

CS626: Speech, Natural Language Processing and the Web

*Algorithmics of Parsing, dependency
parsing*

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Algorithmics of Parsing

Problem Statement

INPUT: (a) grammar rules, (b) input sentence

OUTPUT: Parse Tree
(Constituency/Dependency)

Top Down

- Start with the *S* symbol and draw its children: say, *NP* and *VP*, assuming the input to be a declarative sentence.
- Now the subtrees under *NP*, followed by that under the *VP* are developed.
- For example, $NP \rightarrow DT\ NN$ could be applied.
- After this, only POS tags will need to be resolved. *DT* will absorb, say, the word '*the*' in the input and *NN*, '*man*'.
- This will complete constructing the *NP* subtree.
- Similarly, *VP* subtree also will be constructed.

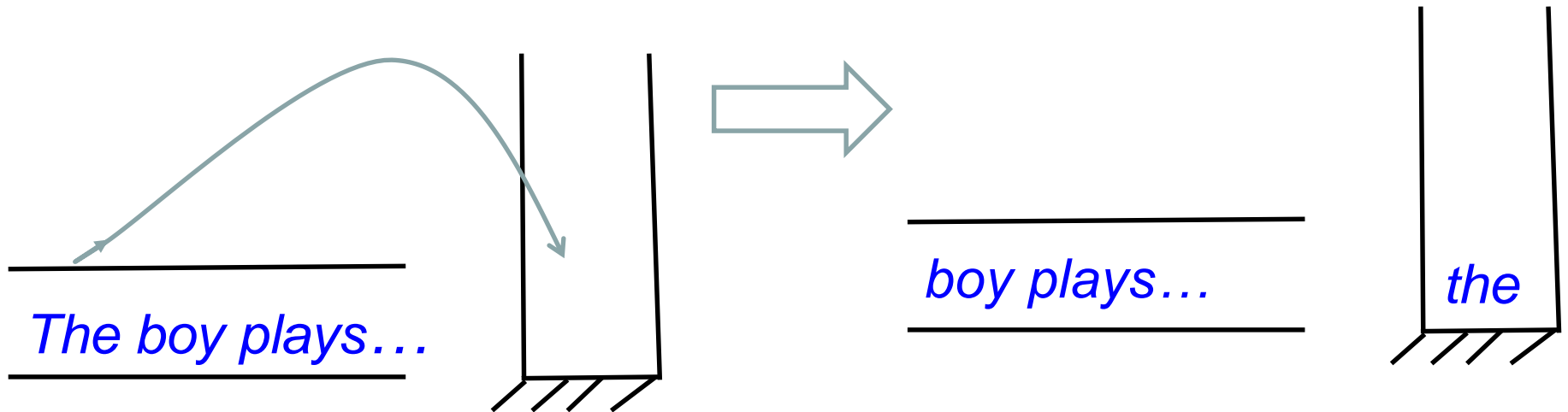
Bottom Up

- The words are resolved to their POS tags.
- Then POS tags are combined by constituency rules, e.g., $NP \rightarrow DT\ NN$. Generated non terminals are then attempted to be combined.
- For example, after generating JJP , NP they are combined to form a bigger NP , by applying $NP \rightarrow JJP\ NP$.

Main Operations

- Doing a left to right scan of the input sentence
- At every word, deciding if the word should (a) create a new constituent or (b) wait until more words get a look-in to create a constituent, and
- On creation of a new constituent, examining if the new constituent can be merged with an adjacent one to form a bigger constituent.

Shift Reduce (1/3)

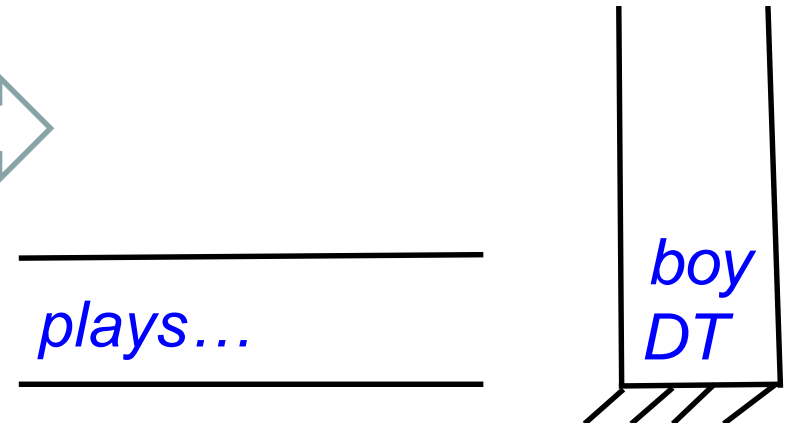


(a) Shift

Shift Reduce (2/3)

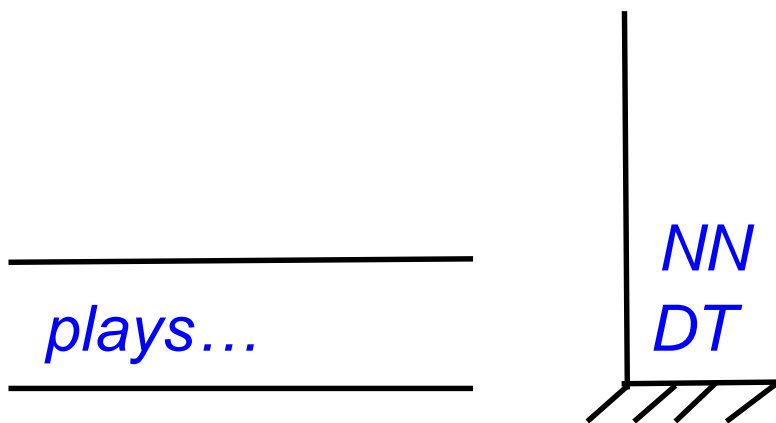


(b) Reduce

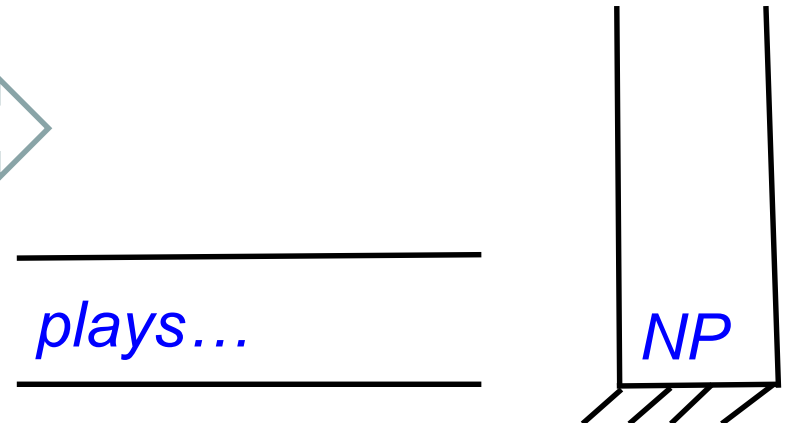


(c) Shift

Shift Reduce (3/3)



(d) Reduce



(e) Reduce

Top-Down Parsing

State	Backup State	Action
1. ((S) 0)	--	Expand S
2. ((NP VP) 0)	-	Expand NP; have backup
3. ((DT NN VP) 0)	((NN VP) 0)	Match DT; fail ; bring backup
4. ((NN VP) 0)	--	Consume ' <i>People</i> '; pop NN; advance input pointer
5. ((VP) 1)	--	Expand VP
6. ((VB RB) 1)	((VB) 1)	Consume ' <i>laugh</i> '; pop VB advance input pointer
7. ((RB) 2)	--	Match RB; fail ; bring backup; Retract input pointer
8. ((VB) 1)	--	Consume ' <i>laugh</i> '; pop VB
9. (() 2)	--	Stack empty; input over; Parsing Succeeds

A Grammar and an input sentence

Grammar:

(1) $S \rightarrow NP VP$

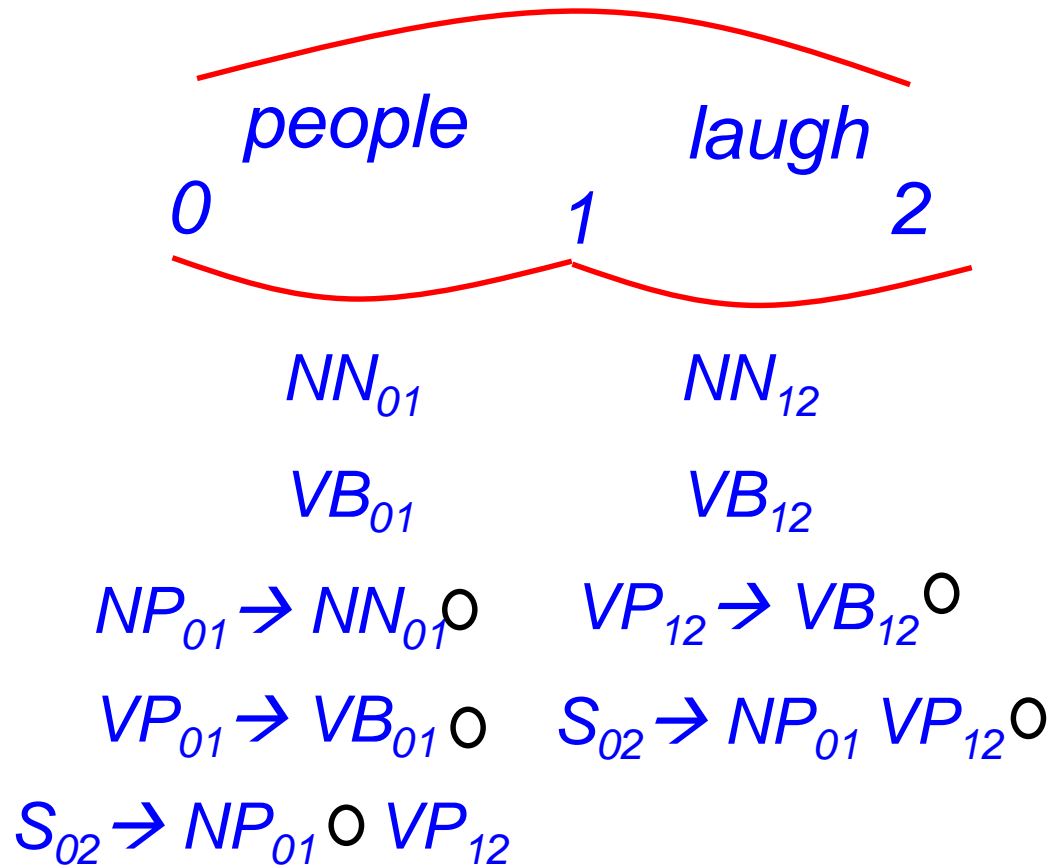
(2) $NP \rightarrow DT N \mid NN$

(3) $VP \rightarrow VB RB \mid VB$

Sentence is

$_0 \textit{People} _1 \textit{laugh} _2$

Bottom-Up Parsing



Commentary on Top-Down Parsing

- Top down parsing- goal driven
- Goal- to reach a state of stack-empty and input-over.
- AKA, *recursive descent parsing*, *predictive parsing* as well as *expectation driven parsing*.
- Names arise from properties:
 - handling of recursive rules, descending from *S* to *NP VP* and their children, and predicting or expecting constituents at different positions in the input

