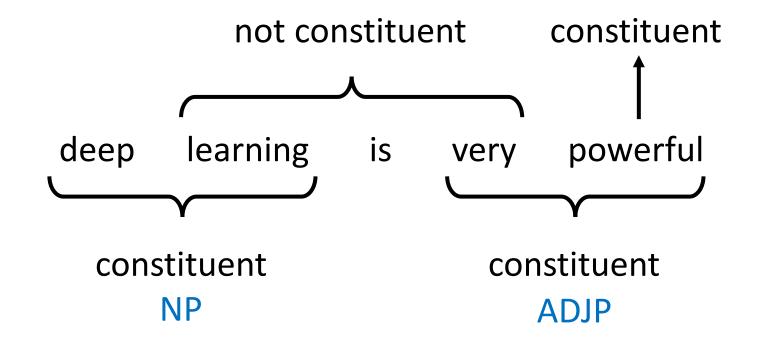
# Constituency Parsing

李宏毅 Hung-yi Lee

	One Sequence	Multiple Sequences	
One Class	Sentiment Classification Stance Detection Veracity Prediction Intent Classification Dialogue Policy	NLI Search Engine Relation Extraction	
Class for each Token	POS tagging Word segmentation Extractive Summarization Slotting Filling NER		
Copy from Input		Extractive QA	
General Sequence	Abstractive Summarization Translation Grammar Correction NLG	General QA Chatbot State Tracker Task Oriented Dialogue	
Other?	Parsing, Coreference Resolution		

## Constituency Parsing

- Some text spans are constituents ("units")
- Each constituent has a label.

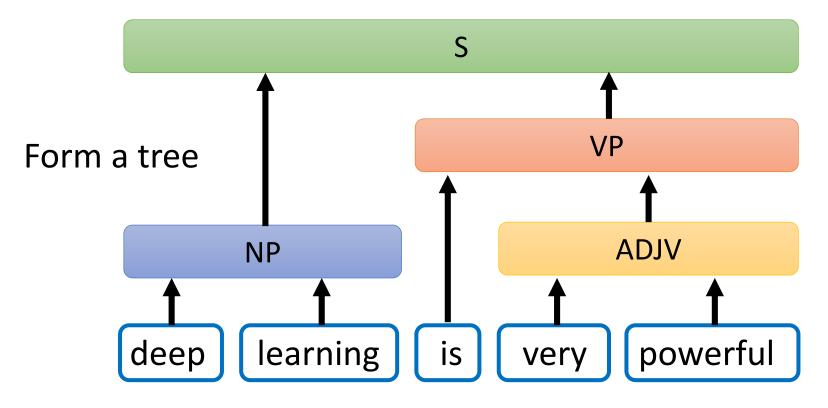


# Constituency Parsing - Labels

Table 1.2. The l	Penn Treebank syntactic tagset	+ All POS tags
ADJP	Adjective phrase	
ADVP	Adverb phrase	
NP	Noun phrase	
PP	Prepositional phrase	
S	Simple declarative clause	
SBAR	Subordinate clause	
SBARQ	Direct question introduced by wh	h-element
SINV	Declarative sentence with subjec	t-aux inversion
SQ	Yes/no questions and subconstitu	ent of SBARQ excluding wh-element
VP	Verb phrase	
WHADVP	Wh-adverb phrase	
WHNP	Wh-noun phrase	
WHPP	Wh-prepositional phrase	
X	Constituent of unknown or uncer	tain category
*	"Understood" subject of infinitiv	e or imperative
0	Zero variant of <i>that</i> in subordinate	•
T	Trace of wh-Constituent	

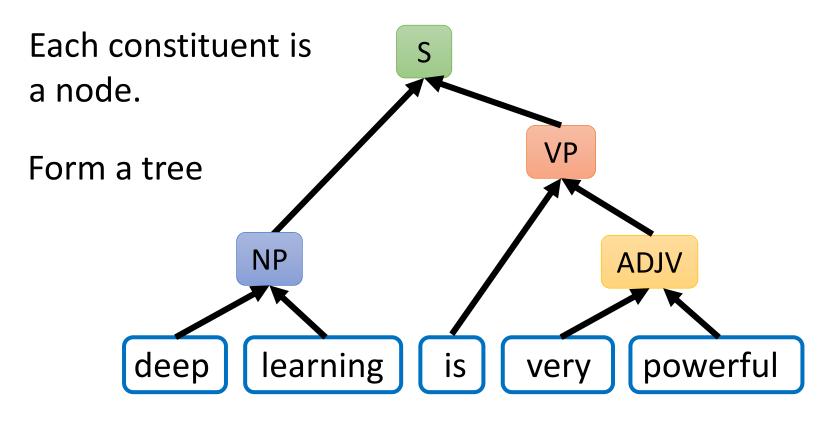
(Only considering binary tree in this course for simplicity)

