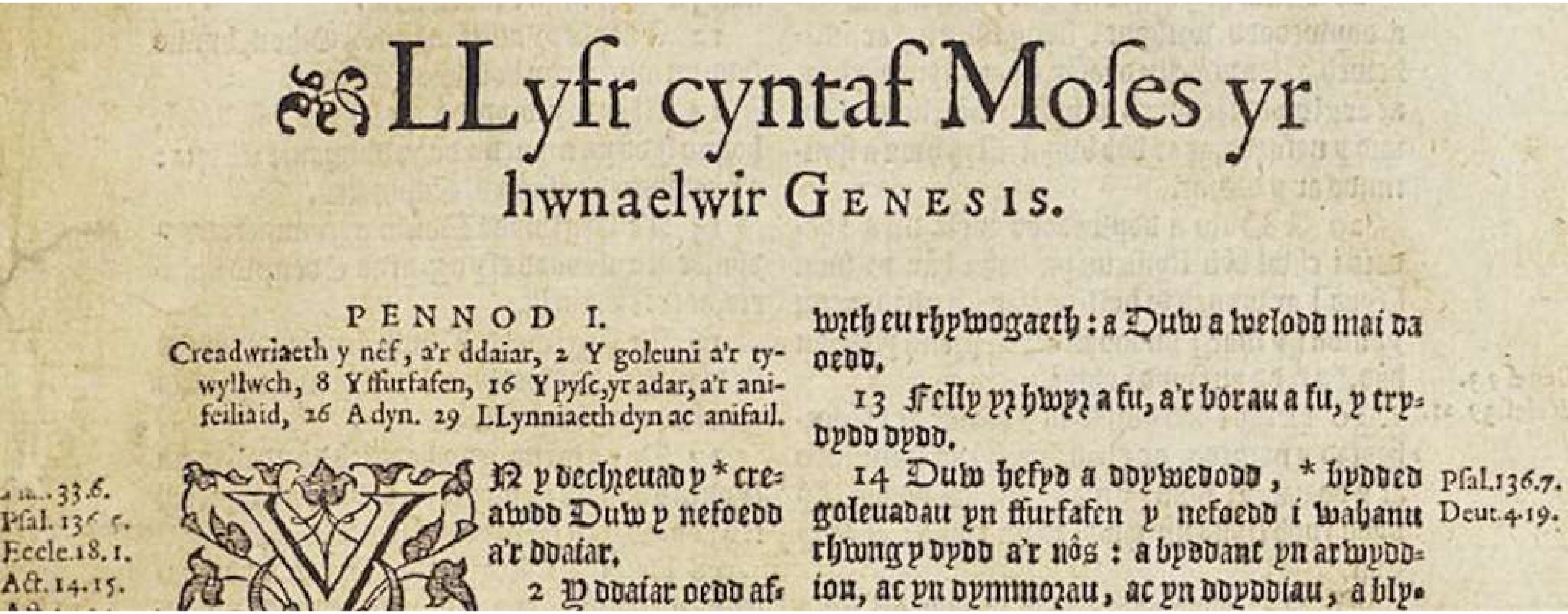


LLyfr cyntaf Moſes yr hwn a elwir GENESIS.

PENNOD I.

Creadwriaeth y nêf, a'r ddaiar, 2 Y goleuni a'r tywyllwch, 8 Y ffurfafen, 16 Y pyſc, yr adar, a'r anifeiliaid, 26 A dyn. 29 LLynniaeth dyn ac anifail.

YN y dechreuad y *creawdd Duw y nefoedd a'r ddaiar.

2 Y ddaiar oedd af-

wrth eu rhywogaeth: a Duw a welodd mai da oedd.

13 Felly yr hwyr a fu, a'r borau a fu, y trydydd dydd.

14 Duw hefyd a ddywedodd, *bydded goleuadau yn ffurfafen y nefoedd i wahanu rhwng y dydd a'r nôs: a byddant yn arwyddion, ac yn dymmorau, ac yn ddyddiau, a bly-

...33.6.
Pſal.13 5.
Eccle.18.1.
Act.14.15.

Pſal.136.7.
Deut.4.19.

Natural Language Processing

Info 159/259

Lecture 17: Dependency parsing (March 19, 2020)

David Bamman, UC Berkeley

Dependency syntax

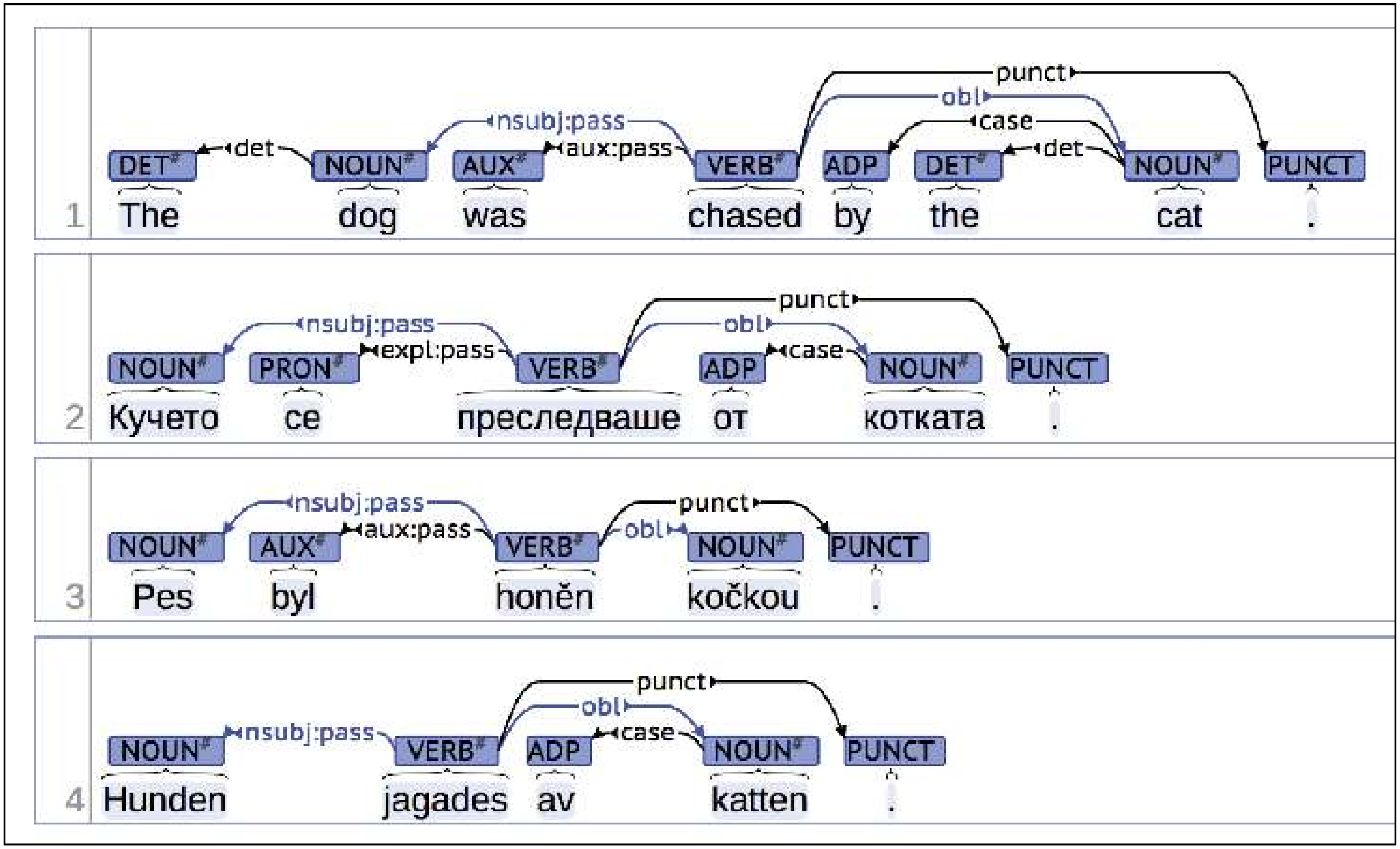
- Syntactic structure = asymmetric, binary relations between words.