Limitations of Top-Down Parsing (1/2)

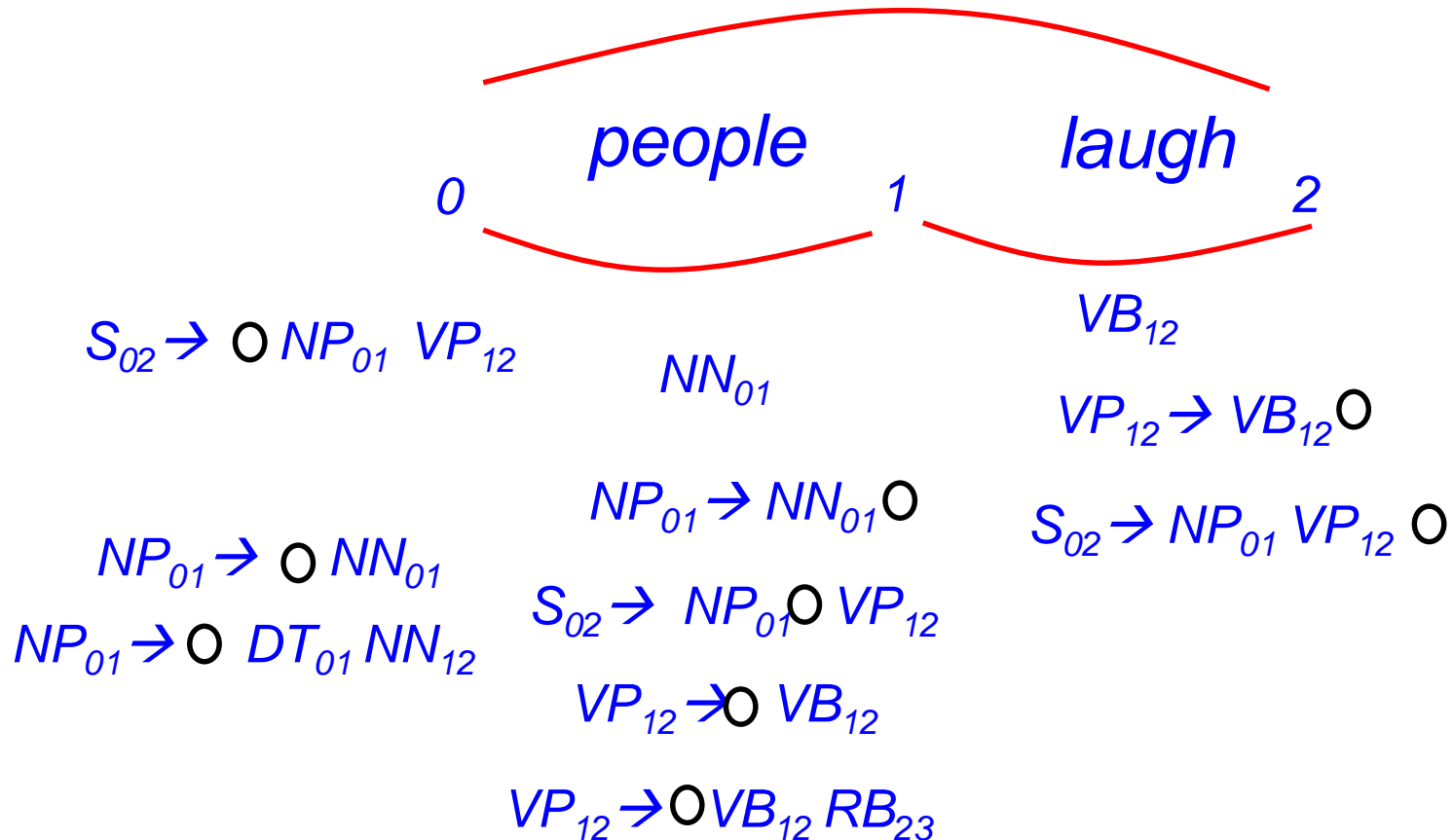
- Useless rule expansions: $NP \rightarrow DT\ NN$,
 $VP \rightarrow VB\ RB$
- Bringing backup states on to stack,
retracting the input pointer- these are
expensive operations.
- Precedence to textually earlier
appearance. If $NP \rightarrow NN$ appeared before
 $NP \rightarrow DT\ NN$, backtracking would have
been avoided. Similarly for $VP \rightarrow VB$ as
against $VP \rightarrow VB\ RB$

Limitations of Top-Down Parsing

(2/2)

- Left recursion causing infinite loop.
 - Consider the rule $JJP \rightarrow JJP JJ$. Once applied, this rule will keep pushing symbols JJP and JJ onto the stack *ad infinitum*.
- The root of all problems with top-down parsing is that the algorithm is blind to the actual data!

Top-Down Bottom-Up Parsing



CYK Parsing

Positions (row-col)	1	2
0	NN → NP	S
1		VB → VP

More involved CYK Parsing: A segment of English

- $S \rightarrow NP VP$
- $NP \rightarrow DT NN$
- $NP \rightarrow NNS$
- $NP \rightarrow NP PP$
- $PP \rightarrow P NP$
- $VP \rightarrow VP PP$
- $VP \rightarrow VBD NP$
- $DT \rightarrow \text{the}$
- $NN \rightarrow \text{gunman}$
- $NN \rightarrow \text{building}$
- $VBD \rightarrow \text{sprayed}$
- $NNS \rightarrow \text{bullets}$

CYK Parsing: Start with (0,1)

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

To From	1	2	3	4	5	6	7
0	DT						
1	-----						
2	-----	-----					
3	-----	-----	-----				
4	-----	-----	-----	-----			
5	-----	-----	-----	-----	-----		
6	-----	-----	-----	-----	-----	-----	

CYK: Keep filling diagonals

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

To From	1	2	3	4	5	6	7
0	DT						
1 →	-----	NN					
2 ↓	-----	-----					
3	-----	-----	-----				
4	-----	-----	-----	-----			
5	-----	-----	-----	-----	-----		
6	-----	-----	-----	-----	-----	-----	



CYK: Try getting higher level structures

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

To From	1	2	3	4	5	6	7
0	DT	NP					
1 →	-----	NN					
2 ↓	-----	-----					
3	-----	-----	-----				
4	-----	-----	-----	-----			
5	-----	-----	-----	-----	-----		
6	-----	-----	-----	-----	-----	-----	

CYK: Diagonal continues

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

To From	1	2	3	4	5	6	7
0	DT	NP					
1 	-----	NN					
2 	-----	-----	VBD				
3	-----	-----	-----				
4	-----	-----	-----	-----			
5	-----	-----	-----	-----	-----		
6	-----	-----	-----	-----	-----	-----	

CYK (cont...)

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

To From	1	2	3	4	5	6	7
0 →	DT	NP	-----				
1 ↓	-----	NN	-----				
2	-----	-----	VBD				
3	-----	-----	-----				
4	-----	-----	-----	-----			
5	-----	-----	-----	-----	-----		
6	-----	-----	-----	-----	-----	-----	

CYK (cont...)

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

To From	1	2	3	4	5	6	7
0 →	DT	NP	-----				
1	-----	NN	-----				
2 ↓	-----	-----	VBD				
3	-----	-----	-----	DT			
4	-----	-----	-----	-----			
5	-----	-----	-----	-----	-----		
6	-----	-----	-----	-----	-----	-----	

CYK (cont...)

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

To From	1	2	3	4	5	6	7
0 →	DT	NP	-----	-----			
1 ↓	-----	NN	-----	-----			
2	-----	-----	VBD	-----			
3	-----	-----	-----	DT			
4	-----	-----	-----	-----	NN		
5	-----	-----	-----	-----	-----		
6	-----	-----	-----	-----	-----	-----	

CYK: starts filling the 5th column

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

To From	1	2	3	4	5	6	7
0	DT	NP	-----	-----			
1	-----	NN	-----	-----			
2	-----	-----	VBD	-----			
3	-----	-----	-----	DT	NP		
4	-----	-----	-----	-----	NN		
5	-----	-----	-----	-----	-----		
6	-----	-----	-----	-----	-----	-----	

CYK (cont...)

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

To From	1	2	3	4	5	6	7
0	DT	NP	-----	-----			
1	-----	NN	-----	-----			
2	-----	-----	VBD	-----	VP		
3	-----	-----	-----	DT	NP		
4	-----	-----	-----	-----	NN		
5	-----	-----	-----	-----	-----		
6	-----	-----	-----	-----	-----	-----	

CYK (cont...)

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

To From	1	2	3	4	5	6	7
0	DT	NP	-----	-----			
1	-----	NN	-----	-----	-----		
2	-----	-----	VBD	-----	VP		
3	-----	-----	-----	DT	NP		
4	-----	-----	-----	-----	NN		
5	-----	-----	-----	-----	-----		
6	-----	-----	-----	-----	-----	-----	

CYK: S found, but NO termination!

