Natural Language Processing

Lecture 6
Dependency parsing

2021

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The dependency parsing task

Syntactic parsing (refresher)

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Syntactic theories aim to characterize

> "the set of rules or principles that govern how words are put together to form phrases, well formed sequences of words." [Koopman et al., 2013, 1]

The most important "well formed sequences" in this context are *sentences*: the central goal of syntactic theories for a given language is to find structural rules or principles that characterize/delineate well formed sentences of the language in question.

Syntactic parsing cont.

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A sentence is well formed if it has a *structural description* or *syntactic parse* which satisfies the syntactic constraints of the theory in question. Syntactic well formedness doesn't guarantee coherence or meaningfulness. To use Chomsky's famous example:

Colorless green ideas sleep furiously.

is syntactically well formed but nonsensical, while

Furiously sleep ideas green colorless.

is not even well formed.

Dependency grammars (refresher)

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Dependency grammars treat the *dependency relation* between words as fundamental.

The precise criteria vary from theory to theory, but typically a d word depends on a h word (equivalently, h heads d) in a sentence if

- d modifies the meaning of h, makes it more specific, e.g. *eats* $\Rightarrow$ *eats bread*, *eats slowly* etc.
- and there is an asymmetric relationship of omissibility between them: d can be omitted from the sentence keeping h but not vice versa.

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Dependency grammars impose important global constraints on the dependency relations within a well formed sentence, e.g.,

- There is exactly one independent word (the root of the sentence).
- All other words depend directly on exactly one word.

As a consequence of the constraints, the direct dependency graph of a sentence is a tree.
Most dependency grammars work with *typed direct dependencies*: there is finite list of direct dependency types with specific constraints on when they can hold.

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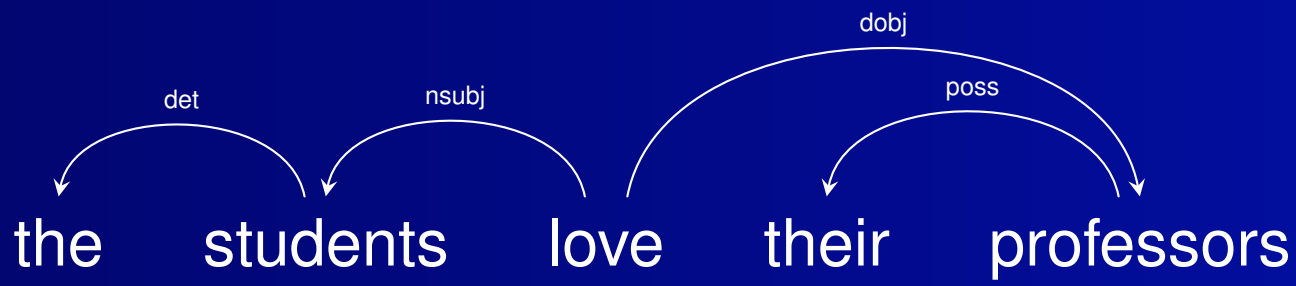
A dependency parse tree of the earlier example:



Compared to the constituency tree, it contains fewer nodes (one per word), but the edges are labeled with the corresponding dependency types.

Projectivity

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An important (not always satisfied) requirement on dependency parse trees is *projectivity*:

> If a w word depends directly on h and a w' word lies between them in the sentence's word order, then the head of this w' is either w or h, or another word between them.

Less formally, the projectivity condition states that dependencies are *nested*, there cannot be *crossing* dependencies between words.

