

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



Outline

Trees and
Grammars

Constituency
Parsing

1 Trees and Grammars

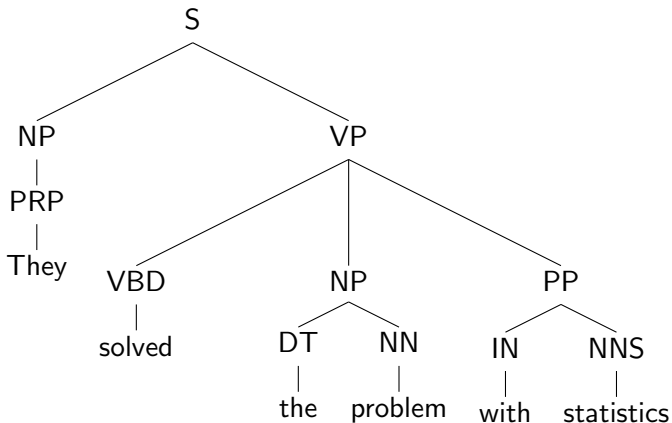
2 Constituency Parsing

- CKY Algorithm
- Earley Algorithm

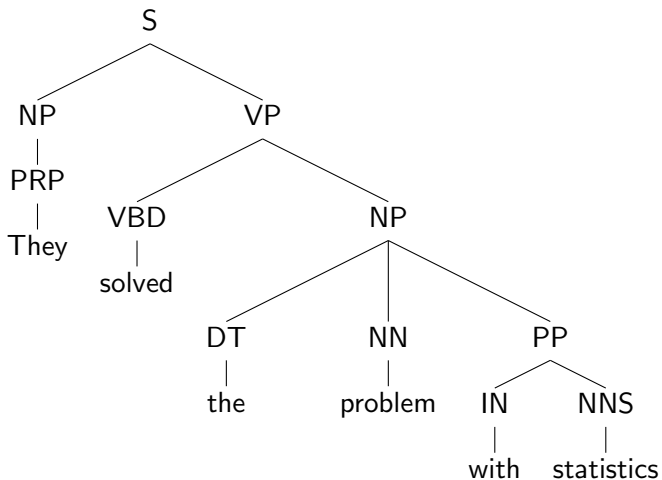
A Syntactic Tree

Trees and
Grammars

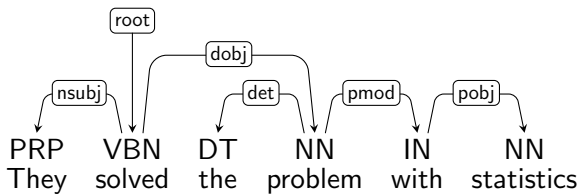
Constituency
Parsing



Another Syntactic Tree



Dependency Trees

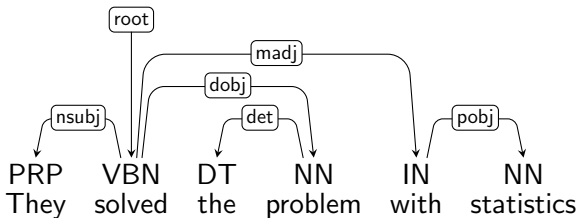
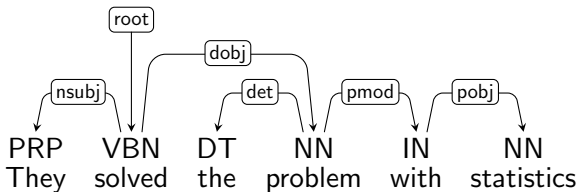


Trees and
Grammars

Constituency
Parsing

Dependency Trees

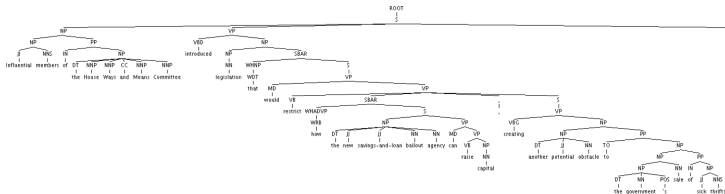
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Constituency
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A “real” sentence

Trees and Grammars

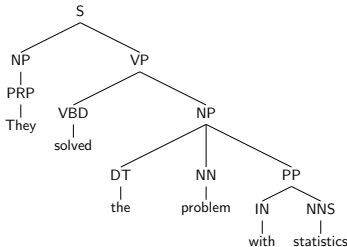
Constituency Parsing



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.

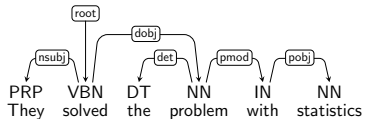
Theories of Syntactic Structure

Constituent Trees



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

Dependency Trees



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

Context Free Grammars (CFGs)

Trees and
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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 $X \rightarrow Y_1 Y_2 \dots Y_n$ where $n \geq 0$, $X \in N$, $Y_i \in N \cup \Sigma$

Context Free Grammars, Example

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

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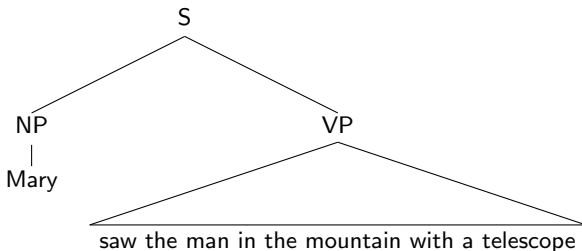
$$R = \left\{ \begin{array}{ll} S \rightarrow NP VP & Vi \rightarrow \text{sleeps} \\ NP \rightarrow DT NN & Vt \rightarrow \text{saw} \\ NP \rightarrow NP PP & NN \rightarrow \text{man} \\ PP \rightarrow IN NP & NN \rightarrow \text{woman} \\ VP \rightarrow Vi & NN \rightarrow \text{telescope} \\ VP \rightarrow Vt NP & DT \rightarrow \text{the} \\ VP \rightarrow VP PP & IN \rightarrow \text{with} \\ & IN \rightarrow \text{in} \end{array} \right\}$$

¹S=sentence, VP=verb phrase, NP=noun phrase, PP=prepositional phrase, DT=determiner, Vi=intransitive verb, Vt=transitive verb, NN=noun, IN=preposition

Properties of CFGs

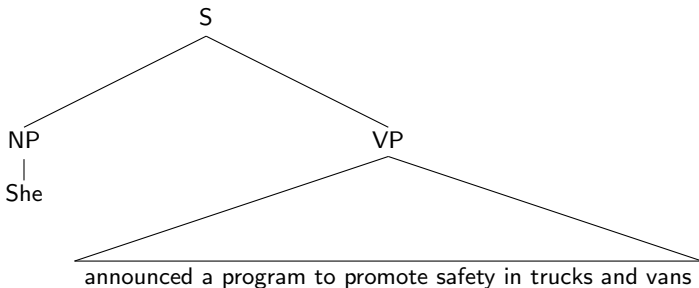
- A CFG defines a set of possible *derivations* (i.e. unique trees)
- A sequence of terminals $s \in \Sigma^*$ is *generated* by the CFG (or *recognized* by it, or *belongs* to the language defined by it) if there is at least a derivation that produces s .
- Some sequences of terminals generated by the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

Ambiguity



- *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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Grammars

Constituency
Parsing

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)

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

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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

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Constituency
Parsing

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$R = \left\{ \begin{array}{ll} S \rightarrow NP \ VP & Vi \rightarrow \text{sleeps} \\ NP \rightarrow DT \ NN & Vt \rightarrow \text{saw} \\ NP \rightarrow NP \ PP & NN \rightarrow \text{man} \\ PP \rightarrow IN \ NP & NN \rightarrow \text{woman} \\ VP \rightarrow Vi & NN \rightarrow \text{telescope} \\ VP \rightarrow Vt \ NP & DT \rightarrow \text{the} \\ VP \rightarrow VP \ PP & IN \rightarrow \text{with} \\ & IN \rightarrow \text{in} \end{array} \right\}$

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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:

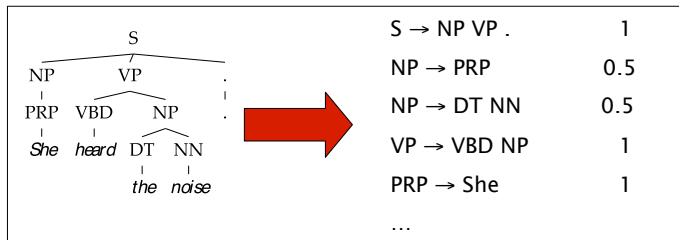
$$p(t) = \prod_{r \in t} q(r)$$

- 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

Outline

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Grammars

Constituency
Parsing

1 Trees and Grammars

2 Constituency Parsing

- CKY Algorithm
- Earley Algorithm

Parsing Natural Language Sentences

Goal of a parser:

- Find all possible trees

Trees and
Grammars

Constituency
Parsing

Parsing Natural Language Sentences

Goal of a parser:

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

Parsing Natural Language Sentences

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Goal of a parser:

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

Parsing Natural Language Sentences

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Goal of a parser:

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

Parsing Natural Language Sentences

Trees and
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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

Trees and
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Constituency
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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

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

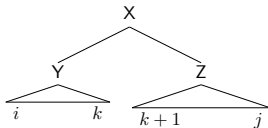
$$\blacksquare \forall i = 1 \dots n, \forall X \rightarrow w_i \in R, \pi(i, i, X) = q(X \rightarrow w_i)$$

Recursive case: Non-terminal nodes

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

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

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



Output:

$$\blacksquare \text{Return } \pi(1, n, S) \text{ and recover backpath through } \psi(1, n, S)$$

CKY Algorithm - Example

Trees and
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Constituency
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CKY Algorithm

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

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CKY Algorithm - Example - CNF

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CKY Algorithm - Example - CNF

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Grammars

Constituency
Parsing

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CKY Algorithm - Example

Trees and
Grammars

Constituency
Parsing

CKY Algorithm

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

Constituency
Parsing

CKY Algorithm

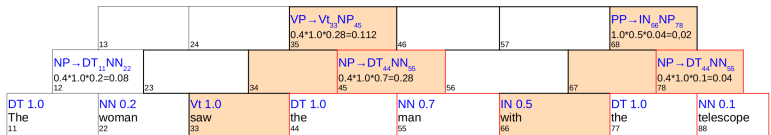
NP → DT ₁₁ NN ₂₂ 0.4*1.0*0.2=0.08 12		23		34		NP → DT ₄₄ NN ₅₅ 0.4*1.0*0.7=0.28 45		56		67		NP → DT ₇₈ NN ₈₈ 0.4*1.0*0.1=0.04 78	
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CKY Algorithm - Example

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Grammars

Constituency
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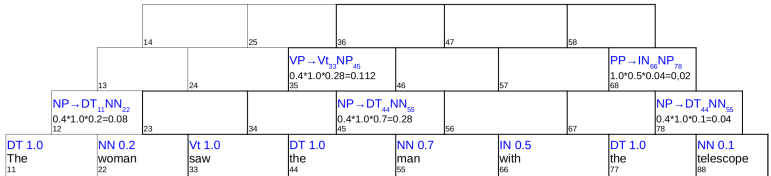


CKY Algorithm - Example

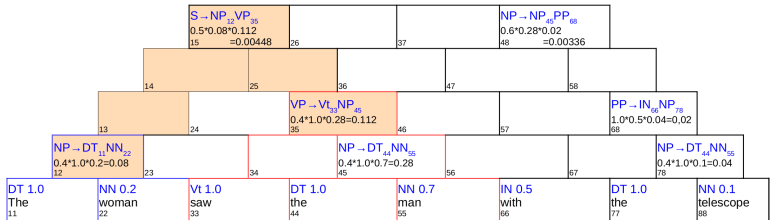
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Grammars

Constituency
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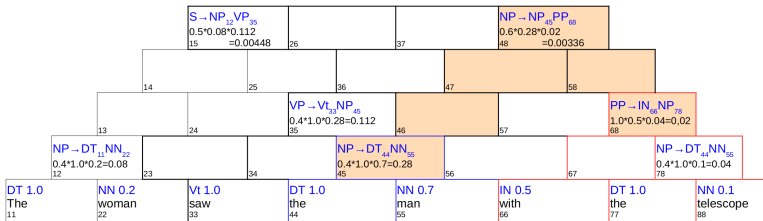
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Trees and Grammars

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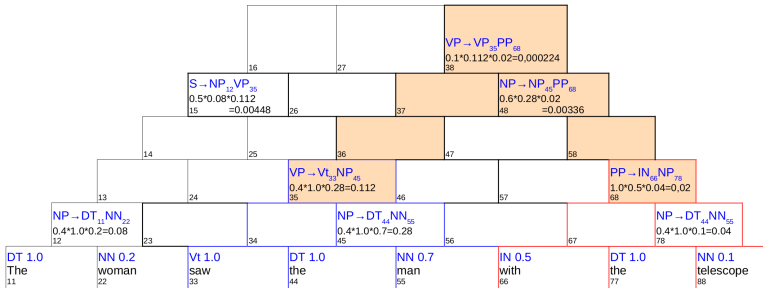


CKY Algorithm - Example

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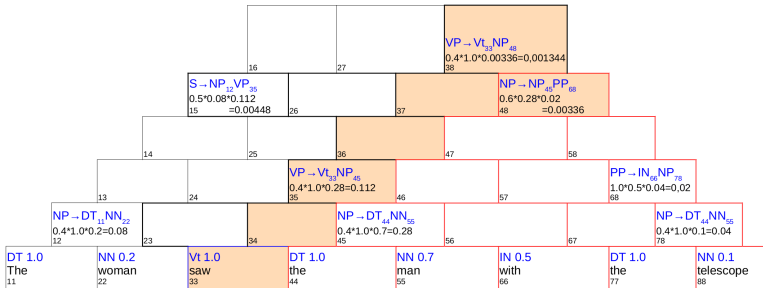


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Constituency
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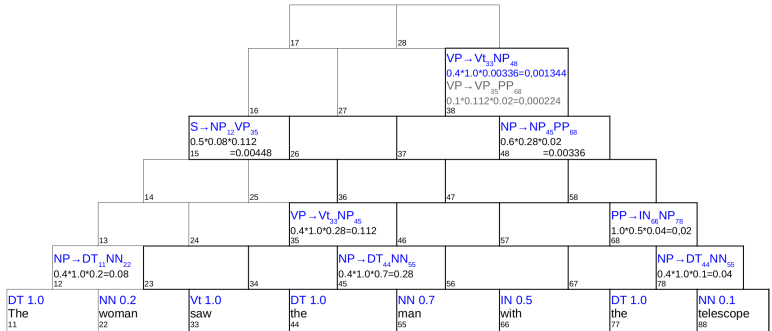


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Constituency
Parsing

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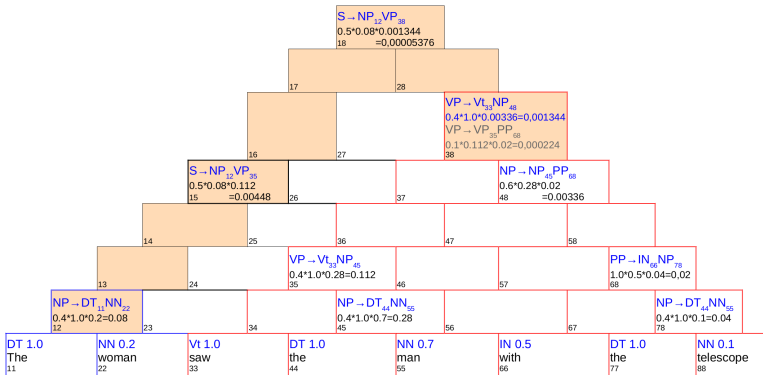


CKY Algorithm - Example

Trees and
Grammars

Constituency
Parsing

CKY Algorithm



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Grammars

Constituency
Parsing

Earley Algorithm

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Earley Algorithm

- 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.

