

Master in Artificial Intelligence

Trees and
Grammars

Constituency
Parsing

Advanced Human Language Technologies

Constituent Parsing



UNIVERSITAT POLITÈCNICA DE CATALUNYA
BARCELONATECH
Facultat d'Informàtica de Barcelona

FIB

Outline

Trees and
Grammars

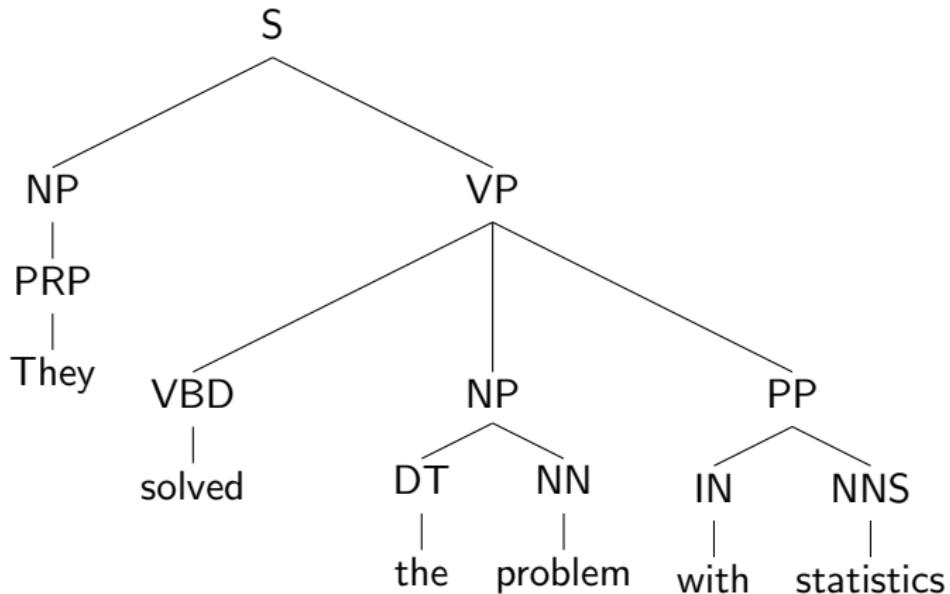
Constituency
Parsing

1 Trees and Grammars

2 Constituency Parsing

- CKY Algorithm
- Earley Algorithm

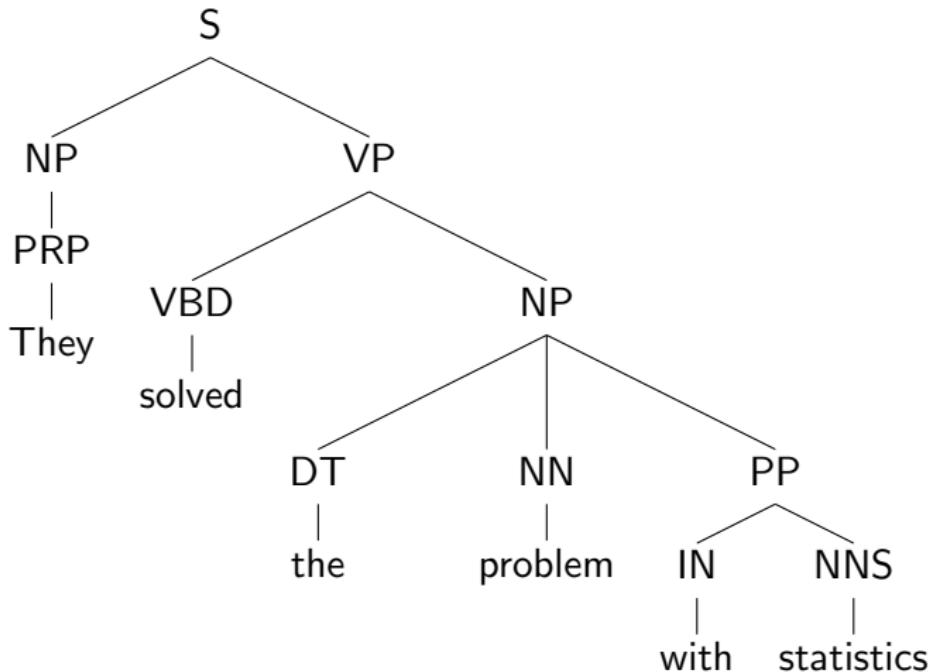
A Syntactic Tree



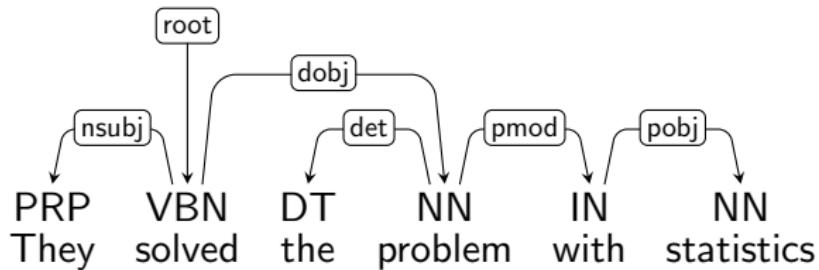
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Another Syntactic Tree



Dependency Trees



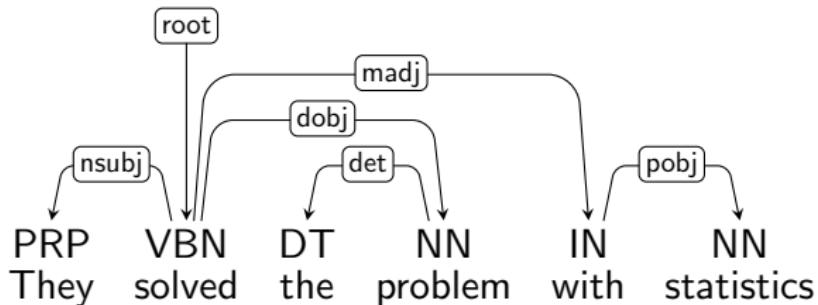
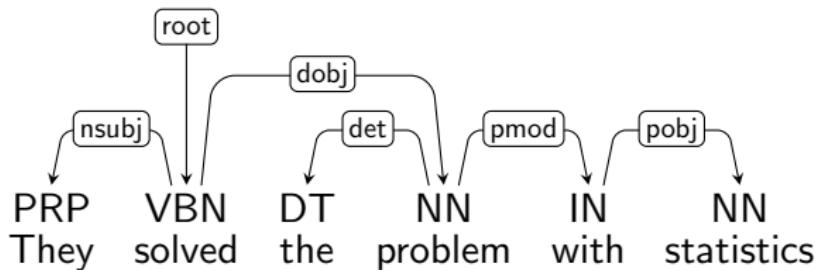
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Dependency Trees

Trees and
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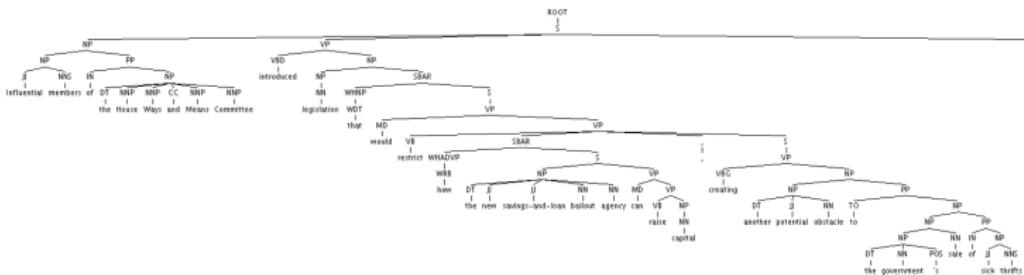
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A “real” sentence

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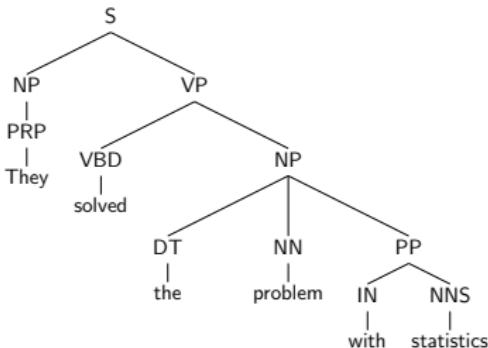
Influential members of the House Ways and Means Committee
introduced legislation that would restrict how the new
savings-and-loan bailout agency can raise capital, creating another
potential obstacle to the government's sale of sick thrifts.

Theories of Syntactic Structure

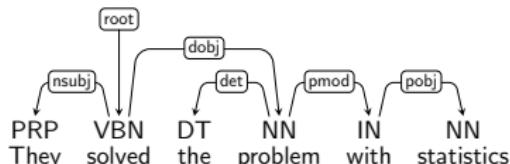
Trees and Grammars

Constituency Parsing

Constituent Trees



Dependency Trees



- Main element: constituents (or phrases, or bracketings)
- Constituents = abstract linguistic units
- Results in nested trees

- Main element: dependency
- Focus on relations between words
- Handles *free word order* nicely.

Context Free Grammars (CFGs)

A context-free grammar is defined as a tuple $G = \langle N, \Sigma, R, S \rangle$ where:

- N is a set of non-terminal symbols
- $S \in N$ is a distinguished start symbol
- Σ is a set of terminal symbols
- R is a set of rules of the form $X \rightarrow Y_1Y_2\dots Y_n$ where $n \geq 0$, $X \in N$, $Y_i \in N \cup \Sigma$

Context Free Grammars, Example

$$N = \{S, VP, NP, PP, DT, Vi, Vt, NN, IN\}^1$$

$$S = \{S\}$$

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Properties of CFGs

Trees and
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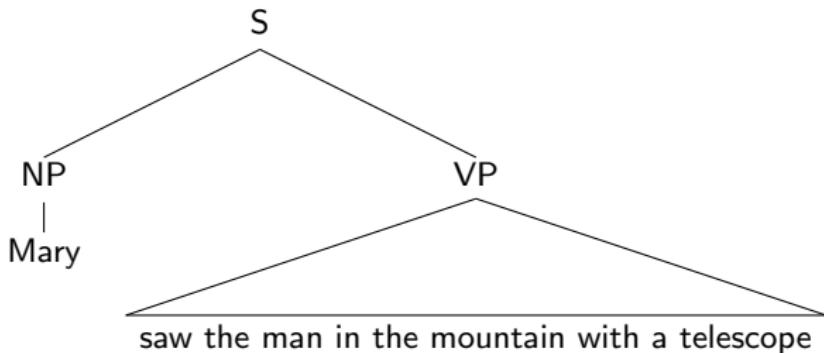
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- A CFG defines a set of possible *derivations* (i.e. unique trees)
- A sequence of terminals $s \in \Sigma^*$ is *generated* by the CFG (or *recognized* by it, or *belongs* to the language defined by it) if there is at least a derivation that produces s .
- Some sequences of terminals generated by the CFG may have more than one derivation (*ambiguity*).

Ambiguity

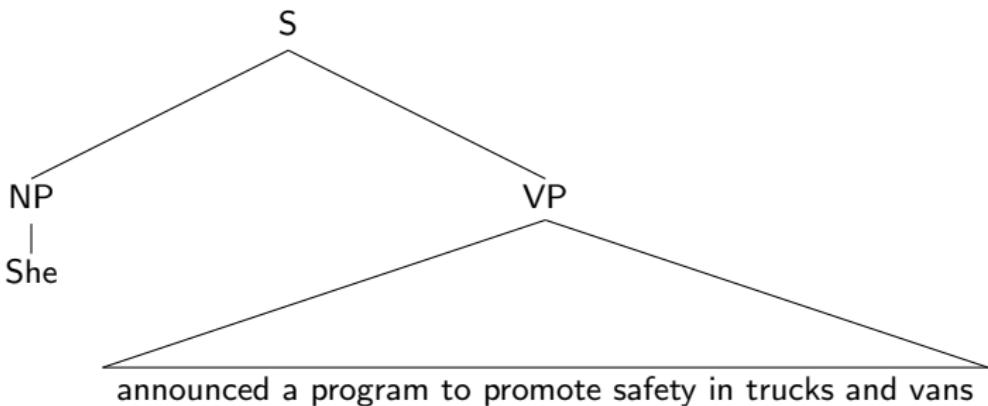
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- *Mary used a telescope to see a man who was in the mountain*
- *Mary saw a man who was in the mountain and carried a telescope*
- *Mary was in the mountain and used a telescope to see a man*
- *Mary was in the mountain that has a telescope and saw a man*
- *Mary saw a man who was in the mountain that has a telescope*
- *Mary was in the mountain and saw a man carrying a telescope*

Ambiguity



- *She announced a program aimed to make trucks and vans safer*
- *She used trucks and vans to announce a program aimed to promote safety*
- *She announced a program aimed to make trucks safer. She also announced vans*
- *She used trucks to announce a program aimed to promote safety. She also announced vans*
- *She announced a program. She did so in order to promote safety in trucks and vans*

Ambiguity

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Some trees are more likely than others...

Ambiguity

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Some trees are more likely than others...

Can we model that?

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Probabilistic Context Free Grammar (PCFGs)

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Probabilistic Context Free Grammar (PCFGs)

A **probabilistic** context-free grammar is defined as a tuple $G = \langle N, \Sigma, R, S, q \rangle$ where:

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- R is a set of rules of the form $X \rightarrow Y_1 Y_2 \dots Y_n$ where $n \geq 0$, $X \in N$, $Y_i \in N \cup \Sigma$
- q is a set of non-negative parameters, one for each rule $X \rightarrow \alpha \in R$ such that, for any $X \in N$,

$$\sum_{(X \rightarrow \alpha) \in R} q(X \rightarrow \alpha) = 1$$

Context Free Grammars, Example

$$N = \{S, VP, NP, PP, DT, Vi, Vt, NN, IN\}^1$$

$$S = \{S\}$$

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Probabilistic Context Free Grammars, Example

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Properties of PCFGs

- The probability of a parse tree $t \in \mathcal{T}_G$ is computed as:

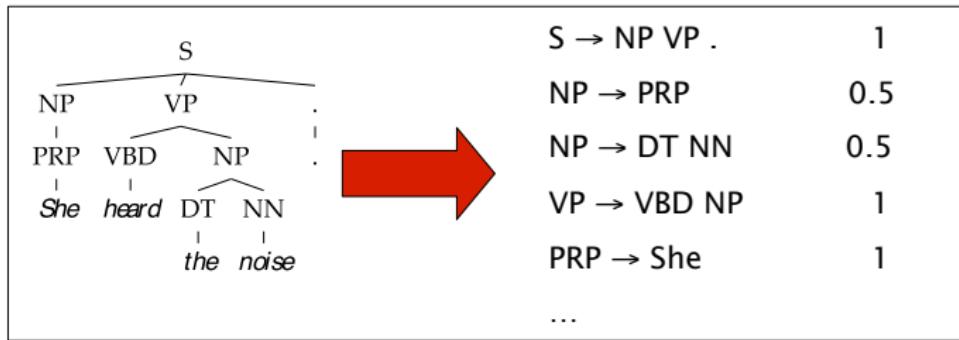
$$p(t) = \prod_{r \in t} q(r)$$

- If there is more than one tree for a sentence, we can rank them by probability.
- The most likely tree for a sentence s is:

$$\arg \max_{t \in \mathcal{T}(s)} p(t)$$

Learning Treebank Grammars

- Read the grammar rules from a treebank



- Set rule weights by maximum likelihood

$$q(\alpha \rightarrow \beta) = \frac{\text{Count}(\alpha \rightarrow \beta)}{\text{Count}(\alpha)}$$

- Smoothing issues apply
- Having the appropriate CFG is critical to success

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Parsing Natural Language Sentences

Goal of a parser:

- Find all possible trees

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Parsing Natural Language Sentences

Goal of a parser:

- Find all possible trees
- Find all possible trees, ranked by probability

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Parsing Natural Language Sentences

Goal of a parser:

- Find all possible trees
- Find all possible trees, ranked by probability
- Find most likely tree

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Parsing Natural Language Sentences

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 - Find all possible trees, ranked by probability
 - Find most likely tree
-
- Many of the possible trees will share subtrees that we don't need to re-parse.

Parsing Natural Language Sentences

Goal of a parser:

- Find all possible trees
 - Find all possible trees, ranked by probability
 - Find most likely tree
-
- Many of the possible trees will share subtrees that we don't need to re-parse.
 - Define a dynamic programming table (aka **chart**) to store intermediate results.

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CKY Algorithm

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CKY Algorithm

- Bottom-up
- Requires a grammar in Chomsky Normal Form (CNF).
- Dynamic programming: Store partial results that can be reused in different candidate solutions.
- Analogous to Viterbi in HMMs.
- Intermediate results stored in a *chart* structure.

CKY Algorithm

Trees and
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CKY Algorithm

Chart content:

- Maximum probability of a subtree with root X spanning words $i \dots j$:

$$\pi(i, j, X)$$

- Backpath to recover which rules produced the maximum probability tree:

$$\psi(i, j, X)$$

The goal is to compute:

- $\max_{t \in \mathcal{T}(s)} p(t) = \pi(1, n, S)$
- $\psi(1, n, S)$
- It is possible to use it without probabilities to get all parse trees (with higher complexity)

CKY Algorithm

Base case: Tree leaves

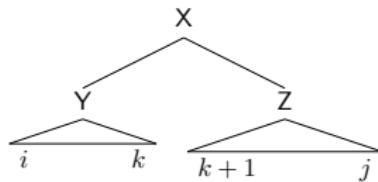
- $\forall i = 1 \dots n, \forall X \rightarrow w_i \in R, \pi(i, i, X) = q(X \rightarrow w_i)$

Recursive case: Non-terminal nodes

- $\forall i = 1 \dots n, \forall j = (i + 1) \dots n, \forall X \in N$

$$\pi(i, j, X) = \max_{\substack{X \rightarrow YZ \in R \\ k: i \leq k < j}} q(X \rightarrow YZ) \times \pi(i, k, Y) \times \pi(k + 1, j, Z)$$

$$\psi(i, j, X) = \arg \max_{\substack{X \rightarrow YZ \in R \\ k: i \leq k < j}} q(X \rightarrow YZ) \times \pi(i, k, Y) \times \pi(k + 1, j, Z)$$



Output:

- Return $\pi(1, n, S)$ and recover backpath through $\psi(1, n, S)$

CKY Algorithm - Example

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CKY Algorithm - Example - CNF

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DT 1.0 The 11	NN 0.2 woman 22	Vt 1.0 saw 33	DT 1.0 the 44	NN 0.7 man 55	IN 0.5 with 66	DT 1.0 the 77	NN 0.1 telescope 88
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CKY Algorithm - Example

Trees and Grammars

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CKY Algorithm

NP → DT ₁₁ NN ₂₂ 0.4*1.0*0.2=0.08 12 23				NP → DT ₄₄ NN ₅₅ 0.4*1.0*0.7=0.28 45 56				NP → DT ₄₄ NN ₅₅ 0.4*1.0*0.1=0.04 78	
DT 1.0 The 11	NN 0.2 woman 22	Vt 1.0 saw 33	DT 1.0 the 44	NN 0.7 man 55	IN 0.5 with 66	DT 1.0 the 77	NN 0.1 telescope 88		

CKY Algorithm - Example

Trees and Grammars

Constituency Parsing

CKY Algorithm

			$VP \rightarrow V_t_{33} NP_{45}$ $0.4 * 1.0 * 0.28 = 0.112$				$PP \rightarrow IN_e NP_{78}$ $1.0 * 0.5 * 0.04 = 0.02$
$NP \rightarrow DT_{11} NN_{22}$ $0.4 * 1.0 * 0.2 = 0.08$			$NP \rightarrow DT_{44} NN_{55}$ $0.4 * 1.0 * 0.7 = 0.28$				$NP \rightarrow DT_{44} NN_{55}$ $0.4 * 1.0 * 0.1 = 0.04$
DT 1.0 The 11	NN 0.2 woman 22	Vt 1.0 saw 33	DT 1.0 the 44	NN 0.7 man 55	IN 0.5 with 66	DT 1.0 the 77	NN 0.1 telescope 88

CKY Algorithm - Example

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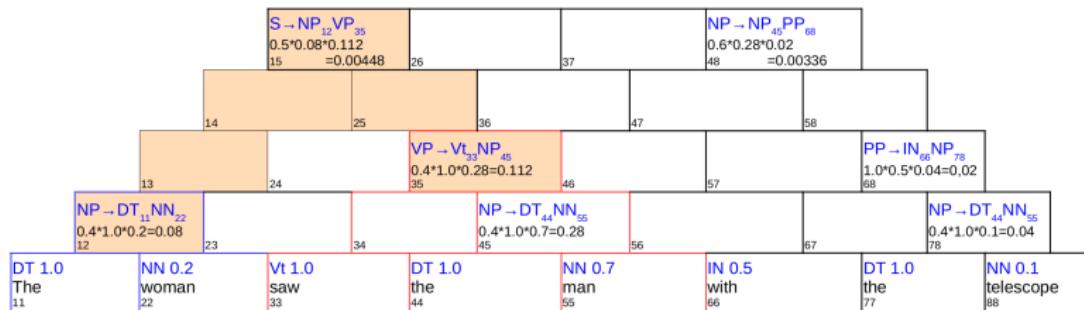
	14	25	36	47	58		
13		24	35	46	57	68	
			VP → Vt ₃₃ NP ₃₅ 0.4*1.0*0.28=0.112			PP → IN ₇₆ NP ₇₈ 1.0*0.5*0.04=0.02	
12	NP → DT ₁₁ NN ₂₂ 0.4*1.0*0.08=0.08	23	34	45	56	67	78
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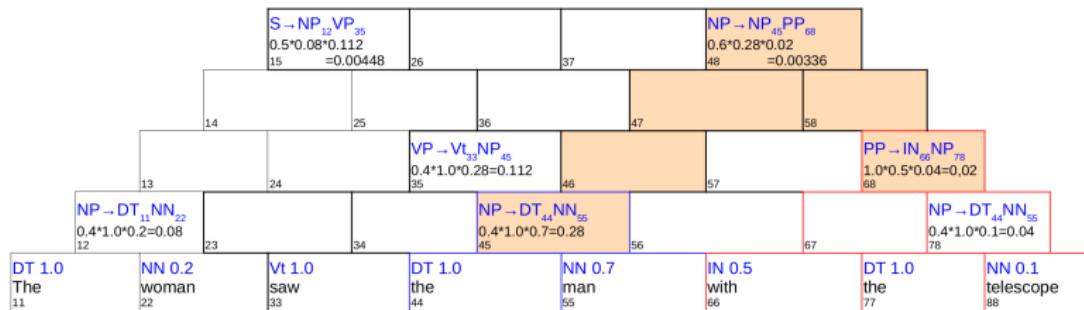


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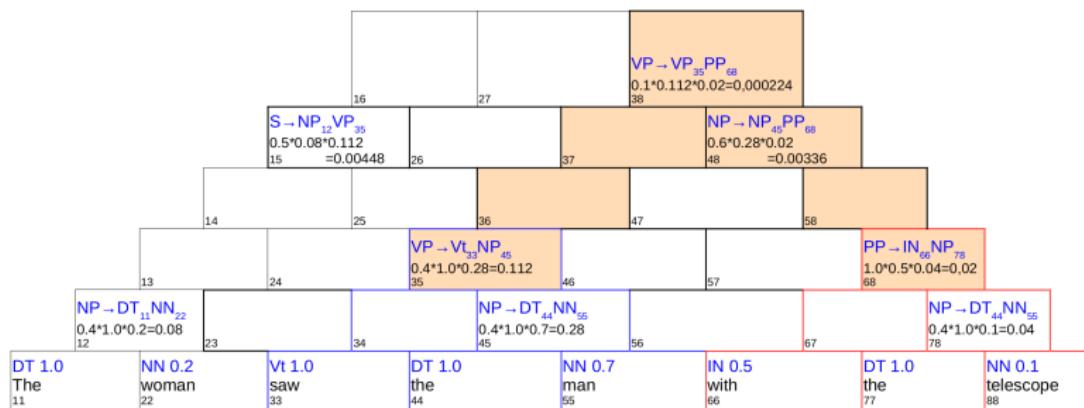


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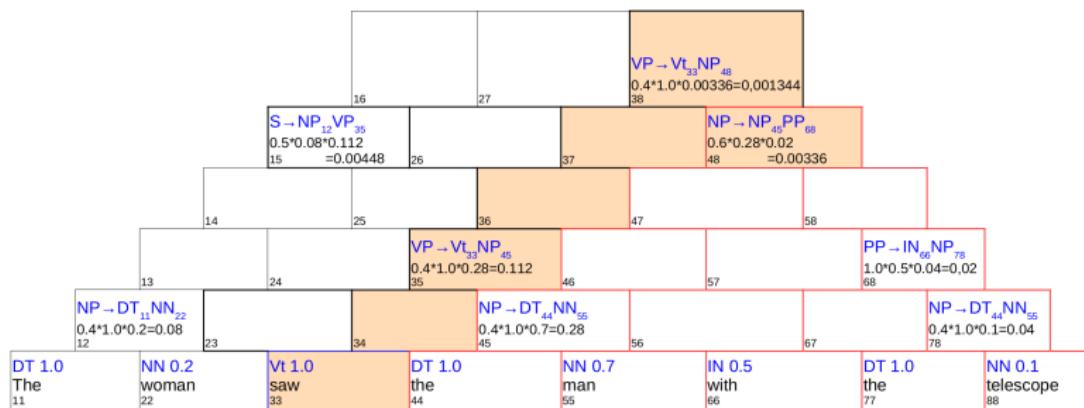