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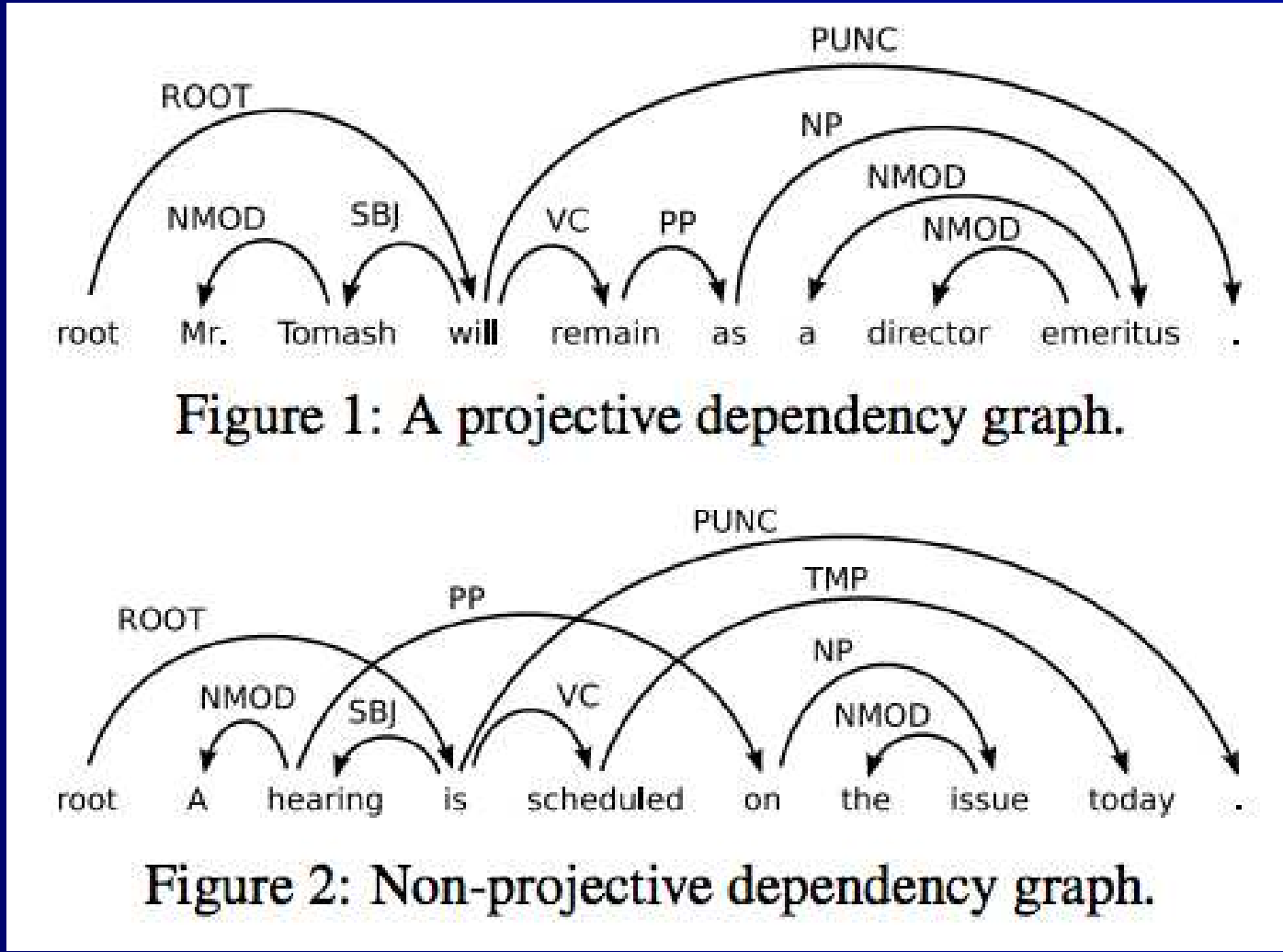

Figure 1: A projective dependency graph.

Figure 2: Non-projective dependency graph.

(Figure from Language Log: Non-projective flavor.)

The advantages of dependency grammars

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Dependency grammars are becoming the dominant syntactic theory used in NLP, since

- dependency trees are in many respect simpler structures than phrase structure parse trees (e.g., have only one node per word);
- the predicate-argument analysis of sentences provided by dependency graphs is a very good starting point for event or frame-oriented semantic analysis.