Tesnier 1959; Nivre 2005

Trees

- A dependency structure is a directed graph G = (V,A) consisting of a set of vertices *V* and arcs *A* between them. Typically constrained to form a tree:
  - Single root vertex with no incoming arcs
  - Every vertex has exactly one incoming arc except root (single head constraint)
  - There is a unique path from the root to each vertex in V (acyclic constraint)

Universal Dependencies



1
DET NOUN AUX VERB ADP DET NOUN PUNCT
det nsubj:pass aux:pass punct obl case det
The dog was chased by the cat .
2
NOUN PRON VERB ADP NOUN PUNCT
nsubj:pass expl:pass punct obl case
Кучето се преследваше от котката .
3
NOUN AUX VERB NOUN PUNCT
nsubj:pass aux:pass punct obl
Pes byl honěn kočkou .
4
NOUN VERB ADP NOUN PUNCT
nsubj:pass punct obl case
Hunden jagades av katten .

English

Bulgarian

Czech

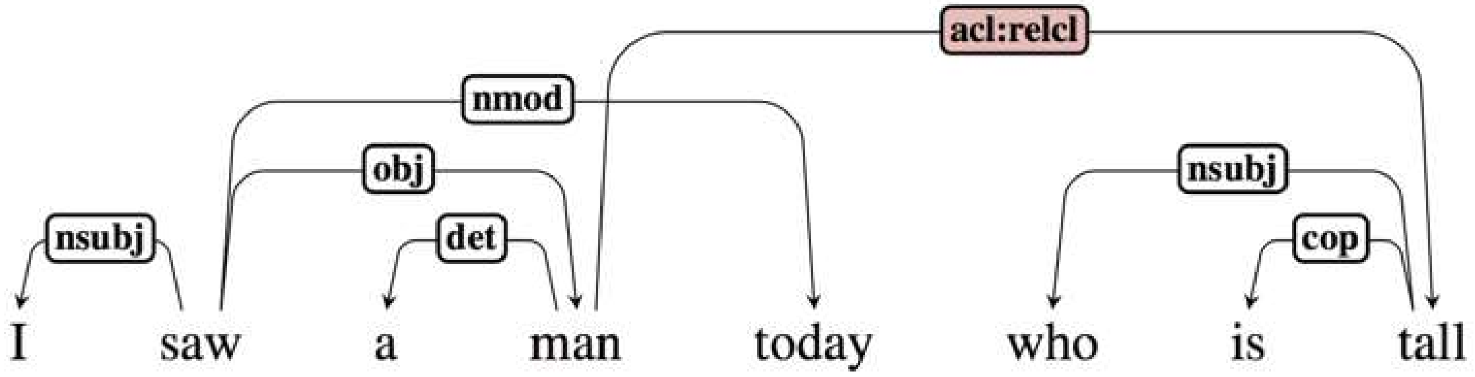
Swedish

http://universaldependencies.org

Dependency parsing

- Transition-based parsing
  - O(n)
  - Only projective structures (pseudo-projective [Nivre and Nilsson 2005])
- Graph-based parsing
  - $O(n^2)$
  - Projective and non-projective trees

Projectivity



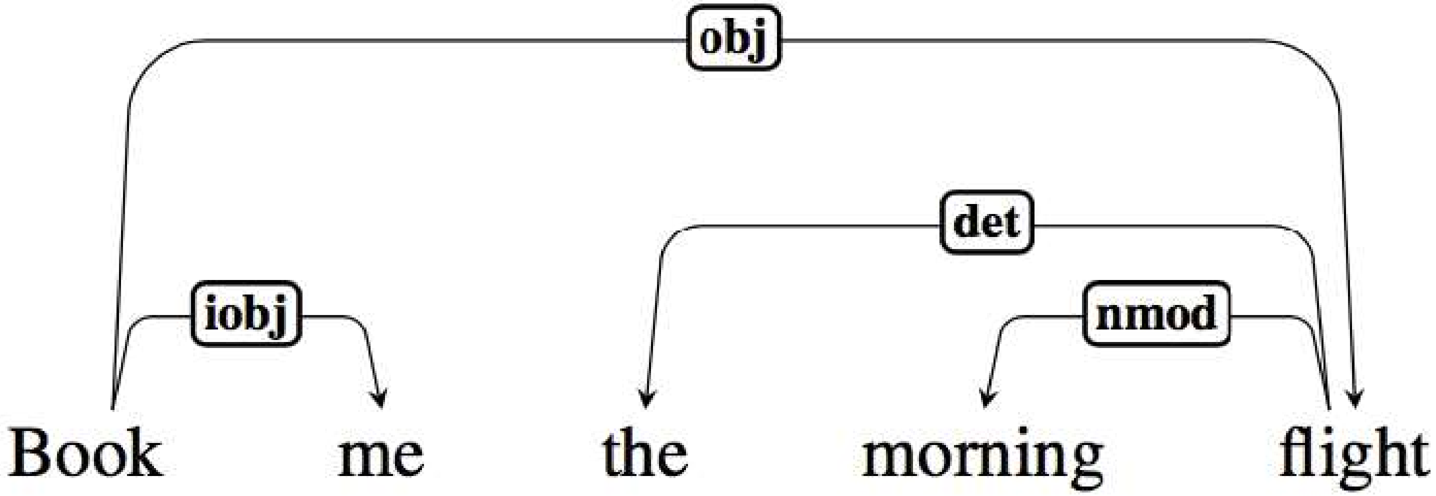
- An arc between a head and dependent is projective if there is a path from the head to every word between the head and dependent. Every word between head and dependent is a descendent of the head.

Transition-based parsing

- Basic idea: parse a sentence into a dependency tree by training a local classifier to predict a parser's next action from its current configuration.

Configuration

- Stack
- Input buffer of words
- Arcs in a parsed dependency tree
- Parsing = sequences of transitions through space of possible configurations


obj
det
iobj
nmod
Book
me
the
morning
flight

∅ book me the morning flight

stack	action	arc

∅ book me the morning flight

stack	action	arc
	LeftArc(label): assert relation between head at stack$_1$ and dependent at stack$_{2:}$ remove stack$_2$ RightArc(label): assert relation between head at stack$_2$ and dependent at stack$_1$; remove stack$_1$ ☞ Shift: Remove word from front of input buffer (∅) and push it onto stack	

book me the morning flight

stack	action	arc
	LeftArc(label): assert relation between head at stack$_1$ (∅) and dependent at stack$_2$: remove stack$_2$	
	RightArc(label): assert relation between head at stack$_2$ and dependent at stack$_1$ (∅); remove stack$_1$ (∅)	
∅	☞ Shift: Remove word from front of input buffer (book) and push it onto stack	

If we remove an element from the stack, it can’t have any further dependents

me the morning flight

stack	action	arc
book ∅	LeftArc(label): assert relation between head at $stack_1$ (book) and dependent at $stack_2$ (∅): remove $stack_2$ (∅) RightArc(label): assert relation between head at $stack_2$ (∅) and dependent at $stack_1$ (book); remove $stack_1$ (book) ☞ Shift: Remove word from front of input buffer (me) and push it onto stack	

the morning flight

stack

me

book

∅

action

LeftArc(label): assert relation between head at stack$_1$ (me) and dependent at stack$_2$ (book): remove stack$_2$ (book)

☞ RightArc(label): assert relation between head at stack$_2$ (book) and dependent at stack$_1$ (me); remove stack$_1$ (me)

Shift: Remove word from front of input buffer (the) and push it onto stack

arc

iobj(book, me)

the morning flight

stack

book

∅

action

LeftArc(label): assert relation between head at stack$_1$ (book) and dependent at stack$_2$ (∅): remove stack$_2$ (∅)

RightArc(label): assert relation between head at stack$_2$ (∅) and dependent at stack$_1$ (book); remove stack$_1$ (book)

Shift: Remove word from front of input buffer (the) and push it onto stack

arc

iobj(book, me)

morning flight

stack

the

book

∅

action

LeftArc(label): assert relation between head at stack$_1$ (the) and dependent at stack$_2$ (book): remove stack$_2$ (book)

RightArc(label): assert relation between head at stack$_2$ (book) and dependent at stack$_1$ (the); remove stack$_1$ (the)

☞ Shift: Remove word from front of input buffer (morning) and push it onto stack

arc

iobj(book, me)

flight

stack

morning

the

book

∅

action

LeftArc(label): assert relation between head at stack_1 (morning) and dependent at stack_2 (the): remove stack_2 (the)