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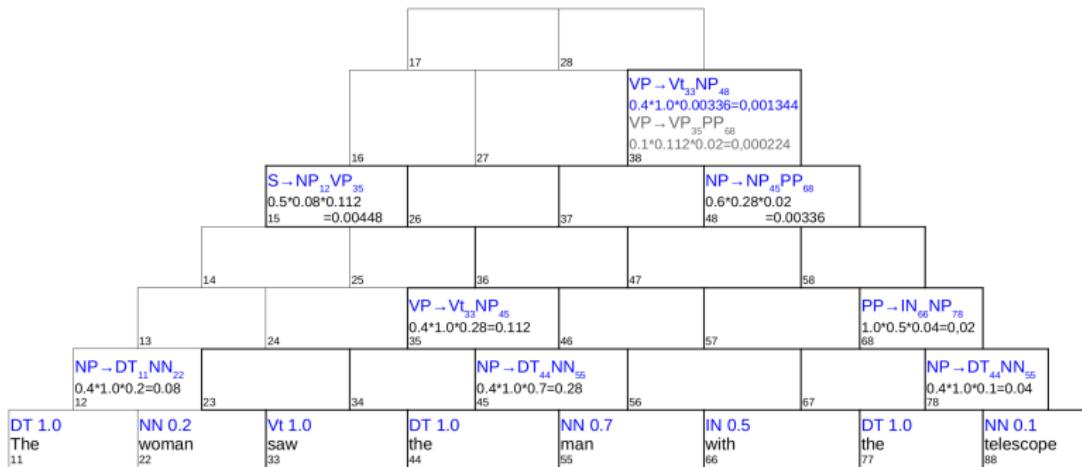


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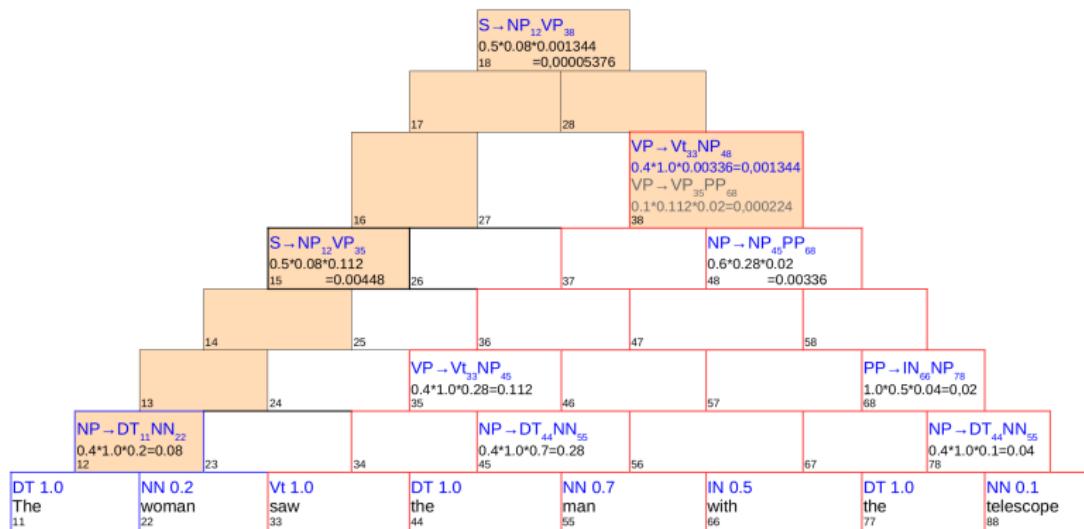


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Constituency Parsing

CKY Algorithm



Outline

Trees and
Grammars

Constituency
Parsing

Earley Algorithm

1 Trees and Grammars

2 Constituency Parsing

- CKY Algorithm
- Earley Algorithm

Earley Algorithm

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- Top-down
- Can deal with any CFG (even left-recursive)
- Dynamic programming: Store partial results that can be reused in different candidate solutions.
- Intermediate results stored in a *chart* structure.

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Chart content:

- Set of items (aka *states*), each describing the applicability status of each rule after each word:

$$[i, j, X \rightarrow \alpha \bullet \beta]$$

- Backpath to recover which rules produced the complete tree:

$$\psi(i, j, X)$$

The goal is:

- Find if it is possible to reach $[1, n, S \rightarrow \alpha \bullet]$
- Recover $\psi(0, n, S)$ if it is
- Probabilistic versions exist, though not as straightforward as in CKY

Earley Algorithm

Parsing state examples:

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[0, 0, S → • NP VP]

A NP is expected at the beginning
of the sentence

[1, 2, NP → DT • NN]

A NP has been partially matched
(DT was found between
positions 1 and 2)

[0, 3, VP → V NP •]

A VP has been completed
between positions 0 and 3

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Earley Algorithm

```
def Earley(words,grammar):
    chart = [ [ ] for i in range(len(words)+1) ]
    chart[0].append([0,0, $\gamma \rightarrow \bullet S$ ])
    for i in range(len(words)+1) :
        for state in chart[i] :
            if state.complete() : Complete(state)
            elif is_PoS(state.next()) : Scan(state)
            else : Predict(state)
    return chart

def Scan([i,j,A → α • Bβ]) :
    if B in words[j].PoS() : chart[j+1].append([j,j+1,B → word[j]•])

def Predict([i,j,A → α • Bβ]) :
    for B → γ in grammar : chart[j].append([j,j,B → •γ])

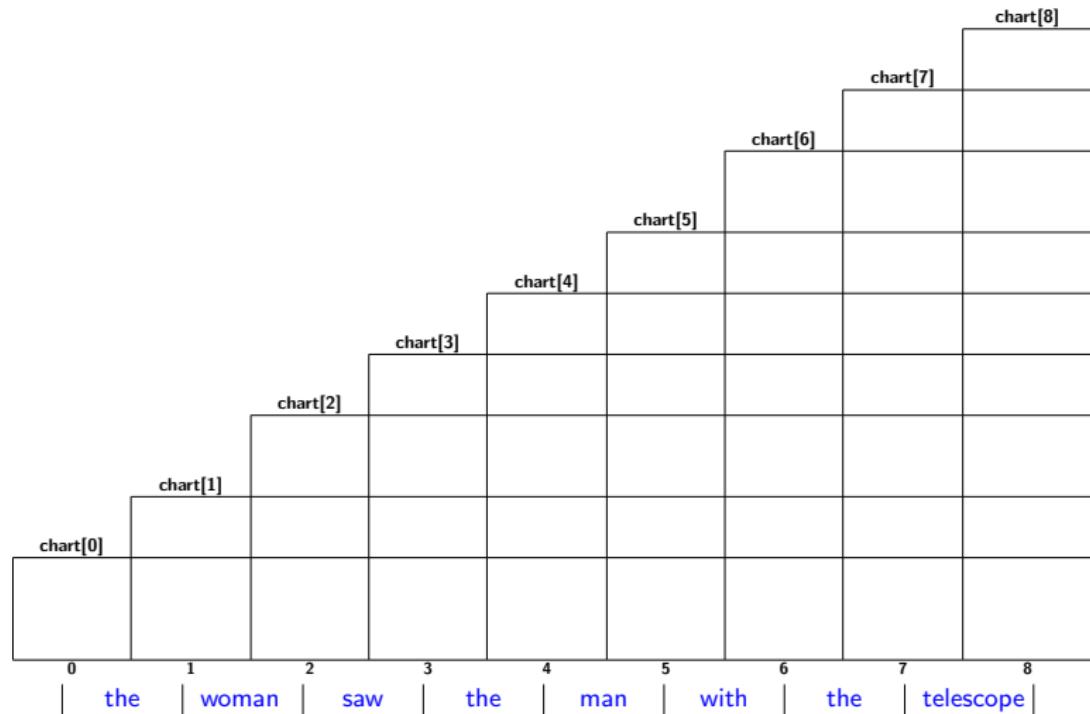
def Complete([k,j,B → γ•]) :
    for [i,k,A → α • Bβ] in chart[k] : chart[j].append([i,j,A → αB • β])
```

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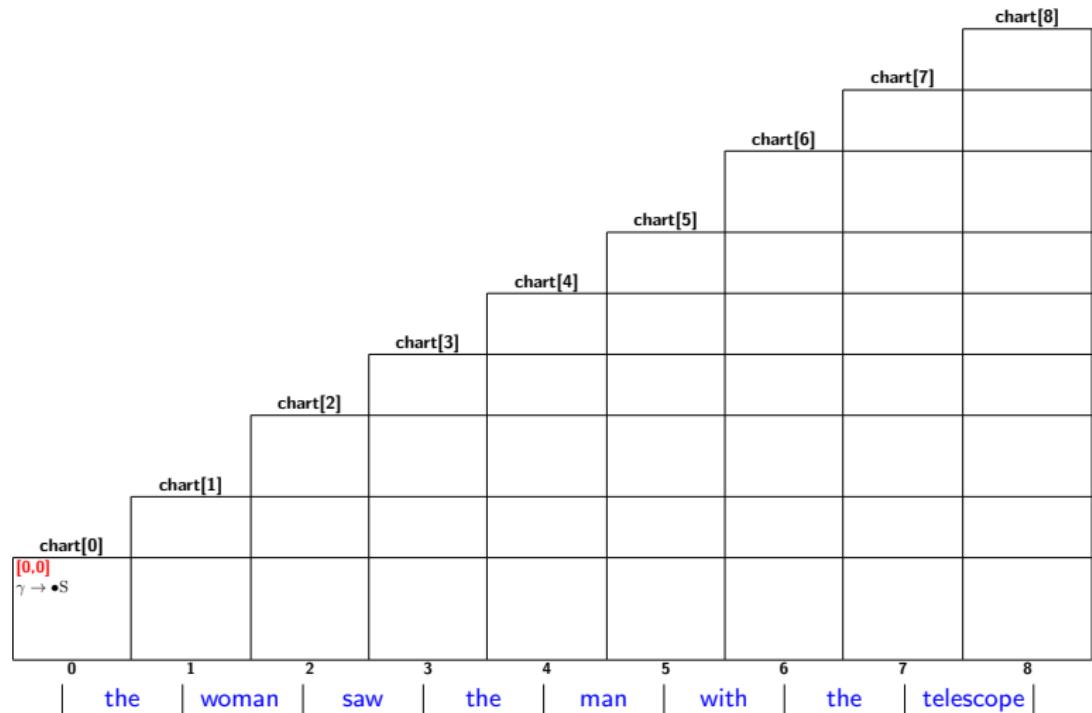


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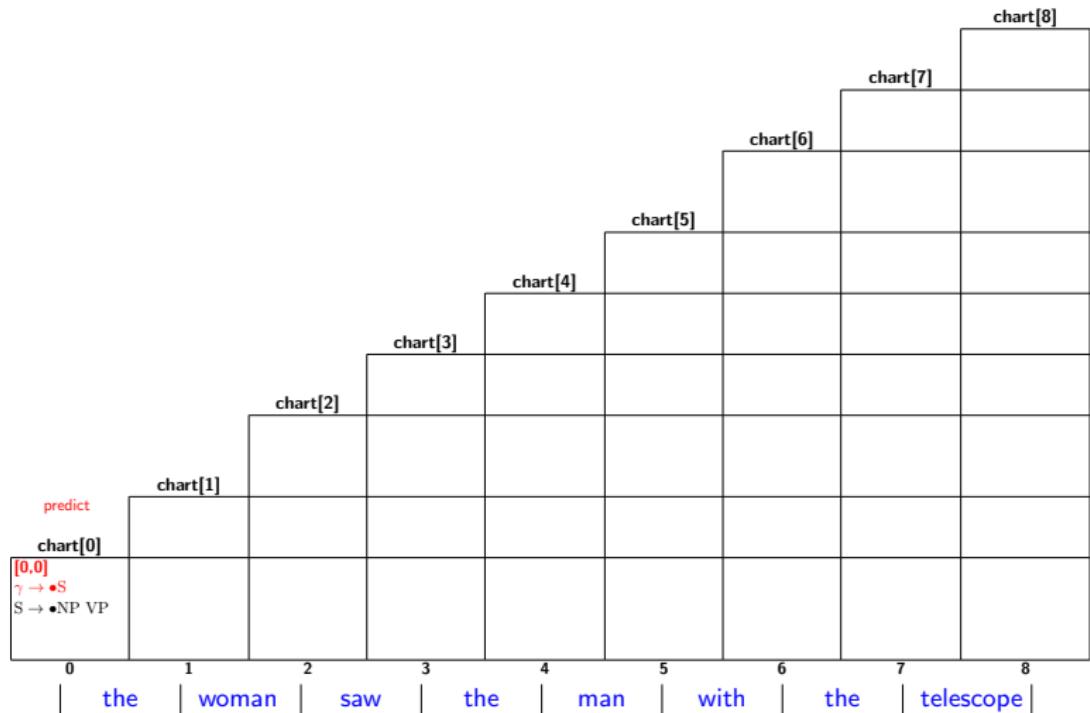


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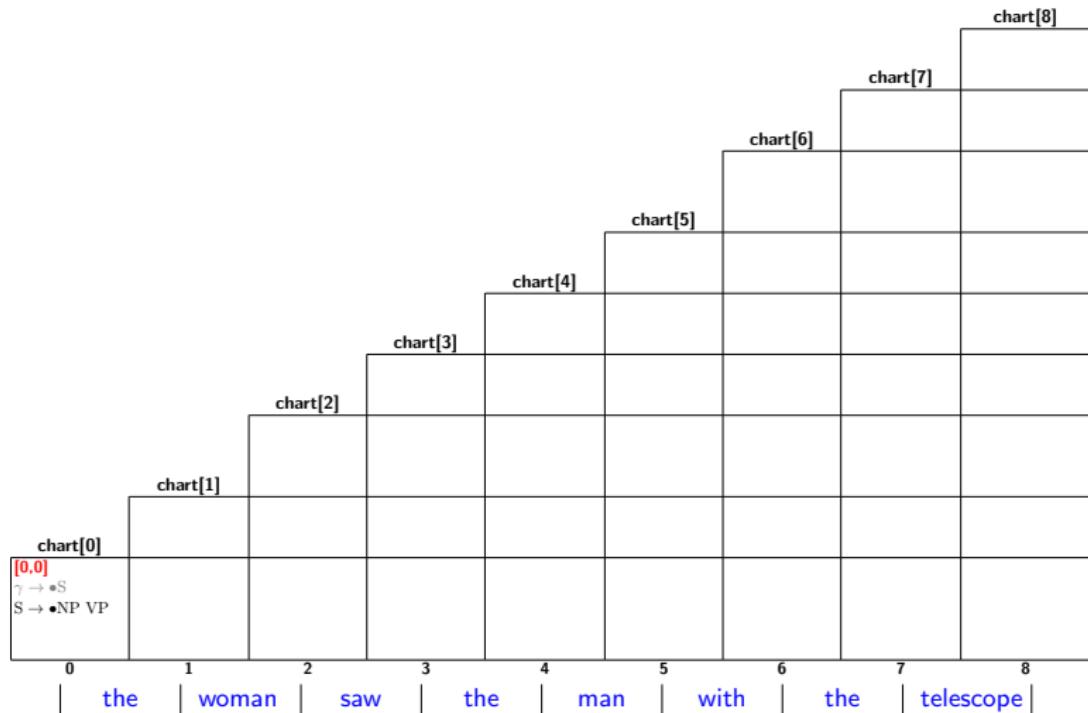


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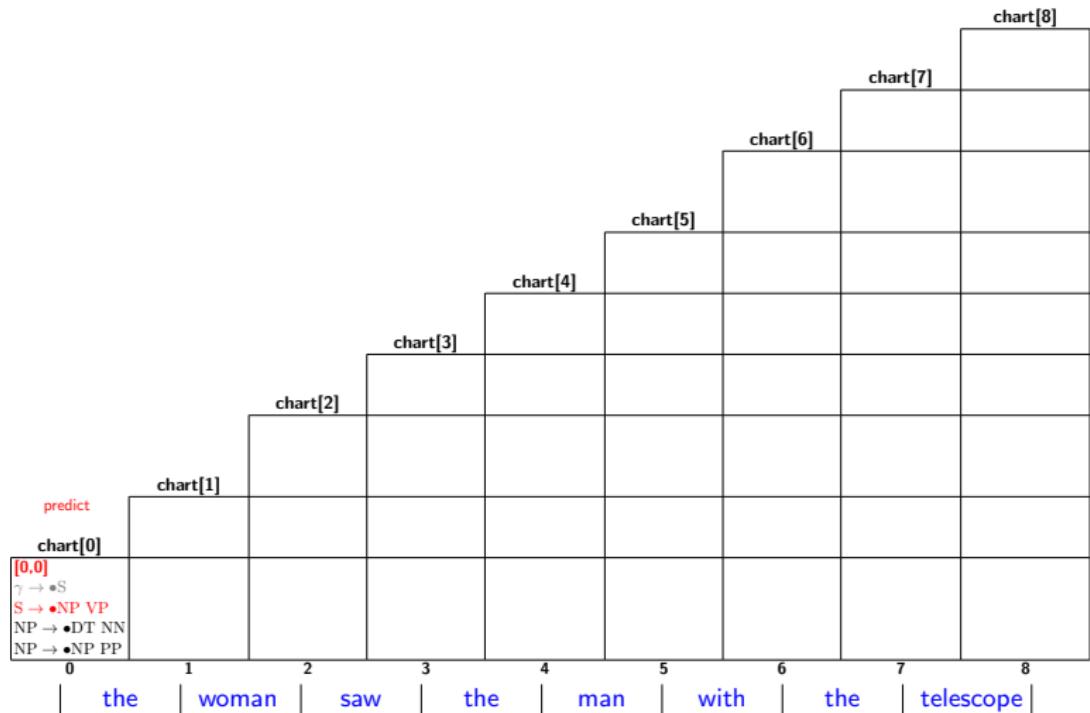


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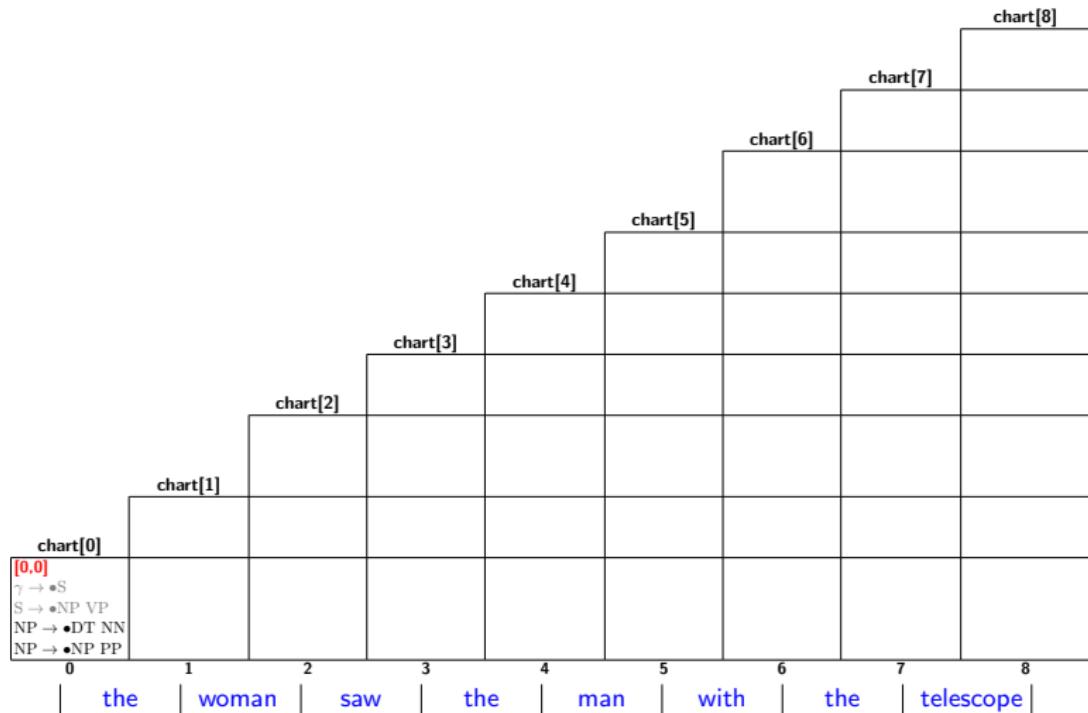


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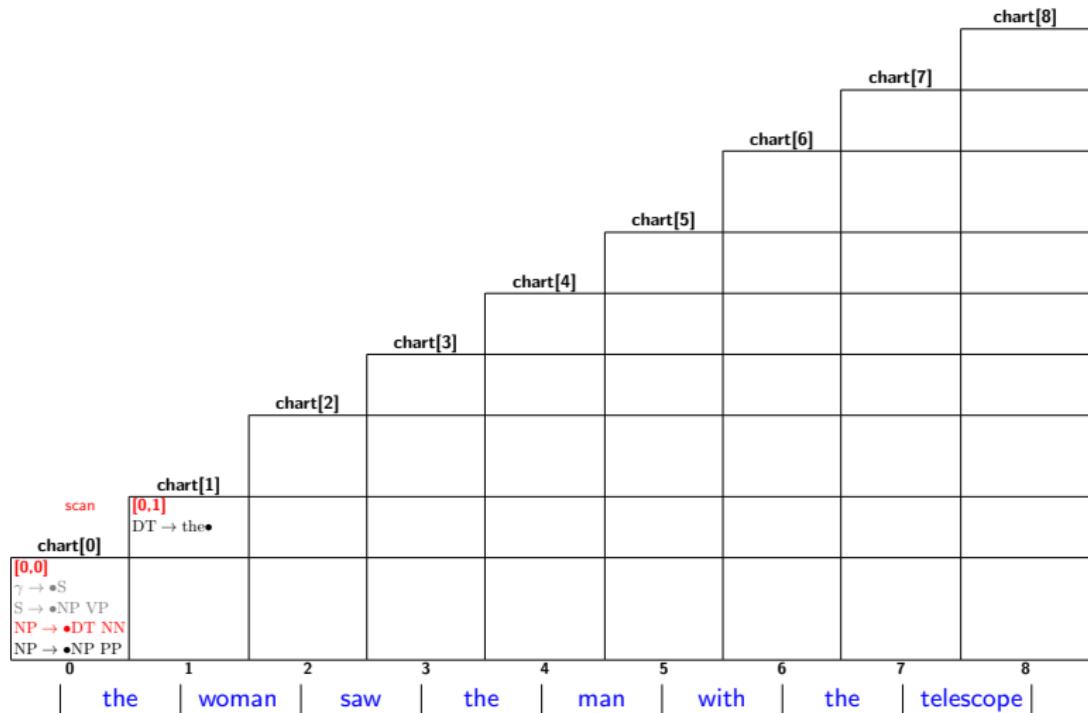


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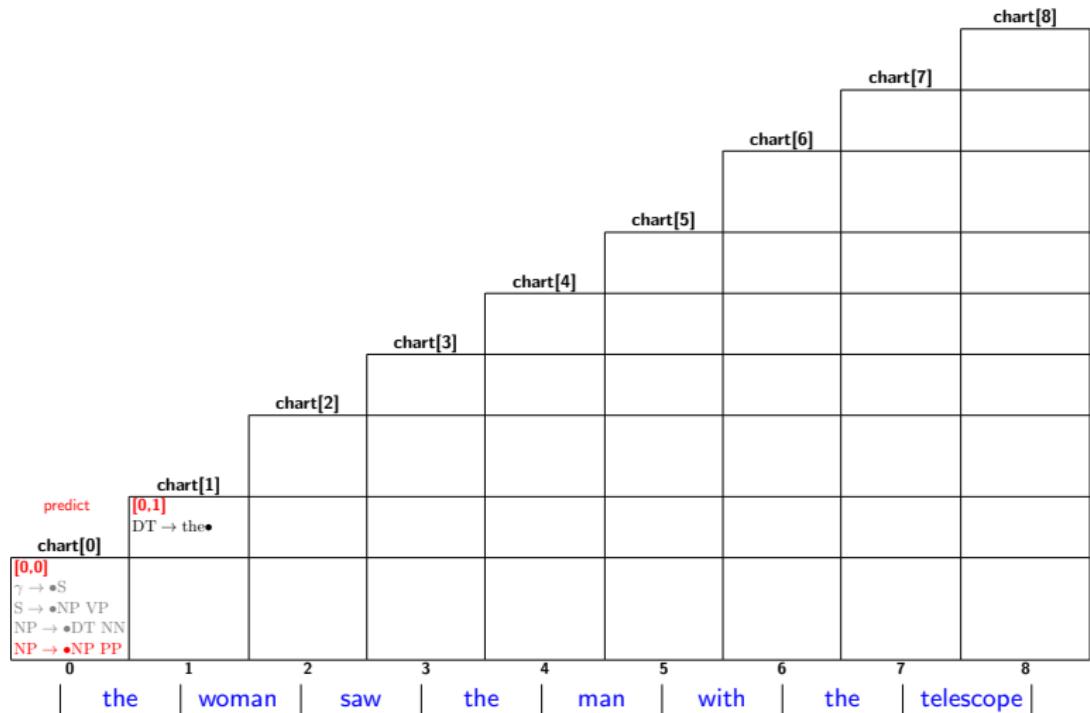


