COS 484: Natural Language Processing

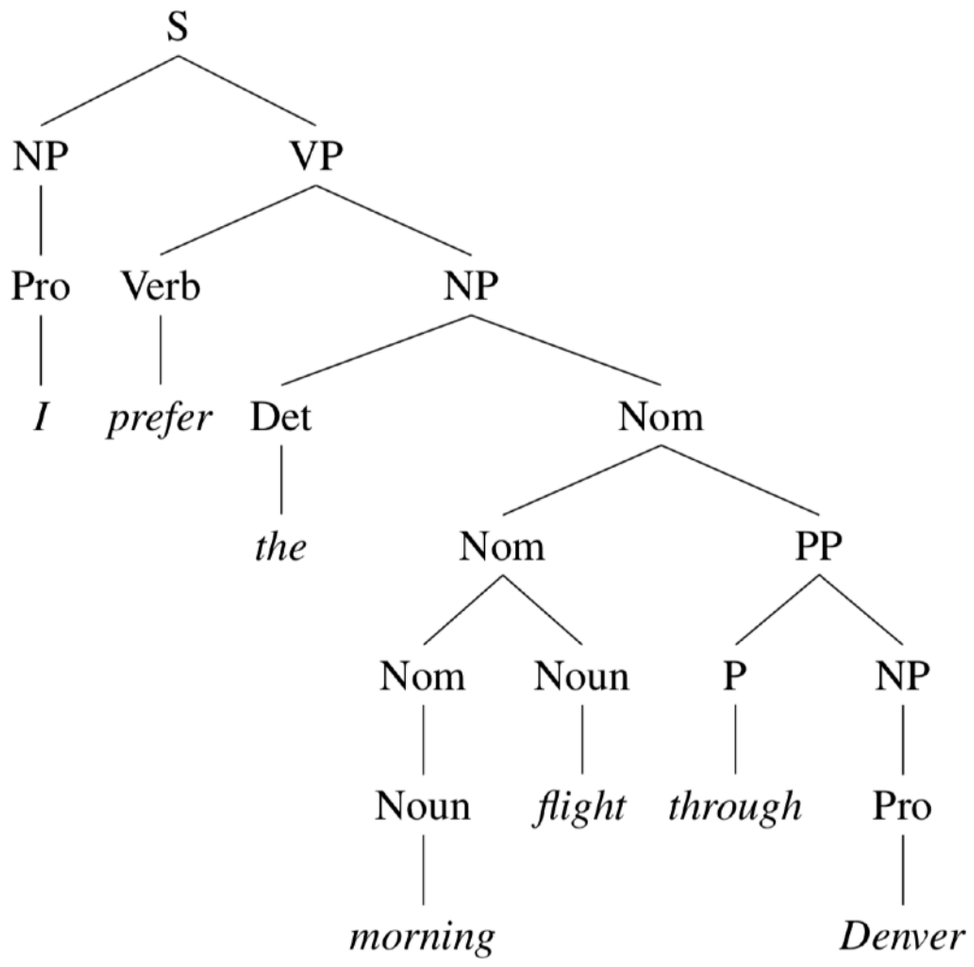
Dependency Parsing

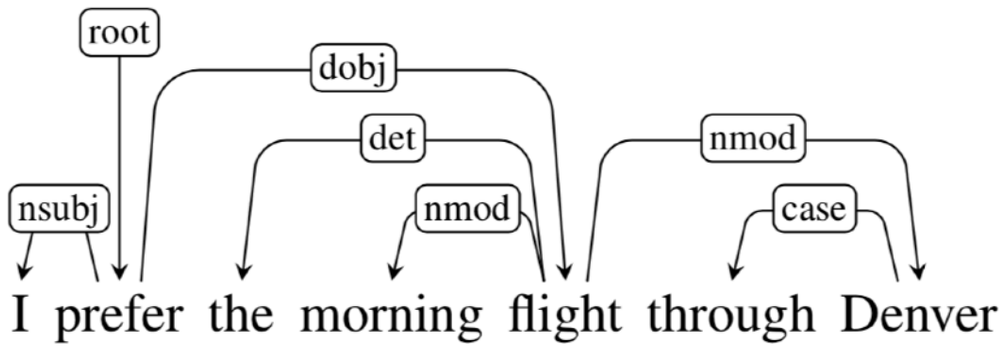
Fall 2019

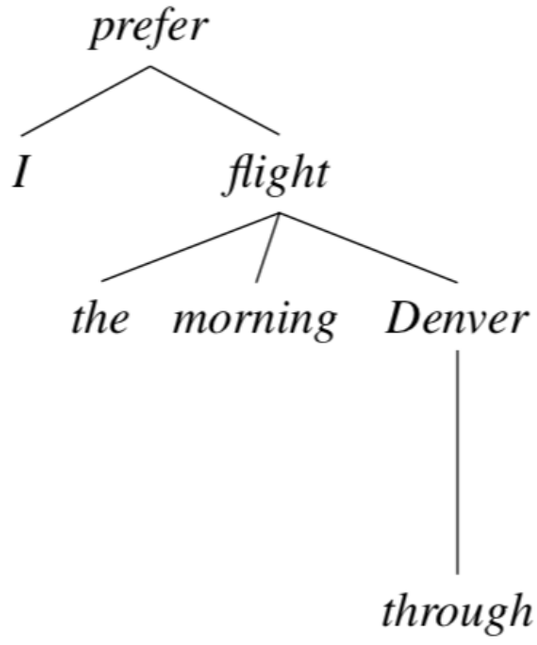
Overview

- What is dependency parsing?
- Two families of algorithms
  - **Transition-based dependency parsing**
  - Graph-based dependency parsing

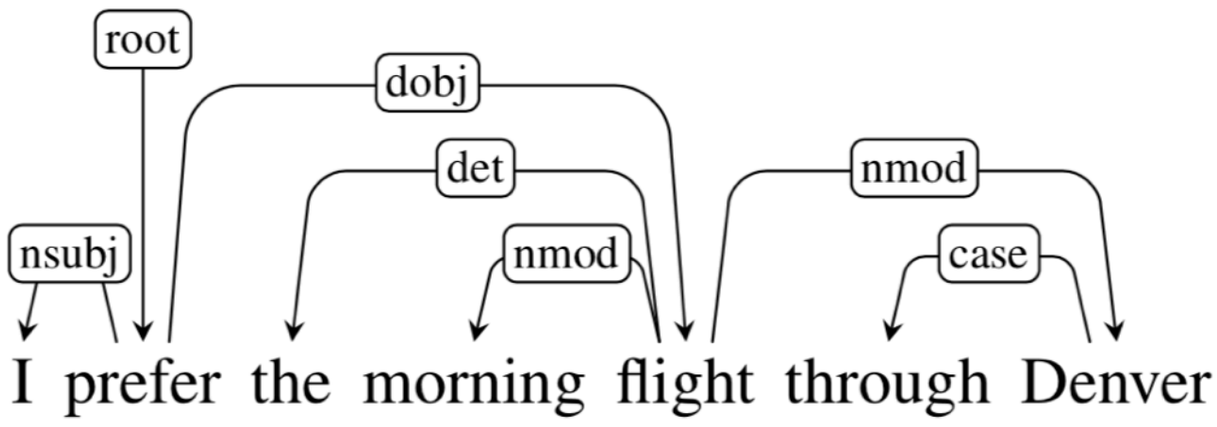
Constituency vs dependency structure







Dependency structure



- Consists of relations between lexical items, normally *binary*, *asymmetric* relations ("arrows") called **dependencies**
- The arrows are commonly typed with the name of grammatical relations (subject, prepositional object, apposition, etc)