RightArc(label): assert relation between head at stack_2 (the) and dependent at stack_1 (morning); remove stack_1 (morning)

☞ Shift: Remove word from front of input buffer (flight) and push it onto stack

arc

iobj(book, me)

stack

flight

morning

the

book

∅

action

☞ LeftArc(label): assert relation between head at stack$_1$ (flight) and dependent at stack$_2$ (morning); remove stack$_2$ (morning)

RightArc(label): assert relation between head at stack$_2$ (morning) and dependent at stack$_1$ (flight); remove stack$_1$ (flight)

~~Shift: Remove word from front of input buffer and push it onto stack~~

arc

iobj(book, me)

nmod(flight, morning)

stack

flight

the

book

∅

action

☞ LeftArc(label): assert relation between head at stack$_1$ (flight) and dependent at stack$_2$ (the): remove stack$_2$ (the)

RightArc(label): assert relation between head at stack$_2$ (the) and dependent at stack$_1$ (flight); remove stack$_1$ (flight)

~~Shift: Remove word from front of input buffer and push it onto stack~~

arc

iobj(book, me)

nmod(flight, morning)

det(flight, the)

stack

flight

book

∅

action

LeftArc(label): assert relation between head at stack$_1$ (flight) and dependent at stack$_2$ (book); remove stack$_2$ (book)

☞ RightArc(label): assert relation between head at stack$_2$ (book) and dependent at stack$_1$ (flight); remove stack$_1$ (flight)

~~Shift: Remove word from front of input buffer and push it onto stack~~

arc

iobj(book, me)

nmod(flight, morning)

det(flight, the)

obj(book, flight)

This is our parse

stack

book

∅

action

LeftArc(label): assert relation between head at stack$_1$ (book) and dependent at stack$_2$ (∅): remove stack$_2$ (∅)

☞ RightArc(label): assert relation between head at stack$_2$ (∅) and dependent at stack$_1$ (book); remove stack$_1$ (book)

~~Shift: Remove word from front of input buffer and push it onto stack~~

arc

iobj(book, me)

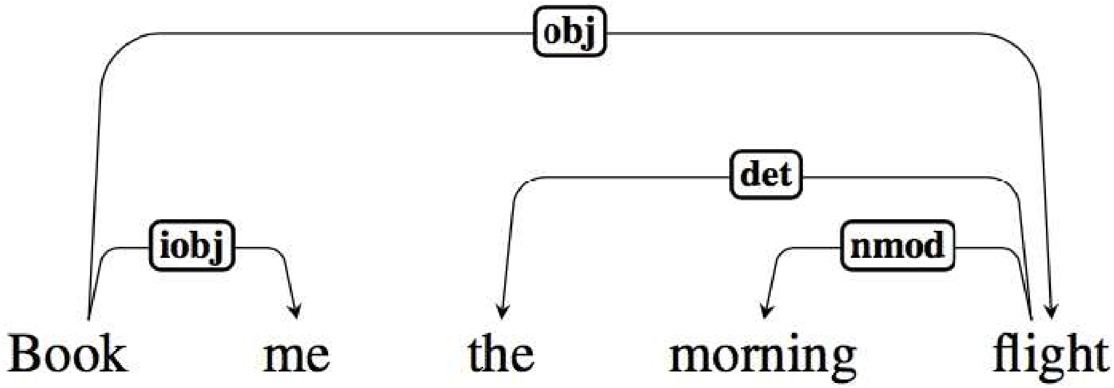
nmod(flight, morning)

det(flight, the)

obj(book, flight)

root(∅, book)

This is our parse



arc

iobj(book, me)

nmod(flight, morning)

det(flight, the)

obj(book, flight)

root(∅, book)

Let’s go back to this earlier configuration

the morning flight

stack

me

book

∅

action

LeftArc(label): assert relation between head at stack_1 (me) and dependent at stack_2 (book): remove stack_2 (book)

RightArc(label): assert relation between head at stack_2 (book) and dependent at stack_1 (me); remove stack_1 (me)

Shift: Remove word from front of input buffer (the) and push it onto stack

arc

Output space $\boldsymbol{\mathcal{Y}}$ =

Shift
LeftArc(nsubj)
RightArc(nsubj)
LeftArc(det)
RightArc(det)
LeftArc(obj)
RightArc(obj)
…

- This is a multi class classification problem: given the current configuration — i.e., the elements in the stack, the words in the buffer, and the arcs created so far, what’s the best transition?

Features are scoped over the stack, buffer, and arcs created so far

stack

me

book

buffer

the morning flight

arc

feature	example
stack_1 = me	1
stack_2 = book	1
stack_1 POS = PRP	1
buffer_1 = the	1
buffer_2 = morning	1
buffer_1 = today	0
buffer_1 POS = RB	0
stack_1 = me AND stack_2 = book	1
stack_1 = PRP AND stack_2 = VB	1
iobj(book,*) in arcs	0

Use any multiclass classification model

- Logistic regression
- SVM
- NB
- Neural network

feature	example	β
stack$_1$ = me	1	0.7
stack$_2$ = book	1	1.3
stack$_1$ POS = PRP	1	6.4
buffer$_1$ = the	1	-1.3
buffer$_2$ = morning	1	-0.07
buffer$_1$ = today	0	0.52
buffer$_1$ POS = RB	0	-2.1
stack$_1$ = me AND stack$_2$ =	1	0
stack$_1$ = PRP AND stack$_2$ =	1	-0.1
iobj(book,*) in arcs	0	3.2

Training

We’re training to predict the parser action —Shift, RightArc(label), LeftArc(label)— given the featurized configuration

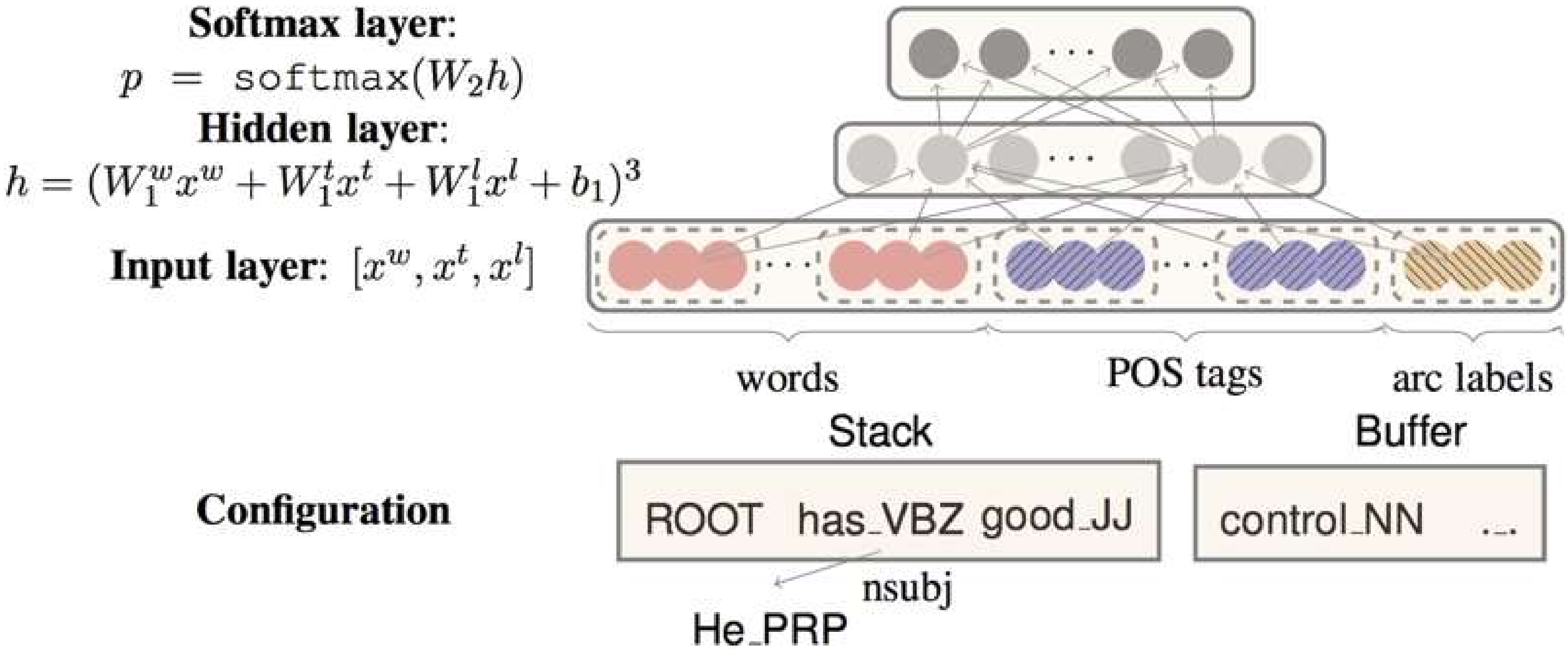
Configuration features	Label
<stack1 = me, 1>, <stack2 = book, 1>, <stack1 POS = PRP, 1>, <buffer1 = the, 1>,	Shift
<stack1 = me, 0>, <stack2 = book, 0>, <stack1 POS = PRP, 0>, <buffer1 = the, 0>,	RightArc(det)
<stack1 = me, 0>, <stack2 = book, 1>, <stack1 POS = PRP, 0>, <buffer1 = the, 0>,	RightArc(nsubj)