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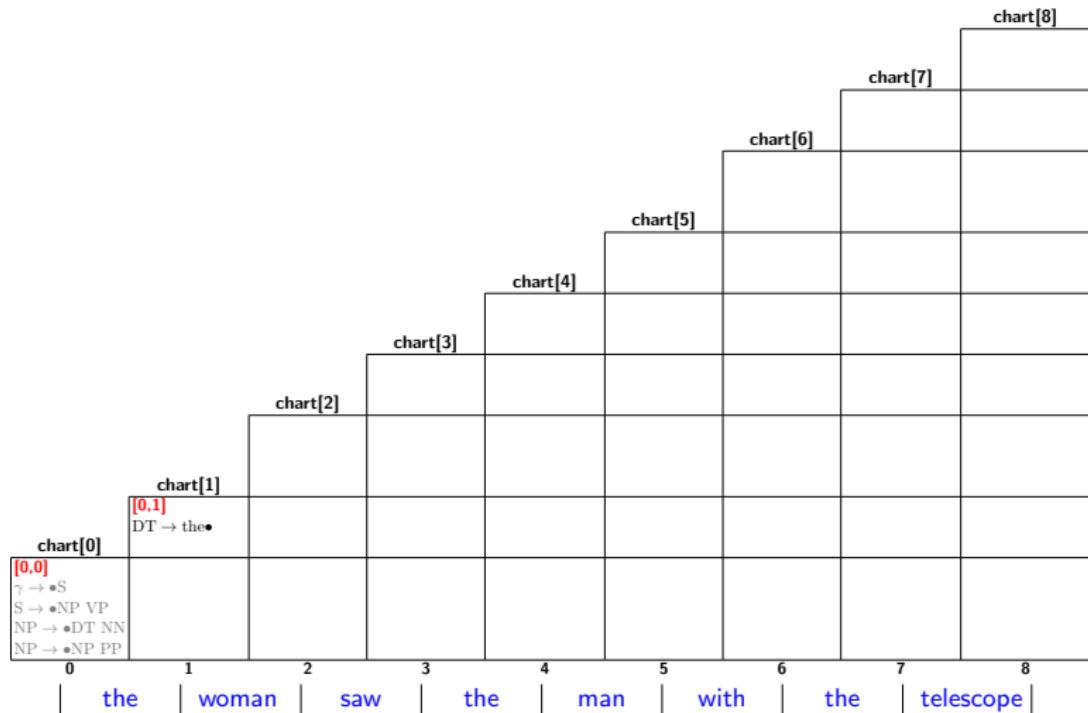


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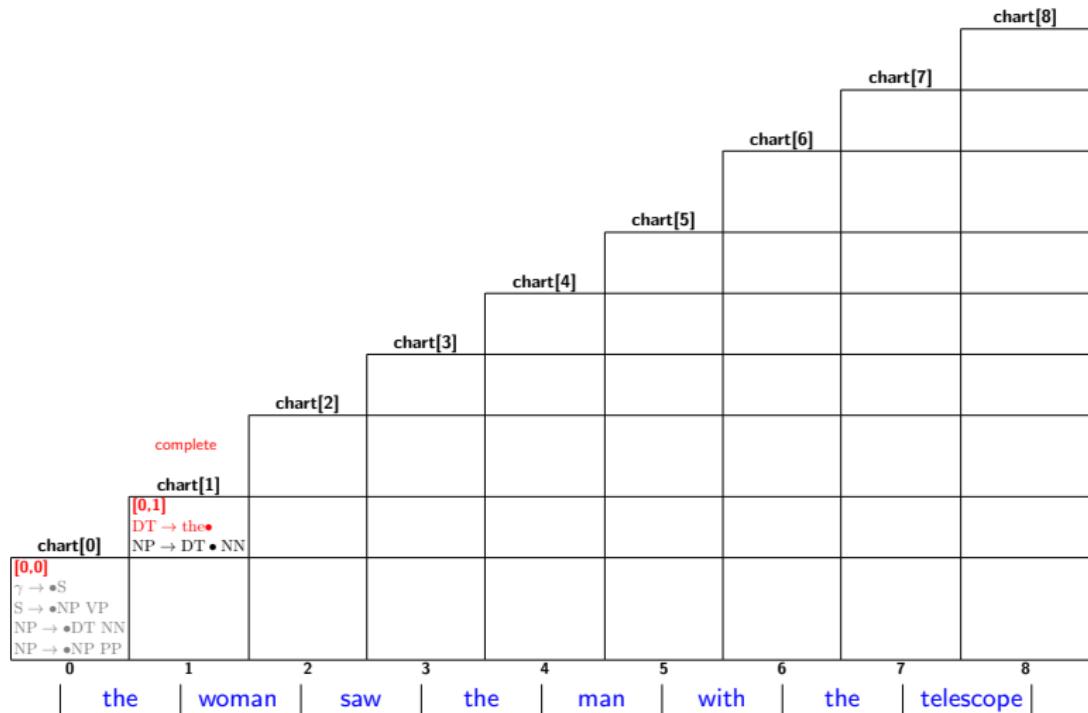


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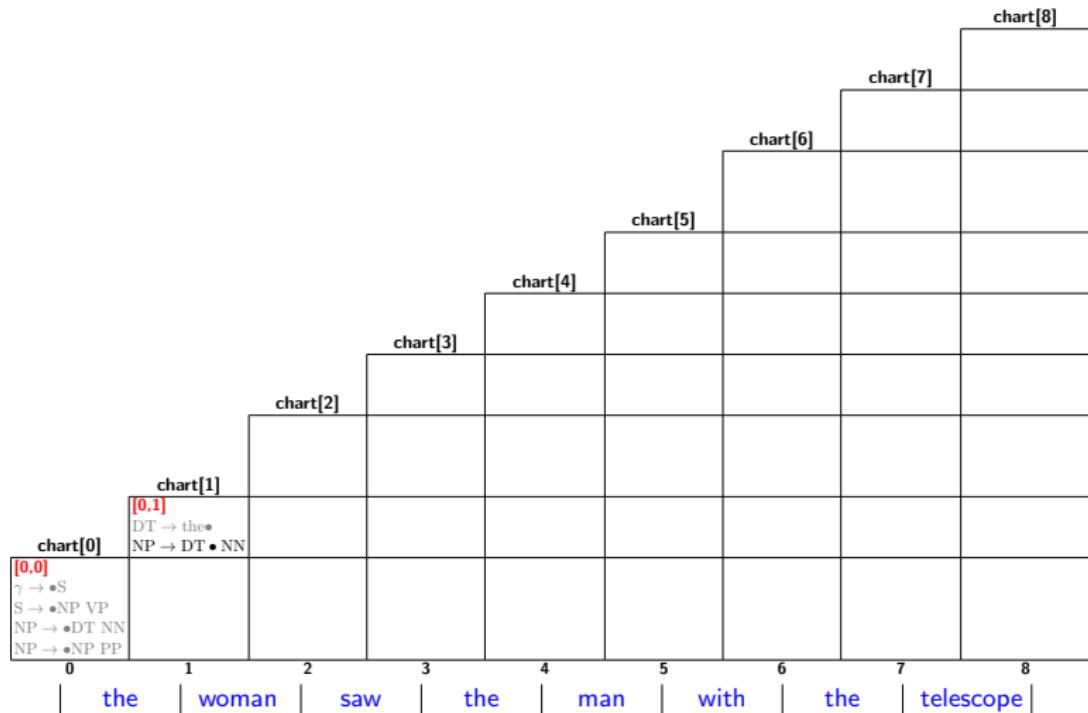


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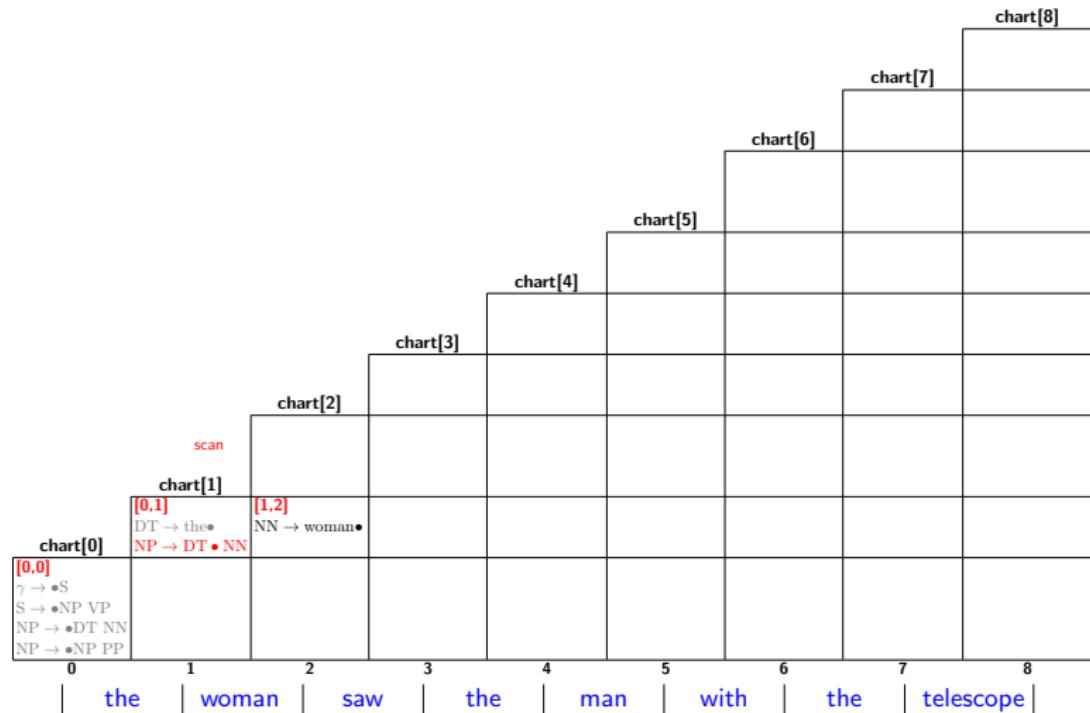


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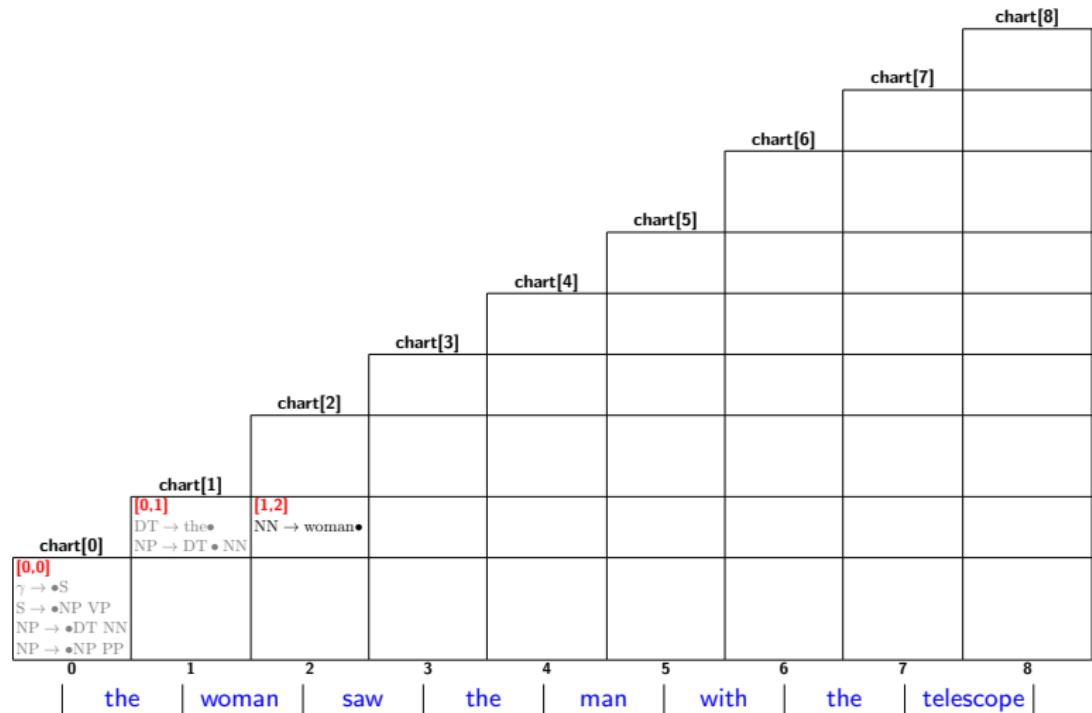


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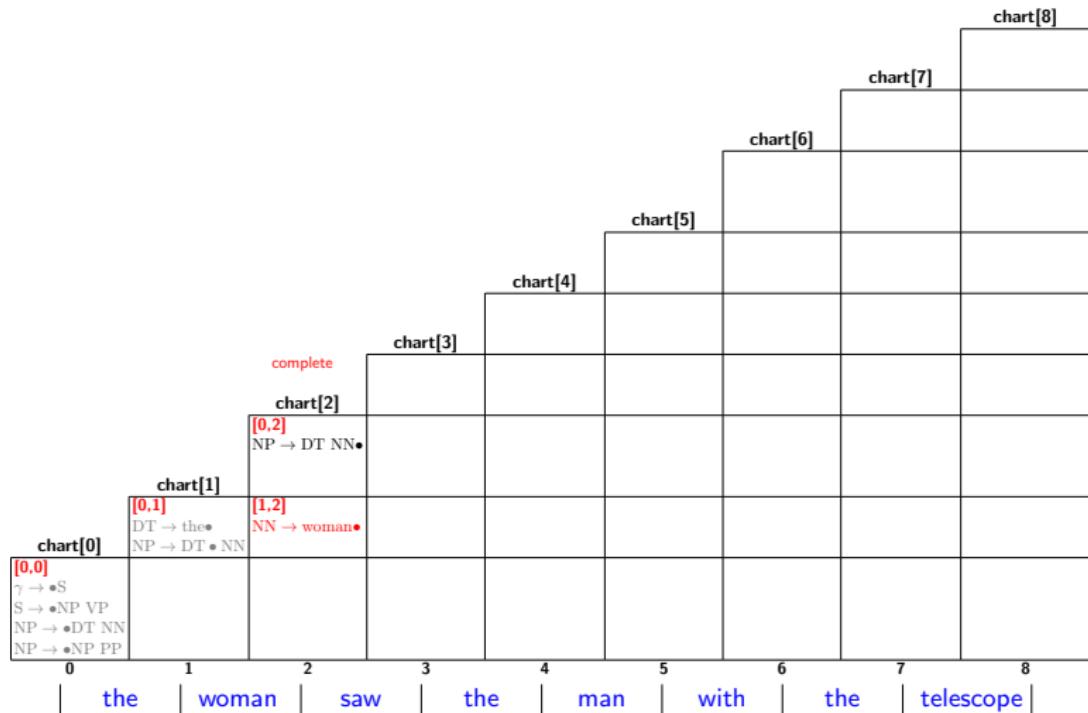


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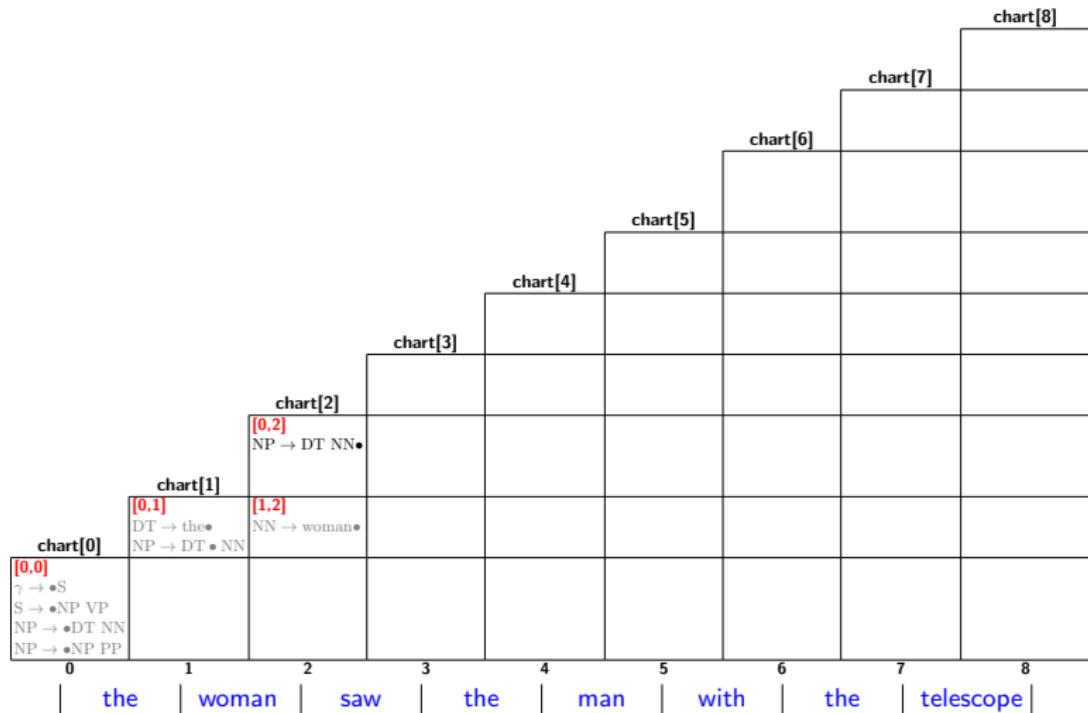


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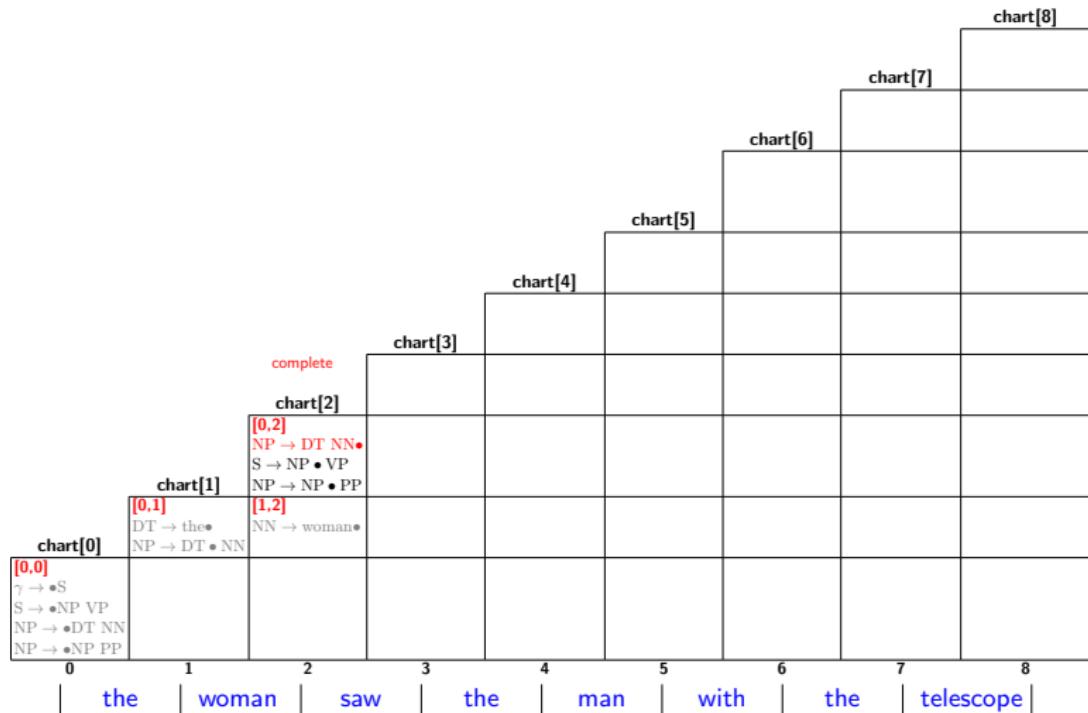


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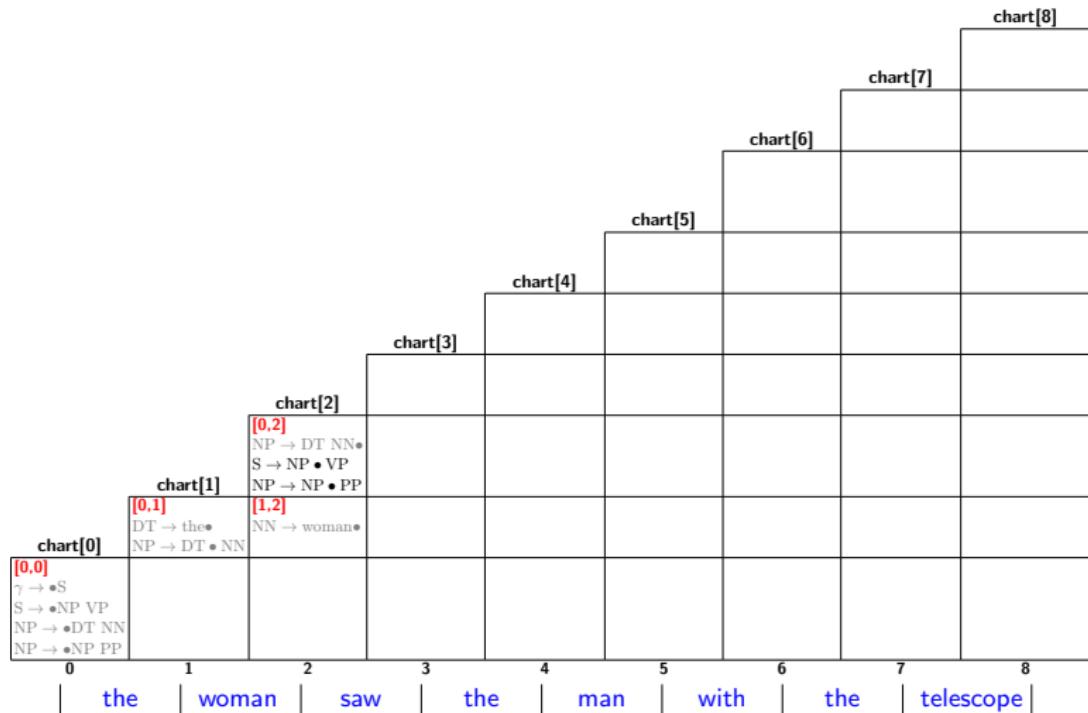


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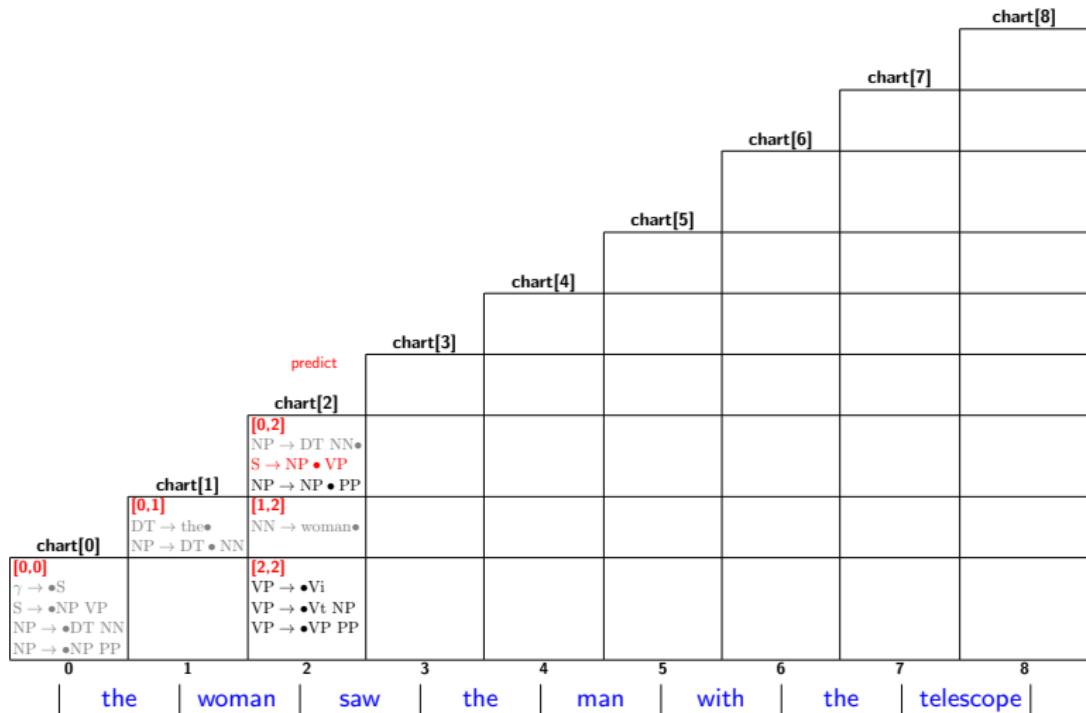