Earley Algorithm

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:

$[0, 0, S \rightarrow \bullet NP VP]$

A NP is expected at the beginning of the sentence

$[1, 2, NP \rightarrow DT \bullet NN]$

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

$[0, 3, VP \rightarrow V NP \bullet]$

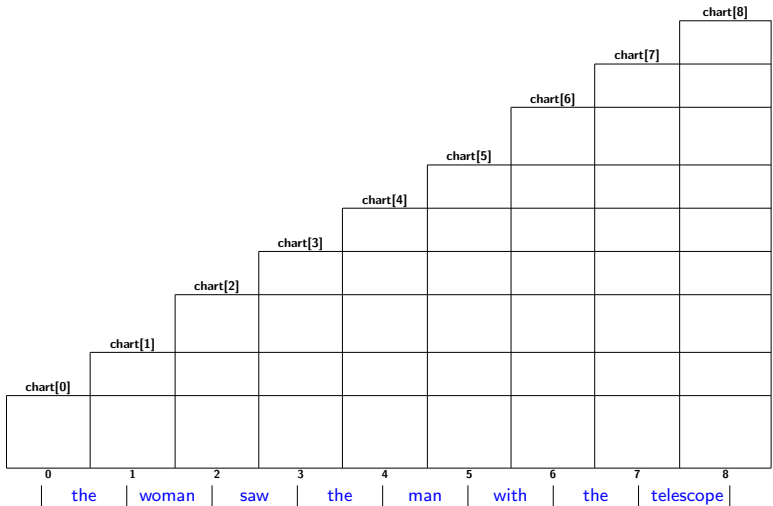
A VP has been completed between positions 0 and 3

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  $\rightarrow \alpha \bullet B\beta$ ]):  
    if B in words[j].PoS() : chart[j+1].append([j,j+1,B  $\rightarrow$  word[j] $\bullet$ ])  
  
def Predict([i,j,A  $\rightarrow \alpha \bullet B\beta$ ):  
    for B  $\rightarrow \gamma$  in grammar : chart[j].append([j,j,B  $\rightarrow \bullet \gamma$ ])  
  