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

To From	1	2	3	4	5	6	7
0	DT	NP	-----	-----	S		
1	-----	NN	-----	-----	-----		
2	-----	-----	VBD	-----	VP		
3	-----	-----	-----	DT	NP		
4	-----	-----	-----	-----	NN		
5	-----	-----	-----	-----	-----		
6	-----	-----	-----	-----	-----	-----	



CYK (cont...)

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

To From	1	2	3	4	5	6	7
0	DT	NP	-----	-----	S		
1	-----	NN	-----	-----	-----		
2	-----	-----	VBD	-----	VP		
3	-----	-----	-----	DT	NP		
4	-----	-----	-----	-----	NN		
5	-----	-----	-----	-----	-----	P	
6	-----	-----	-----	-----	-----	-----	

CYK (cont...)

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

To From	1	2	3	4	5	6	7
0	DT	NP	-----	-----	S	-----	
1 	-----	NN	-----	-----	-----	-----	
2 	-----	-----	VBD	-----	VP	-----	
3	-----	-----	-----	DT	NP	-----	
4	-----	-----	-----	-----	NN	-----	
5	-----	-----	-----	-----	-----	P	
6	-----	-----	-----	-----	-----	-----	

[illegible]

[illegible]

CYK (cont...)

0 The 1 gunman 2 sprayed 3 the 4 building 5 with 6 bullets 7.

[illegible]

[illegible]

CYK: filling the last column

0 The 1 gunman 2 sprayed 3 the 4 building 5 with 6 bullets 7.

[illegible]

CYK: terminates with S in (0,7)

0 The 1 gunman 2 sprayed 3 the 4 building 5 with 6 bullets 7.

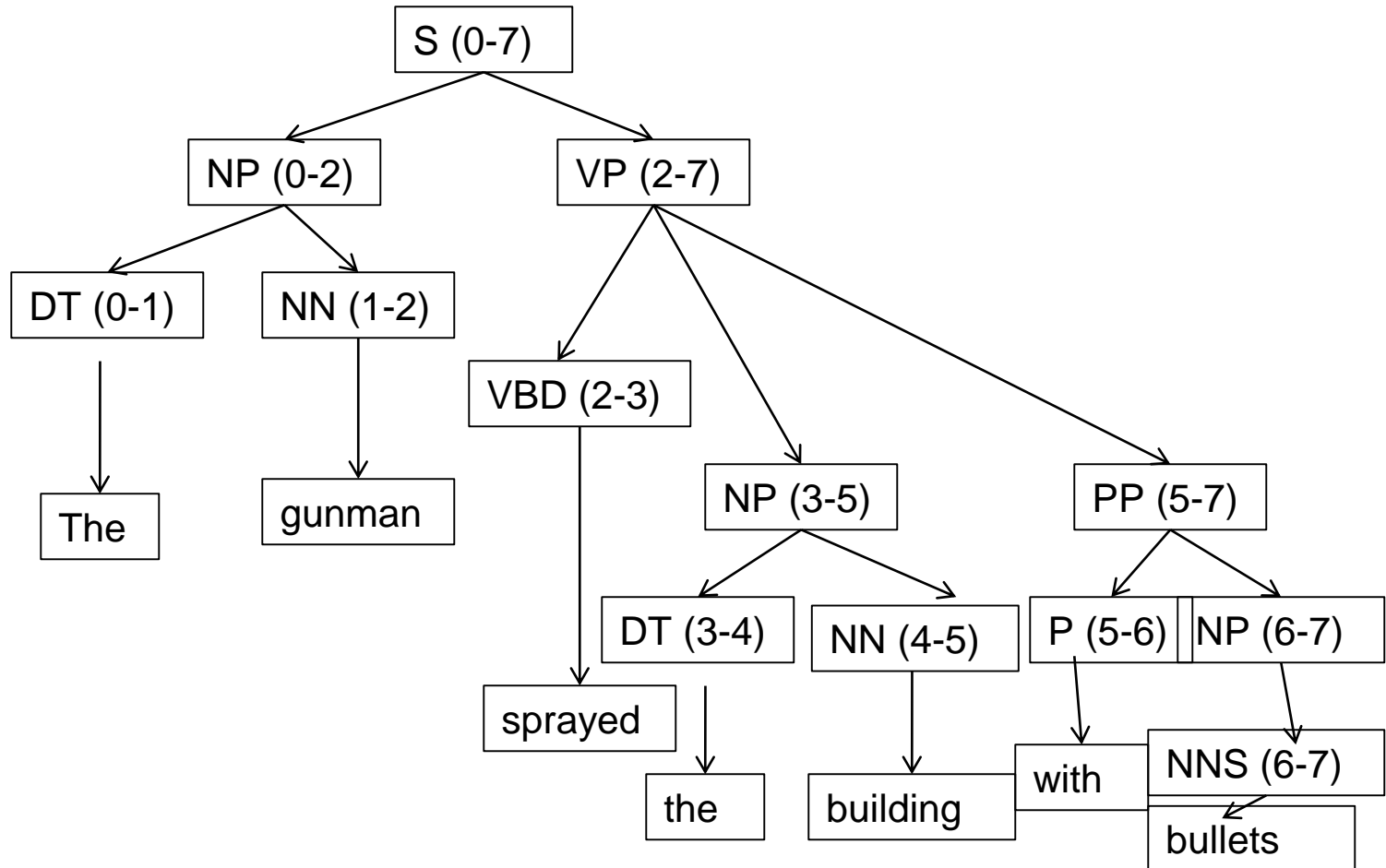
[illegible]

CYK: Extracting the Parse Tree

- The parse tree is obtained by keeping back pointers.

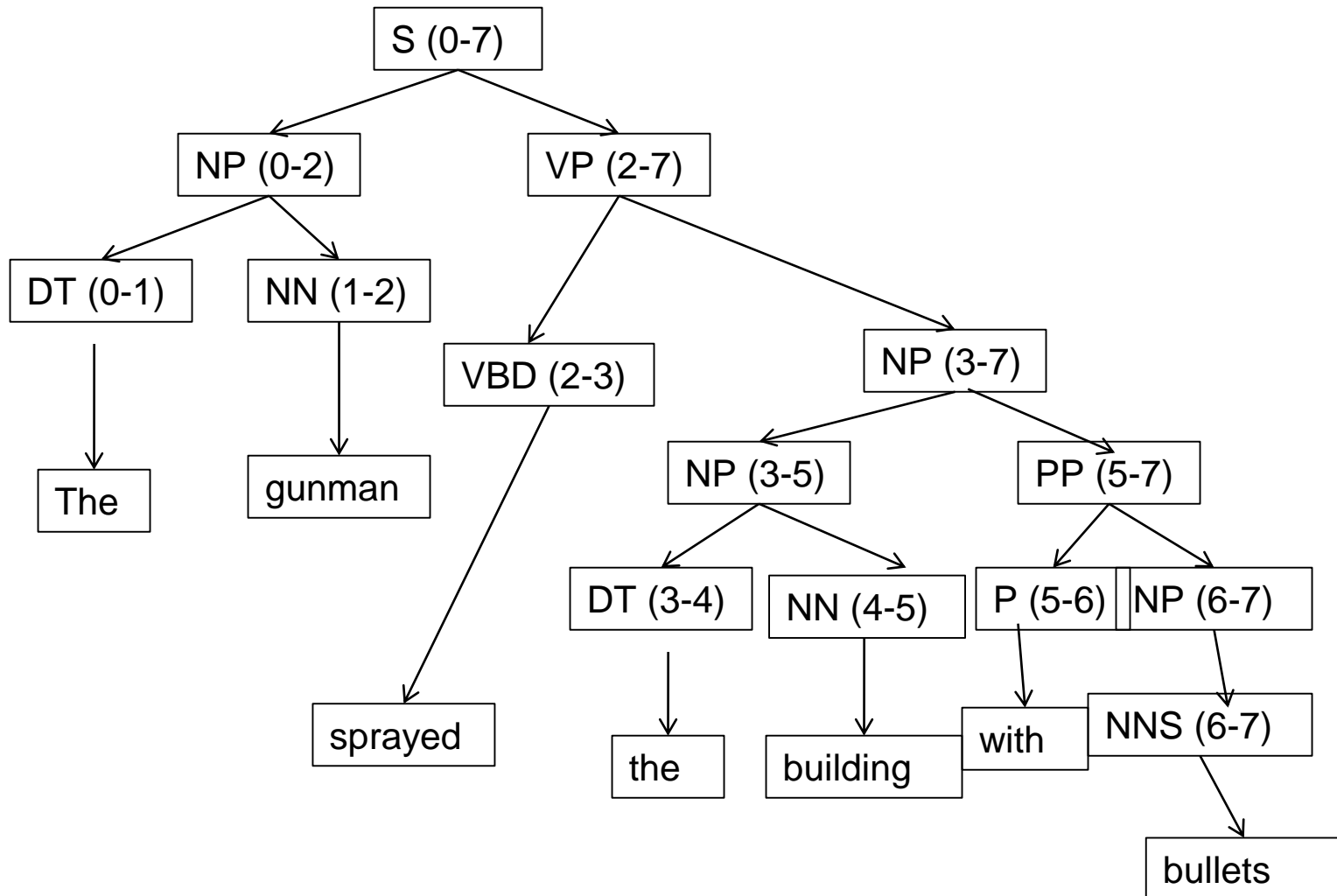
Parse Tree #1

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.