- The arrow connects a **head** (governor) and a **dependent** (modifier)
- Usually, dependencies form a tree (single-head, connected, acyclic)

Dependency relations

Clausal Argument Relations	Description
NSUBJ	Nominal subject
DOBJ	Direct object
IOBJ	Indirect object
CCOMP	Clausal complement
XCOMP	Open clausal complement
Nominal Modifier Relations	**Description**
NMOD	Nominal modifier
AMOD	Adjectival modifier
NUMMOD	Numeric modifier
APPOS	Appositional modifier
DET	Determiner
CASE	Prepositions, postpositions and other case markers
Other Notable Relations	**Description**
CONJ	Conjunct
CC	Coordinating conjunction

(de Marneffe and Manning, 2008): Stanford typed dependencies manual

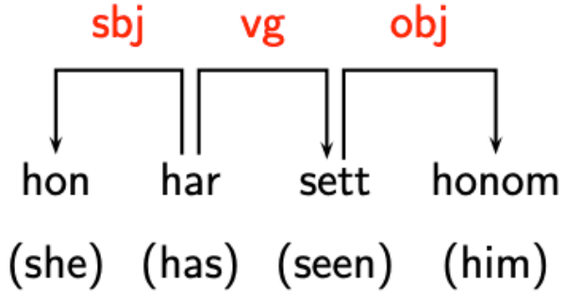
Dependency relations

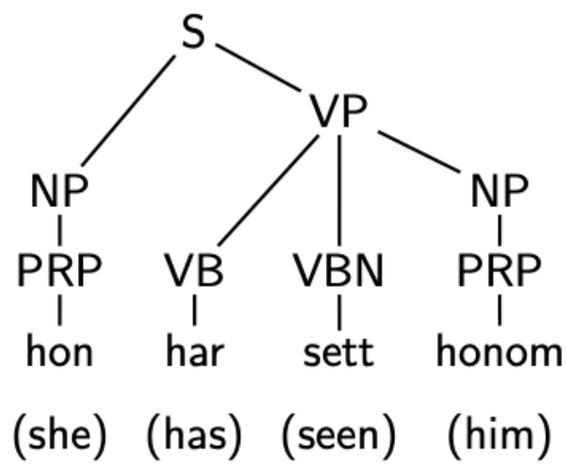
Relation	Examples with *head* and **dependent**
NSUBJ	**United** *canceled* the flight.
DOBJ	United *diverted* the **flight** to Reno.
	We *booked* her the first **flight** to Miami.
IOBJ	We *booked* **her** the flight to Miami.
NMOD	We took the **morning** *flight*.
AMOD	Book the **cheapest** *flight*.
NUMMOD	Before the storm JetBlue canceled **1000** *flights*.
APPOS	*United*, a **unit** of UAL, matched the fares.
DET	**The** *flight* was canceled.
	Which *flight* was delayed?
CONJ	We *flew* to Denver and **drove** to Steamboat.
CC	We flew to Denver **and** *drove* to Steamboat.
CASE	Book the flight **through** *Houston*.

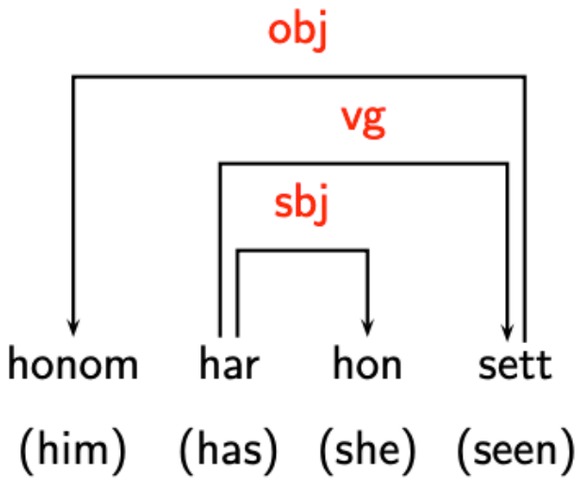
(de Marneffe and Manning, 2008): Stanford typed dependencies manual

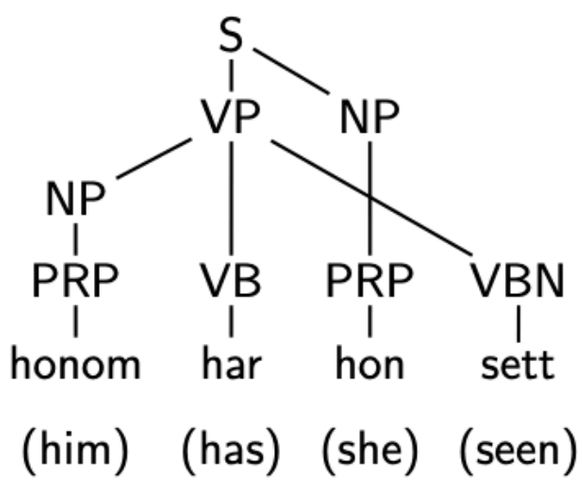
Advantages of dependency structure

- More suitable for free word order languages









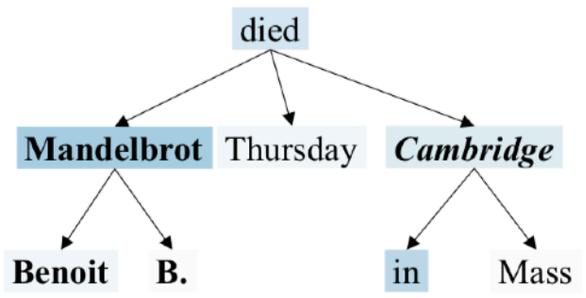
Advantages of dependency structure

- More suitable for free word order languages

- The predicate-argument structure is more useful for many applications

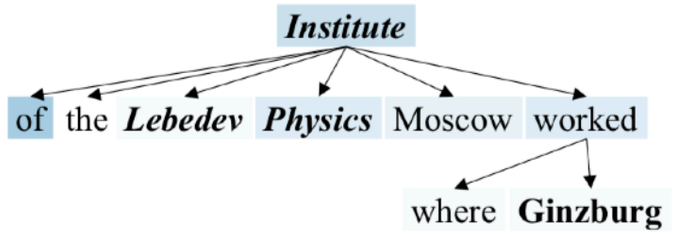
Relation: *per:city_of_death*

Benoit B. Mandelbrot, a maverick mathematician who developed an innovative theory of roughness and applied it to physics, biology, finance and many other fields, died Thursday in ***Cambridge***, Mass.