## Constituency Parsing



- Each word is a constituent (their labels are POS tags)
- Some consecutive constituents can form a larger one.

## Constituency Parsing



- Each word is a constituent (their labels are POS tags)
- Some consecutive constituents can form a larger one.

# Chart-based Approach

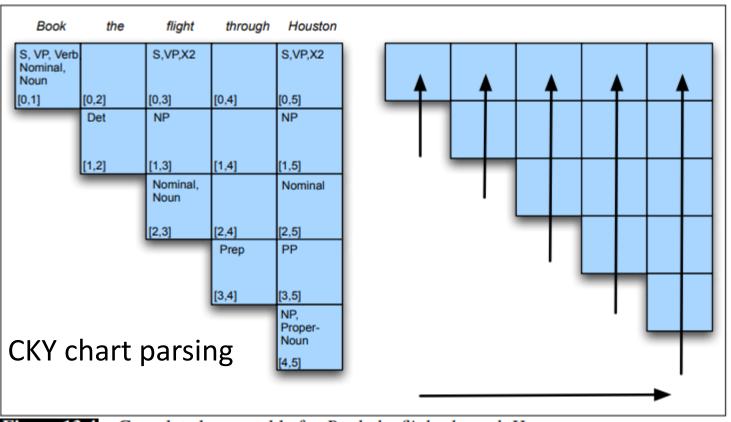
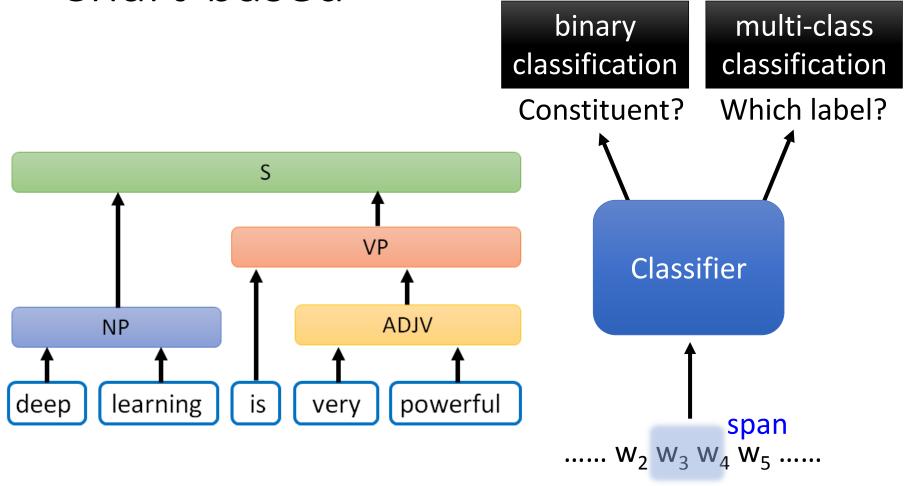
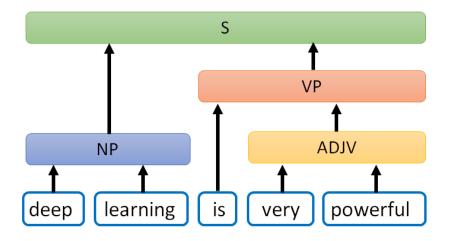
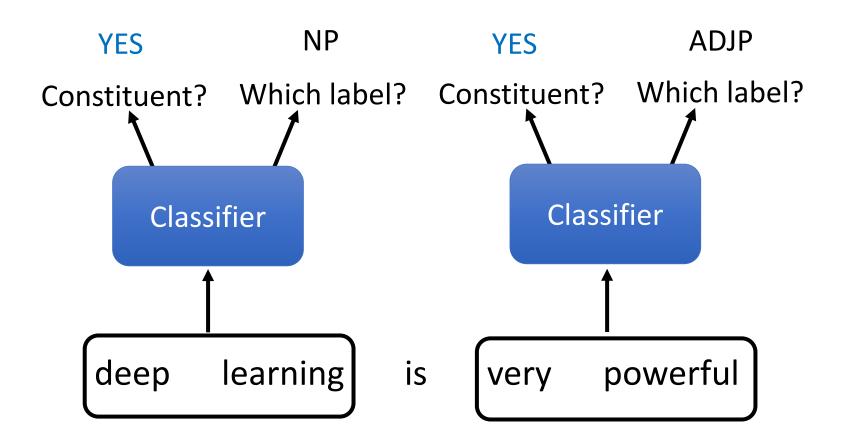