def Complete([k,j,B  $\rightarrow \gamma \bullet$ ):  
    for [i,k,A  $\rightarrow \alpha \bullet B\beta$ ] in chart[k] : chart[j].append([i,j,A  $\rightarrow \alpha B \bullet \beta$ ])
```

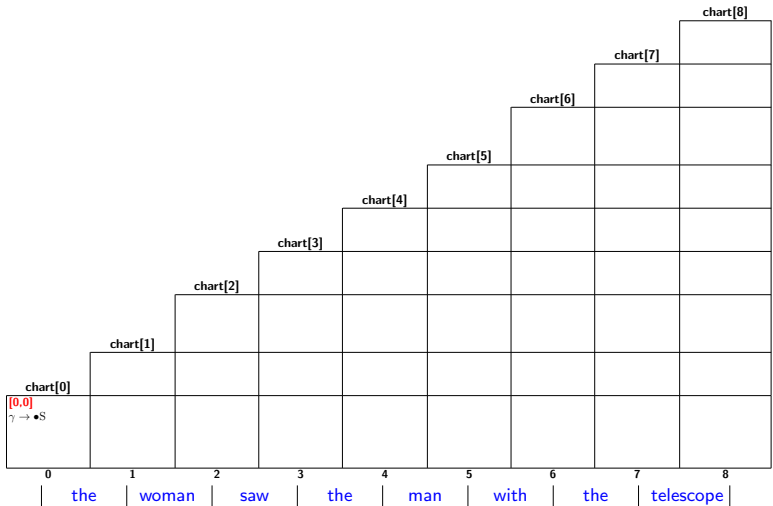
Earley Algorithm

Trees and
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Constituency
Parsing
Earley Algorithm



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Trees and
Grammars
Constituency
Parsing
Earley Algorithm

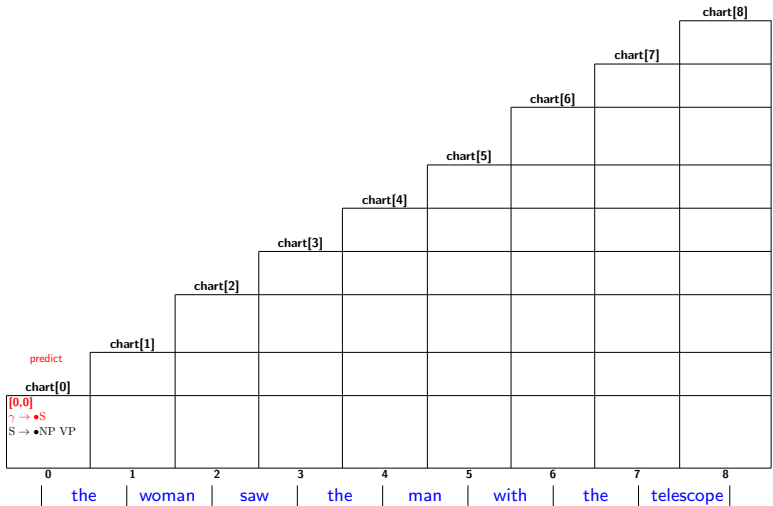


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

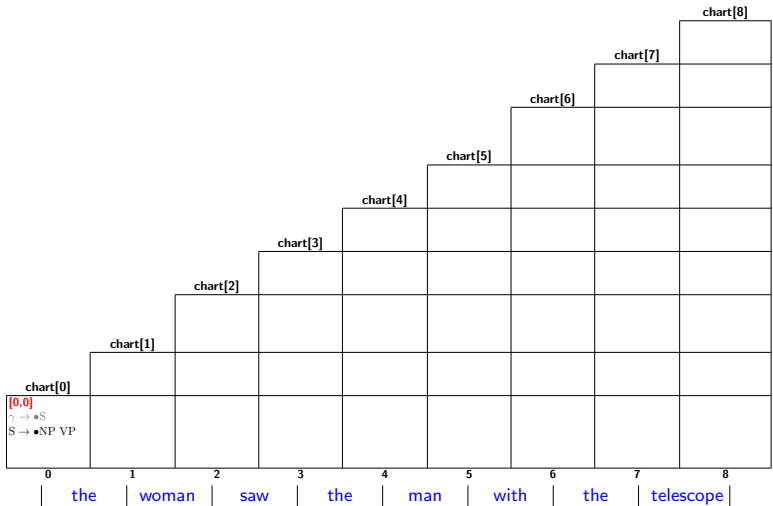


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

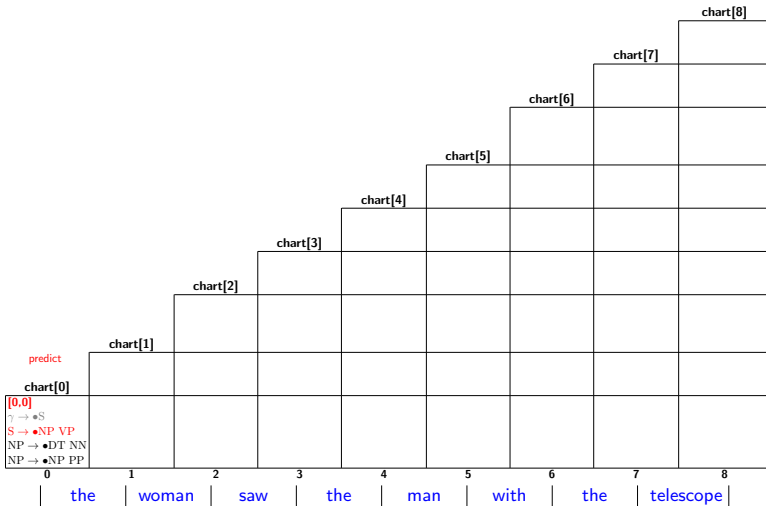


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Trees and
Grammars

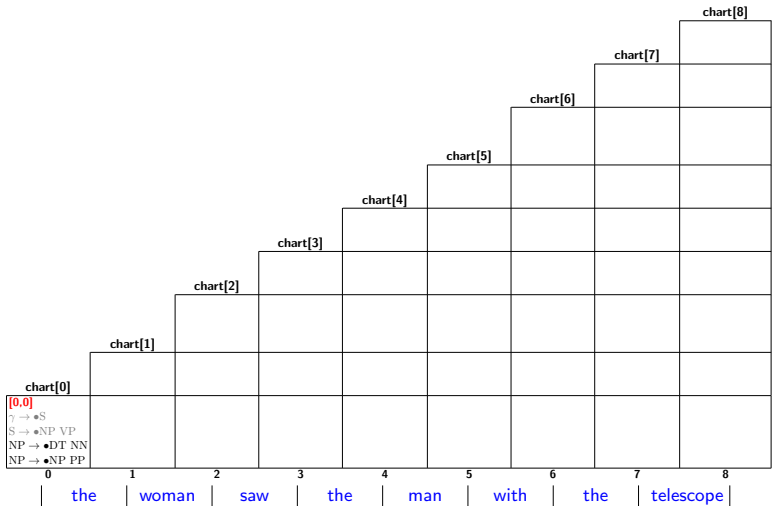
Constituency
Parsing

Earley Algorithm



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Trees and
Grammars
Constituency
Parsing
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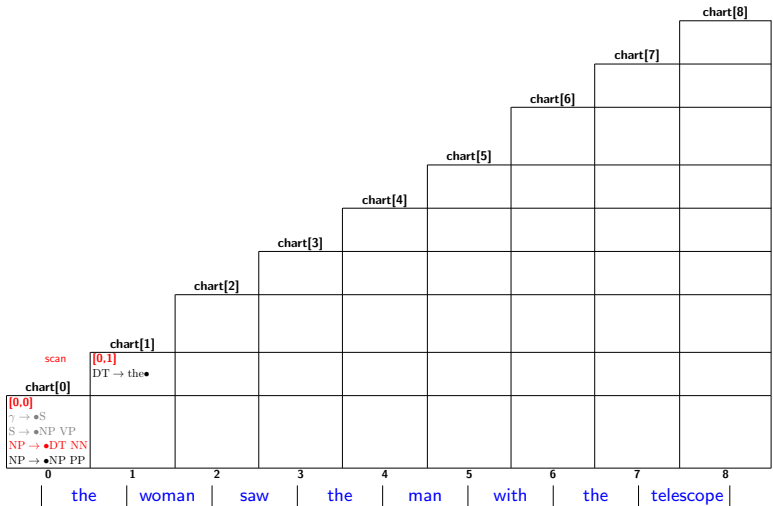


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Constituency
Parsing

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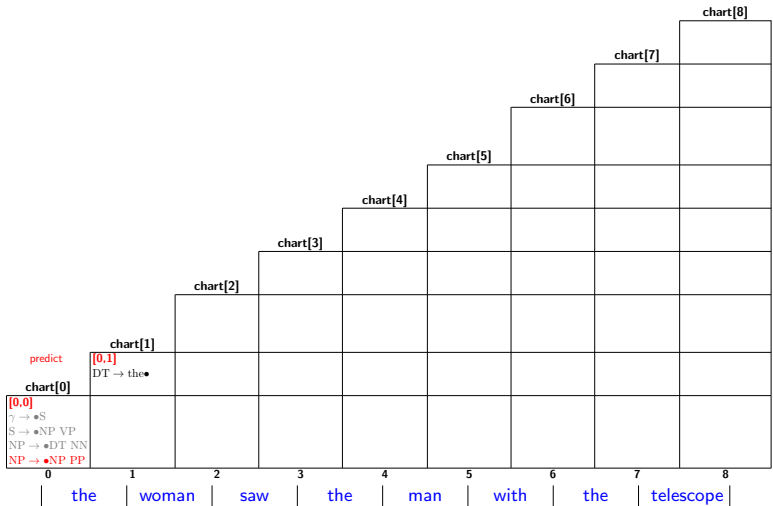


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

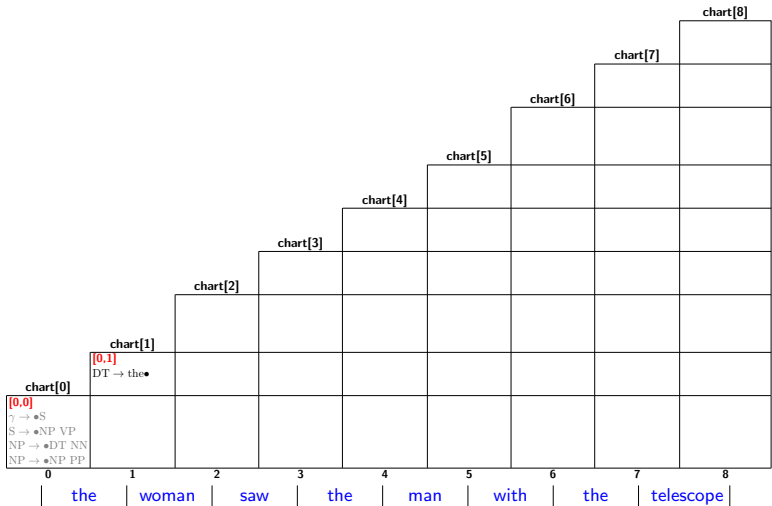


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Constituency
Parsing

Earley Algorithm

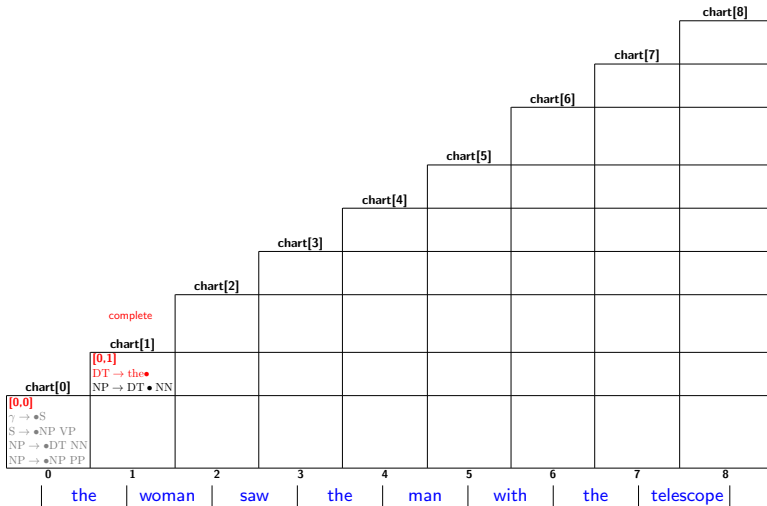


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Constituency
Parsing

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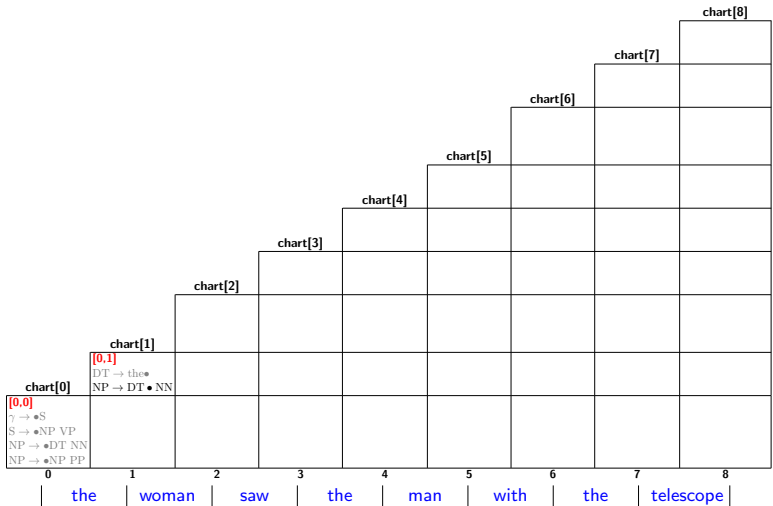


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

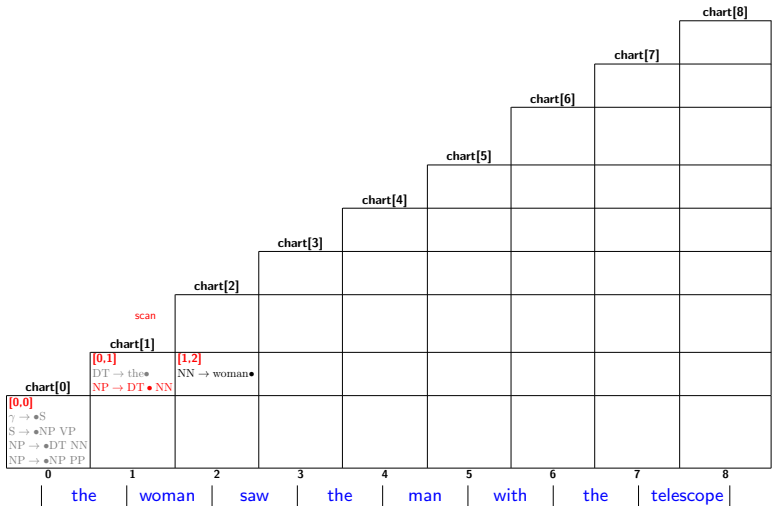


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