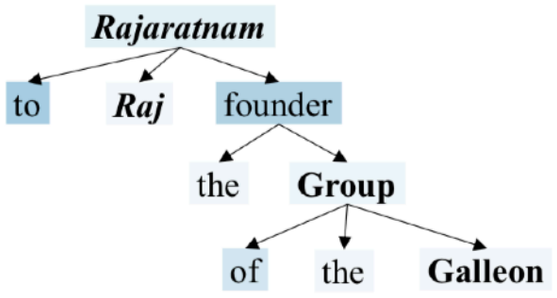
Relation: *per:employee_of*

In a career that spanned seven decades, Ginzburg authored several groundbreaking studies in various fields -- such as quantum theory, astrophysics, radio-astronomy and diffusion of cosmic radiation in the Earth's atmosphere -- that were of "Nobel Prize caliber," said Gennady Mesyats, the director of the ***Lebedev Physics Institute*** in Moscow, where **Ginzburg** worked .



Relation: *org:founded_by*

Anil Kumar, a former director at the consulting firm McKinsey & Co, pleaded guilty on Thursday to providing inside information to ***Raj Rajaratnam***, the founder of the **Galleon Group**, in exchange for payments of at least $ 175 million from 2004 through 2009.

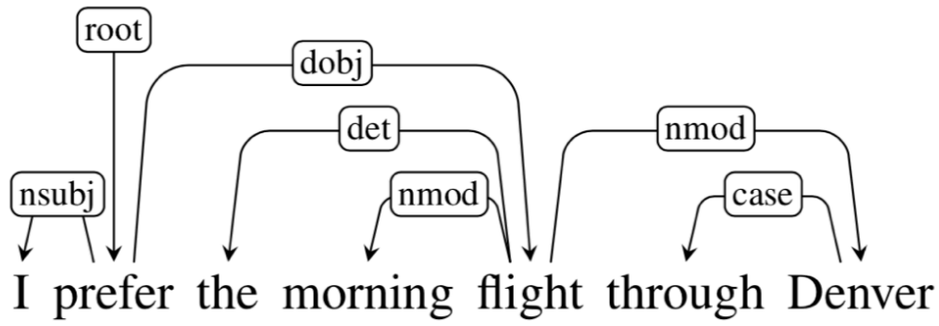


Dependency parsing

Input:

I prefer the morning flight through Denver

Output:



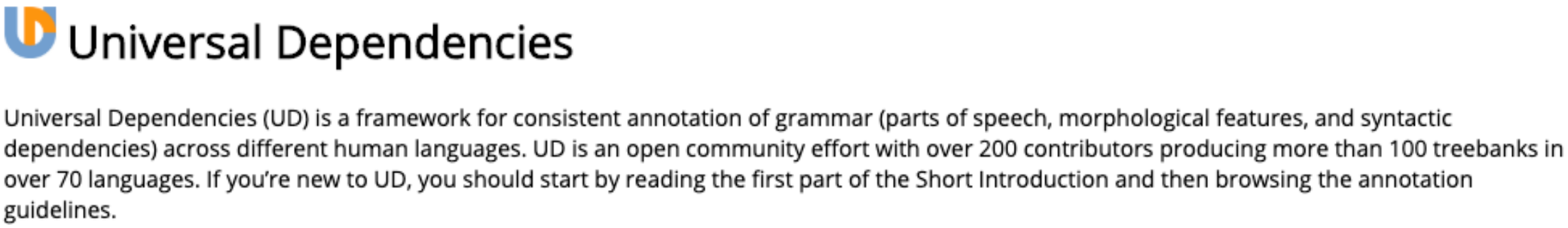
- A sentence is parsed by choosing for each word what other word is it a dependent of (and also the relation type)
- We usually add a fake ROOT at the beginning so every word has one head

- Usually some constraints:
  - Only one word is a dependent of ROOT
  - No cycles: A —> B, B —> C, C —> A

Learning from data: treebanks!

Dependency treebanks

- The major English dependency treebank: converting from Penn Treebank using rule-based algorithms
    - (De Marneffe et al, 2006): Generating typed dependency parses from phrase structure parses
    - (Johansson and Nugues, 2007): Extended Constituent-to-dependency Conversion for English
- Universal Dependencies: more than 100 treebanks in 70 languages were collected since 2016



https://universaldependencies.org/

Universal Dependencies

Afrikaans	1	49K		IE, Germanic
Akkadian	1	1K		Afro-Asiatic, Semitic
Amharic	1	10K		Afro-Asiatic, Semitic
Ancient Greek	2	416K		IE, Greek
Arabic	3	1,042K	W	Afro-Asiatic, Semitic
Armenian	1	36K		IE, Armenian
Assyrian	1	<1K		Afro-Asiatic, Semitic
Bambara	1	13K		Mande
Basque	1	121K		Basque
Belarusian	1	13K		IE, Slavic
Breton	1	10K	W	IE, Celtic
Bulgarian	1	156K		IE, Slavic
Buryat	1	10K		Mongolic
Cantonese	1	13K		Sino-Tibetan
Catalan	1	531K		IE, Romance
Chinese	5	161K	W	Sino-Tibetan
Classical Chinese	1	55K		Sino-Tibetan
Coptic	1	25K		Afro-Asiatic, Egyptian
Croatian	1	199K	W	IE, Slavic
Czech	5	2,222K	W	IE, Slavic
Danish	2	100K		IE, Germanic
Dutch	2	307K	W	IE, Germanic
English	6	603K	W	IE, Germanic
Erzya	1	15K		Uralic, Mordvin
Estonian	2	461K		Uralic, Finnic
Faroese	1	10K	W	IE, Germanic
Finnish	3	377K	W	Uralic, Finnic
French	8	1,156K	W	IE, Romance
Galician	2	164K		IE, Romance
German	4	3,409K	W	IE, Germanic
Gothic	1	55K		IE, Germanic
Greek	1	63K	W	IE, Greek
Hebrew	1	161K		Afro-Asiatic, Semitic
Hindi	2	375K	W	IE, Indic
Hindi English	1	26K		Code switching
Hungarian	1	42K		Uralic, Ugric
Indonesian	2	141K	W	Austronesian, Malayo-Sumbawan
Irish	1	23K		IE, Celtic
Italian	6	781K	W	IE, Romance
Japanese	5	1,688K	W	Japanese
Karelian	1	3K		Uralic, Finnic
Kazakh	1	10K	W	Turkic, Northwestern
Komi Zyrian	2	3K		Uralic, Permic
Korean	5	446K	W	Korean