Neural Shift-Reduce Parsing

- We can train a neural shift-reduce parser by just changing how we:
    - represent the configuration
    - predict the label from that representation
- Otherwise training and prediction remains the same.

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

Neural Shift-Reduce Parsing



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

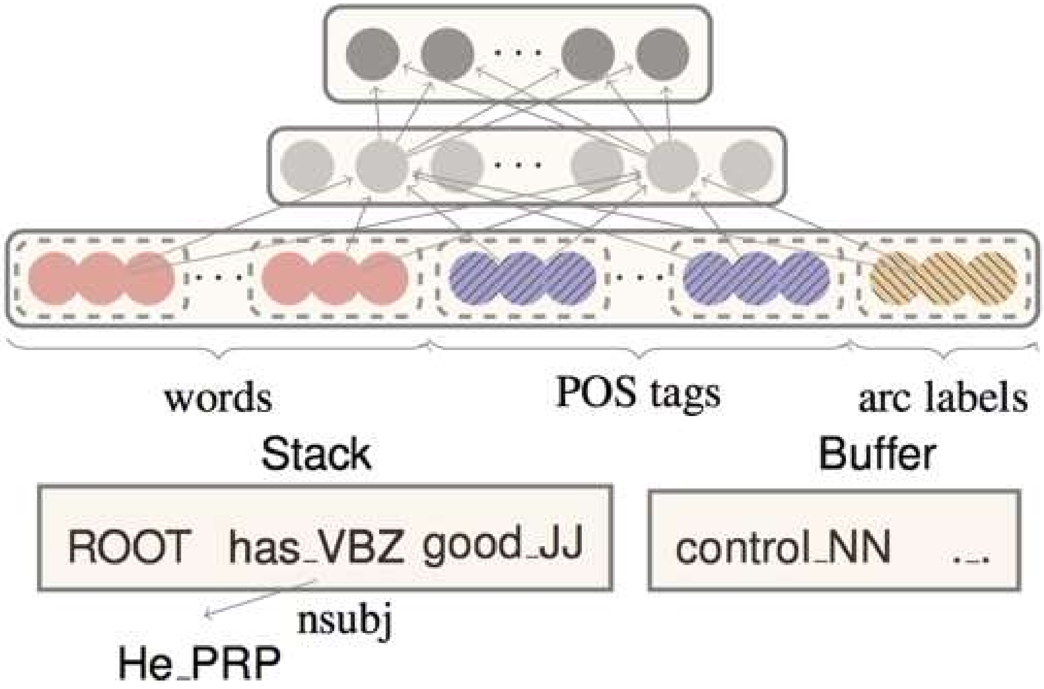
Neural Shift-Reduce Parsing

Representation for configuration:

- Embeddings for words/POS tags on top of stack
- Embeddings for words/POS tags at front of buffer
- Embeddings for existing arc labels at specific positions

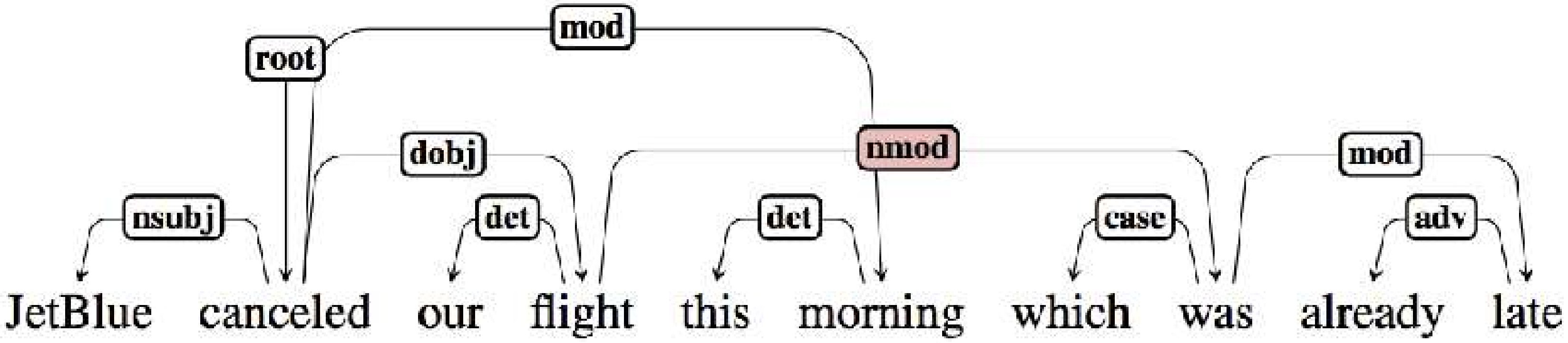
Classifier:

- Feed-forward neural network (input representation has a fixed dimensionality)



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

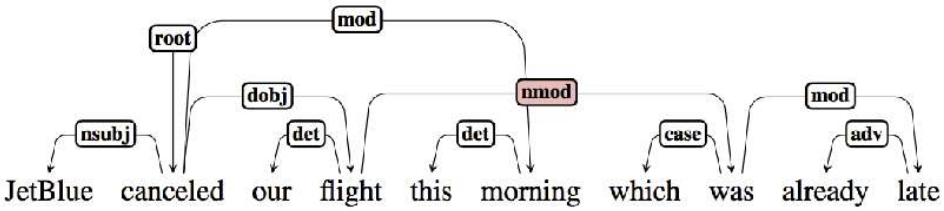
Training data



Our training data comes from treebanks (native dependency syntax or converted to dependency trees).

Oracle

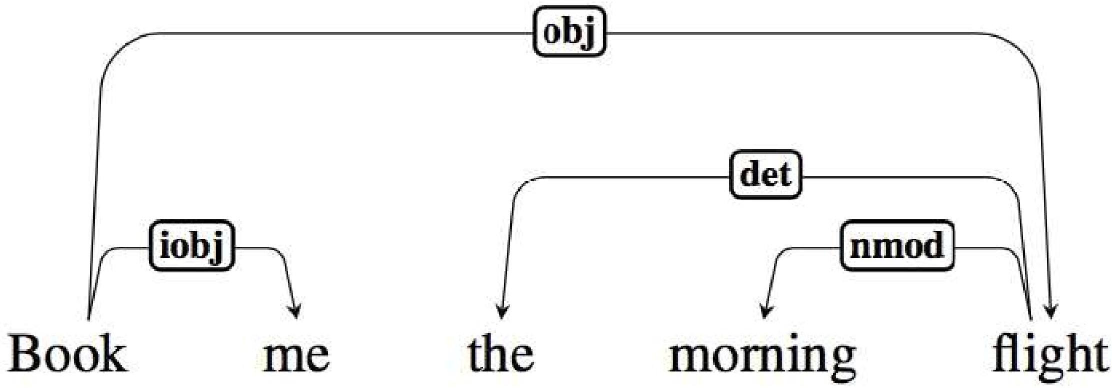
- An algorithm for converting a gold-standard dependency tree into a series of actions a transition-based parser should follow to yield the tree.