Usability for semantic representation

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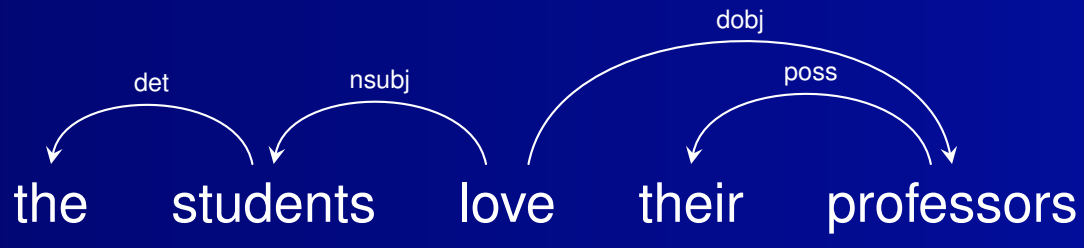
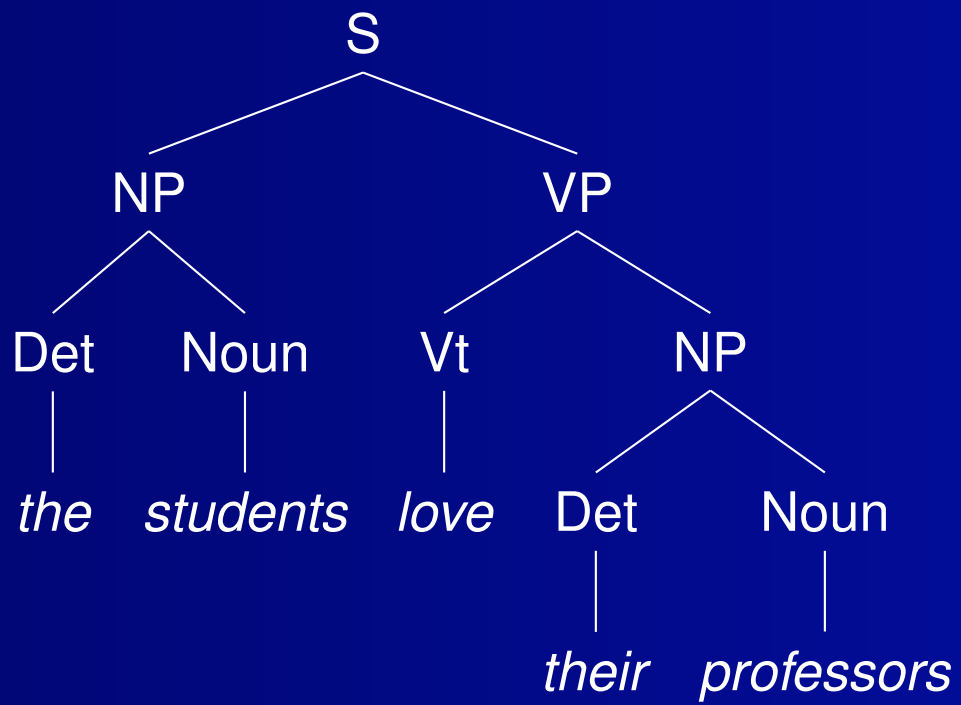
Compare, for event-semantic aspects





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Given a syntactic theory, the parsing task is to assign syntactic structure to input sentences which satisfy the constraints/conditions of the theory. For dependency grammars, this means assigning a *dependency structure*:

- identifying direct dependencies between words of the sentence,
- in such a way that together they constitute a *dependecy tree* which satisfies all of the the theory's constraints.

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In modern NLP practice, the dependency grammar underlying a parsing task is typically specified implicitly, using a so called *treebank*, that is, a dataset consisting of sentences annotated with their parse trees.

This makes parsing a *structured supervised learning task*: given a training set consisting of a large number of $\langle \text{sentence}, \text{parse tree} \rangle$ pairs, learn to predict the parse tree of unseen sentences.

Performance metrics

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For dependency grammar parsers, the most commonly used evaluation metrics are

- *UAS (Unlabeled Attachment Score):* The percentage of words that are attached to the correct head.
- *LAS (Labeled Attachment Score):* The percentage of words that are attached to the correct head with the correct dependency label.

Parsing algorithms

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Like most sequence tagging approaches, dependency parsing algorithms use the strategy of breaking down the prediction task into individual decisions over elements of the structure. In this case,

- the individual decisions are about individual dependencies between words, and
- the central problem is to ensure that the individual decisions lead to a coherent dependency tree.

Dependency parsers typically use either a

- *transition-based*, or
- *graph-based* approach.

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Transition-based parsing

The transition-based approach

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The algorithm is based on a formal model of a parsing process which moves from left to right in the sentence to be parsed and at every step chooses one of the following actions:

- "assign the current word as the head of some previously seen word,
- assign some previously seen word as the head of the current word,
- or postpone doing anything with the current word, adding it to a store for later processing."[1]

[1] Jurafsky and Martin [2019, ch. 15].

