	Ma and Hovy, 2016 Lample et al., 2016	91.21	-
Deep BLSTM	Strubell et al., 2017	-	86.19
Deep-BLSTM-CNN		-	86.41
ID-CNN-CRF	Strubell et al., 2017	90.65	86.84

Outline

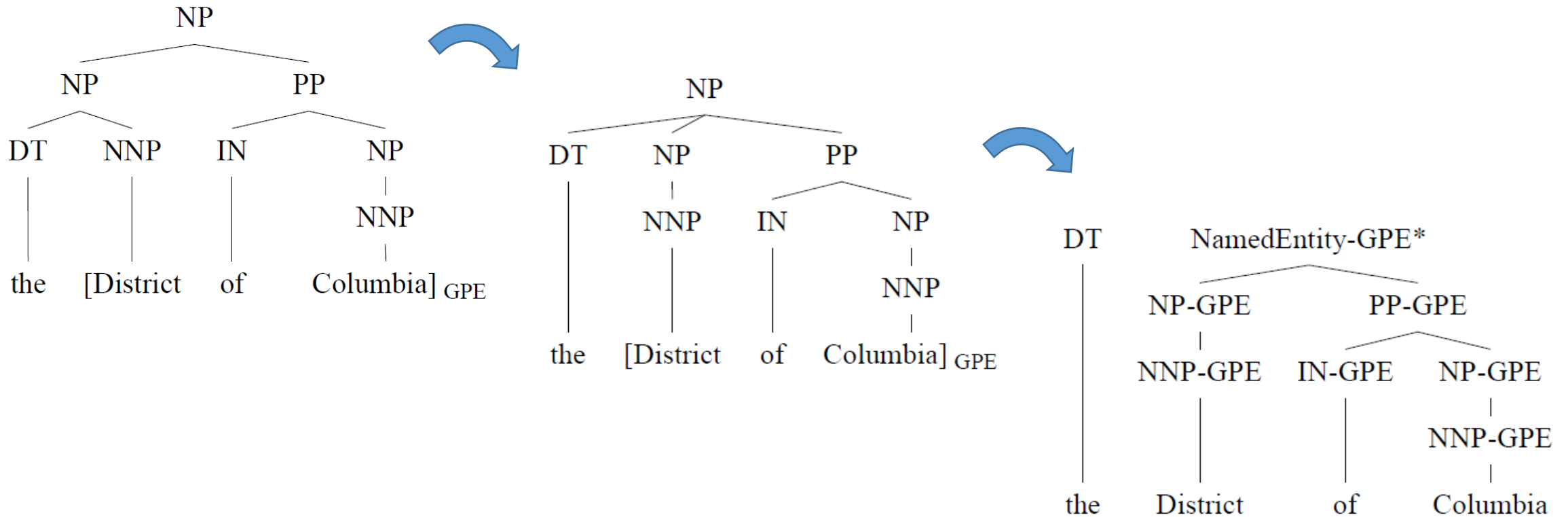
- Named Entity Recognition
- Leveraging Linguistic Structures for NER
 - Joint parsing and NER
 - Tree-LSTM for NER
 - Mitigating inconsistencies between parsing and NER

Constituent Prediction



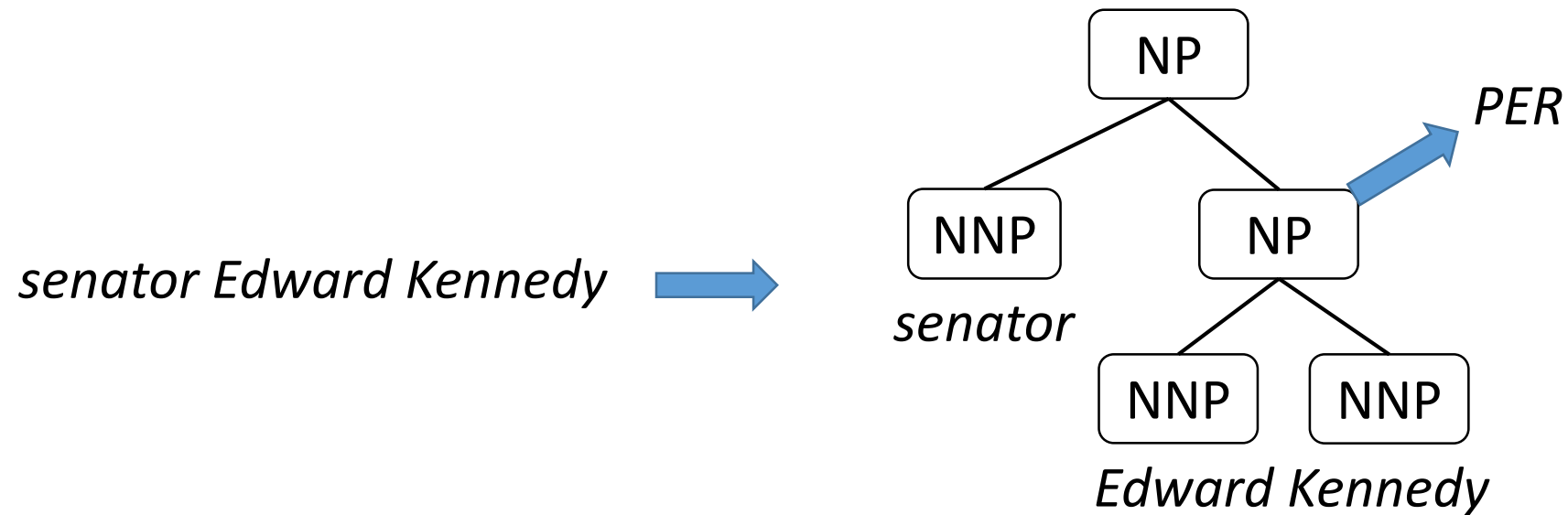
- Constituent → A plausible NE candidate
- Ungrammatical → Unlikely an NE