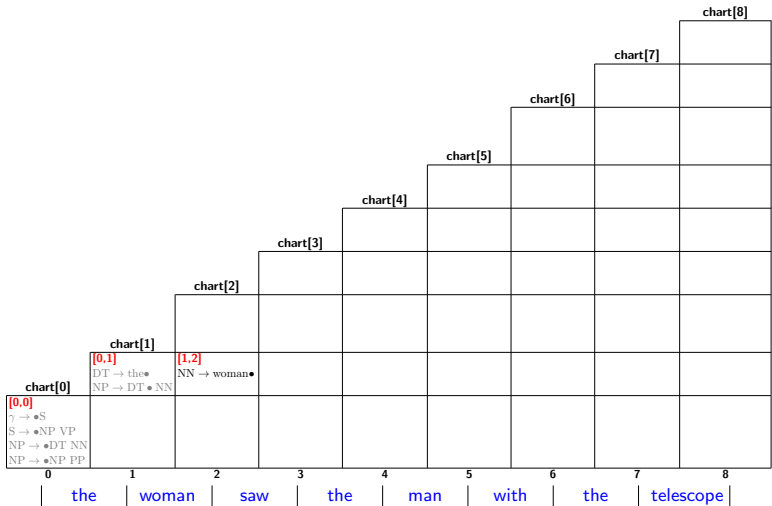


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

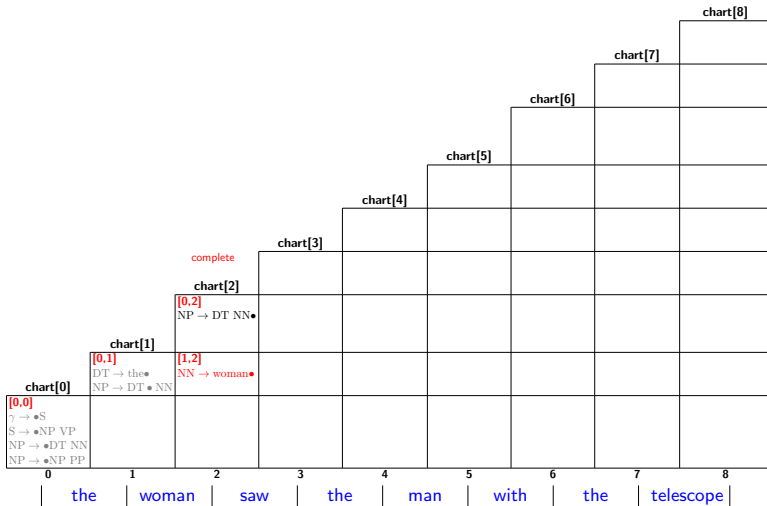


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

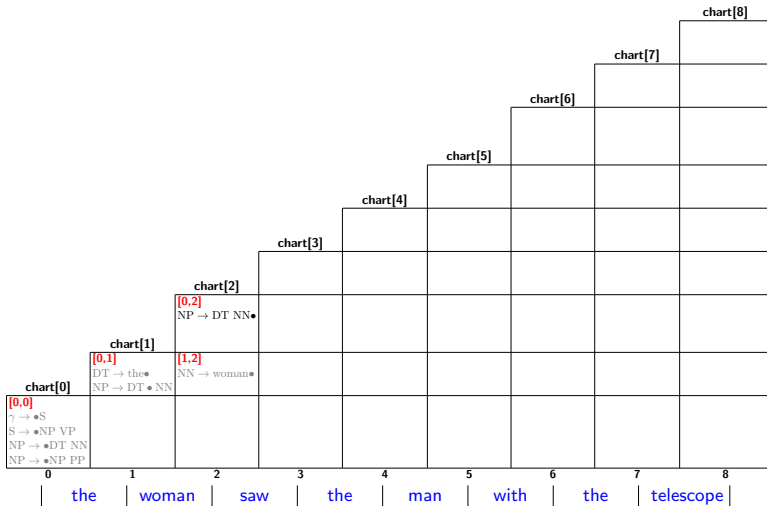


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

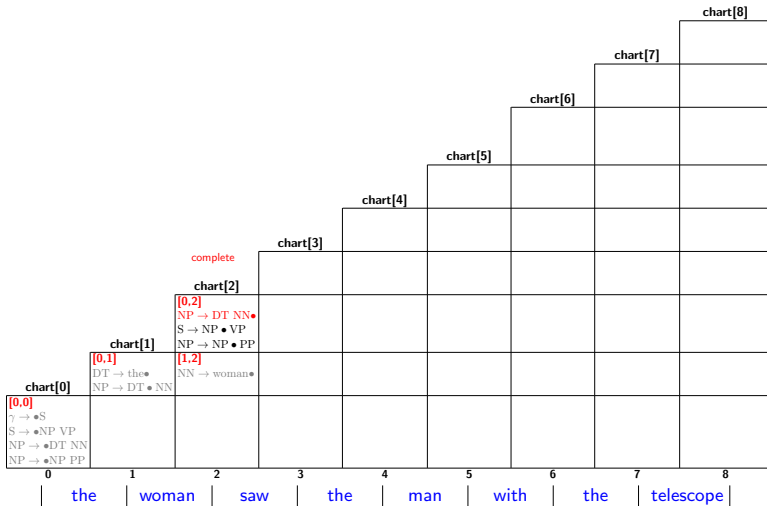


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Trees and
Grammars

Constituency
Parsing

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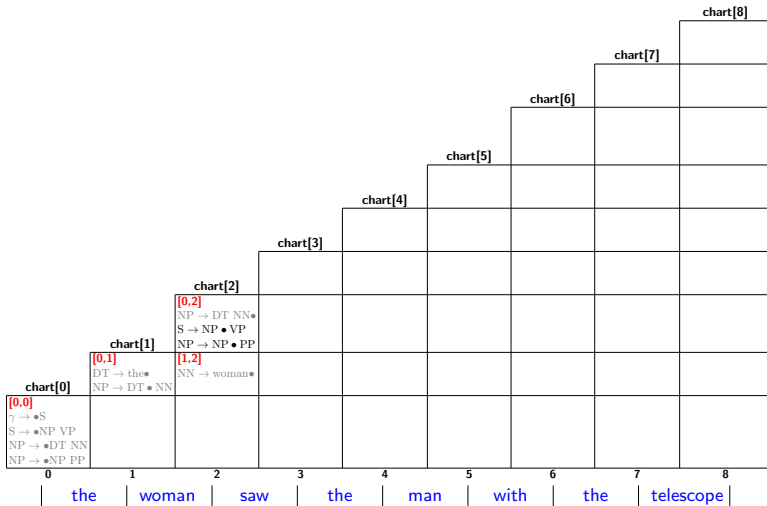


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

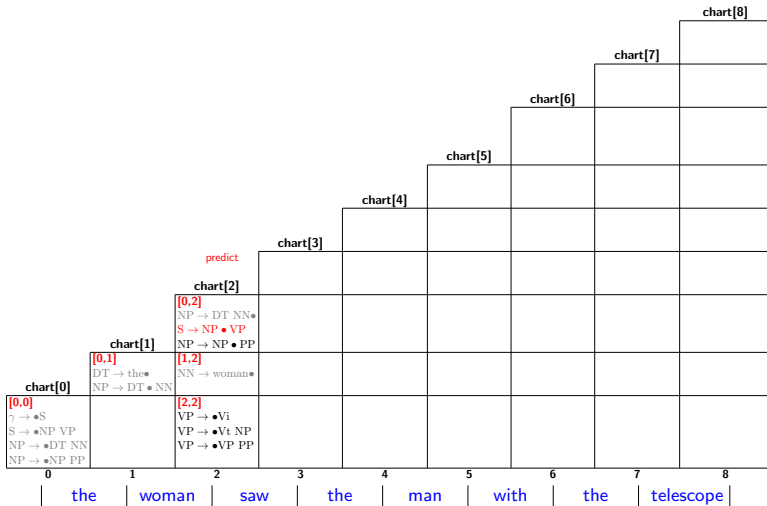


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

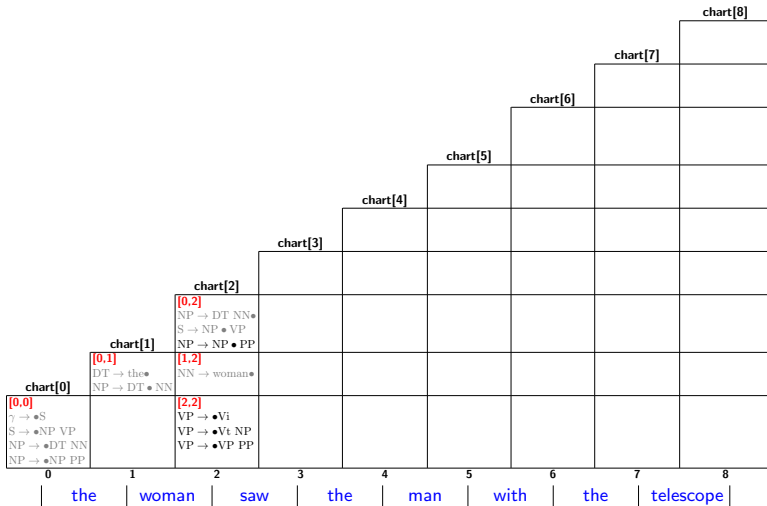


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Constituency
Parsing

Earley Algorithm

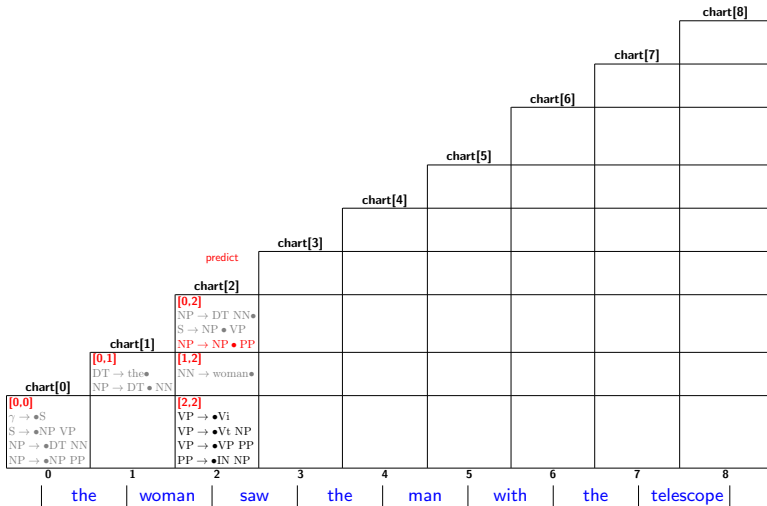


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

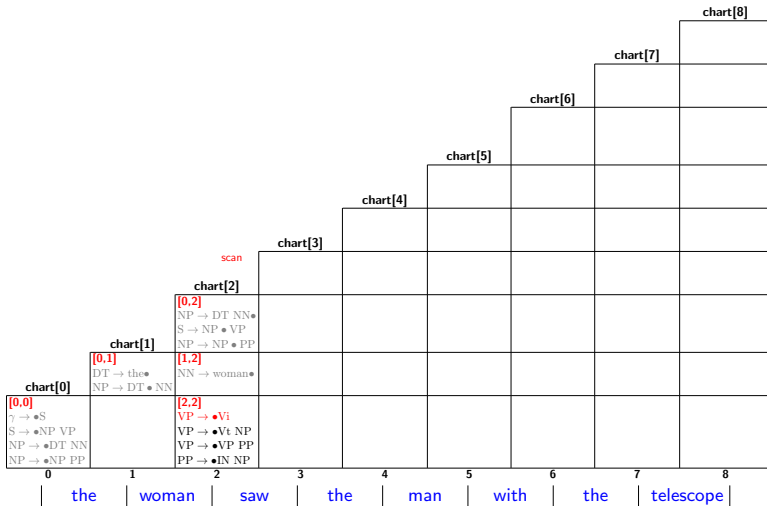


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

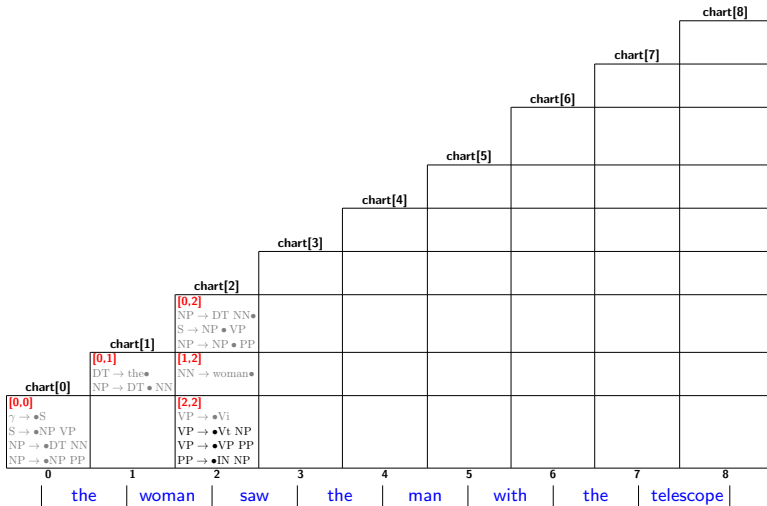


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

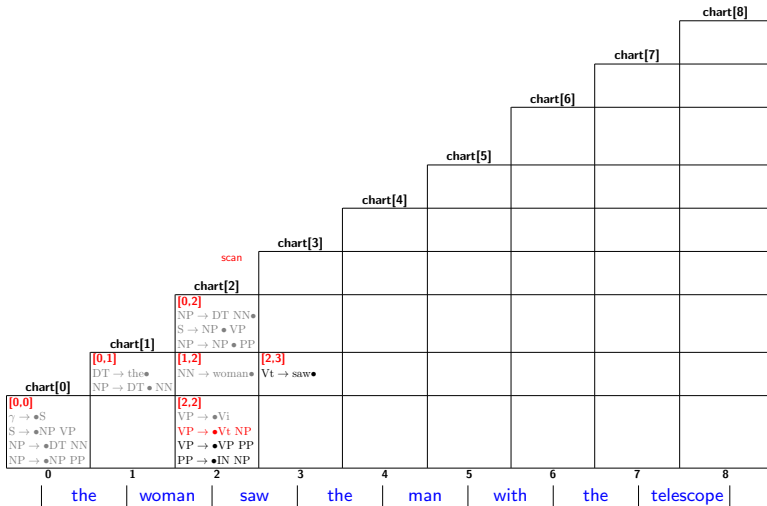


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

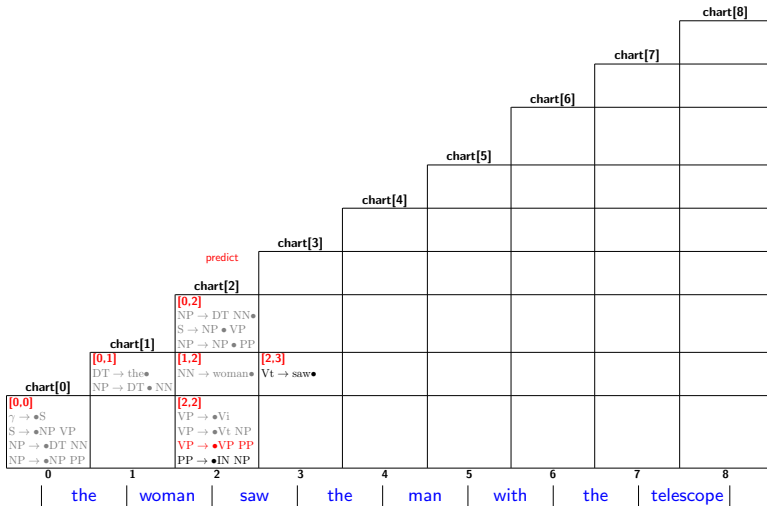


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

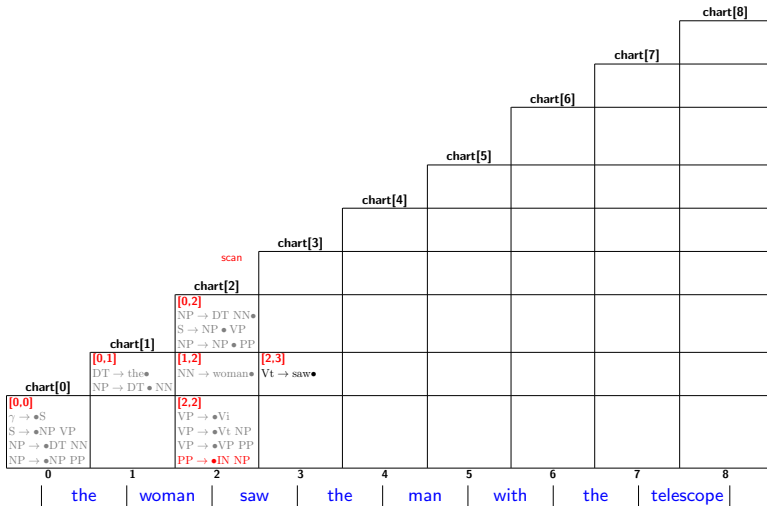


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Trees and
Grammars

Constituency
Parsing

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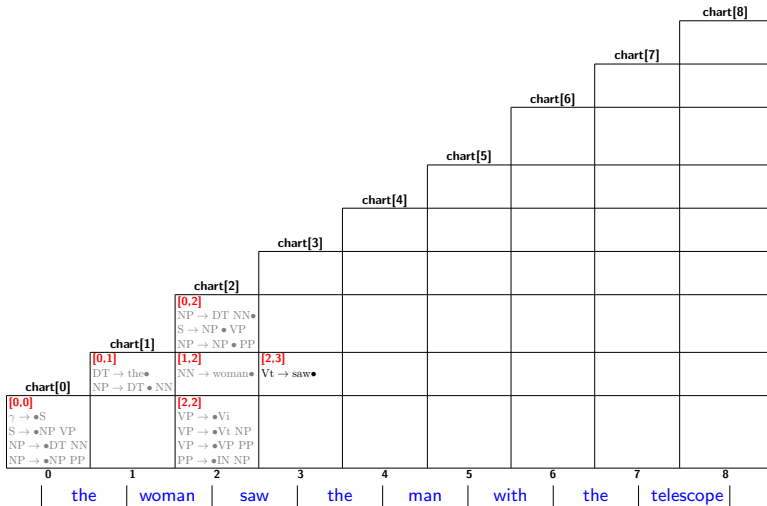


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

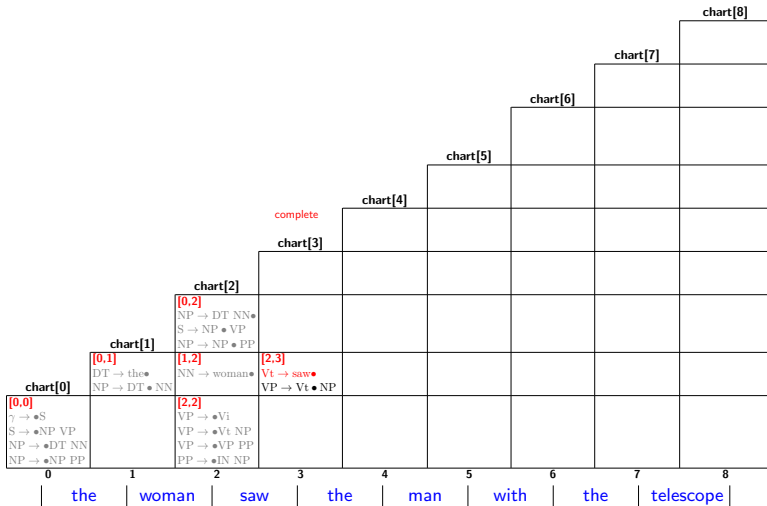


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

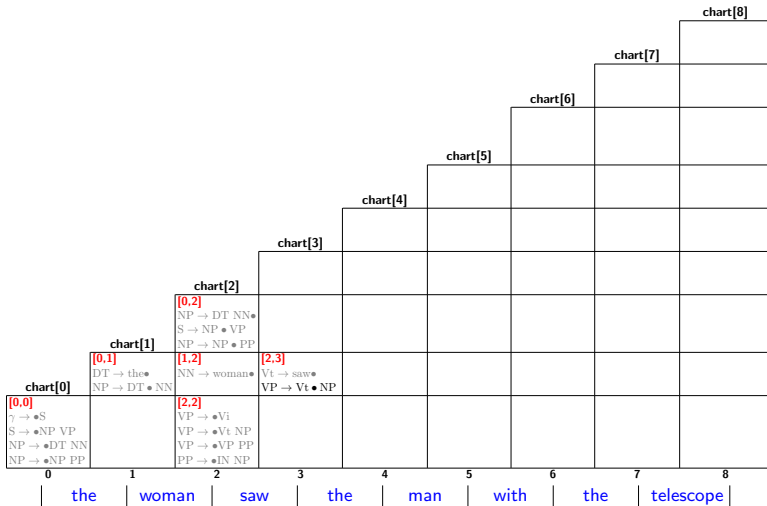


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