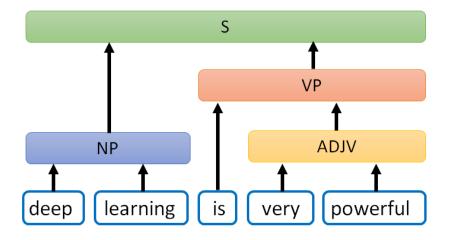
Figure 13.4 Completed parse table for *Book the flight through Houston*.

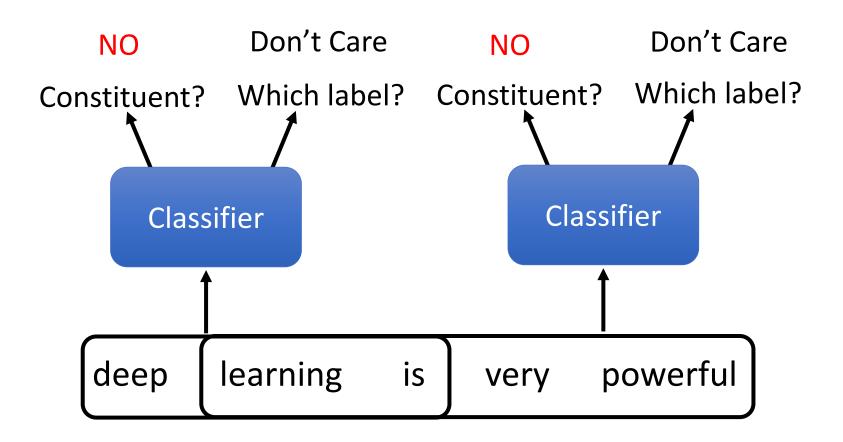
Source of image: https://web.stanford.edu/~jurafsky/slp3/13.pdf