The transition-based approach

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The formal model of this process consists of the following component:

- a *buffer*, in which the unprocessed tokens of the input are contained;
- a *stack* containing tokens for current operation and storing postponed elements;
- a *dependency graph*, which is being built for the input sentence.

Model configuration

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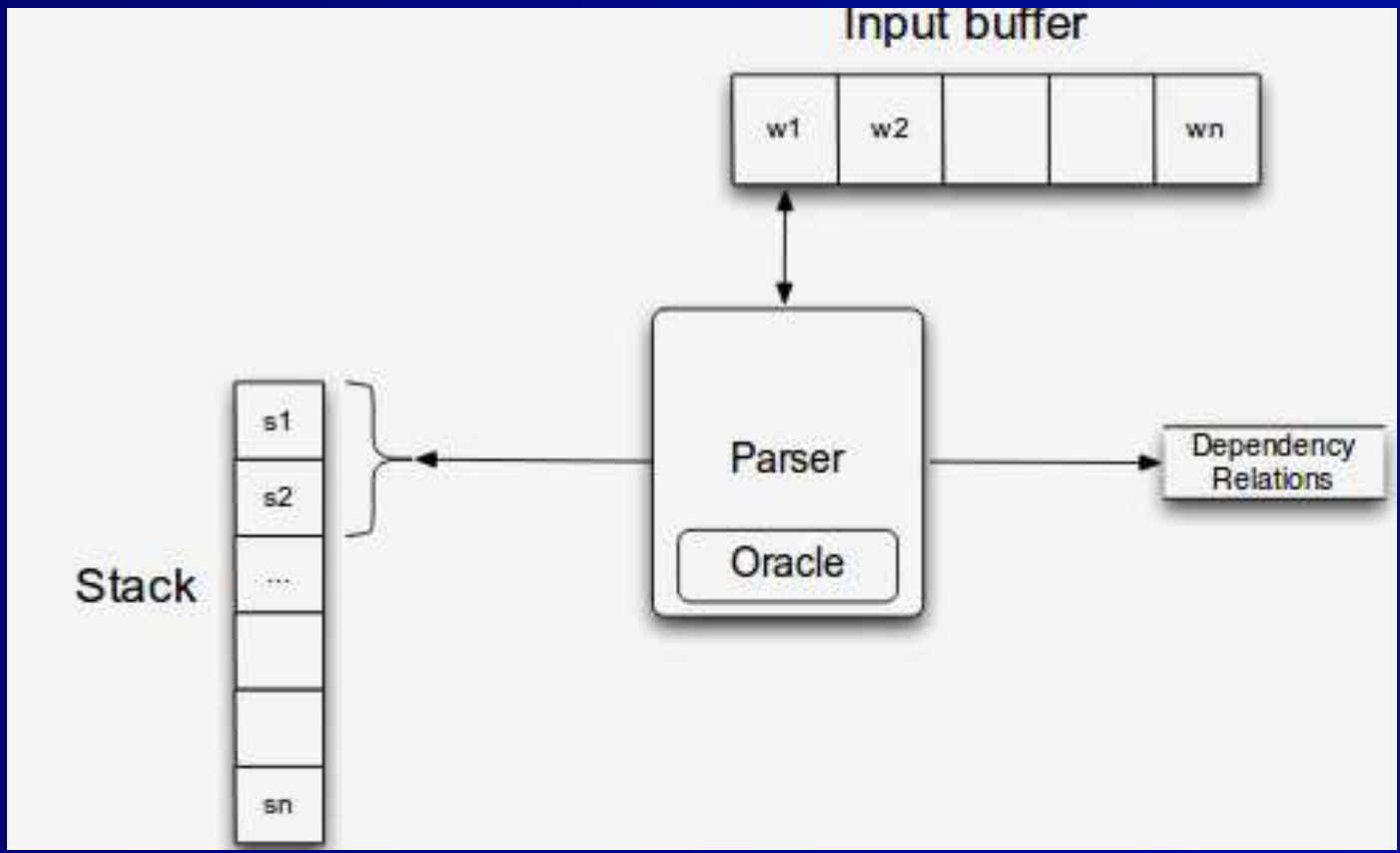
The model is in a certain *configuration* at every step of the process:



(Figure from Jurafsky and Martin [2019, ch. 15].)