Parse Tree #2

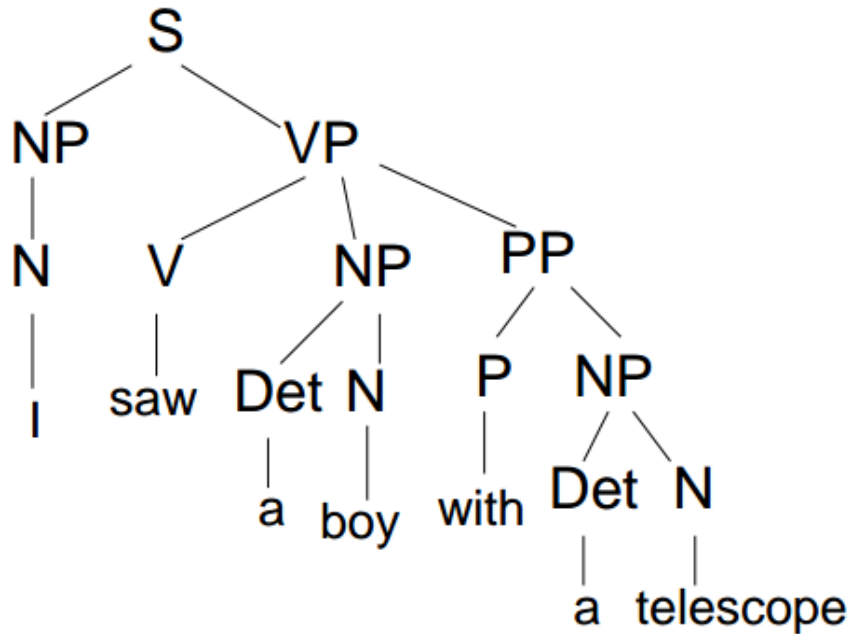
0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.



Notion of Domination

- A sentence is dominated by the symbol S through domination of segments by phrases
- Analogy
 - The capital of a country dominates the whole country.
 - The capital of a state dominates the whole state.
 - The district headquarter dominates the district.

Domination: Example



- Dominations
 - NP dominates “a telescope”
 - VP dominates “saw a boy with a telescope”
 - S dominates the whole sentence
- Domination is composed of many sub-domination.
- I saw a boy with a telescope
 - Meaning: I used the telescope to see the boy

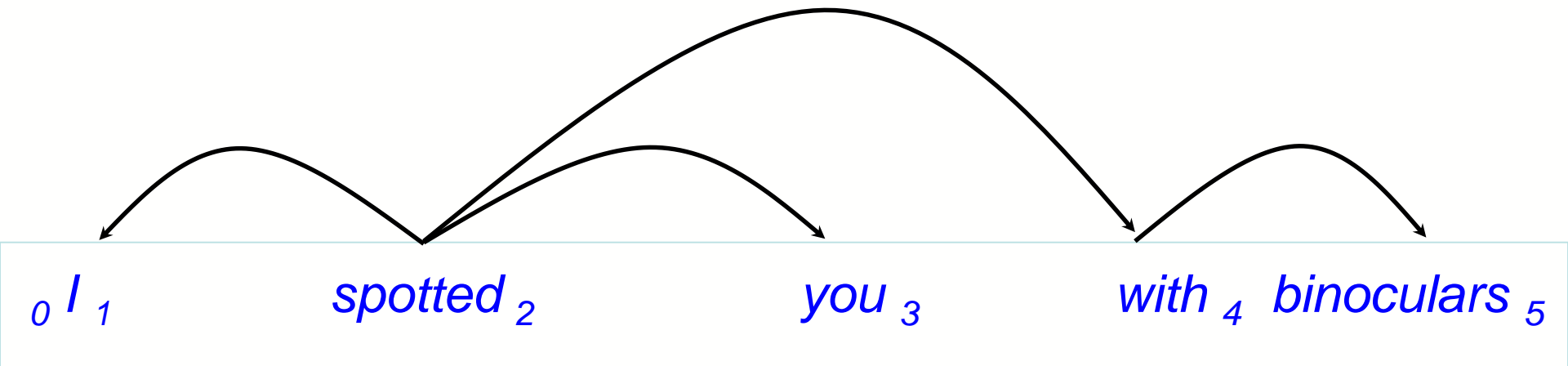
Dependency Parsing

“I spotted you with binoculars”.

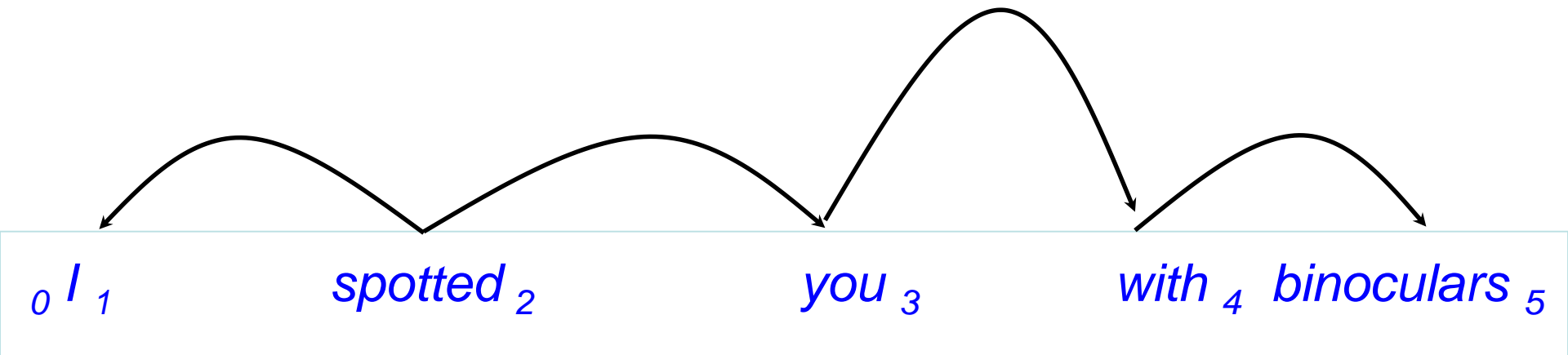
$_0$ I $_1$ spotted $_2$ you $_3$ with $_4$ binoculars $_5$