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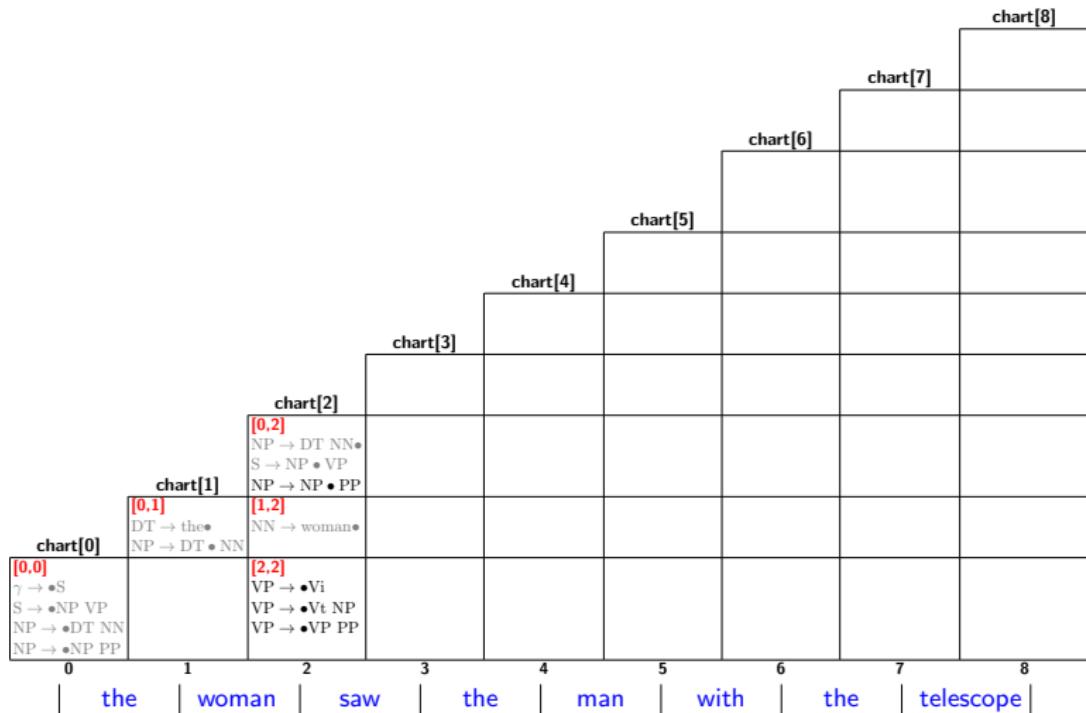


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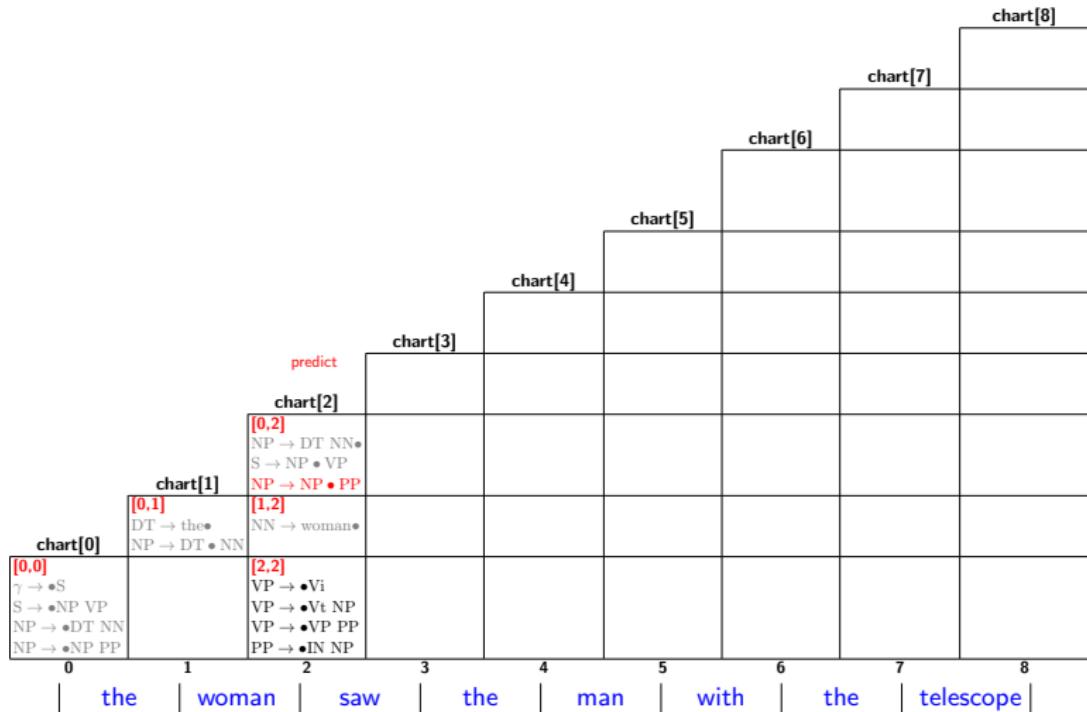


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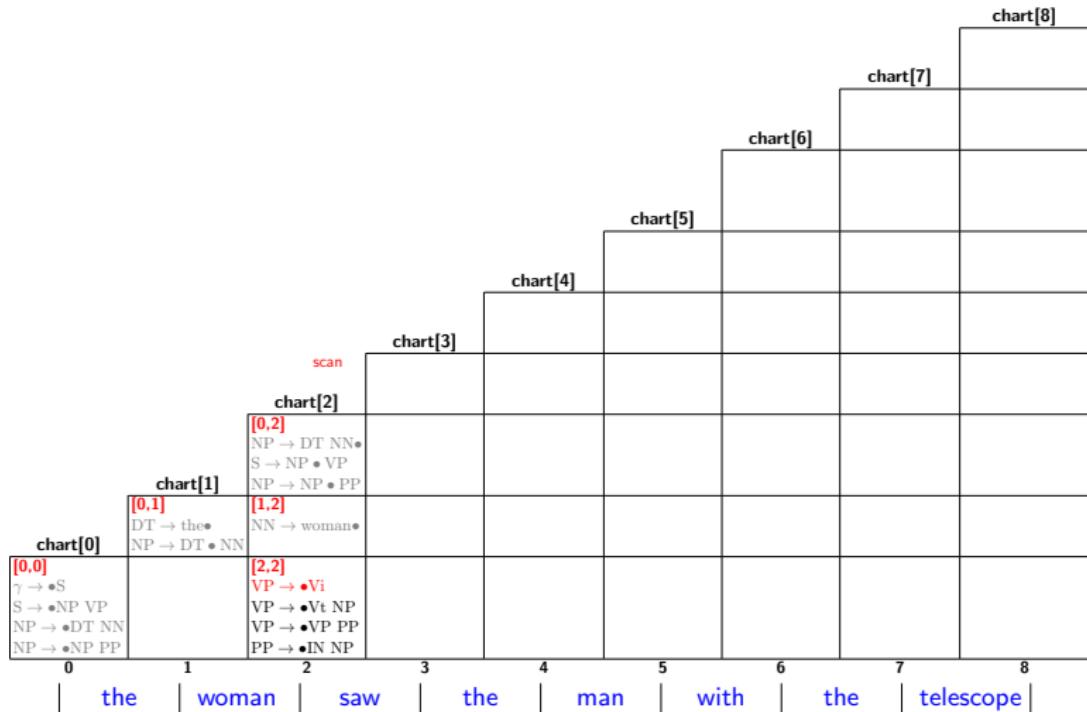


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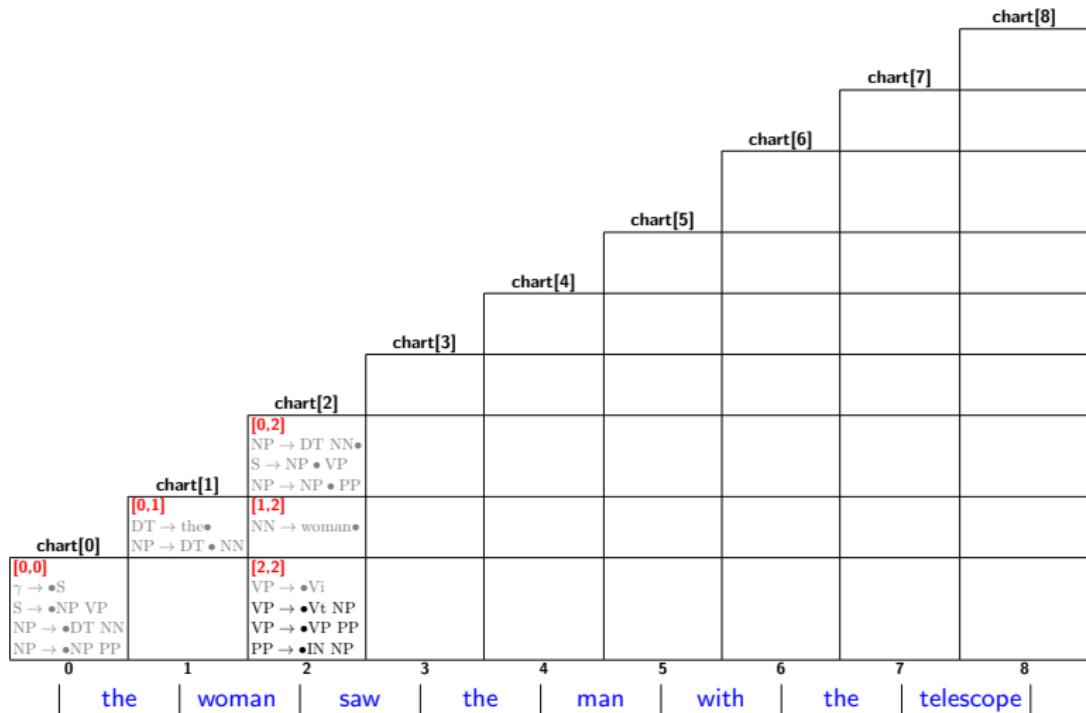


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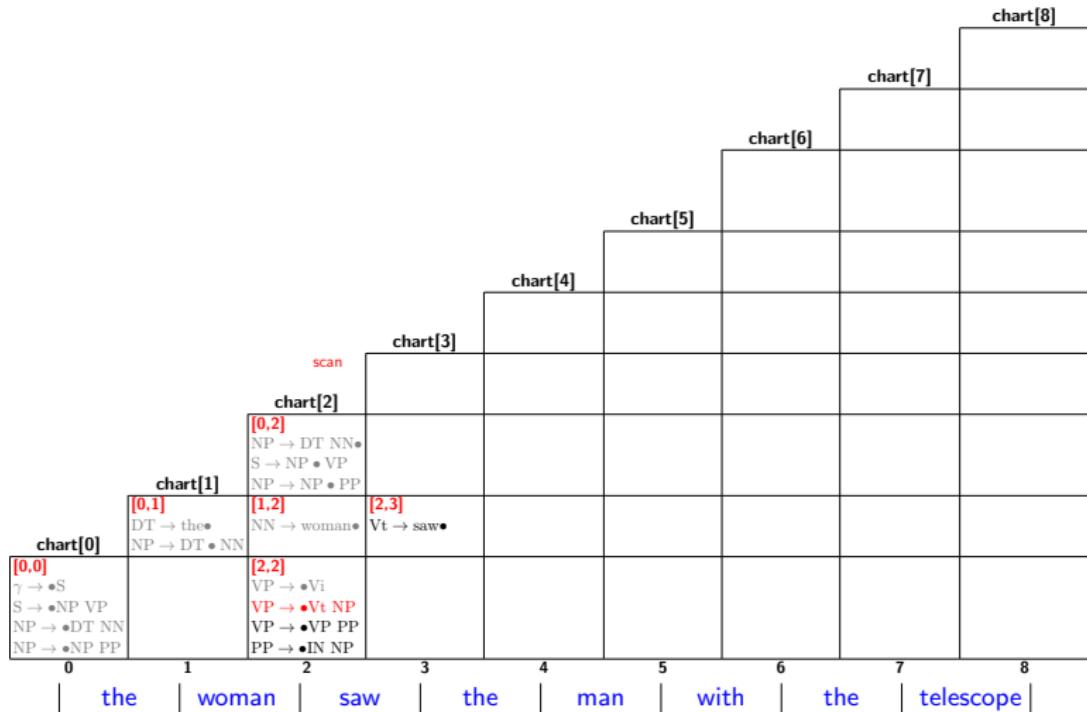


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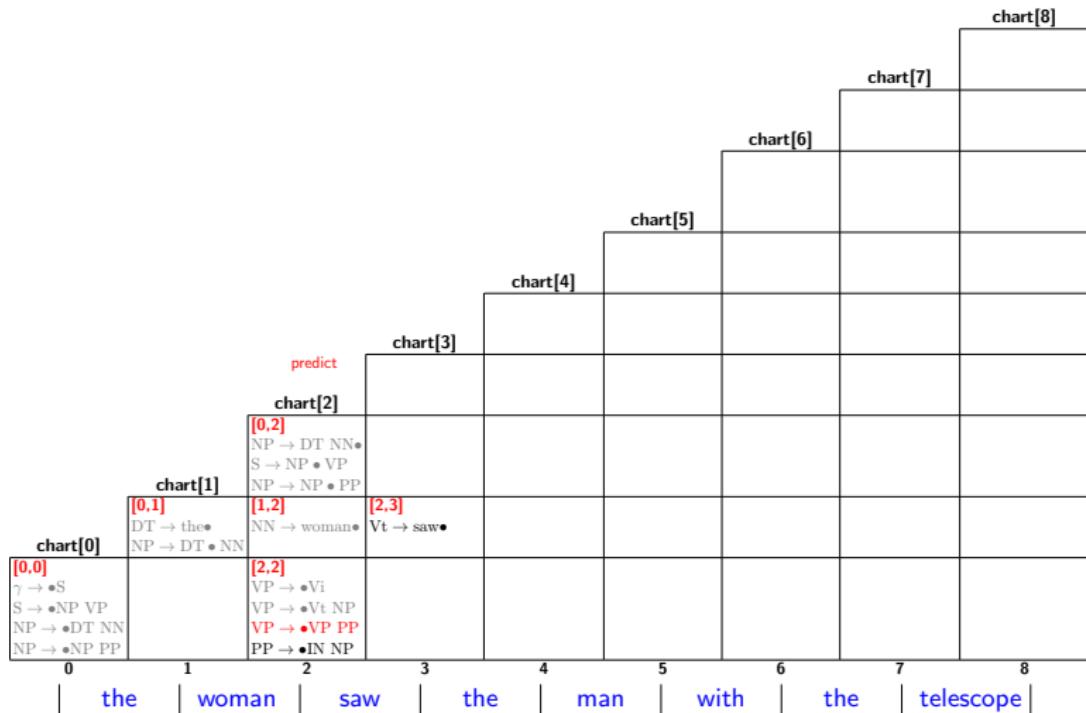


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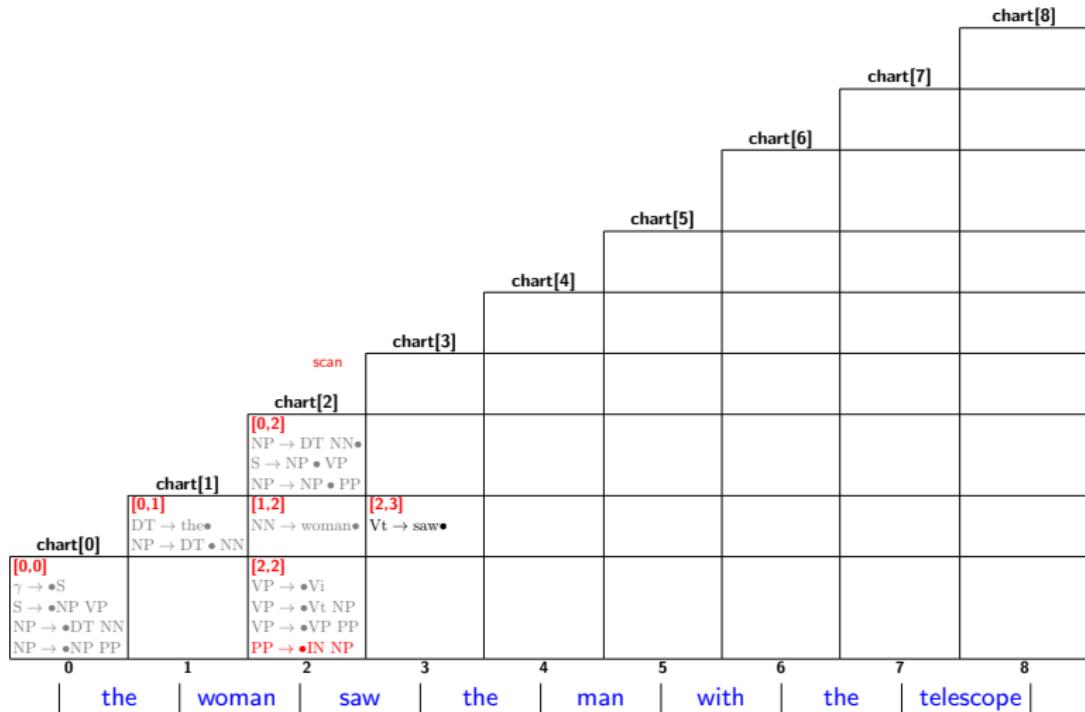


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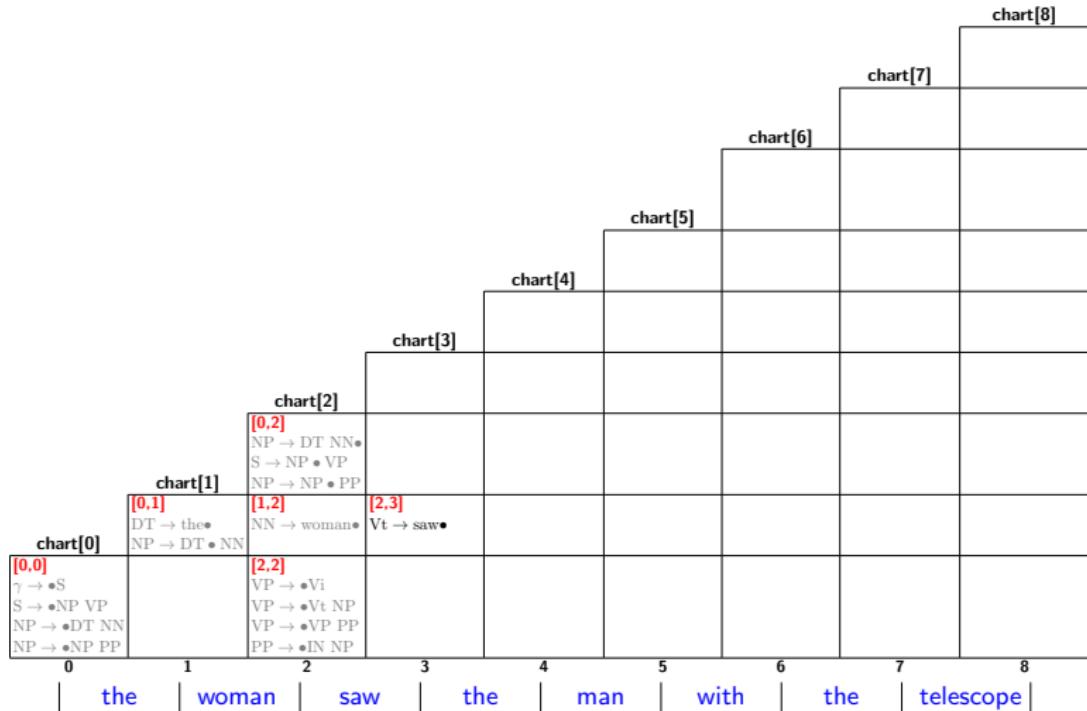


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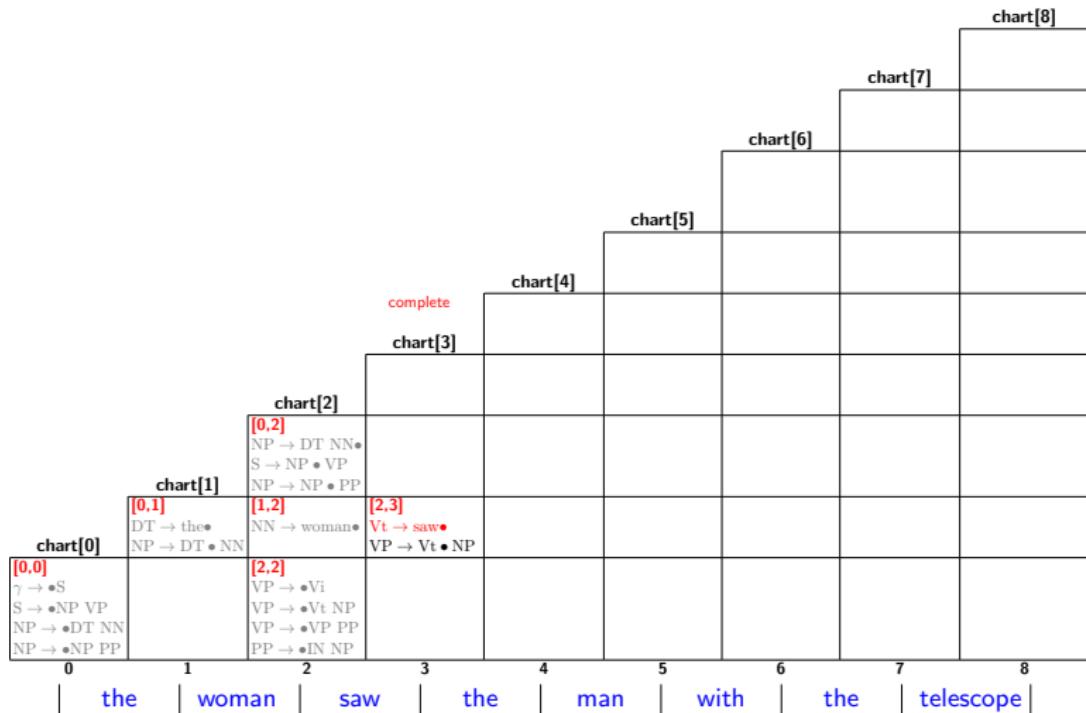


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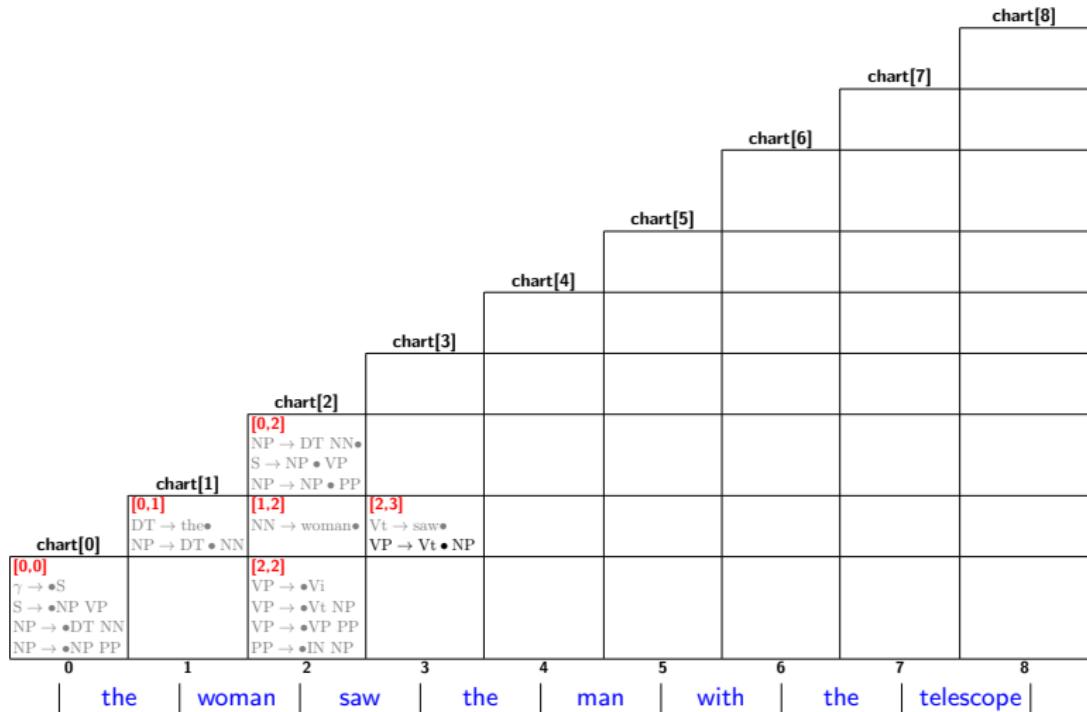


