CS11-711: Algorithms for NLP

Dependency parsing

Yulia Tsvetkov



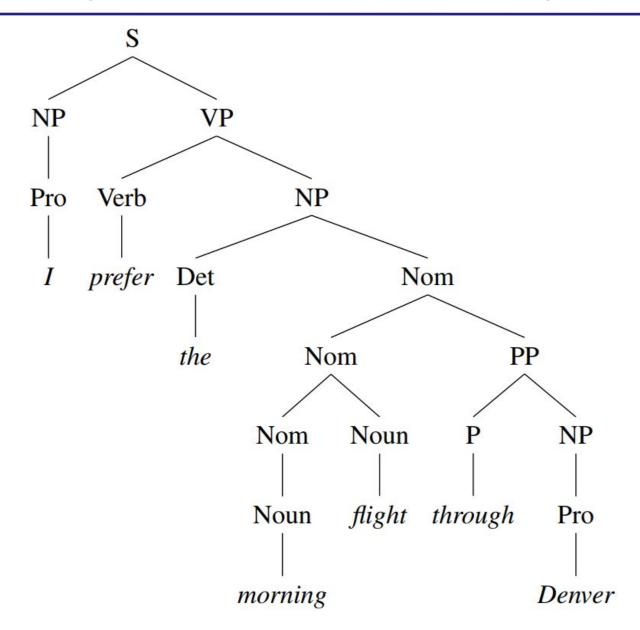


Announcements

- Today: Sanket will give an overview of HW1 grading
- Reading for today's lecture:
 - https://web.stanford.edu/~jurafsky/slp3/15.pdf
 - Eisenstein ch11

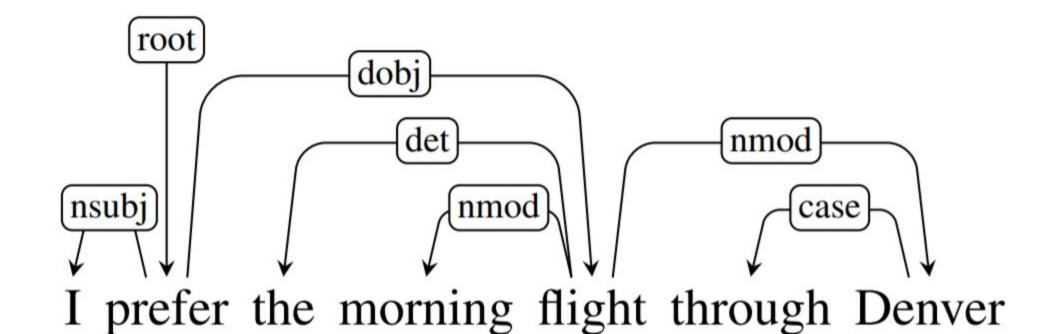


Constituent (phrase-structure) representation



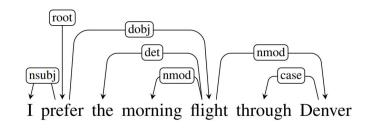


Dependency representation





Dependency representation



- A dependency structure can be defined as a directed graph G, consisting of
 - a set V of nodes vertices, words, punctuation, morphemes
 - a set A of arcs directed edges,
 - a linear precedence order < on V (word order).
- Labeled graphs
 - nodes in V are labeled with word forms (and annotation).
 - arcs in A are labeled with dependency types
 - $L = \{l_1, \dots, l_{|L|}\}$ is the set of permissible arc labels;
 - Every arc in A is a triple (i,j,k), representing a dependency from w_i to w_j with label l_k .



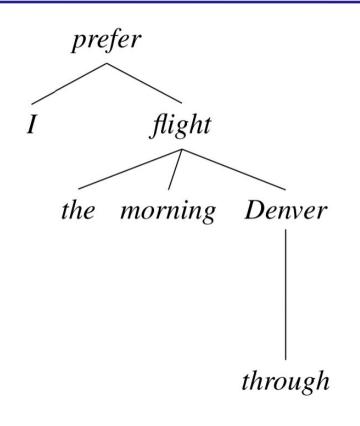
Dependency vs Constituency

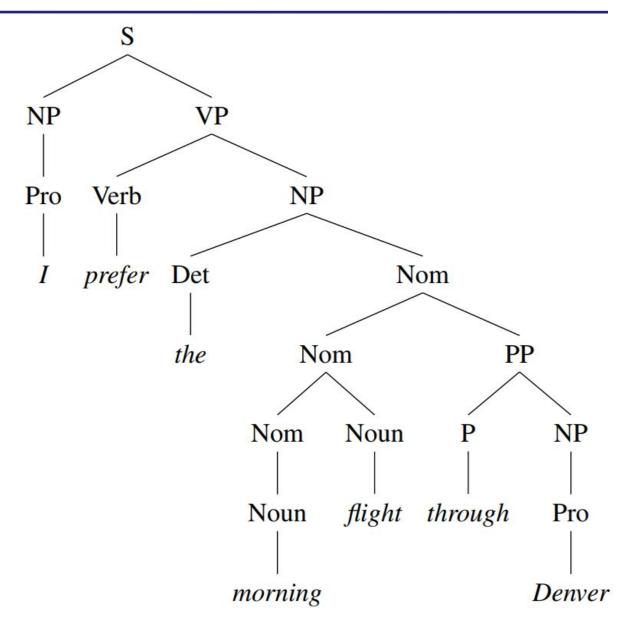
- Dependency structures explicitly represent
 - head-dependent relations (directed arcs),
 - functional categories (arc labels)
 - possibly some structural categories (parts of speech)

- Phrase (aka constituent) structures explicitly represent
 - phrases (nonterminal nodes),
 - structural categories (nonterminal labels)



Dependency vs Constituency trees





I prefer the morning flight through Denver

Я предпочитаю утренний перелет через Денвер



Languages with free word order

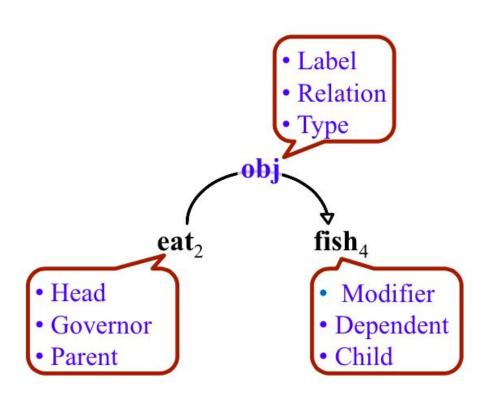
I prefer the morning flight through Denver

Я предпочитаю утренний перелет через Денвер Я предпочитаю через Денвер утренний перелет Утренний перелет я предпочитаю через Денвер Перелет утренний я предпочитаю через Денвер Через Денвер я предпочитаю утренний перелет Я через Денвер предпочитаю утренний перелет

. . .