Universal Dependencies

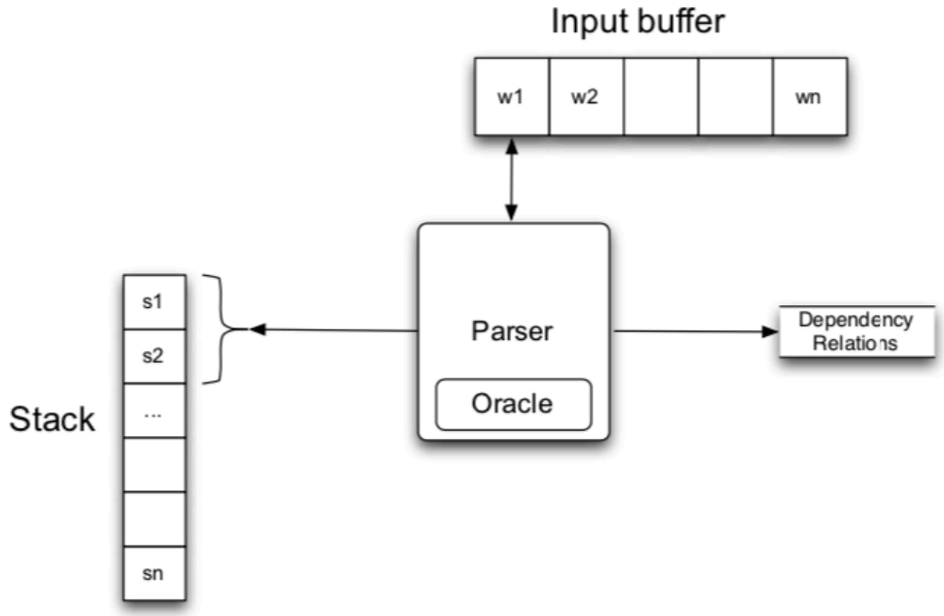
Manning's Law:

- UD needs to be satisfactory for analysis of individual languages.
- UD needs to be good for linguistic typology.
- UD must be suitable for rapid, consistent annotation.
- UD must be suitable for computer parsing with high accuracy.
- UD must be easily comprehended and used by a non-linguist.
- UD must provide good support for downstream NLP tasks.

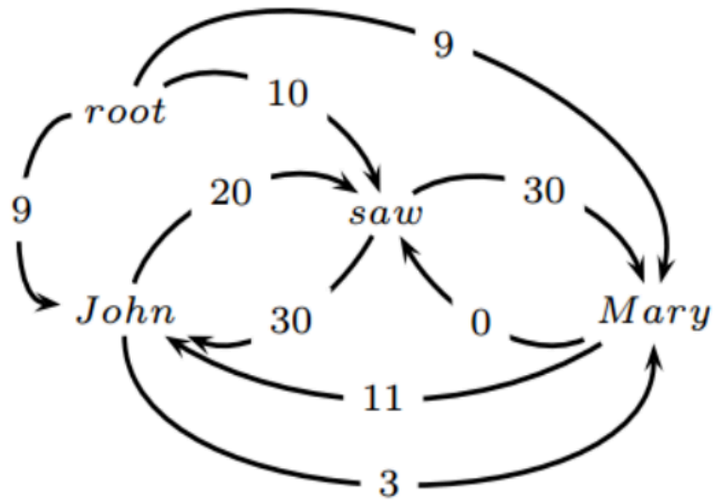
Two families of algorithms

Transition-based dependency parsing

- Also called “shift-reduce parsing”



Graph-based dependency parsing



Two families of algorithms

Parser		Test UAS	Test LAS
(Chen and Manning, 2014)	T	91.8	89.6
(Dyer et al., 2015)	T	93.1	90.9
(Ballesteros et al., 2016)	T	93.56	92.41
(Weiss et al., 2015)	T	94.26	91.42
(Andor et al., 2016)	T	94.61	92.79
(Ma et al., 2018) §	T	95.87	94.19
(Kiperwasser and Goldberg, 2016a) §	G	93.0	90.9
(Kiperwasser and Goldberg, 2016b)	G	93.1	91.0
(Wang and Chang, 2016)	G	94.08	91.82
(Cheng et al., 2016)	G	94.10	91.49
(Kuncoro et al., 2016)	G	94.26	92.06
(Zheng, 2017) §	G	95.53	93.94
(Dozat and Manning, 2017)	G	95.74	94.08
Baseline	G	95.68	93.96
Our Model §	G	**95.97**	**94.31**

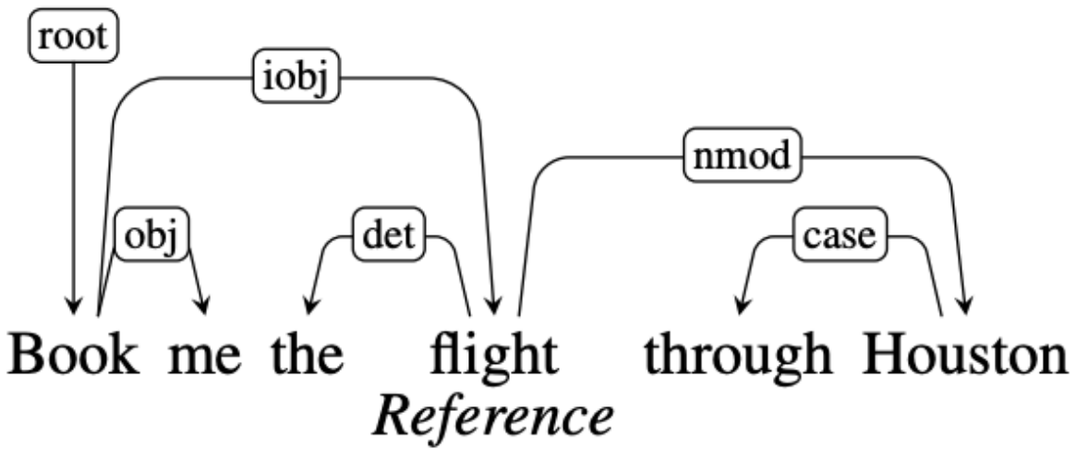
T: transition-based / G: graph-based

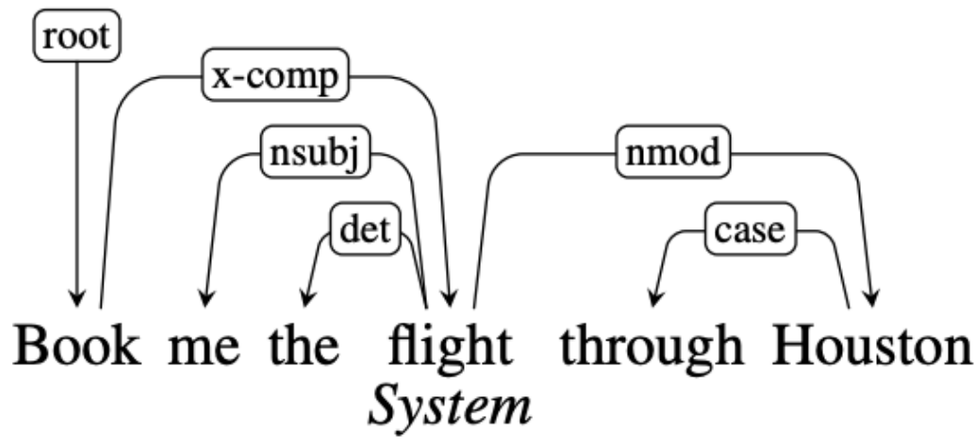
Evaluation

- Unlabeled attachment score (UAS)