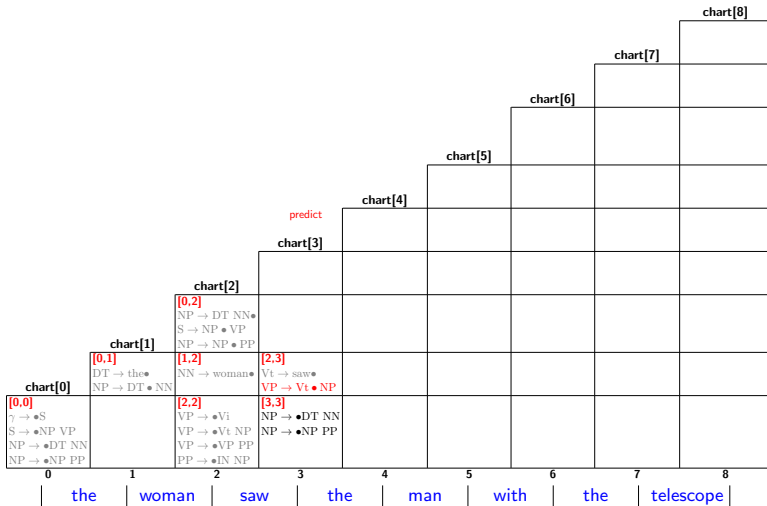


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

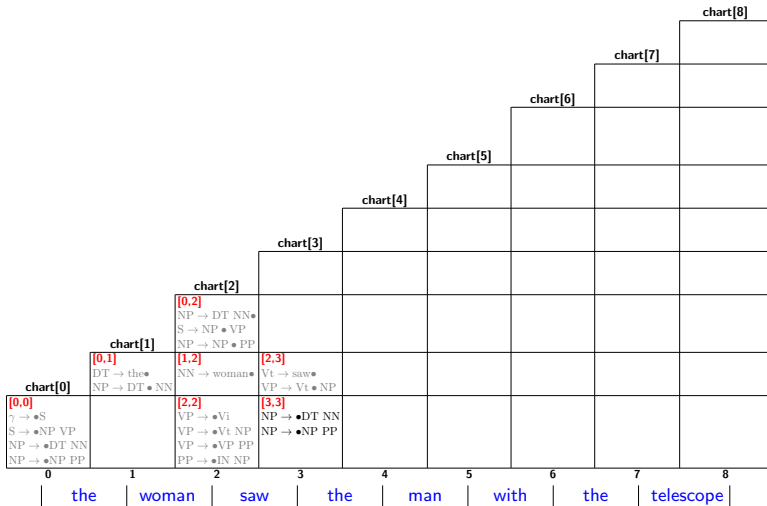


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

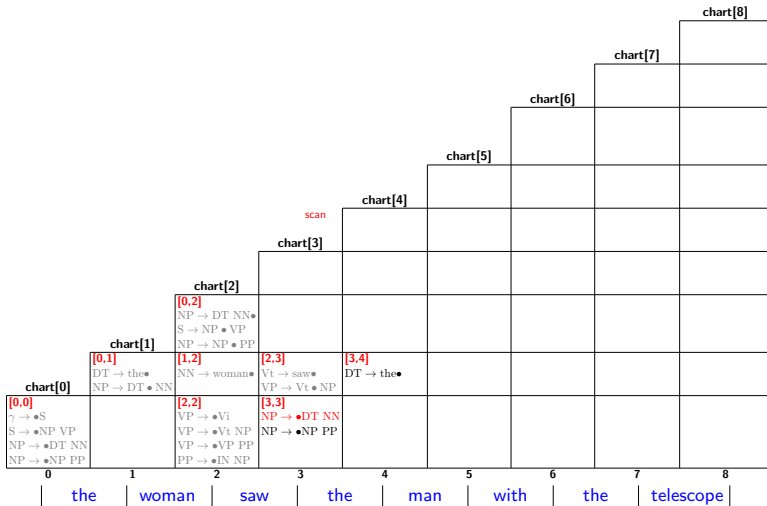


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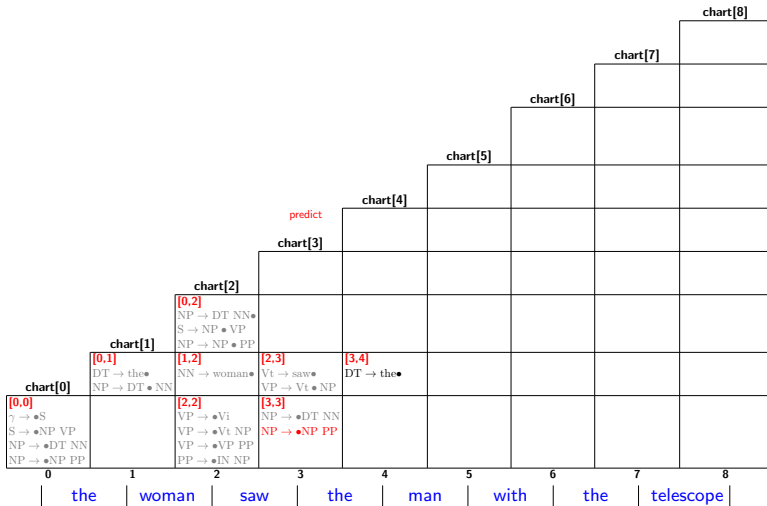
Trees and
Grammars

Constituency
Parsing

Earley Algorithm



- Trees and Grammars
- Constituency Parsing
- Earley Algorithm

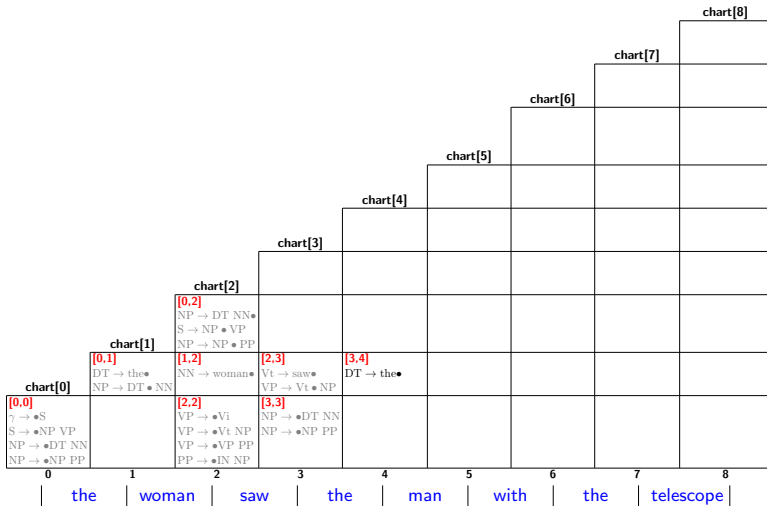


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

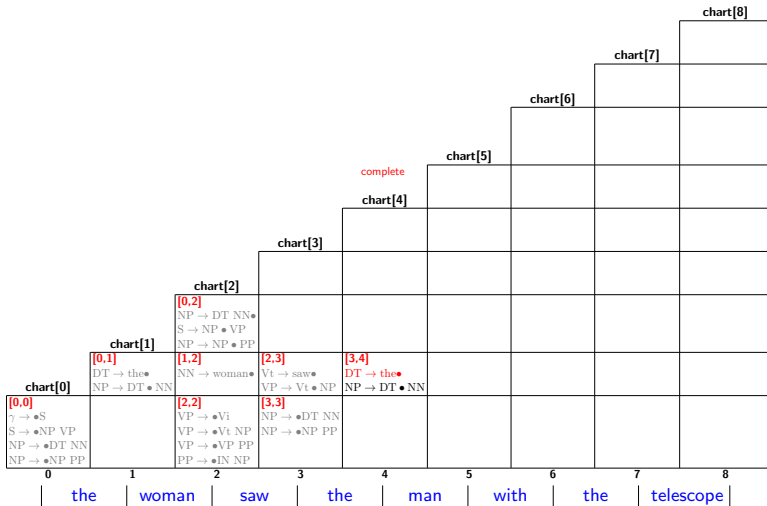


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

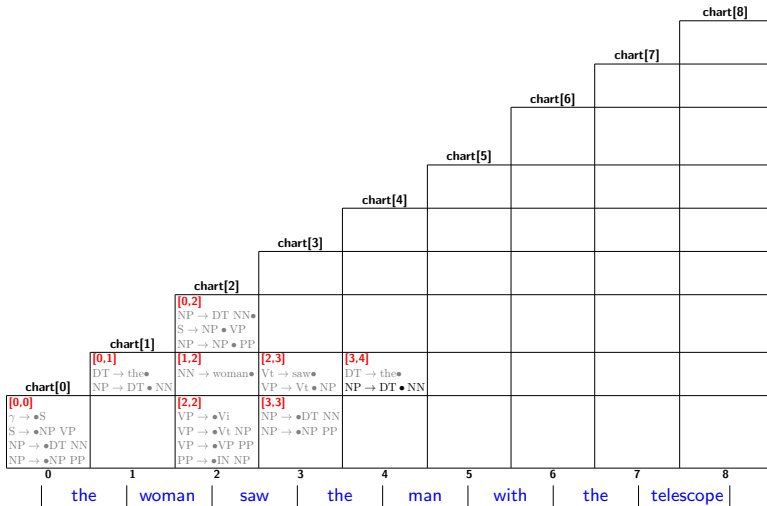


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

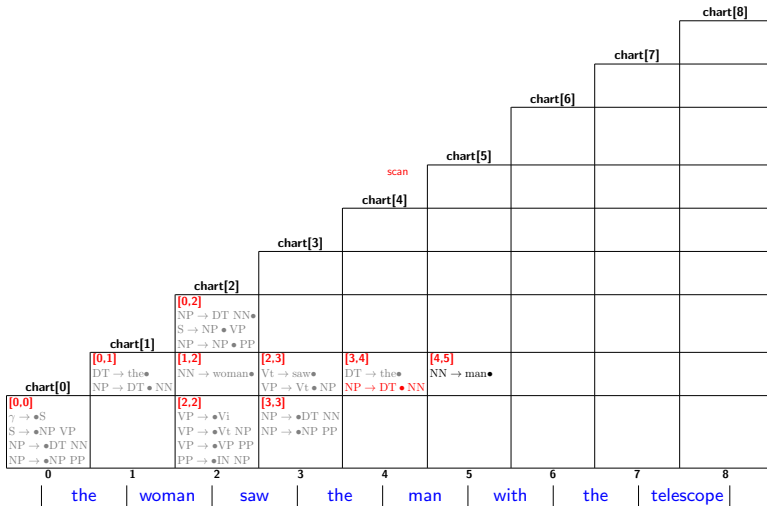


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

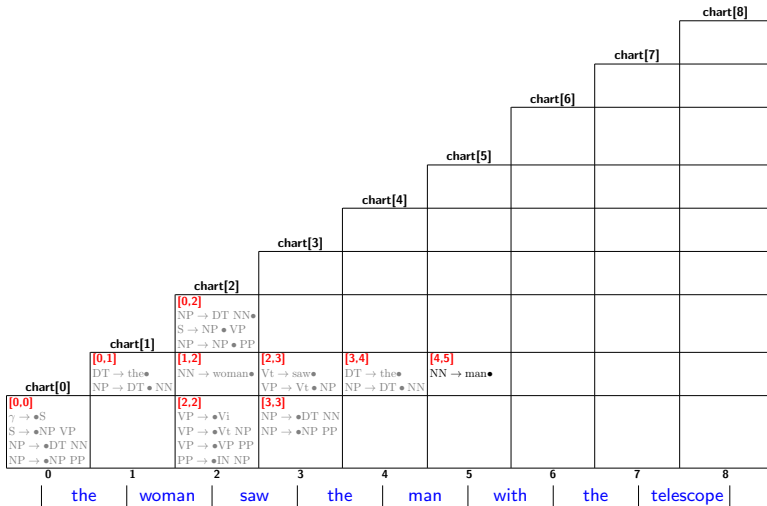


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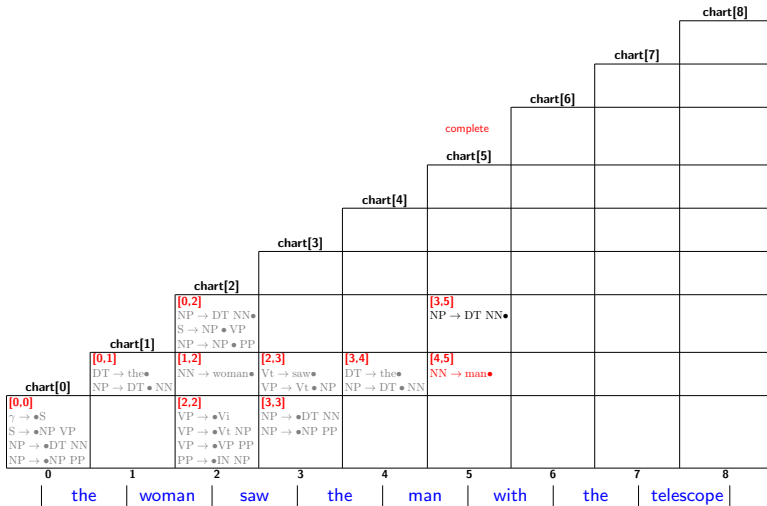
Trees and
Grammars

Constituency
Parsing

Earley Algorithm



- Trees and Grammars
- Constituency Parsing
- Earley Algorithm

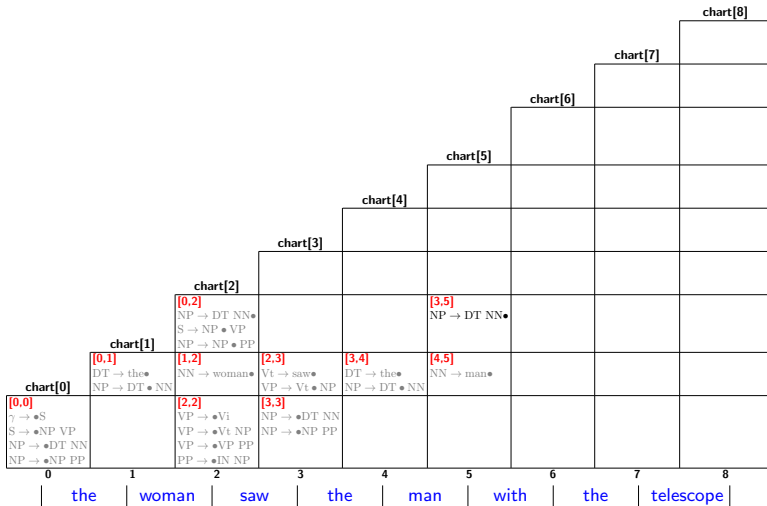


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

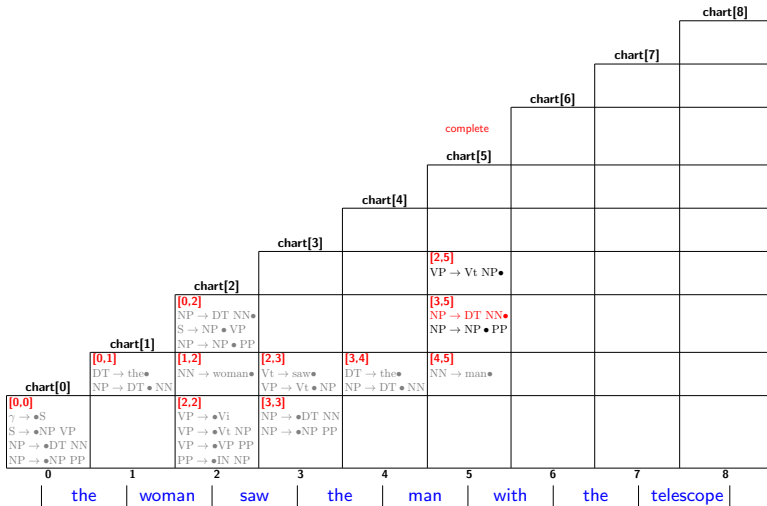


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

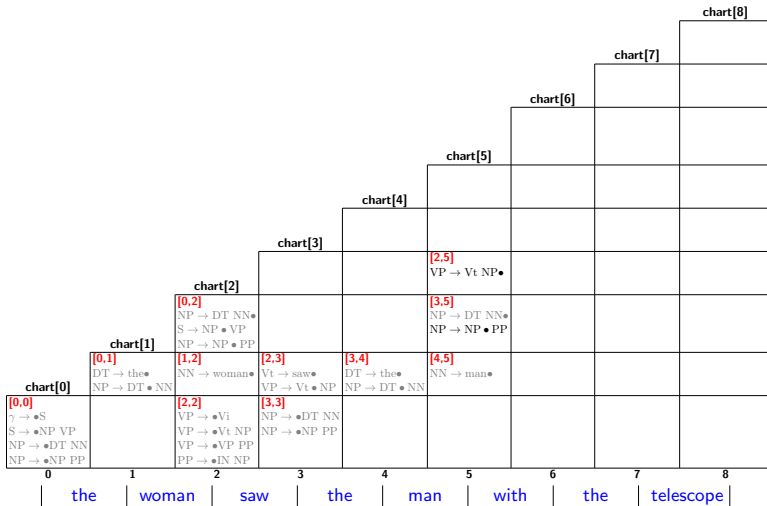


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

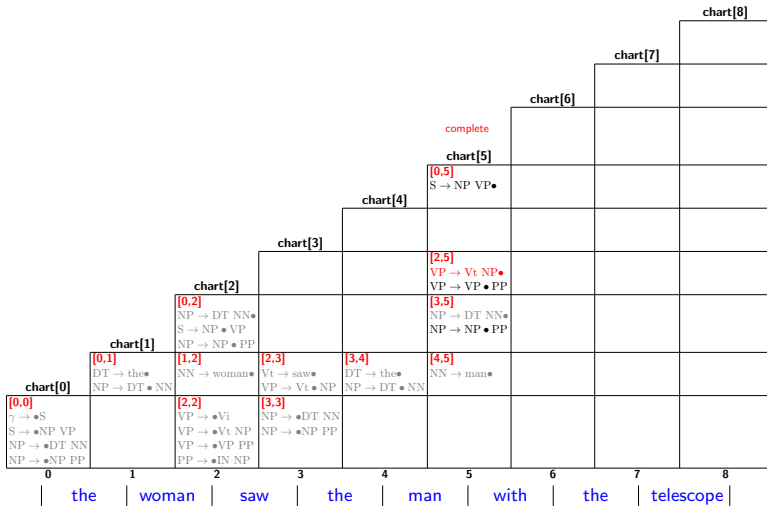


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

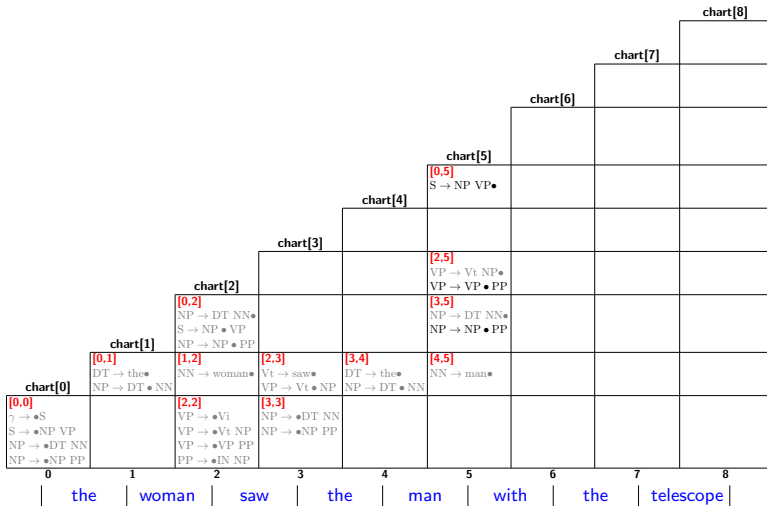


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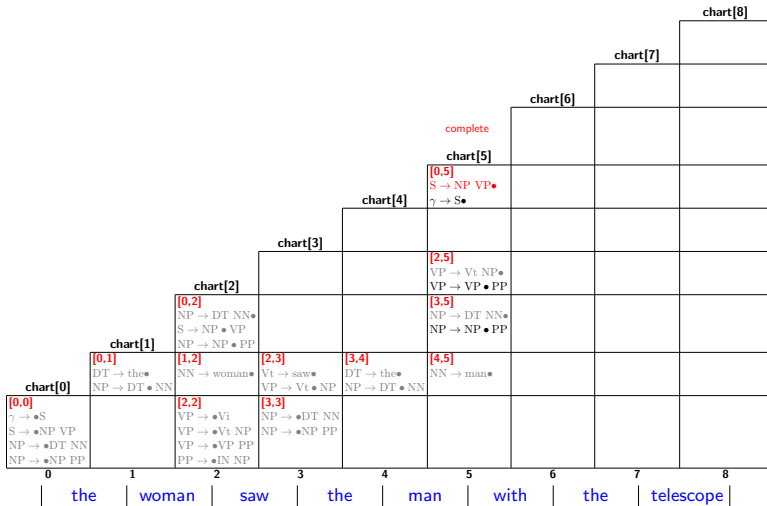
Trees and
Grammars

Constituency
Parsing

Earley Algorithm



- Trees and Grammars
- Constituency Parsing
- Earley Algorithm

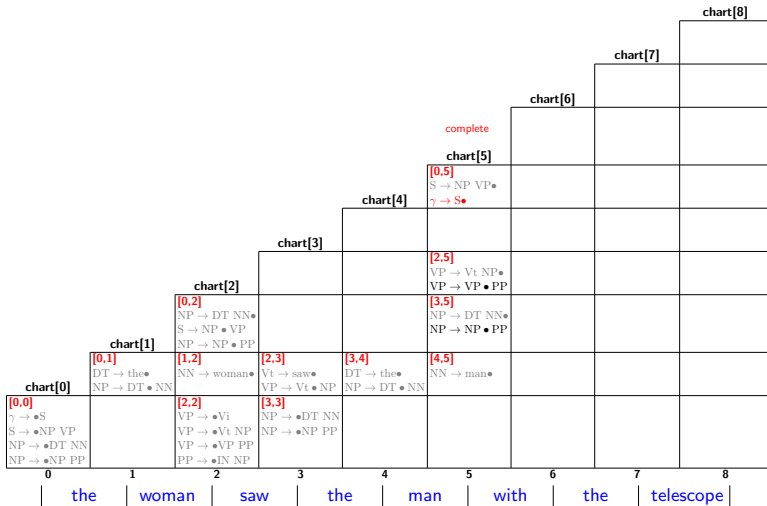