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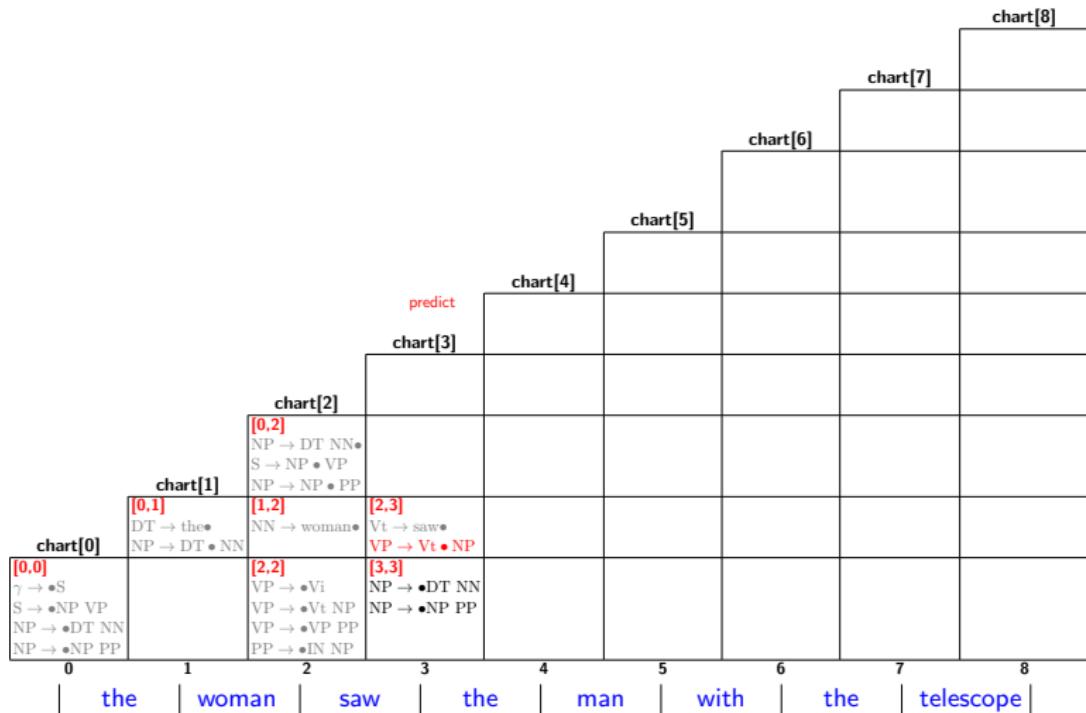


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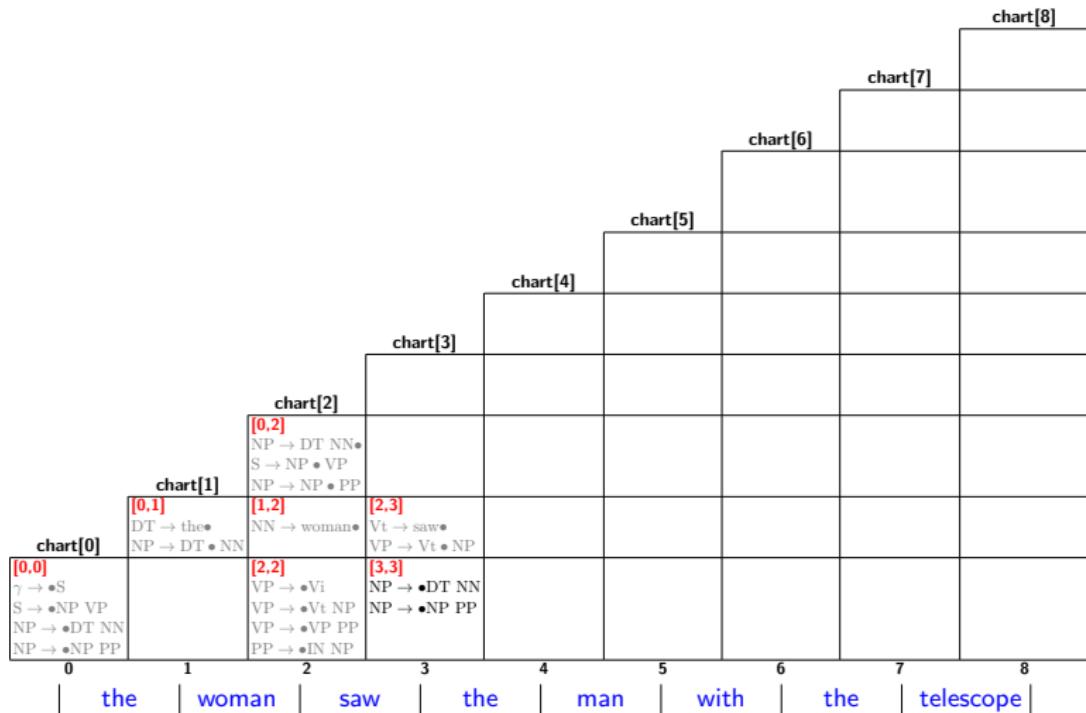


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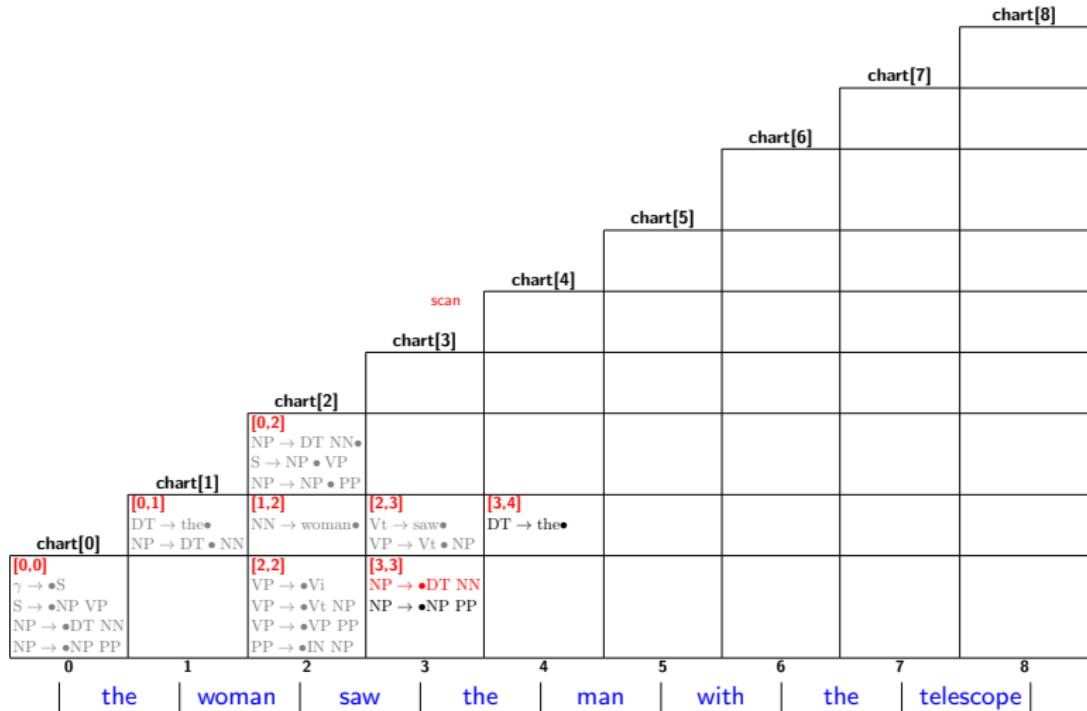


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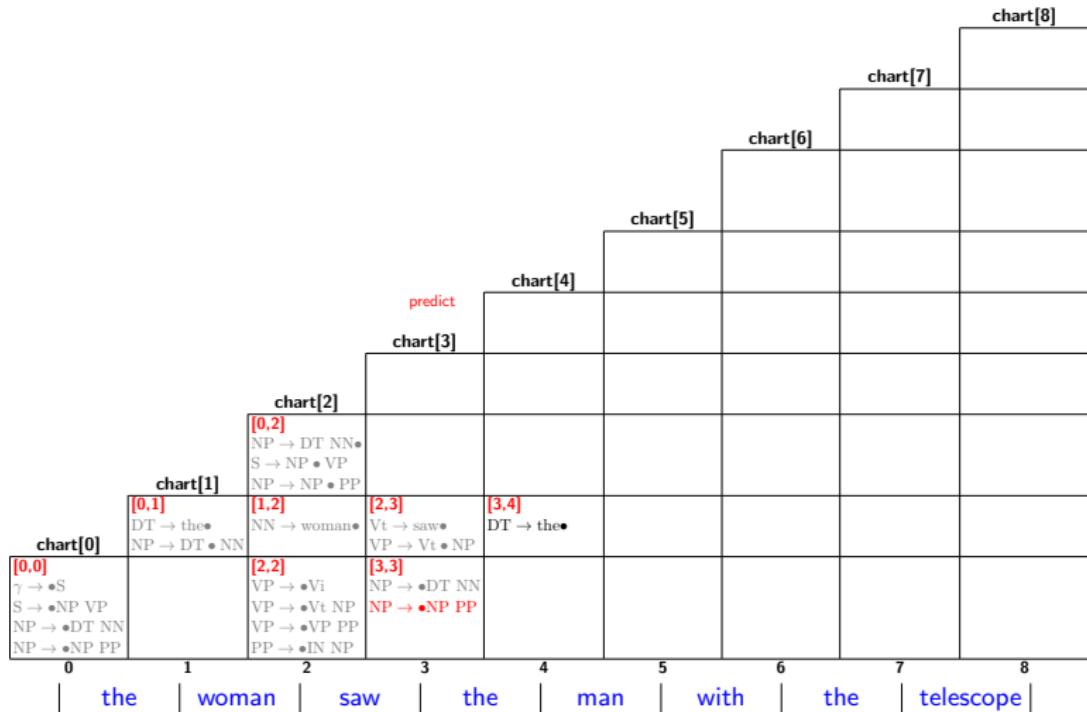


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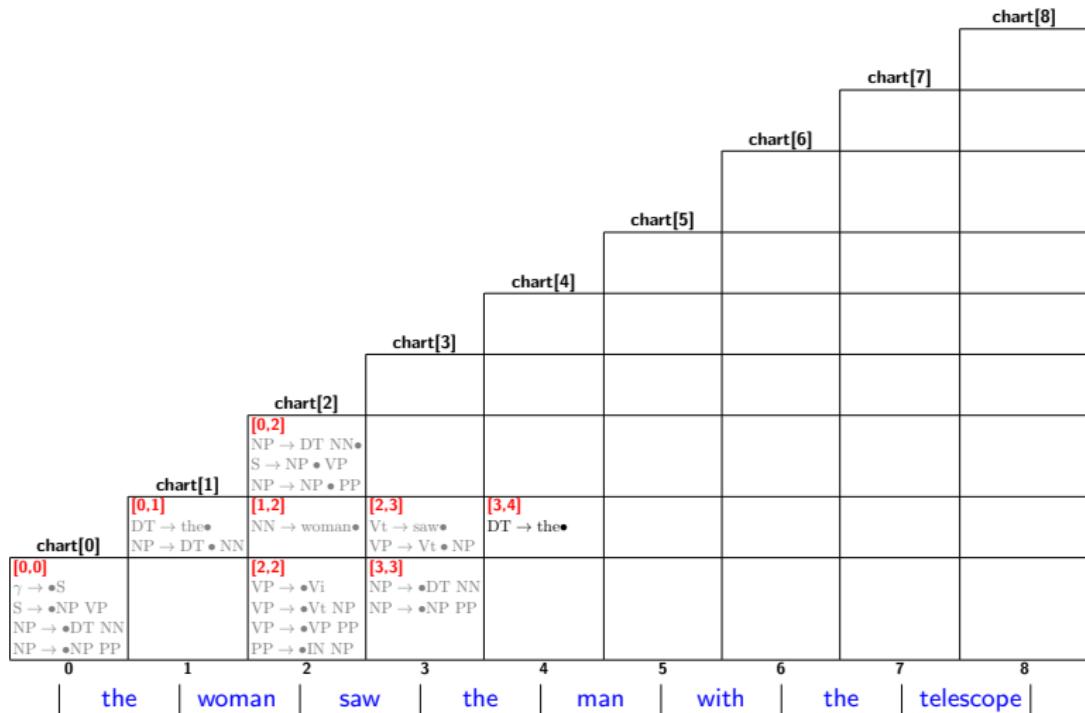


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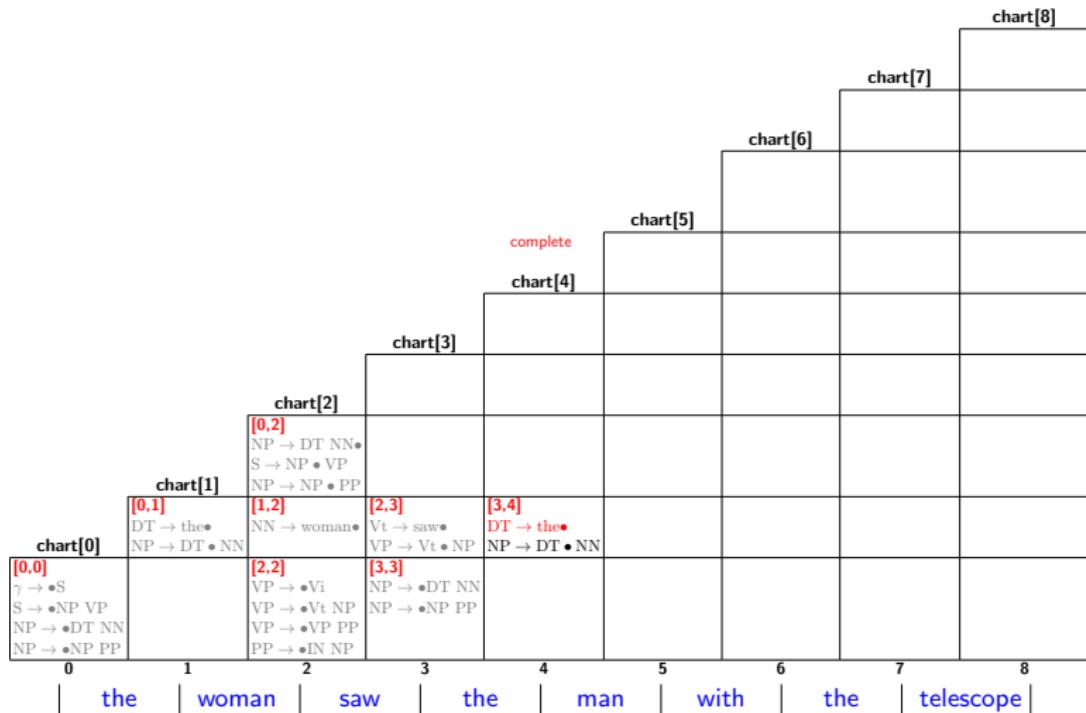


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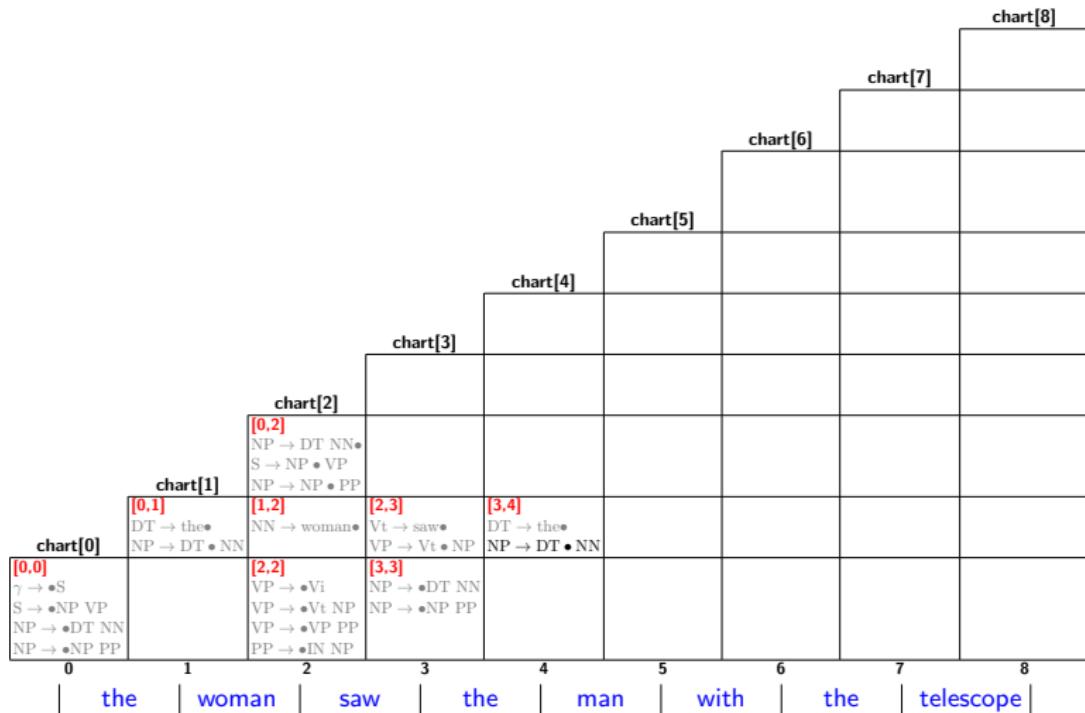


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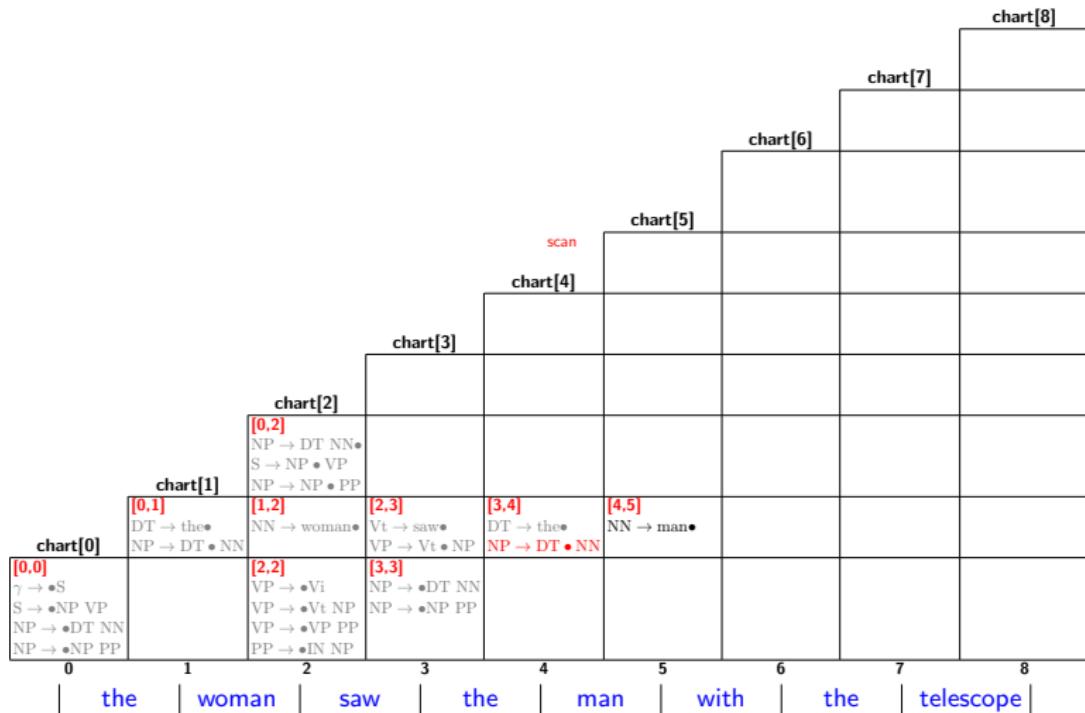


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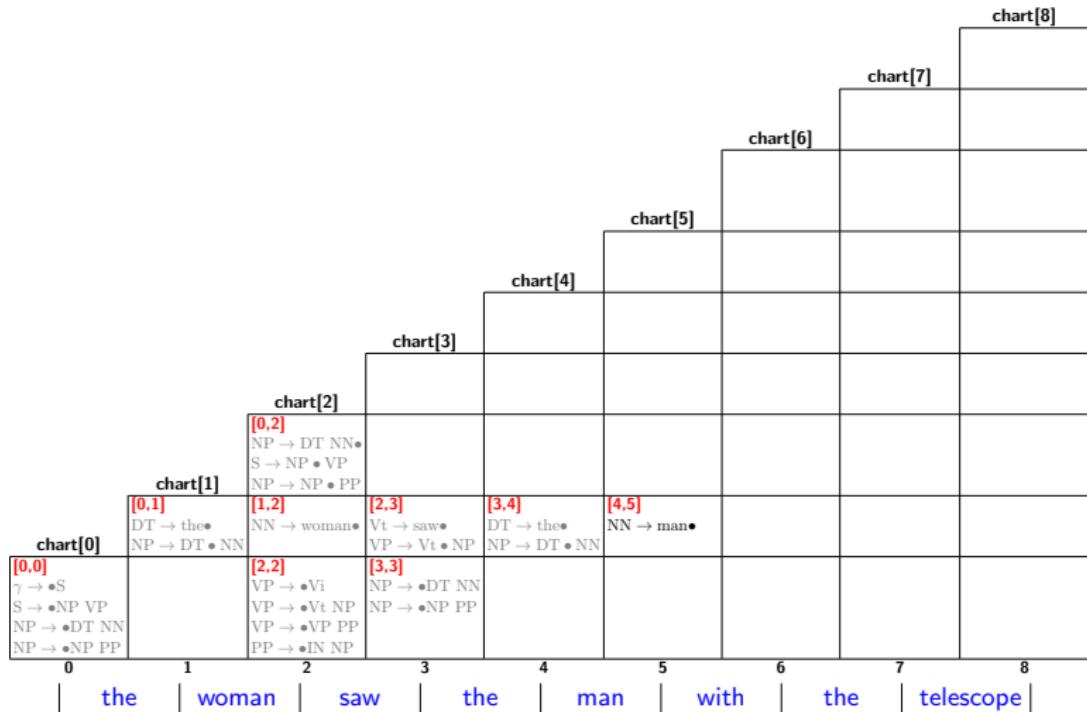


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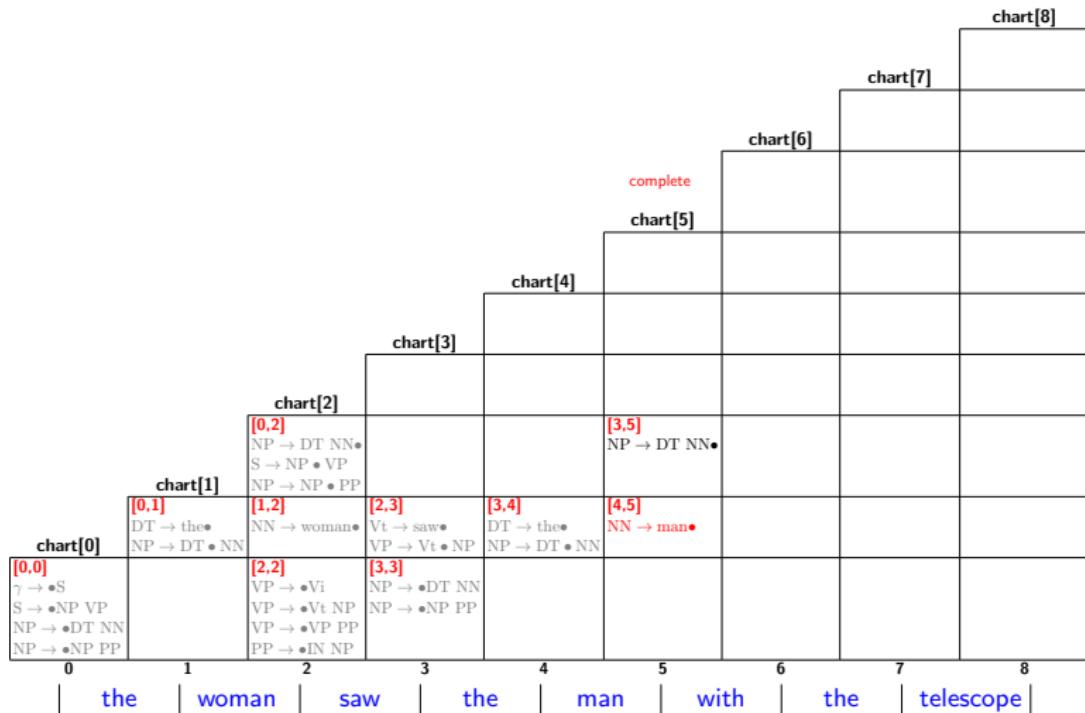