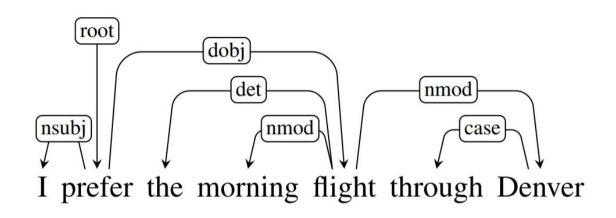


Dependency relations





Types of relationships



- The clausal relations NSUBJ and DOBJ identify the arguments:
 the subject and direct object of the predicate cancel
- The NMOD, DET, and CASE relations denote modifiers of the nouns flights and Houston.



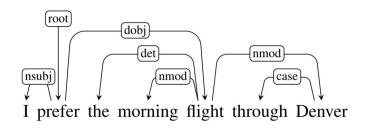
Grammatical functions

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

Figure 13.2 Selected dependency relations from the Universal Dependency set. (de Marneffe et al., 2014)



Dependency Constraints

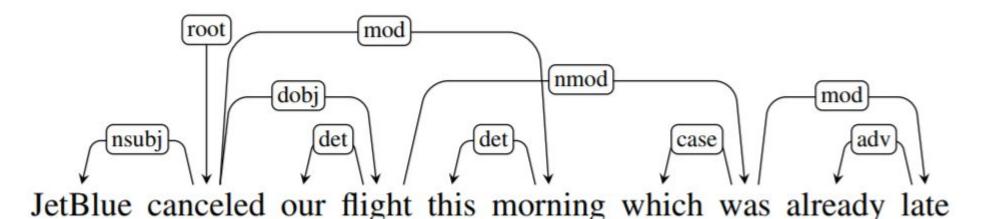


- Syntactic structure is complete (connectedness)
 - connectedness can be enforced by adding a special root node
- Syntactic structure is hierarchical (acyclicity)
 - there is a unique pass from the root to each vertex
- Every word has at most one syntactic head (single-head constraint)
 - except root that does not have incoming arcs

This makes the dependencies a tree

Projectivity

- Projective parse
 - arcs don't cross each other
 - mostly true for English
- Non-projective structures are needed to account for
 - long-distance dependencies
 - flexible word order





Projectivity

- Dependency grammars do not normally assume that all dependency-trees are projective, because some linguistic phenomena can only be achieved using non-projective trees.
- But a lot of parsers assume that the output trees are projective

Reasons

- conversion from constituency to dependency
- the most widely used families of parsing algorithms impose projectivity



Detecting Projectivity/Non-Projectivity

- The idea is to use the inorder traversal of the tree: <left-child, root, right-child>
 - This is well defined for binary trees. We need to extend it to n-ary trees.
- If we have a projective tree, the inorder traversal will give us the original linear order.



Non-Projective Statistics

Arabic: 11.2 %

Bulgarian: 5.4 %

Chinese: 0.0 %

Czech: 23.2 %

Danish: 15.6 %

Dutch: 36.4 %

German: 27.8 %

Japanese: 5.3 %

Polish: 18.9 %

Slovene: 22.2 %

Spanish 1.7 %

Swedish: 9.8 %

Turkish: 11.6 %

English: 0.0% (SD: 0.1%)



Dependency Treebanks

- the major English dependency treebanks converted from the WSJ sections of the PTB (Marcus et al., 1993)
- OntoNotes project (Hovy et al. 2006, Weischedel et al. 2011)
 adds conversational telephone speech, weblogs, usenet
 newsgroups, broadcast, and talk shows in English, Chinese and
 Arabic
- annotated dependency treebanks created for morphologically rich languages such as Czech, Hindi and Finnish, eg Prague Dependency Treebank (Bejcek et al., 2013)
- http://universaldependencies.org/
 - 122 treebanks, 71 languages

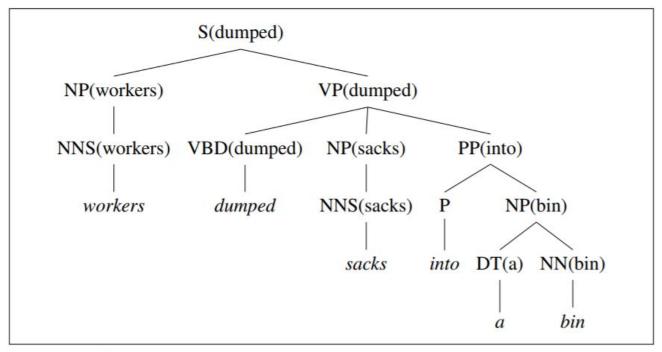


Conversion from constituency to dependency

- Xia and Palmer (2001)
 - mark the head child of each node in a phrase structure, using the appropriate head rules

make the head of each non-head child depend on the head of the

head-child





Parsing problem

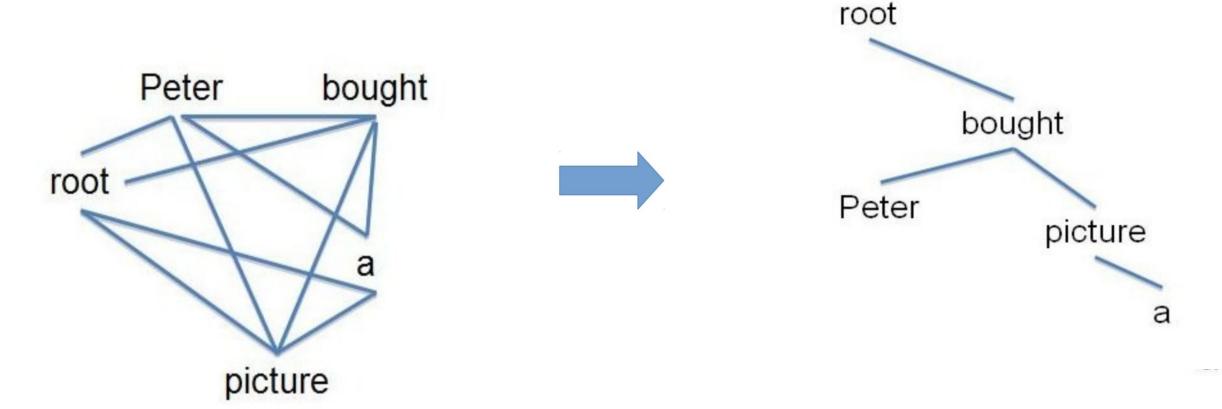
The parsing problem for a dependency parser is to find the optimal dependency tree **y** given an input sentence **x**