- Has two meanings
- I have the binoculars OR
- You have the binoculars

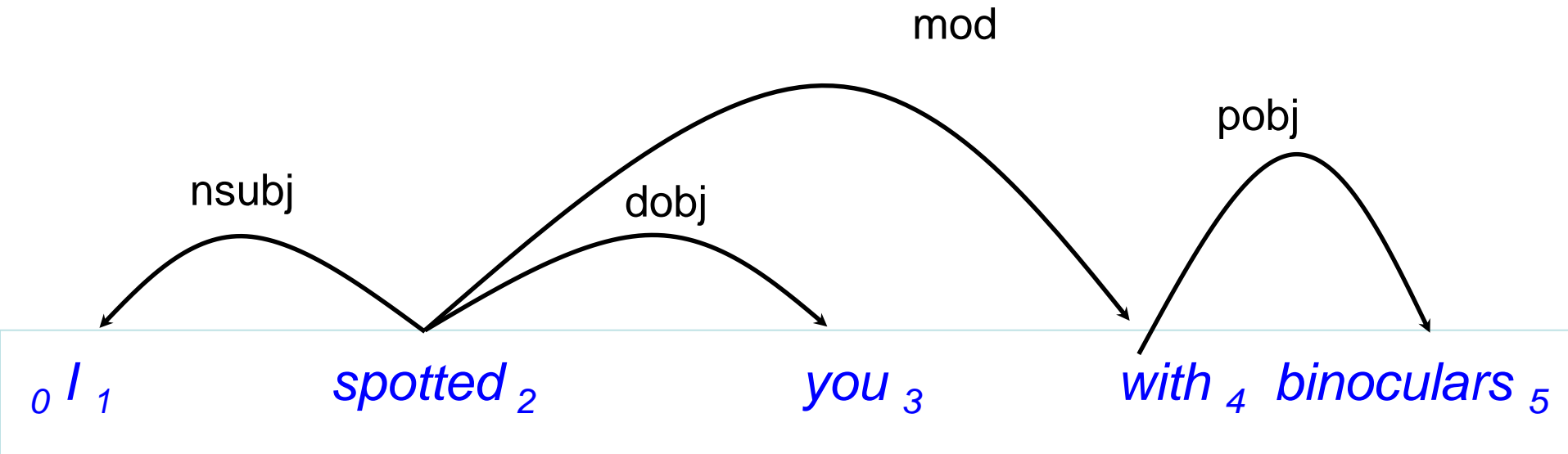
Unlabeled Dependency Tree-1



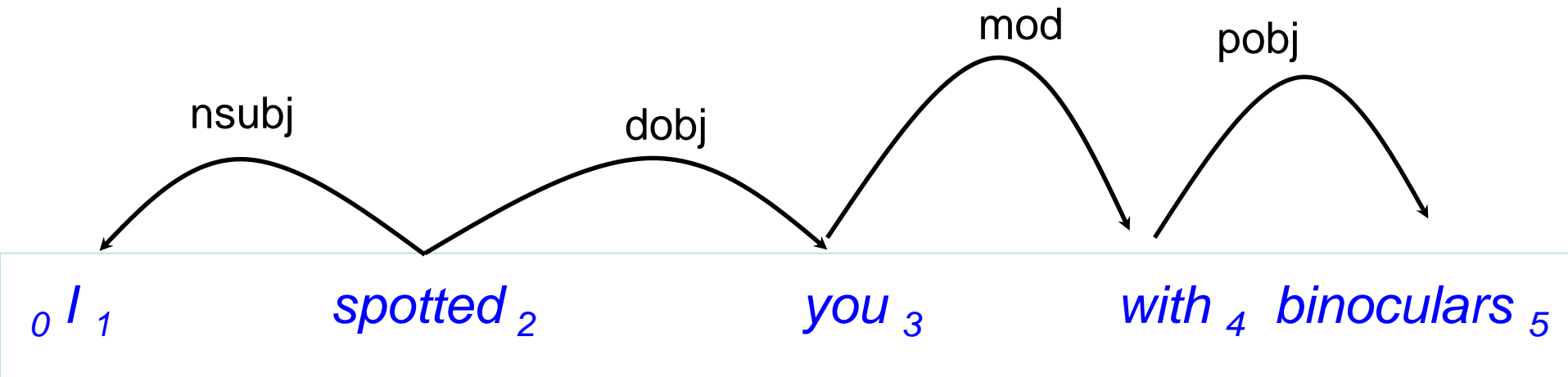
Unlabeled Dependency Tree-2



Labeled Dependency Tree-1



Labeled Dependency Tree-2



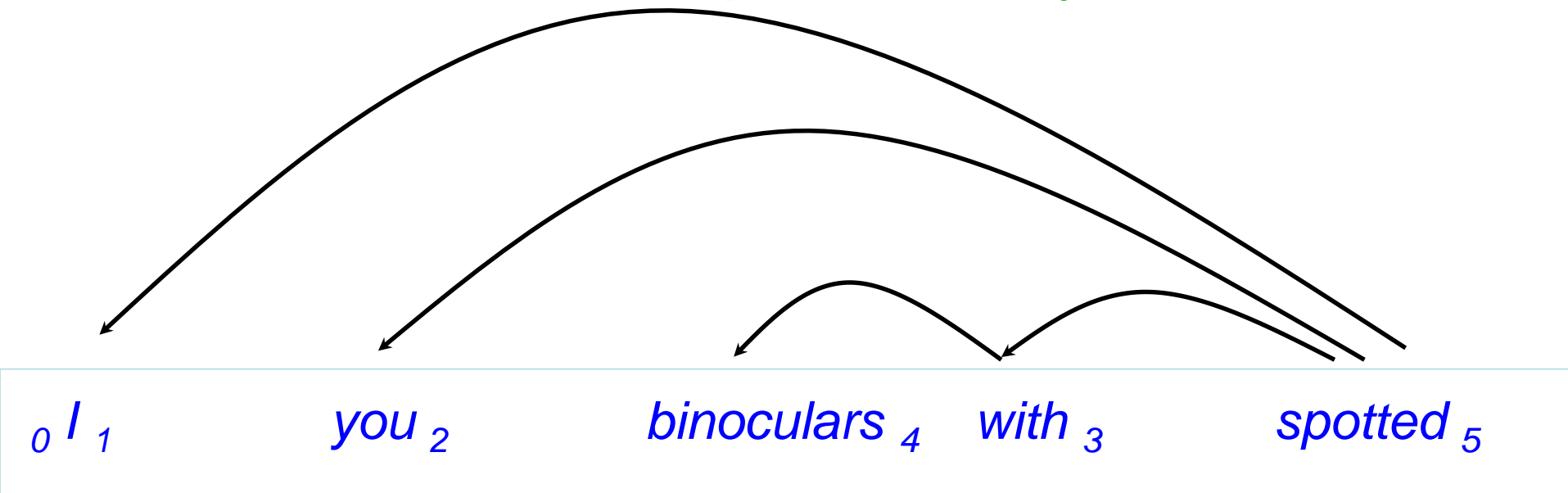
For SOV Syntax

“I you binoculars with spotted”

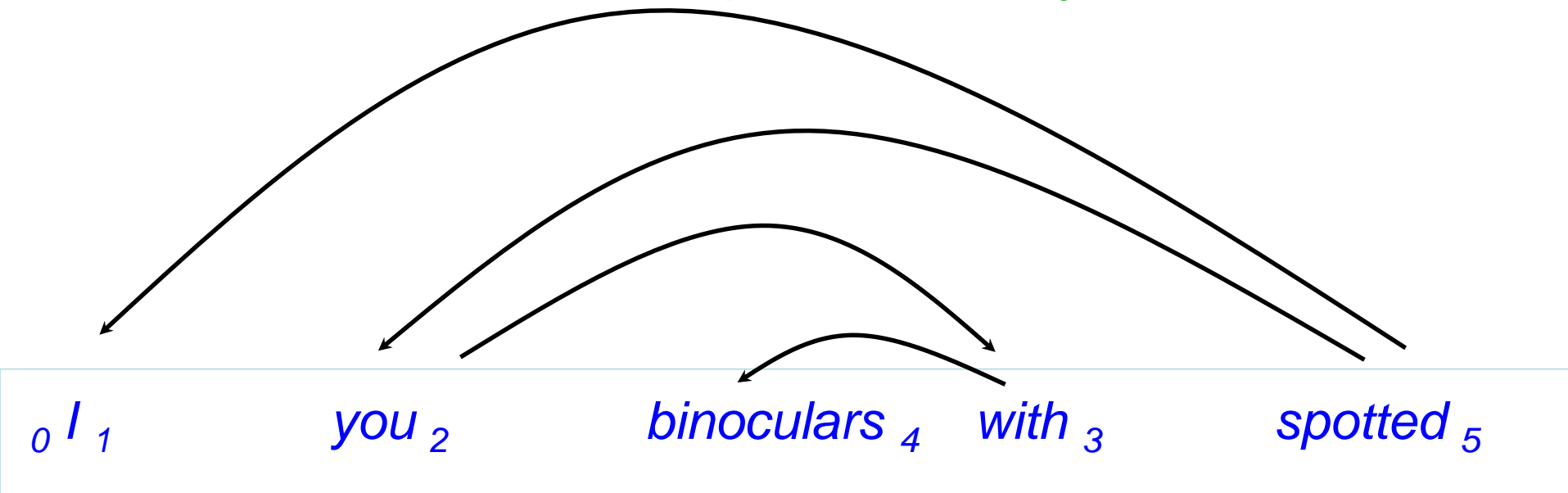
0 I 1 spotted 2 you 3 with 4 binoculars 5

- Has two meanings
- I have the binoculars OR
- You have the binoculars

Unlabeled Dependency Tree-1



Unlabeled Dependency Tree-2



Dependency Parsing Example

- Transition based parsing
- Shift and Reduce

Q8: Justification: Parse-1

1. [root]	[I spotted you with binoculars]	shift	no-relation-added
2. [root I]	[spotted you with binoculars]	shift	no-relation-added
3. [root I spotted]	[you with binoculars]	left-arc	I←spotted
4. [root spotted]	[you with binoculars]	shift	no-relation-added
5. [root spotted you]	[with binoculars]	right-arc	spotted→you
6. [root spotted]	[with binoculars]	shift	no-relation-added
7. [root spotted with]	[binoculars]	shift	no-relation added
8. [root spotted with binoculars]	[]	right-arc	with→binoculars
9. [root spotted with]	[]	right-arc	spotted→with
10. [root spotted]	[]	right-arc	root→spotted
11. [root]	[]	parsing ends	

Q8: Justification: Parse-2

1. [root] [I spotted you with binoculars]		shift	no-relation-added
2. [root I] [spotted you with binoculars]		shift	no-relation-added
3. [root I spotted] [you with binoculars]		left-arc	I←spotted
4. [root spotted] [you with binoculars]		shift	no-relation-added
5. [root spotted you] [with binoculars]		shift	no-relation-added
6. [root spotted you with] [binoculars]		shift	no-relation-added
7. [root spotted you with binoculars]	[]	right-arc	with→binoculars
8. [root spotted you with]	[]	right-arc	you→with
9. [root spotted you]	[]	right-arc	spotted→you
10. [root spotted]	[]	right-arc	root→spotted
11. [root]	[]		parsing ends

Need Classification

Decision making

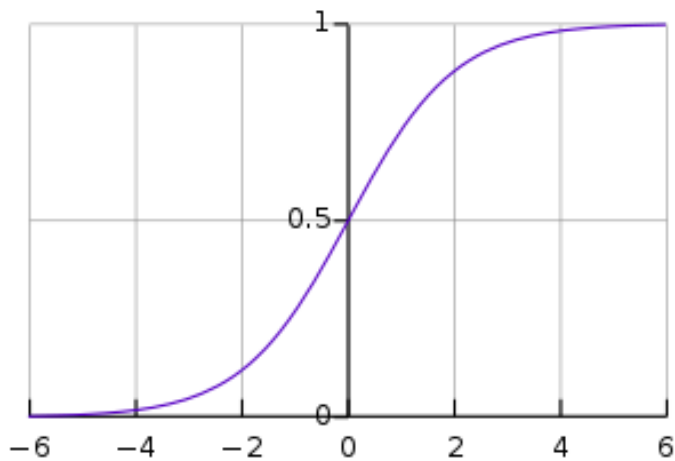
- Constituency Parsing
 - Shift
 - Reduce
- Dependency Parsing
 - Shift
 - Right Arc
 - Left Arc

2-class: Sigmoid or Logit function

$$y = \frac{1}{1 + e^{-x}}$$

$$\frac{dy}{dx} = y(1 - y)$$

Sigmoid function



$$f(x) = \frac{1}{1+e^{-x}}$$

$$\begin{aligned} f(x) &= \frac{1}{1+e^{-x}} \\ \frac{df(x)}{dx} &= \frac{d}{dx} \left(\frac{1}{1+e^{-x}} \right) \\ &= \frac{e^{-x}}{(1+e^{-x})^2} \\ &= \frac{1}{1+e^{-x}} \left(1 - \frac{1}{1+e^{-x}} \right) \\ &= f(x) \cdot (1 - f(x)) \end{aligned}$$

Decision making under sigmoid

- Output of sigmoid is between 0-1
- Look upon this value as probability of Class-1 (C_1)
- $1-\text{sigmoid}(x)$ is the probability of Class-2 (C_2)
- Decide C_1 , if $P(C_1) > P(C_2)$, else C_2

multiclass: SOFTMAX

- 2-class \rightarrow multi-class (C classes)
- Sigmoid \rightarrow softmax
- i^{th} input, c^{th} class (small c), k varies over classes
- In softmax, decide for that class which has the highest probability

What is softmax

- Turns a vector of K real values into a vector of K real values that sum to 1
- Input values can be positive, negative, zero, or greater than one
- But softmax transforms them into values between 0 and 1
- so that they can be interpreted as probabilities.