  = percentage of words that have been assigned the correct head
- Labeled attachment score (LAS)

  = percentage of words that have been assigned the correct head & label

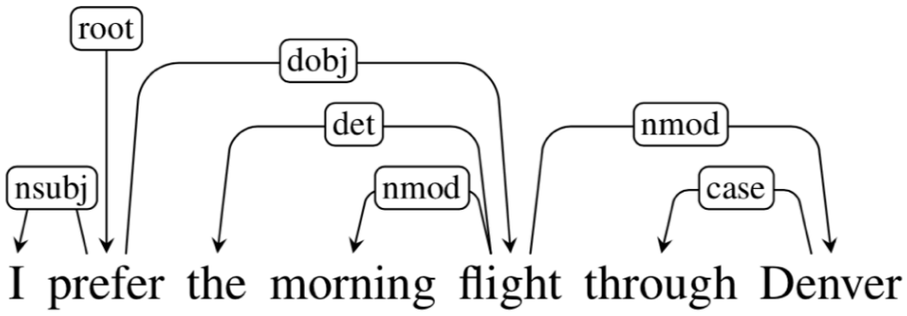




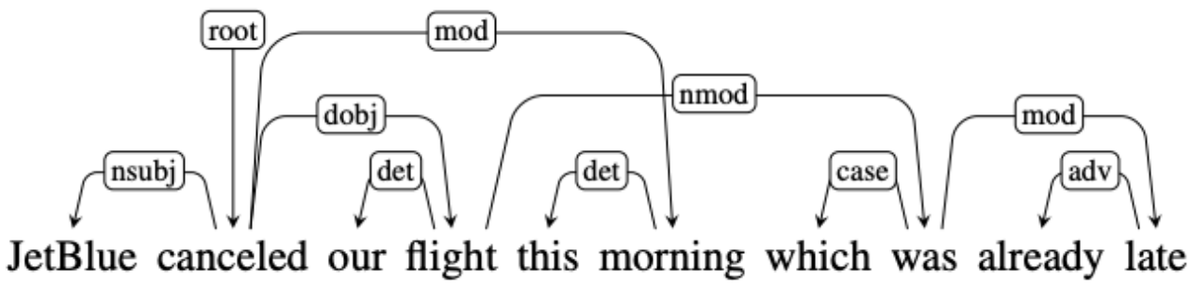
UAS = ? LAS = ?

Projectivity

- **Definition**: there are no crossing dependency arcs when the words are laid out in their linear order, with all arcs above the words



projective



non-projective

Non-projectivity arises due to long distance dependencies or in languages with flexible word order.

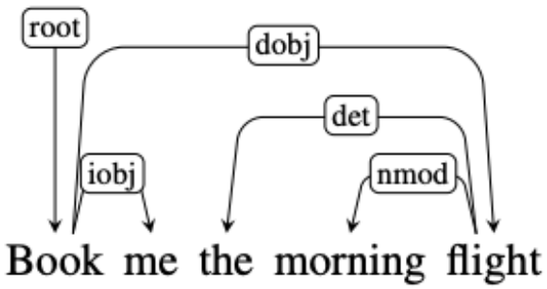
Dataset	# Sentences	(%) Projective
English	39,832	99.9
Chinese	16,091	100.0
Czech	72,319	76.9
German	38,845	72.2

This class: focuses on projective parsing

Transition-based dependency parsing

- The parsing process is modeled as a sequence of transitions
- A configuration consists of a stack s, a buffer b and a set of dependency arcs A: $c = (s, b, A)$
- Initially, $s = [\text{ROOT}], b = [w_1, w_2, \ldots, w_n], A = \emptyset$
- Three types of transitions (s_1, s_2: the top 2 words on the stack; b_1: the first word in the buffer)
  - LEFT-ARC (r): add an arc ($s_1 \xrightarrow{r} s_2$) to A, remove s_2 from the stack
  - RIGHT-ARC (r): add an arc ($s_2 \xrightarrow{r} s_1$) to A, remove s_1 from the stack
  - SHIFT: move b_1 from the buffer to the stack
- A configuration is terminal if $s = [\text{ROOT}]$ and $b = \emptyset$

This is called “Arc-standard”; There are other transition schemes…

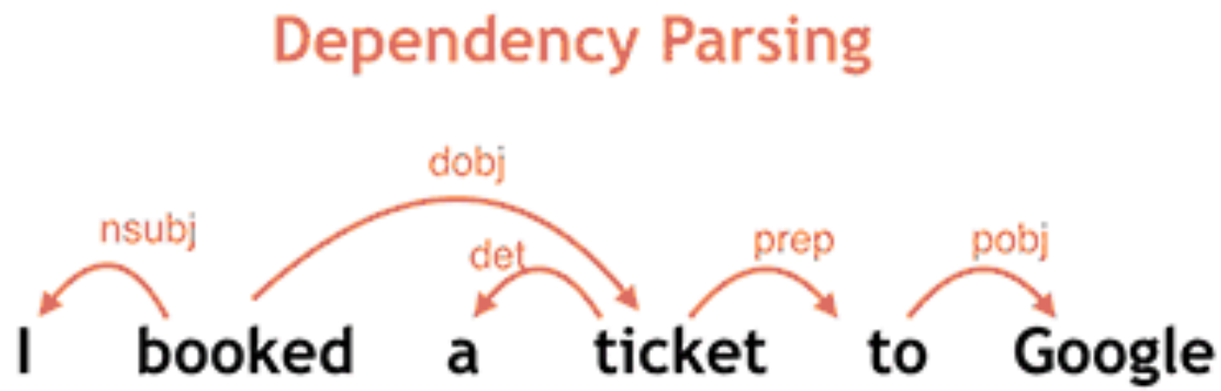


"Book me the morning flight"