This amounts to assigning a syntactic head *i* and a label *I* to every node *j* corresponding to a word *x*, in such a way that the resulting graph is a tree rooted at the node 0



Parsing problem

 This is equivalent to finding a spanning tree in the complete graph containing all possible arcs





Parsing algorithms

Transition based

- greedy choice of local transitions guided by a goodclassifier
- deterministic
- MaltParser (Nivre et al. 2008)

Graph based

- Minimum Spanning Tree for a sentence
- McDonald et al.'s (2005) MSTParser
- Martins et al.'s (2009) Turbo Parser



Transition Based Parsing

- greedy discriminative dependency parser
- motivated by a stack-based approach called shift-reduce parsing originally developed for analyzing programming languages (Aho & Ullman, 1972).
- Nivre 2003

Configuration

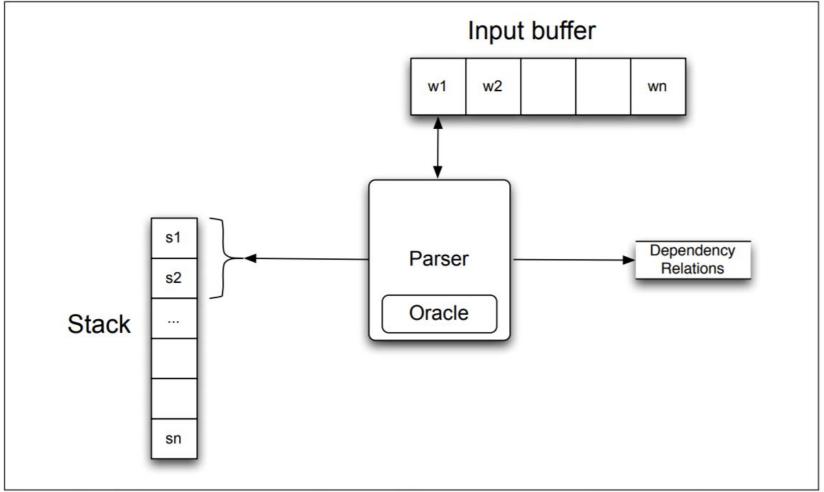
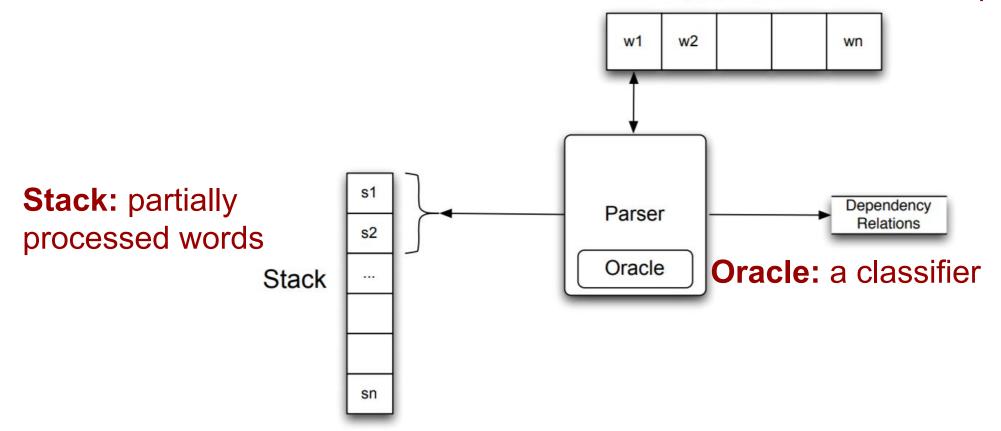


Figure 13.5 Basic transition-based parser. The parser examines the top two elements of the stack and selects an action based on consulting an oracle that examines the current configuration.