CRF-CFG for Constituent Prediction



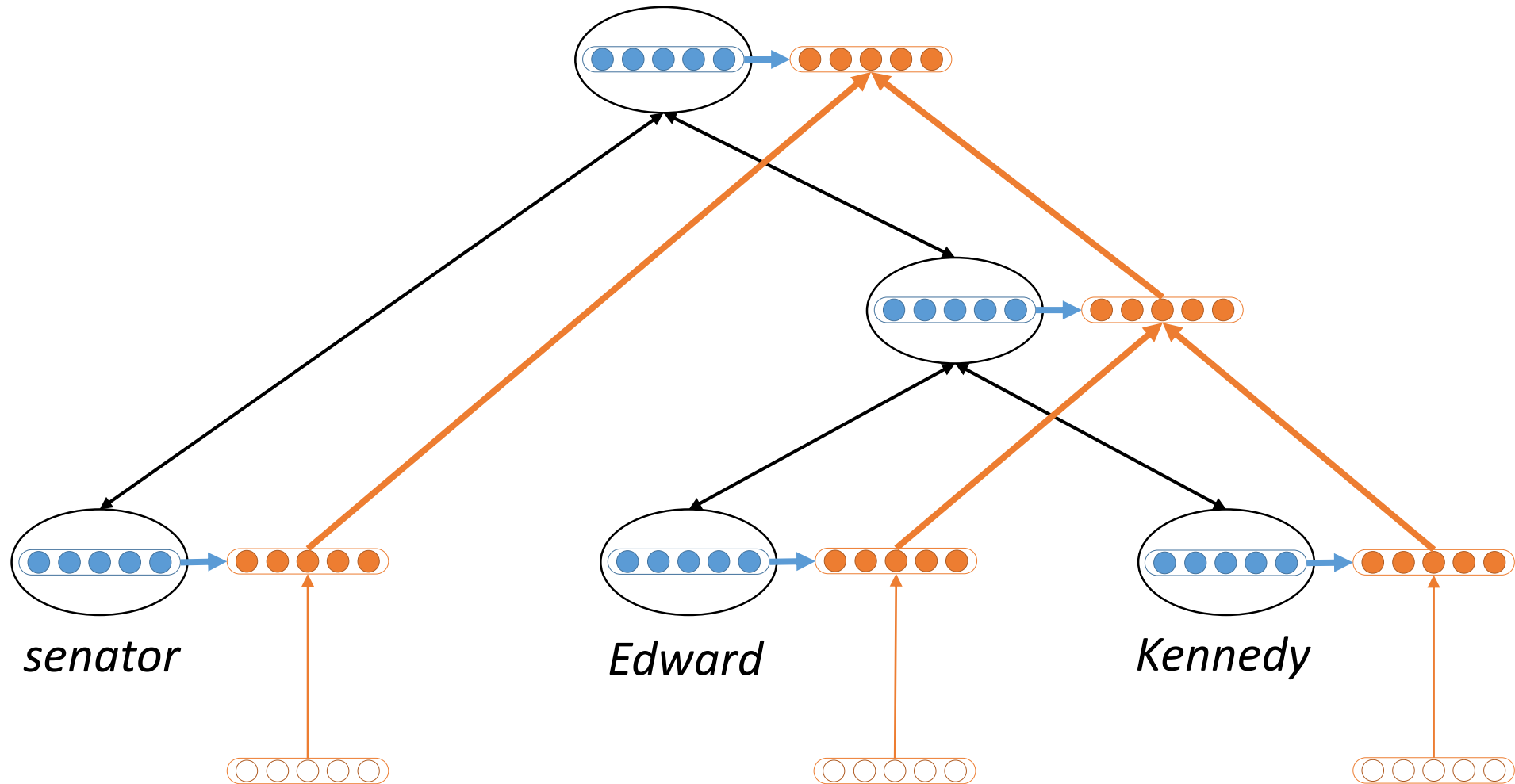
Jenny Rose Finkel and Christopher D. Manning. 2009.
Joint Parsing and Named Entity Recognition. In
Proceedings of HLT-NAACL.