A running example

	stack	buffer	action	added arc
0	[ROOT]	[Book, me, the, morning, flight]	SHIFT	
1	[ROOT, Book]	[me, the, morning, flight]	SHIFT	
2	[ROOT, Book, me]	[the, morning, flight]	RIGHT-ARC(iobj)	(Book, iobj, me)
3	[ROOT, Book]	[the, morning, flight]	SHIFT	
4	[ROOT, Book, the]	[morning, flight]	SHIFT	
5	[ROOT, Book, the, morning]	[flight]	SHIFT	
6	[ROOT, Book, the,morning,flight]	[]	LEFT-ARC(nmod)	(flight,nmod,morning)
7	[ROOT, Book, the, flight]	[]	LEFT-ARC(det)	(flight,det,the)
8	[ROOT, Book, flight]	[]	RIGHT-ARC(dobj)	(Book,dobj,flight)
9	[ROOT, Book]	[]	RIGHT-ARC(root)	(ROOT,root,Book)
10	[ROOT]	[]		

Transition-based dependency parsing



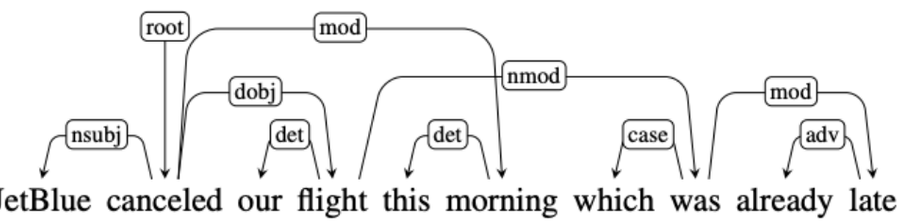
https://ai.googleblog.com/2016/05/announcing-syntaxnet-worlds-most.html

Transition-based dependency parsing

How many transitions are needed? How many times of SHIFT?

Correctness:

- For every complete transition sequence, the resulting graph is a projective dependency forest (soundness)
- For every projective dependency forest G, there is a transition sequence that generates G (completeness)



- However, one parse tree can have multiple valid transition sequences. Why?
  - "He likes dogs"
    - Stack = [ROOT He likes]
    - Buffer = [dogs]
    - Action = ??

Train a classifier to predict actions!

- Given $\{x_i, y_i\}$ where x_i is a sentence and y_i is a dependency parse
- For each x_i with n words, we can construct a transition sequence of length $2n$ which generates y_i, so we can generate 2n training examples: $\{(c_k, a_k)\}$ c_k: configuration, a_k: action
  - "shortest stack" strategy: prefer LEFT-ARC over SHIFT.

> Given this information, the oracle chooses transitions as follows:
>
> LEFTARC(r): **if** $(S_1\ r\ S_2) \in R_p$
>
> RIGHTARC(r): **if** $(S_2\ r\ S_1) \in R_p$ **and** $\forall r', w\ s.t. (S_1\ r'\ w) \in R_p$ **then** $(S_1\ r'\ w) \in R_c$
>
> SHIFT: **otherwise**

- The goal becomes how to learn a classifier from c_i to a_i

How many training examples? How many classes?

Train a classifier to predict actions!

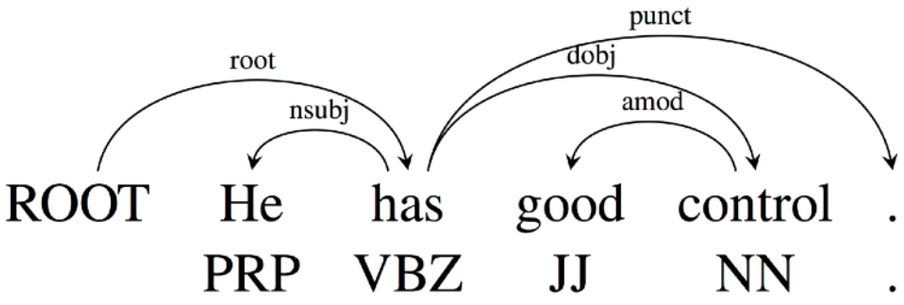
- During testing, we use the classifier to repeat predicting the action, until we reach a terminal configuration

function DEPENDENCYPARSE(*words*) **returns** dependency tree

state ← {[root], [*words*], [] } ; initial configuration
while *state* **not final**
t ← **Classifier** (*state*) ; choose a transition operator to apply
state ← APPLY(*t*, *state*) ; apply it, creating a new state
return *state*

- This is also called "greedy transition-based parsing" because we always make a local decision at each step
  - It is very fast (linear time!) but less accurate
  - Can easily do beam search

MaltParser



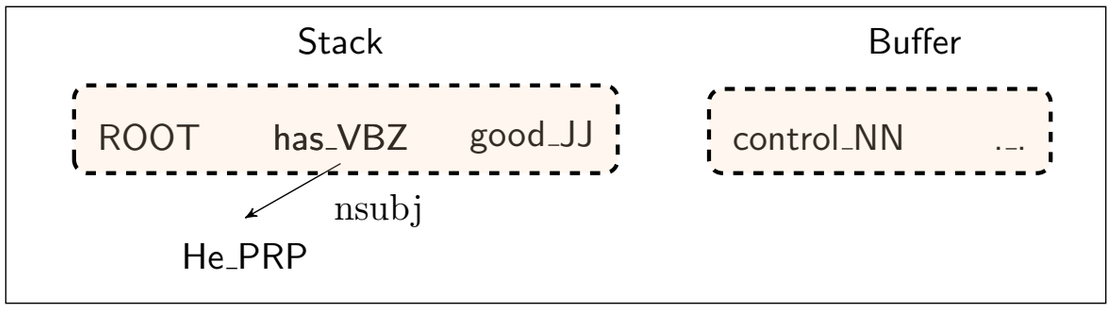
- Extract features from the configuration
- Use your favorite classifier: logistic regression, SVM…

Source	Feature templates		
One word	$s_1.w$	$s_1.t$	$s_1.wt$
	$s_2.w$	$s_2.t$	$s_2.wt$
	$b_1.w$	$b_1.w$	$b_0.wt$
Two word	$s_1.w \circ s_2.w$	$s_1.t \circ s_2.t$	$s_1.t \circ b_1.w$
	$s_1.t \circ s_2.wt$	$s_1.w \circ s_2.w \circ s_2.t$	$s_1.w \circ s_1.t \circ s_2.t$
	$s_1.w \circ s_1.t \circ s_2.t$	$s_1.w \circ s_1.t$	

w: word, t: part-of-speech tag

(Nivre 2008): Algorithms for Deterministic Incremental Dependency Parsing

MaltParser



Feature templates

$s_2 . w \circ s_2 . t$

$s_1 . w \circ s_1 . t \circ b_1 . w$

$lc(s_2) . t \circ s_2 . t \circ s_1 . t$

$lc(s_2) . w \circ lc(s_2) . l \circ s_2 . w$

Features

$s_2 . w = \text{has} \circ s_2 . t = \text{VBZ}$

$s_1 . w = \text{good} \circ s_1 . t = \text{JJ} \circ b_1 . w = \text{control}$

$lc(s_2) . t = \text{PRP} \circ s_2 . t = \text{VBZ} \circ s_1 . t = \text{JJ}$

$lc(s_2) . w = \text{He} \circ lc(s_2) . l = \text{nsubj} \circ s_2 . w = \text{has}$