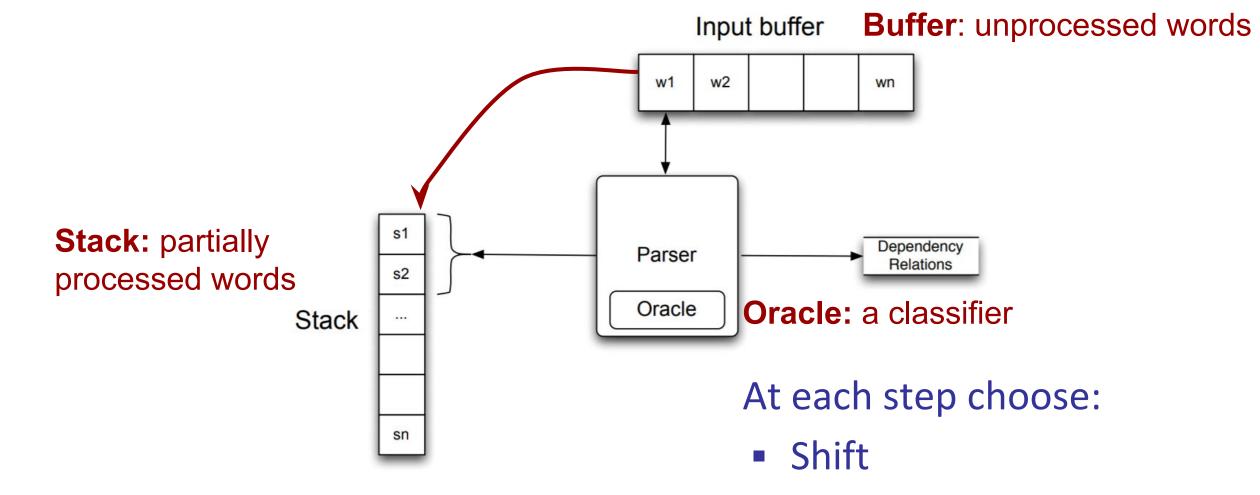
Configuration

Input buffer Buffer: unprocessed words



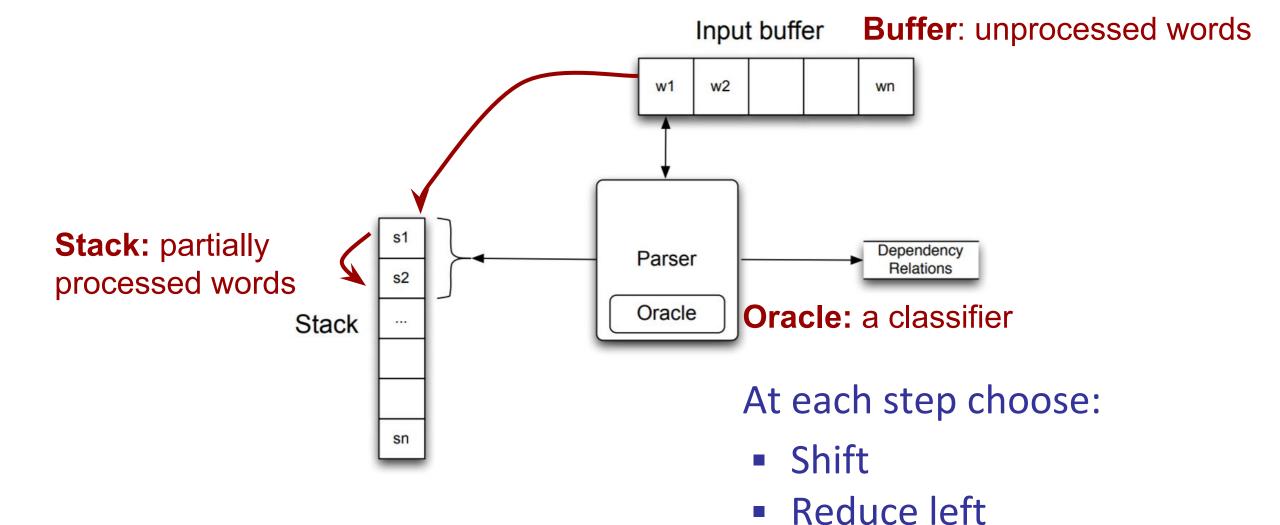


Operations



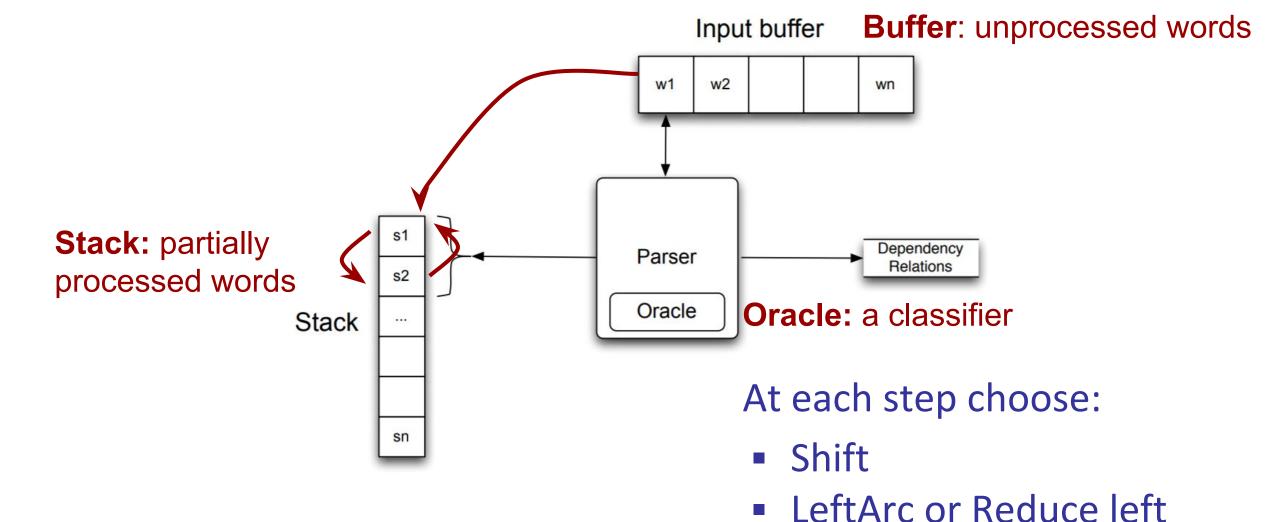


Operations





Operations



RightArc or Reduce right



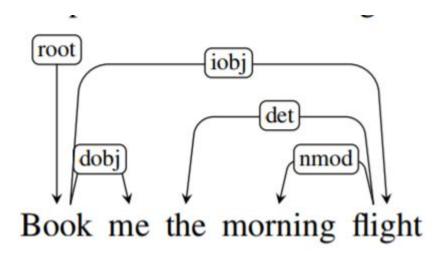
Configuration:

Stack, Buffer, Oracle, Set of dependency relations

Operations by a classifier at each step:

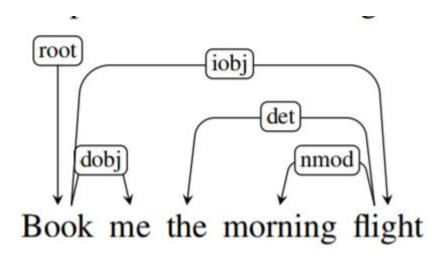
- Shift
 - remove w1 from the buffer, add it to the top of the stack as s1
- LeftArc or Reduce left
 - assert a head-dependent relation between s1 and s2
 - remove s2 from the stack
- RightArc or Reduce right
 - assert a head-dependent relation between s2 and s1
 - remove s1 from the stack





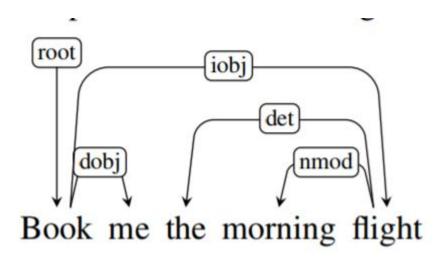
Stack	Word List	Action	Relation Added
[root]	[book, me, the, morning, flight]		
	A Section of the sect	Stack Word List [root] [book, me, the, morning, flight]	





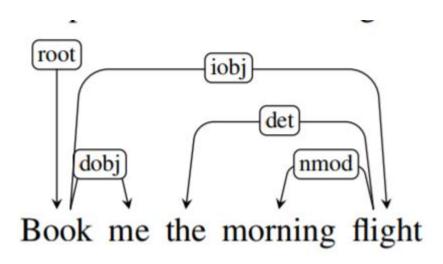
Stack	Word List	Action	Relation Added
[root]	[book, me, the, morning, flight]	SHIFT	
		Stack Word List [root] [book, me, the, morning, flight]	





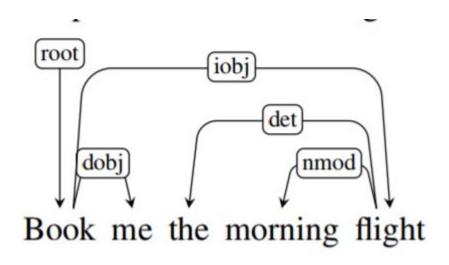
Step	Stack	Word List	Action	Relation Added
0	[root]	[book, me, the, morning, flight]	SHIFT	
1	[root, book]	[me, the, morning, flight]	SHIFT	