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

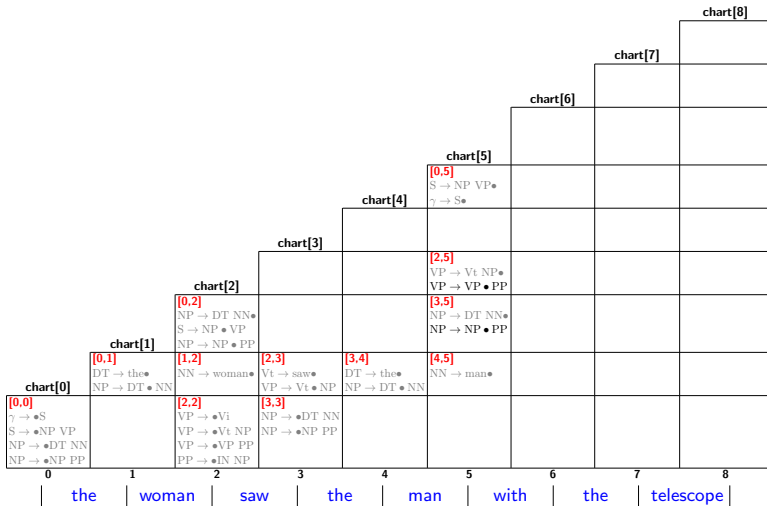


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

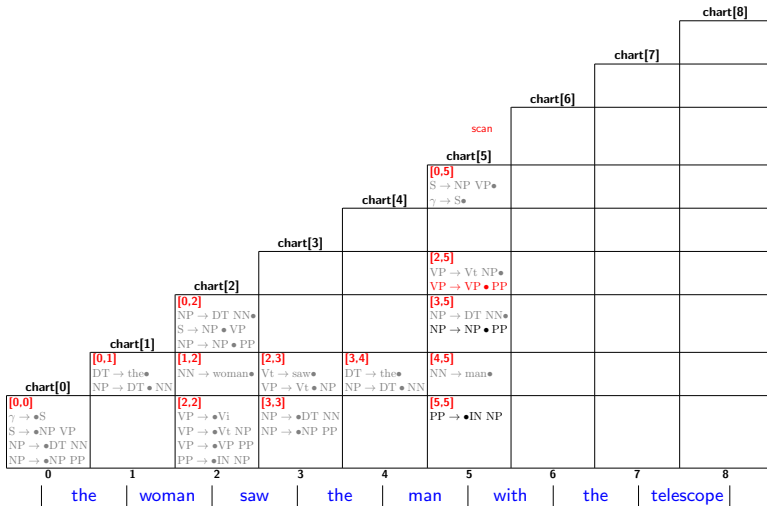


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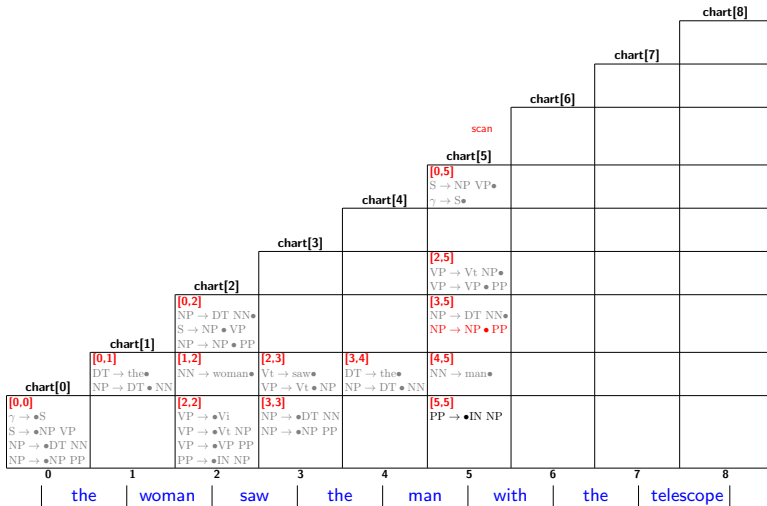
Trees and
Grammars

Constituency
Parsing

Earley Algorithm



- Trees and Grammars
- Constituency Parsing
- Earley Algorithm

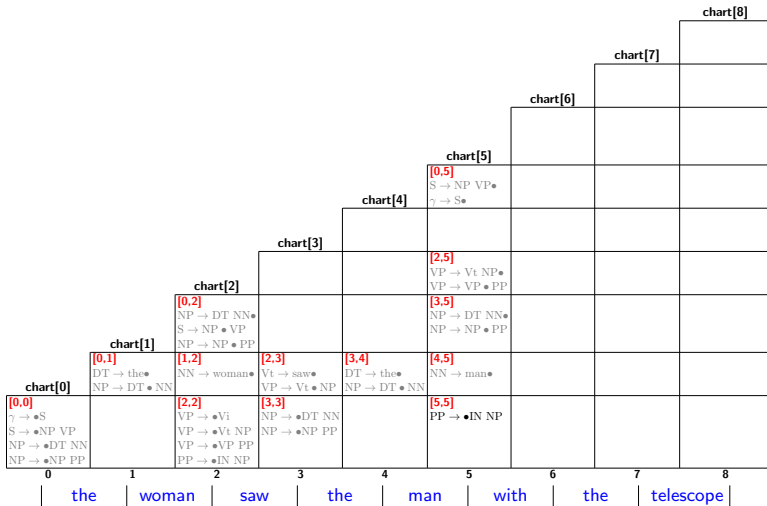


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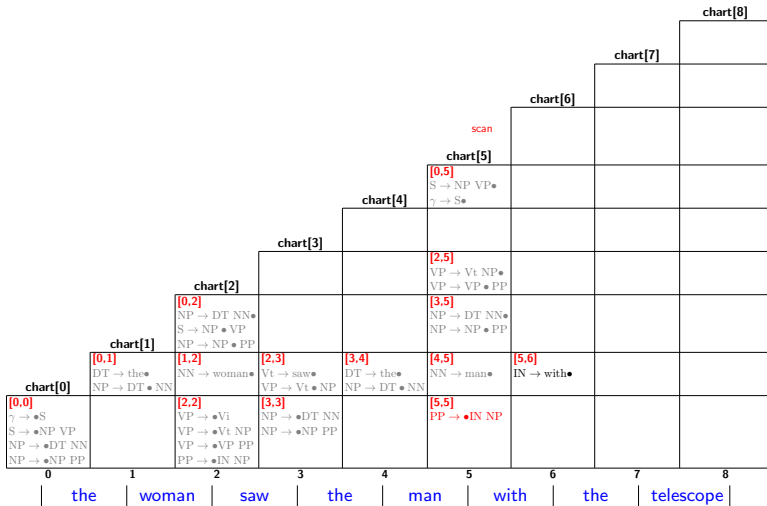
Trees and
Grammars

Constituency
Parsing

Earley Algorithm



- Trees and Grammars
- Constituency Parsing
- Earley Algorithm

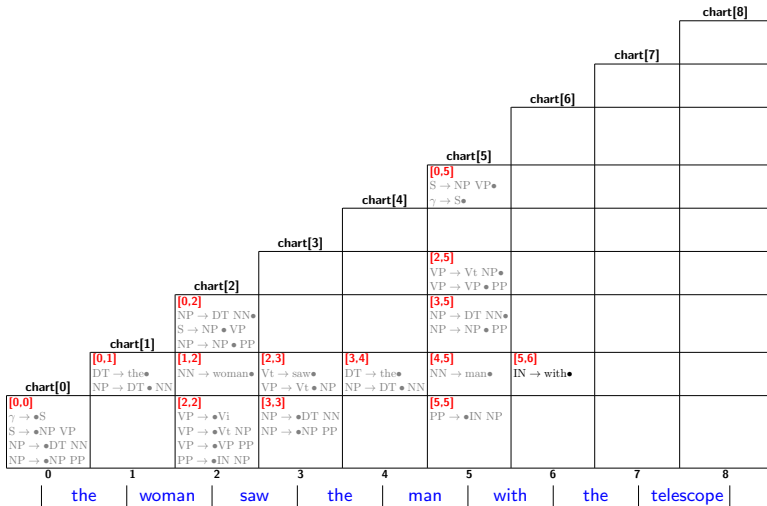


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

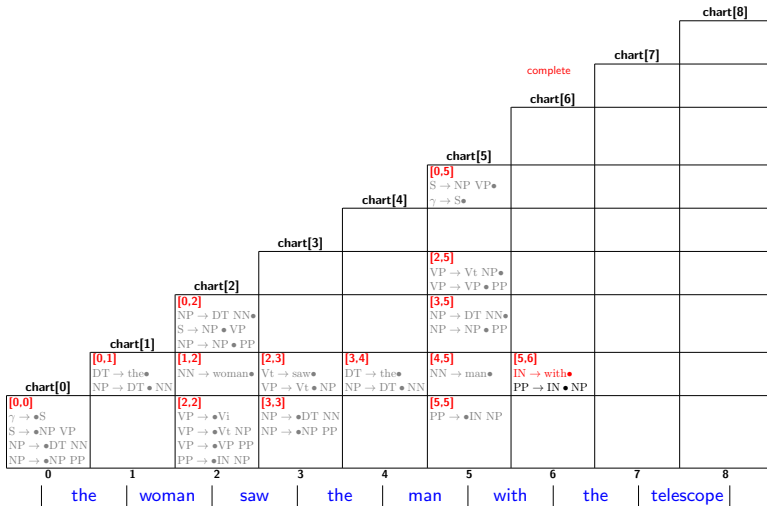


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

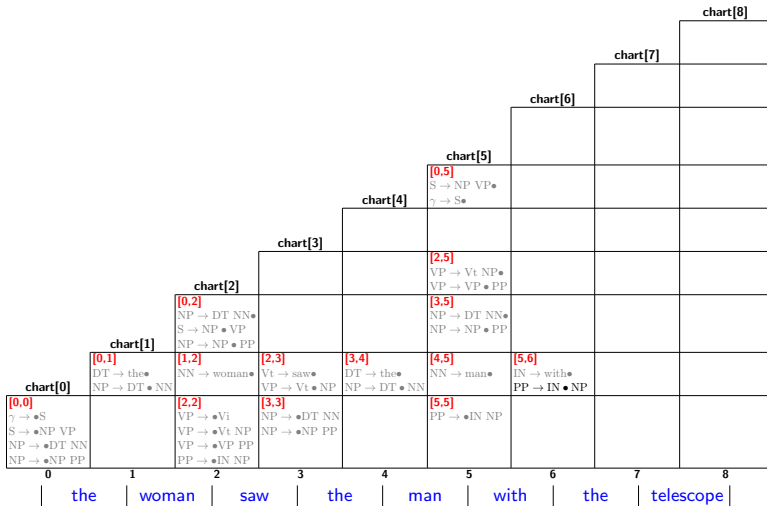


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

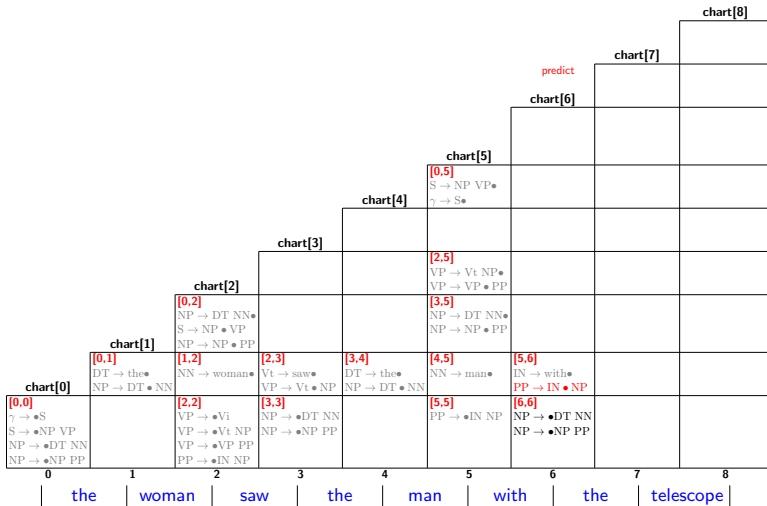


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

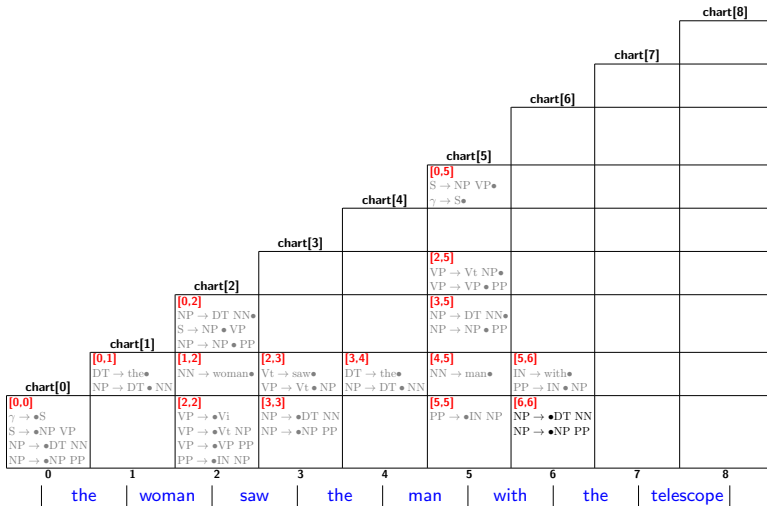


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

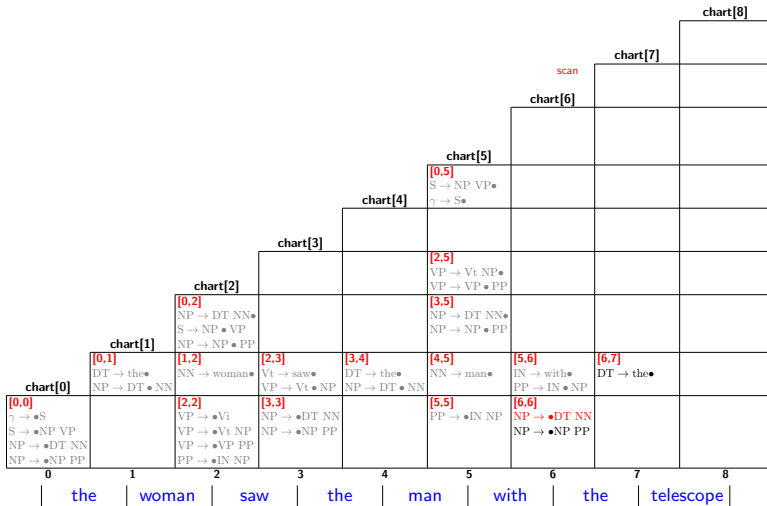


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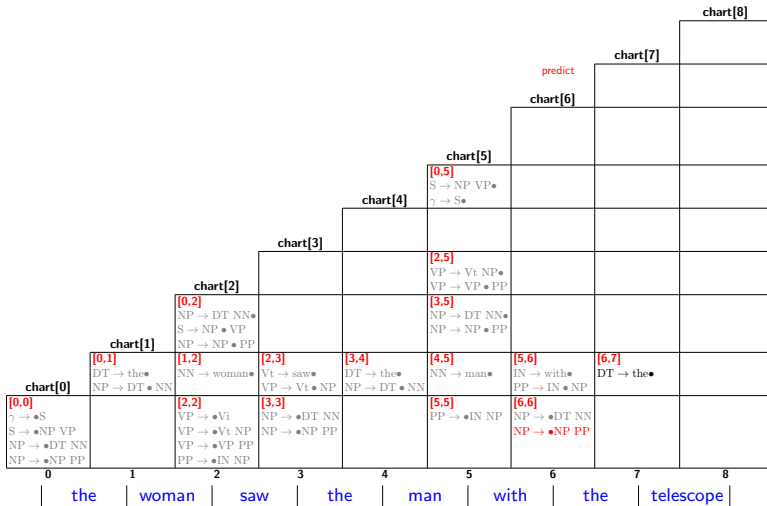
Trees and
Grammars

Constituency
Parsing

Earley Algorithm



- Trees and Grammars
- Constituency Parsing
- Earley Algorithm

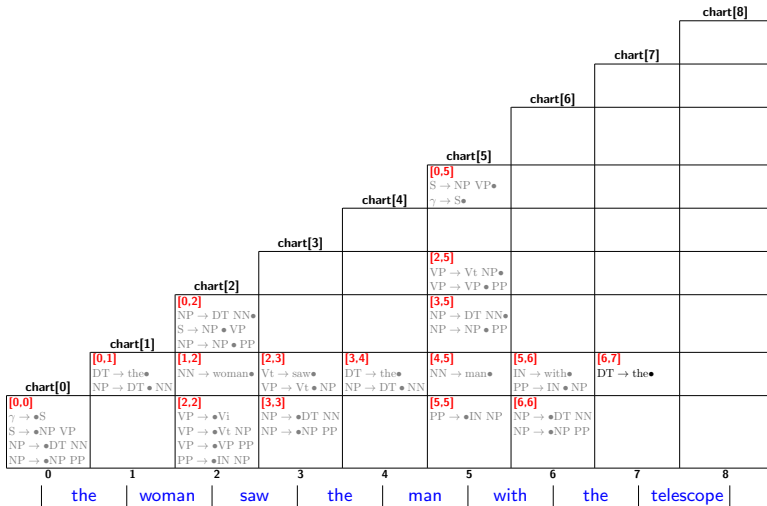


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

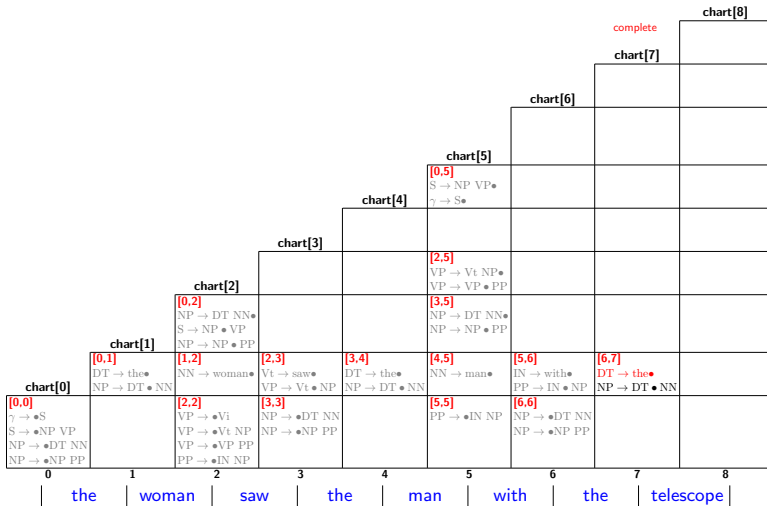


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

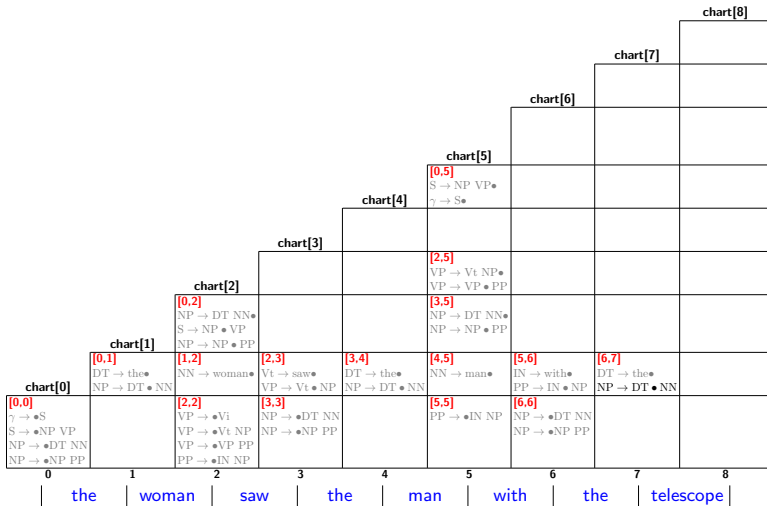


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

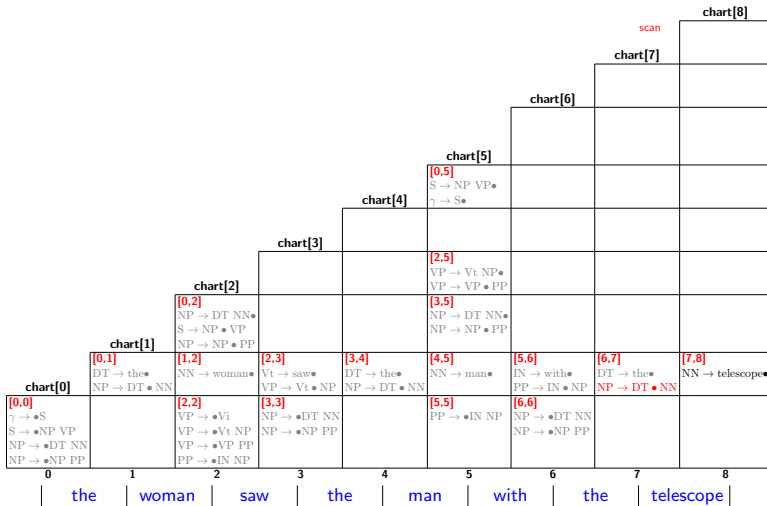


Earley Algorithm