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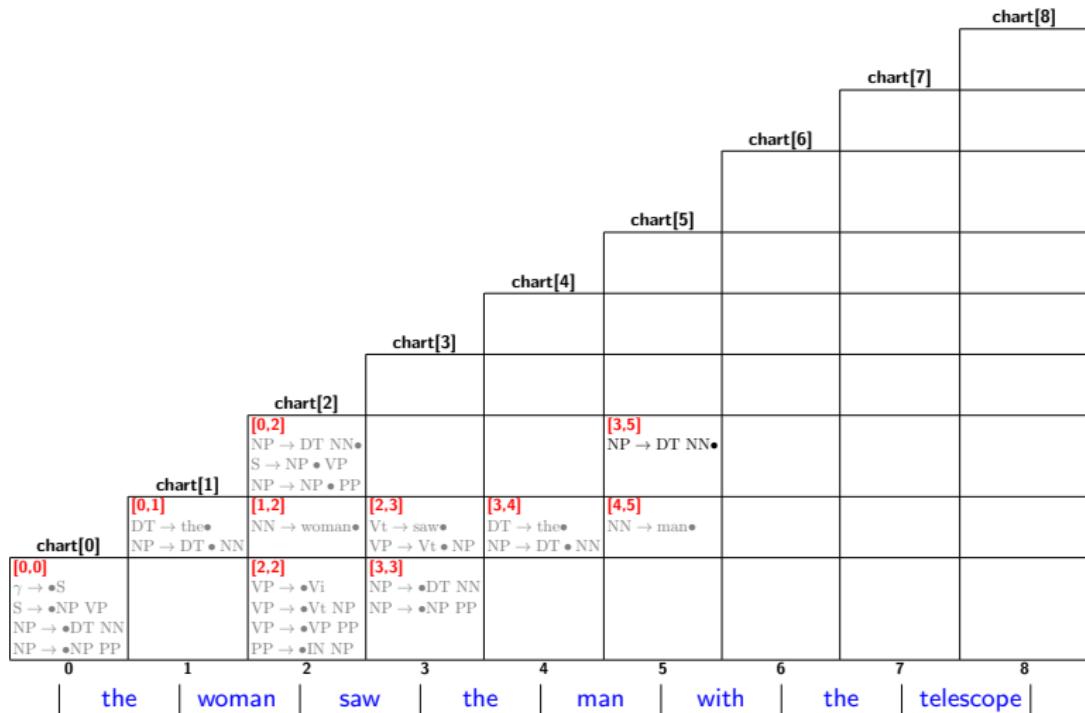


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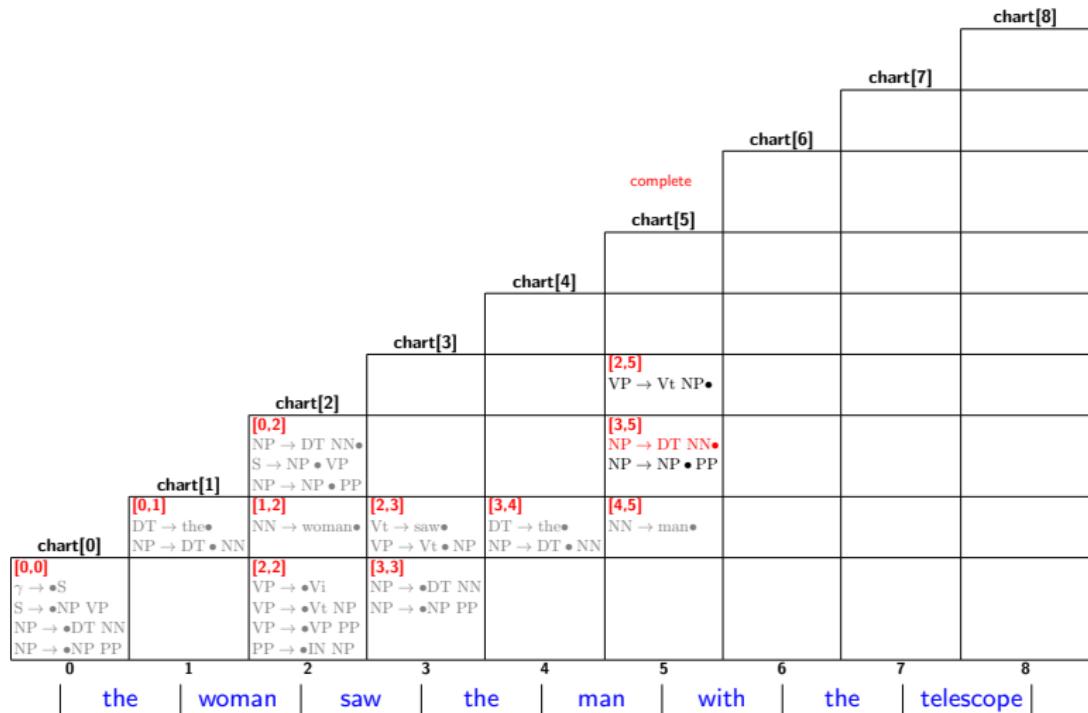


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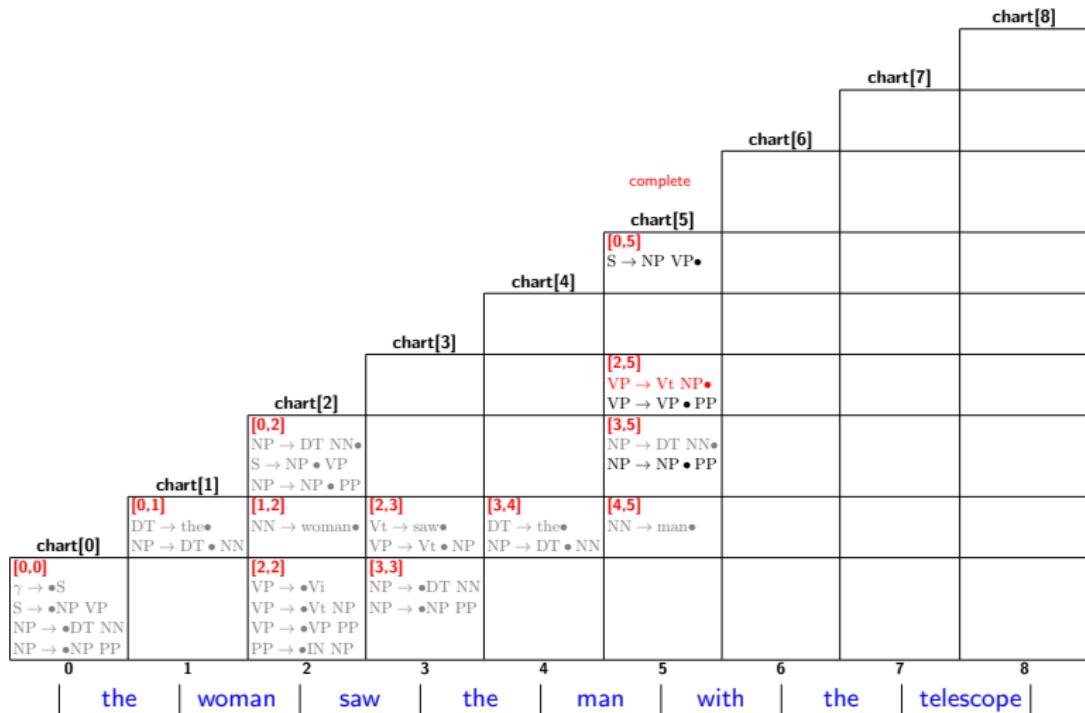
chart[8]									
chart[7]									
chart[6]									
chart[5]									
chart[4]				chart[3]		chart[2]		chart[1]	
chart[0]		[0,1]	[1,2]	[2,3]	[3,4]	[2,5]	[3,5]		
[0,0]						VP → Vt NP•	NP → DT NN• NP → NP • PP		
γ → •S S → •NP VP NP → •DT NN NP → •NP PP			VP → •Vi VP → •Vt NP VP → •VP PP PP → •IN NP	NP → •DT NN NP → •NP PP	DT → the• NP → DT • NN	NN → man•			
0	the	woman	saw	the	man	with	the	telescope	8

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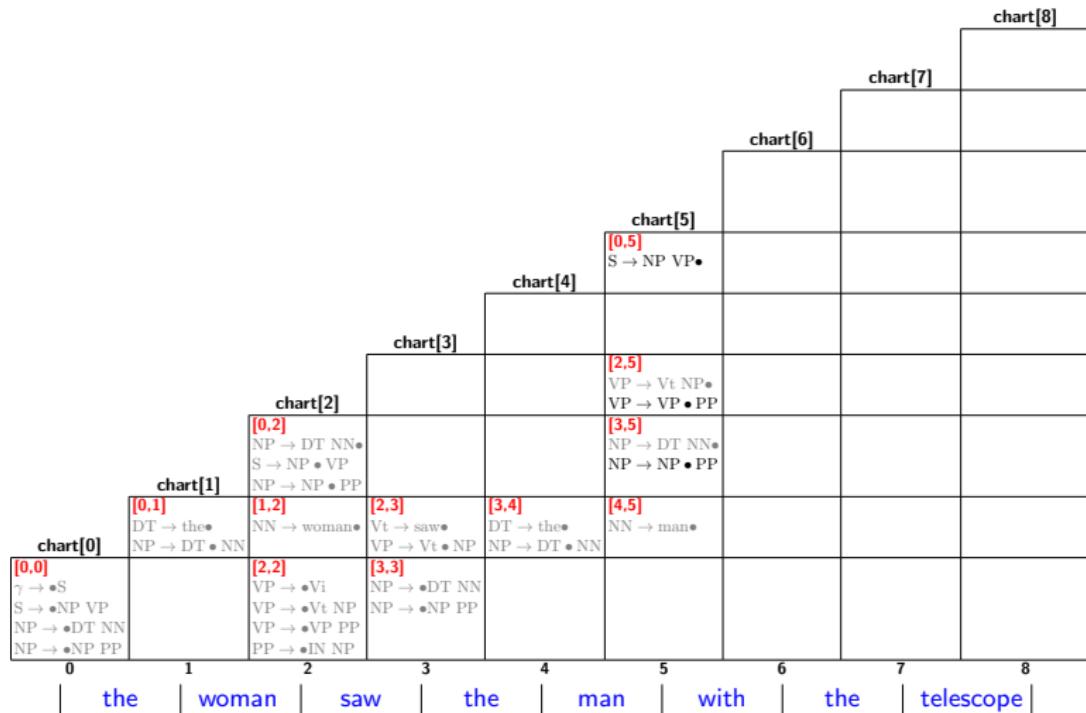


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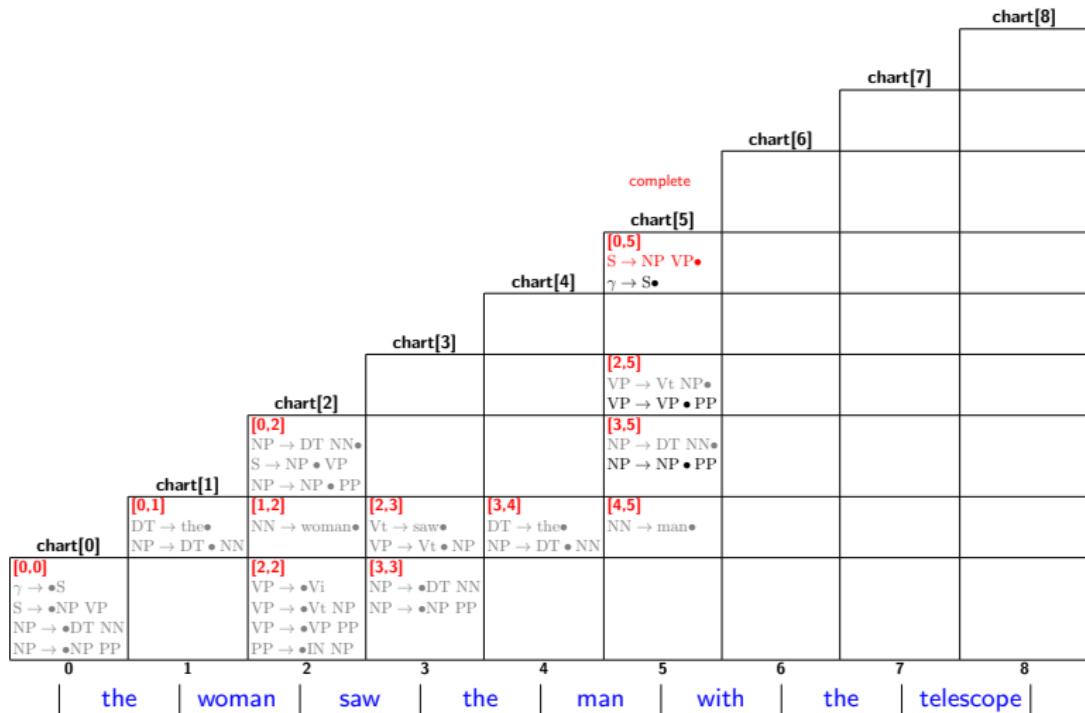


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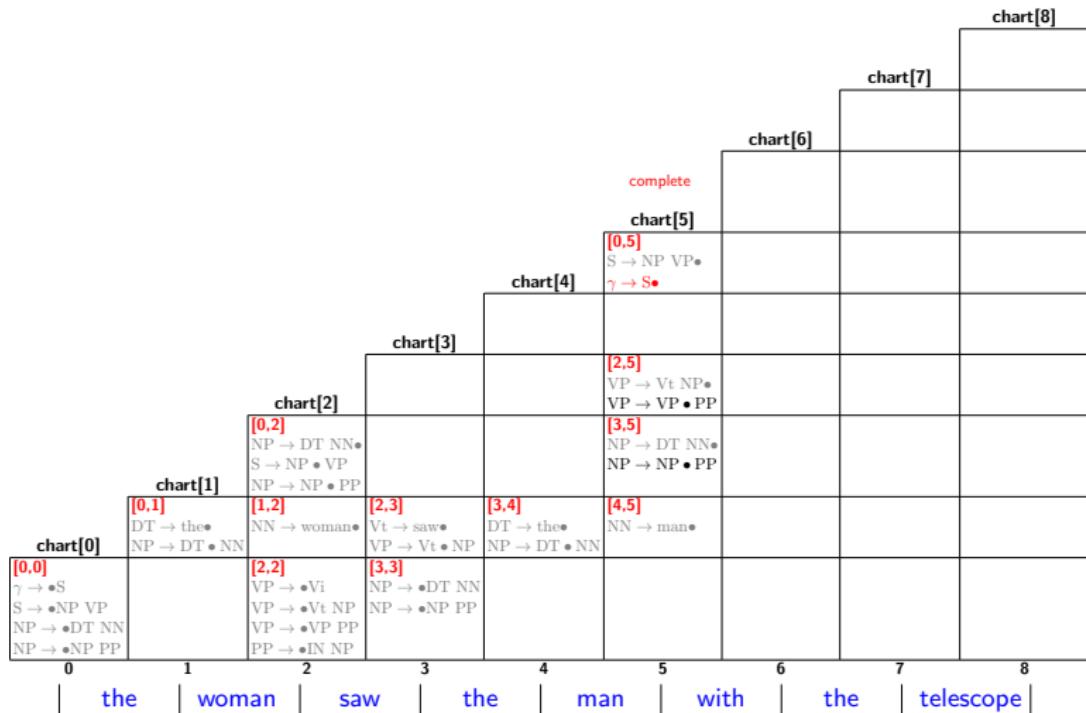


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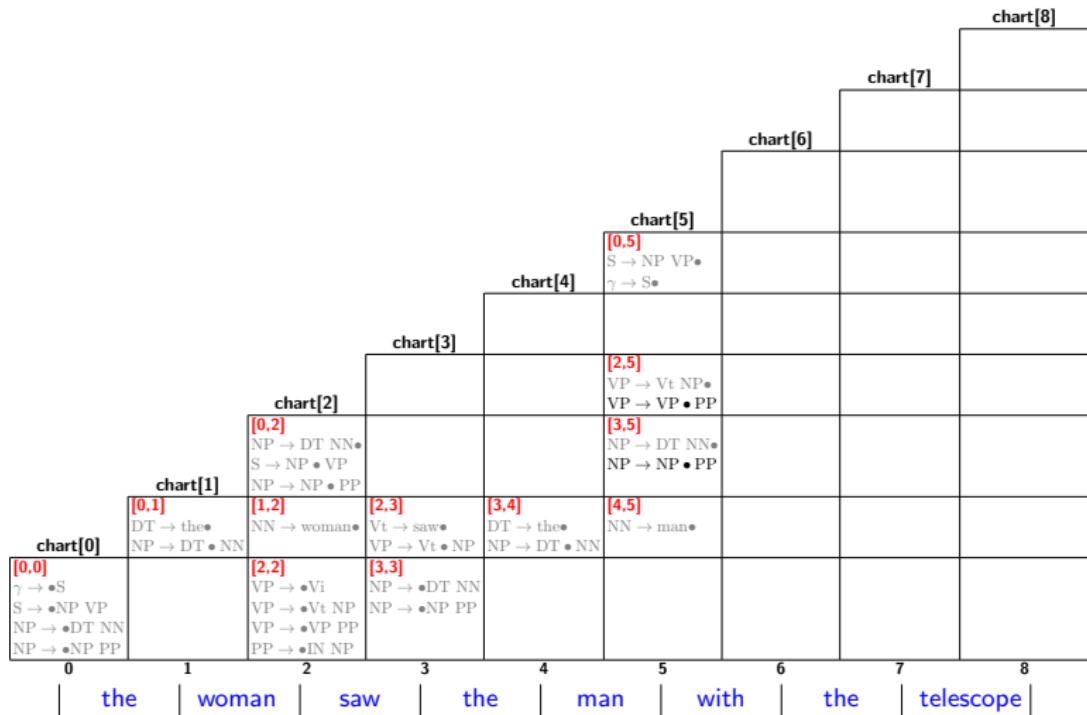


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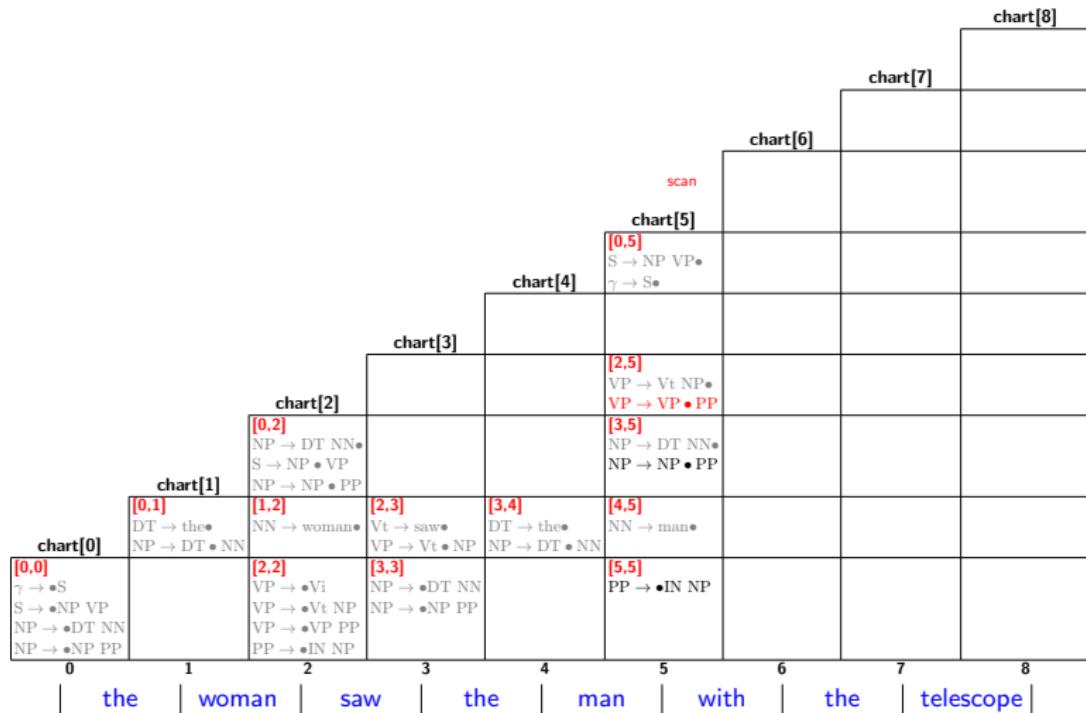


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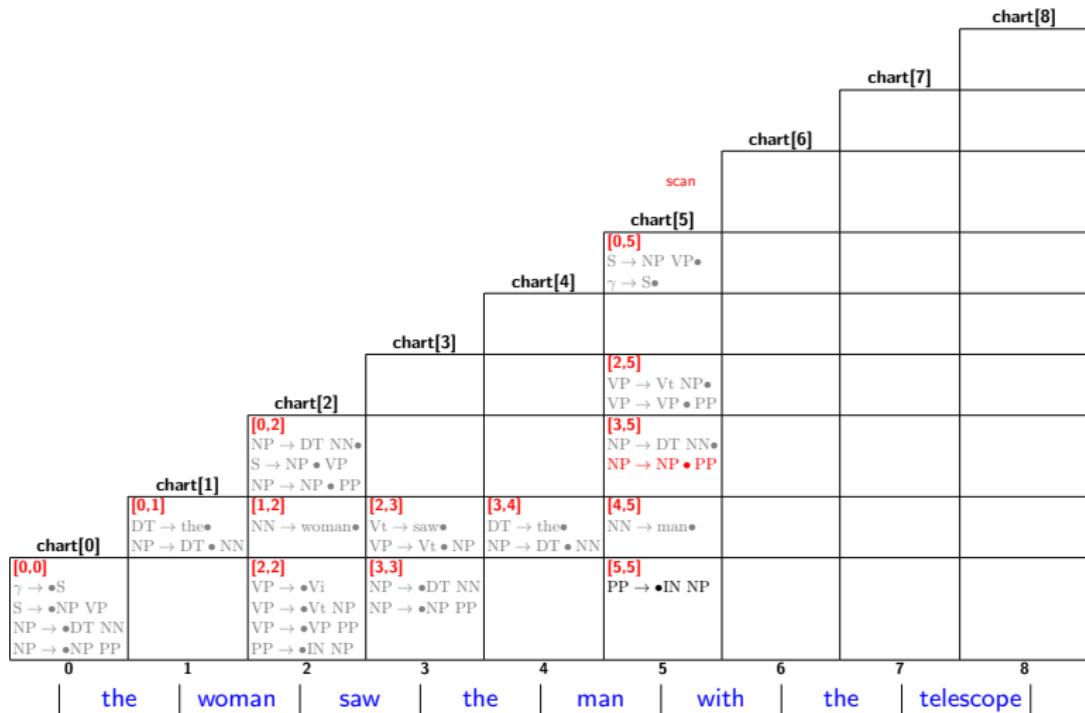


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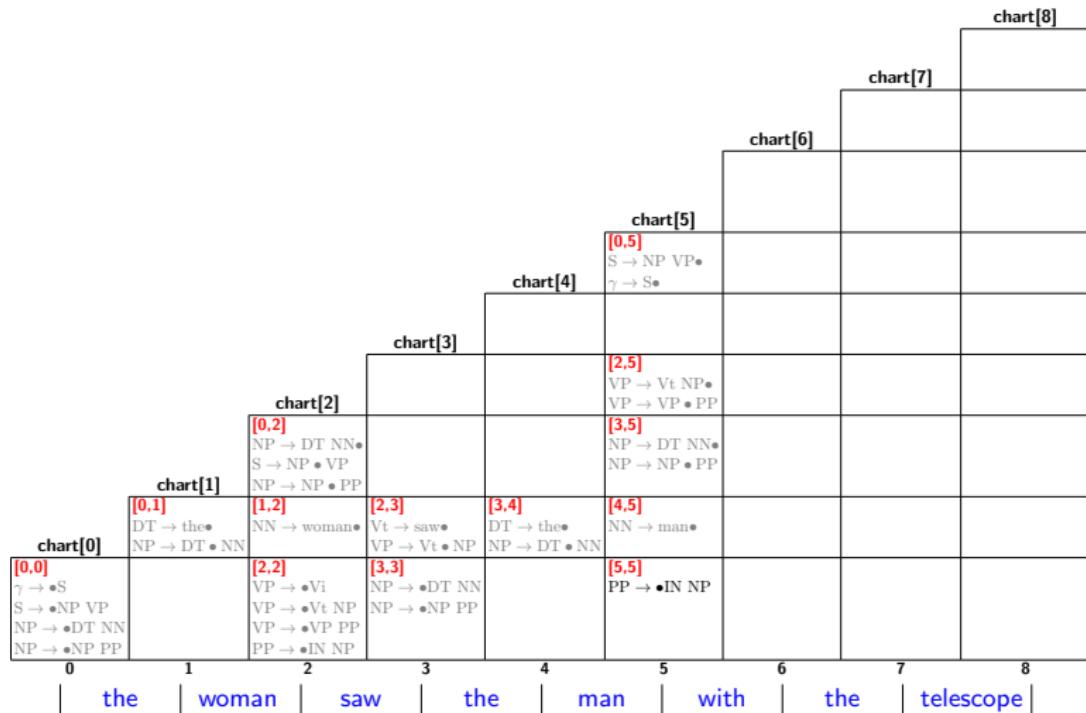