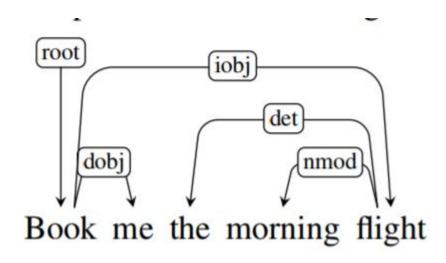
Step	Stack	Word List	Action	Relation Added
0	[root]	[book, me, the, morning, flight]	SHIFT	
1	[root, book]	[me, the, morning, flight]	SHIFT	
2	[root, book, me]	[the, morning, flight]		





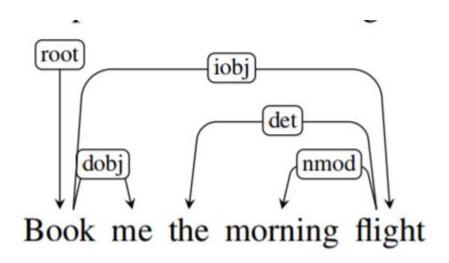
Step	Stack	Word List	Action	Relation Added
0	[root]	[book, me, the, morning, flight]	SHIFT	
1	[root, book]	[me, the, morning, flight]	SHIFT	
2	[root, book, me]	[the, morning, flight]	RIGHTARC	$(book \rightarrow me)$





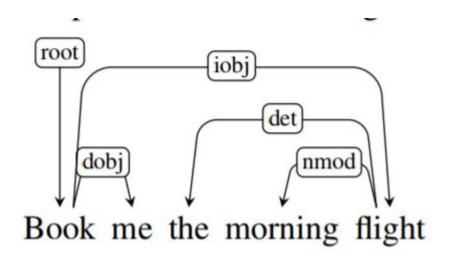
Step	Stack	Word List	Action	Relation Added
0	[root]	[book, me, the, morning, flight]	SHIFT	
1	[root, book]	[me, the, morning, flight]	SHIFT	
2	[root, book, me]	[the, morning, flight]	RIGHTARC	$(book \rightarrow me)$
3	[root, book]	[the, morning, flight]	SHIFT	~





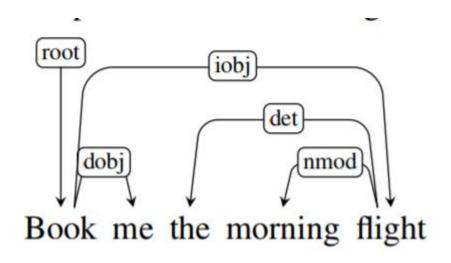
Step	Stack	Word List	Action	Relation Added
0	[root]	[book, me, the, morning, flight]	SHIFT	
1	[root, book]	[me, the, morning, flight]	SHIFT	
2	[root, book, me]	[the, morning, flight]	RIGHTARC	$(book \rightarrow me)$
3	[root, book]	[the, morning, flight]	SHIFT	
4	[root, book, the]	[morning, flight]	SHIFT	





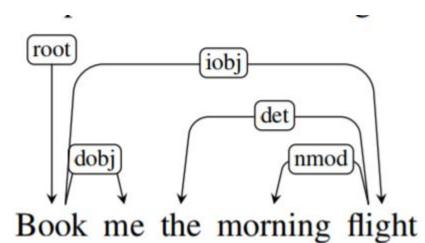
Step	Stack	Word List	Action	Relation Added
0	[root]	[book, me, the, morning, flight]	SHIFT	
1	[root, book]	[me, the, morning, flight]	SHIFT	
2	[root, book, me]	[the, morning, flight]	RIGHTARC	$(book \rightarrow me)$
3	[root, book]	[the, morning, flight]	SHIFT	
4	[root, book, the]	[morning, flight]	SHIFT	
5	[root, book, the, morning]	[flight]	SHIFT	





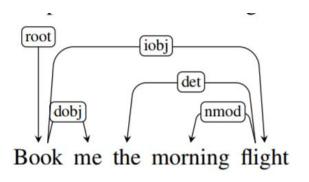
Step	Stack	Word List	Action	Relation Added
0	[root]	[book, me, the, morning, flight]	SHIFT	
1	[root, book]	[me, the, morning, flight]	SHIFT	
2	[root, book, me]	[the, morning, flight]	RIGHTARC	$(book \rightarrow me)$
3	[root, book]	[the, morning, flight]	SHIFT	
4	[root, book, the]	[morning, flight]	SHIFT	
5	[root, book, the, morning]	[flight]	SHIFT	
6	[root, book, the, morning, flight]		LEFTARC	$(morning \leftarrow flight)$





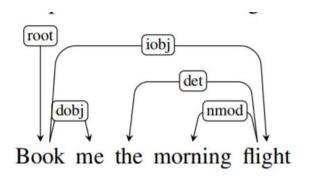
Step	Stack	Word List	Action	Relation Added
0	[root]	[book, me, the, morning, flight]	SHIFT	
1	[root, book]	[me, the, morning, flight]	SHIFT	
2	[root, book, me]	[the, morning, flight]	RIGHTARC	$(book \rightarrow me)$
3	[root, book]	[the, morning, flight]	SHIFT	
4	[root, book, the]	[morning, flight]	SHIFT	
5	[root, book, the, morning]	[flight]	SHIFT	
6	[root, book, the, morning, flight]		LEFTARC	$(morning \leftarrow flight)$
7	[root, book, the, flight]		LEFTARC	$(the \leftarrow flight)$





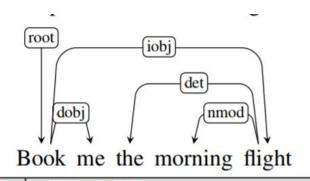
Step	Stack	Word List	Action	Relation Added
0	[root]	[book, me, the, morning, flight]	SHIFT	
1	[root, book]	[me, the, morning, flight]	SHIFT	
2	[root, book, me]	[the, morning, flight]	RIGHTARC	$(book \rightarrow me)$
3	[root, book]	[the, morning, flight]	SHIFT	
4	[root, book, the]	[morning, flight]	SHIFT	
5	[root, book, the, morning]	[flight]	SHIFT	
6	[root, book, the, morning, flight]		LEFTARC	$(morning \leftarrow flight)$
7	[root, book, the, flight]		LEFTARC	$(the \leftarrow flight)$
8	[root, book, flight]		RIGHTARC	$(book \rightarrow flight)$





Step	Stack	Word List	Action	Relation Added
0	[root]	[book, me, the, morning, flight]	SHIFT	
1	[root, book]	[me, the, morning, flight]	SHIFT	
2	[root, book, me]	[the, morning, flight]	RIGHTARC	$(book \rightarrow me)$
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]		LEFTARC	$(morning \leftarrow flight)$
7	[root, book, the, flight]		LEFTARC	$(the \leftarrow flight)$
8	[root, book, flight]		RIGHTARC	$(book \rightarrow flight)$
9	[root, book]		RIGHTARC	$(\text{root} \rightarrow \text{book})$





Step	Stack	Word List	Action	Relation Added
0	[root]	[book, me, the, morning, flight]	SHIFT	
1	[root, book]	[me, the, morning, flight]	SHIFT	
2	[root, book, me]	[the, morning, flight]	RIGHTARC	$(book \rightarrow me)$
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]		LEFTARC	$(morning \leftarrow flight)$
7	[root, book, the, flight]		LEFTARC	$(the \leftarrow flight)$
8	[root, book, flight]		RIGHTARC	$(book \rightarrow flight)$
9	[root, book]		RIGHTARC	$(root \rightarrow book)$
10	[root]		Done	



Configuration:

Stack, Buffer, Oracle, Set of dependency relations

Operations by a classifier at each step:

Complexity?