Initial configuration

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The parsing process starts with the special initial configuration in which

- the buffer contains all words of the input,
- the stack contains the single root node of the dependency graph,
- and the dependency graph is empty (contains no dependency edges).

Parsing process

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At every step, one of the permitted configuration manipulating actions (configuration transitions) are performed. The permitted actions vary; a very simple set of actions is used in the so called *arc standard* approach:

- *left arc with label* l: add edge $s_2 \overset{l}{\leftarrow} s_1$ to the graph and remove s_2 (s_2 cannot be the root element);
- *right arc with label* l: add edge $s_2 \overset{l}{\rightarrow} s_1$ to the graph and remove s_1 (s_1 cannot be the root element);
- *shift*: remove the first word w_1 from the buffer and put it on the top of the stack.

The process ends when a configuration is reached in which none of the actions can be performed.

Parsing process cont.

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The process is guaranteed to end after a finite number of steps, in a configuration in which the buffer is empty and the created dependency graph is a well-formed dependency tree for the whole input:

- it ends because at every step we decrease the total number of tokens in the buffer and the stack;
- the buffer must be empty because otherwise the shift action would be available, and the stack can contain only the root element for similar reasons;
- each input token has exactly one head in the graph;
- there cannot be a *circle* in the graph.

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An example run from Jurafsky and Martin [2019, ch. 16]:

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 → 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 ← flight)
7	[root, book, the, flight]	[]	LEFTARC	(the ← flight)
8	[root, book, flight]	[]	RIGHTARC	(book → flight)
9	[root, book]	[]	RIGHTARC	(root → book)
10	[root]	[]	Done	

Figure 14.7 Trace of a transition-based parse.

Choosing the right action

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How does a parser decide which action to choose? The model has to act as a *classifier over possible configurations*: if there are n labels, then there will be $2n + 1$ actions/classes.

To have training data for this classifier, dependency treebank annotations have to be turned into supervised datasets containing

$$\langle \text{parser configuration}, \text{correct action} \rangle$$

pairs, i.e., treebanks have to be turned into datasets about the actions of a "*parsing oracle*", which always chooses the right action.

Converting a parse tree “to oracle actions”

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Given the correct parse tree, the configurations and actions of the *oracle* can be reconstructed using a straightforward algorithm:

- (obviously) start with the stack containing only the root and a buffer with the full input;
- choose the *left arc* action with the correct label if it leads to a correct edge,
- else choose the *right arc* action with the correct label if (i) it leads to a correct edge (ii) all dependencies with s_1 as head were already added to to the dependency graph;
- otherwise choose shift.

Alternative action/transitions sets

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Arc-standard is not the only transition system used for transition-based parsers – an important alternative is *arc-eager*, which can radically simplify some derivations. Arc-eager has the following actions:

- *Right-arc*: add edge $s_1 \xrightarrow{l} w_1$ and move w_1 to the top of the stack.
- *Left-arc*: add edge $s_1 \xleftarrow{l} w_1$ and remove w_1 from the buffer. Precondition: s_1 does not have a head yet.
- *Shift*: move w_1 to the top of the stack.
- *Reduce*: remove s_1 from the stack. Precondition: s_1 already has a head.

The problem of non-projectivity

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Arc-standard and arc-eager transitions can produce only projective trees, but most treebanks contain a sizeable amount of non-projective sentences:

Language	Trees	Arcs
Arabic [Hajič et al. 2004]	11.2%	0.4%
Basque [Aduriz et al. 2003]	26.2%	2.9%
Czech [Hajič et al. 2001]	23.2%	1.9%
Danish [Kromann 2003]	15.6%	1.0%
Greek [Prokopidis et al. 2005]	20.3%	1.1%
Russian [Boguslavsky et al. 2000]	10.6%	0.9%
Slovene [Džeroski et al. 2006]	22.2%	1.9%
Turkish [Oflazer et al. 2003]	11.6%	1.5%

(Table from Nivre [2013].)

Non-projectivity: solutions

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- Use transition systems that can create (a certain amount of) non-projective edges.
- *Pseudo-projective parsing*:
  - find a φ mapping between all relevant (projective + non-projective) trees and projective ones;
  - for training, the training set is "projectivized" using φ, and the parser is trained on the transformed dataset;
  - for prediction/inference, φ^{-1} is applied to the parser's output to get the final (possibly non-projective) result.[2]

[2] See, e.g., Nivre and Nilsson [2005] for details.