→

Configuration	Label
<stack1 = me, 1>,	Shift
<stack1 = me, 0>,	RightArc(det)
<stack1 = me, 0>,	RightArc(nsu

This is our parse



arc

iobj(book, me)

nmod(flight, morning)

det(flight, the)

obj(book, flight)

root(∅, book)

∅   book   me   the   morning   flight

stack	action	gold tree
		iobj(book, me)
		nmod(flight, morning)
		det(flight, the)
		obj(book, flight)
		root(∅, book)

∅ book me the morning flight

stack

action

Choose LeftArc(label) if label(stack$_1$,stack$_2$) exists in gold tree. Remove stack$_2$.

Else choose RightArc(label) if label(stack$_2$, stack$_1$) exists in gold tree and all arcs label(stack$_1$, *). have been generated. Remove stack$_1$

Else shift: Remove word from front of input buffer and push it onto stack

gold tree

iobj(book, me)

nmod(flight, morning)

det(flight, the)

obj(book, flight)

root(∅, book)

root(∅, book) exists but book has dependents in gold tree!

k me the morning flight

stack

∅

action

Choose LeftArc(label) if label(stack$_1$,stack$_2$) exists in gold tree. Remove stack$_2$.

Else choose RightArc(label) if label(stack$_2$, stack$_1$) exists in gold tree and all arcs label(stack$_1$, *). have been generated. Remove stack$_1$

Else shift: Remove word from front of input buffer and push it onto stack

gold tree

iobj(book, me)

nmod(flight, morning)

det(flight, the)

obj(book, flight)

root(∅, book)

iobj(book, me) exists and me has no dependents in gold tree

me the morning flight

stack

book

∅

action

Choose LeftArc(label) if label($stack_1$,$stack_2$) exists in gold tree. Remove $stack_2$.

Else choose RightArc(label) if label($stack_2$, $stack_1$) exists in gold tree and all arcs label($stack_1$, *). have been generated. Remove $stack_1$

Else shift: Remove word from front of input buffer and push it onto stack

gold tree

iobj(book, me)

nmod(flight, morning)

det(flight, the)

obj(book, flight)

root(∅, book)

the morning flight

stack

me

book

∅

action

Choose LeftArc(label) if label(stack$_1$,stack$_2$) exists in gold tree. Remove stack$_2$.

Else choose RightArc(label) if label(stack$_2$, stack$_1$) exists in gold tree and all arcs label(stack$_1$, *). have been generated. Remove stack$_1$

Else shift: Remove word from front of input buffer and push it onto stack

gold tree

✓ *iobj(book, me)*

nmod(flight, morning)

det(flight, the)

obj(book, flight)

root(∅, book)

morning flight

stack

the

book

∅

action

Choose LeftArc(label) if label($stack_1$,$stack_2$) exists in gold tree. Remove $stack_2$.

Else choose RightArc(label) if label($stack_2$, $stack_1$) exists in gold tree and all arcs label($stack_1$, *). have been generated. Remove $stack_1$

Else shift: Remove word from front of input buffer and push it onto stack

gold tree

✅ *iobj(book, me)*

nmod(flight, morning)

det(flight, the)

obj(book, flight)

root(∅, book)

flight

stack

morning

the

book

∅

action

Choose LeftArc(label) if label(stack$_1$,stack$_2$) exists in gold tree. Remove stack$_2$.

Else choose RightArc(label) if label(stack$_2$, stack$_1$) exists in gold tree and all arcs label(stack$_1$, *). have been generated. Remove stack$_1$

Else shift: Remove word from front of input buffer and push it onto stack

gold tree

✅ *iobj(book, me)*

nmod(flight, morning)

det(flight, the)

obj(book, flight)

root(∅, book)

nmod(flight,morning)

stack

flight

morning

the

book

∅

action

Choose LeftArc(label) if label(stack$_1$,stack$_2$) exists in gold tree. Remove stack$_2$.

Else choose RightArc(label) if label(stack$_2$, stack$_1$) exists in gold tree and all arcs label(stack$_1$, *). have been generated. Remove stack$_1$

Else shift: Remove word from front of input buffer and push it onto stack

gold tree

✅ *iobj(book, me)*

✅ *nmod(flight, morning)*

det(flight, the)

obj(book, flight)

root(∅, book)

det(flight,the)

stack

flight

the

book

∅

action

Choose LeftArc(label) if label(stack$_1$,stack$_2$) exists in gold tree. Remove stack$_2$.

Else choose RightArc(label) if label(stack$_2$, stack$_1$) exists in gold tree and all arcs label(stack$_1$, *). have been generated. Remove stack$_1$

Else shift: Remove word from front of input buffer and push it onto stack

gold tree

✅ *iobj(book, me)*

✅ *nmod(flight, morning)*

✅ *det(flight, the)*

obj(book, flight)

root(∅, book)

obj(book,flight)

stack

flight

book

∅

action

Choose LeftArc(label) if label(stack$_1$,stack$_2$) exists in gold tree. Remove stack$_2$.

Else choose RightArc(label) if label(stack$_2$, stack$_1$) exists in gold tree and all arcs label(stack$_1$, *). have been generated. Remove stack$_1$

Else shift: Remove word from front of input buffer and push it onto stack

gold tree

☑ *iobj(book, me)*

☑ *nmod(flight, morning)*

☑ *det(flight, the)*

☑ *obj(book, flight)*

root(∅, book)

root(∅, book) *and* book has no more dependents we haven’t seen

stack

book

∅

action

Choose LeftArc(label) if label(stack$_1$,stack$_2$) exists in gold tree. Remove stack$_2$.

Else choose RightArc(label) if label(stack$_2$, stack$_1$) exists in gold tree and all arcs label(stack$_1$, *). have been generated. Remove stack$_1$

Else shift: Remove word from front of input buffer and push it onto stack

gold tree

✅ *iobj(book, me)*

✅ *nmod(flight, morning)*

✅ *det(flight, the)*

✅ *obj(book, flight)*

✅ *root(∅, book)*

With only ∅ left on the stack and nothing in the buffer, we're done

stack

∅

action

Choose LeftArc(label) if label(stack$_1$,stack$_2$) exists in gold tree. Remove stack$_2$.

Else choose RightArc(label) if label(stack$_2$, stack$_1$) exists in gold tree and all arcs label(stack$_1$, *). have been generated. Remove stack$_1$

Else shift: Remove word from front of input buffer and push it onto stack

gold tree

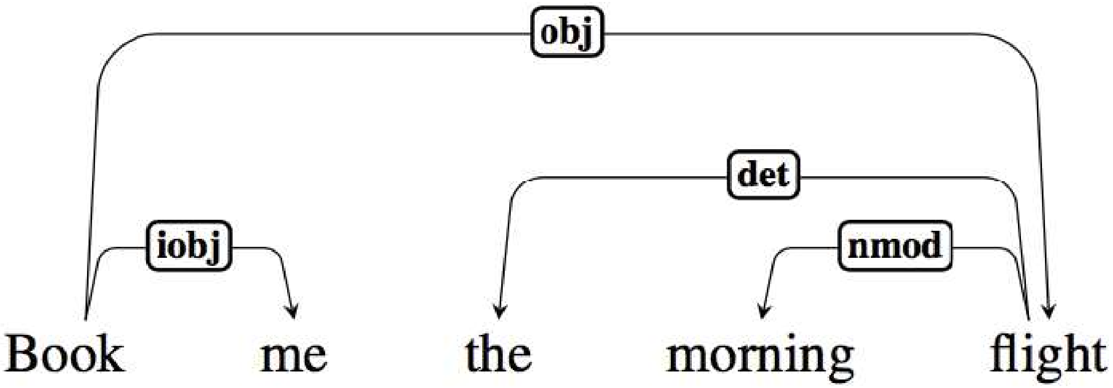
✅ *iobj(book, me)*

✅ *nmod(flight, morning)*

✅ *det(flight, the)*

✅ *obj(book, flight)*

✅ *root(∅, book)*



Shift

Shift

Shift

RightArc(iobj)