- Shift
 - remove w1 from the buffer, add it to the top of the stack as s1
- LeftArc or Reduce left
 - assert a head-dependent relation between Oracle decisions can
 - remove s2 from the stack
- RightArc or Reduce right
 - assert a head-dependent relation between s2 and s1
 - remove s1 from the stack

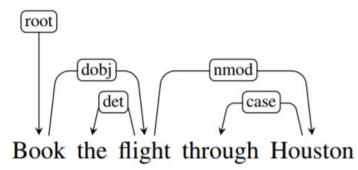
Oracle decisions can correspond to unlabeled or labeled arcs



- Oracle is a supervised classifier that learns a function from the configuration to the next operation
- How to extract the training set?



- How to extract the training set?
 - if LeftArc → LeftArc
 - if RightArc
 - if s1 dependents have been processed → RightArc
 - else \rightarrow Shift





root

nmod

Book the flight through Houston

- How to extract the training set?
 - if LeftArc → LeftArc
 - if RightArc
 - if s1 dependents have been processed → RightArc
 - else \rightarrow Shift

Step	Stack	Word List	Predicted Action
0	[root]	[book, the, flight, through, houston]	SHIFT
1	[root, book]	[the, flight, through, houston]	SHIFT
2	[root, book, the]	[flight, through, houston]	SHIFT
3	[root, book, the, flight]	[through, houston]	LEFTARC
4	[root, book, flight]	[through, houston]	SHIFT
5	[root, book, flight, through]	[houston]	SHIFT
6	[root, book, flight, through, houston]		LEFTARC
7	[root, book, flight, houston]		RIGHTARC
8	[root, book, flight]		RIGHTARC
9	[root, book]	П	RIGHTARC

- Oracle is a supervised classifier that learns a function from the configuration to the next operation
- How to extract the training set?
 - if LeftArc → LeftArc
 - if RightArc
 - if s1 dependents have been processed → RightArc
 - else \rightarrow Shift
- What features to use?



Features

- POS, word-forms, lemmas on the stack/buffer
- morphological features for some languages
- previous relations
- conjunction features (e.g. Zhang&Clark'08; Huang&Sagae'10; Zhang&Nivre'11)

Source	Feature templates		
One word	s ₁ .w	<i>s</i> ₁ . <i>t</i>	s ₁ .wt
	s ₂ .w	s ₂ .t	s ₂ .wt
	$b_1.w$	$b_1.w$	$b_0.wt$
Two word	$s_1.w \circ s_2.w$	$s_1.t \circ s_2.t$	$s_1.t \circ b_1.w$
	$s_1.t \circ s_2.wt$	$s_1.w \circ s_2.w \circ s_2.t$	$s_1.w \circ s_1.t \circ s_2.t$
	$s_1.w \circ s_1.t \circ s_2.t$	$s_1.w \circ s_1.t$	

$$\langle s_1.w = flights, op = shift \rangle$$

 $\langle s_2.w = canceled, op = shift \rangle$
 $\langle s_1.t = NNS, op = shift \rangle$
 $\langle s_2.t = VBD, op = shift \rangle$
 $\langle b_1.w = to, op = shift \rangle$
 $\langle b_1.t = TO, op = shift \rangle$

$$\langle s_1.wt = flightsNNS, op = shift \rangle$$

$$\langle s_1.t \circ s_2.t = NNSVBD, op = shift \rangle$$

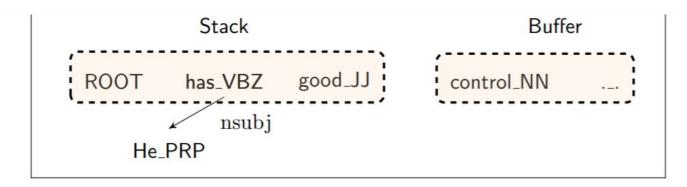


Learning

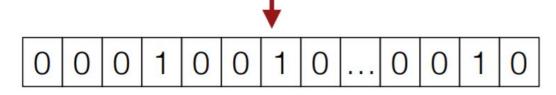
Before 2014: SVMs,

After 2014: Neural Nets





binary, sparse dim = $10^6 \sim 10^7$



Indicator features

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

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

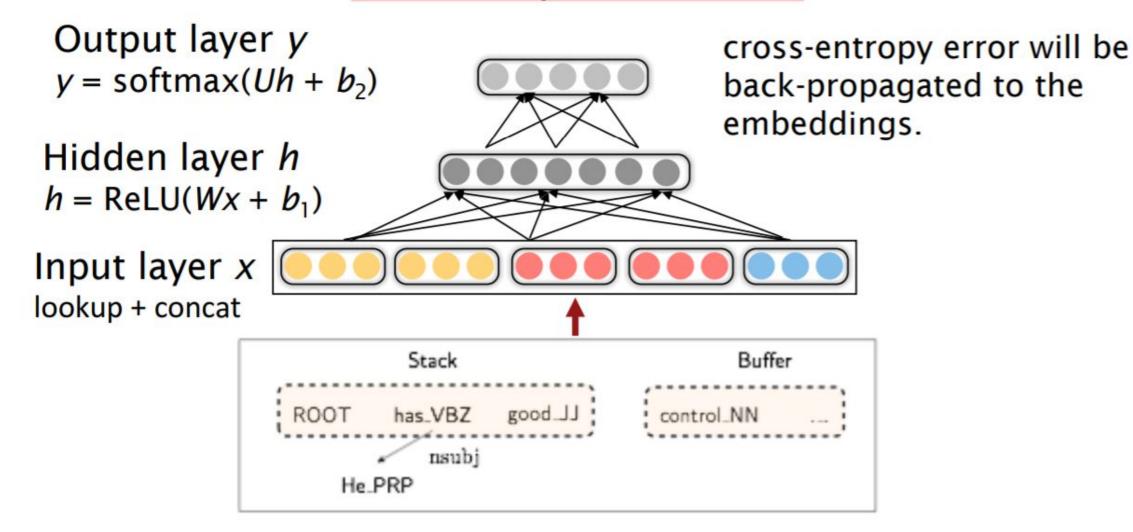
$$lc(s_2).t = \text{PRP} \land s_2.t = \text{VBZ} \land s_1.t = \text{JJ}$$

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

Slides by Danqi Chen & Chris Manning



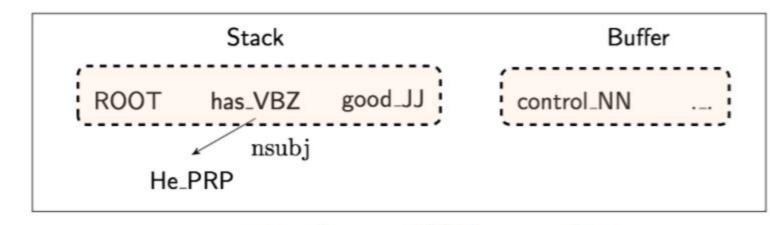
Softmax probabilities

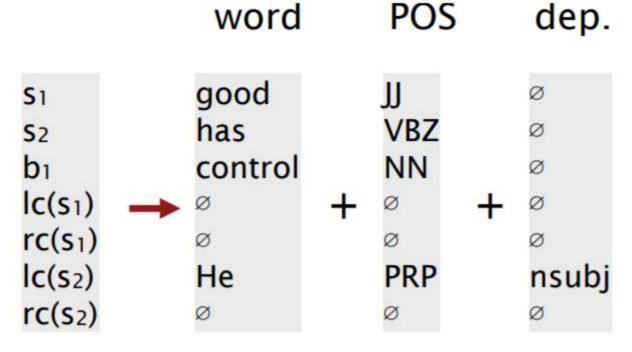




Features

- s1, s2, s3, b1, b2, b3
- leftmost/rightmost children of s1 and s2
- leftmost/rightmost grandchildren of s1 and s2
- POS tags for the above
- arc labels for children/grandchildren





Evaluation of Dependency Parsers

 $\frac{\#correct\ dependencies}{\#of\ dependencies}$

- LAS labeled attachment score
- UAS unlabeled attachment score



Parser	UAS	LAS	sent. / s
MaltParser	89.8	87.2	469
MSTParser	91.4	88.1	10
TurboParser	92.3*	89.6*	8
C & M 2014	92.0	89.7	654



Follow-up

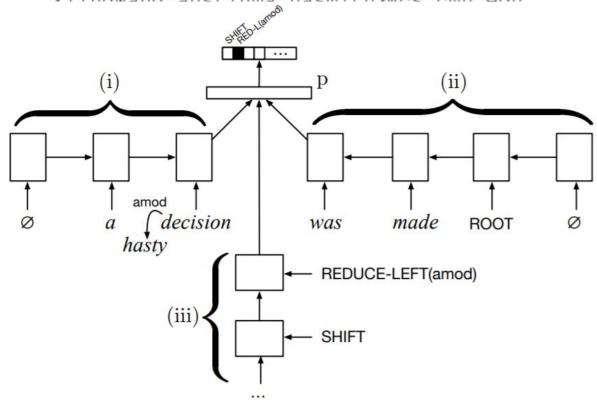
Method	UAS	LAS (PTB WSJ SD 3.3
Chen & Manning 2014	92.0	89.7
Weiss et al. 2015	93.99	92.05
Andor et al. 2016	94.61	92.79



Stack LSTMs (Dyer et al. 2015)

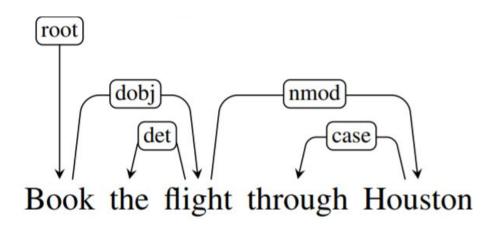
Transition-Based Dependency Parsing with Stack Long Short-Term Memory

Chris Dyer ♣♠ Miguel Ballesteros ♦♠ Wang Ling ♠ Austin Matthews ♠ Noah A. Smith ♠ Marianas Labs ♦ NLP Group, Pompeu Fabra University ♠ Carnegie Mellon University chris@marianaslabs.com, miguel.ballesteros@upf.edu,





Arc-Eager



- LEFTARC: Assert a head-dependent relation between s1 and b1; pop the stack.
- RIGHTARC: Assert a head-dependent relation between s1 and b1; shift b1 to be s1.
- SHIFT: Remove b1 and push it to be s1.
- REDUCE: Pop the stack.



Arc-Eager

Step	Stack Word List		Action	Relation Added
0	[root]	[book, the, flight, through, houston]	RIGHTARC	$(root \rightarrow book)$
1	[root, book]	[the, flight, through, houston]	SHIFT	
2	[root, book, the]	[flight, through, houston]	LEFTARC	$(the \leftarrow flight)$
3	[root, book]	[flight, through, houston]	RIGHTARC	$(book \rightarrow flight)$
4	[root, book, flight]	[through, houston]	SHIFT	
5	[root, book, flight, through]	[houston]	LEFTARC	$(through \leftarrow houston)$
6	[root, book, flight]	[houston]	RIGHTARC	$(flight \rightarrow houston)$
7	[root, book, flight, houston]		REDUCE	
8	[root, book, flight]		REDUCE	
9	[root, book]		REDUCE	
10	[root]		Done	

Beam Search

function DEPENDENCYBEAMPARSE(words, width) returns dependency tree

```
state \leftarrow \{[root], [words], [], 0.0\}; initial configuration
 agenda \leftarrow \langle state \rangle;
                           initial agenda
  while agenda contains non-final states
    newagenda \leftarrow \langle \rangle
    for each state \in agenda do
        for all \{t \mid t \in VALIDOPERATORS(state)\}\ do
          child \leftarrow APPLY(t, state)
          newagenda \leftarrow ADDTOBEAM(child, newagenda, width)
    agenda ← newagenda
  return BESTOF(agenda)
function ADDTOBEAM(state, agenda, width) returns updated agenda
 if LENGTH(agenda) < width then
      agenda \leftarrow INSERT(state, agenda)
  else if SCORE(state) > SCORE(WORSTOF(agenda))
      agenda \leftarrow REMOVE(WORSTOF(agenda))
      agenda \leftarrow INSERT(state, agenda)
  return agenda
```



Parsing algorithms

Transition based

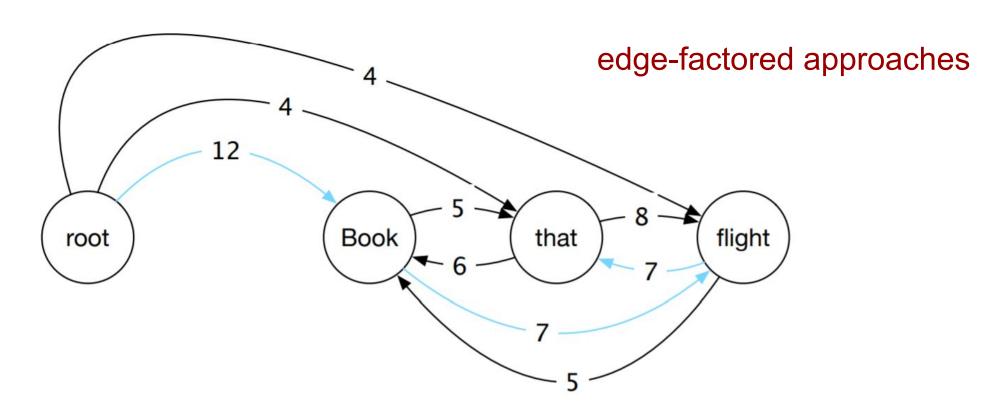
- greedy choice of local transitions guided by a goodclassifier
- deterministic
- MaltParser (Nivre et al. 2008), Stack LSTM (Dyer et al. 2015)

Graph based

- Minimum Spanning Tree for a sentence
- non-projective
- globally optimized
- McDonald et al.'s (2005) MSTParser
- Martins et al.'s (2009) Turbo Parser



Graph-Based Parsing Algorithms



- Start with a fully-connected directed graph
- Find a Minimum Spanning Tree
 - Chu and Liu (1965) and Edmonds (1967) algorithm

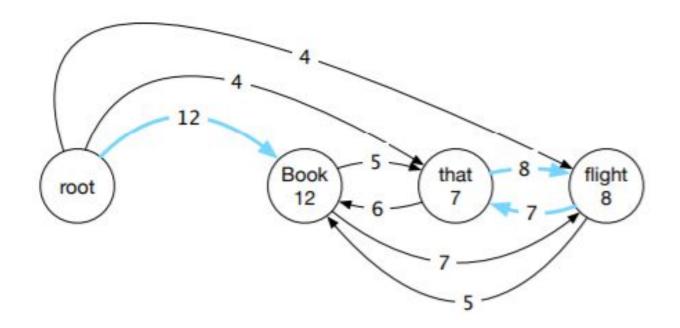


function MAXSPANNINGTREE(G=(V,E), root, score) **returns** spanning tree

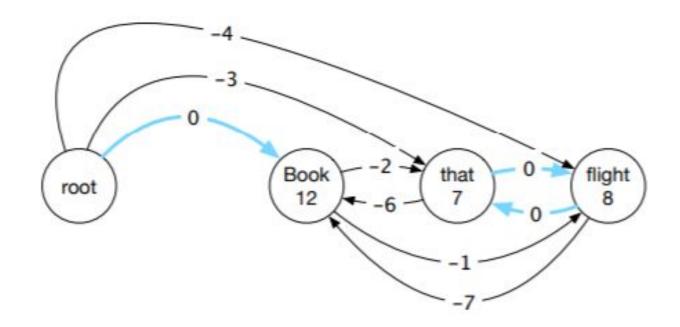
```
F \leftarrow []
   T'\leftarrow[]
   score' \leftarrow \square
   for each v \in V do
                                                         Select best incoming edge for each node
     bestInEdge \leftarrow argmax_{e=(u,v) \in E} score[e]
     F \leftarrow F \cup bestInEdge
     for each e=(u,v) \in E do
                                                           Subtract its score from all incoming edges
        score'[e] \leftarrow score[e] - score[bestInEdge]
     if T=(V,F) is a spanning tree then return it
                                                                  Stopping condition
     else
        C \leftarrow a cycle in F
                                                             Contract nodes if there are cycles
        G' \leftarrow \text{CONTRACT}(G, C)
        T' \leftarrow \text{MAXSPANNINGTREE}(G', root, score')
                                                                       Recursively compute MST
        T \leftarrow EXPAND(T', C)
        return T
                                                                      Expand contracted nodes
function CONTRACT(G, C) returns contracted graph
```

function EXPAND(T, C) **returns** *expanded graph*

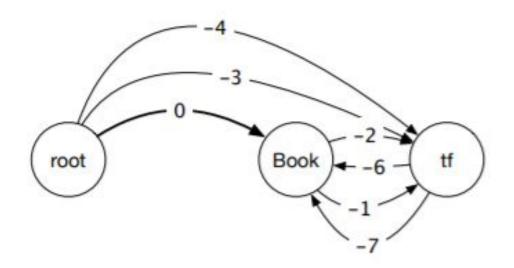
Select best incoming edge for each node



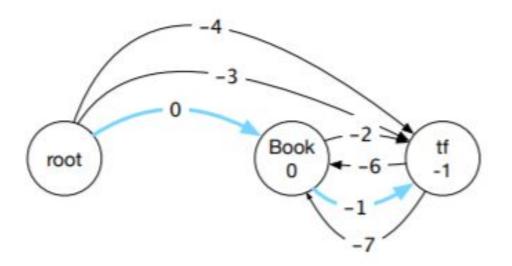
Subtract its score from all incoming edges



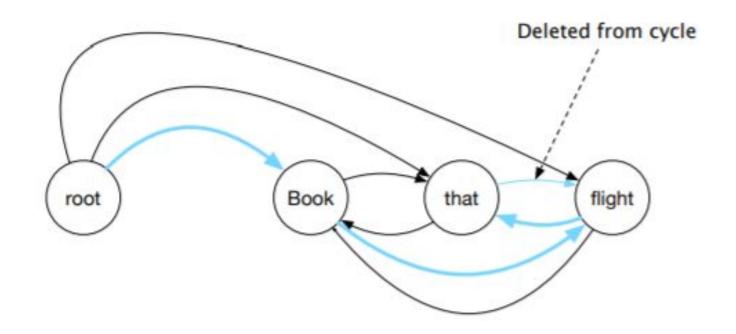
Contract nodes if there are cycles



Recursively compute MST



Expand contracted nodes



Scores

$$score(S,e) = w \cdot f$$

- Wordforms, lemmas, and parts of speech of the headword and its dependent.
- Corresponding features derived from the contexts before, after and between the words.
- Word embeddings.
- The dependency relation itself.
- The direction of the relation (to the right or left).
- The distance from the head to the dependent.

Summary

- Transition-based
 - + Fast
 - + Rich features of context
 - Greedy decoding
- Graph-based
 - + Exact or close to exact decoding
 - Weaker features

Well-engineered versions of the approaches achieve comparable accuracy (on English), but make different errors

→ combining the strategies results in a substantial boost in performance