

Lecture 4: Dependency parsing

Presenter: Chu Đình Đức

Lecture plan

1. Dependency Parsing
2. Greedy Deterministic Transition-Based Parsing
3. Neural Dependency Parsing

1. Dependency Parsing

- Dependency parsing is the task of analyzing the syntactic dependency structure of a given input sentence S
- Formally, the dependency parsing problem asks to create a mapping from the input sentence with words $S = w_0 w_1 \dots w_n$ (where w_0 is the ROOT) to its dependency tree graph G
- Model:
 1. Learning: Given a training set D of sentences annotated with dependency graphs, induce a parsing model M that can be used to parse new sentences
 2. Parsing: Given a parsing model M and a sentence S , derive the optimal dependency graph D for S according to M

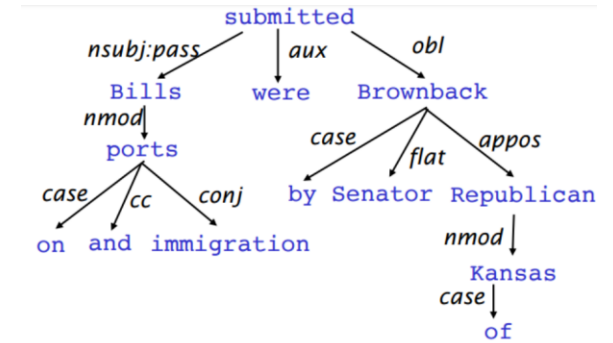


Figure 1: Dependency tree for the sentence "Bills on ports and immigration were submitted by Senator Brownback, Republican of Kansas"

2. Greedy Deterministic Transition-Based Parsing

This transition system is a state machine, which consists of *states* and *transitions* between those states

State:

For any sentence $S = w_0w_1...w_n$, a state can be described with a triple $c = (\sigma, \beta, A)$

- a stack σ of words w_i from S
- a buffer β of words w_i from S
- a set of dependency arcs A of the form (w_i, r, w_j) , where w_i, w_j are from S , and r describes a dependency relation

It follows that for any sentence $S = w_0w_1...w_n$

- initial state: $([w_0]_\sigma, [w_1, ..., w_n]_\beta, \emptyset)$
- terminal state: $(\sigma, []_\beta, A)$

2. Greedy Deterministic Transition-Based Parsing

The model induces a sequence of transitions from *initial state* to *terminal state*

1. Shift $\sigma, w_i | \beta, A \rightarrow \sigma | w_i, \beta, A$
2. Left-Arc_r $\sigma | w_i | w_j, \beta, A \rightarrow \sigma | w_j, \beta, A \cup \{r(w_i, w_j)\}$
3. Right-Arc_r $\sigma | w_i | w_j, \beta, A \rightarrow \sigma | w_i, \beta, A \cup \{r(w_i, w_j)\}$

Transitions: 3 types of transitions between states

- **SHIFT:** remove the first word in the buffer and push it on top of the stack (pre-condition: buffer has to be non-empty)
- **LEFT-ARC_r:** add a dependency arc (w_j, r, w_i) to the arc set A , where w_j is the word at the top of the stack, w_i is the word second to the top of the stack. Remove w_i from the stack (pre-condition: the stack needs to contain at least two items and w_i can't be the ROOT)
- **RIGHT-ARC_r:** add a dependency arc (w_i, r, w_j) to the arc set A , where w_j is the word at the top of the stack, w_i is the word second to the top of the stack. Remove w_j from the stack (pre-condition: the stack needs to contain at least two items)

Figure 2: Transitions for Dependency Parsing.

3. Neural Dependency Parsing

- The primary distinction from previous models is the reliance on dense rather than sparse feature representations
- The model employs the arc-standard system for transitions, as presented in section 2
- Ultimately, the aim of the model is to predict a transition sequence from initial configuration c to a terminal configuration
- As the model is greedy, it attempts to correctly predict one transition $T \in \{SHIFT, LEFT-ARC_r, RIGHT-ARC_r\}$ at a time, based on features extracted from the configuration $c = (\sigma, \beta, A)$

3. Neural Dependency Parsing

The model we will describe employs the arc-standard system for transitions, as presented in section 2. Ultimately, the aim of the model is to predict a transition sequence from initial configuration c to a terminal configuration

Feature Selection: the features for a given sentence S generally include some subset of:

- S_{word} : vector representations for some of the words in S (and their dependents) at the top of the stack σ and buffer β
- S_{tag} : Part-of-Speech (*POS*) tags for some of the words in S . *POS* tags comprise a small, discrete set $P = \{NN, NNP, NNS, DT, JJ, \dots\}$
- S_{label} : the arc-labels for some of the words in S . The arc-labels comprise a small, discrete set, describing the dependency relation: $L = \{amod, tmod, nsubj, csubj, dobj, \dots\}$

3. Neural Dependency Parsing

Feature Selection Example:

- S_{word} : the top 3 words on the stack and buffer: $s_1, s_2, s_3, b_1, b_2, b_3$. The first and second leftmost/rightmost children of the top two words on the stack: $lc_1(s_i), rc_1(s_i), lc_2(s_i), rc_2(s_i), i = 1, 2$. The leftmost of leftmost/rightmost of rightmost children of the top two words on the stack: $lc_1(lc_1(s_i)), rc_1(rc_1(s_i)), i = 1, 2$. The total S_{word} contains $n_w = 18$ elements
- S_{tag} : the corresponding *POS* tags for S_{word} ($n_t = 18$)
- S_{label} : the corresponding arc labels of words ($n_l = 12$)

3. Neural Dependency Parsing

- We use a special NULL token for non-existent elements
- For each feature type, we will have a corresponding embedding matrix (E^w, E^t, E^l) , mapping from the feature's one hot encoding to a d -dimensional dense vector representation, then concatenate these vectors into our inputs $[x^w, x^t, x^l]$

3. Neural Dependency Parsing

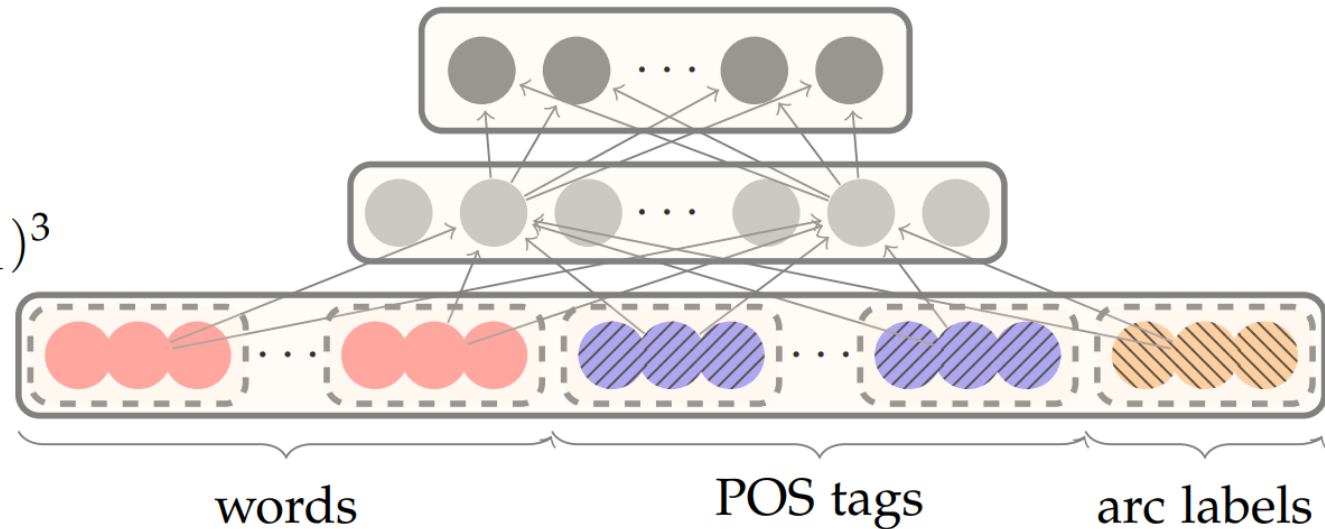
Softmax layer:

$$p = \text{softmax}(W_2 h)$$

Hidden layer:

$$h = (W_1^w x^w + W_1^t x^t + W_1^l x^l + b_1)^3$$

Input layer: $[x^w, x^t, x^l]$



Configuration

Stack
ROOT has_VBZ good_JJ

He_PRP

nsubj

Buffer
control_NN ._.

Note

- Relation set: [here](#)
- Example:
 - *nsubj:pass*: passive nominal subject
 - *nmod*: nominal modifier
 - *case*: case marking
 - *cc*: coordination
 - *conj*: conjunct
 - *aux*: auxiliary
 - *obl*: oblique nominal
 - *flat*: flat multiword expression
 - *appos*: appositional modifier

THANK YOU
Any question?