Shift

Shift

Shift

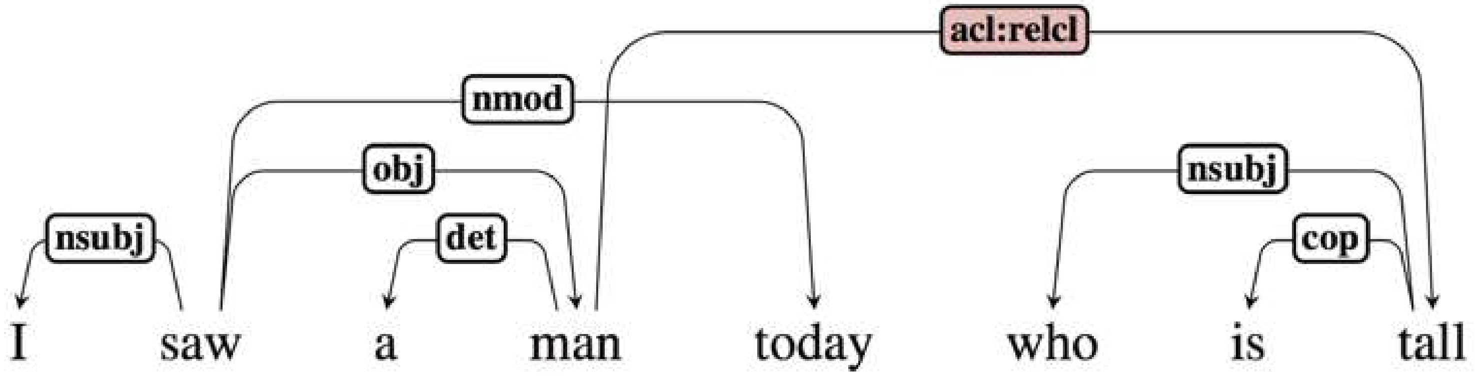
LeftArc(nmod)

LeftArc(det)

RightArc(obj)

RightArc(root)

Projectivity



- What happens if you run an oracle on a sentence with a non-projective parse tree?

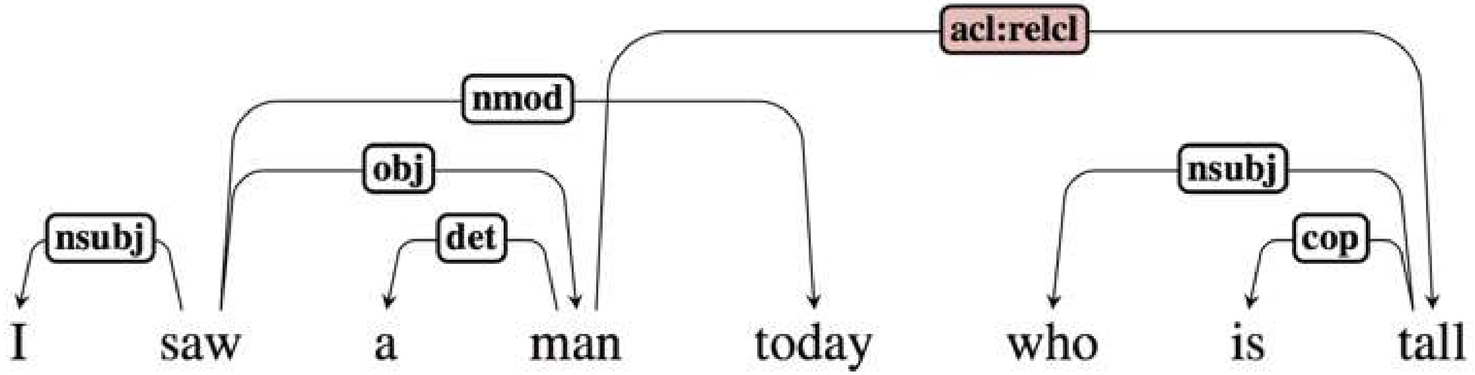
Graph-based parsing

- For a given sentence S, we want to find the highest-scoring tree among all possible trees for that sentence $\mathcal{G}_S$

$$\hat{T}(S) = \arg\max_{t \in \mathcal{G}_S} \text{score}(t, S)$$

- Edge-factored scoring: the total score of a tree is the sum of the scores for all of its edges (arcs):

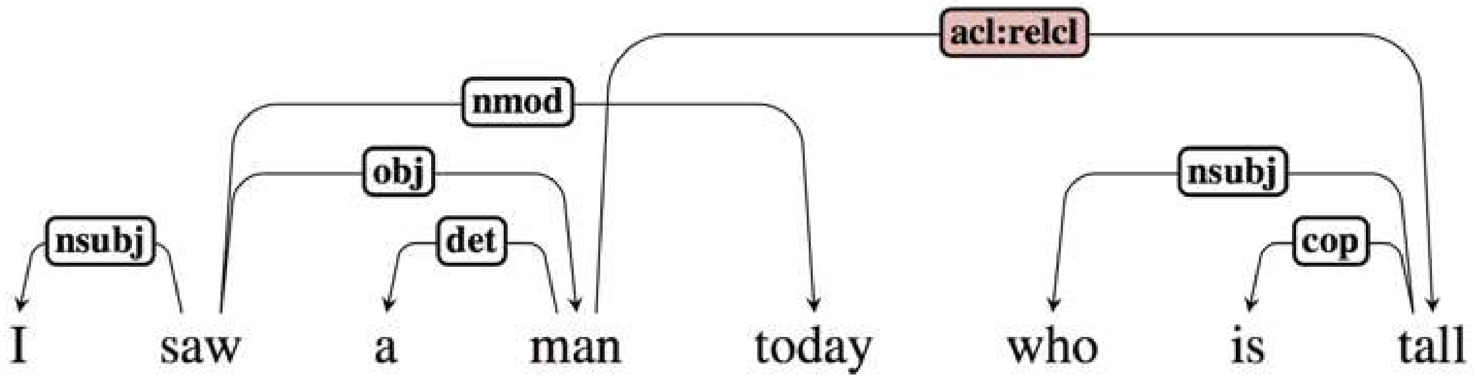
$$\text{score}(t, S) = \sum_{e \in t} \text{score}(e)$$



Edge-factored features

- Word form of head/dependent
- POS tag of head/dependent
- Distributed representation of h/d
- Distance between h/d
- POS tags between h/d
- Head to left of dependent?

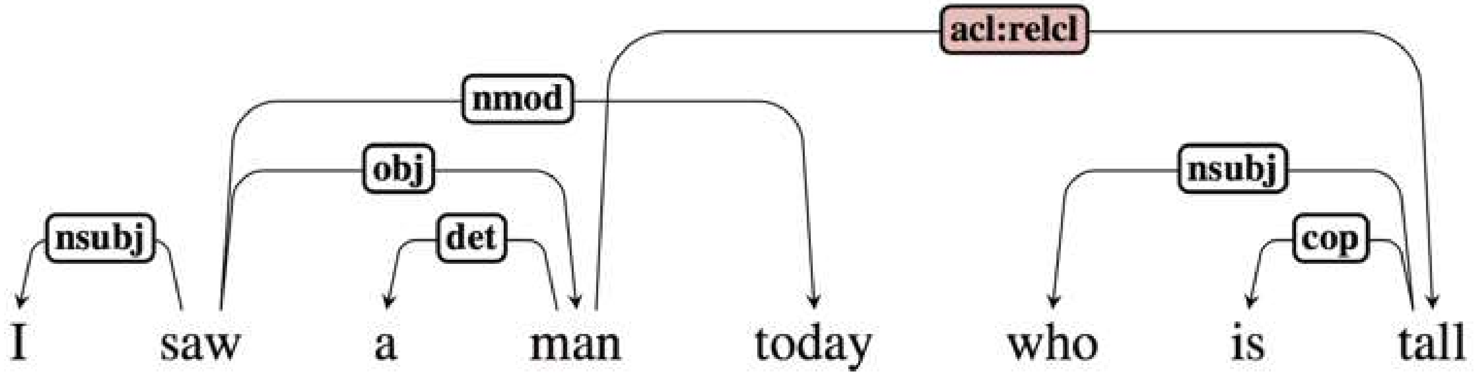
head$_{t}$ = man	1
head$_{pos}$ = NN	1
distance	4
child$_{pos}$ = JJ and head$_{pos}$ = NN	1
child$_{pos}$ = NN and head$_{pos}$ = JJ	0