Bi-Tree-LSTM for Constituent Prediction

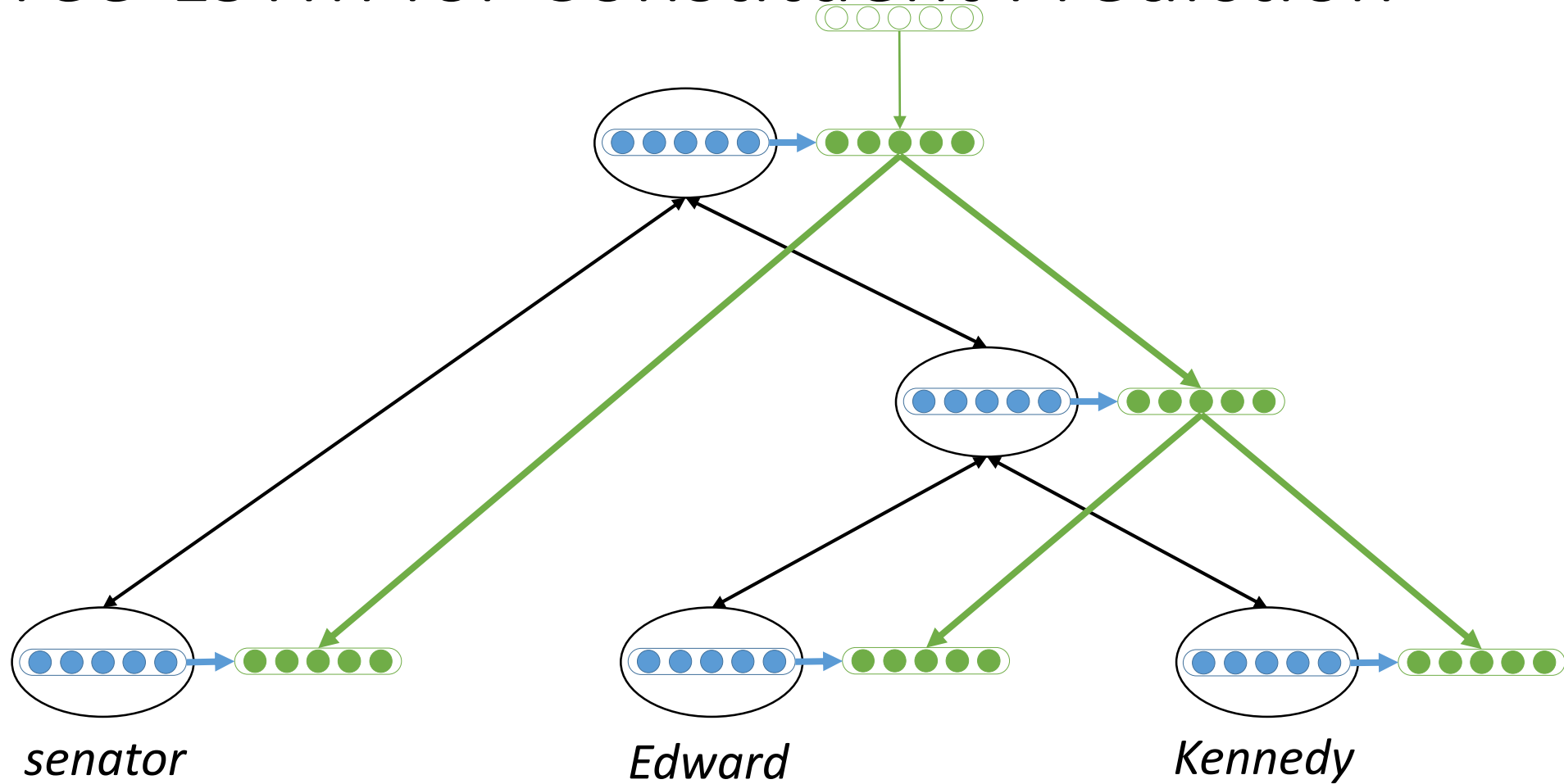


Peng-Hsuan Li, Ruo-Ping Dong, Yu-Siang Wang, Ju-Chieh Chou, and Wei-Yun Ma. 2017. Leveraging Linguistic Structures for Named Entity Recognition with Bidirectional Recursive Neural Networks. In Proceedings of EMNLP.