Usually a combination of 1-3 elements from the configuration

Binary, sparse, millions of features

(Nivre 2008): Algorithms for Deterministic Incremental Dependency Parsing

More feature templates

```
# From Single Words
pair { stack.tag stack.word }
stack { word tag }
pair { input.tag input.word }
input { word tag }
pair { input(1).tag input(1).word }
input(1) { word tag }
pair { input(2).tag input(2).word }
input(2) { word tag }

# From word pairs
quad { stack.tag stack.word input.tag input.word }
triple { stack.tag stack.word input.word }
triple { stack.word input.tag input.word }
triple { stack.tag stack.word input.tag }
triple { stack.tag input.tag input.word }
pair { stack.word input.word }
pair { stack.tag input.tag }
pair { input.tag input(1).tag }

# From word triples
triple { input.tag input(1).tag input(2).tag }
triple { stack.tag input.tag input(1).tag }
triple { stack.head(1).tag stack.tag input.tag }
triple { stack.tag stack.child(-1).tag input.tag }
triple { stack.tag stack.child(1).tag input.tag }
triple { stack.tag input.tag input.child(-1).tag }

# Distance
pair { stack.distance stack.word }
pair { stack.distance stack.tag }
pair { stack.distance input.word }
pair { stack.distance input.tag }
triple { stack.distance stack.word input.word }
triple { stack.distance stack.tag input.tag }
```

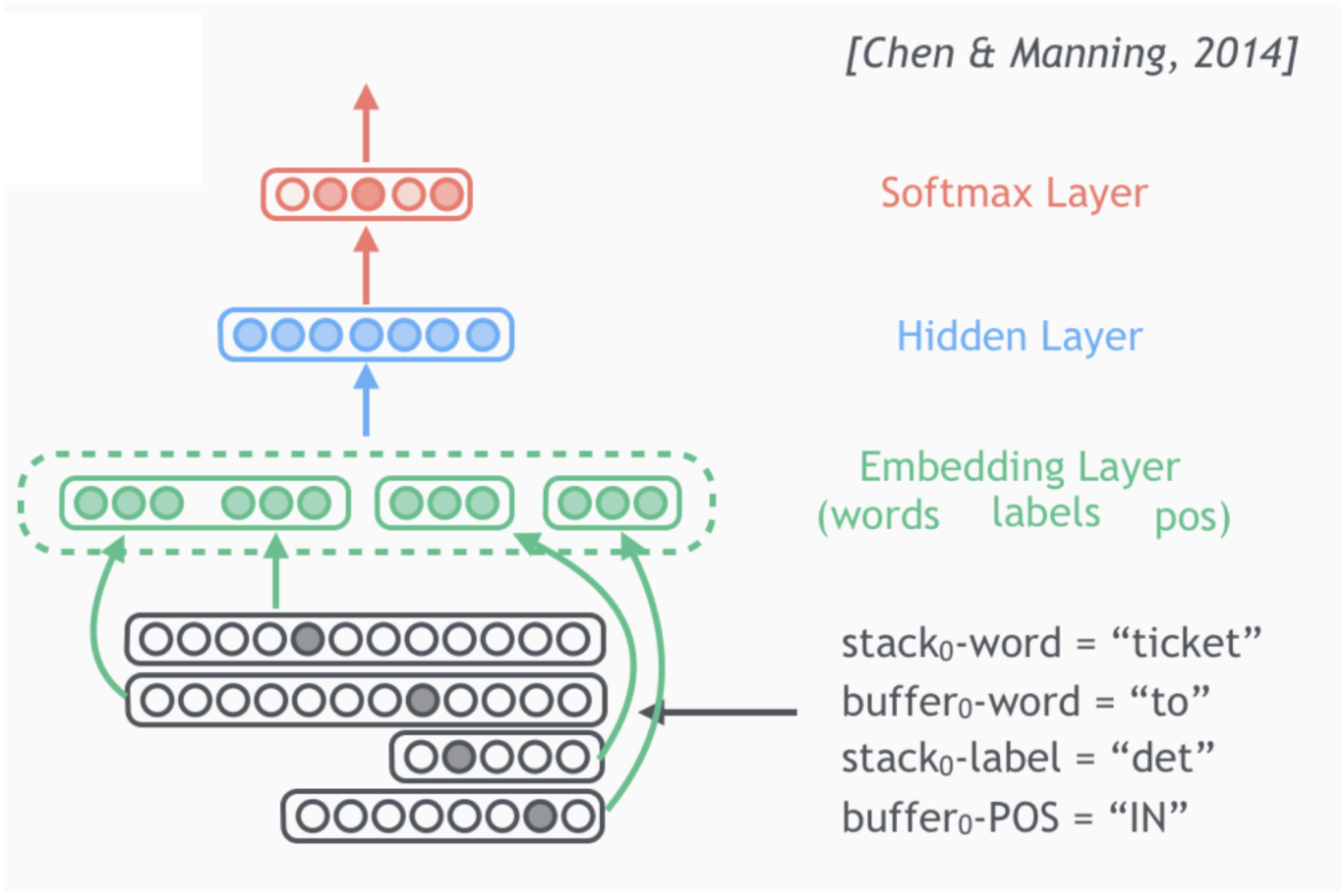
```
# valency
pair { stack.word stack.valence(-1) }
pair { stack.word stack.valence(1) }
pair { stack.tag stack.valence(-1) }
pair { stack.tag stack.valence(1) }
pair { input.word input.valence(-1) }
pair { input.tag input.valence(-1) }

# unigrams
stack.head(1) {word tag}
stack.label
stack.child(-1) {word tag label}
stack.child(1) {word tag label}
input.child(-1) {word tag label}

# third order
stack.head(1).head(1) {word tag}
stack.head(1).label
stack.child(-1).sibling(1) {word tag label}
stack.child(1).sibling(-1) {word tag label}
input.child(-1).sibling(1) {word tag label}
triple { stack.tag stack.child(-1).tag stack.child(-1).sibling(1)
triple { stack.tag stack.child(1).tag stack.child(1).sibling(-1).
triple { stack.tag stack.head(1).tag stack.head(1).head(1).tag }
triple { input.tag input.child(-1).tag input.child(-1).sibling(1)

# label set
pair { stack.tag stack.child(-1).label }
triple { stack.tag stack.child(-1).label stack.child(-1).sibling(
quad { stack.tag stack.child(-1).label stack.child(-1).sibling(1)
pair { stack.tag stack.child(1).label }
triple { stack.tag stack.child(1).label stack.child(1).sibling(-1
quad { stack.tag stack.child(1).label stack.child(1).sibling(-1).
pair { input.tag input.child(-1).label }
triple { input.tag input.child(-1).label input.child(-1).sibling(
quad { input.tag input.child(-1).label input.child(-1).sibling(1)
```

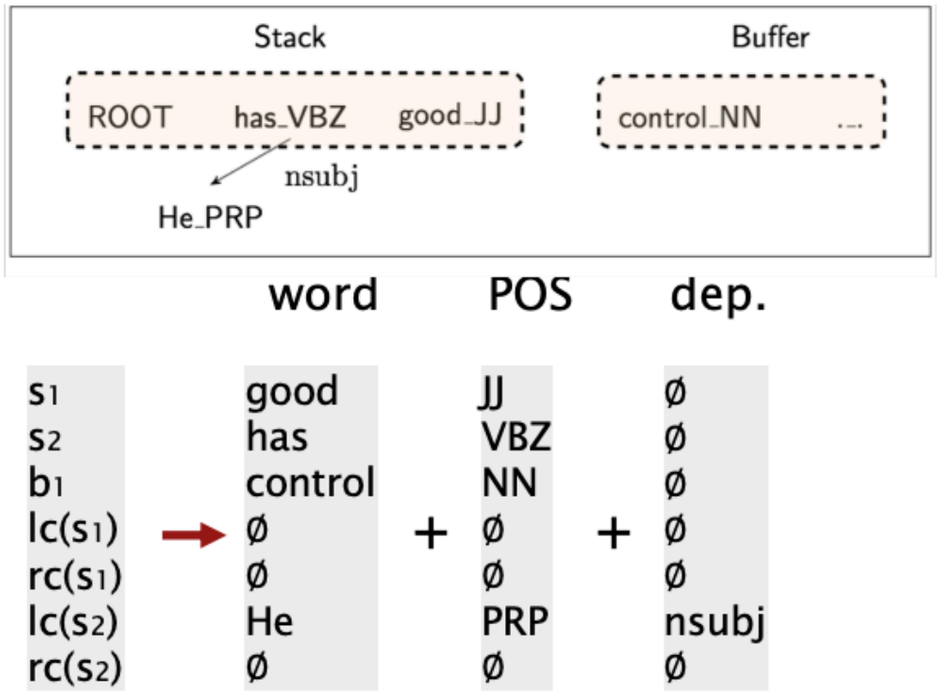
Parsing with neural networks

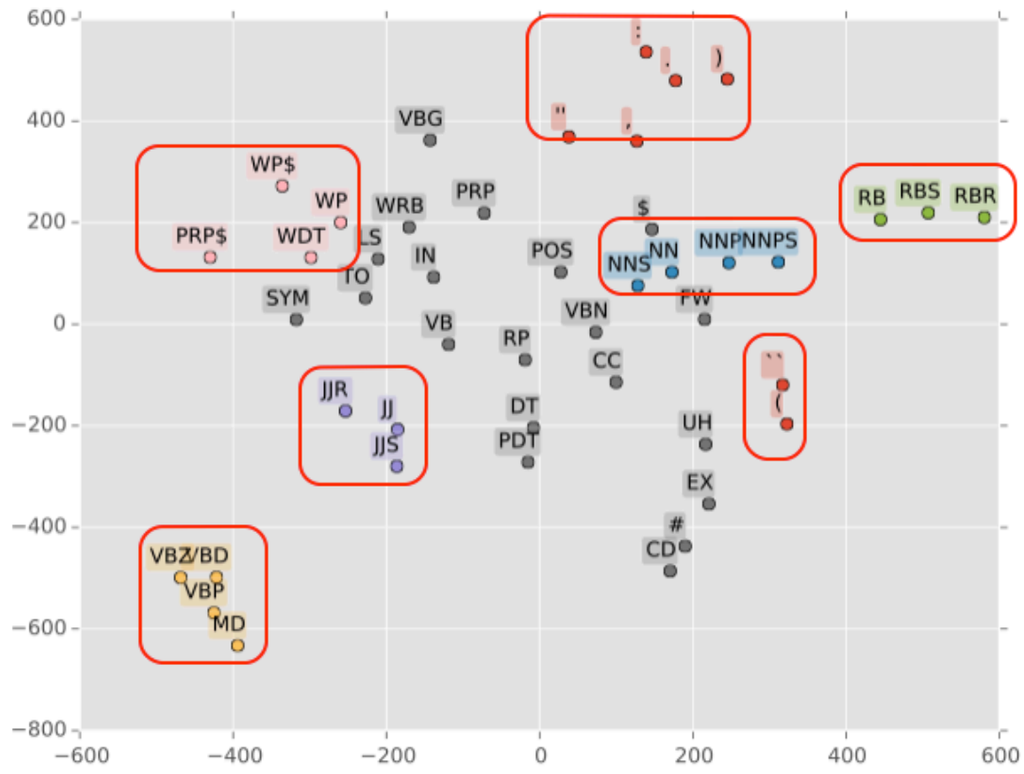


(Chen and Manning, 2014): A Fast and Accurate Dependency Parser using Neural Networks

Parsing with neural networks

- Used pre-trained word embeddings
- Part-of-speech tags and dependency labels are also represented as vectors
- No feature template any more!





- A simple feedforward NN: what is left is backpropagation!

(Chen and Manning, 2014): A Fast and Accurate Dependency Parser using Neural Networks

Further improvements

- Bigger, deeper networks with better tuned hyperparameters
- Beam search
- Global normalization

Method	UAS	LAS (PTB WSJ SD 3.3)
Chen & Manning 2014	92.0	89.7
Weiss et al. 2015	93.99	92.05
Andor et al. 2016	94.61	92.79

Google's SyntaxNet and the Parsey McParseFace (English) model

> Announcing SyntaxNet: The World's Most Accurate Parser Goes Open Source
>
> Thursday, May 12, 2016

Handling non-projectivity

- The arc-standard algorithm we presented only builds projective dependency trees
- Possible directions:
    - Give up!
    - Post-processing
    - Add new transition types (e.g., SWAP)
    - Switch to a different algorithm (e.g., graph-based parsers such as MSTParser)

Graph-based dependency parsing

- **Basic idea**: let's predict the dependency tree directly

$$Y^* = argmax_{Y \in \Phi(X)} score(X, Y)$$

X: sentence, Y: any possible dependency tree

- **Factorization**:

$$score(X, Y) = \sum_{e \in Y} score(e) = \sum_{e \in Y} w^\intercal f(e)$$

- **Inference**: finding maximum spanning tree (MST) for weighted, directed graph