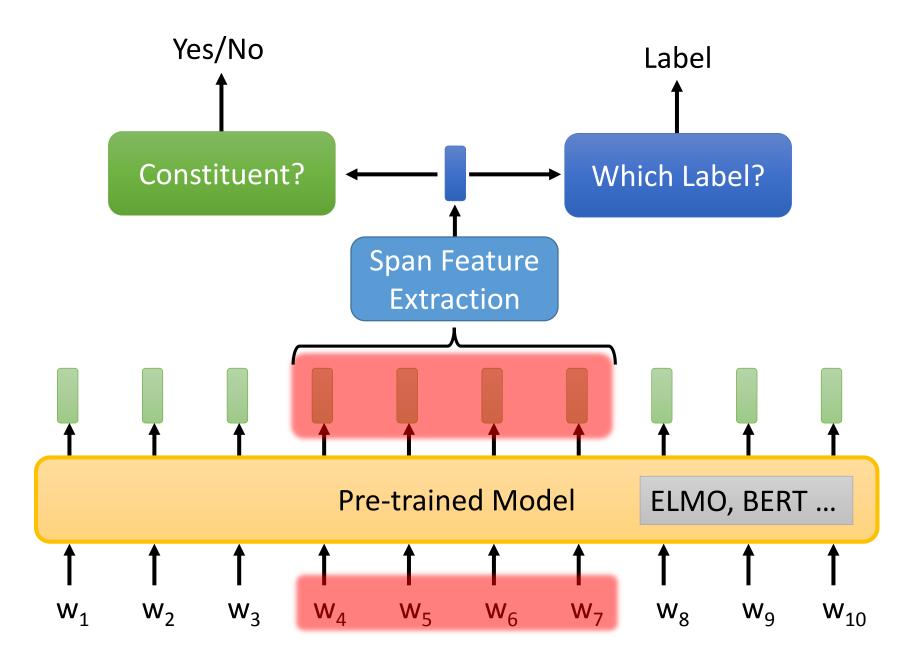




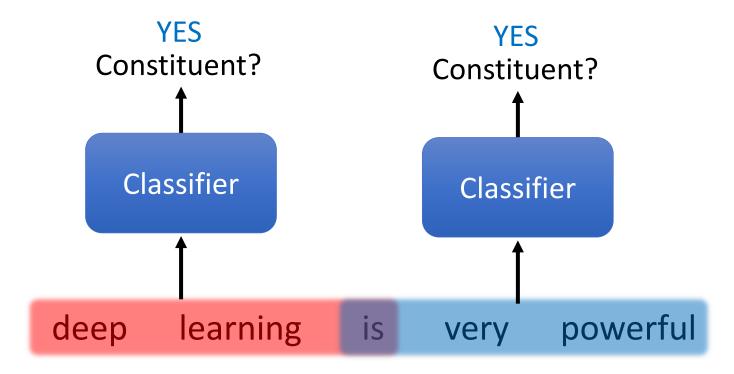




#### Chart-based – Classifier



 Given a sequence with N tokens, then run the classifier N(N-1)/2 times .....
 Contradiction!



Inference Enumerate all possible trees, and use the classifier to give scores. where you need CKY algorithm **Training?** [Stern, et al., ACL'17] 0.1 0.9 Classifier Classifier good good am am 8.0 0.9 Classifier Classifier good good am am

1	Input: The hungry cat meows.					
	Stack	Buffer	Action			
0		The   hungry   cat   meows  .	NT(S)			
1	(S	The   hungry   cat   meows  .	NT(NP)			
2	(S   (NP	The   hungry   cat   meows  .	SHIFT			
3	(S   (NP   <i>The</i>	hungry   cat   meows   .	SHIFT			
4	(S   (NP   The   hungry	cat   meows  .	SHIFT			
5	(S   (NP   The   hungry   cat	meows  .	REDUCE			
6	(S   (NP The hungry cat)	meows  .	NT(VP)			
7	(S   (NP The hungry cat)   (VP	meows  .	SHIFT			
8	(S   (NP The hungry cat)   (VP meows		REDUCE			
9	(S   (NP The hungry cat)   (VP meows)		SHIFT			
10	(S   (NP The hungry cat)   (VP meows)  .		REDUCE			
11	(S (NP The hungry cat) (VP meows) .)					

Source of image: https://arxiv.org/pdf/1602.07776.pdf

[Dyer, et al., NAACL'16]

**Stack** (empty at the beginning)

<u>Buffer</u>

deep

learning

is

very

powerful

#### **Actions**

CREATE(X)

Create a constitute X

(X = NP, VP ...)