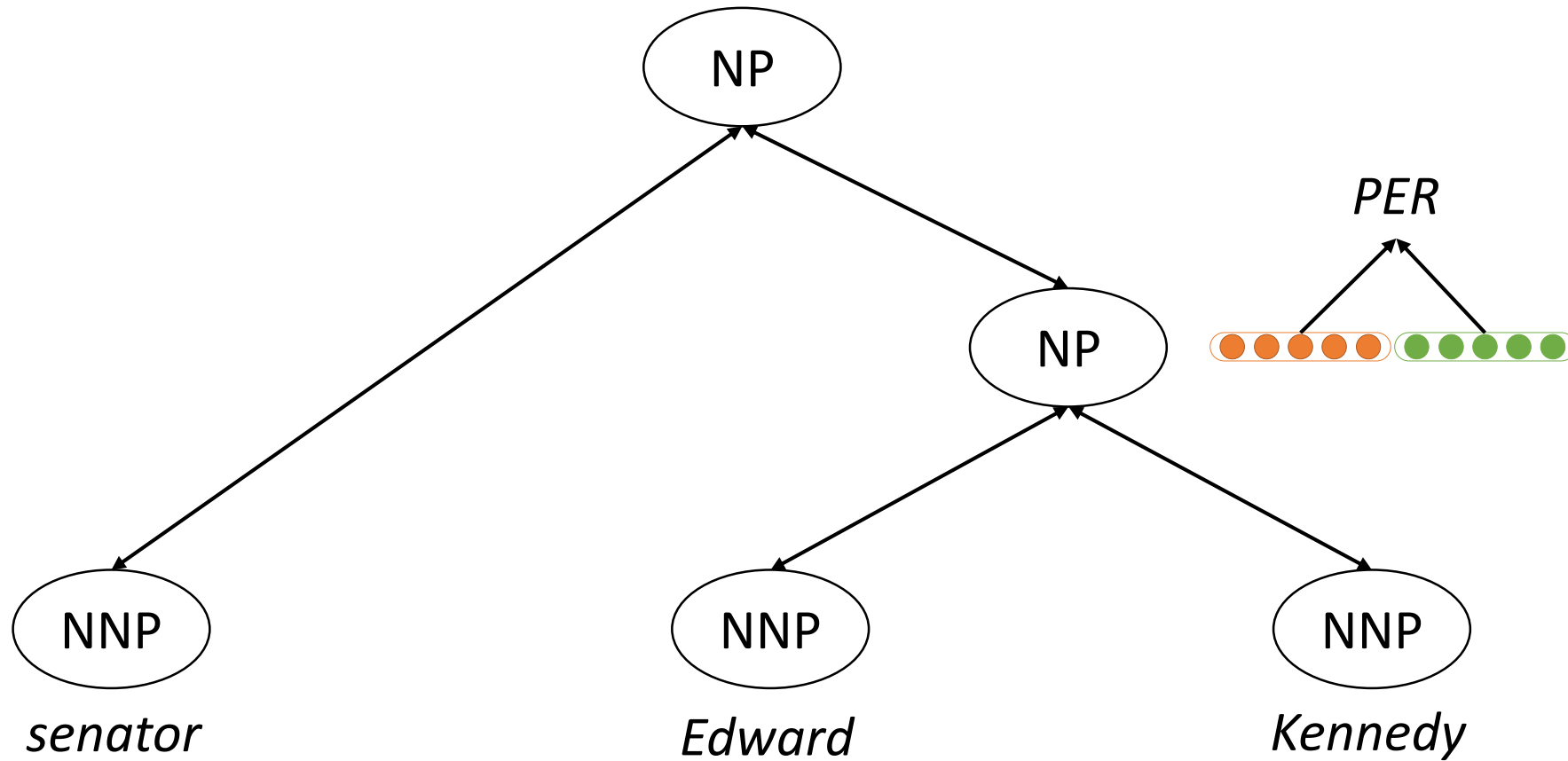
Bi-Tree-LSTM for Constituent Prediction



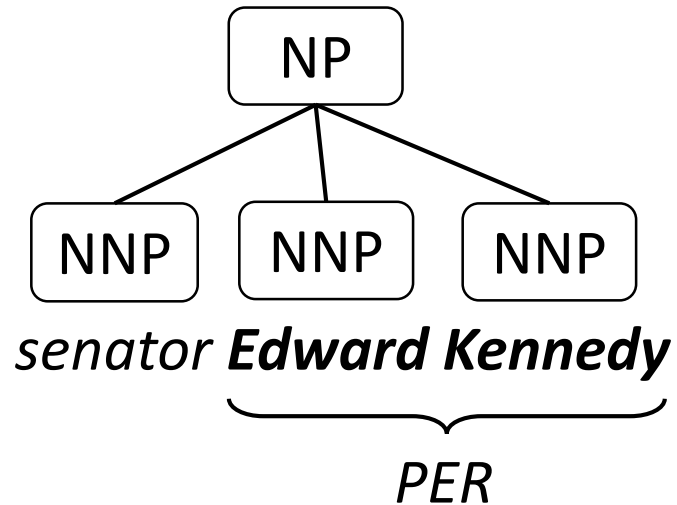
Bi-Tree-LSTM for Constituent Prediction



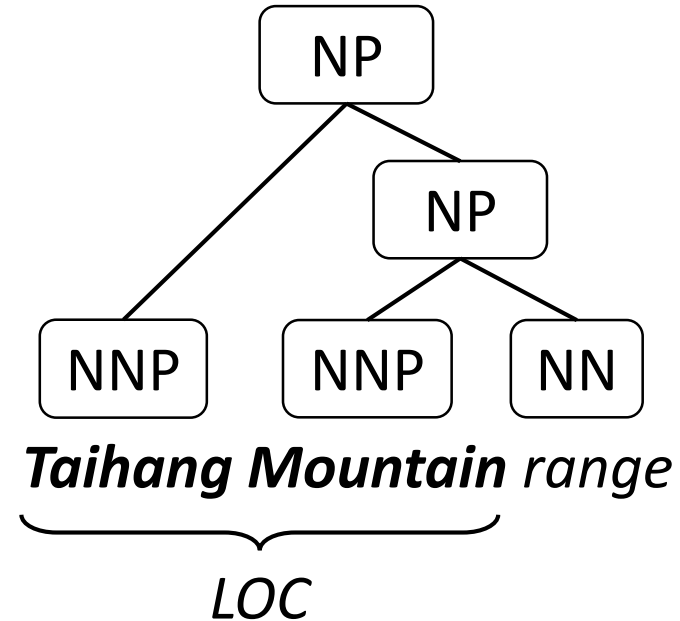
Bi-Tree-LSTM for Constituent Prediction



Inconsistencies between Parse and NER

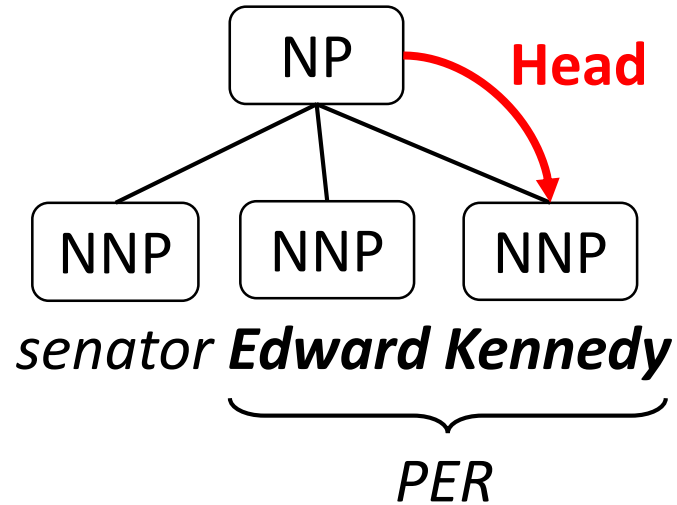


Type-1
Cross Siblings

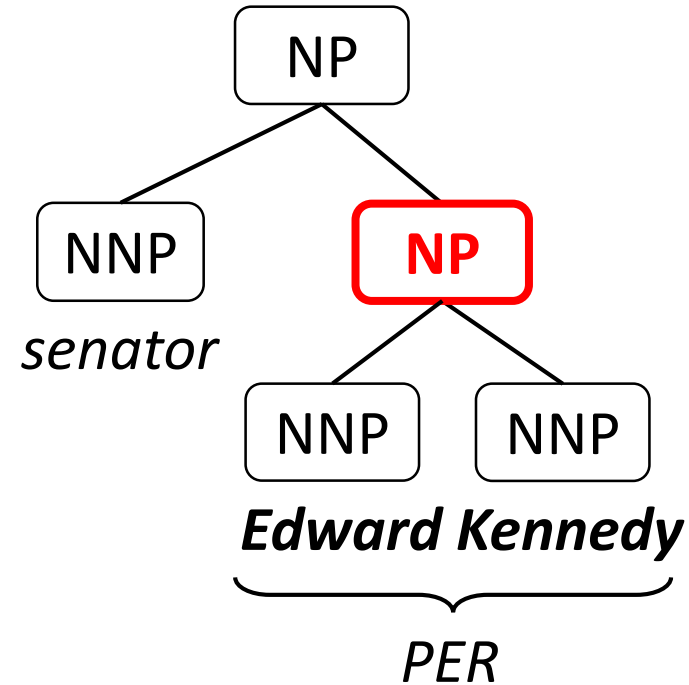


Type-2
Cross Branches

Eliminate Type-1: Constituency Tree Binarization

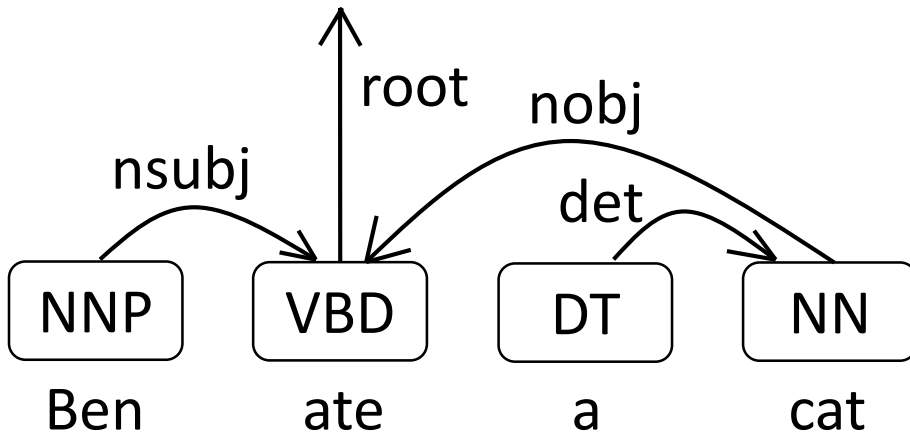


Type-1
Cross Siblings

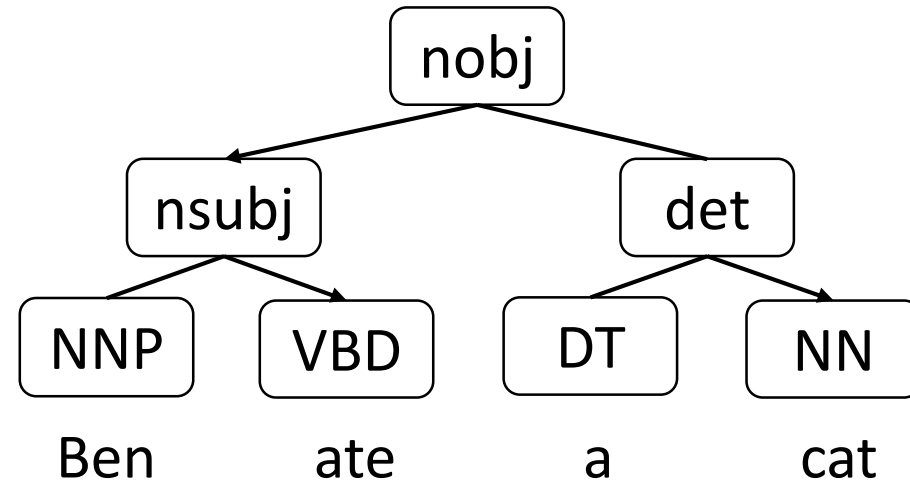


Consistent

Eliminate Type-1: Dependency Transformation