Mathematical form

$$\sigma(\bar{Z})_i = \frac{e^{Z_i}}{\sum_{j=1}^K e^{Z_j}}$$

- σ is the **softmax** function
- Z is the input vector of size K
- The RHS gives the i^{th} component of the output vector
- Input to softmax and output of softmax are of the same dimension

Example

$$\bar{Z} = \langle 1, 2, 3 \rangle$$

$$Z_1 = 1, Z_2 = 2, Z_3 = 3$$

$$e^1 = 2.72, e^2 = 7.39, e^3 = 20.09$$

$$\sigma(\bar{Z}) = \left\langle \frac{2.72}{2.72 + 7.39 + 20.09}, \frac{7.39}{2.72 + 7.39 + 20.09}, \frac{20.09}{2.72 + 7.39 + 20.09} \right\rangle$$
$$= \langle .09, 0.24, 0.67 \rangle$$

Softmax and Cross Entropy

- Intimate connection between softmax and cross entropy
- Softmax gives a vector of probabilities
- Winner-take-all strategy will give a classification decision

Winner-take-all with softmax

- Consider the softmax vector obtained from the example where the softmax vector is $\langle 0.09, 0.24, 0.65 \rangle$
- These values correspond to 3 classes
 - For example, - *positive (+), negative (-) and neutral (0)* sentiments, given an input sentence like
 - (a) *I like the story line of the movie (+).* (b) *However the acting is weak (-).* (c) *The protagonist is a sports coach (0)*

Sentence vs. Sentiment

Sentence vs. Sentiment	Positive	Negative	Neutral
	(a) <i>I like the story line of the movie (+).</i> (b) <i>However the acting is weak (-).</i> (c) <i>The protagonist is a sports coach (0)</i>		
Sent (a)	1 <i>(P_{max} from softmax)</i>	0	0
Sentence (b)	0	1 <i>(P_{max} from softmax)</i>	0
Sentence (C)	0	0	1 <i>(P_{max} from softmax)</i>

Training data

- *(a) I like the story line of the movie (+).*
- *(b) However the acting is weak (-).*
- *(c) The protagonist is a sports coach (0)*

Input

Output

(a)

$\langle 1, 0, 0 \rangle$

(b)

$\langle 0, 1, 0 \rangle$

(c)

$\langle 0, 0, 1 \rangle$

Finding the error

- Difference between target (T) and obtained (Y)
- Difference is called **LOSS**
- Options:
 - Total Sum Square Loss (TSS)
 - Cross Entropy (*measures difference between two probability distributions*)
- Softmax goes with cross entropy

Cross Entropy Function

$$H(P, Q) = -\sum_x P(x) \log_2 Q(x)$$

P is target distribution

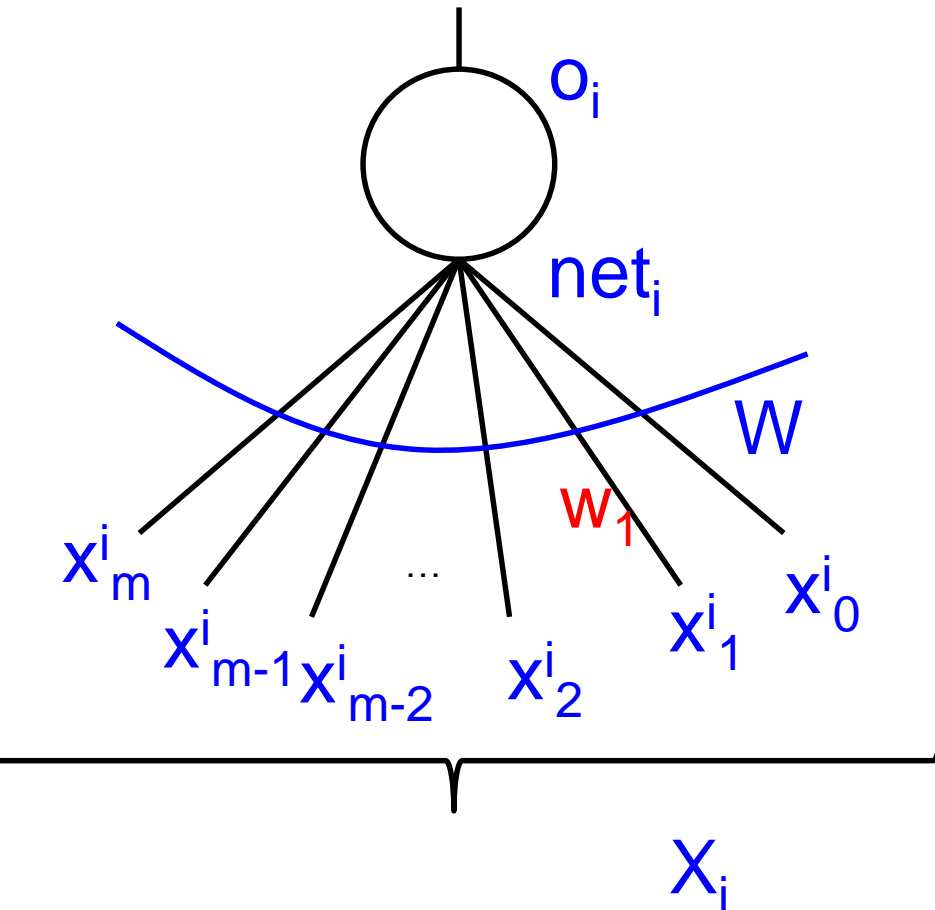
Q is observed distribution

How to minimize loss

- Gradient descent approach
- Backpropagation Algorithm
- Involves derivative of the input out function for each neuron
- FFNN with BP is one of the most important TECHNIQUES

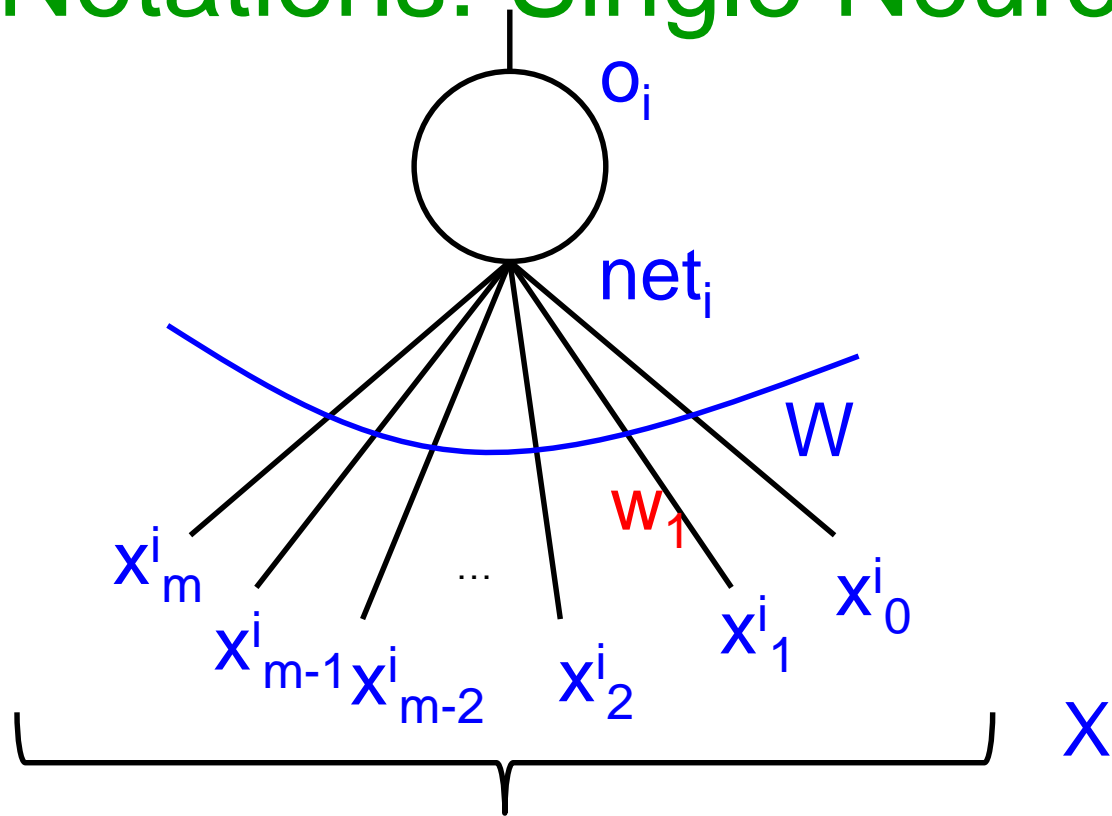
Sigmoid and Softmax Neurons

Fix Notations: Single Neuron (1/2)



- Capital letter for vectors
- Small letter for scalars (therefore for vector components)
- X_i : i th input vector
- o_i : output (scalar)
- W : weight vector
- net_i : $W \cdot X_i$
- There are n input-output observations

Fix Notations: Single Neuron (2/2)