$$\text{score}(e) = \sum_{i=1}^{F} x_i \beta_i$$

Feature value

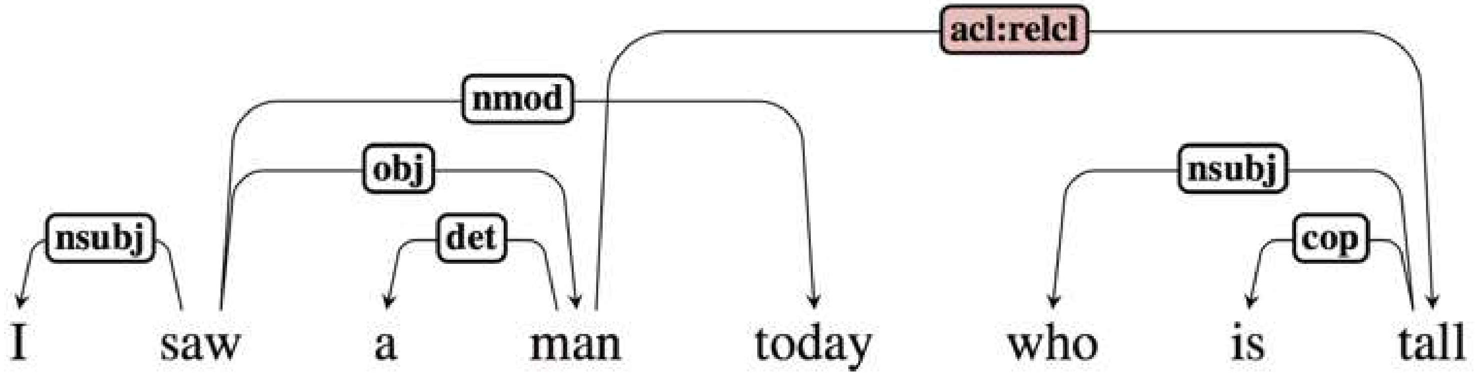
Learned coefficient for that feature

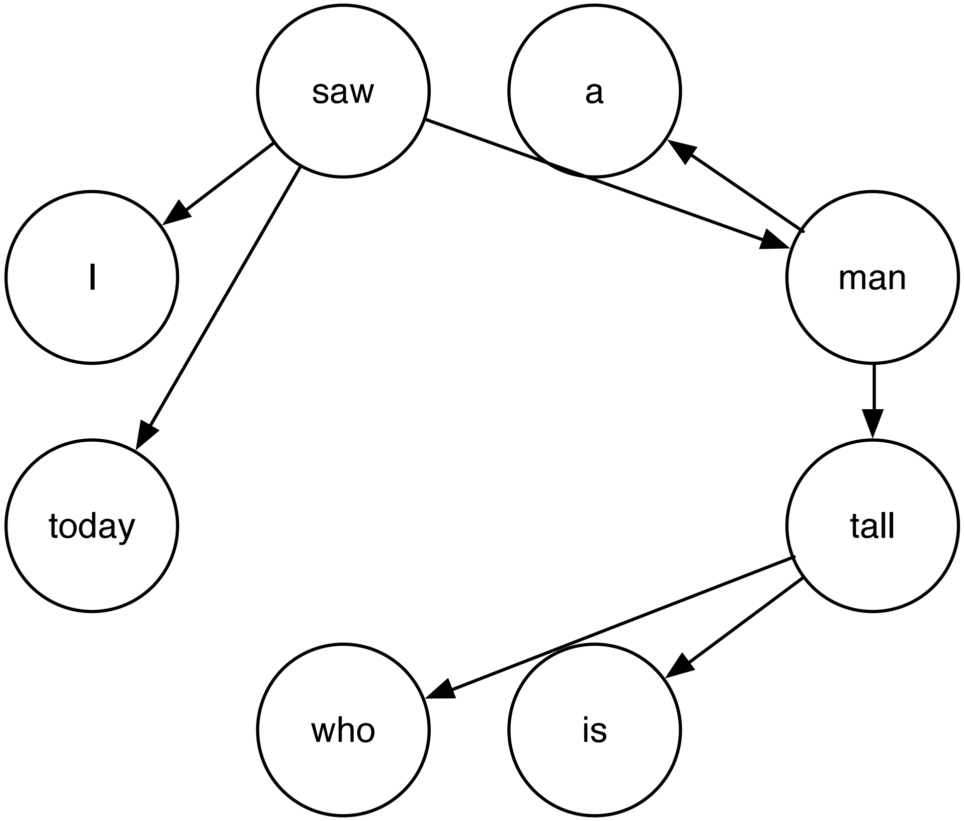


$$\text{score}(e) = \sum_{i=1}^{F} x_i \beta_i$$

	x	β
head$_t$ = man	1	3.7
head$_t$ = man	1	1.3
distance	4	0.7
child$_{pos}$ = JJ and	1	0.3
child$_{pos}$ = NN and	0	-2.7

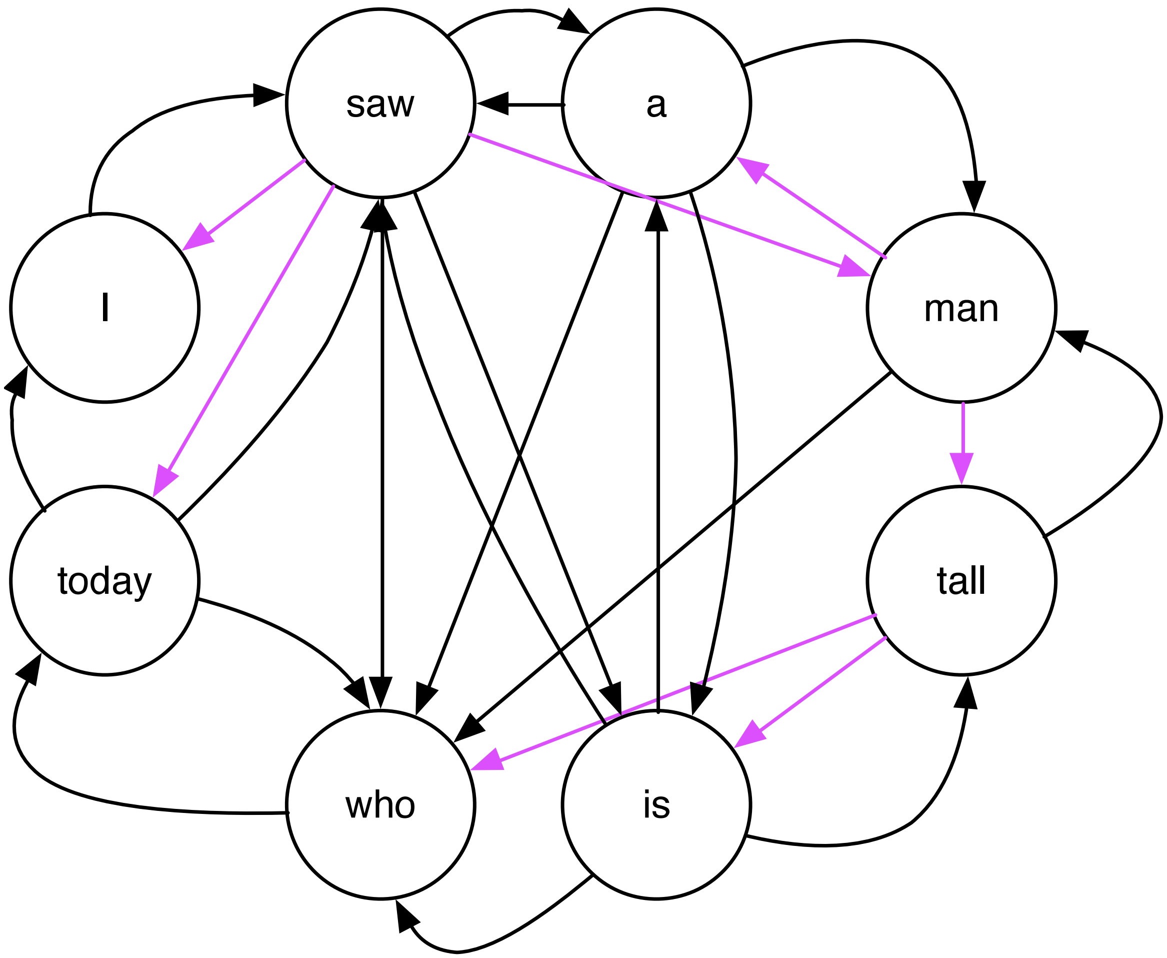
$\text{score}(e) = 8.1$


acl:relcl
nmod
obj
nsubj
det
nsubj
cop
I
saw
a
man
today
who
is
tall


saw
a
I
man
today
tall
who
is

MST Parsing

- We start out with a fully connected graph with a score for each edge
- N^2 edges total