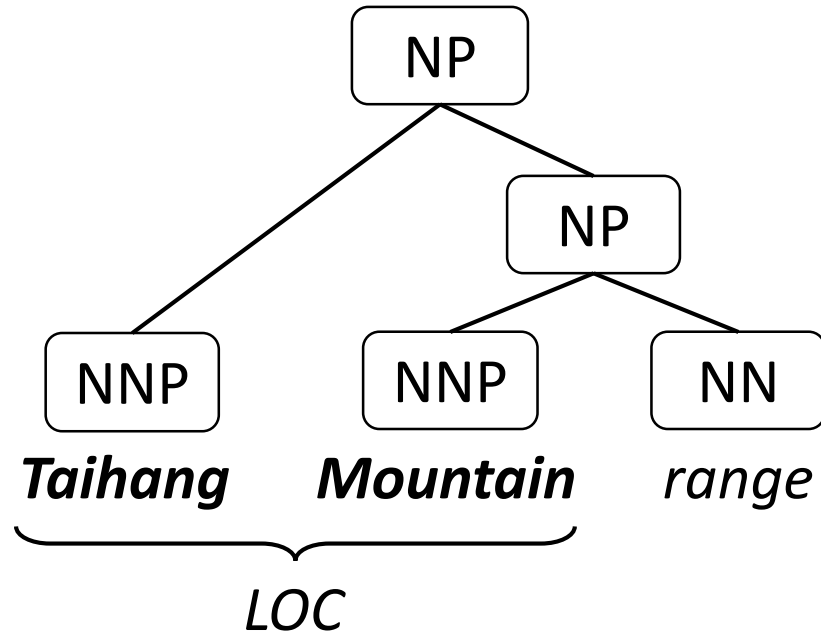


No Constituents

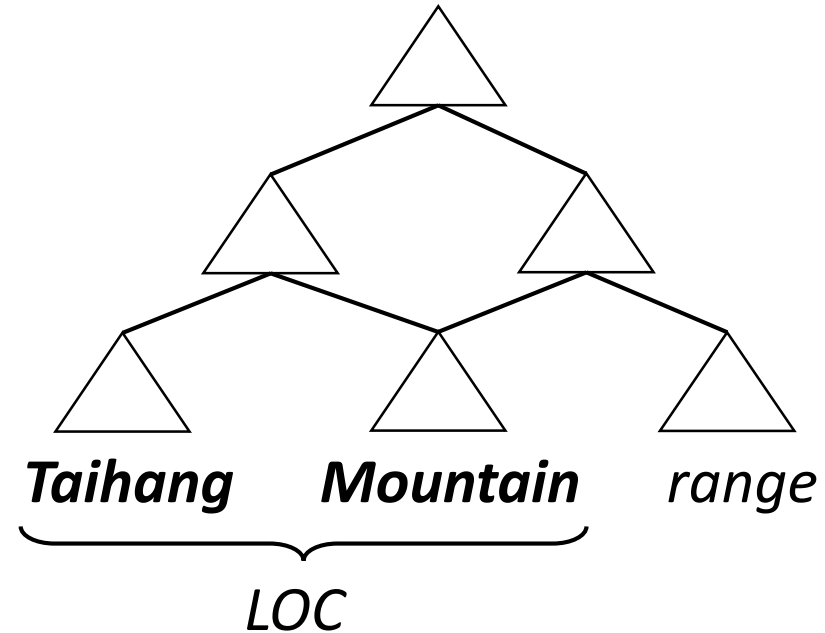


No Type-1 Inconsistencies

Eliminate Type-2: Pyramid Construction

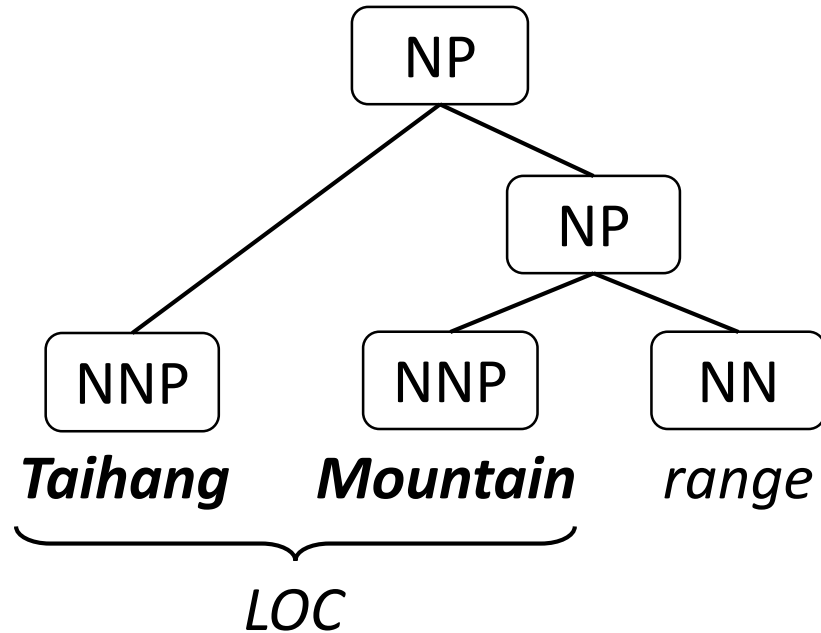


Type-2
Cross Branches

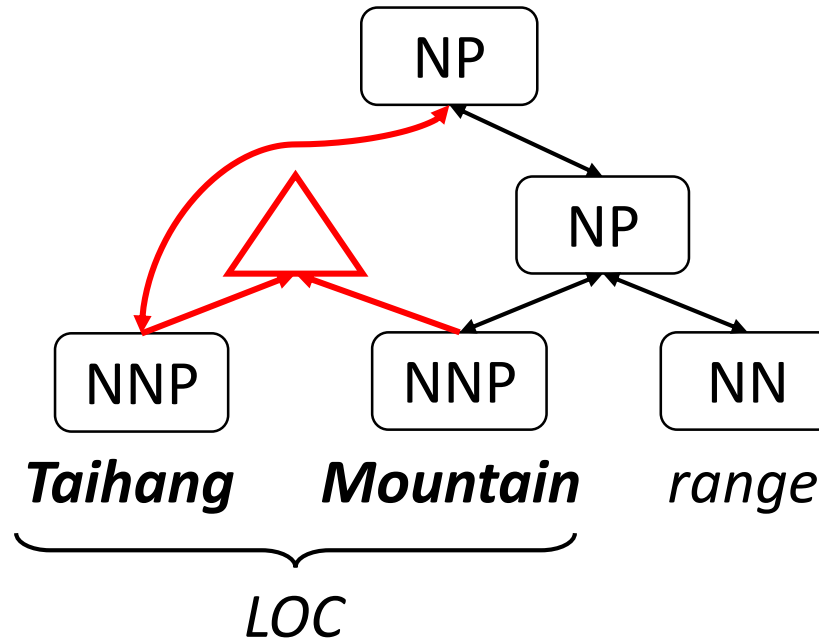


No Linguistic Structures

Eliminate Type-2: Pyramid Construction



Type-2
Cross Branches



No Inconsistencies

Results of Constituent Prediction

Method	Model	Sources	CoNLL-2003	OntoNotes 5.0
Sequence Tagging	BLSTM		90.67	83.76
	BLSTM-CRF	Huang et al., 2015	90.94	86.99
	BLSTM-CNN	Chiu and Nichols, 2016	90.98	-
	BLSTM-CNN-CRF	Ma and Hovy, 2016 Lample et al., 2016	91.21	-