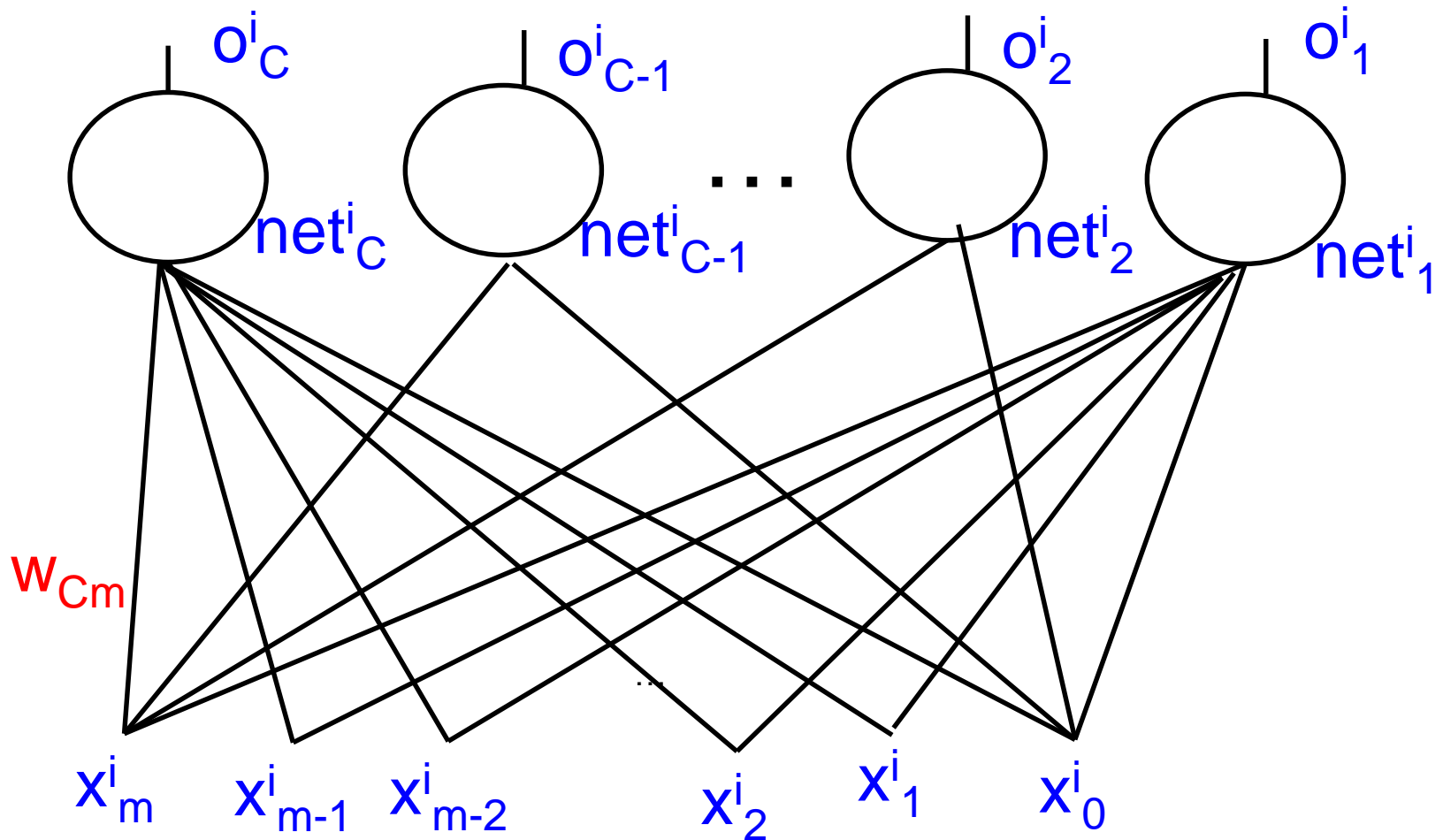
W and each X_i has m components

$W: \langle w_m, w_{m-1}, \dots, w_2, w_0 \rangle$

$X_i: \langle x_m^i, x_{m-1}^i, \dots, x_2^i, x_0^i \rangle$

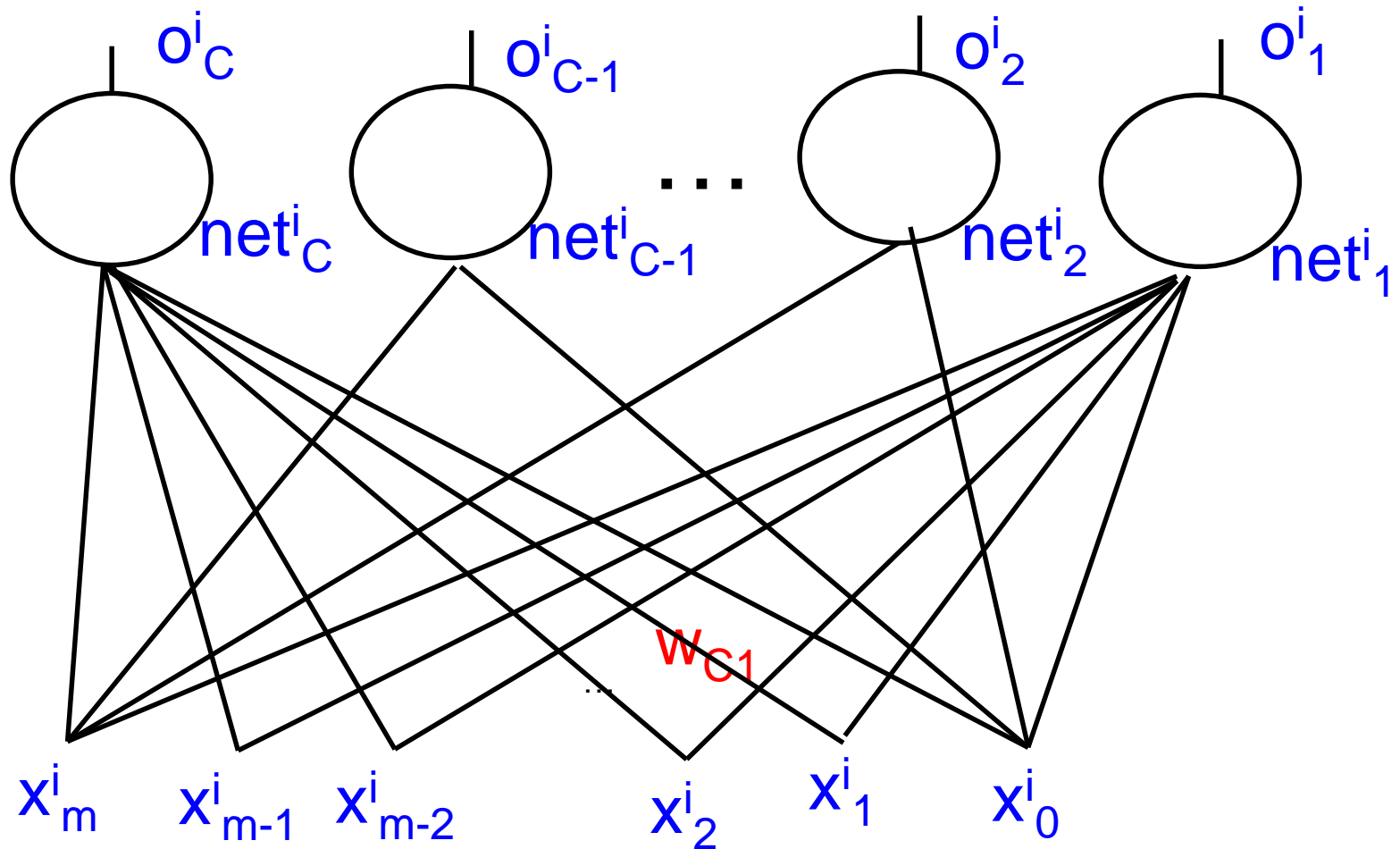
Upper suffix i indicates i^{th} input

Fixing Notations: Multiple neurons in o/p layer



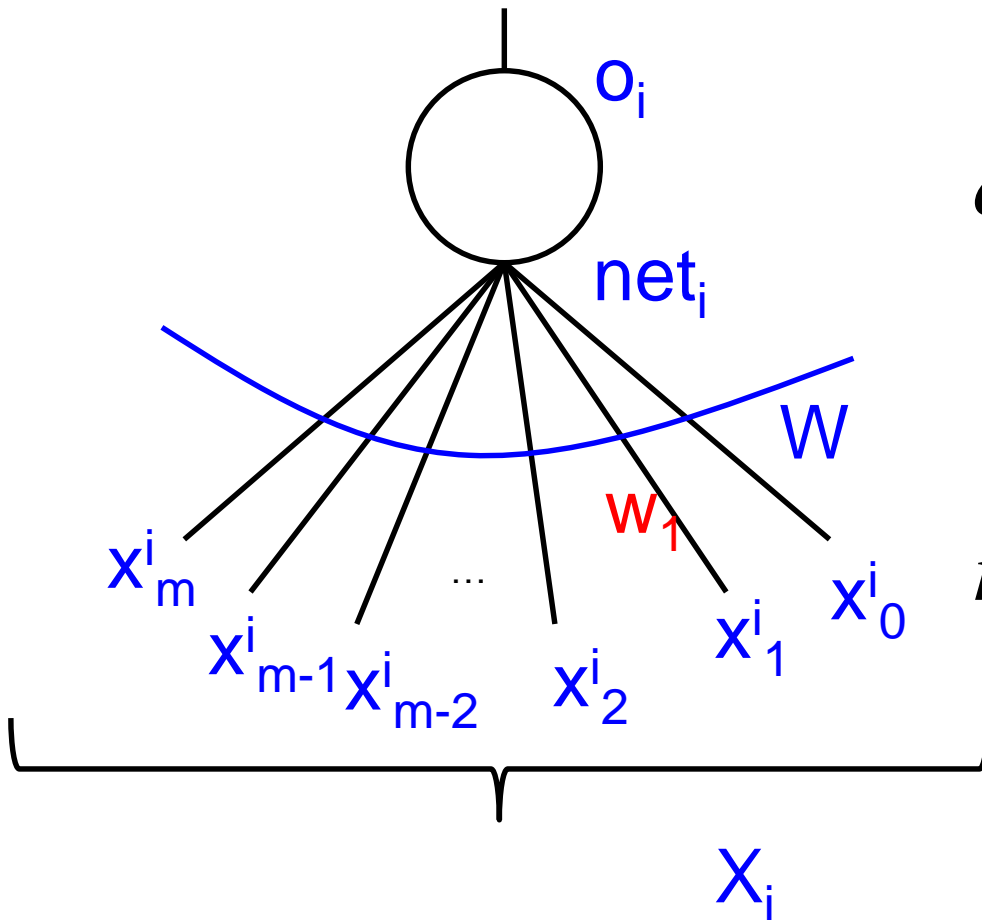
Now, O_i and NET_i are vectors for i^{th} input
 W_k is the weight vector for k^{th} output neuron,
 $k=1 \dots C$

Fixing Notations



Target Vector, $T_i: \langle t_c^i t_{c-1}^i \dots t_2^i t_1^i \rangle$, $i \rightarrow$ for i^{th} input. Only one of these C componets is 1, rest are 0