Trees and
Grammars

Constituency
Parsing

Earley Algorithm

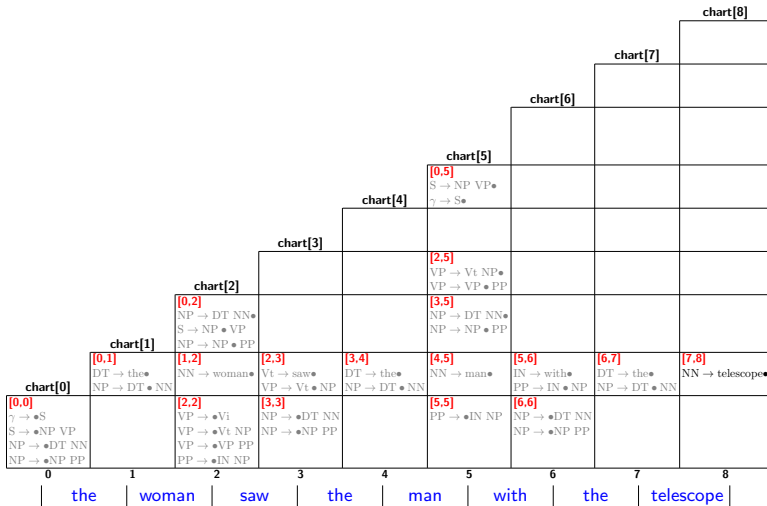


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Trees and
Grammars

Constituency
Parsing

Earley Algorithm

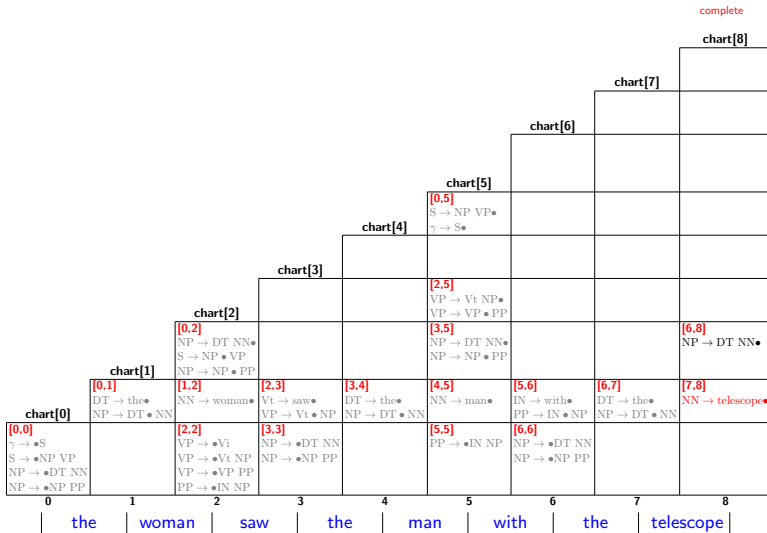


Earley Algorithm

Trees and
Grammars

Constituency
Parsing

Earley Algorithm

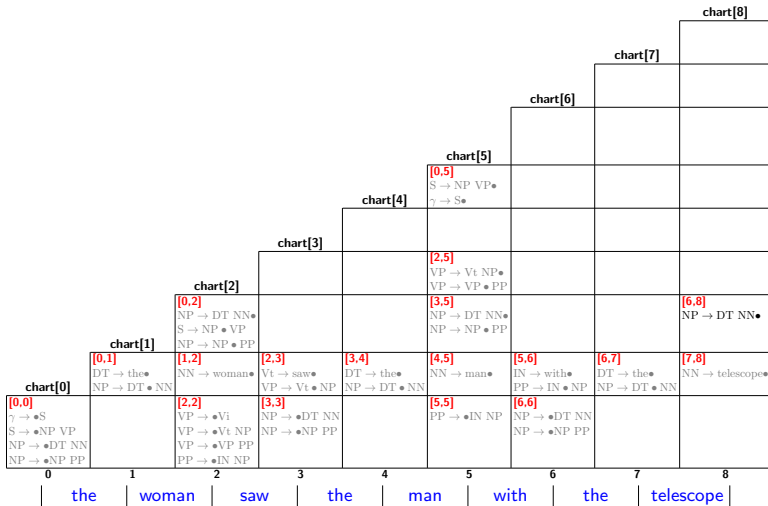


Earley Algorithm

Trees and
Grammars

Constituency
Parsing

Earley Algorithm

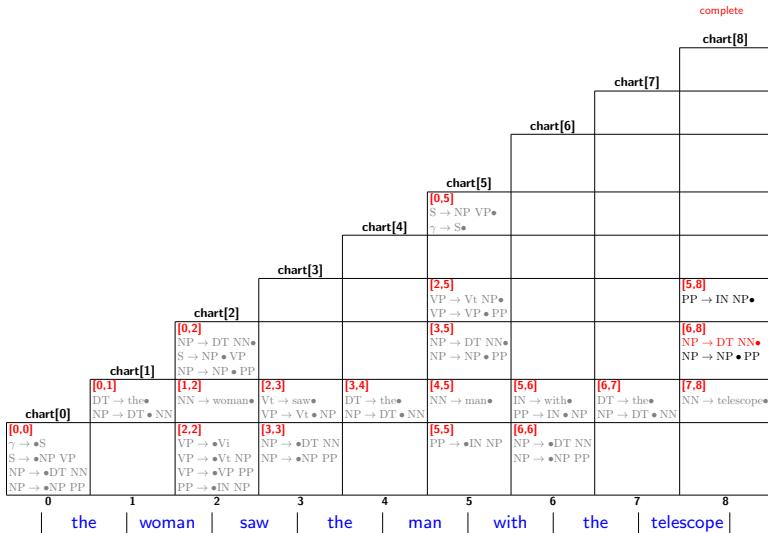


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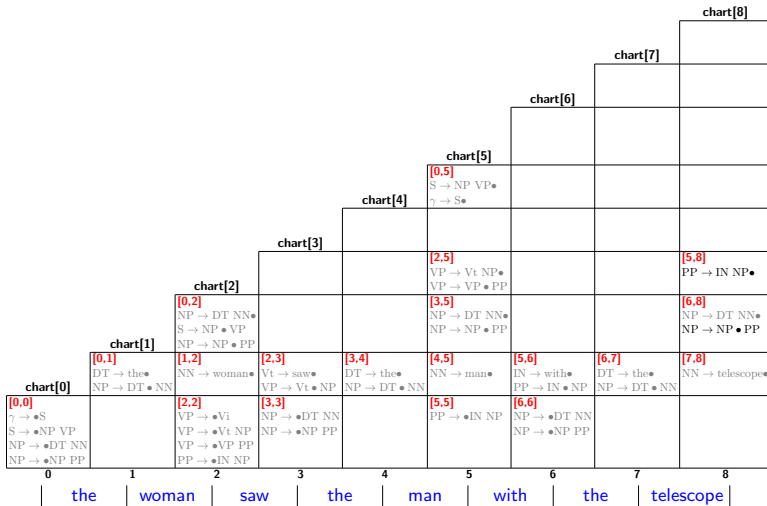
Trees and
Grammars

Constituency
Parsing

Earley Algorithm



- Trees and Grammars
- Constituency Parsing
- Earley Algorithm

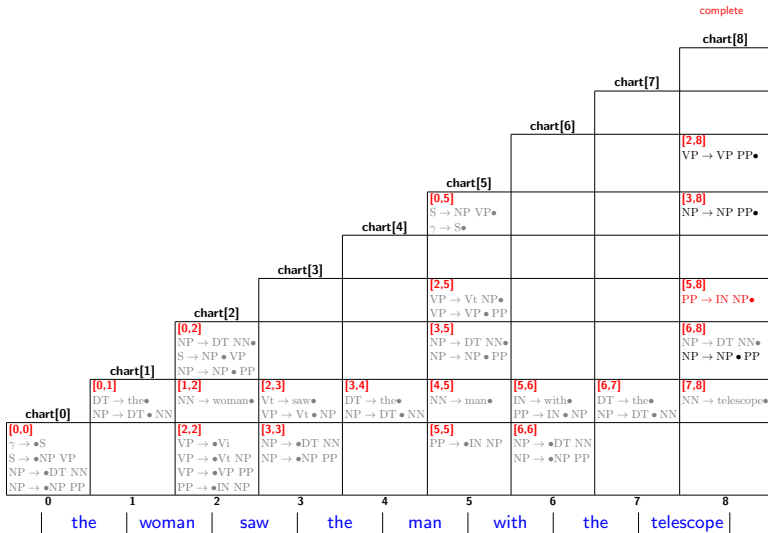


Earley Algorithm

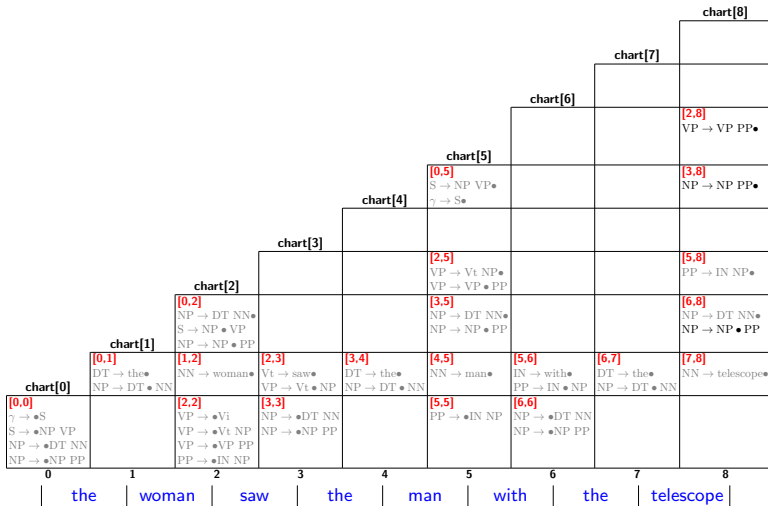
Trees and
Grammars

Constituency
Parsing

Earley Algorithm



- Trees and Grammars
- Constituency Parsing
- Earley Algorithm

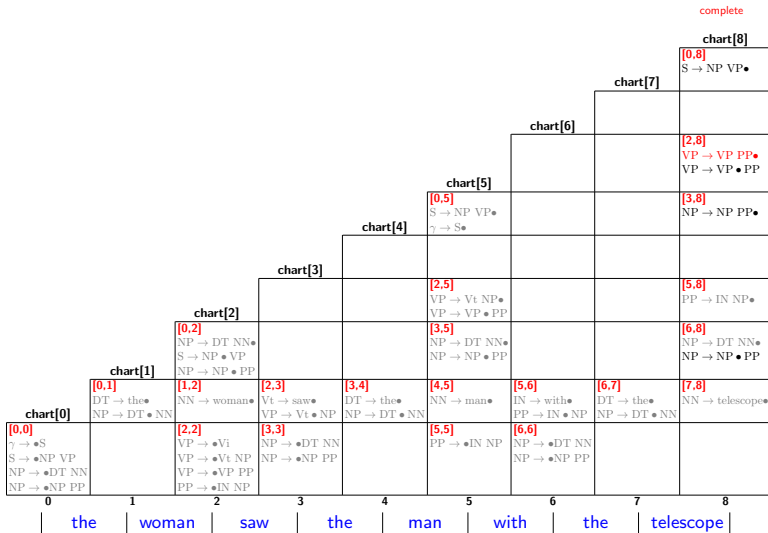


Earley Algorithm

Trees and
Grammars

Constituency
Parsing

Earley Algorithm

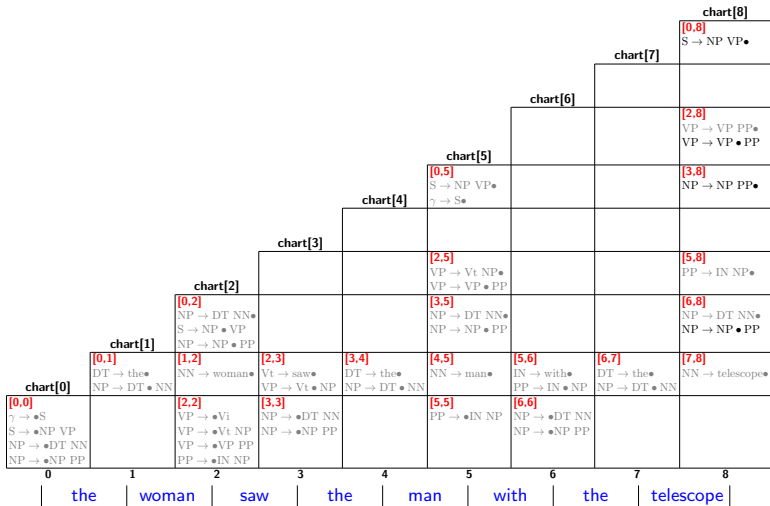


Earley Algorithm

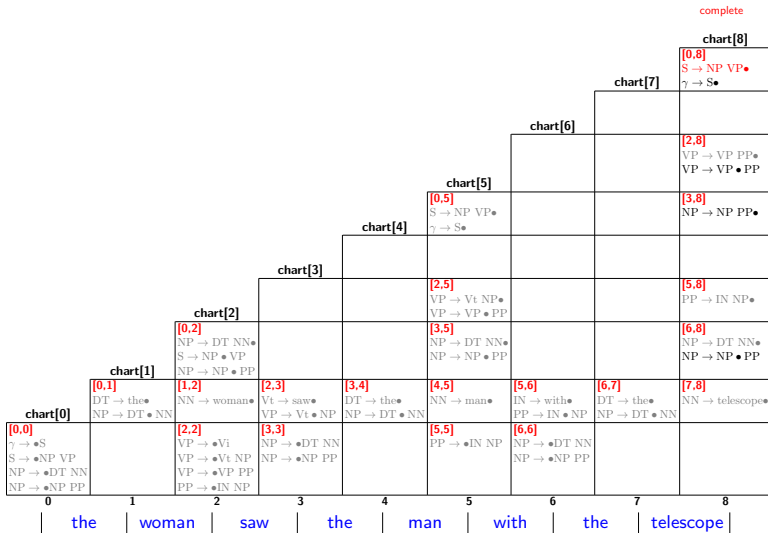
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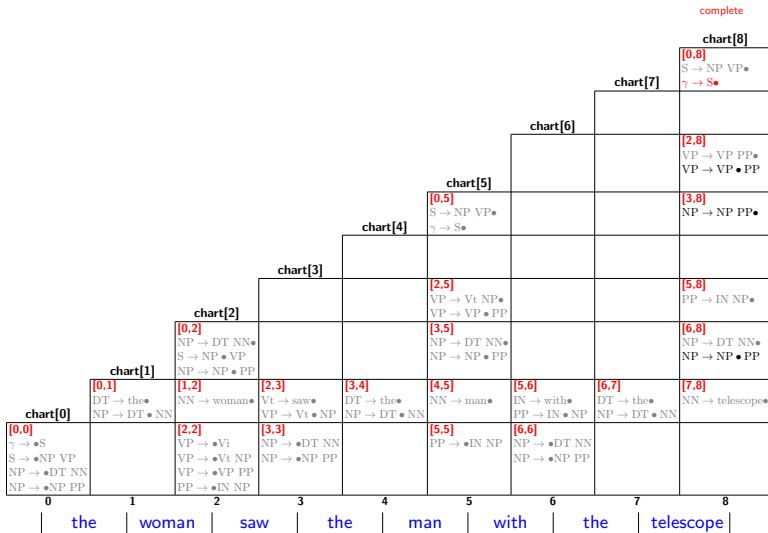


Earley Algorithm

Trees and
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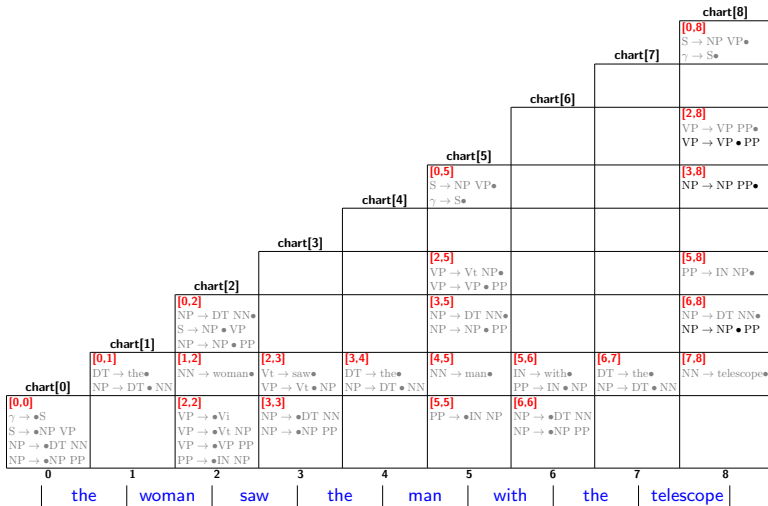


Earley Algorithm

Trees and
Grammars

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Parsing

Earley Algorithm

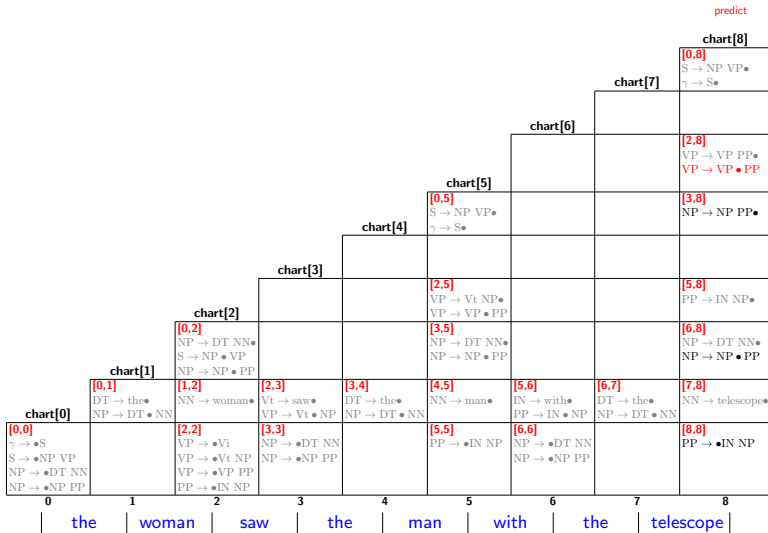


Earley Algorithm

Trees and
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Parsing

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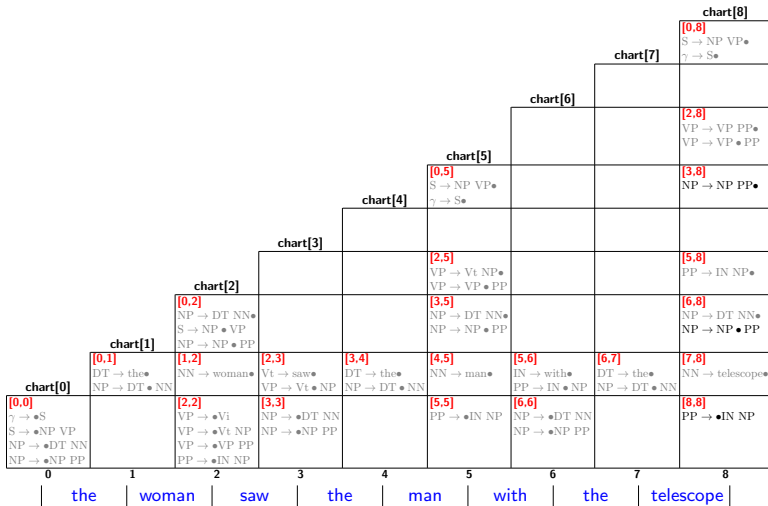


Earley Algorithm