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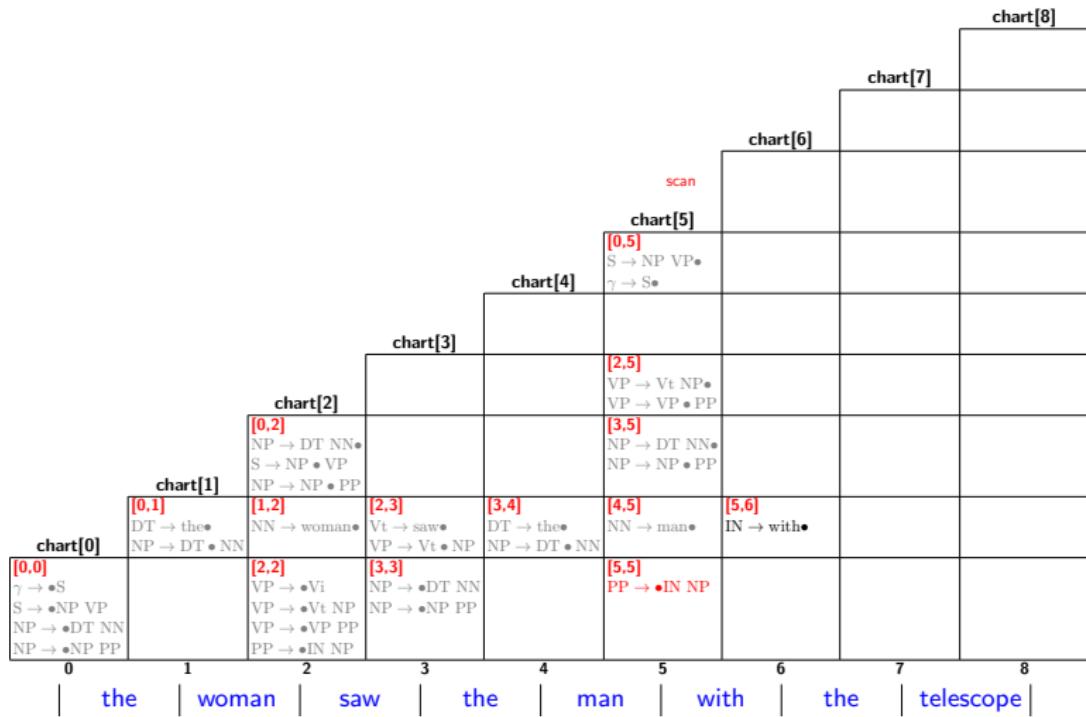


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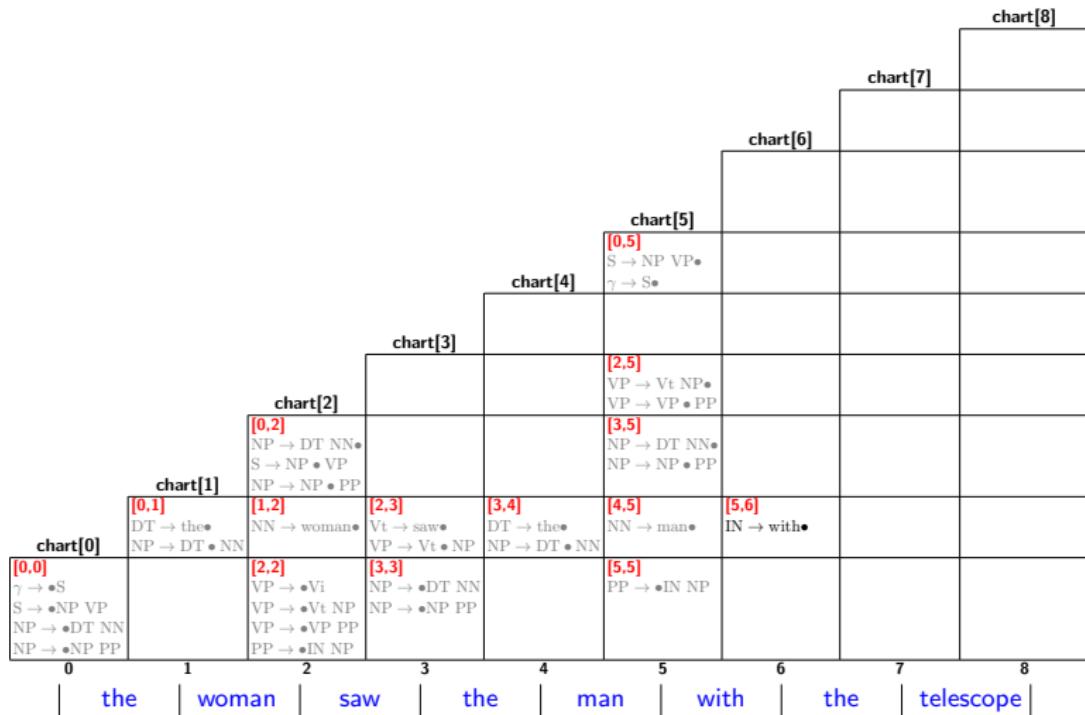


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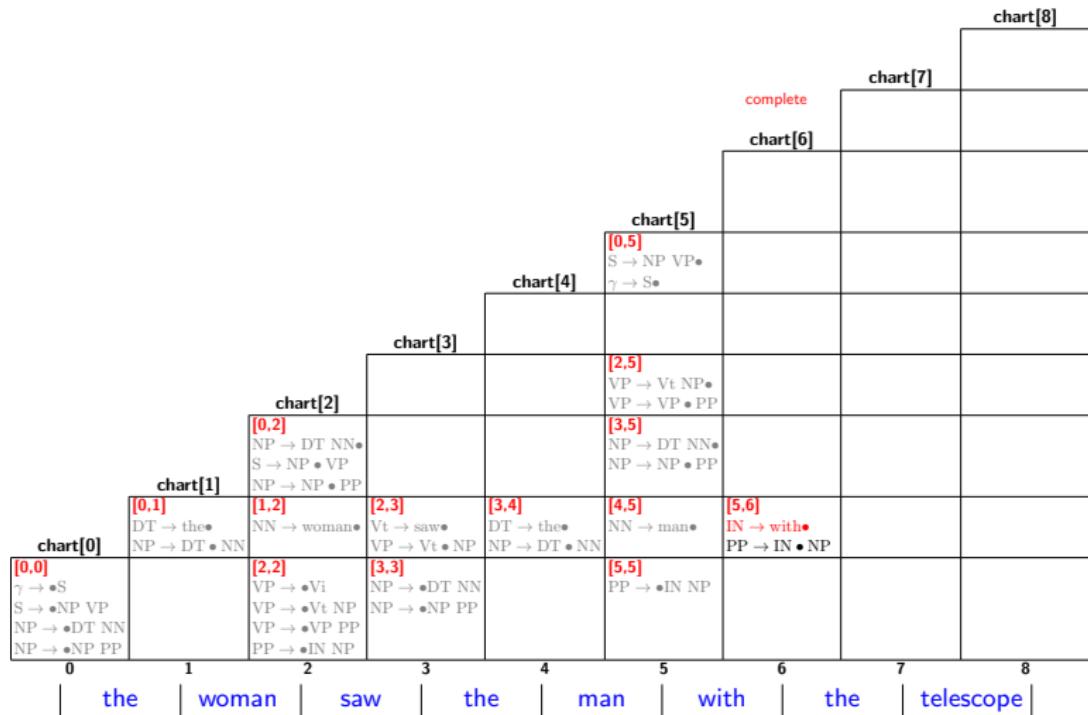


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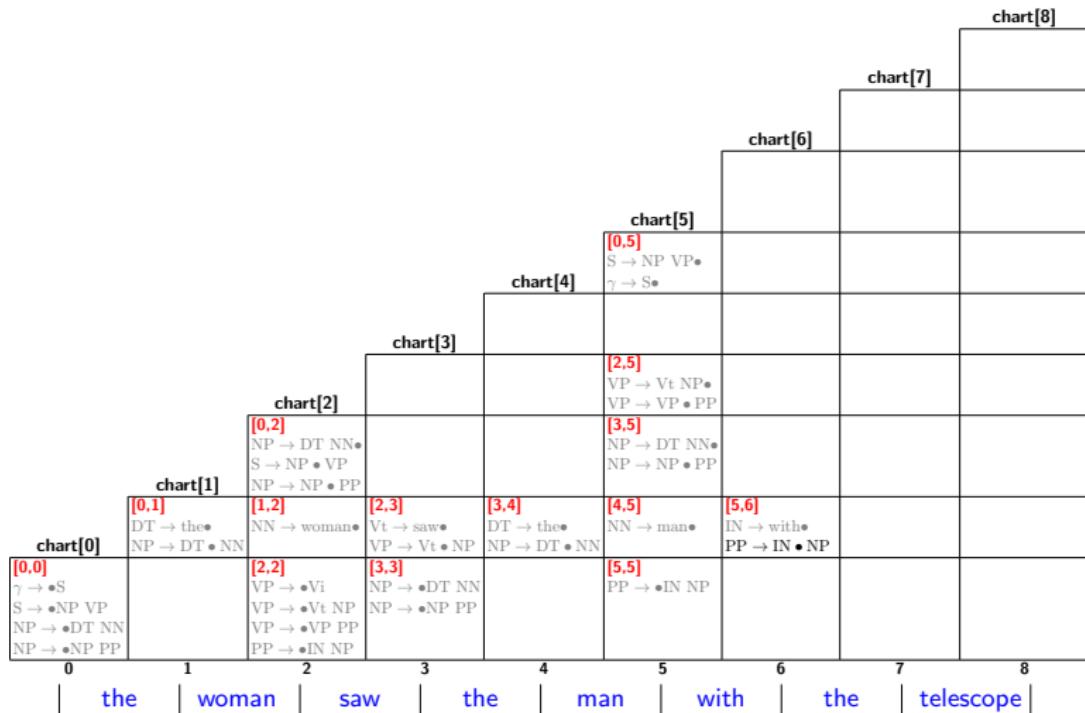


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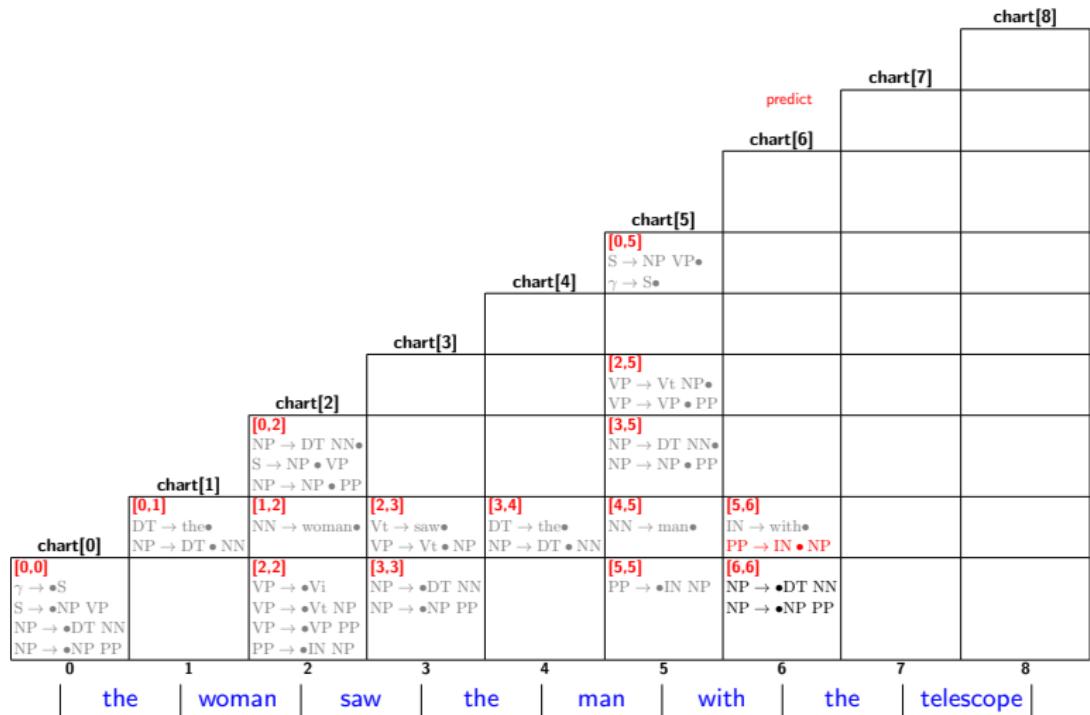


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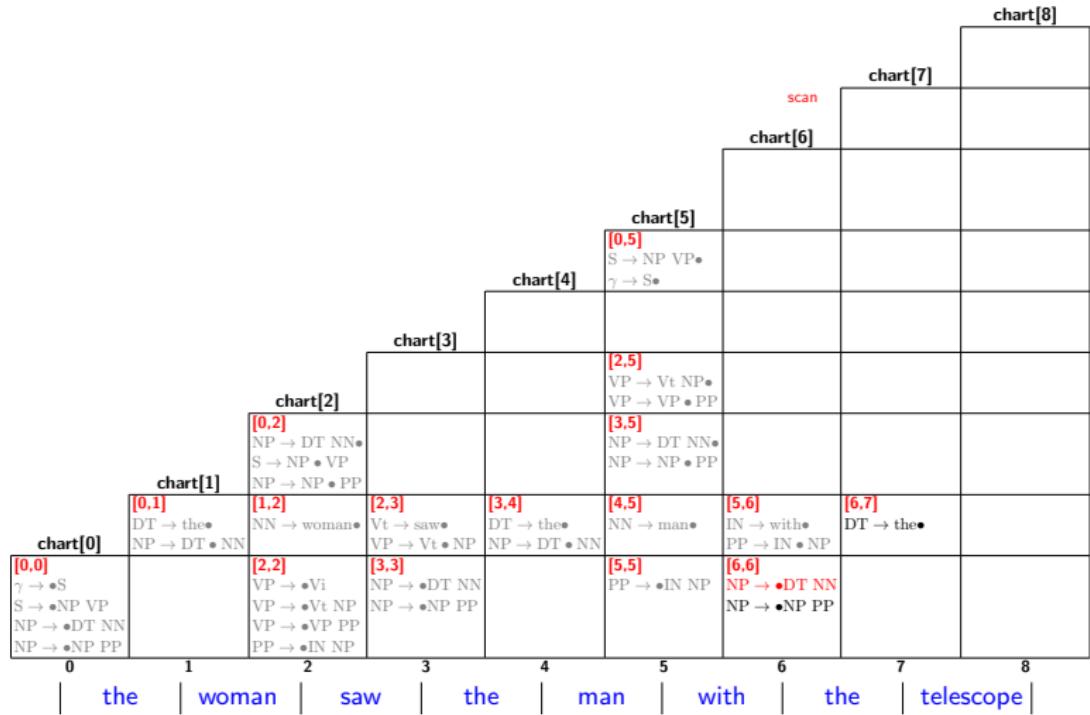


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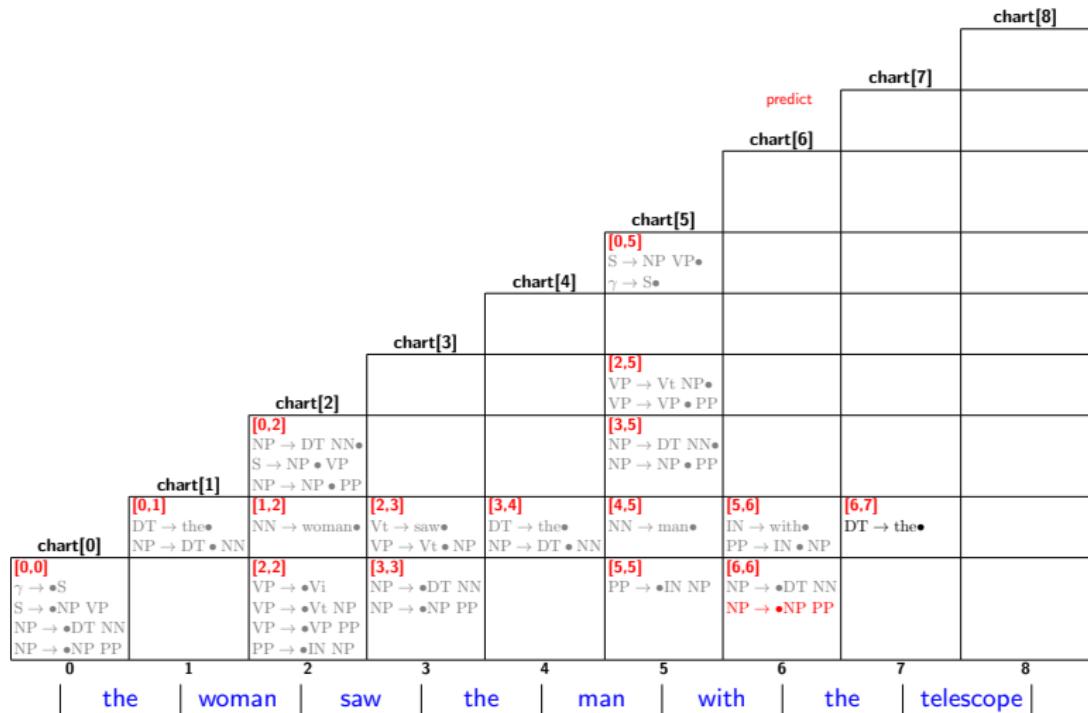


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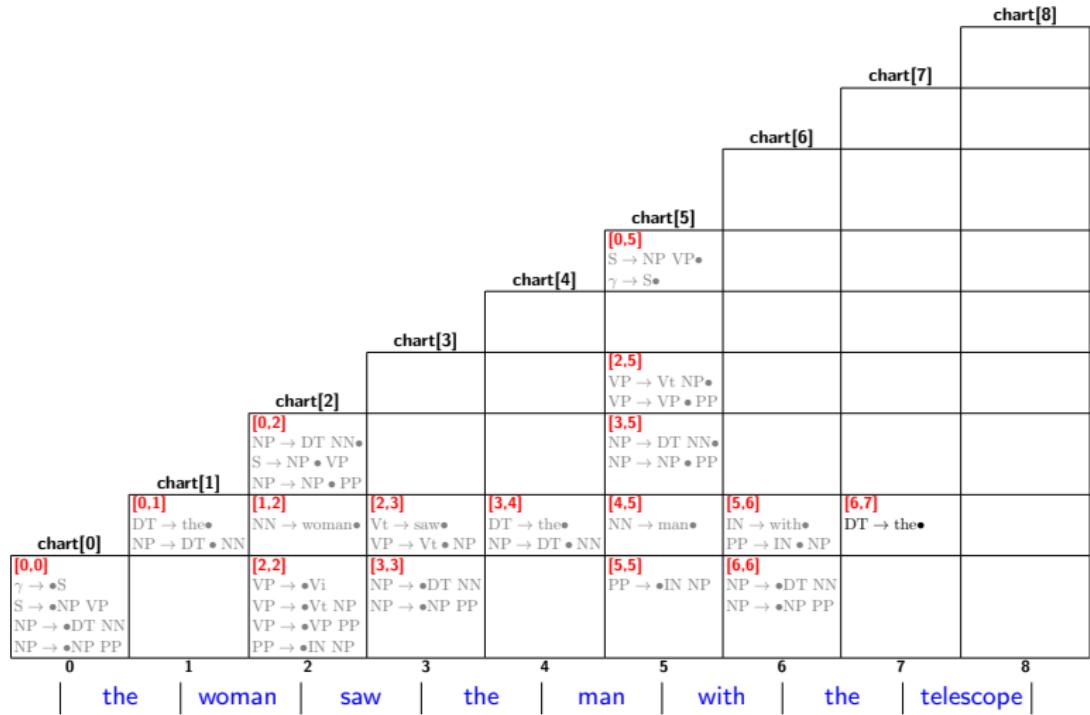


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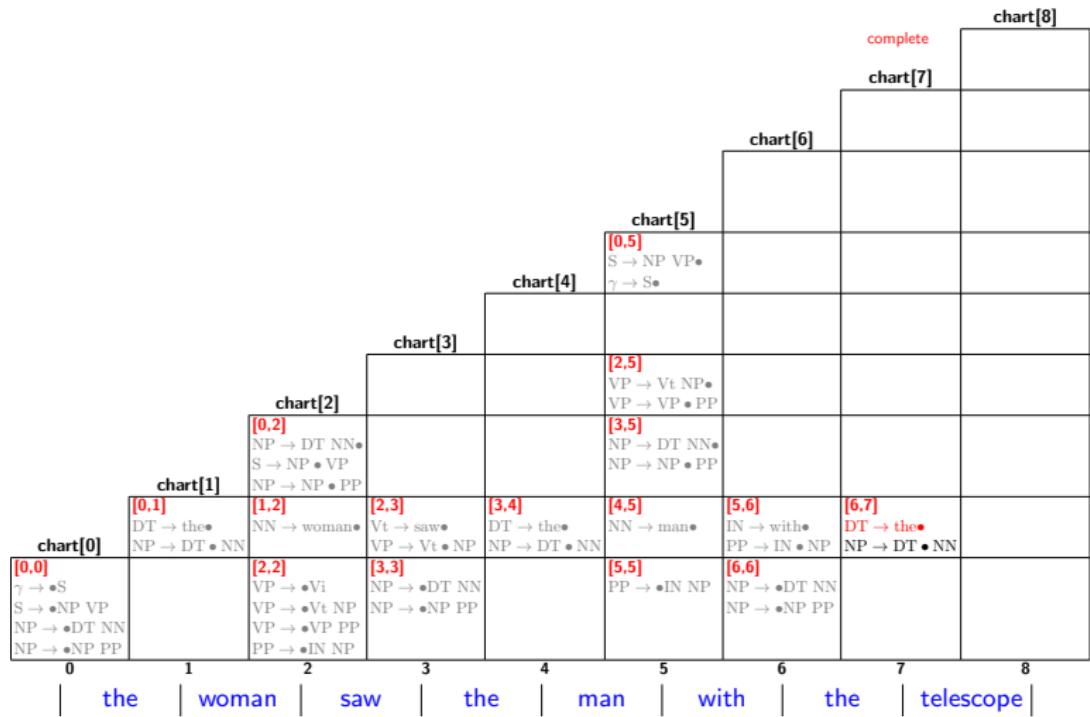


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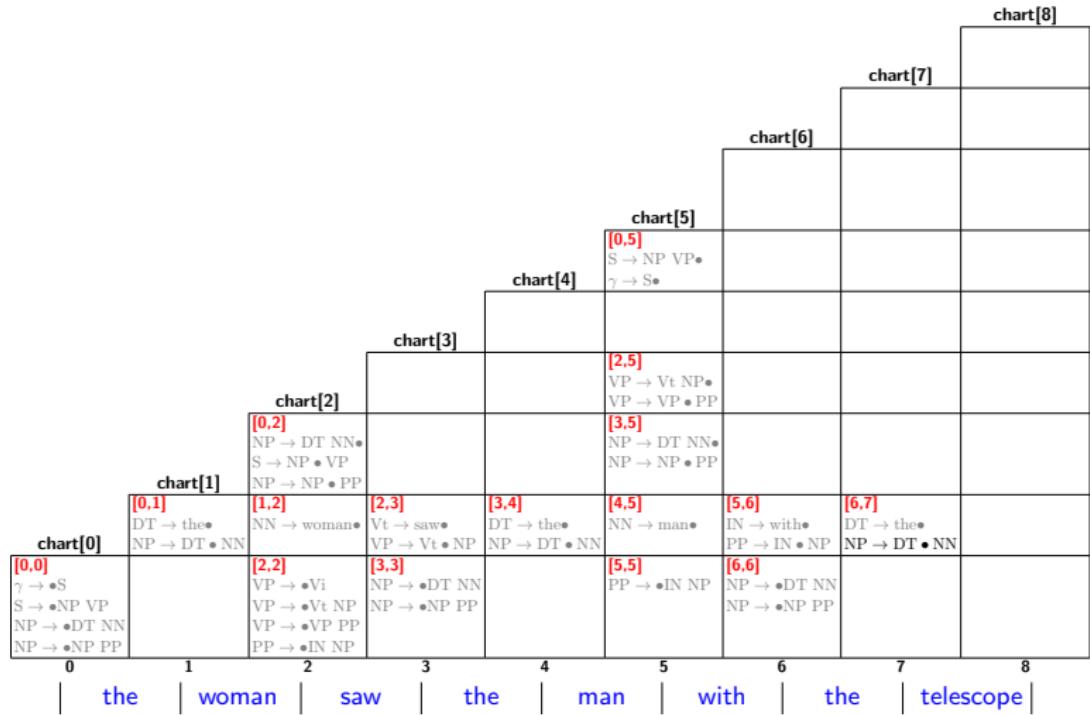