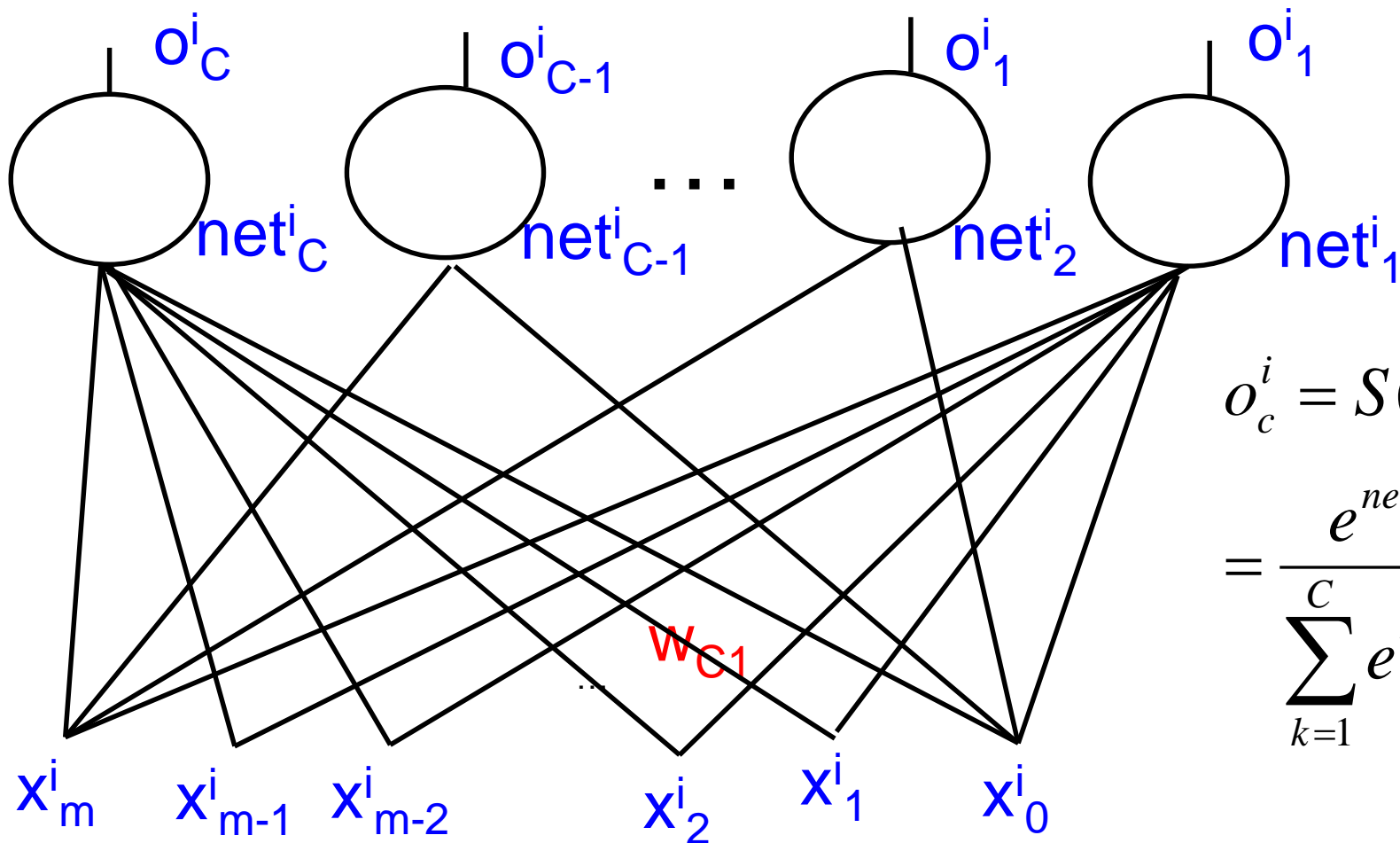
Sigmoid neuron



$$o_i = \frac{1}{1 + e^{-net_i}}$$

$$net_i = W \cdot X_i = \sum_{j=0}^m w_j x_j^i$$

Softmax Neuron



$$o_c^i = S(\bar{NET}_i)_c$$

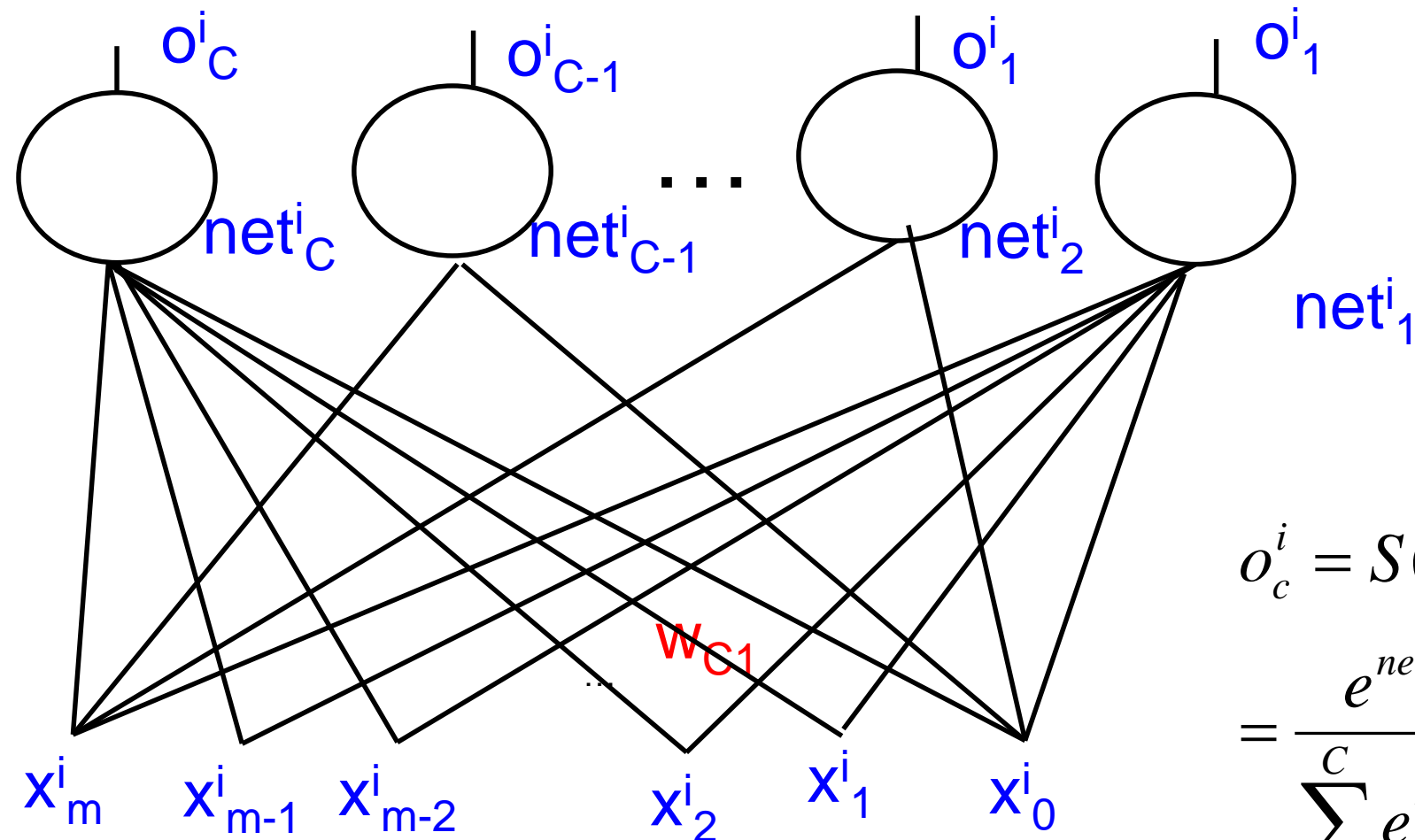
$$= \frac{e^{net_c^i}}{\sum_{k=1}^C e^{net_k^i}},$$

Output for class c (small c), c:1 to C

Notation Again

- $i=1..N$, N i-o pairs, i runs over training data
- $j=0...m$, m components in the input vector, j runs over the input dimension (also weight vector dimension)
- $k=1...C$, C classes (C components in the output vector)

Softmax Neuron



$$o_c^i = S(\overline{NET}_i)_c$$

$$= \frac{e^{net_c^i}}{\sum_{k=1}^C e^{net_k^i}},$$

Target Vector, $T_i: \langle t_c^i t_{c-1}^i \dots t_2^i t_1^i \rangle$, $i \rightarrow$ for i^{th} input.
Only one of these C components is 1, rest are 0.

Compare and contrast Sigmoid and Softmax

$$\text{sigmoid} : o_i = \frac{1}{1 + e^{-net_i}}, \text{ for } i^{th} \text{ input}$$

$$\text{soft max} : o_c^i = \frac{e^{net_c^i}}{\sum_{k=1}^C e^{net_k^i}},$$

i^{th} input, c^{th} class (small c), k varies over classes 1 to C

Interpreting o_c^i

- o_c^i value is between 0 and 1
- Interpreted as probability
- Multi-class situation
- o_c^i value is the probability of the class being 'c' for the i^{th} input
- That is,
$$P(\text{Class of } i^{th} \text{ input} = c) = o_c^i$$

Derivatives

Derivative of sigmoid

$$o_i = \frac{1}{1 + e^{-net_i}}, \text{ for } i^{th} \text{ input}$$

$$\ln o_i = -\ln(1 + e^{-net_i})$$

$$\frac{1}{o_i} \frac{\partial o_i}{\partial net_i} = -\frac{1}{1 + e^{-net_i}} \cdot -e^{-net_i} = \frac{e^{-net_i}}{1 + e^{-net_i}} = (1 - o_i)$$

$$\Rightarrow \frac{\partial o_i}{\partial net_i} = o_i(1 - o_i)$$

Derivative of Softmax

$$o_c^i = \frac{e^{net_c^i}}{\sum_{k=1}^C e^{net_k^i}}, \text{ } i^{th} \text{ input pattern}$$

Derivative of Softmax: Case-1, class c for O and NET same

$$\ln o_c^i = net_c^i - \ln\left(\sum_{k=1}^C e^{net_k^i}\right)$$

$$\frac{1}{o_c^i} \frac{\partial o_c^i}{\partial net_c^i} = 1 - \frac{1}{\sum_{k=1}^C e^{net_k^i}} \cdot e^{net_c^i} = 1 - o_c^i$$

$$\Rightarrow \frac{\partial o_c^i}{\partial net_c^i} = o_c^i (1 - o_c^i)$$

Derivative of Softmax: Case-2, class c' in net_c^i , different from class c of O

$$\ln o_c^i = net_c^i - \ln\left(\sum_{k=1}^C e^{net_k^i}\right)$$

$$\frac{1}{o_c^i} \frac{\partial o_c^i}{\partial net_c^i} = 0 - \frac{1}{\sum_{k=1}^C e^{net_k^i}} \cdot e^{net_c^i} = -o_c^i$$

$$\Rightarrow \frac{\partial O_k^i}{\partial net_c^i} = -o_c^i o_{c'}^i$$