**SHIFT** 

More a token from buffer to stack

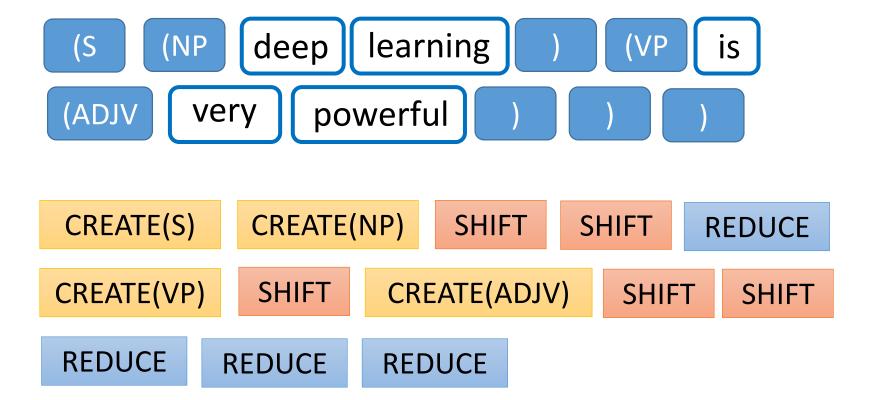
**REDUCE** 

Close a constitute

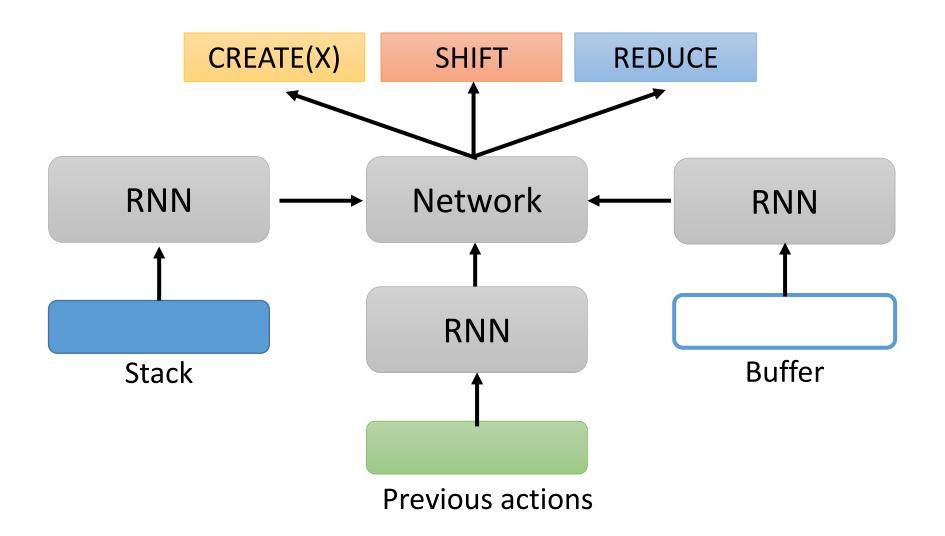
(empty at the beginning)

CREATE(S)