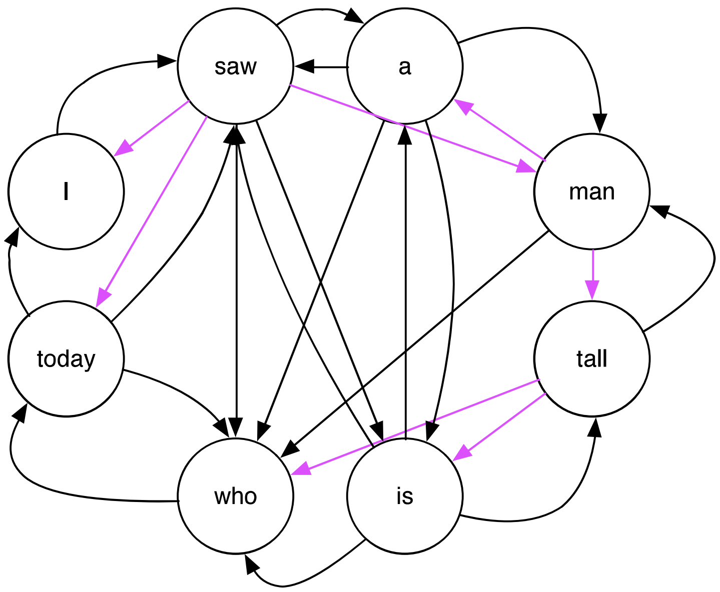


(Assume one edge connects each node as dependent and node as head, N^2 total)

MST Parsing

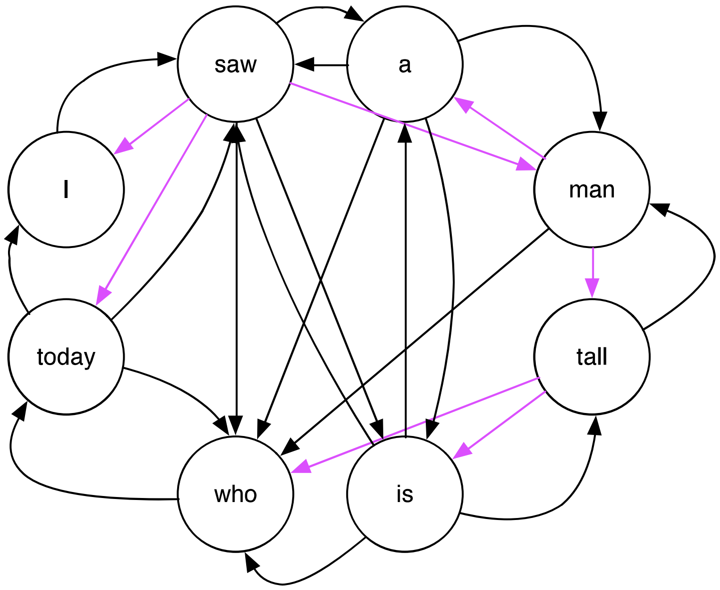
- From this graph G, we want to find a spanning tree (tree that spans G [includes all the vertices in G])

- If the edges have weights, the best parse is the maximal spanning tree (the spanning tree with the highest total weight).



MST Parsing

- To find the MST of any graph, we can use the Chu-Liu-Edmonds algorithm in $O(n^3)$ time.
- More efficient Gabow et al. find the MST in $O(n^2+n \log n)$



Learning

$$\hat{T}(S) = \arg\max_{t \in \mathcal{G}_S} \mathrm{score}(t, S)$$

ϕ is our feature vector scoped over the source dependent, target head and entire sentence x

both are vectors

$$\hat{T}(S) = \arg\max_{t \in \mathcal{G}_S} \sum_{e \in E} \phi(e, x)^\top \beta$$

$$\hat{T}(S) = \arg\max_{t \in \mathcal{G}_S} \left[\sum_{e \in E} \phi(e, x) \right]^\top \beta$$

Learning

$$\hat{T}(S) = \arg\max_{t \in \mathcal{G}_{\mathcal{S}}} \text{score}(t, S)$$

- Given this formulation, we want to learn weights for β that make the score for the gold tree higher than for all other possible trees.

- That's expensive, so let's just try to make the score for the gold tree higher than the single best tree we predict (if it's wrong)

Learning

$$\left[\sum_{e \in E} \phi(e, x)\right]^\top \beta = \Phi_{gold}(E, x)^\top \beta$$

score for gold tree in treebank

$$\left[\sum_{e \in \hat{E}} \phi(e, x)\right]^\top \beta = \hat{\Phi}_{gold}(\hat{E}, x)^\top \beta$$

score for argmax tree in our model

Learning

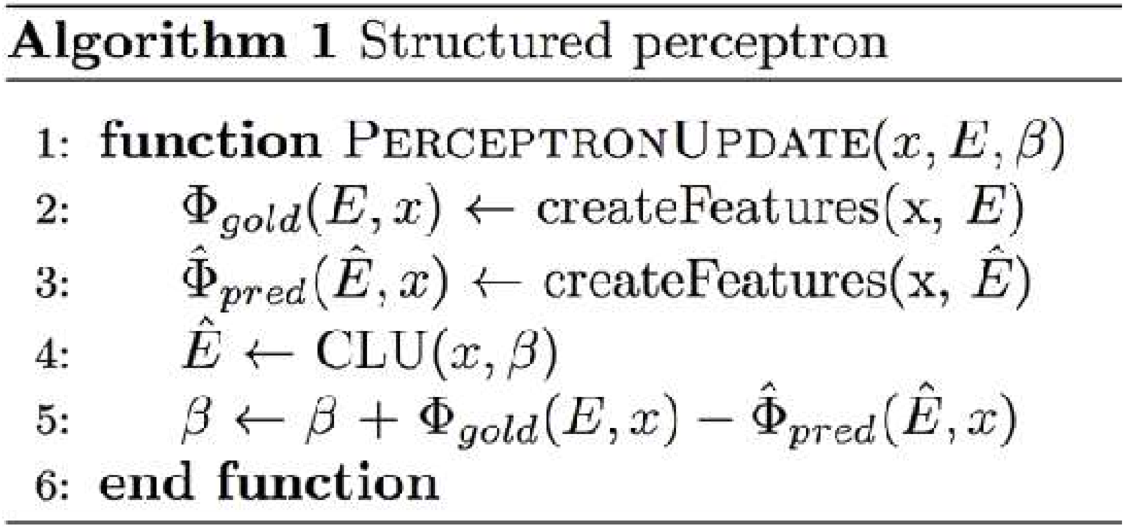
- We can optimize this using SGD by taking the derivative with respect to the difference in scores.

$$\Phi_{gold}(E,x)^\top \beta - \hat{\Phi}_{pred}(\hat{E},x)^\top \beta$$

$$= \left[\Phi_{gold}(E,x) - \hat{\Phi}_{pred}(\hat{E},x)\right]^\top \beta$$

$$\frac{\partial}{\partial \beta}\left[\Phi_{gold}(E,x) - \hat{\Phi}_{pred}(\hat{E},x)\right]^\top \beta = \Phi_{gold}(E,x) - \hat{\Phi}_{pred}(\hat{E},x)$$

Structured Perceptron



Algorithm 1 Structured perceptron

```
function PERCEPTRONUPDATE($x, E, \beta$)
    $\Phi_{gold}(E, x) \leftarrow$ createFeatures(x, $E$)
    $\hat{\Phi}_{pred}(\hat{E}, x) \leftarrow$ createFeatures(x, $\hat{E}$)
    $\hat{E} \leftarrow$ CLU($x, \beta$)
    $\beta \leftarrow \beta + \Phi_{gold}(E, x) - \hat{\Phi}_{pred}(\hat{E}, x)$
end function
```

Create feature vector from true tree

Use CLU to find best tree given scores from current β

Update β with the difference between the feature vectors