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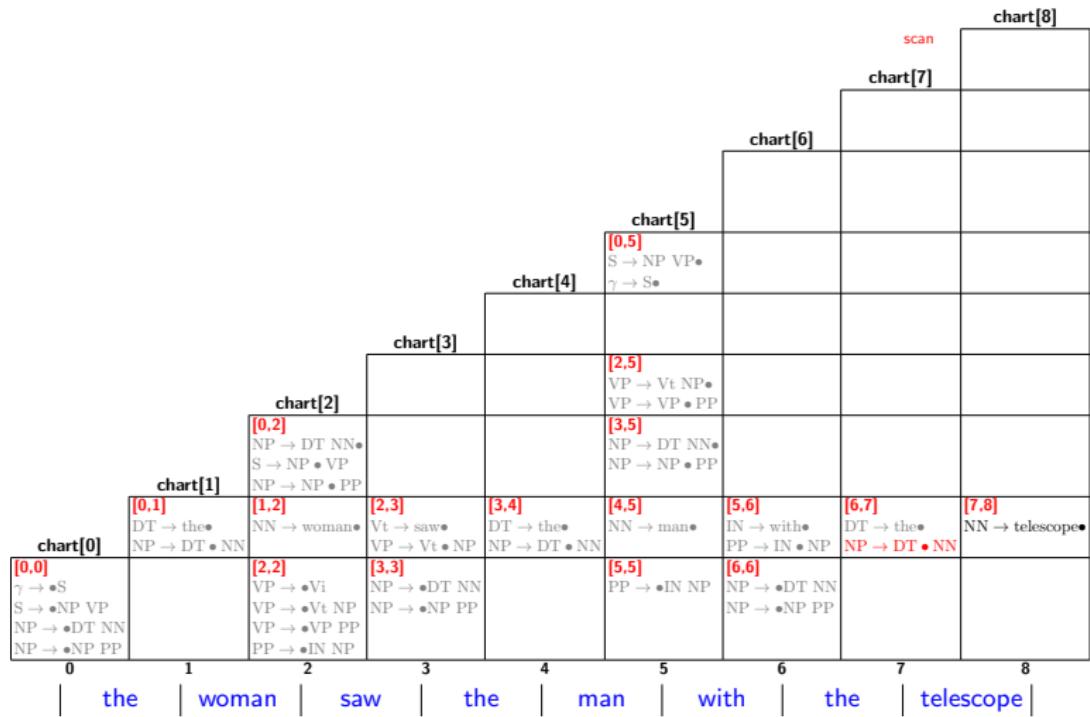


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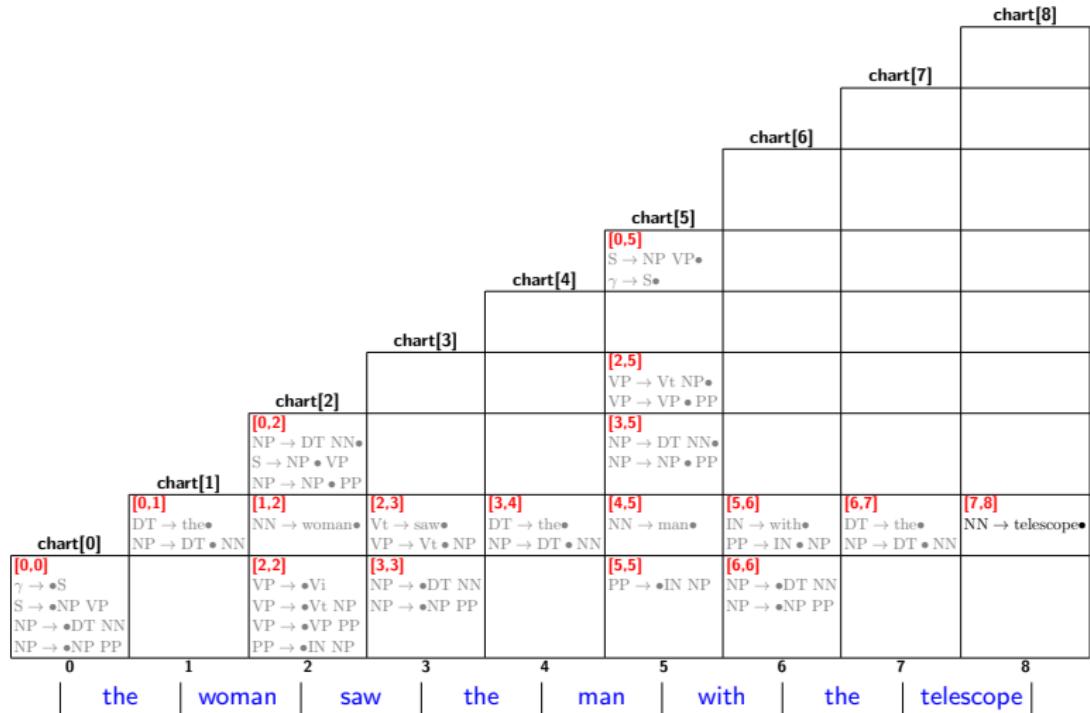


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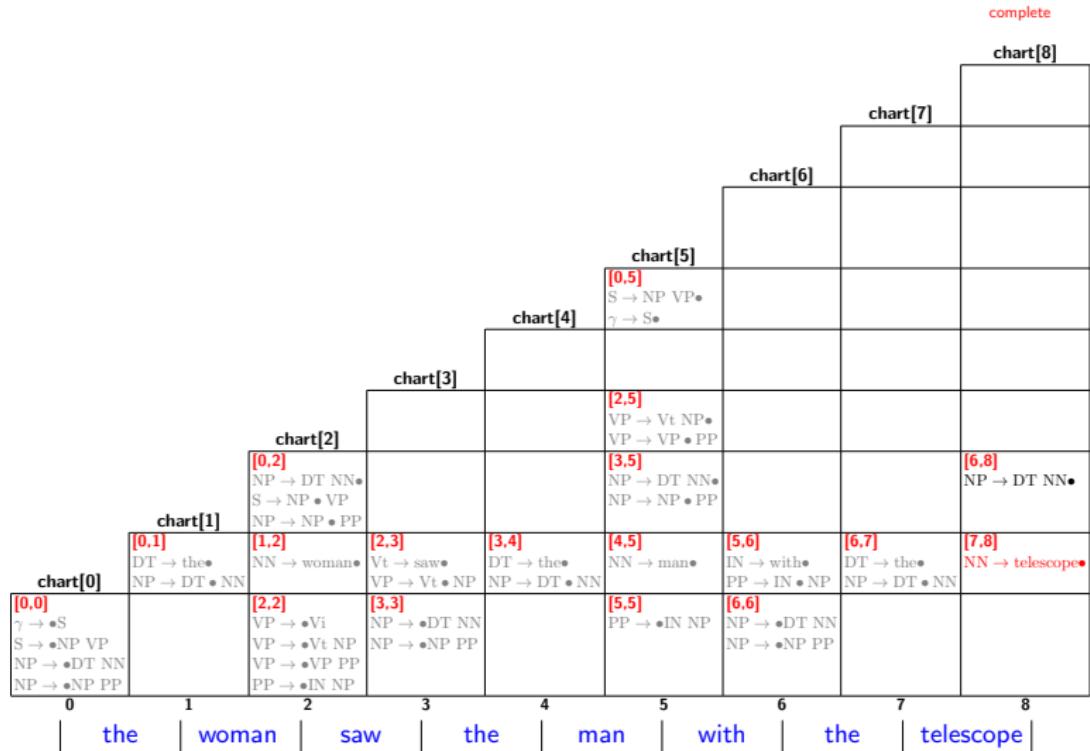


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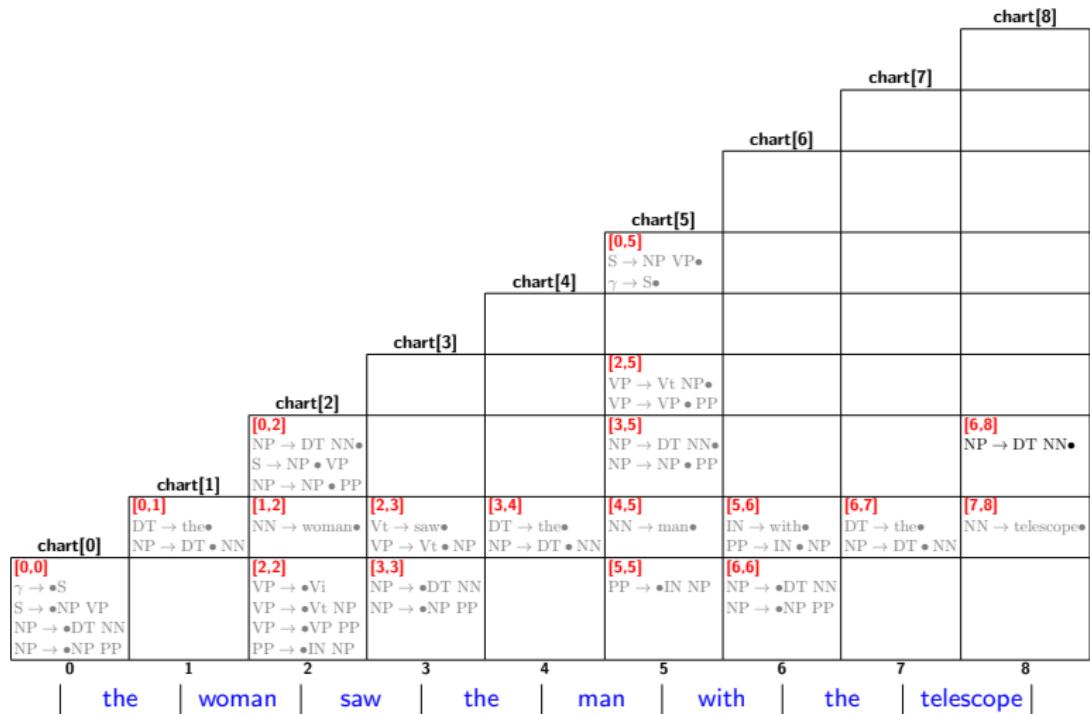


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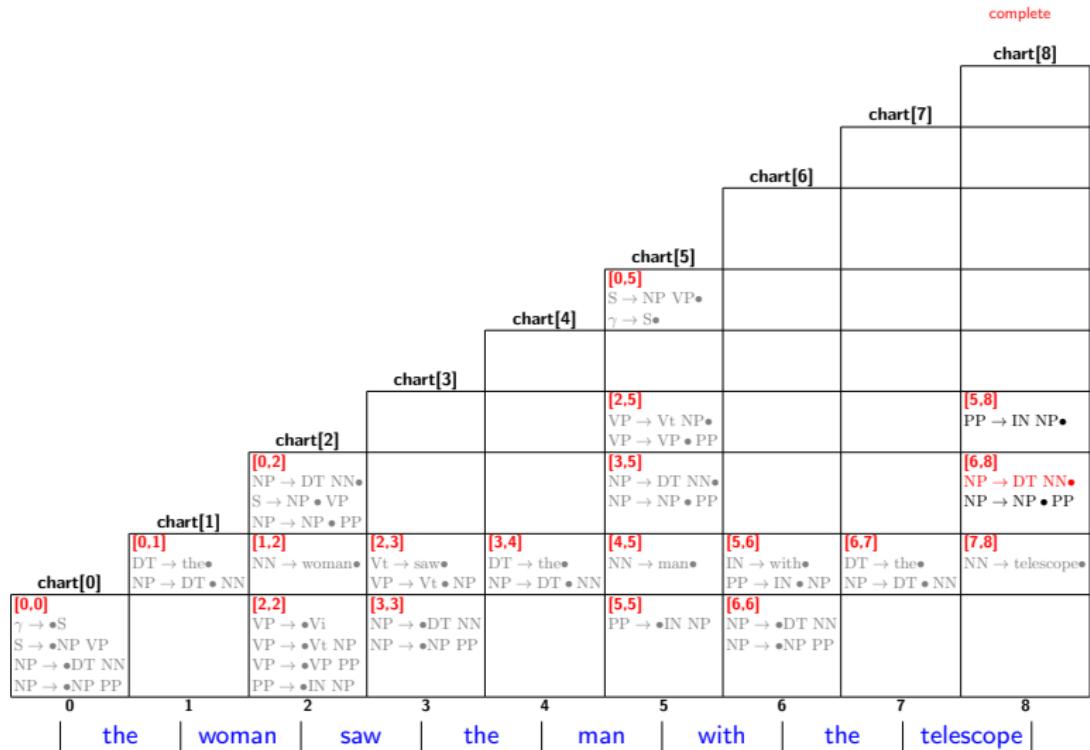


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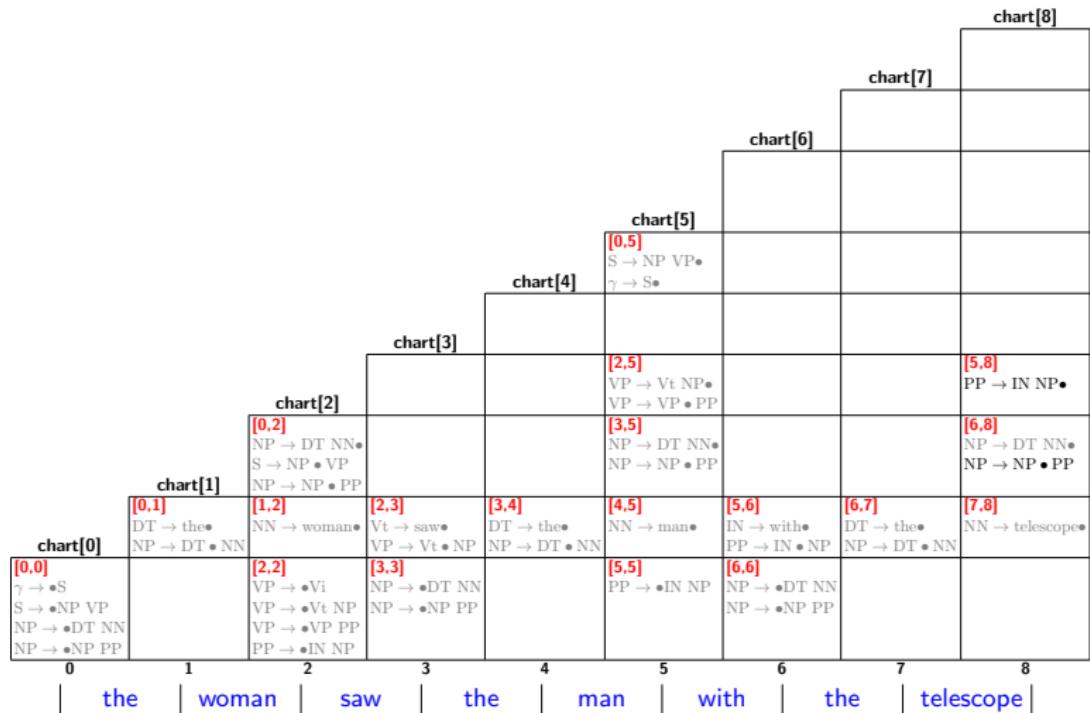


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Trees and Grammars

Constituency Parsing

Earley Algorithm

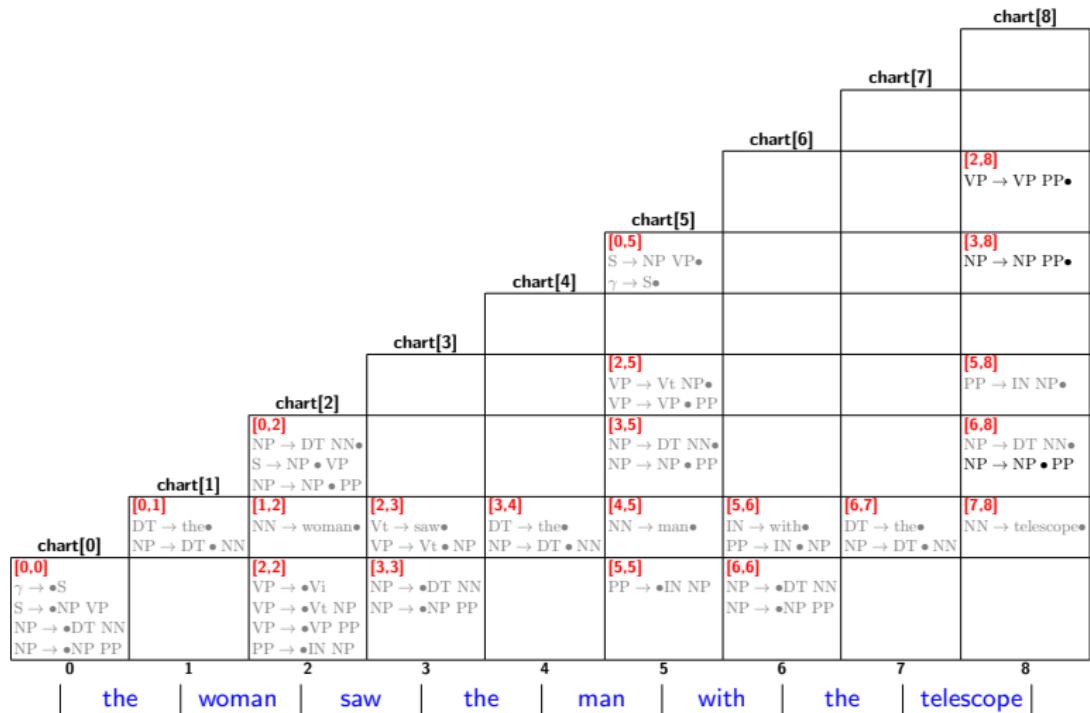
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γ → *S S → *NP VP NP → *DT NN NP → *NP PP	VP → *Vi VP → *Vt NP VP → *VP PP PP → *IN NP	NP → *DT NN NP → *NP PP		PP → *IN NP	NP → *DT NN NP → *NP PP			

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$\gamma \rightarrow *S$	$DT \rightarrow \text{the}$	$NN \rightarrow \text{woman}$	$Vt \rightarrow \text{saw}$	$DT \rightarrow \text{thee}$	$NN \rightarrow \text{man}$	$IN \rightarrow \text{with}$	$DT \rightarrow \text{the}$	$NN \rightarrow \text{telescope}$
$S \rightarrow *NP VP$	$NP \rightarrow DT NN$	$VP \rightarrow Vt NP$	$VP \rightarrow Vt NP$	$NP \rightarrow DT NN$	$NN \rightarrow man$	$PP \rightarrow IN NP$	$NP \rightarrow DT NN$	$NN \rightarrow telescope$
$NP \rightarrow *DT NN$	$NP \rightarrow *NP PP$	$VP \rightarrow *VP PP$	$PP \rightarrow *IN NP$					
$NP \rightarrow *NP PP$								
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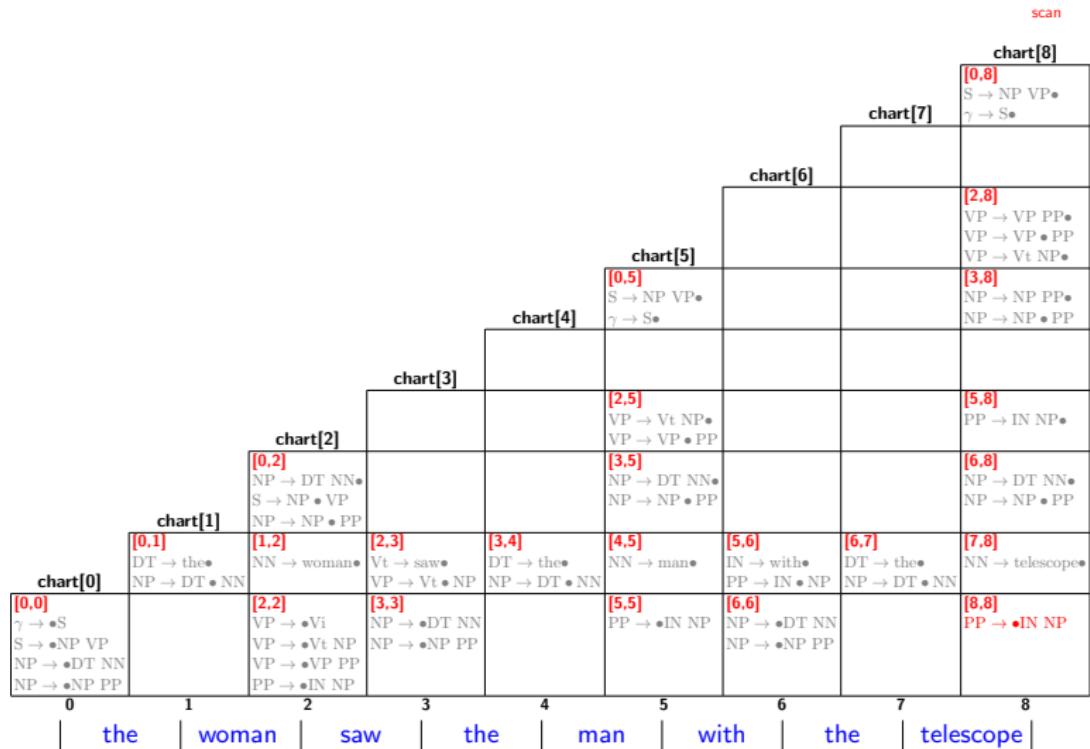
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$\gamma \rightarrow *S$	$DT \rightarrow \text{the}$	$NN \rightarrow \text{woman}$	$Vt \rightarrow \text{saw}$	$DT \rightarrow \text{thee}$	$NN \rightarrow \text{man}$	$IN \rightarrow \text{with}$	$DT \rightarrow \text{the}$	$NN \rightarrow \text{telescope}$
$S \rightarrow *NP VP$	$NP \rightarrow DT NN$	$VP \rightarrow Vt NP$	$VP \rightarrow Vt NP$	$NP \rightarrow DT NN$	$NN \rightarrow man$	$PP \rightarrow IN NP$	$NP \rightarrow DT NN$	$NN \rightarrow telescope$
$NP \rightarrow *DT NN$	$NP \rightarrow *VP PP$	$VP \rightarrow *VP PP$	$PP \rightarrow *IN NP$					
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CKY vs Earley

CKY

- Bottom-up
- Requires CNF
- Can compute all trees
- $\mathcal{O}(n^3)$
- Straightforward
probabilistic version

Earley

- Top-down
- Any CFG can be used, no need for CNF
- Can compute all trees
- $\mathcal{O}(n^3)$
- Not so straightforward
probabilistic version

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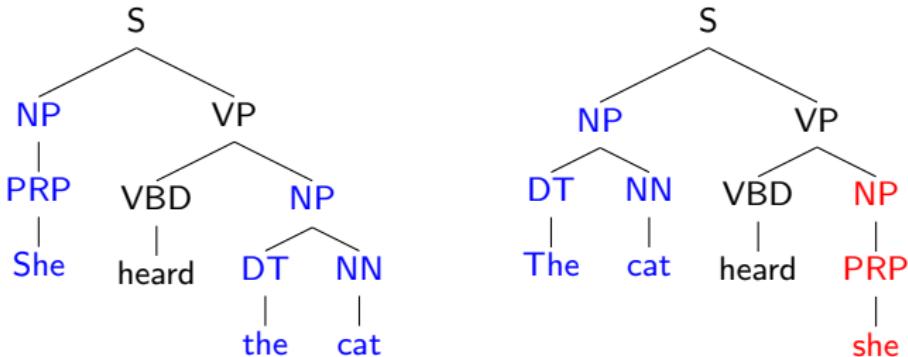
Earley Algorithm

Why *context-free* ?

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- Context-free means *independent of the context*, i.e, assumes that any expansion of a non-terminal is applicable, regardless of the context in which it occurs.



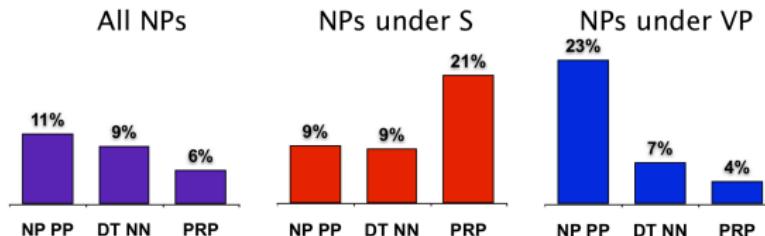
Natural Language is not Context-Free

Trees and Grammars

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- NP expansion (for instance) is highly dependent on the parent of the NP



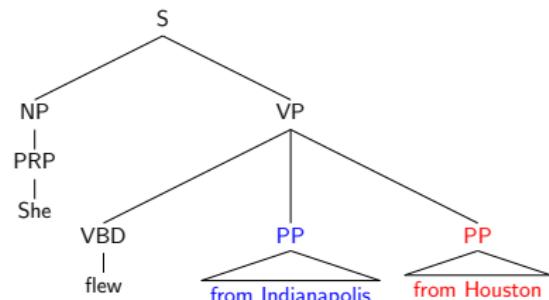
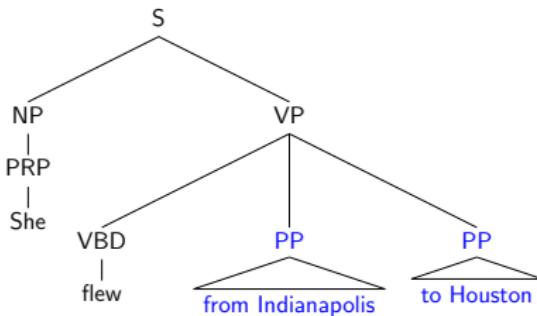
- Complete context independence is a too strong independence assumption for natural language.

Natural Language is not Context-Free

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- The application of a rule may affect the applicability of others

Natural Language is not Context-Free

- May contain non-projective structures:

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