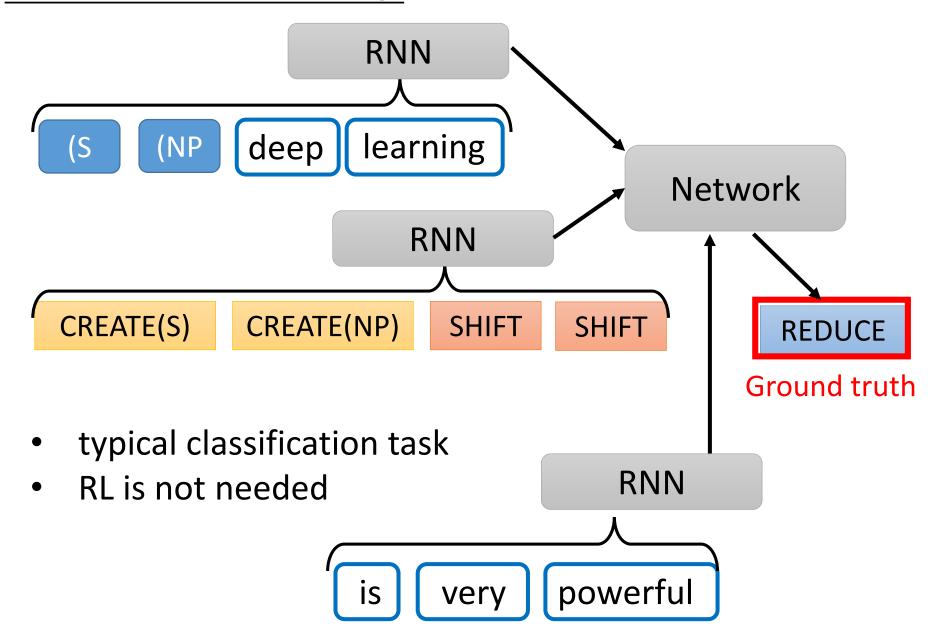
deep learning is very powerful



## **RNN Grammar**



#### RNN Grammar – Training



#### Grammar as a Foreign Language

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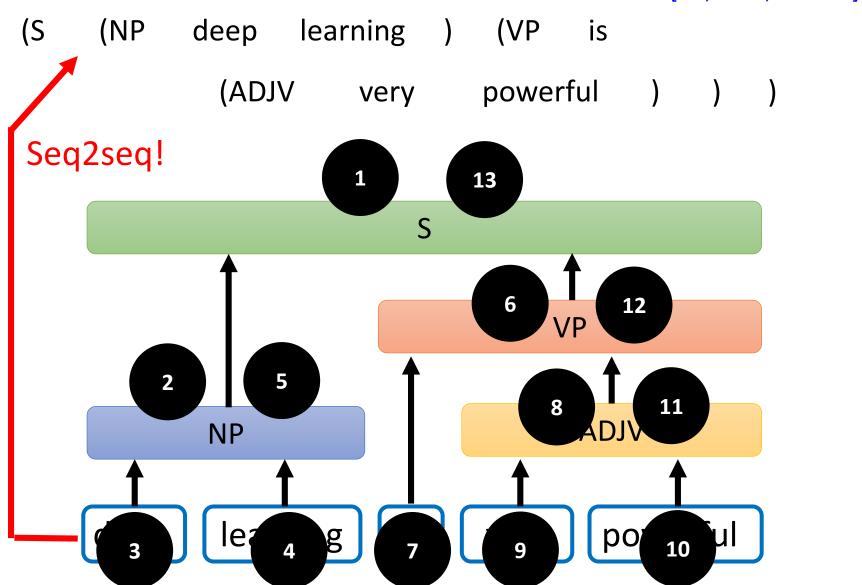
Geoffrey Hinton Google geoffhinton@google.com [Vinyals, et al., **NIPS'15**]

Source of image: https://papers.nips.cc/paper/5635-grammar-as-a-foreign-language.pdf

#### Tree to Sequence

Of course, you can try other tree traversal approaches

[Liu, et al., TACL'17]

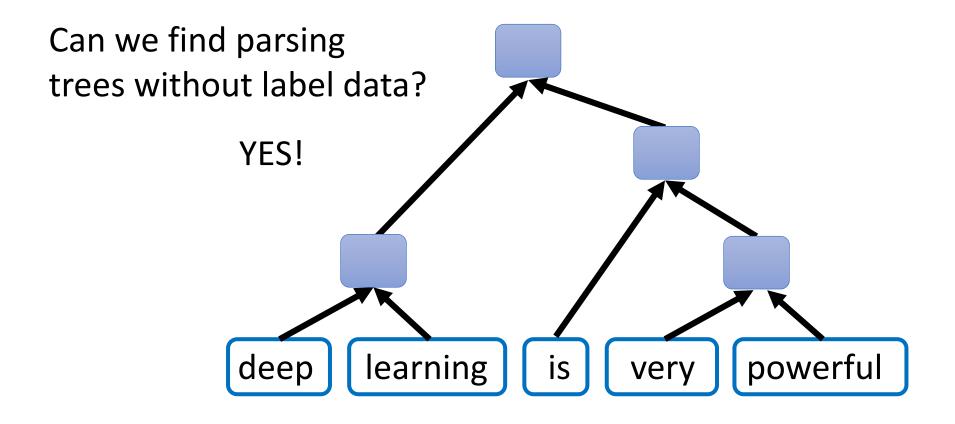


#### Seq2seq v.s. RNN grammar

```
(S
      (NP
             deep
                     learning )
                                     (VP
                                            İS
               (ADJV
                                    powerful)
                          very
                                          [Vinyals, et al., NIPS'15]
 CREATE(S)
               CREATE(NP)
                               SHIFT
                                         SHIFT
                                                   REDUCE
CREATE(VP)
                SHIFT
                          CREATE(ADJV)
                                             SHIFT
                                                      SHIFT
 REDUCE
             REDUCE
                          REDUCE
                                          [Dyer, et al., NAACL'16]
```

deep learning is very powerful

# Unsupervised Parsing?



Reference: https://youtu.be/YluBHB9Ejok

### Reference

- [Vinyals, et al., NIPS'15] Oriol Vinyals, Lukasz Kaiser, Terry Koo, Slav Petrov, Ilya Sutskever, Geoffrey Hinton, Grammar as a foreign language, NIPS, 2015
- [Dyer, et al., NAACL'16] Chris Dyer, Adhiguna Kuncoro, Miguel Ballesteros, Noah
   A. Smith, Recurrent Neural Network Grammars, NAACL, 2016
- [Stern, et al., ACL'17] Mitchell Stern, Jacob Andreas, Dan Klein, A Minimal Span-Based Neural Constituency Parser, ACL, 2017
- [Liu, et al., TACL'17] Jiangming Liu, Yue Zhang, In-Order Transition-based Constituent Parsing, TACL, 2017