	Deep BLSTM	Strubell et al., 2017	-	86.19
	Deep BLSTM-CNN		-	86.41
	ID-CNN-CRF	Strubell et al., 2017	90.65	86.84
Constituent Prediction	CRF-CFG	Finkel and Manning, 2009	-	82.42
	Bi-Tree-RNN-CNN	Li et al., 2017	88.91	87.21

Analyses of Constituent Prediction

- Sequence Tagging vs. Constituent Prediction

Method	CoNLL-2003	OntoNotes 5.0
Sequence Tagging	91.21	86.99
Constituent Prediction	88.91	87.21/88.92

93% Consistency

97%/100% Consistency

Analyses of Constituent Prediction

- Sequence vs Tree

*the first couple moves out of the **White House** on January 20th .*

			<u>OntoNotes 5.0</u>		
<u>Model</u>	<u>Const-Only</u>	<u>Prediction</u>	<u>Precision</u>	<u>Recall</u>	<u>F1</u>
Bi-RNN	X	<i>the White</i>	85.7	86.5	86.10
Bi-RNN	O	-	87.2	85.1	86.14
Bi-Tree-RNN	O	<i>White House</i>	88.0	86.2	87.10

Ablation Study: Constituency Tree Binarization

		<u>OntoNotes 5.0</u>			
<u>Model</u>	<u>Binarize</u>	<u>Consistency</u>	<u>Precision</u>	<u>Recall</u>	<u>F1</u>
BRNN	X	93%	87.3	83.0	85.11
BRNN	O	97%	88.0	86.2	87.10

Ablation Study: Dependency Transformation

		<u>CoNLL 2003</u>		
<u>Model</u>	<u>Parser</u>	<u>Precision</u>	<u>Recall</u>	<u>F1</u>
BRNN	StanfordRNN	88.9	86.9	87.91
BRNN	SyntaxNet	90.2	87.7	88.91

Ablation Study: Pyramid Construction

		<u>CoNLL 2003</u>		
<u>Model</u>	<u>Pyramid</u>	<u>Precision</u>	<u>Recall</u>	<u>F1</u>
BRNN	X	89.1	82.9	85.89
BRNN	O	90.2	87.7	88.91

Ablation Study: Bidirectional

		<u>OntoNotes 5.0</u>		
<u>Model</u>	<u>Koran</u>	<u>Precision</u>	<u>Recall</u>	<u>F1</u>
Top-Down	-	79.2	69.3	73.93
Bottom-Up	PERSON	86.6	86.2	86.41
BRNN	WORK OF ART	88.0	86.2	87.10

```

|--PP
|--IN by
|--S
|--VP
|--VBG repeating
|--NP
|--NP
|--NP
|--NP
|--NP
|--PP
|--IN from
|--NP
|--DT the
|--NP
|--JJ noble
|--NNP Koran
|--CC and
|--NP
|--DT the
|--NP
|--CD two
|--NNS testimonies
|--. .

```

He confirmed it by repeating the verses from the noble Koran and the two testimonies.