Classifier features

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Proper feature extraction from configurations is important for performance. Traditional (e.g., perceptron-based) solutions used complex, expert-engineered feature templates, e.g.,

Type	Features		
Unigram	s_t	$T(s_t)$	$s_t \circ T(s_t)$
	s_{t-1}	$T(s_{t-1})$	$s_{t-1} \circ T(s_{t-1})$
	w_i	$T(w_i)$	$w_i \circ T(w_i)$
Bigram	$s_t \circ s_{t-1}$	$T(s_t) \circ T(s_{t-1})$	$T(s_t) \circ T(w_i)$
	$T(s_t) \circ s_{t-1} \circ T(s_{t-1})$	$s_t \circ s_{t-1} \circ T(s_{t-1})$	$s_t \circ T(s_t) \circ T(s_{t-1})$
	$s_t \circ T(s_t) \circ s_{t-1}$	$s_t \circ T(s_t) \circ s_{t-1} \circ T(s_{t-1})$	
Trigram	$T(s_t) \circ T(w_i) \circ T(w_{i+1})$	$T(s_{t-1}) \circ T(s_t) \circ T(w_i)$	$T(s_{t-2}) \circ T(s_{t-1}) \circ T(s_t)$
	$s_t \circ T(w_i) \circ T(w_{i+1})$	$T(s_{t-1}) \circ s_t \circ T(w_i)$	
Modifier	$T(s_{t-1}) \circ T(lc(s_{t-1})) \circ T(s_t)$	$T(s_{t-1}) \circ T(rc(s_{t-1})) \circ T(s_t)$	$T(s_{t-1}) \circ T(s_t) \circ T(lc(s_t))$
	$T(s_{t-1}) \circ T(s_t) \circ T(rc(s_t))$	$T(s_{t-1}) \circ T(lc(s_{t-1})) \circ s_t$	$T(s_{t-1}) \circ T(rc(s_{t-1})) \circ s_t$
	$T(s_{t-1}) \circ s_t \circ T(lc(s_t))$		

Table 2: Feature templates of the baseline parser. s_t, s_{t-1} denote the top and next to top words on the stack; w_i and w_{i+1} denote the current and next words on the queue. $T(\cdot)$ denotes the POS tag of a given word, and $lc(\cdot)$ and $rc(\cdot)$ represent the leftmost and rightmost child. Symbol $\circ$ denotes feature conjunction. Each of these templates is further conjoined with the 3 actions shift, reduce_L, and reduce_R.

(Table from Huang et al. [2009].)

Classifier features cont.

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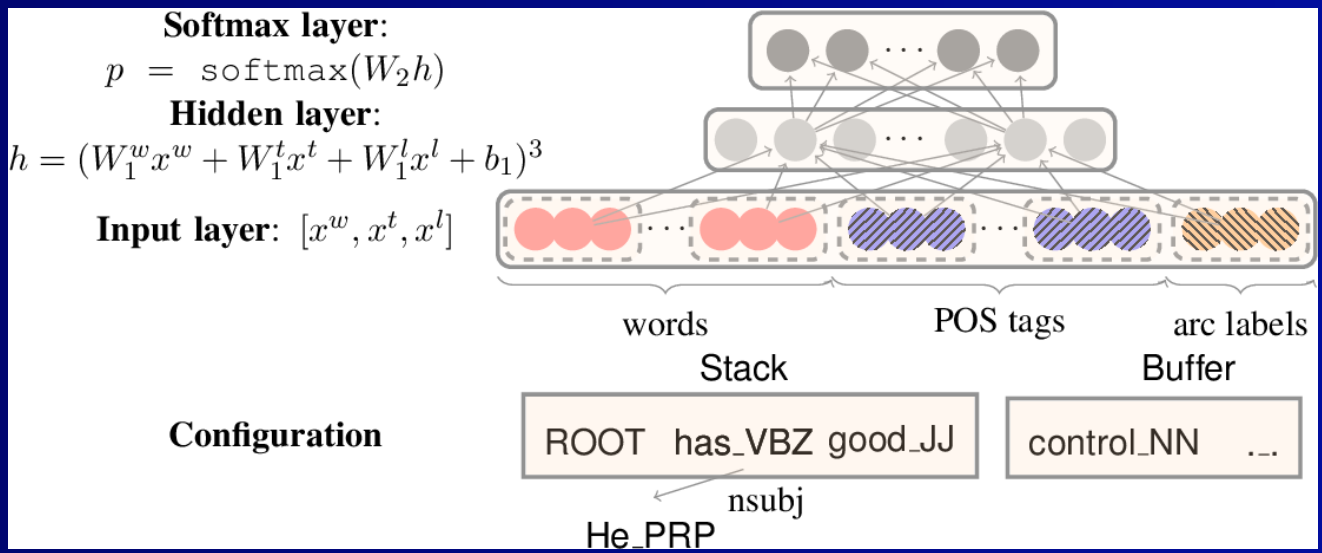
As in other areas, the problems with manual feature engineering and data sparsity led to the development of deep learning solutions, which rely on *embeddings* for classification. The Stanford neural dependency parser is a simple but representative example:



(Figure from from Chen and Manning [2014].)

Architectures

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The used model architectures are the typical classification architectures used in NLP:

- Before the emergence of DL-based parsers, mainly linear models were used (with weighted perceptron or SVM as the learning algorithm), but k-NN-based solutions also existed.
- In deep learning, CNN and LSTM-based models were dominant before the appearance of transformer-based solutions, which rely heavily on pretrained contextual embeddings such as BERT.

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The graph-based approach

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Two contrasting ways of scoring parse trees:

- The *transition-based* approach transforms the problem of scoring a dependency-graph into scoring the *steps* of a somewhat complicated *graph building process*.
- *Graph-based* parsers, in contrast, score directly the graphs themselves and try to find the dependency graph with the maximal score:

$$\hat{g} = \underset{g \in G}{\operatorname{argmax}}\, S(g)$$

The graph-based approach cont.

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A simple but surprisingly well performing approach is to

- score all the possible edges individually (this requires scoring $n(n-1)l$ directed edges if there are n tokens and l labels), and then
- find the (correctly directed) tree with the largest sum total score.

The assumption is simply that

$$S(g) = \sum_{e \in g} S(e).$$

This way of scoring a graph is called the *edge-* or *arc-factored* approach.

Finding the tree with the maximal score

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A brute-force search over all possible graphs would be obviously unfeasible. Fortunately, there are relatively fast algorithms for finding the maximally scoring tree (the so-called *maximum spanning tree*).

A frequently used algorithm is the *Chu–Liu–Edmonds algorithm*, which has time complexity $\mathcal{O}(n^3 l)$ for n input tokens and l possible labels, what can be reduced to $\mathcal{O}(n^2 l)$ by storing the edge scores in a special data structure, a so-called Fibonacci-heap.

Edge scoring features

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Graph-based dependency parsers are *regressors*: they have to produce scores for the possible edges between the input tokens. The used feature templates are analogous to those in transition-based parsers:

- the dependent and its affixes, POS etc.;
- the head and its affixes, POS etc;
- the edge label;
- the relationship between the head and the dependent in the sentence, e.g. their distance;
- for neural architectures, embeddings for the nodes and the label of the edge.

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Analogously to the transition-based case, both classic ML and neural graph-based parsers have been developed over the years, the highest performing parsers using self-attention layers.

An important aspect of some of the recent architectures, introduced by a paper by Dozat and Manning [2016], is that they use different sets of embeddings for the head and dependent representations of the same words.

Transition- vs graph-based parsing

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There are important trade-offs between the two approaches.

Time complexity: the time-complexity of parsing n tokens with l possible edge labels is

- typically $\mathcal{O}(n)$ for transition-based parsers, while
- graph-based parsers precompute scores for all possible edges, so they start with an $\mathcal{O}(n^2 l)$ operation, and the time of finding the maximum spanning tree is added to this. Even if we treat finding labels as a separate task the $\mathcal{O}(n^2)$ complexity is inescapable.

Transition- vs graph-based parsing cont.

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Non-projectivity: as we have seen, non-projectivity is a serious problem for the most wide-spread transition systems which needs special treatment. Graph-based approaches don not suffer from this problem.

Performance: Transition-based systems tend to have problems with long-distance dependencies, graph-based models do not have this performance issue. As a consequence, the dependency parser leader boards are dominated by graph-based systems.

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