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Parsing

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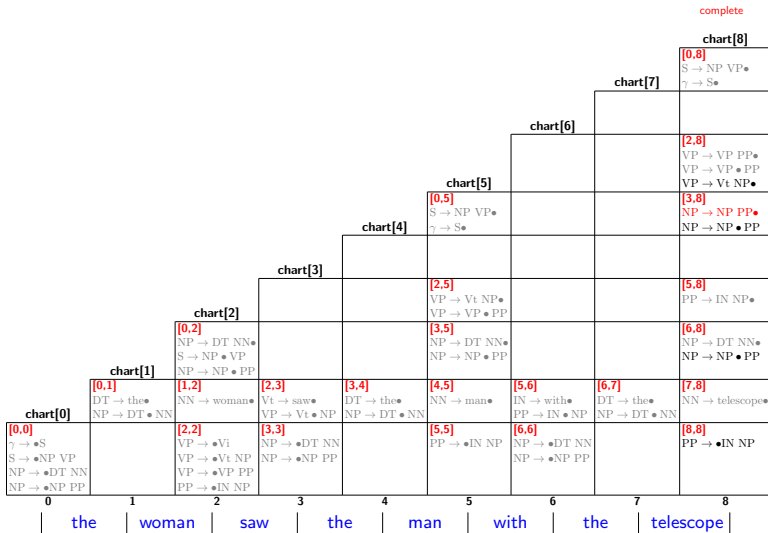


Earley Algorithm

Trees and
Grammars

Constituency
Parsing

Earley Algorithm

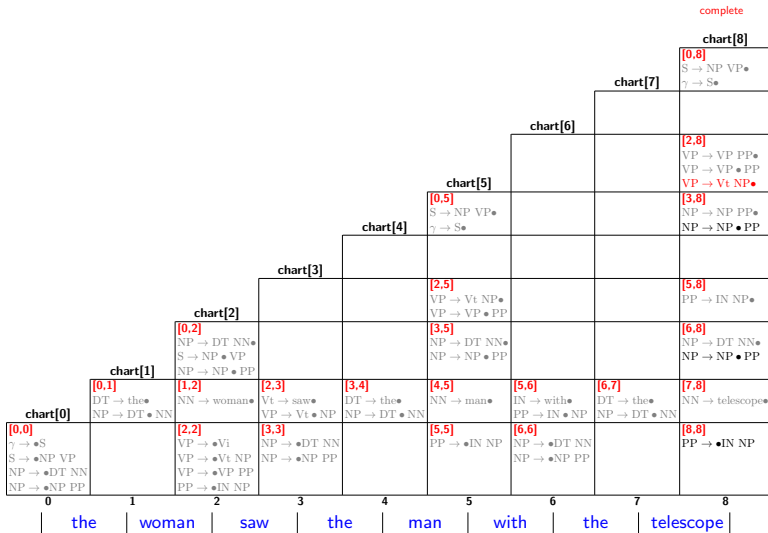


Earley Algorithm

Trees and
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Constituency
Parsing

Earley Algorithm

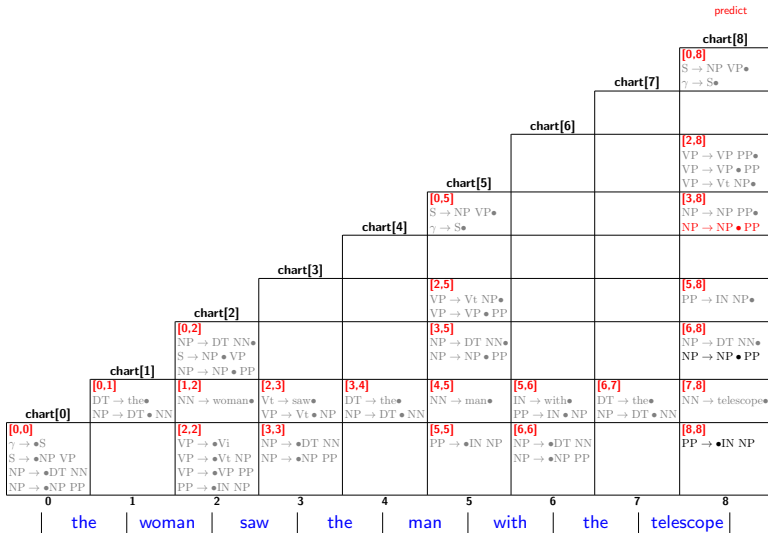


Earley Algorithm

Trees and
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Parsing

Earley Algorithm

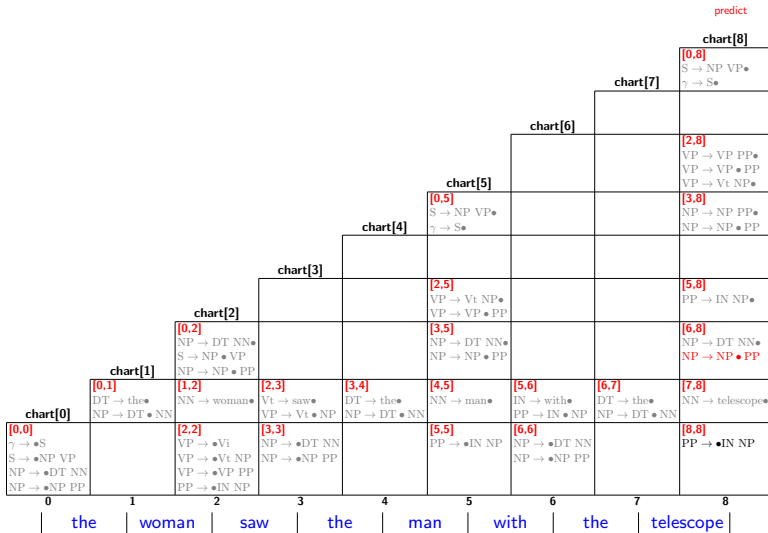


Earley Algorithm

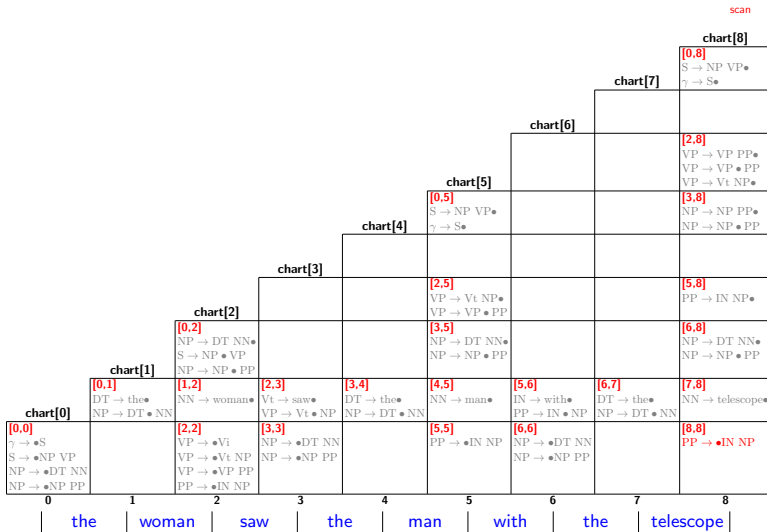
Trees and
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Earley Algorithm



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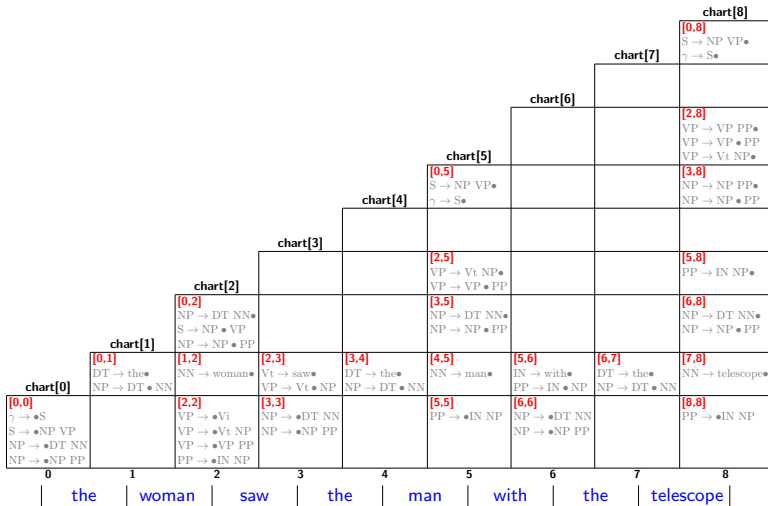


Earley Algorithm

Trees and
Grammars

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Earley Algorithm



CKY vs Earley

CKY

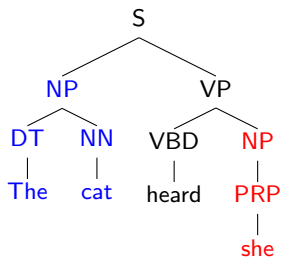
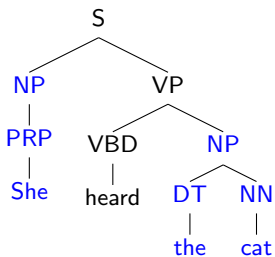
- Bottom-up
- Requires CNF
- Can compute all trees
- $\mathcal{O}(n^3)$
- Straightforward probabilistic version

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

Why *context-free* ?

- 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.



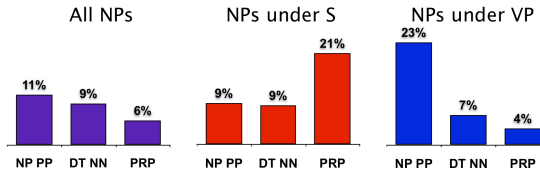
Natural Language is not Context-Free

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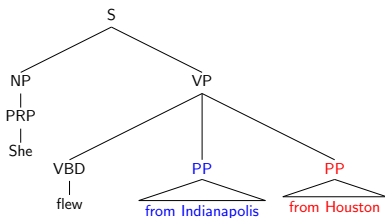
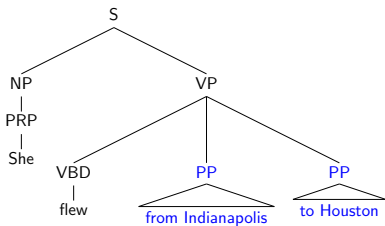
- NP expansion (for instance) is highly dependent on the parent of the NP



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

Natural Language is not Context-Free

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



Natural Language is not Context-Free

- May contain non-projective structures:

