Master in Artificial Intelligence

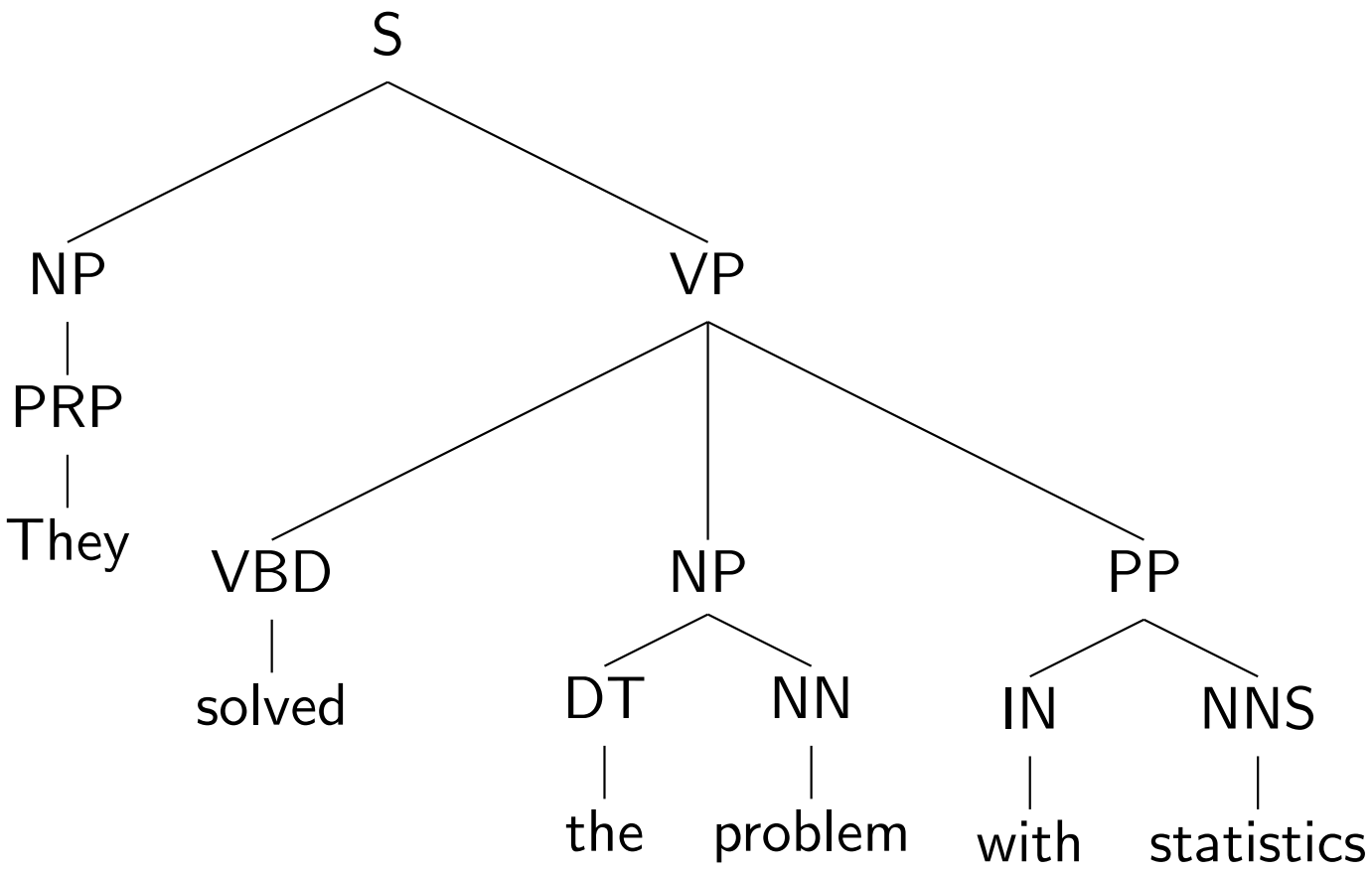
Advanced Human Language Technologies

UNIVERSITAT POLITÈCNICA DE CATALUNYA
BARCELONATECH
Facultat d'Informàtica de Barcelona

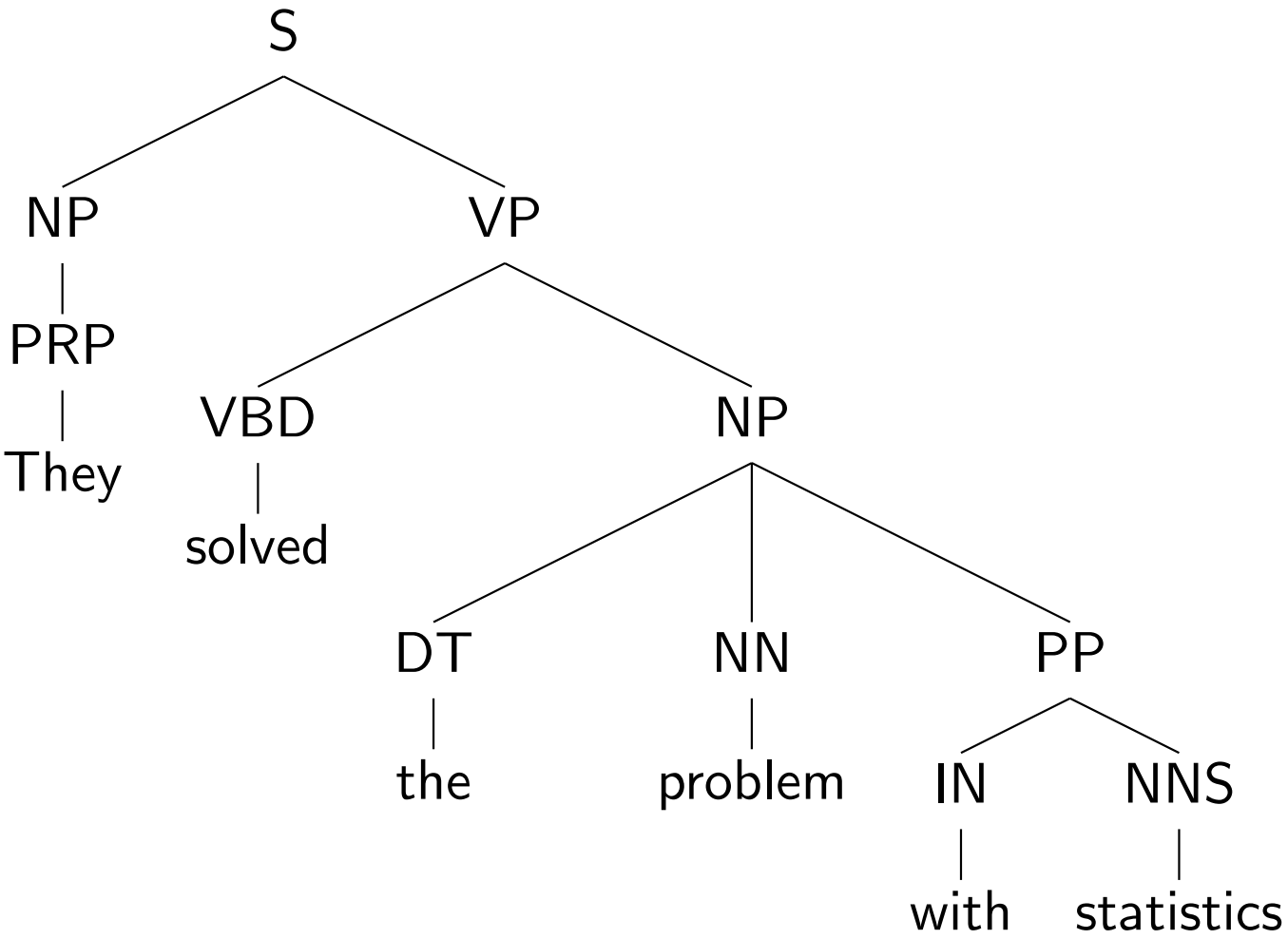
FIB

Outline

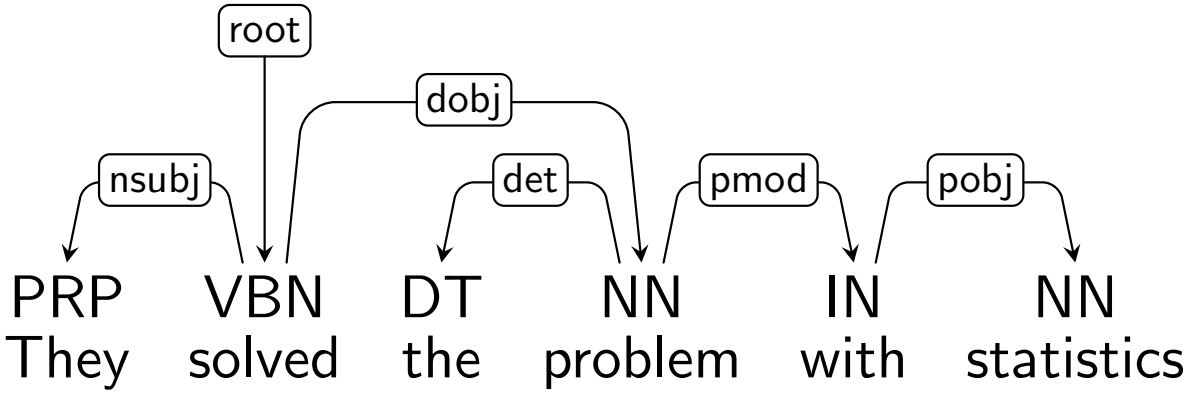
A Syntactic Tree



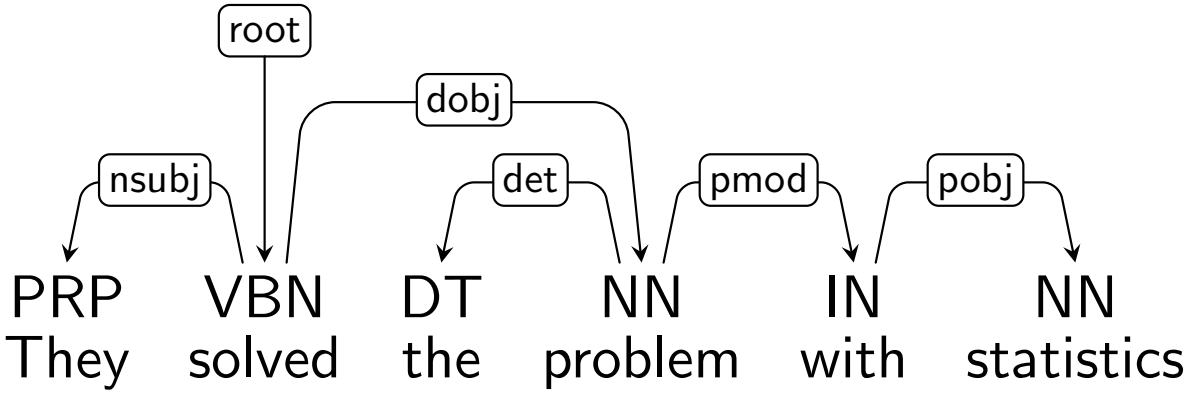
Another Syntactic Tree

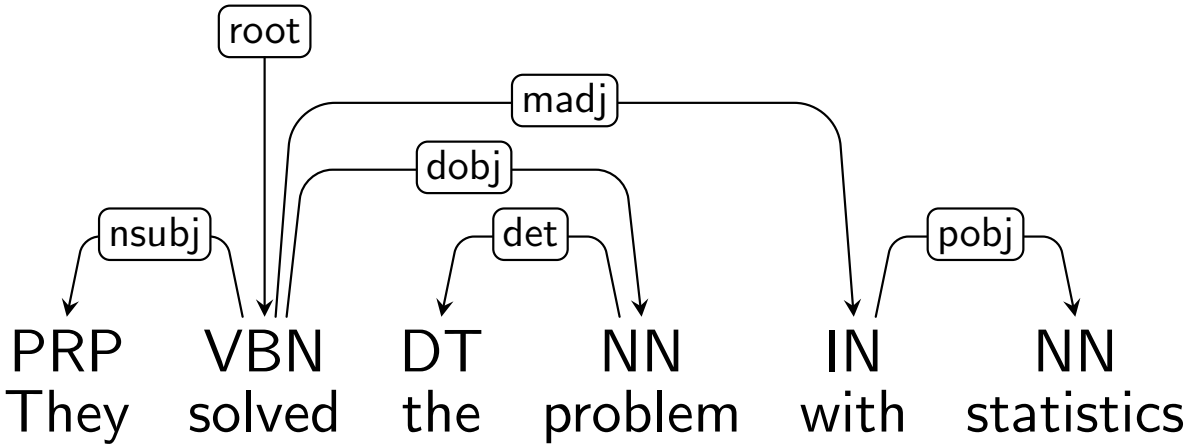


Dependency Trees

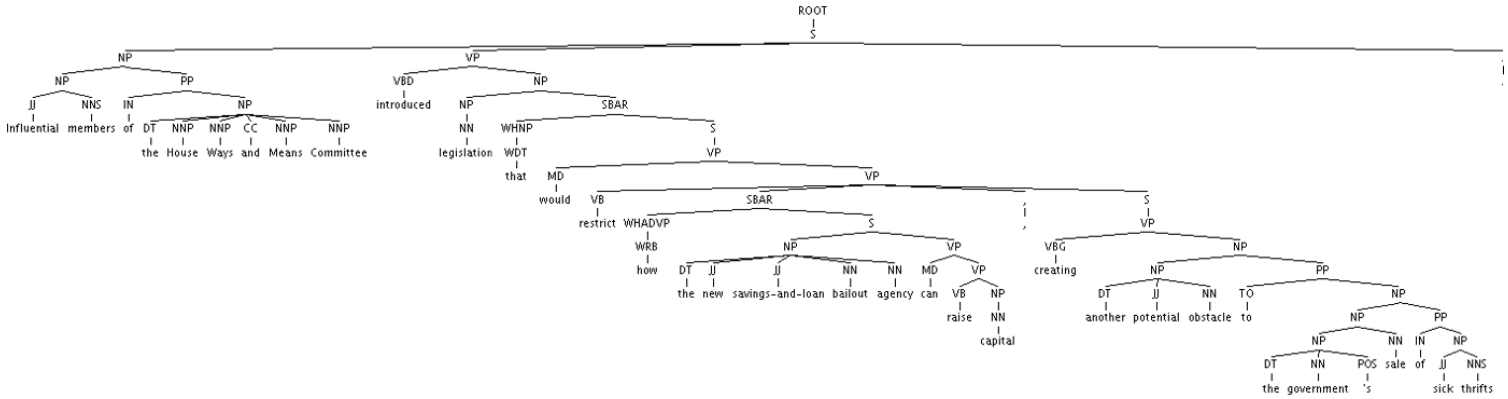


Dependency Trees





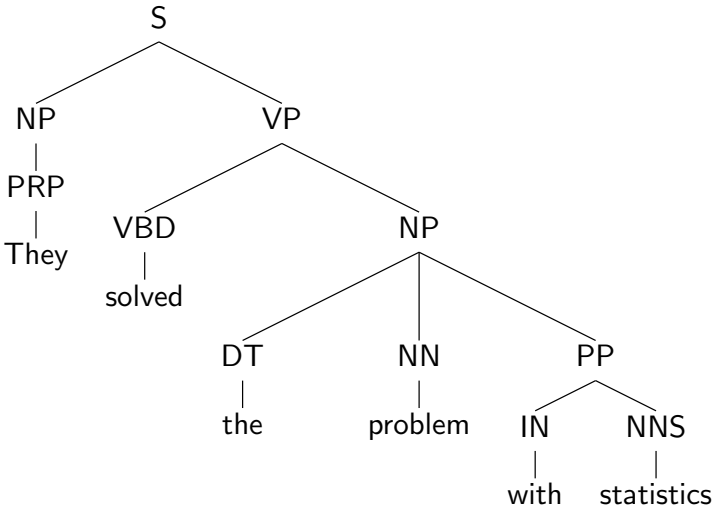
A “real” sentence



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.

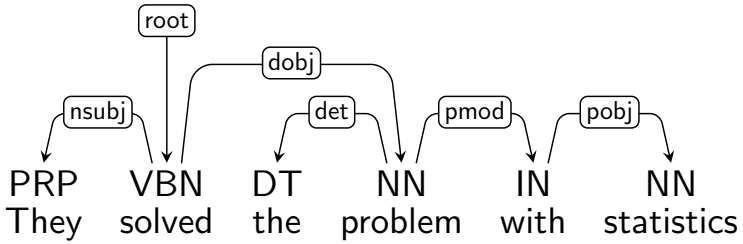
Theories of Syntactic Structure

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)

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

Context Free Grammars, Example

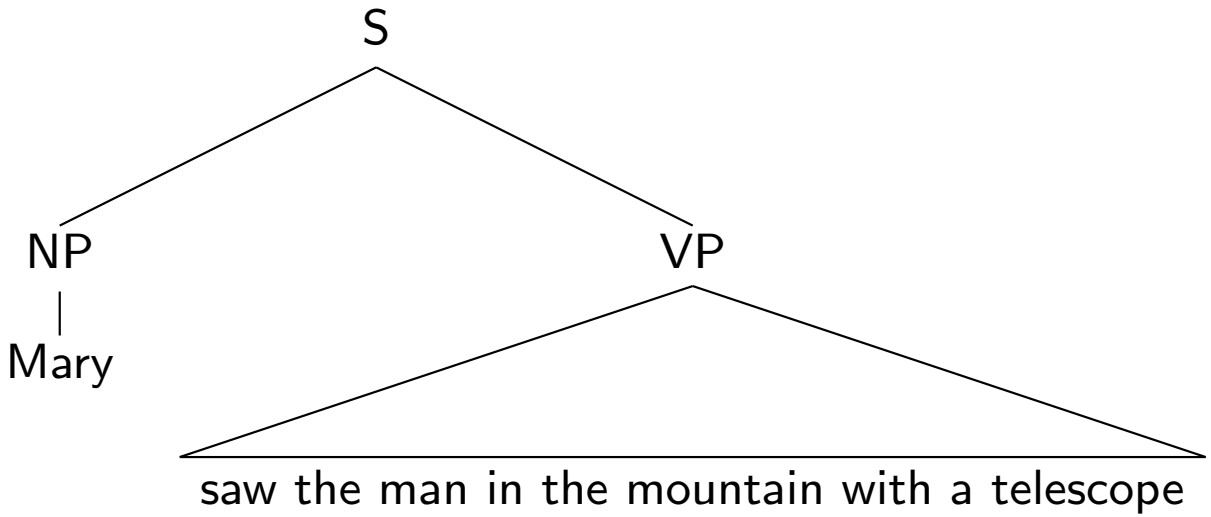
$$
\begin{aligned}
N &= \{\mathrm{S}, \mathrm{VP}, \mathrm{NP}, \mathrm{PP}, \mathrm{DT}, \mathrm{Vi}, \mathrm{Vt}, \mathrm{NN}, \mathrm{IN}\}^{1} \\
S &= \{\mathrm{S}\} \\
\Sigma &= \{\mathrm{sleeps}, \mathrm{saw}, \mathrm{man}, \mathrm{woman}, \mathrm{telescope}, \mathrm{the}, \mathrm{with}, \mathrm{in}\} \\
R &= \left\{ \begin{array}{ll}
\mathrm{S} \rightarrow \mathrm{NP\ VP} & \mathrm{Vi} \rightarrow \mathrm{sleeps} \\
\mathrm{NP} \rightarrow \mathrm{DT\ NN} & \mathrm{Vt} \rightarrow \mathrm{saw} \\
\mathrm{NP} \rightarrow \mathrm{NP\ PP} & \mathrm{NN} \rightarrow \mathrm{man} \\
\mathrm{PP} \rightarrow \mathrm{IN\ NP} & \mathrm{NN} \rightarrow \mathrm{woman} \\
\mathrm{VP} \rightarrow \mathrm{Vi} & \mathrm{NN} \rightarrow \mathrm{telescope} \\
\mathrm{VP} \rightarrow \mathrm{Vt\ NP} & \mathrm{DT} \rightarrow \mathrm{the} \\
\mathrm{VP} \rightarrow \mathrm{VP\ PP} & \mathrm{IN} \rightarrow \mathrm{with} \\
 & \mathrm{IN} \rightarrow \mathrm{in}
\end{array} \right\}
\end{aligned}
$$

[1] S=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

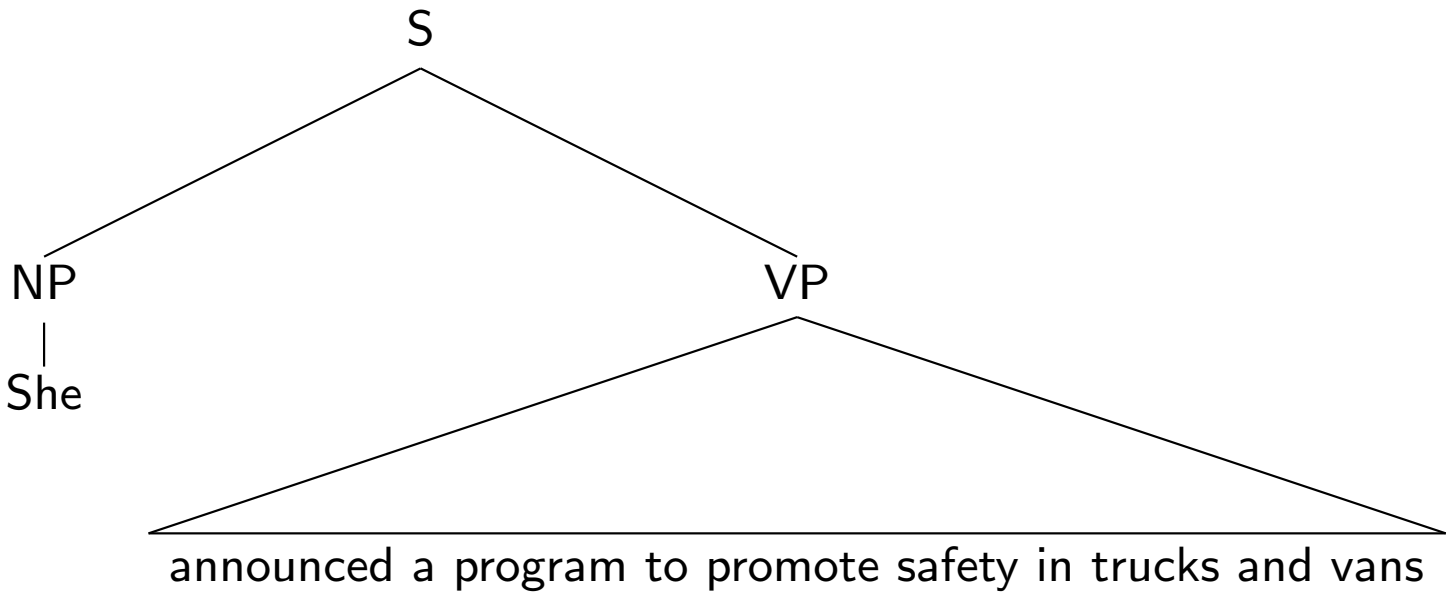
- A CFG defines a set of possible *derivations* (i.e. unique trees)
- A sequence of terminals $s \in \Sigma^*$ is *generated* by the CFG (or *recognized* by it, or *belongs* to the language defined by it) if there is at least a derivation that produces s.
- Some sequences of terminals generated by the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

Ambiguity

Some trees are more likely than others...

Ambiguity

Some trees are more likely than others...

Can we model that?

Context Free Grammar (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 $X \rightarrow Y_1 Y_2 \ldots Y_n$ where $n \geq 0,\ X \in N,\ Y_i \in N \cup \Sigma$

Context Free Grammar (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 $X \rightarrow Y_1 Y_2 \ldots Y_n$ where $n \geq 0,\ X \in N,\ Y_i \in N \cup \Sigma$

Probabilistic Context Free Grammar (**P**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 $X \rightarrow Y_1 Y_2 \ldots Y_n$ where $n \geq 0,\ X \in N,\ Y_i \in N \cup \Sigma$

Probabilistic Context Free Grammar (**P**CFGs)

A probabilistic 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 $X \rightarrow Y_1 Y_2 \ldots Y_n$ where $n \geq 0,\ X \in N,\ Y_i \in N \cup \Sigma$

Probabilistic Context Free Grammar (**P**CFGs)

A probabilistic context-free grammar is defined as a tuple $G = \langle N, \Sigma, R, S, q \rangle$ 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 $X \rightarrow Y_1 Y_2 \ldots Y_n$ where $n \geq 0,\ X \in N,\ Y_i \in N \cup \Sigma$

Probabilistic Context Free Grammar (**P**CFGs)

A probabilistic context-free grammar is defined as a tuple $G = \langle N, \Sigma, R, S, q \rangle$ 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 $X \rightarrow Y_1 Y_2 \ldots Y_n$ 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

$$
\begin{aligned}
N &= \{\mathrm{S}, \mathrm{VP}, \mathrm{NP}, \mathrm{PP}, \mathrm{DT}, \mathrm{Vi}, \mathrm{Vt}, \mathrm{NN}, \mathrm{IN}\}^{1} \\
S &= \{\mathrm{S}\} \\
\Sigma &= \{\text{sleeps}, \text{saw}, \text{man}, \text{woman}, \text{telescope}, \text{the}, \text{with}, \text{in}\} \\
R &= \left\{ \begin{array}{ll}
\mathrm{S} \rightarrow \mathrm{NP\ VP} & \mathrm{Vi} \rightarrow \text{sleeps} \\
\mathrm{NP} \rightarrow \mathrm{DT\ NN} & \mathrm{Vt} \rightarrow \text{saw} \\
\mathrm{NP} \rightarrow \mathrm{NP\ PP} & \mathrm{NN} \rightarrow \text{man} \\
\mathrm{PP} \rightarrow \mathrm{IN\ NP} & \mathrm{NN} \rightarrow \text{woman} \\
\mathrm{VP} \rightarrow \mathrm{Vi} & \mathrm{NN} \rightarrow \text{telescope} \\
\mathrm{VP} \rightarrow \mathrm{Vt\ NP} & \mathrm{DT} \rightarrow \text{the} \\
\mathrm{VP} \rightarrow \mathrm{VP\ PP} & \mathrm{IN} \rightarrow \text{with} \\
 & \mathrm{IN} \rightarrow \text{in}
\end{array} \right\}
\end{aligned}
$$

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

Probabilistic Context Free Grammars, Example

$$
\begin{aligned}
N &= \{\mathrm{S}, \mathrm{VP}, \mathrm{NP}, \mathrm{PP}, \mathrm{DT}, \mathrm{Vi}, \mathrm{Vt}, \mathrm{NN}, \mathrm{IN}\}^{1} \\
S &= \{\mathrm{S}\} \\
\Sigma &= \{\text{sleeps}, \text{saw}, \text{man}, \text{woman}, \text{telescope}, \text{the}, \text{with}, \text{in}\} \\
R &= \left\{
\begin{array}{lll}
\mathrm{S} \rightarrow \mathrm{NP\ VP} & 1.0 & \mathrm{Vi} \rightarrow \text{sleeps} \quad 1.0 \\
\mathrm{NP} \rightarrow \mathrm{DT\ NN} & 0.4 & \mathrm{Vt} \rightarrow \text{saw} \quad 1.0 \\
\mathrm{NP} \rightarrow \mathrm{NP\ PP} & 0.6 & \mathrm{NN} \rightarrow \text{man} \quad 0.7 \\
\mathrm{PP} \rightarrow \mathrm{IN\ NP} & 1.0 & \mathrm{NN} \rightarrow \text{woman} \quad 0.2 \\
\mathrm{VP} \rightarrow \mathrm{Vi} & 0.5 & \mathrm{NN} \rightarrow \text{telescope} \quad 0.1 \\
\mathrm{VP} \rightarrow \mathrm{Vt\ NP} & 0.4 & \mathrm{DT} \rightarrow \text{the} \quad 1.0 \\
\mathrm{VP} \rightarrow \mathrm{VP\ PP} & 0.1 & \mathrm{IN} \rightarrow \text{with} \quad 0.5 \\
 & & \mathrm{IN} \rightarrow \text{in} \quad 0.5
\end{array}
\right\}
\end{aligned}
$$

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

Properties of PCFGs

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

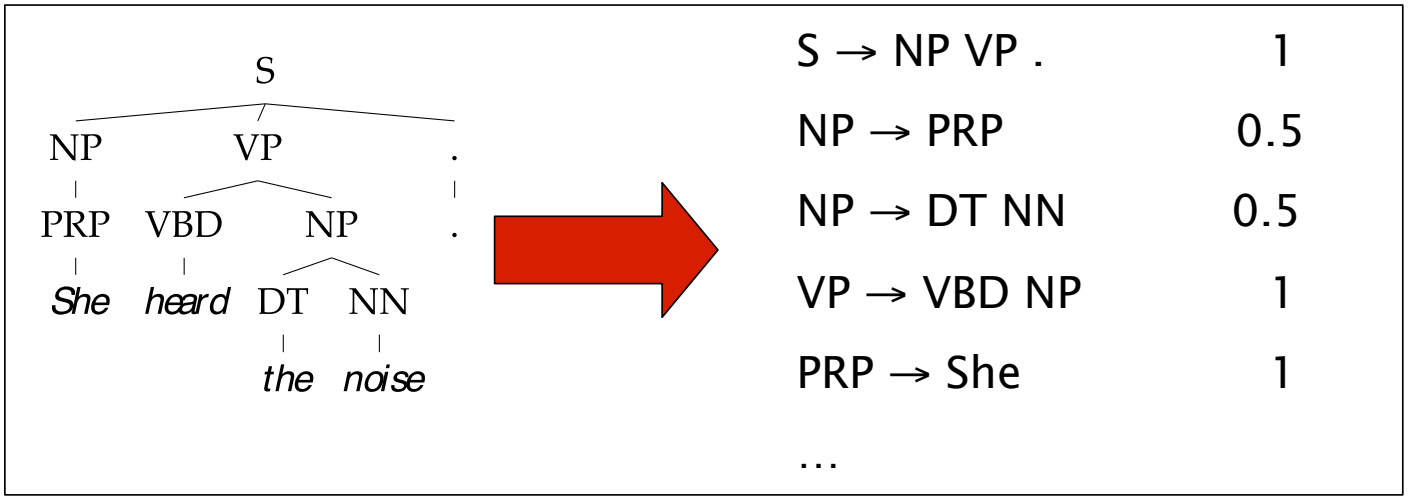
$$p(t) = \prod_{r \in t} q(r)$$

- 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

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

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

Outline

Parsing Natural Language Sentences

Goal of a parser:

- Find all possible trees

Parsing Natural Language Sentences

Goal of a parser:

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

Parsing Natural Language Sentences

Goal of a parser:

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

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.

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 dynammic programming table (*aka* **chart**) to store intermediate results.

Outline

CKY Algorithm

- Bottom-up
- Requires a grammar in Chomsky Normal Form (CNF).
- Dynammic 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

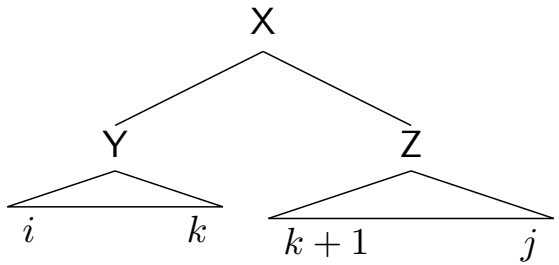
- $\forall i = 1 \dots n, \forall X \to w_i \in R, \quad \pi(i, i, X) = q(X \to w_i)$

Recursive case: Non-terminal nodes

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

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

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



Output:

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

CKY Algorithm - Example

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

$$S = \{\text{S}\}$$

$$\Sigma = \{\text{sleeps}, \text{saw}, \text{man}, \text{woman}, \text{telescope}, \text{the}, \text{with}, \text{in}\}$$

$$R = \left\{ \begin{array}{lll} \text{S} \rightarrow \text{NP VP} & 1.0 & \text{Vi} \rightarrow \text{sleeps} \quad 1.0 \\ \text{NP} \rightarrow \text{DT NN} & 0.4 & \text{Vt} \rightarrow \text{saw} \quad 1.0 \\ \text{NP} \rightarrow \text{NP PP} & 0.6 & \text{NN} \rightarrow \text{man} \quad 0.7 \\ \text{PP} \rightarrow \text{IN NP} & 1.0 & \text{NN} \rightarrow \text{woman} \quad 0.2 \\ \text{VP} \rightarrow \text{Vi} & 0.5 & \text{NN} \rightarrow \text{telescope} \quad 0.1 \\ \text{VP} \rightarrow \text{Vt NP} & 0.4 & \text{DT} \rightarrow \text{the} \quad 1.0 \\ \text{VP} \rightarrow \text{VP PP} & 0.1 & \text{IN} \rightarrow \text{with} \quad 0.5 \\ & & \text{IN} \rightarrow \text{in} \quad 0.5 \end{array} \right\}$$

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

CKY Algorithm - Example - CNF

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

$$S = \{\text{S}\}$$

$$\Sigma = \{\text{sleeps}, \text{saw}, \text{man}, \text{woman}, \text{telescope}, \text{the}, \text{with}, \text{in}\}$$

$$R = \left\{ \begin{array}{lll} \text{S} \rightarrow \text{NP VP} & 1.0 & \text{Vi} \rightarrow \text{sleeps} \quad 1.0 \\ \text{NP} \rightarrow \text{DT NN} & 0.4 & \text{Vt} \rightarrow \text{saw} \quad 1.0 \\ \text{NP} \rightarrow \text{NP PP} & 0.6 & \text{NN} \rightarrow \text{man} \quad 0.7 \\ \text{PP} \rightarrow \text{IN NP} & 1.0 & \text{NN} \rightarrow \text{woman} \quad 0.2 \\ \text{VP} \rightarrow \text{Vi} & 0.5 & \text{NN} \rightarrow \text{telescope} \quad 0.1 \\ \text{VP} \rightarrow \text{Vt NP} & 0.4 & \text{DT} \rightarrow \text{the} \quad 1.0 \\ \text{VP} \rightarrow \text{VP PP} & 0.1 & \text{IN} \rightarrow \text{with} \quad 0.5 \\ & & \text{IN} \rightarrow \text{in} \quad 0.5 \end{array} \right\}$$

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

CKY Algorithm - Example - CNF

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

$$S = \{\text{S}\}$$

$$\Sigma = \{\text{sleeps}, \text{saw}, \text{man}, \text{woman}, \text{telescope}, \text{the}, \text{with}, \text{in}\}$$

$$R = \left\{ \begin{array}{llll}
\text{S} \rightarrow \text{NP VP} & 0.5 & \text{Vi} \rightarrow \text{sleeps} & 1.0 \\
\text{S} \rightarrow \text{NP Vi} & 0.5 & \text{Vt} \rightarrow \text{saw} & 1.0 \\
\text{NP} \rightarrow \text{DT NN} & 0.4 & \text{NN} \rightarrow \text{man} & 0.7 \\
\text{NP} \rightarrow \text{NP PP} & 0.6 & \text{NN} \rightarrow \text{woman} & 0.2 \\
\text{PP} \rightarrow \text{IN NP} & 1.0 & \text{NN} \rightarrow \text{telescope} & 0.1 \\
\text{VP} \rightarrow \text{Vi} & 0.5 & \text{DT} \rightarrow \text{the} & 1.0 \\
\text{VP} \rightarrow \text{Vt NP} & 0.4 & \text{IN} \rightarrow \text{with} & 0.5 \\
\text{VP} \rightarrow \text{VP PP} & 0.1 & \text{IN} \rightarrow \text{in} & 0.5
\end{array} \right\}$$

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

CKY Algorithm - Example - CNF

$$
\begin{aligned}
N &= \{\text{S}, \text{VP}, \text{NP}, \text{PP}, \text{DT}, \text{Vi}, \text{Vt}, \text{NN}, \text{IN}\}^1 \\
S &= \{\text{S}\} \\
\Sigma &= \{\text{sleeps}, \text{saw}, \text{man}, \text{woman}, \text{telescope}, \text{the}, \text{with}, \text{in}\} \\
R &= \left\{
\begin{array}{llll}
\text{S} \rightarrow \text{NP VP} & 0.5 & \text{Vi} \rightarrow \text{sleeps} & 1.0 \\
\text{S} \rightarrow \text{NP Vi} & 0.5 & \text{Vt} \rightarrow \text{saw} & 1.0 \\
\text{NP} \rightarrow \text{DT NN} & 0.4 & \text{NN} \rightarrow \text{man} & 0.7 \\
\text{NP} \rightarrow \text{NP PP} & 0.6 & \text{NN} \rightarrow \text{woman} & 0.2 \\
\text{PP} \rightarrow \text{IN NP} & 1.0 & \text{NN} \rightarrow \text{telescope} & 0.1 \\
\text{VP} \rightarrow \text{Vi} & 0.5 & \text{DT} \rightarrow \text{the} & 1.0 \\
\text{VP} \rightarrow \text{Vt NP} & 0.4 & \text{IN} \rightarrow \text{with} & 0.5 \\
\text{VP} \rightarrow \text{VP PP} & 0.05 & \text{IN} \rightarrow \text{in} & 0.5 \\
\text{VP} \rightarrow \text{Vi PP} & 0.05 &
\end{array}
\right\}
\end{aligned}
$$

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

CKY Algorithm - Example - CNF

$$
\begin{aligned}
N &= \{\mathrm{S}, \mathrm{VP}, \mathrm{NP}, \mathrm{PP}, \mathrm{DT}, \mathrm{Vi}, \mathrm{Vt}, \mathrm{NN}, \mathrm{IN}\}^{1} \\
S &= \{\mathrm{S}\} \\
\Sigma &= \{\text{sleeps}, \text{saw}, \text{man}, \text{woman}, \text{telescope}, \text{the}, \text{with}, \text{in}\}
\end{aligned}
$$

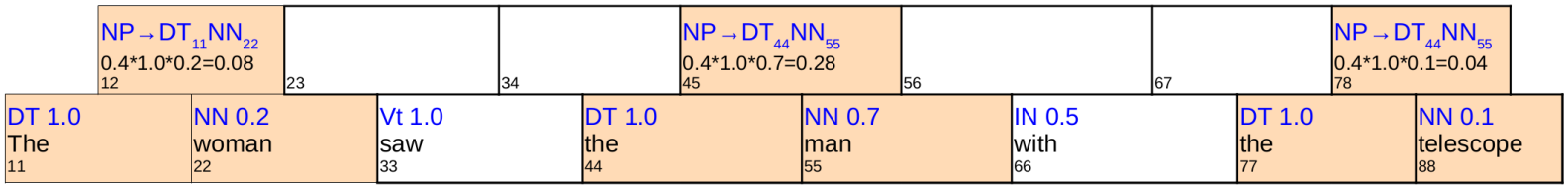
$$
R = \left\{
\begin{array}{llll}
\mathrm{S} \rightarrow \mathrm{NP\ VP} & 0.5 & \mathrm{Vi} \rightarrow \text{sleeps} & 1.0 \\
\mathrm{S} \rightarrow \mathrm{NP\ Vi} & 0.5 & \mathrm{Vt} \rightarrow \text{saw} & 1.0 \\
\mathrm{NP} \rightarrow \mathrm{DT\ NN} & 0.4 & \mathrm{NN} \rightarrow \text{man} & 0.7 \\
\mathrm{NP} \rightarrow \mathrm{NP\ PP} & 0.6 & \mathrm{NN} \rightarrow \text{woman} & 0.2 \\
\mathrm{PP} \rightarrow \mathrm{IN\ NP} & 1.0 & \mathrm{NN} \rightarrow \text{telescope} & 0.1 \\
\mathrm{VP} \rightarrow \mathrm{Vt\ NP} & 0.8 & \mathrm{DT} \rightarrow \text{the} & 1.0 \\
\mathrm{VP} \rightarrow \mathrm{VP\ PP} & 0.1 & \mathrm{IN} \rightarrow \text{with} & 0.5 \\
\mathrm{VP} \rightarrow \mathrm{Vi\ PP} & 0.1 & \mathrm{IN} \rightarrow \text{in} & 0.5
\end{array}
\right\}
$$

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

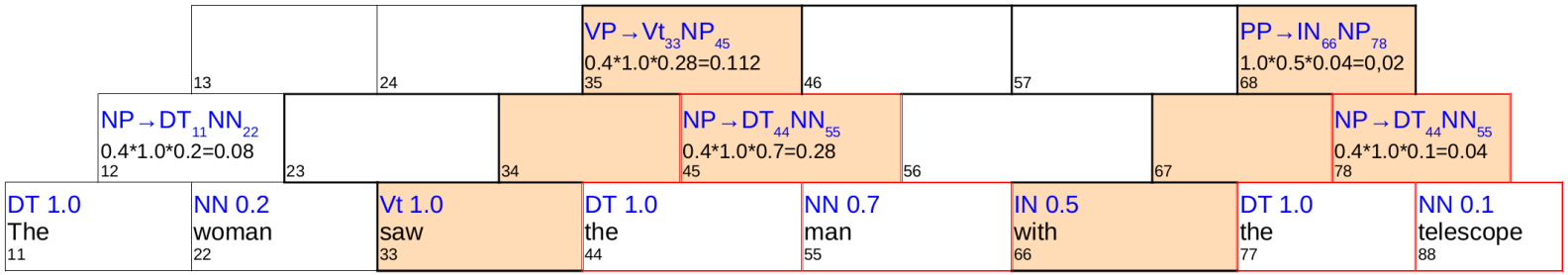
CKY Algorithm - Example

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

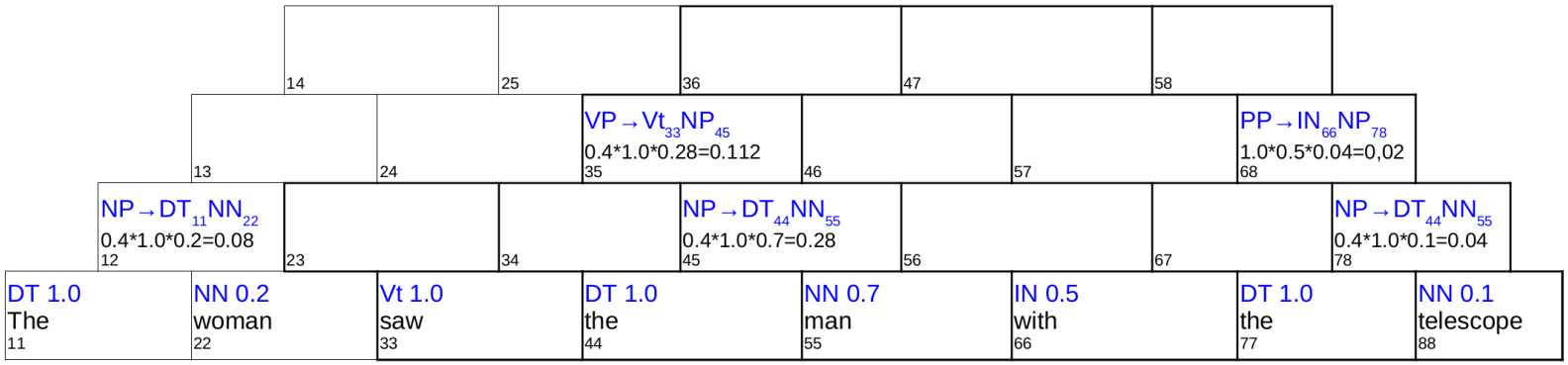
CKY Algorithm - Example



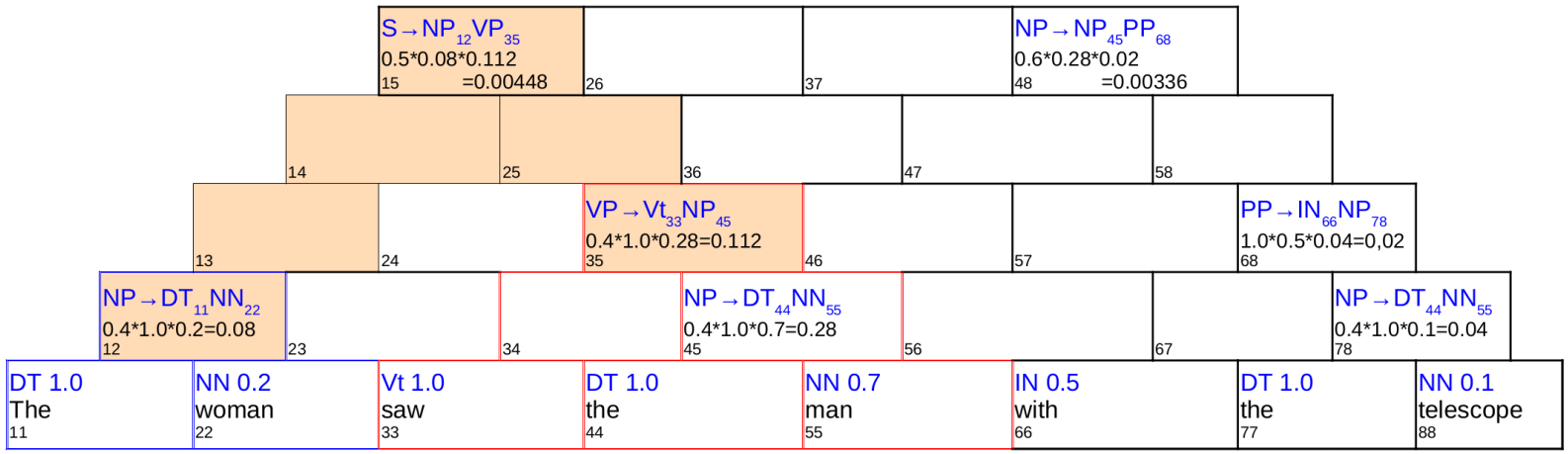
CKY Algorithm - Example



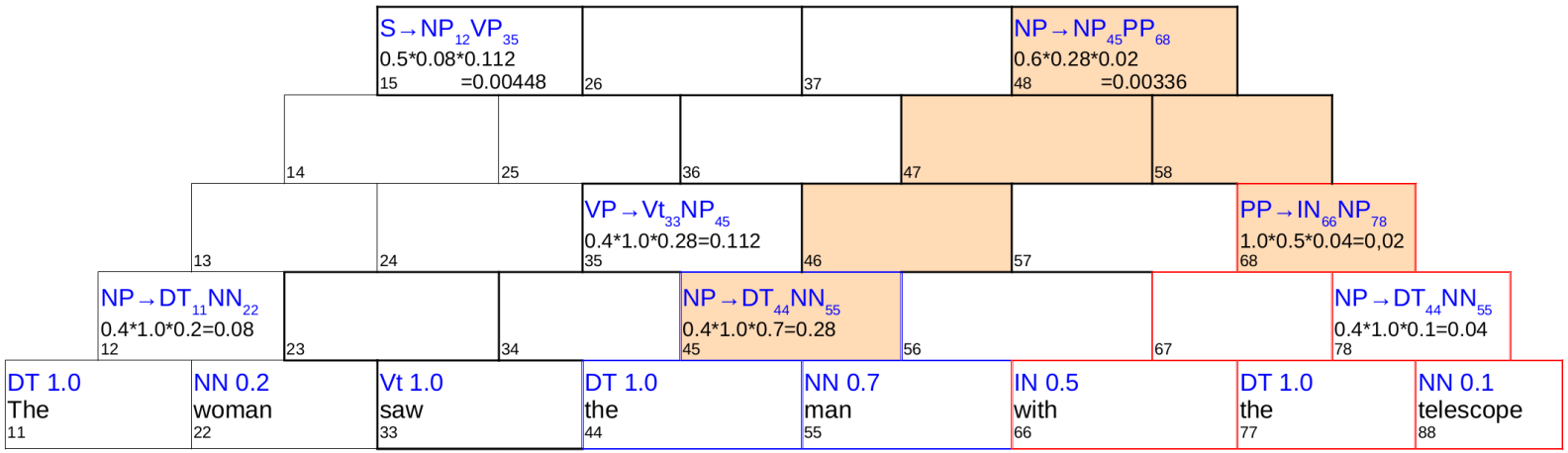
CKY Algorithm - Example



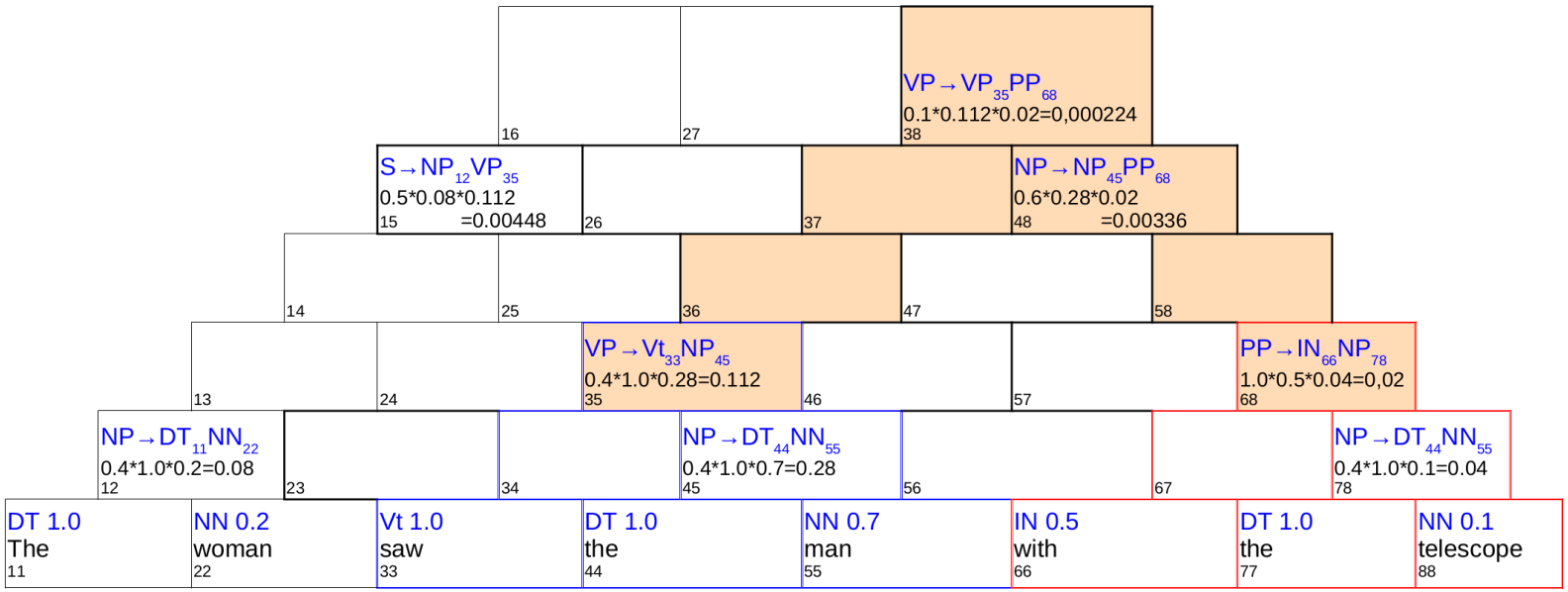
CKY Algorithm - Example



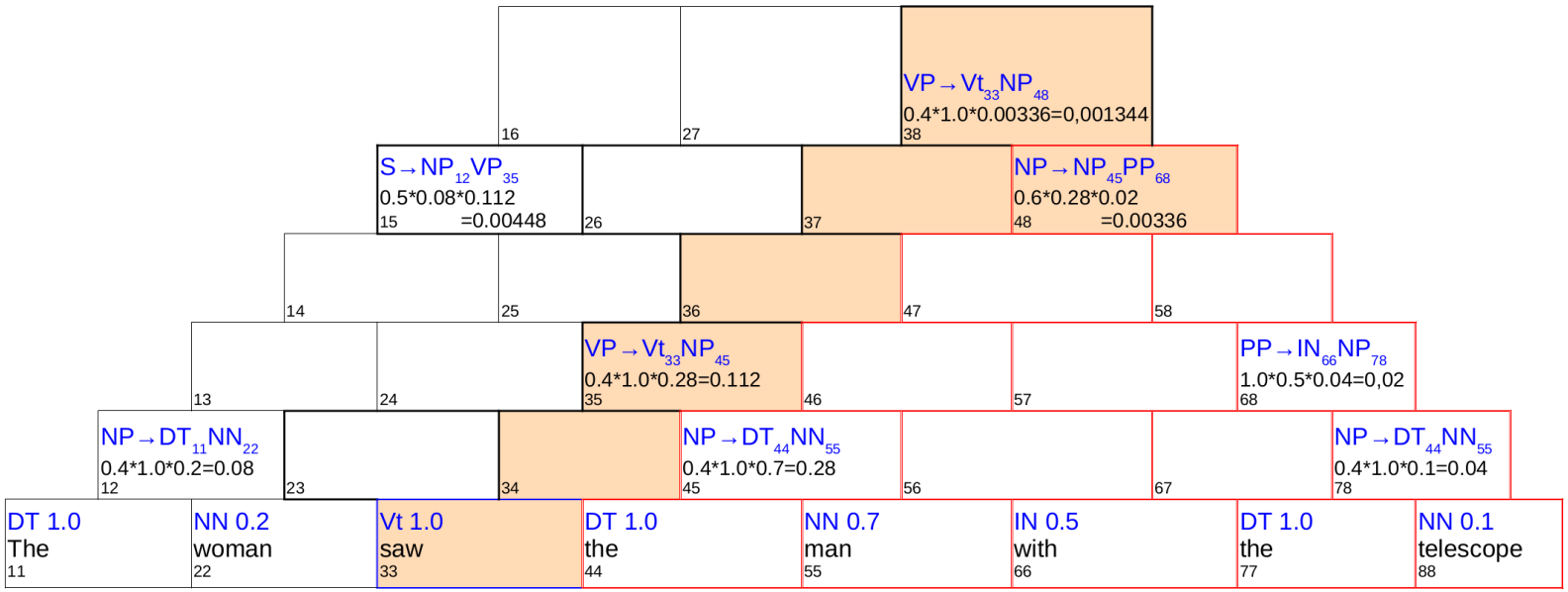
CKY Algorithm - Example



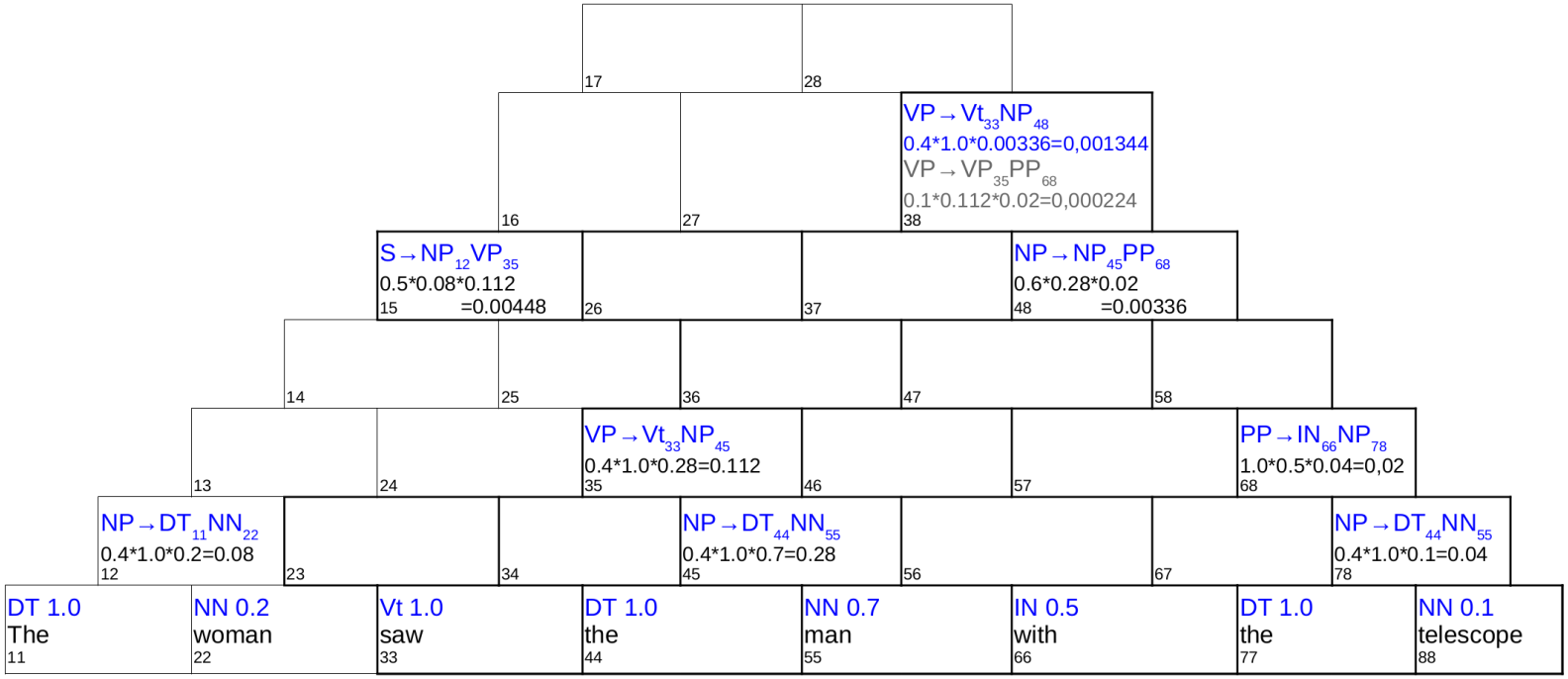
CKY Algorithm - Example



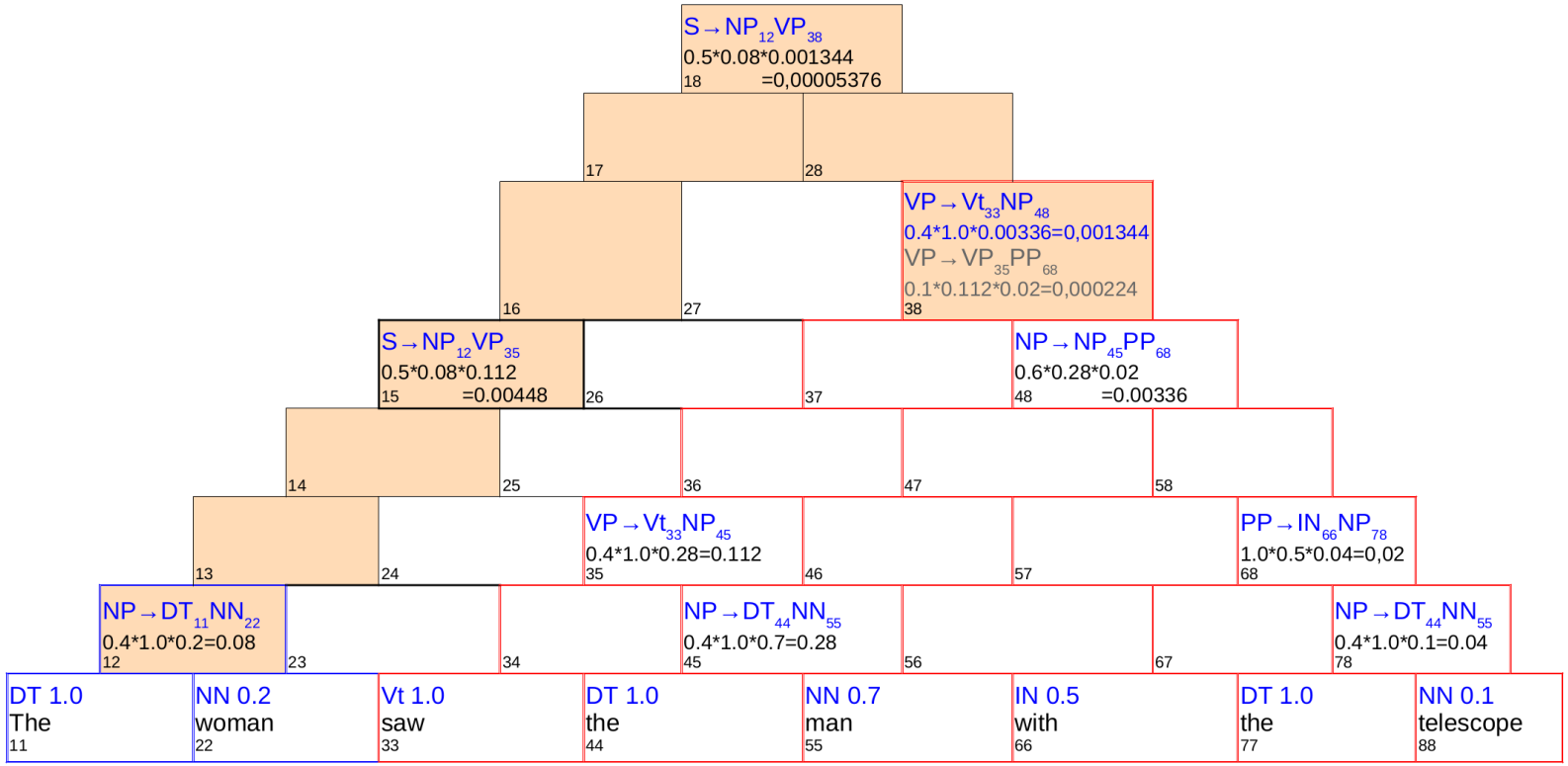
CKY Algorithm - Example



CKY Algorithm - Example



CKY Algorithm - Example



Outline

Earley Algorithm

- Top-down
- Can deal with any CFG (even left-recursive)
- Dynammic 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

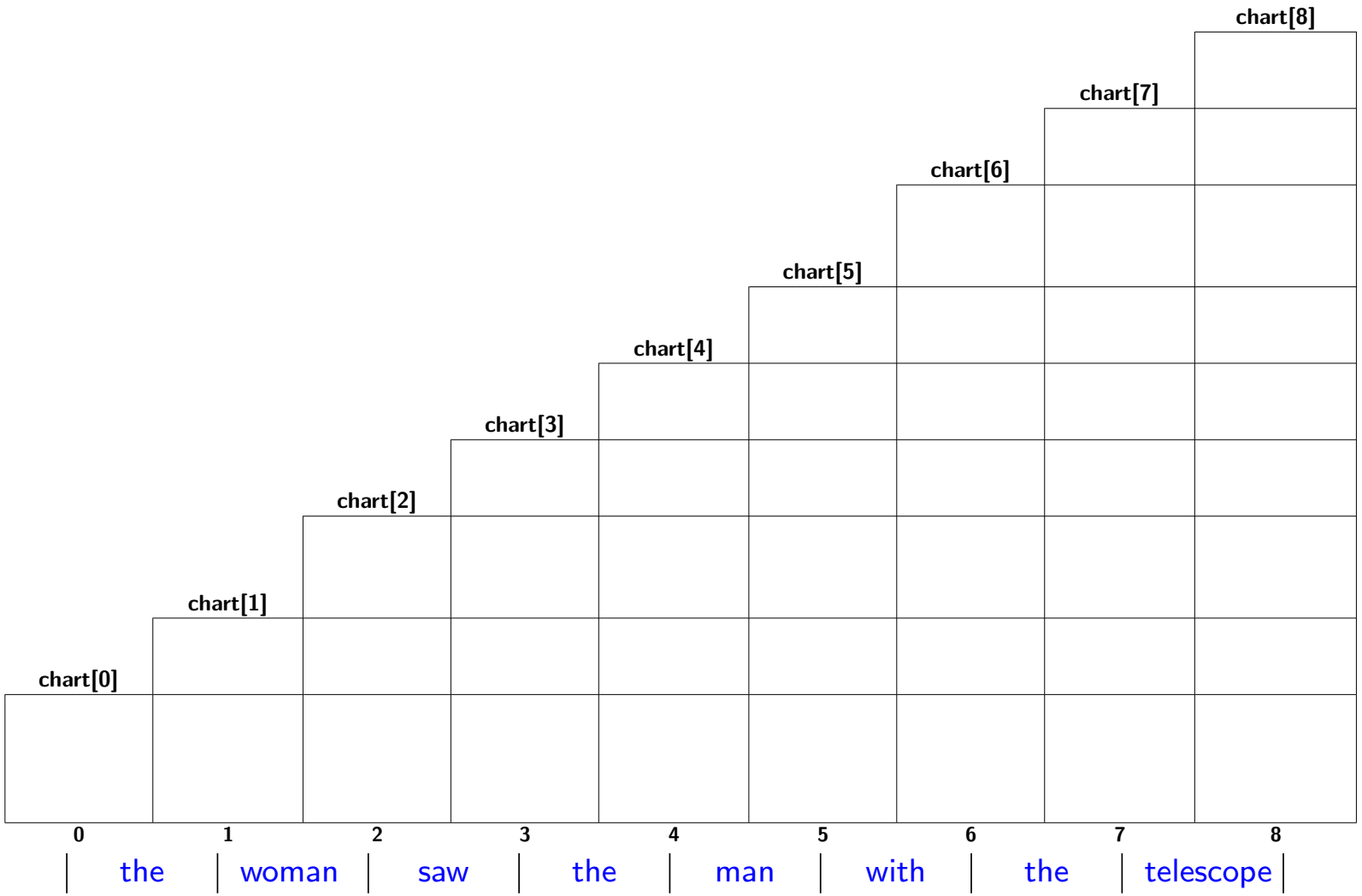
Parsing state examples:

$[0, 0, \mathrm{S} \rightarrow \bullet\ \mathrm{NP}\ \mathrm{VP}]$	A NP is expected at the beginning of the sentence
$[1, 2, \mathrm{NP} \rightarrow \mathrm{DT} \bullet \mathrm{NN}]$	A NP has been partially matched (DT was found between positions 1 and 2)
$[0, 3, \mathrm{VP} \rightarrow \mathrm{V}\ \mathrm{NP} \bullet]$	A VP has been completed between positions 0 and 3

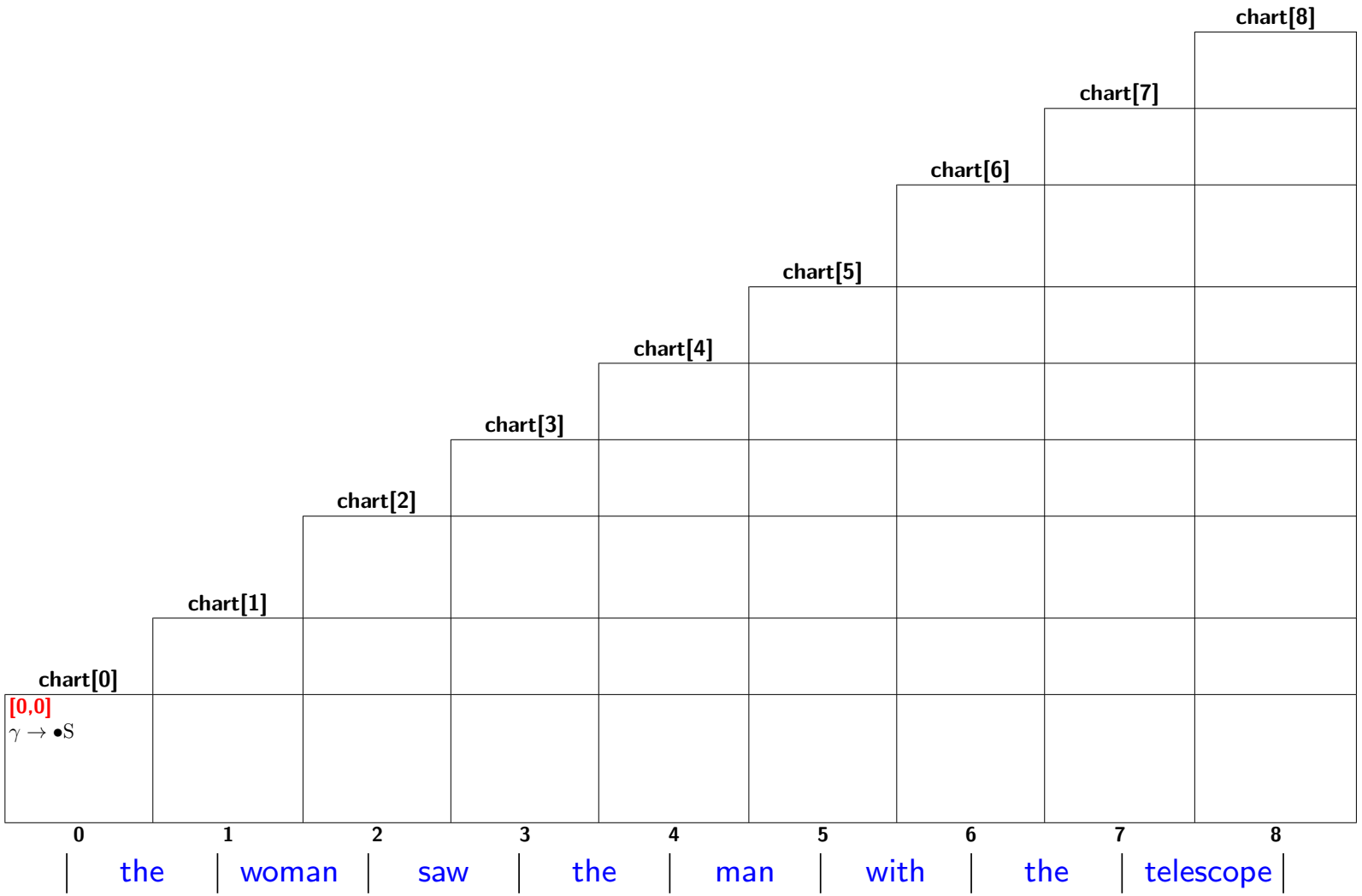
Earley Algorithm


```
def Earley(words,grammar):
    chart = [ [ ] for i in range(len(words)+1) ]
    chart[0].append([0,0,γ → •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])
```

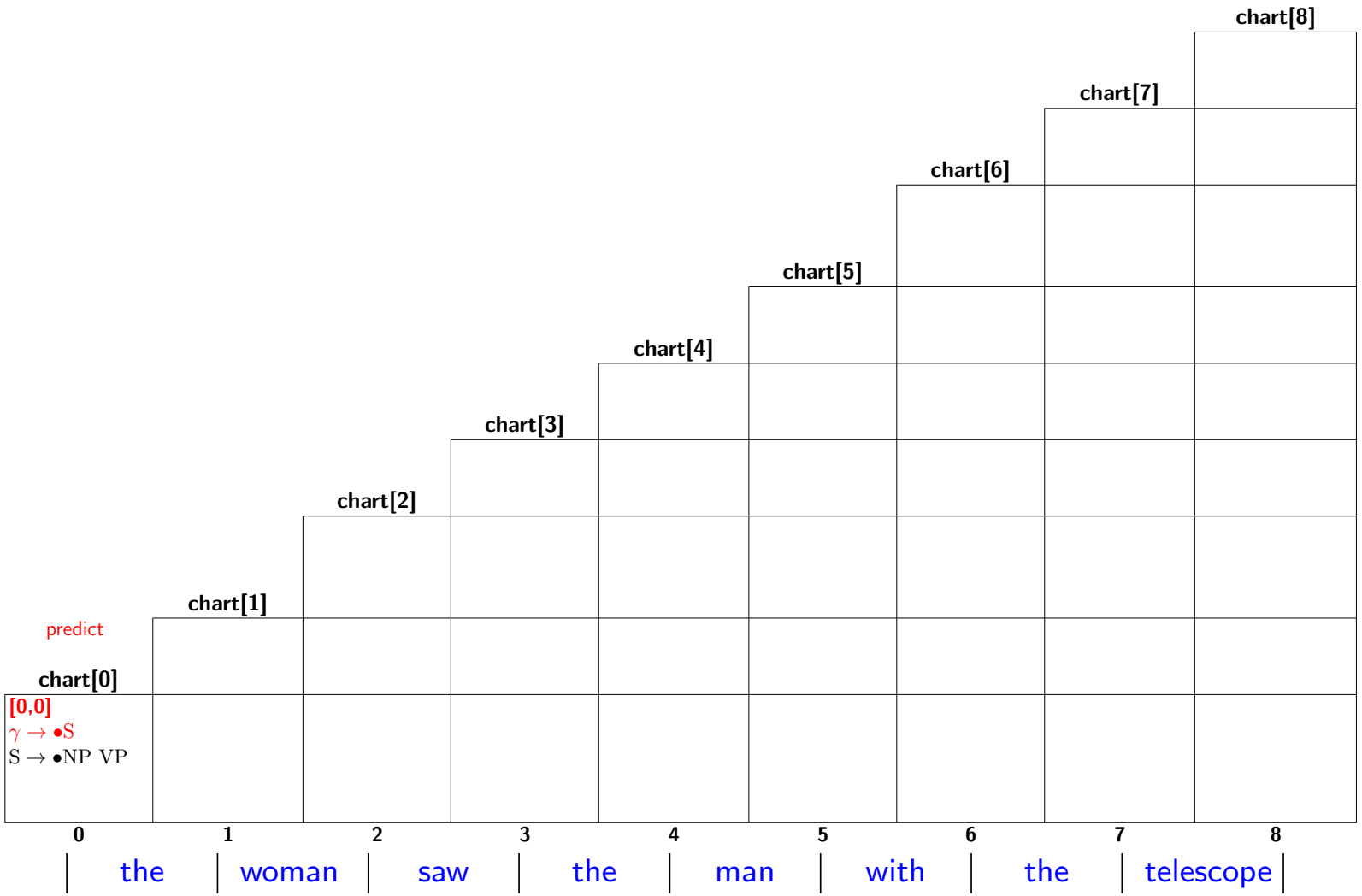
Earley Algorithm



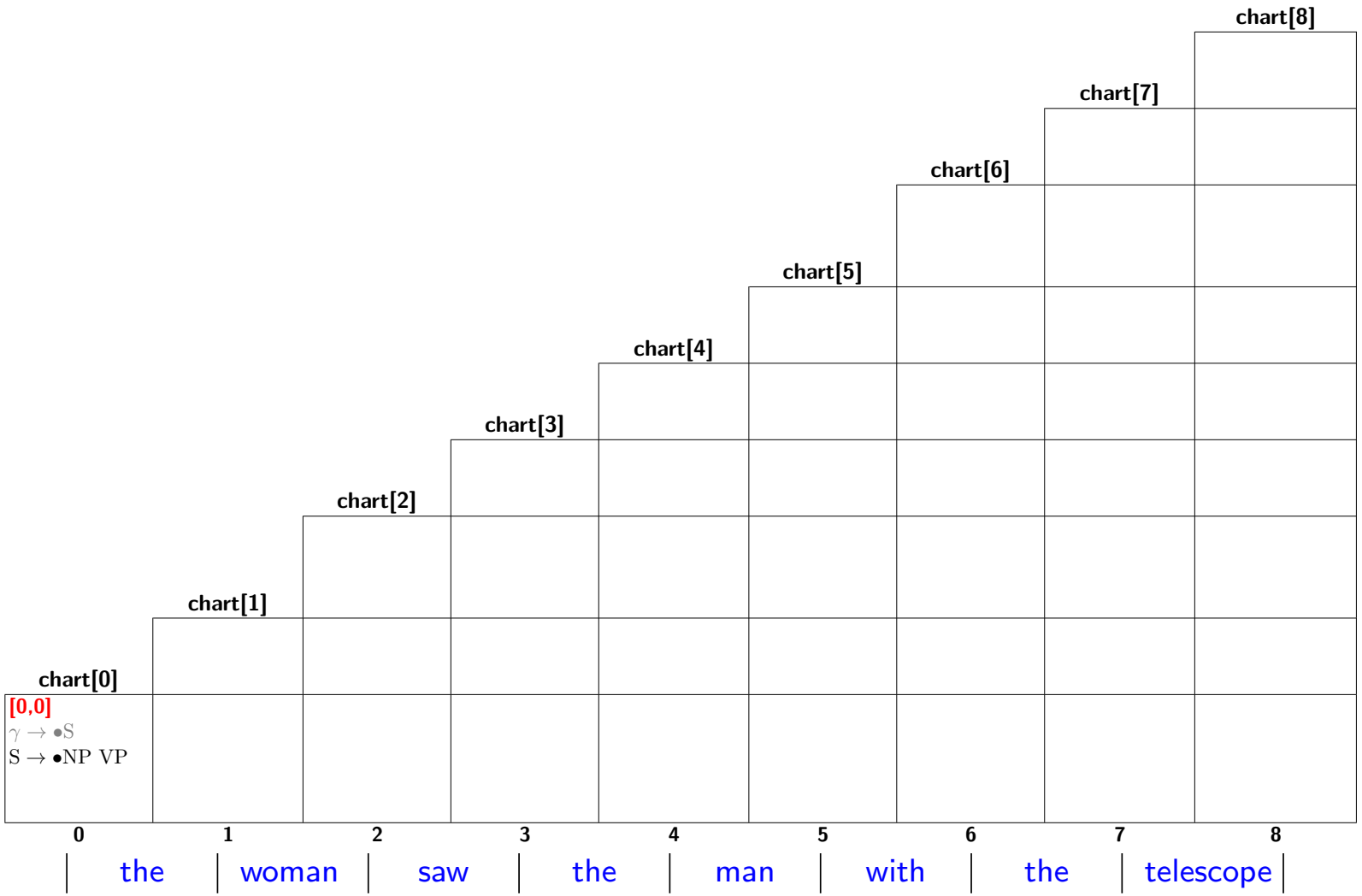
Earley Algorithm



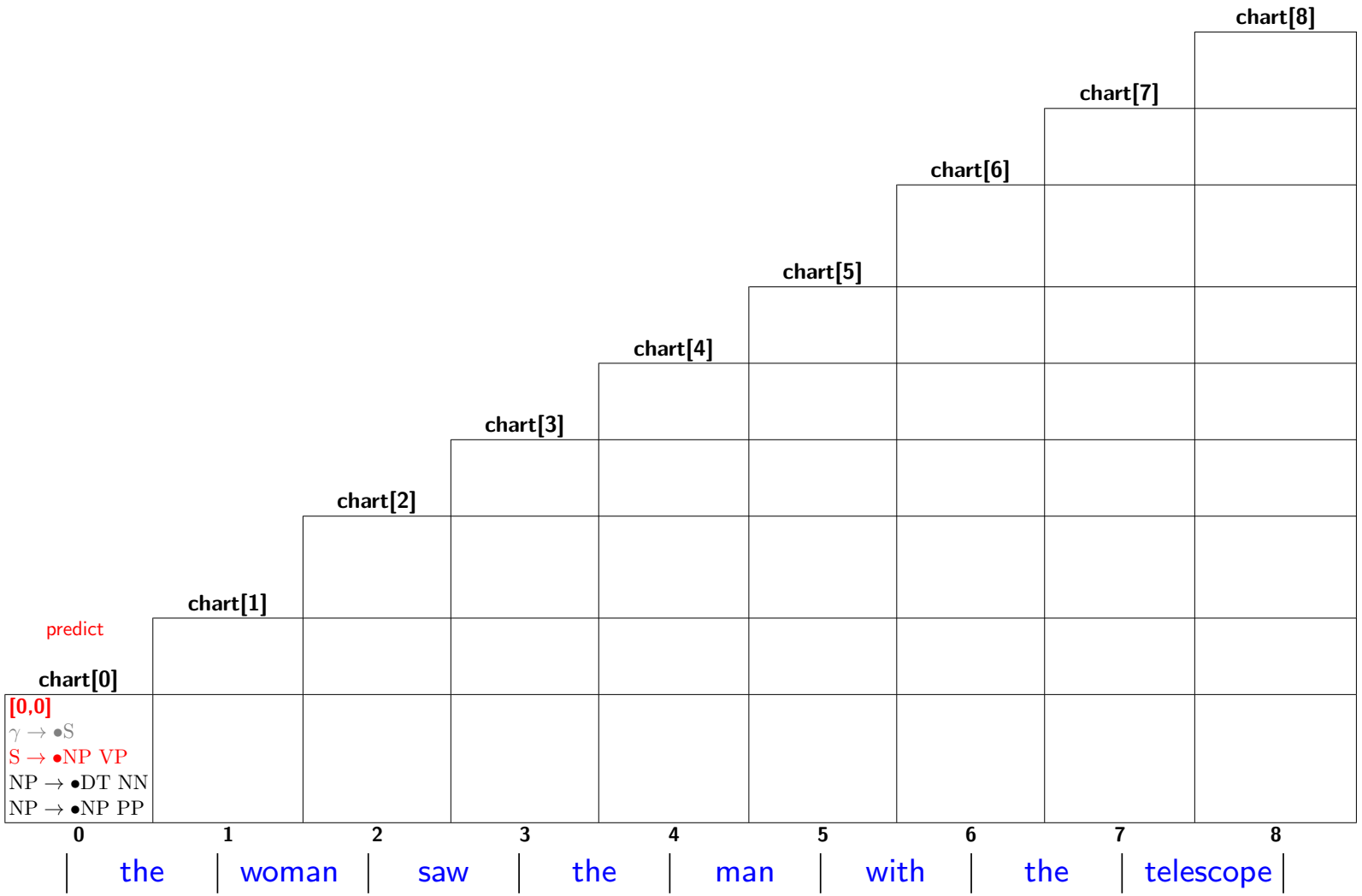
Earley Algorithm



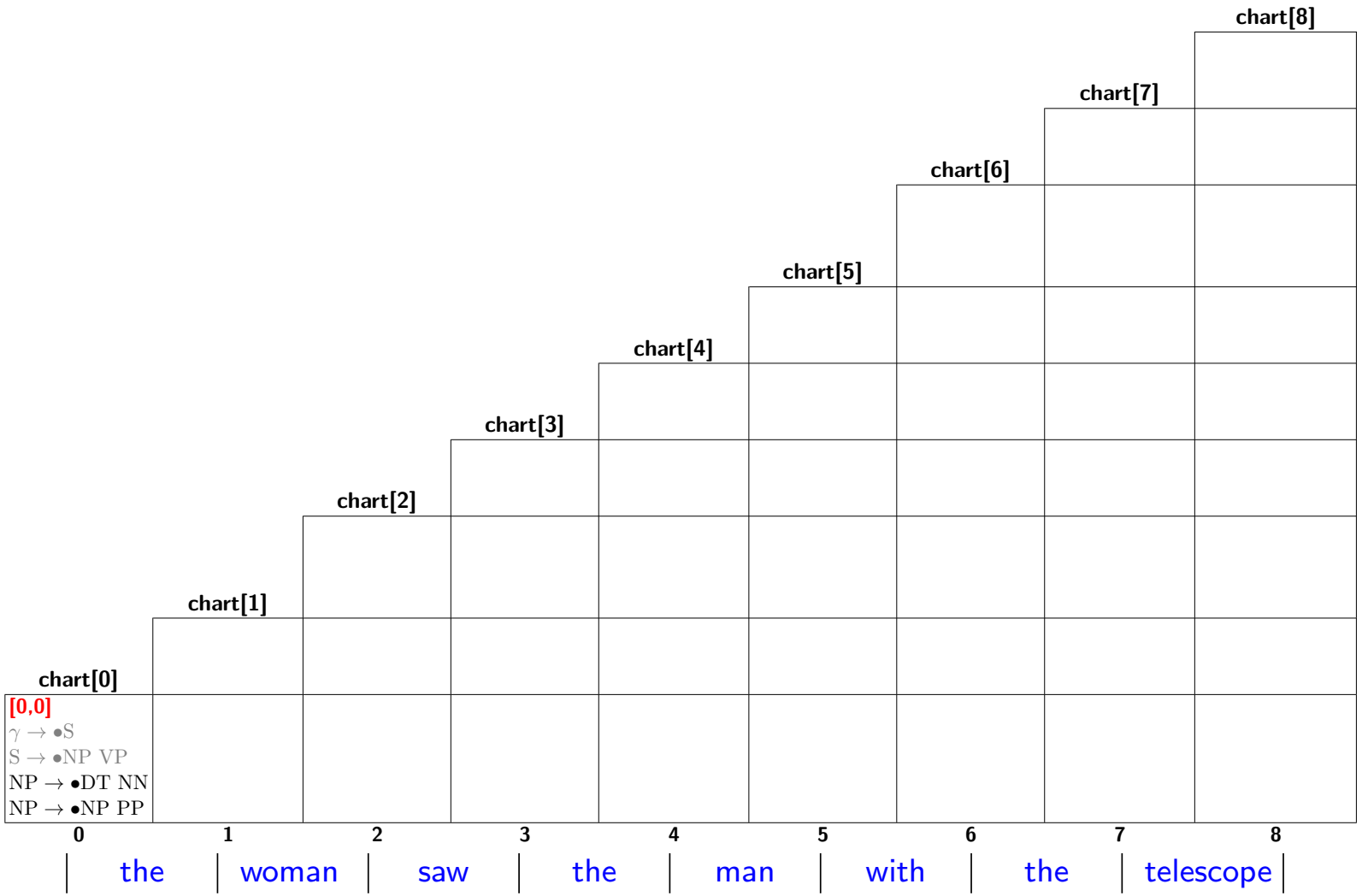
Earley Algorithm



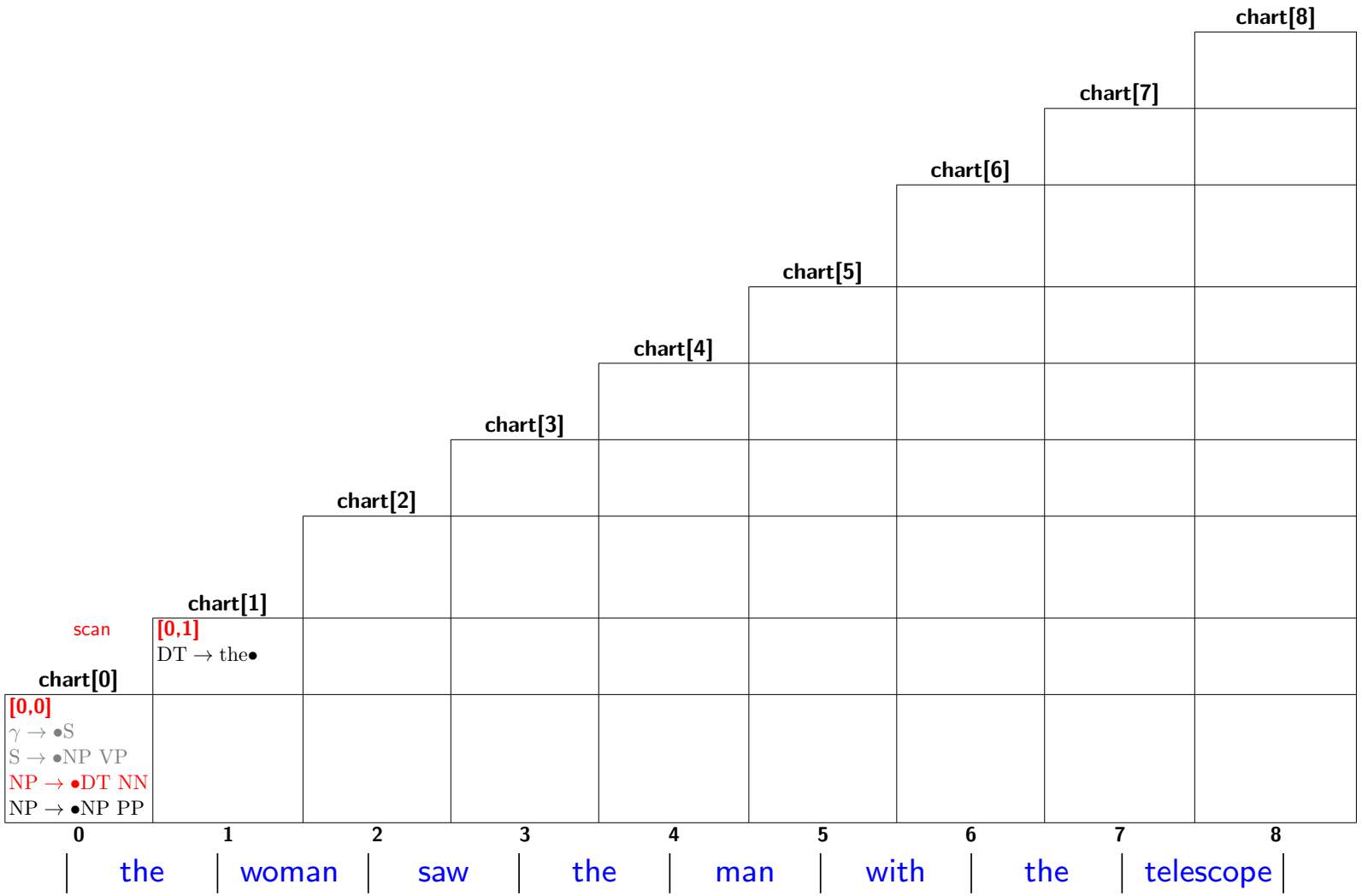
Earley Algorithm



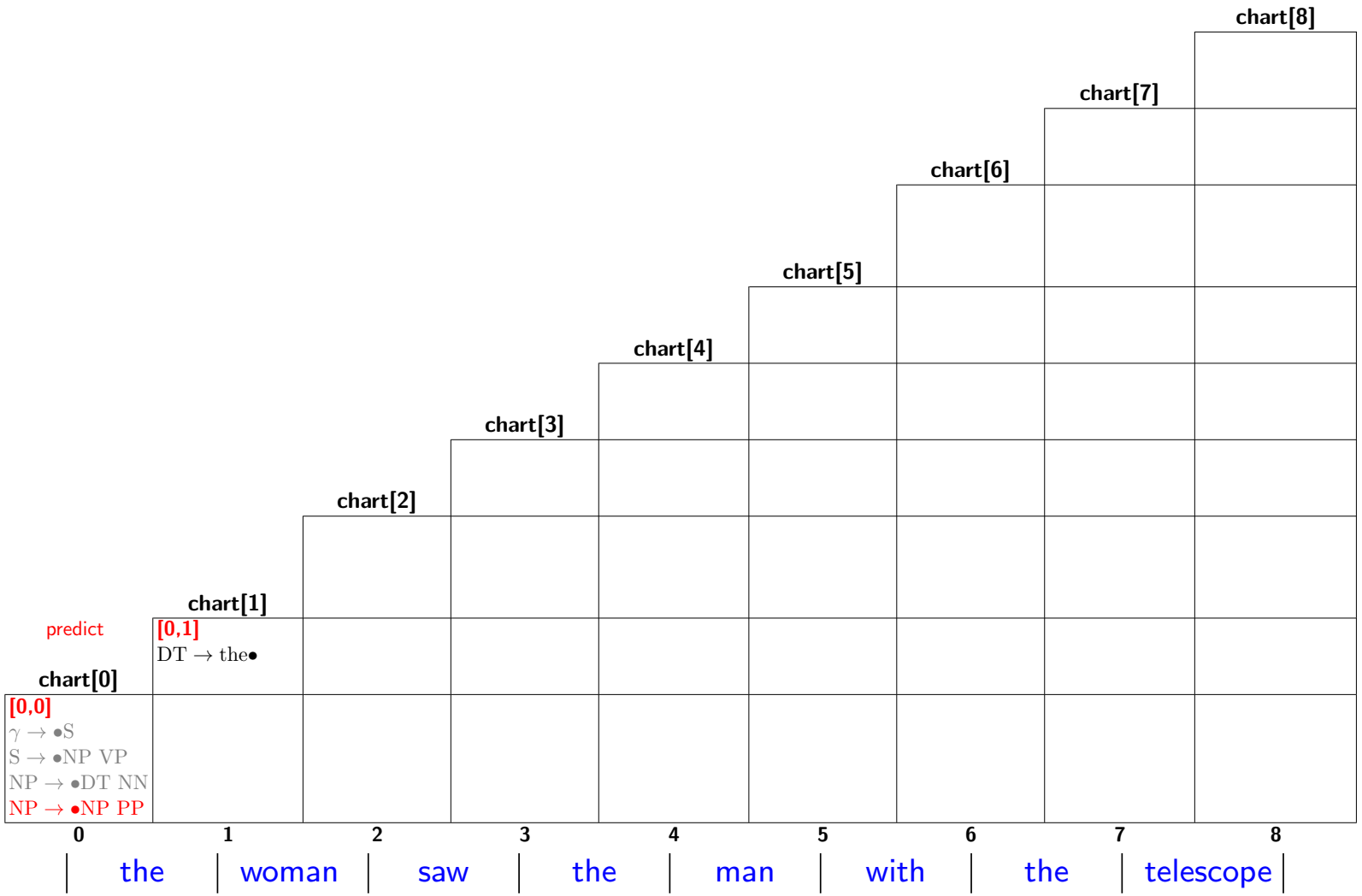
Earley Algorithm



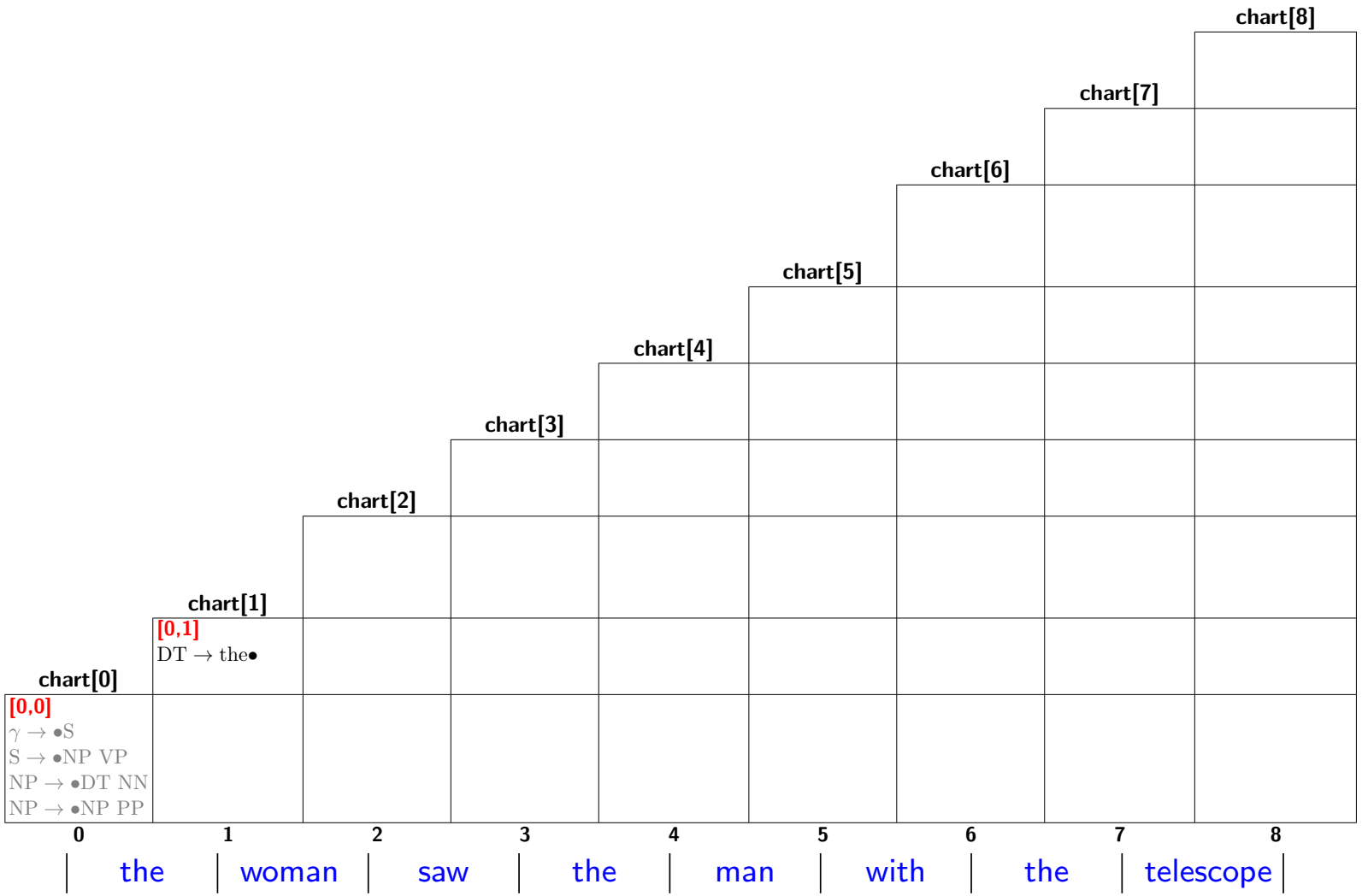
Earley Algorithm



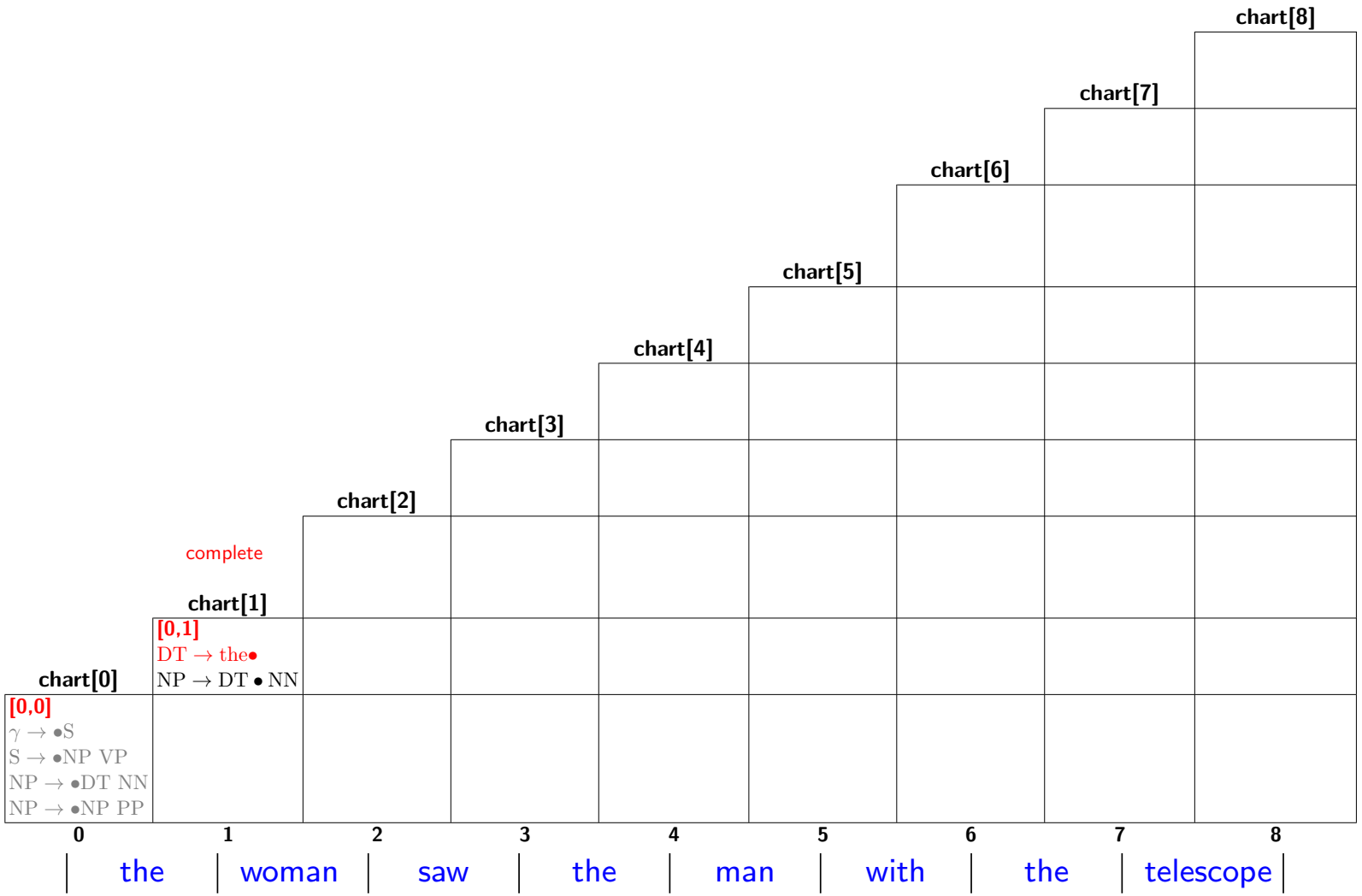
Earley Algorithm



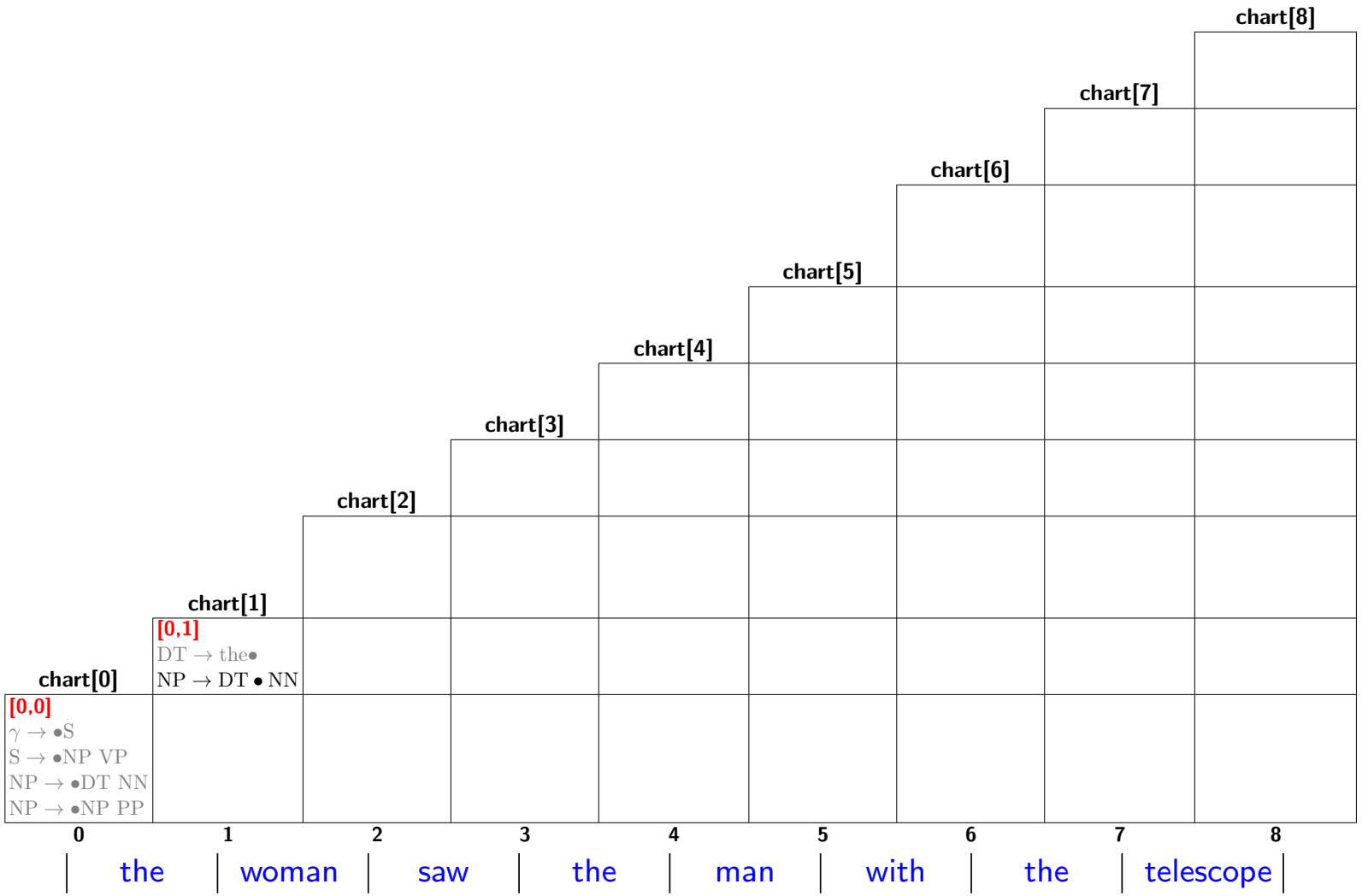
Earley Algorithm



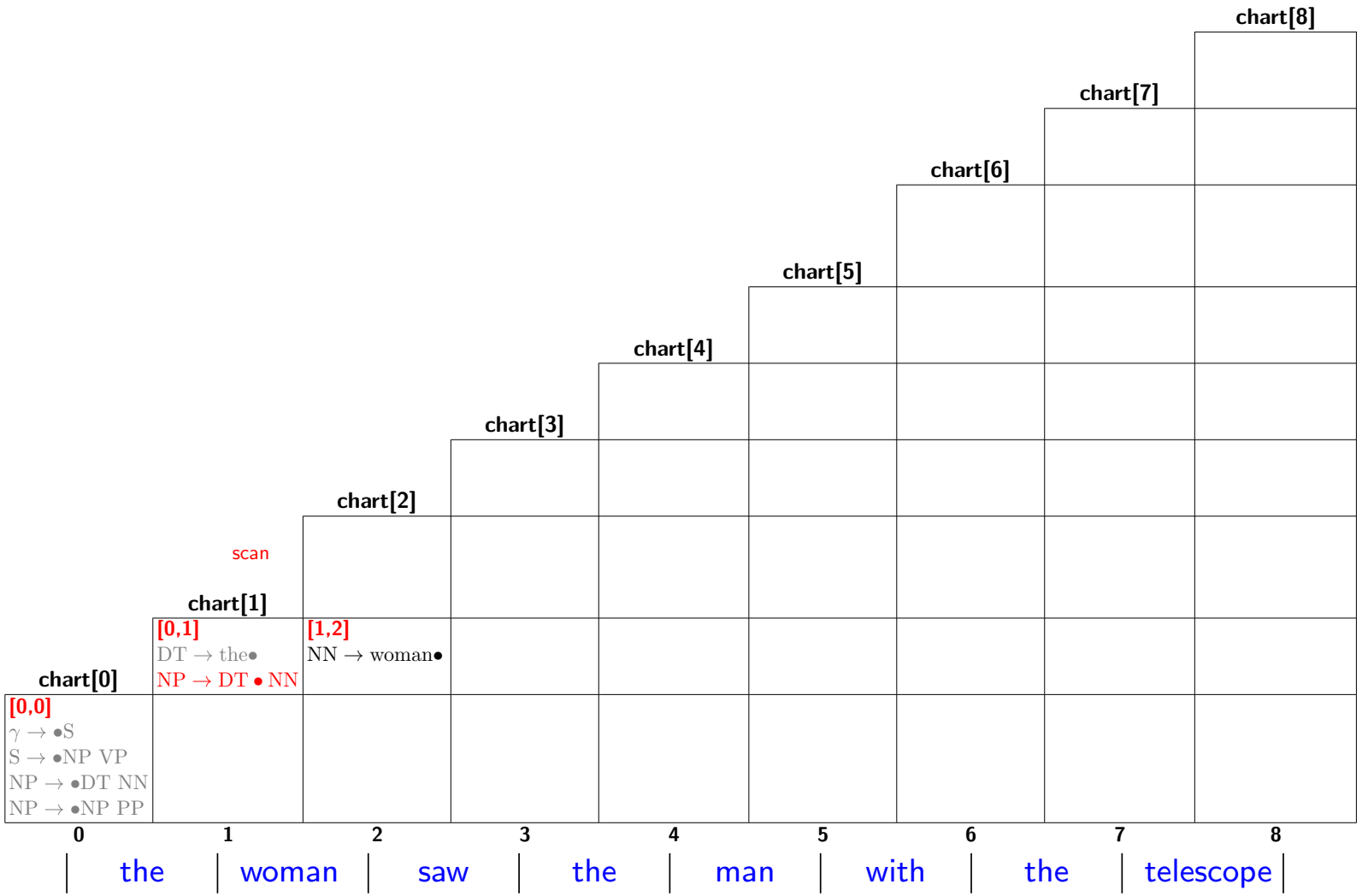
Earley Algorithm



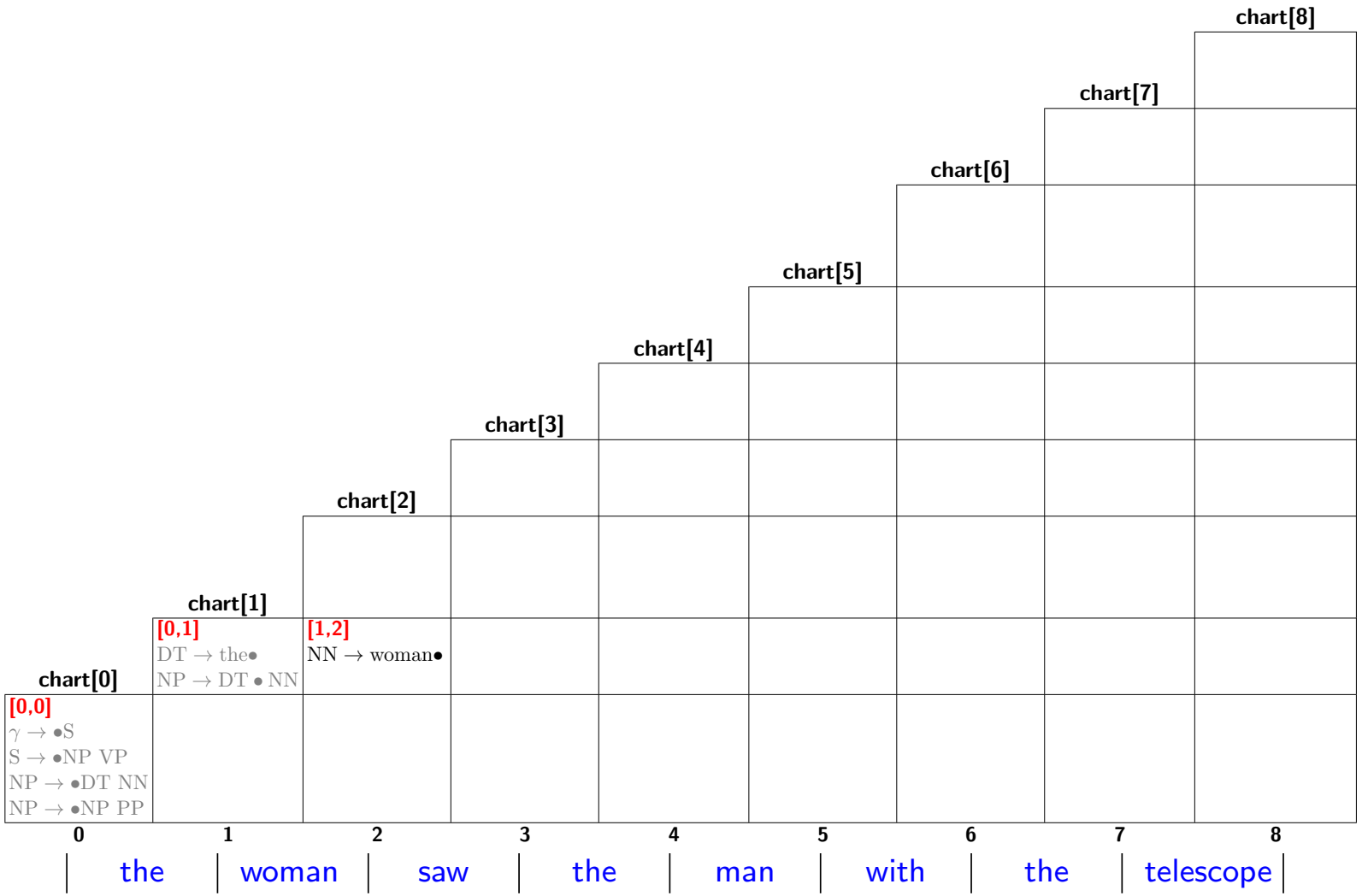
Earley Algorithm



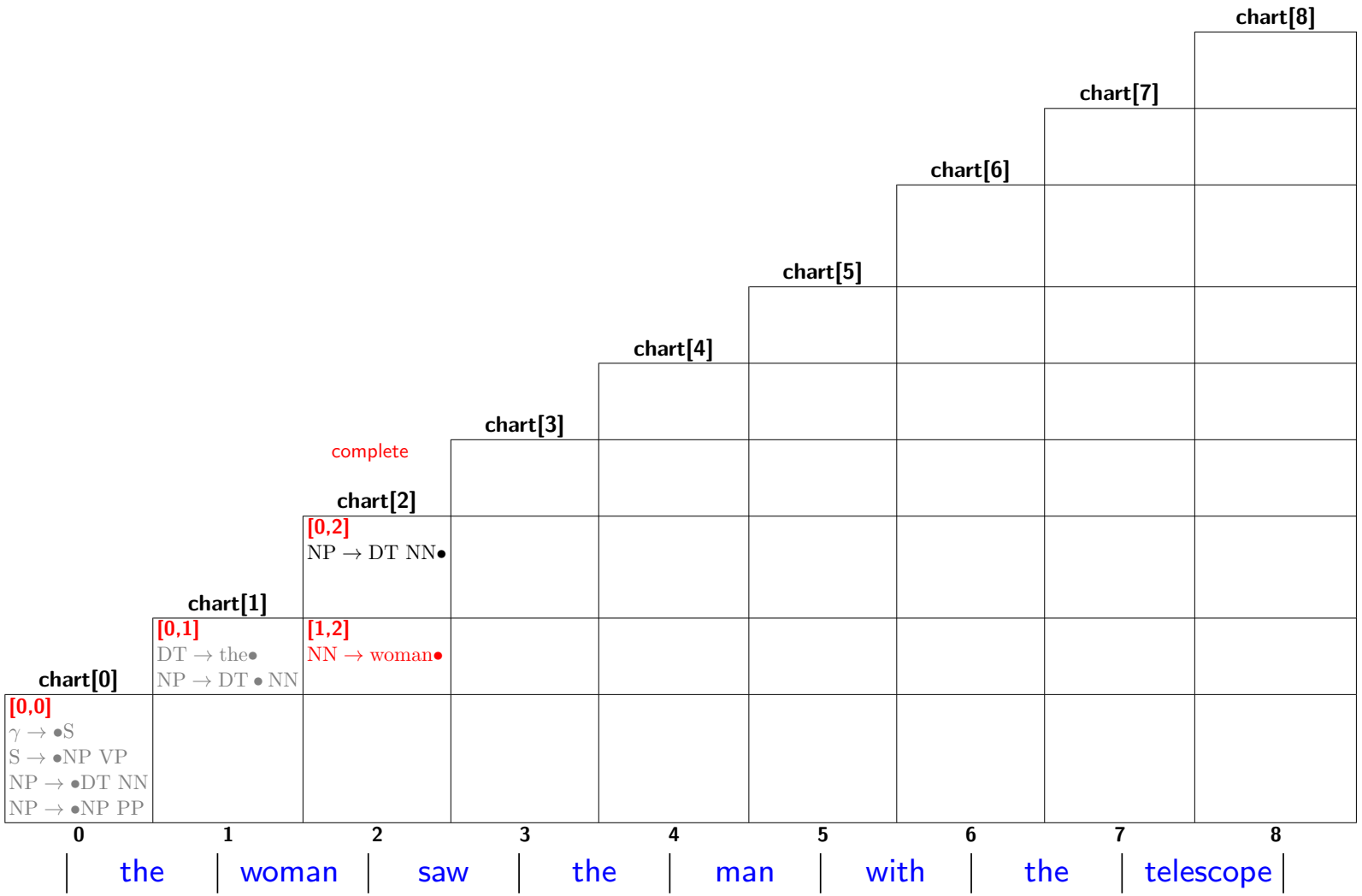
Earley Algorithm



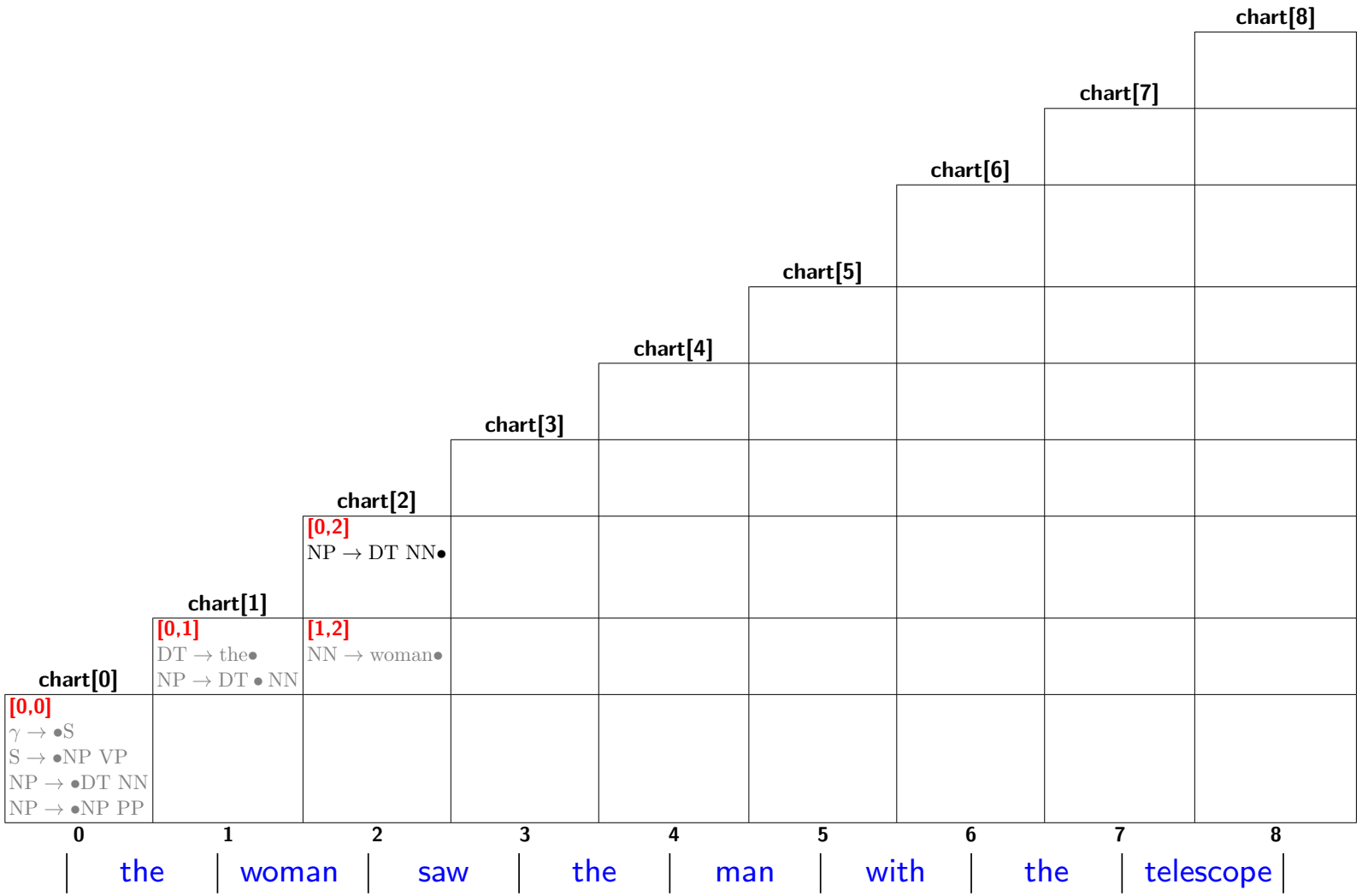
Earley Algorithm



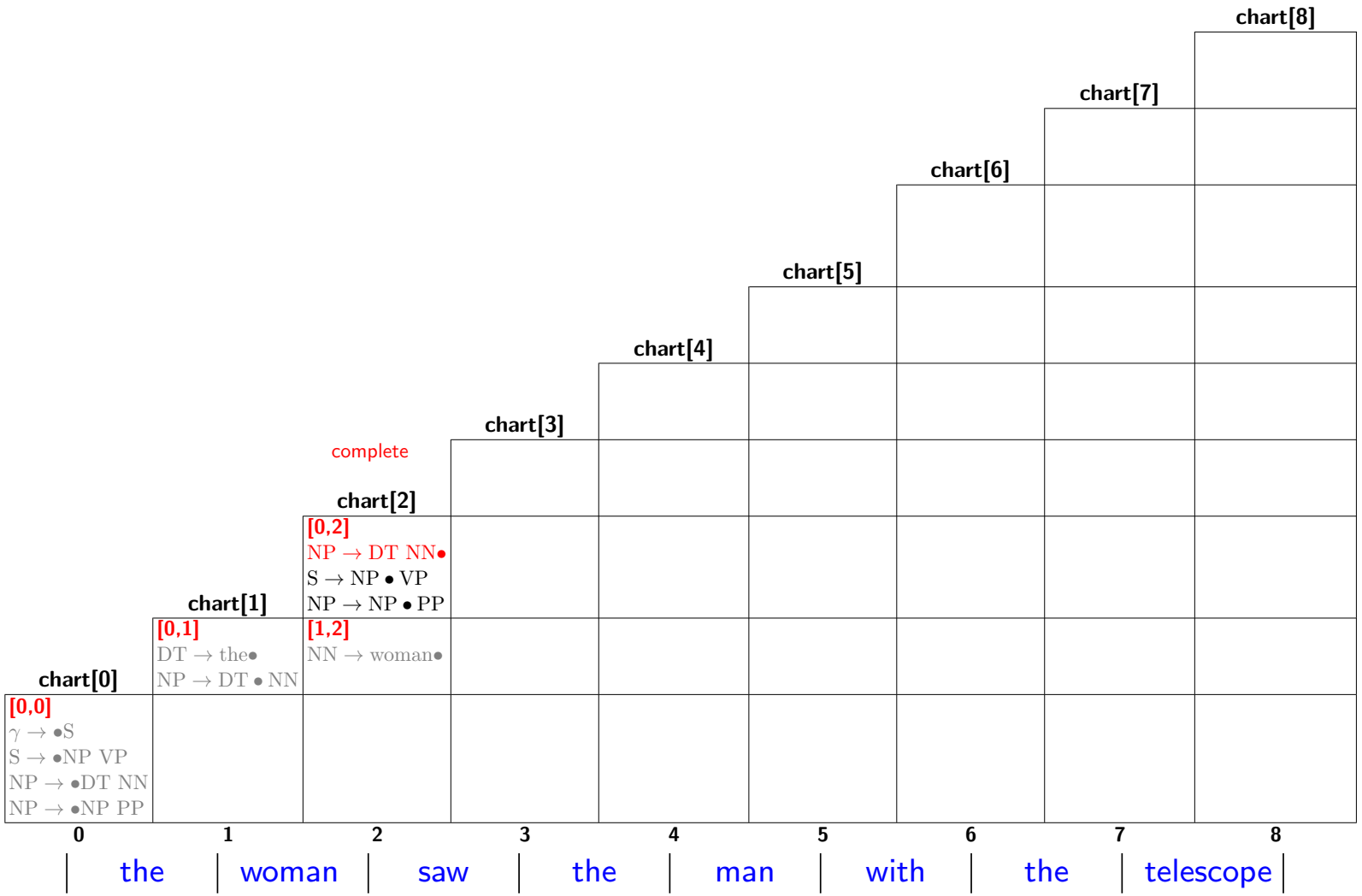
Earley Algorithm



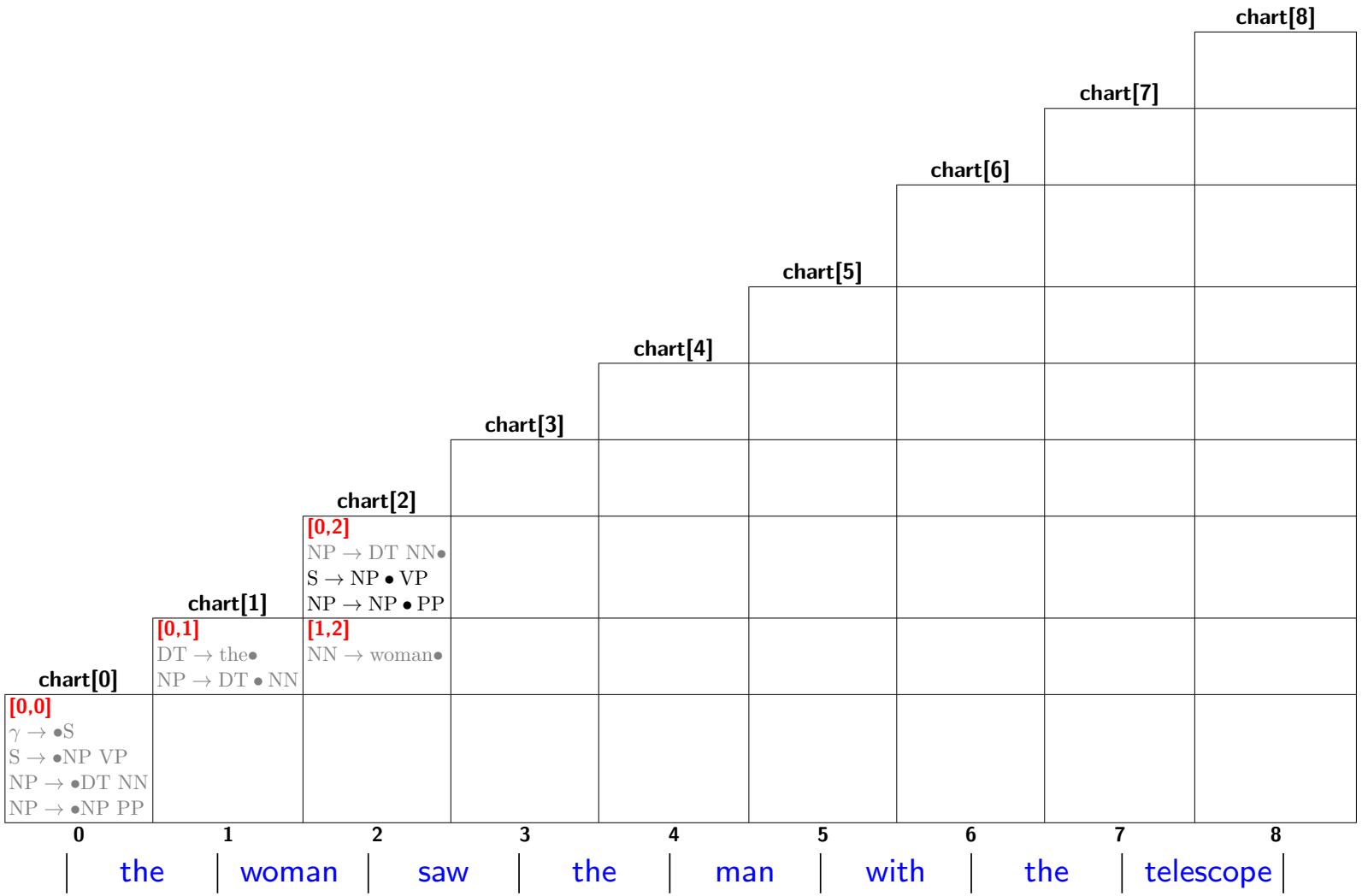
Earley Algorithm



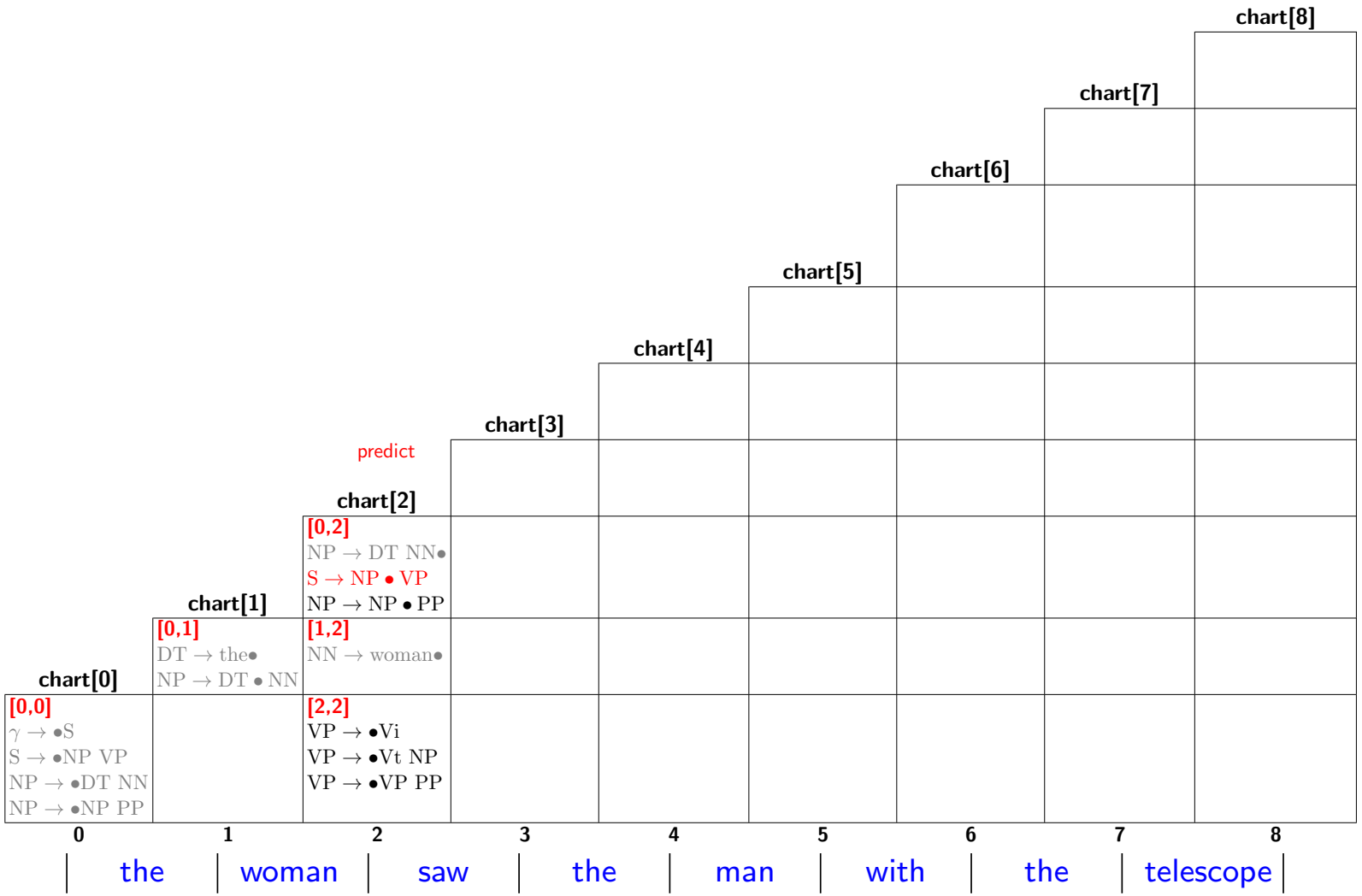
Earley Algorithm



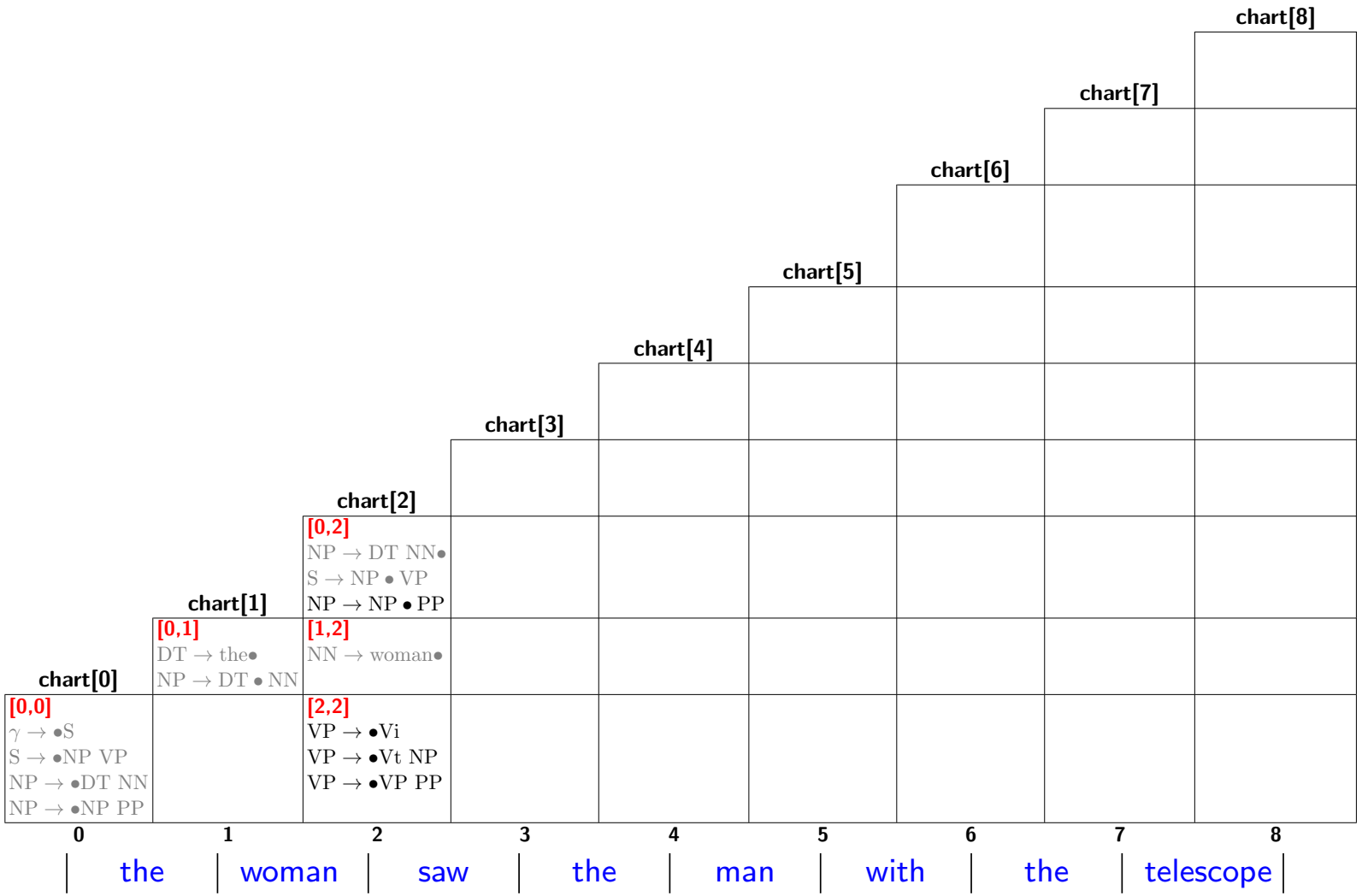
Earley Algorithm



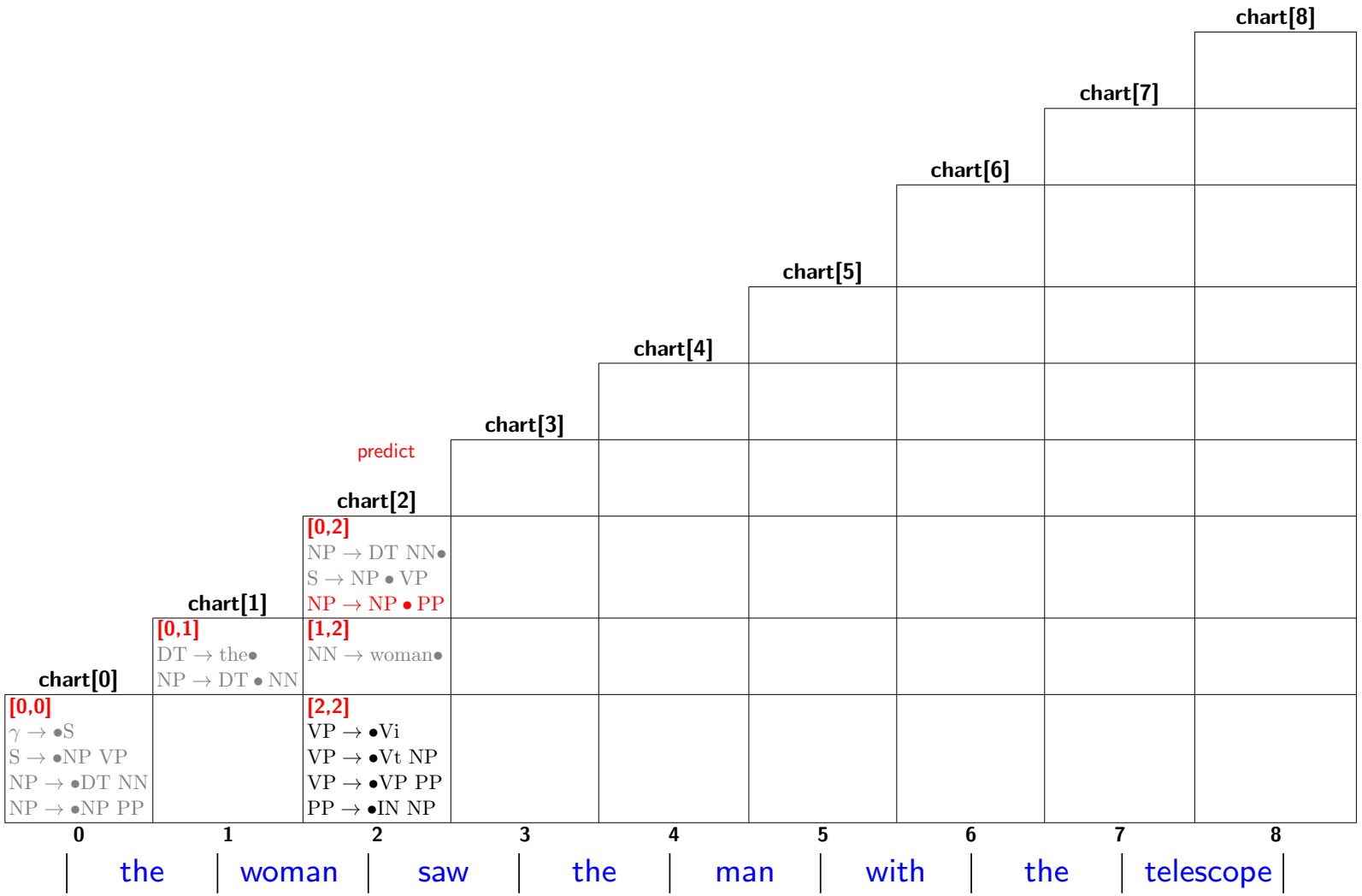
Earley Algorithm



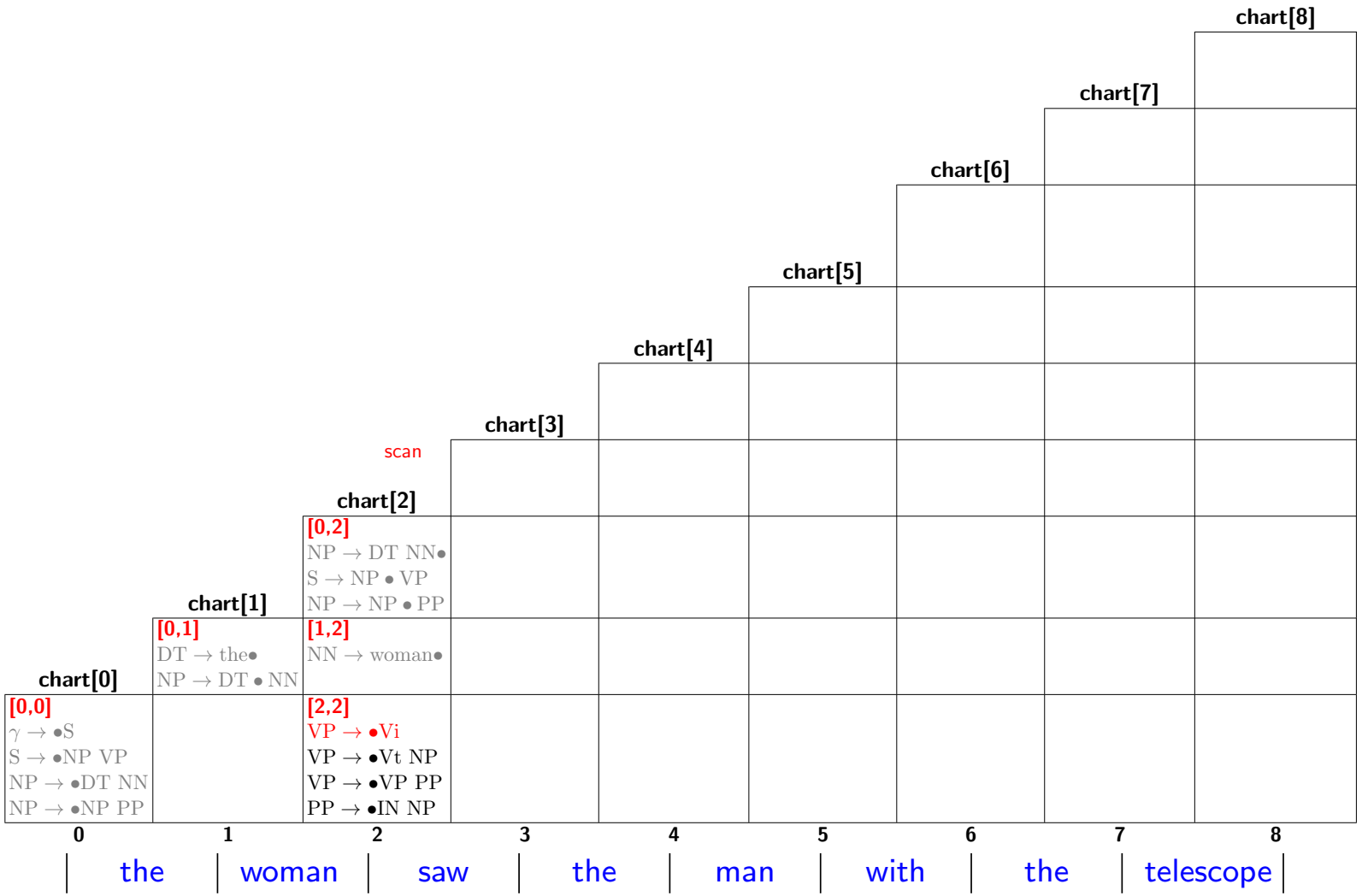
Earley Algorithm



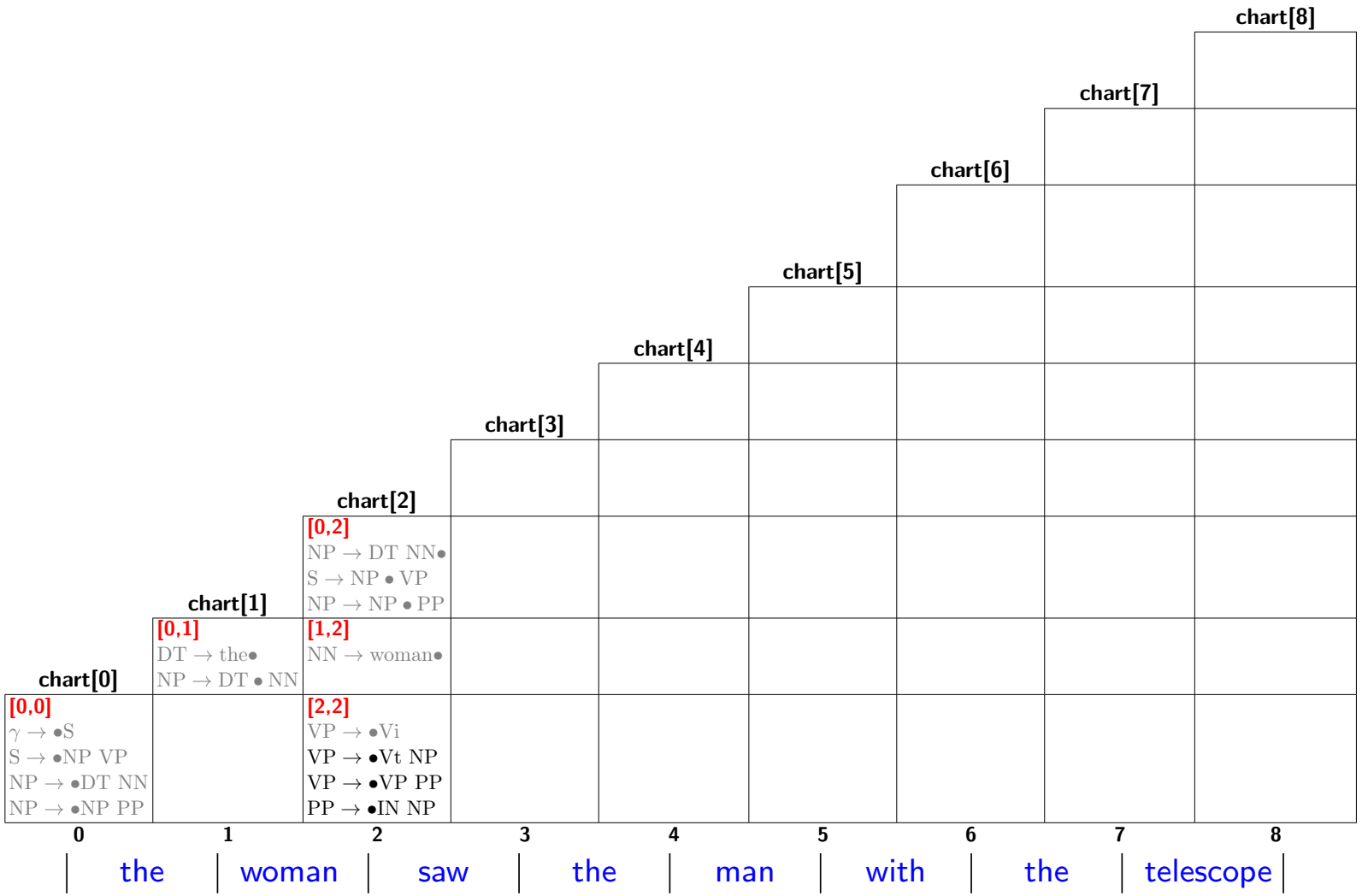
Earley Algorithm



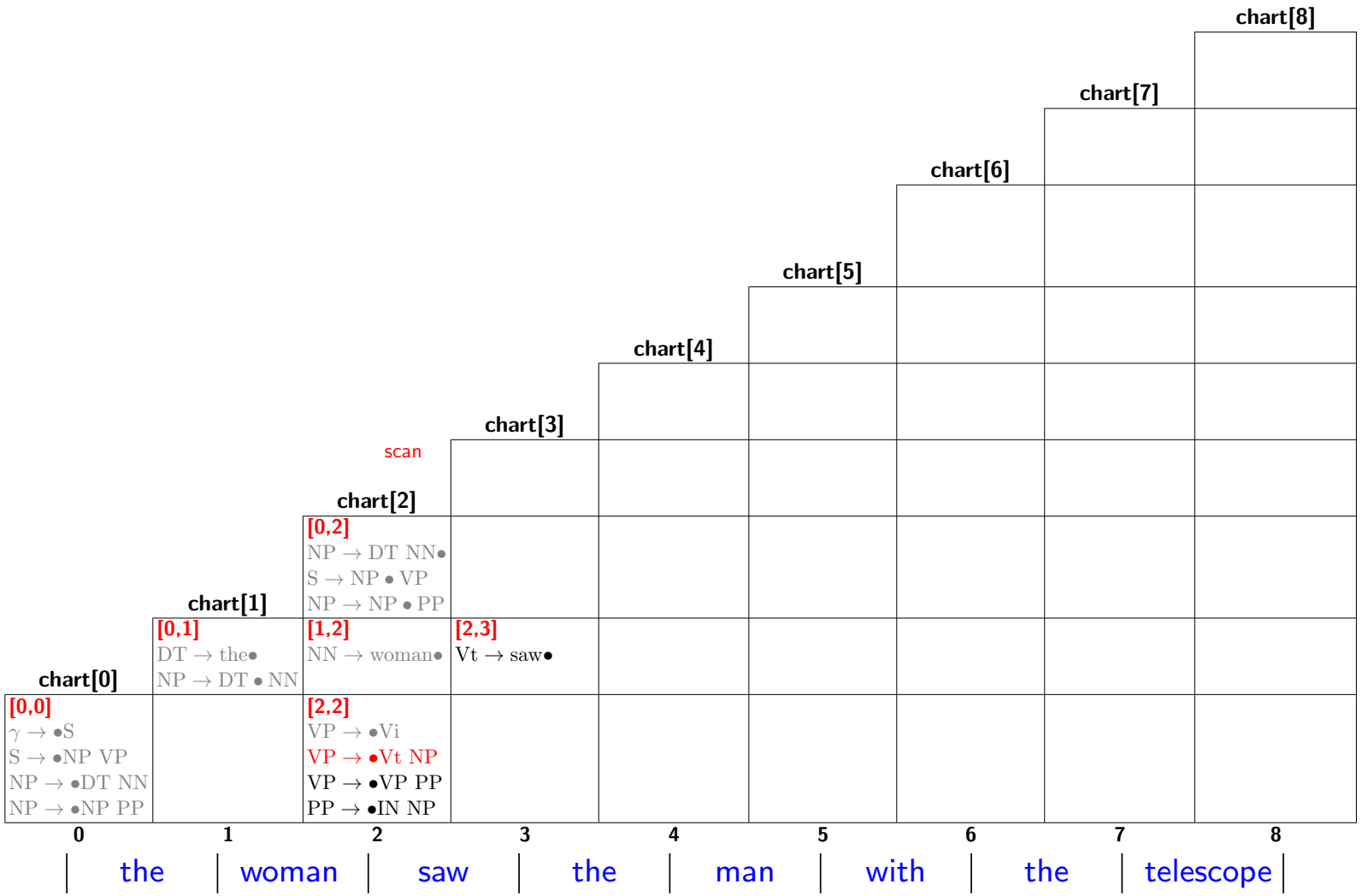
Earley Algorithm



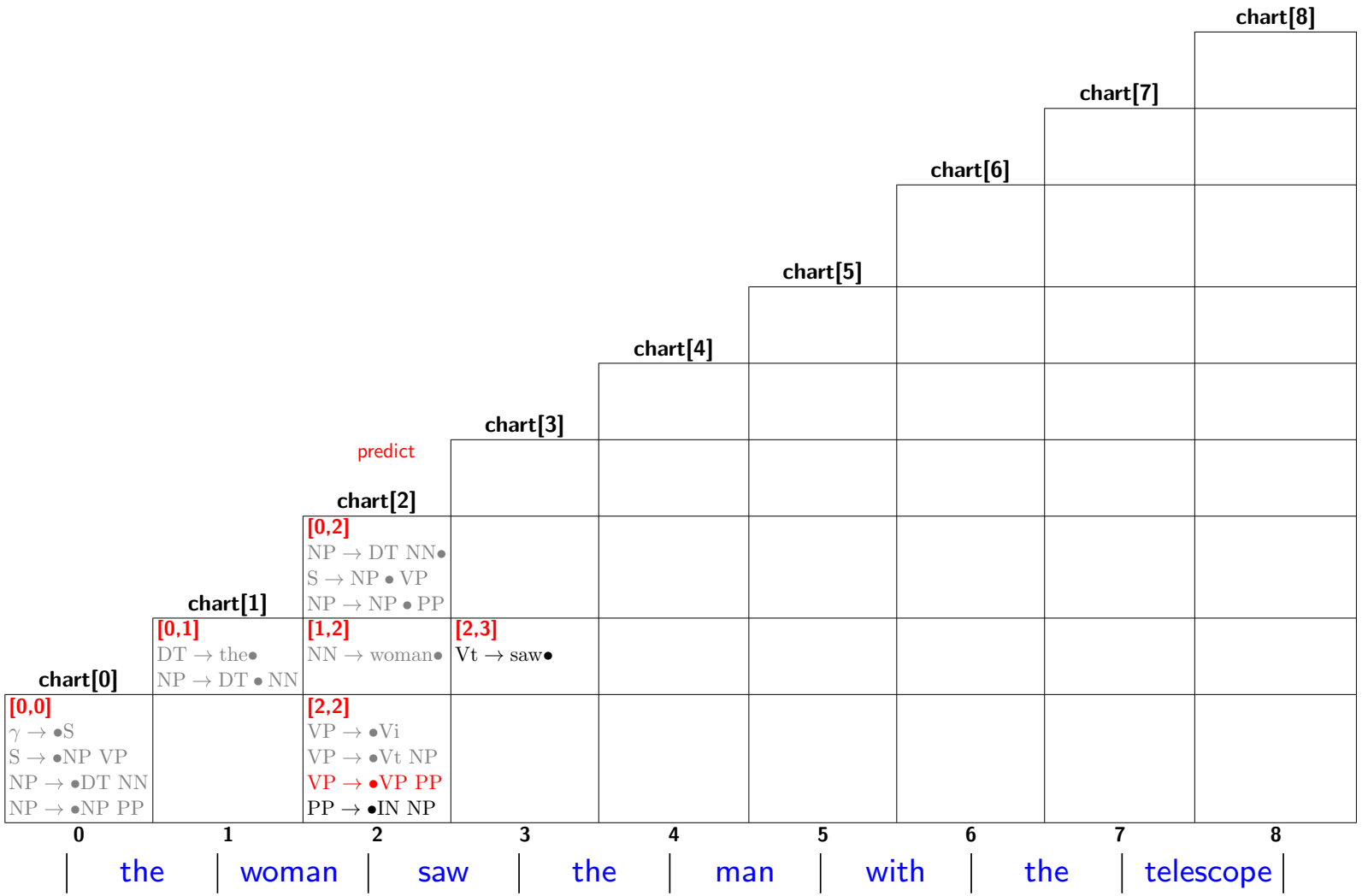
Earley Algorithm



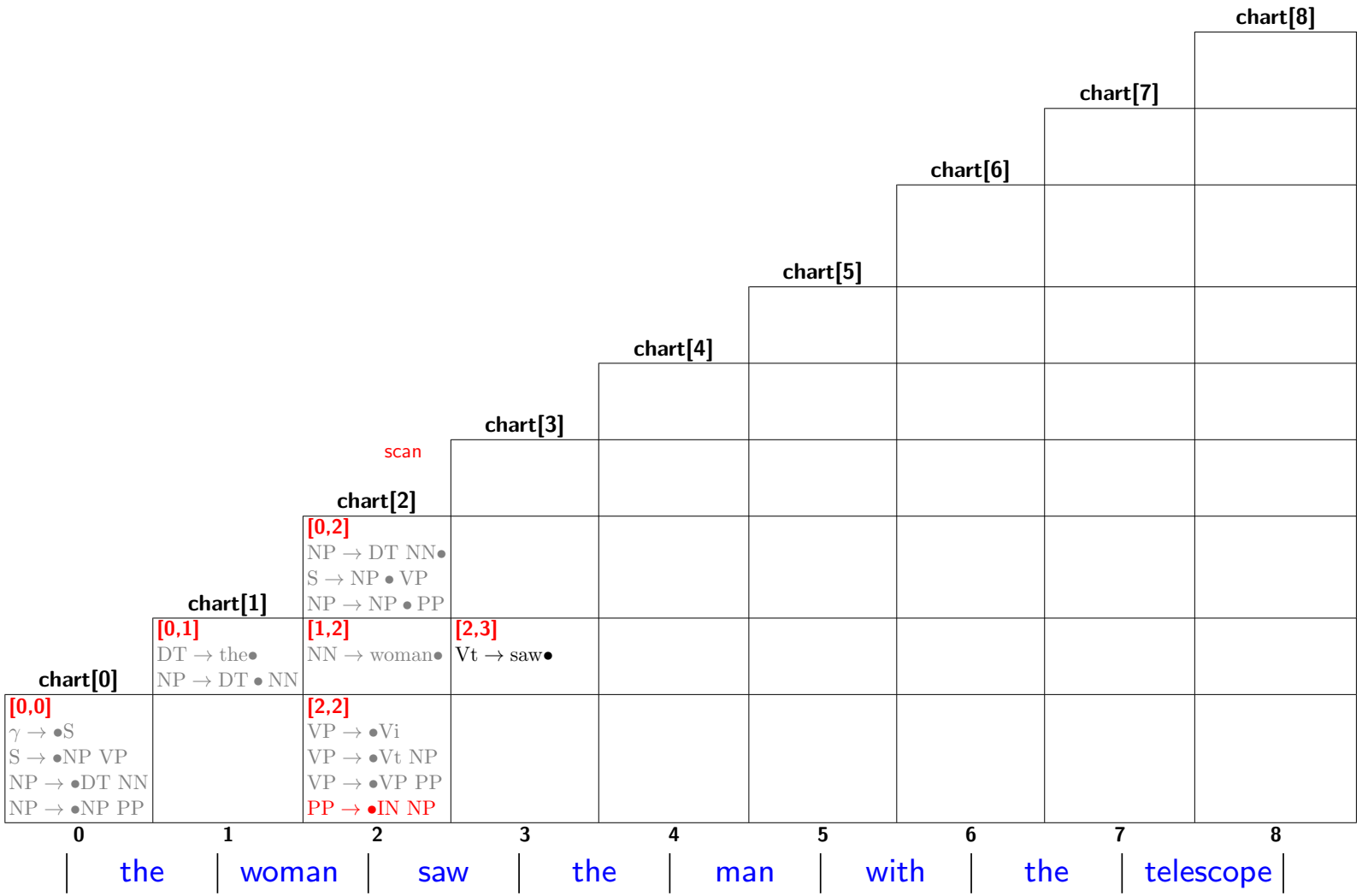
Earley Algorithm



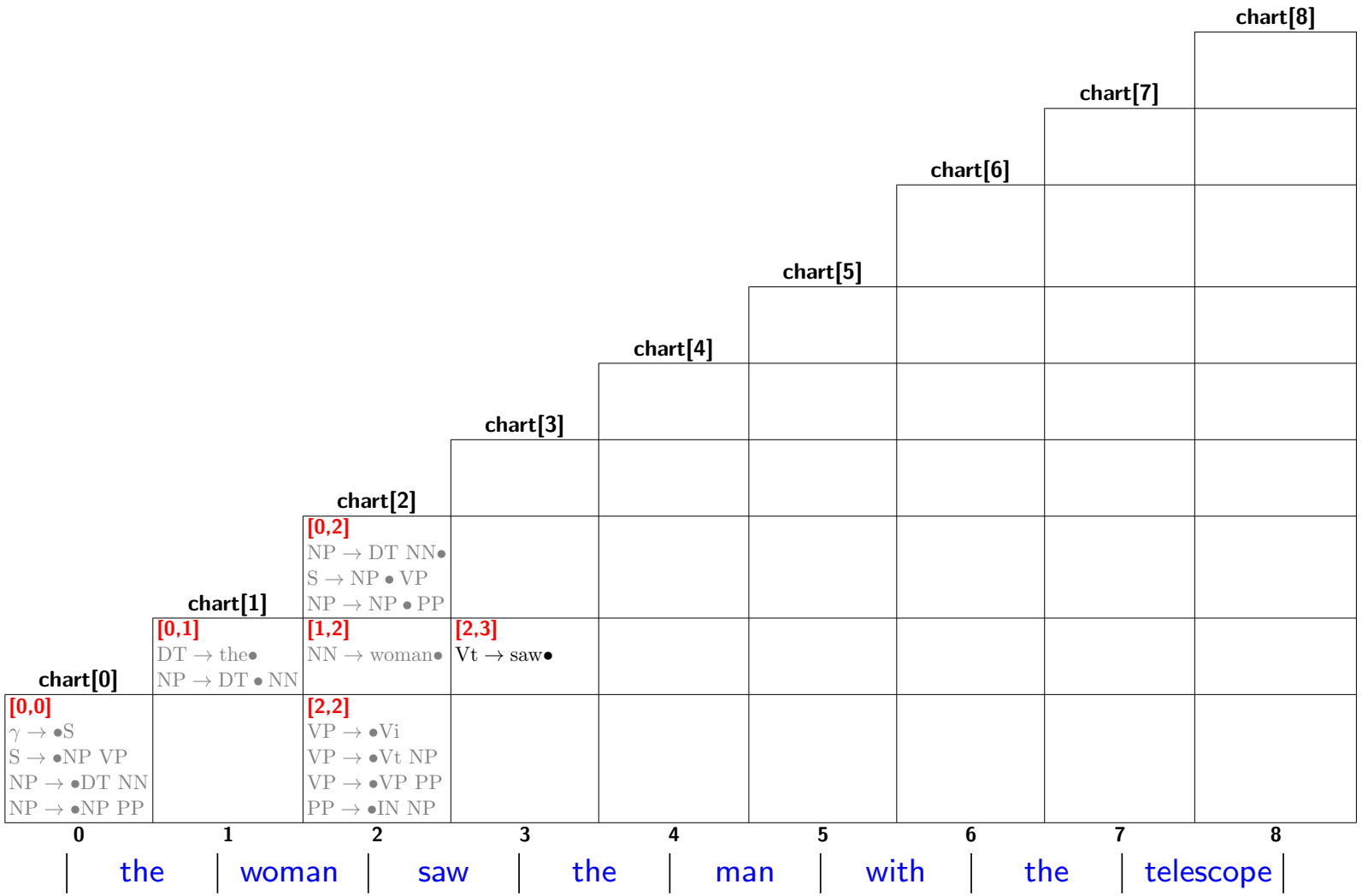
Earley Algorithm



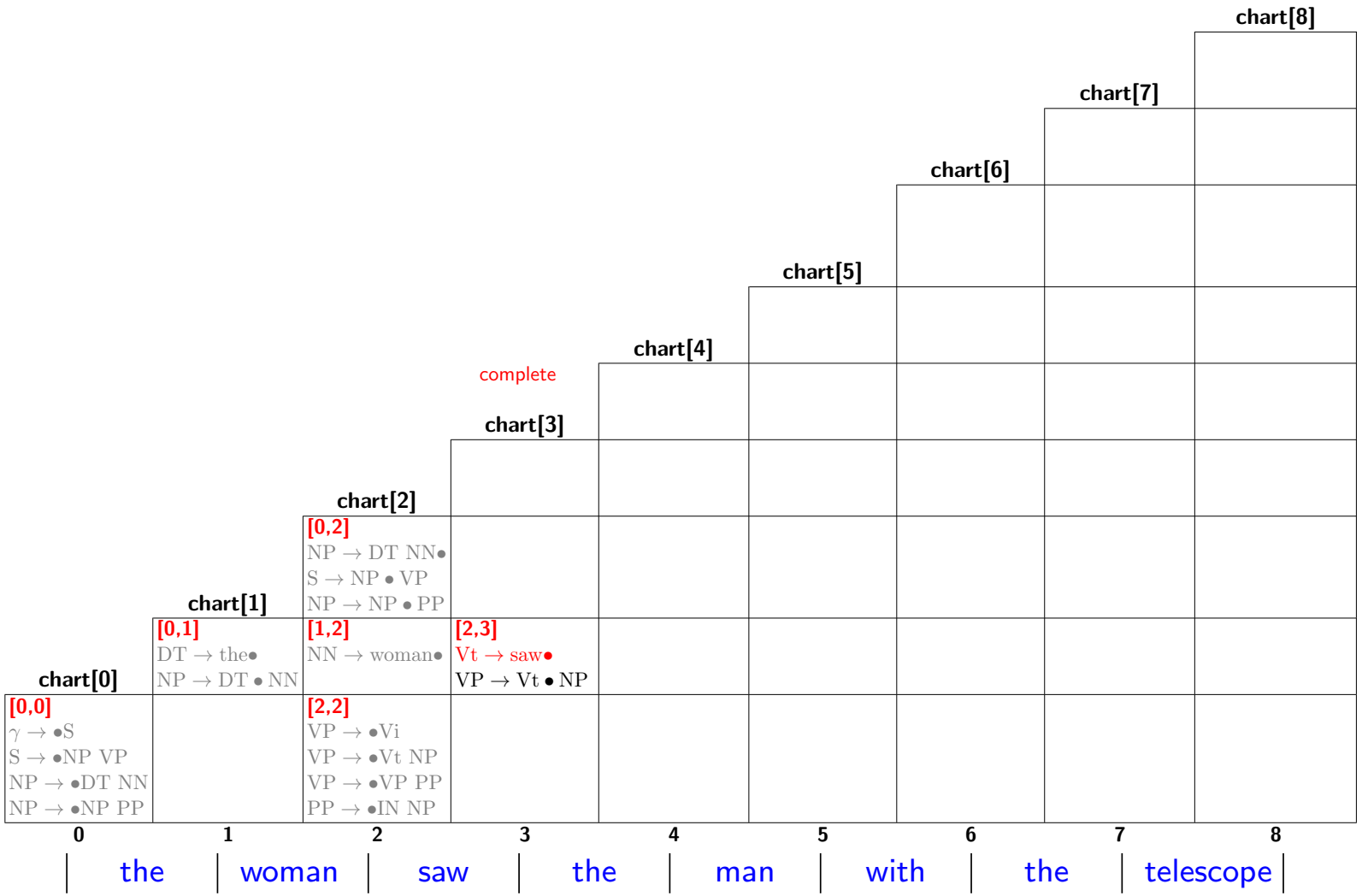
Earley Algorithm



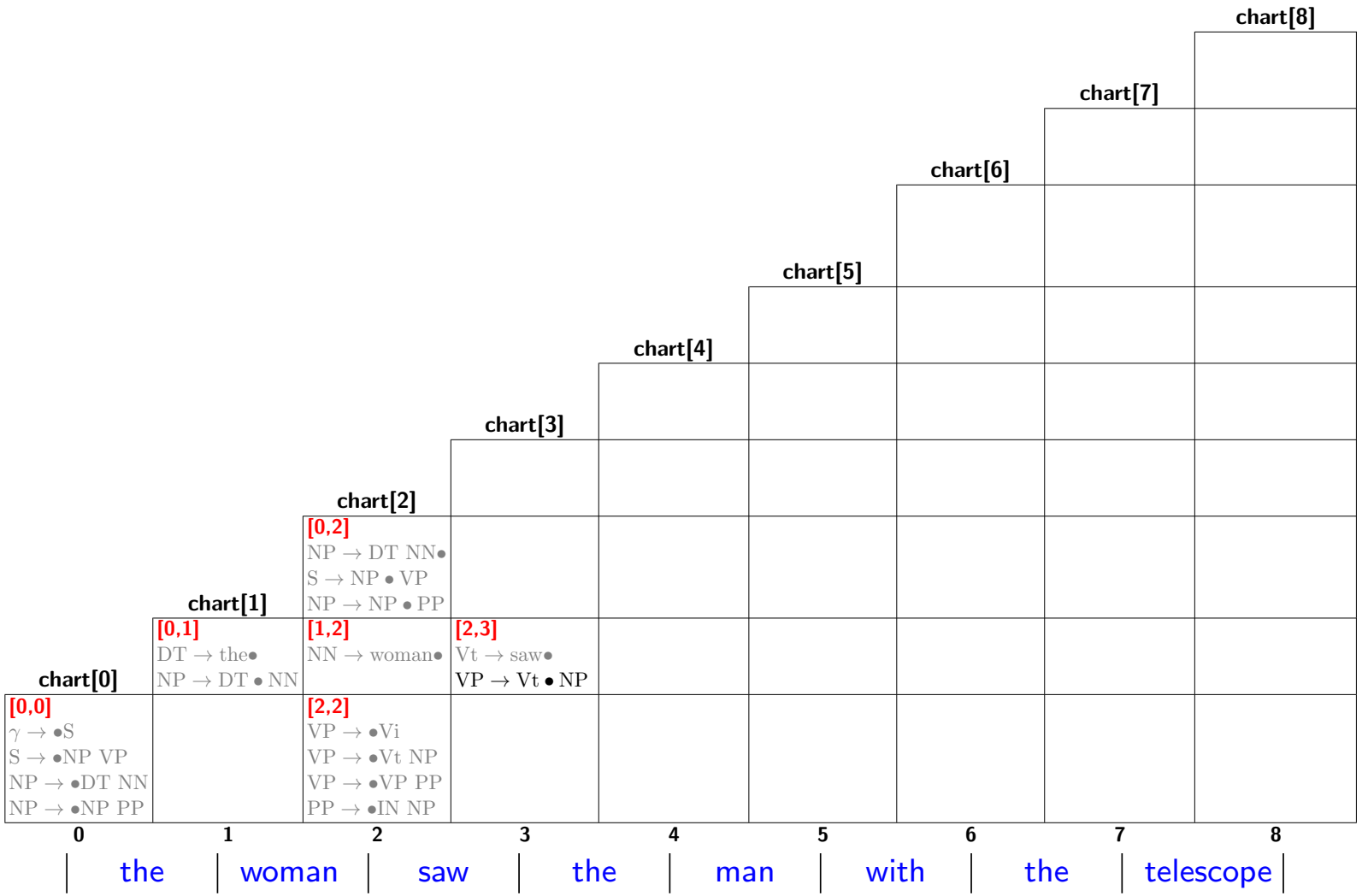
Earley Algorithm



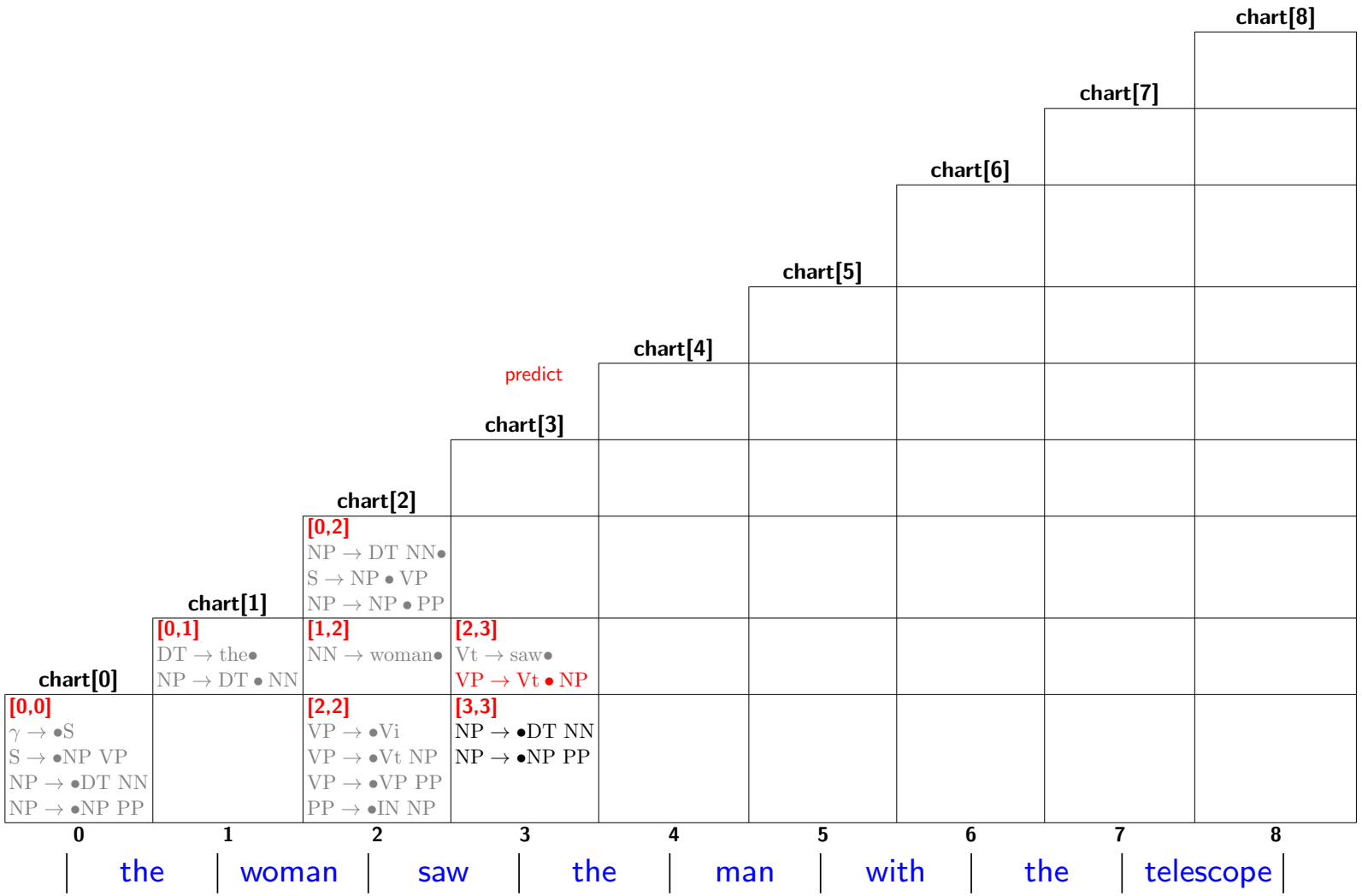
Earley Algorithm



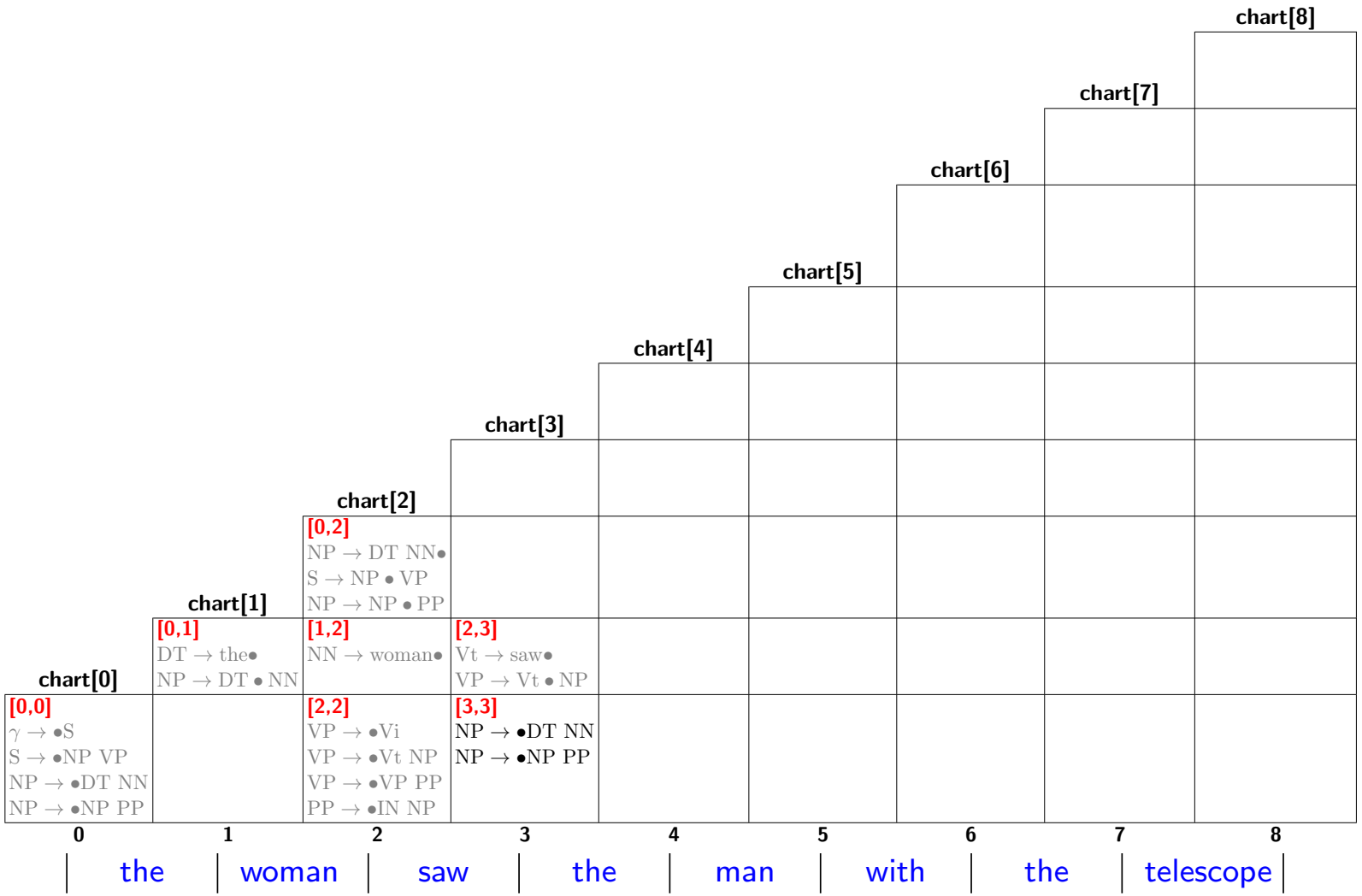
Earley Algorithm



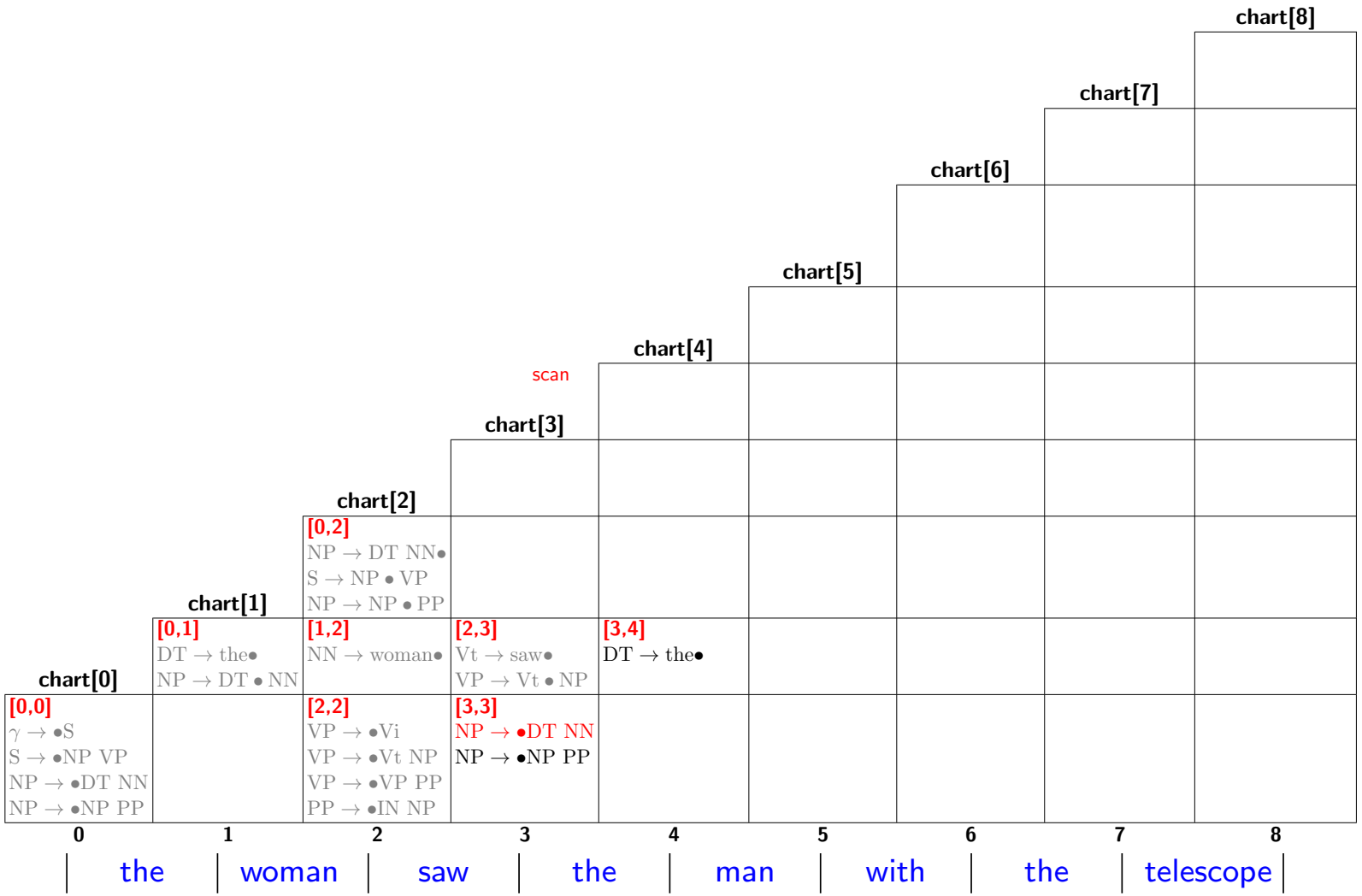
Earley Algorithm



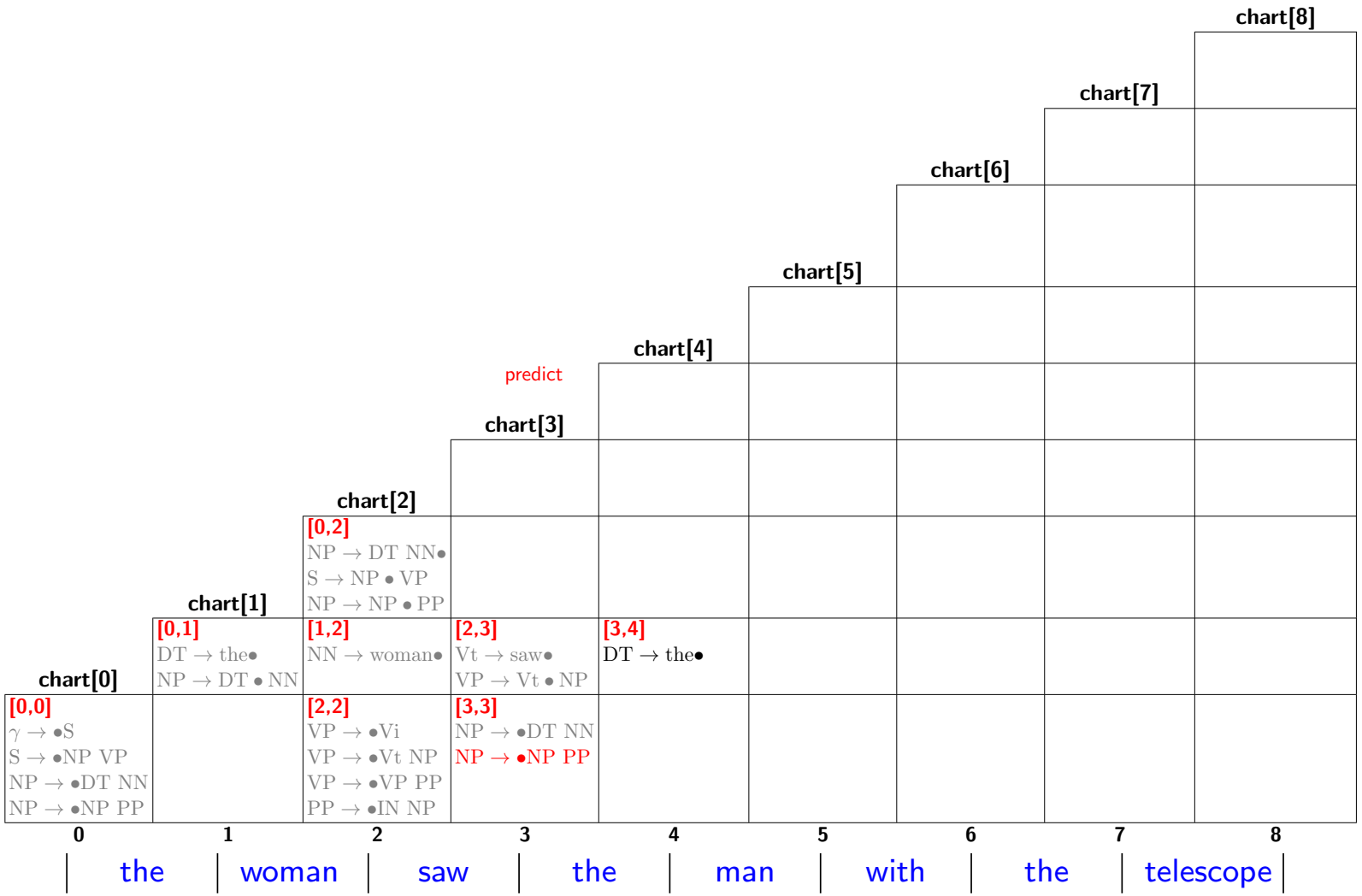
Earley Algorithm



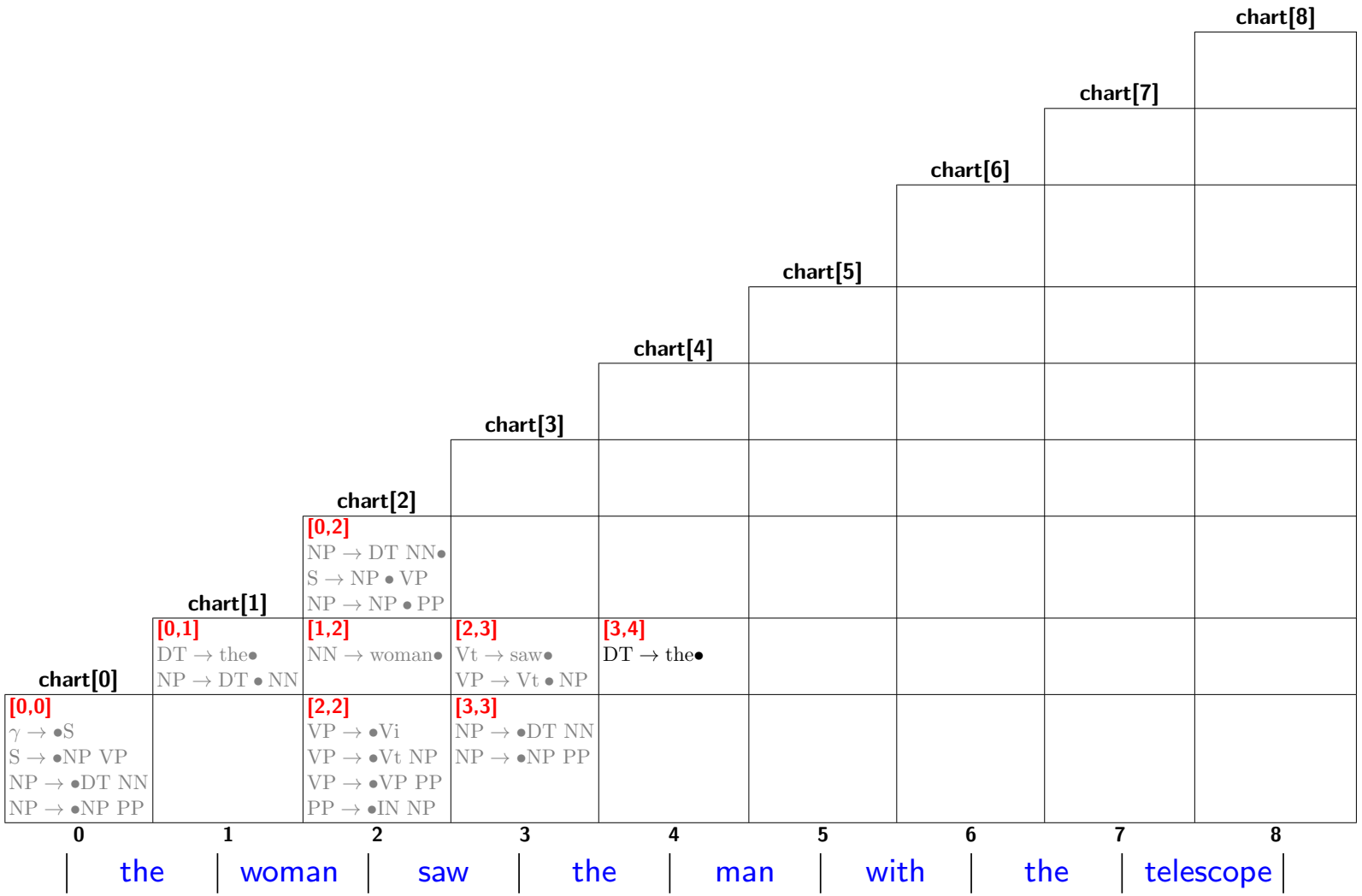
Earley Algorithm



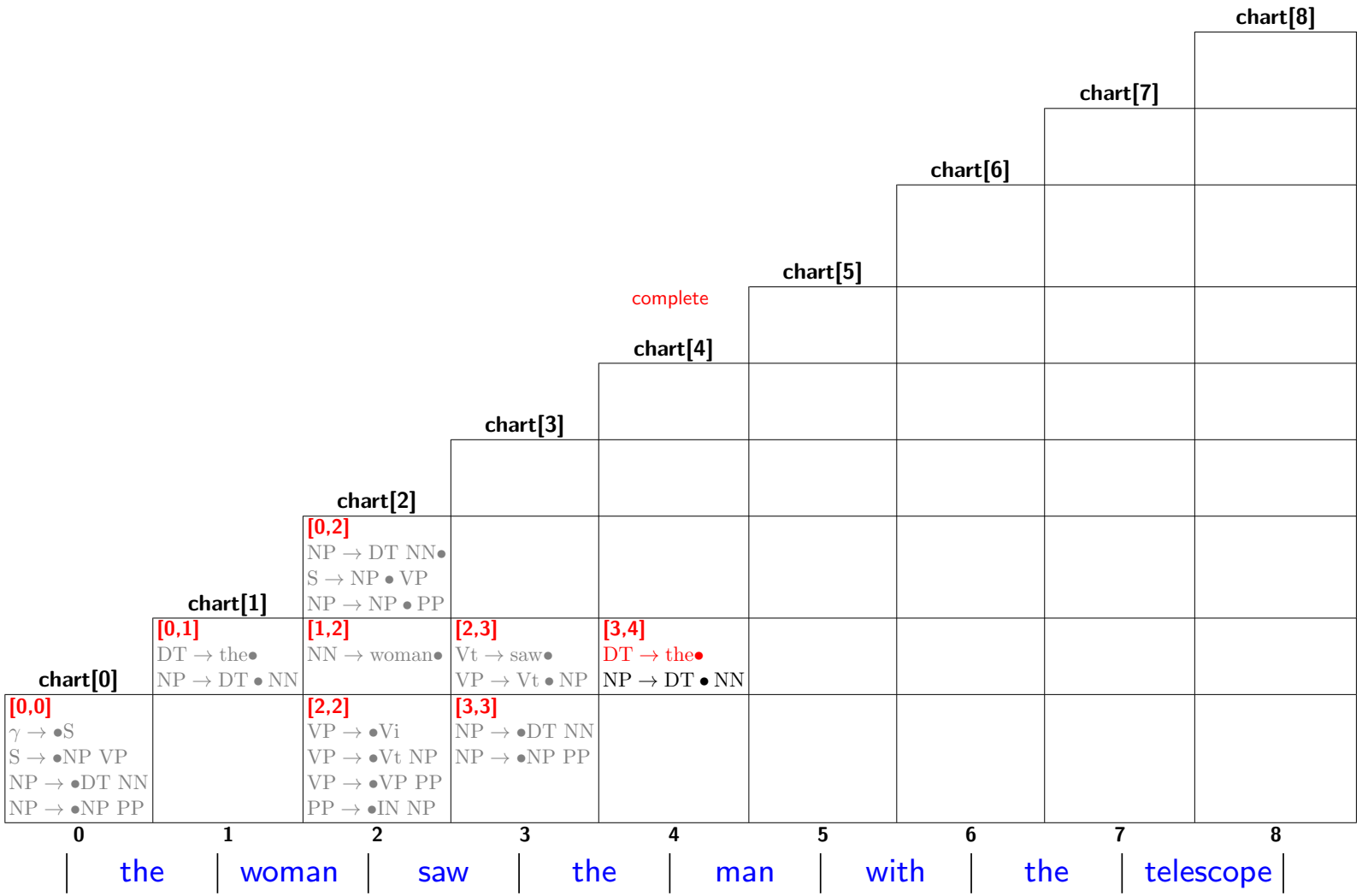
Earley Algorithm



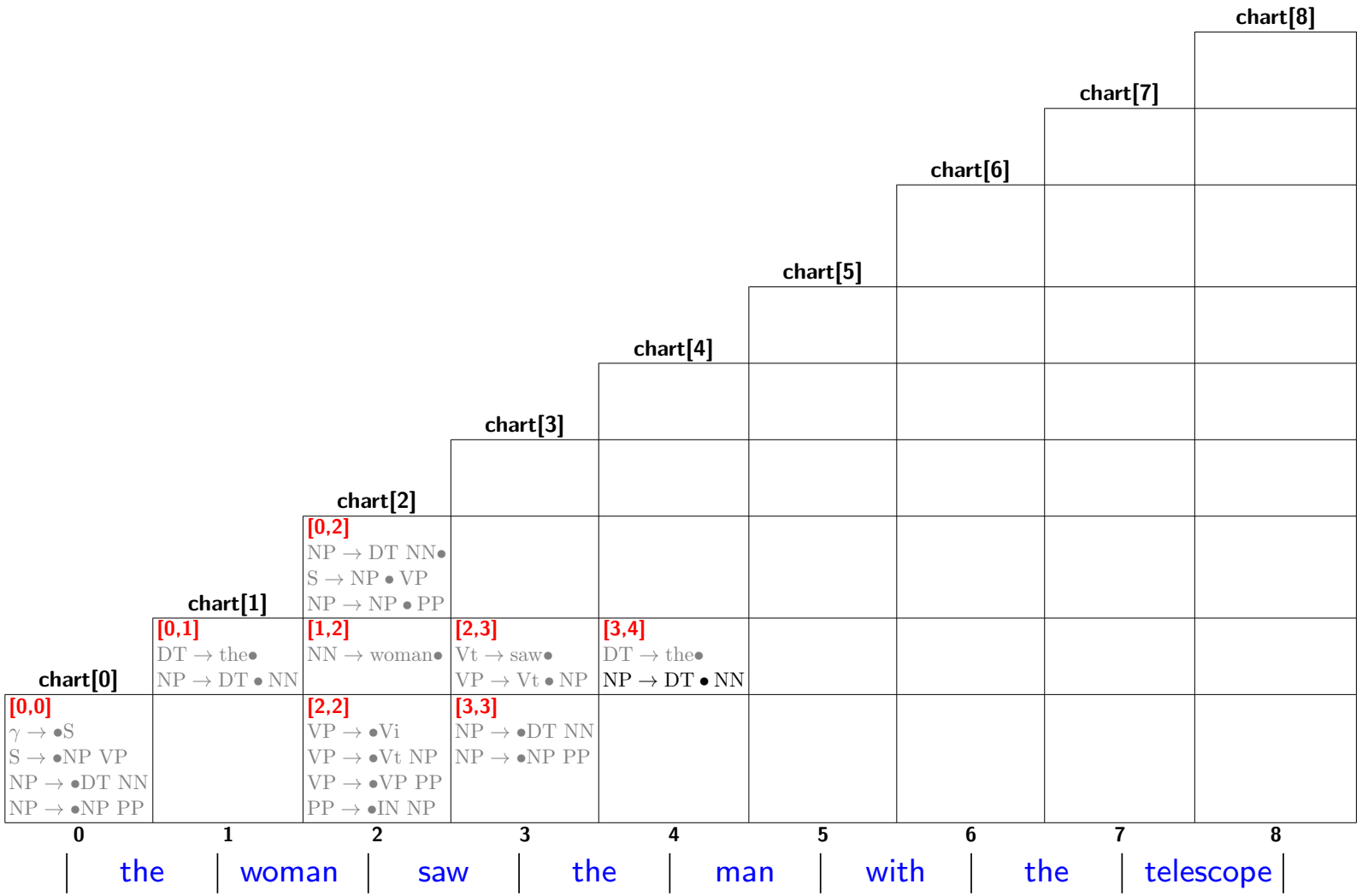
Earley Algorithm



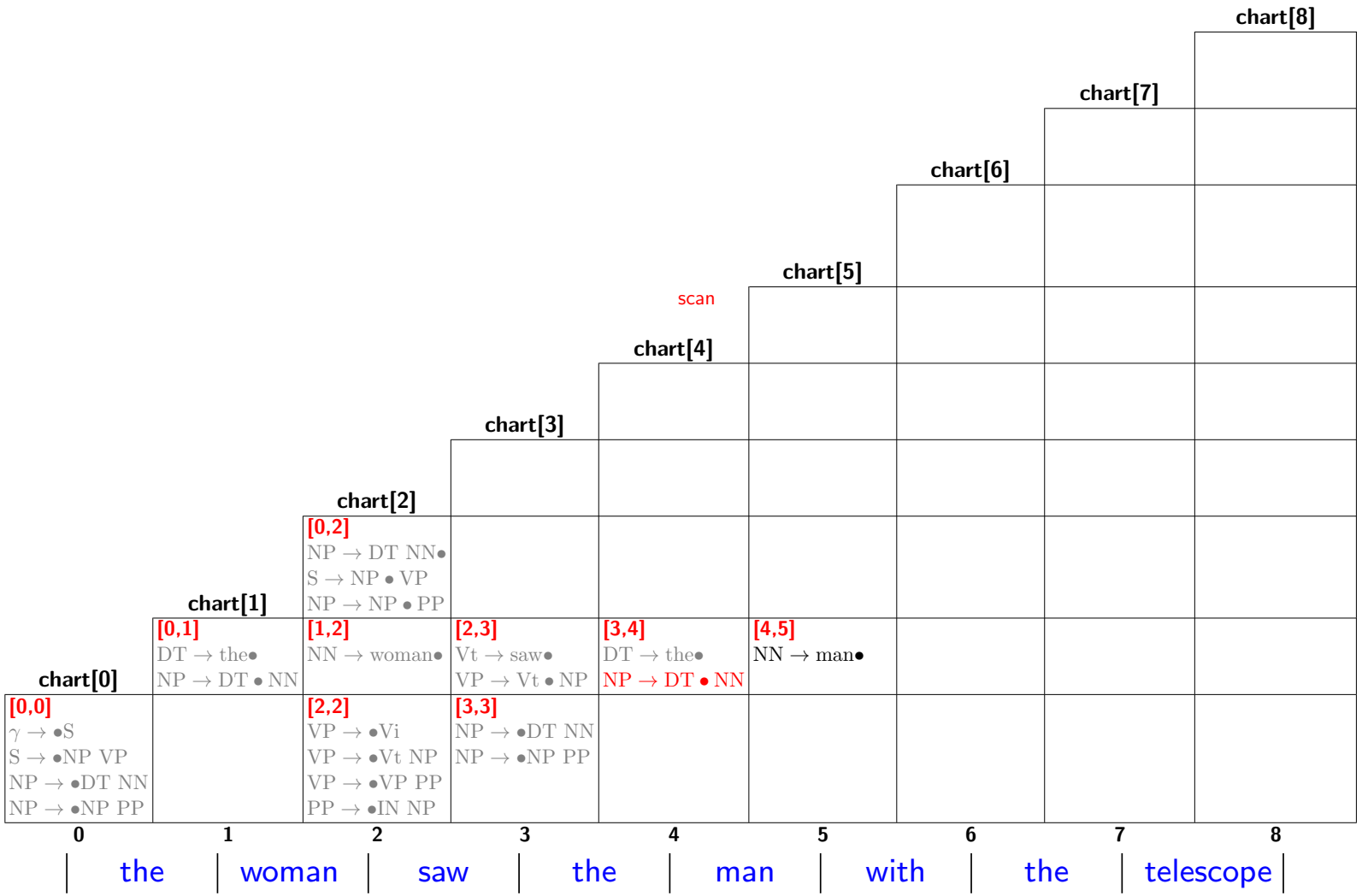
Earley Algorithm



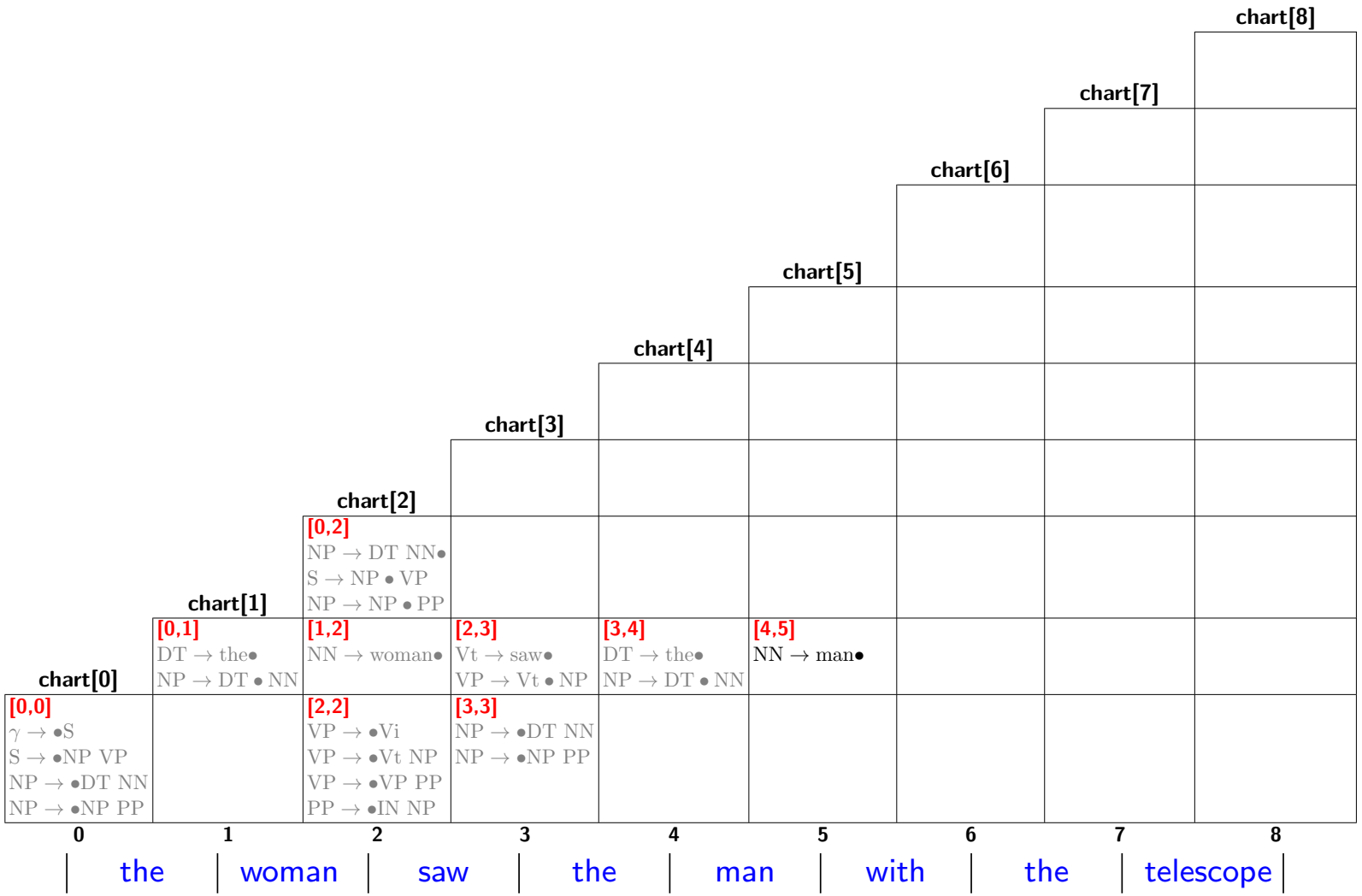
Earley Algorithm



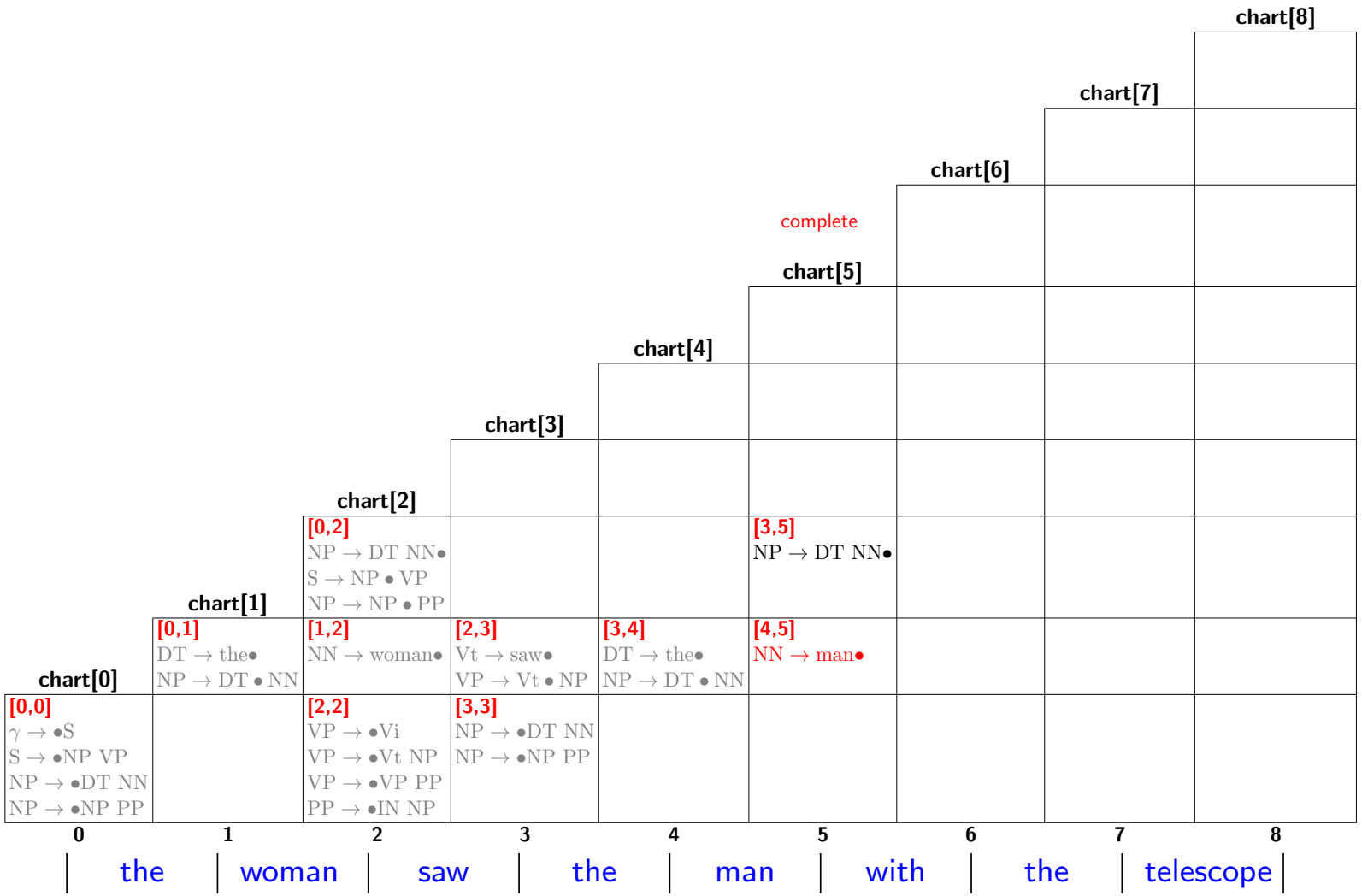
Earley Algorithm



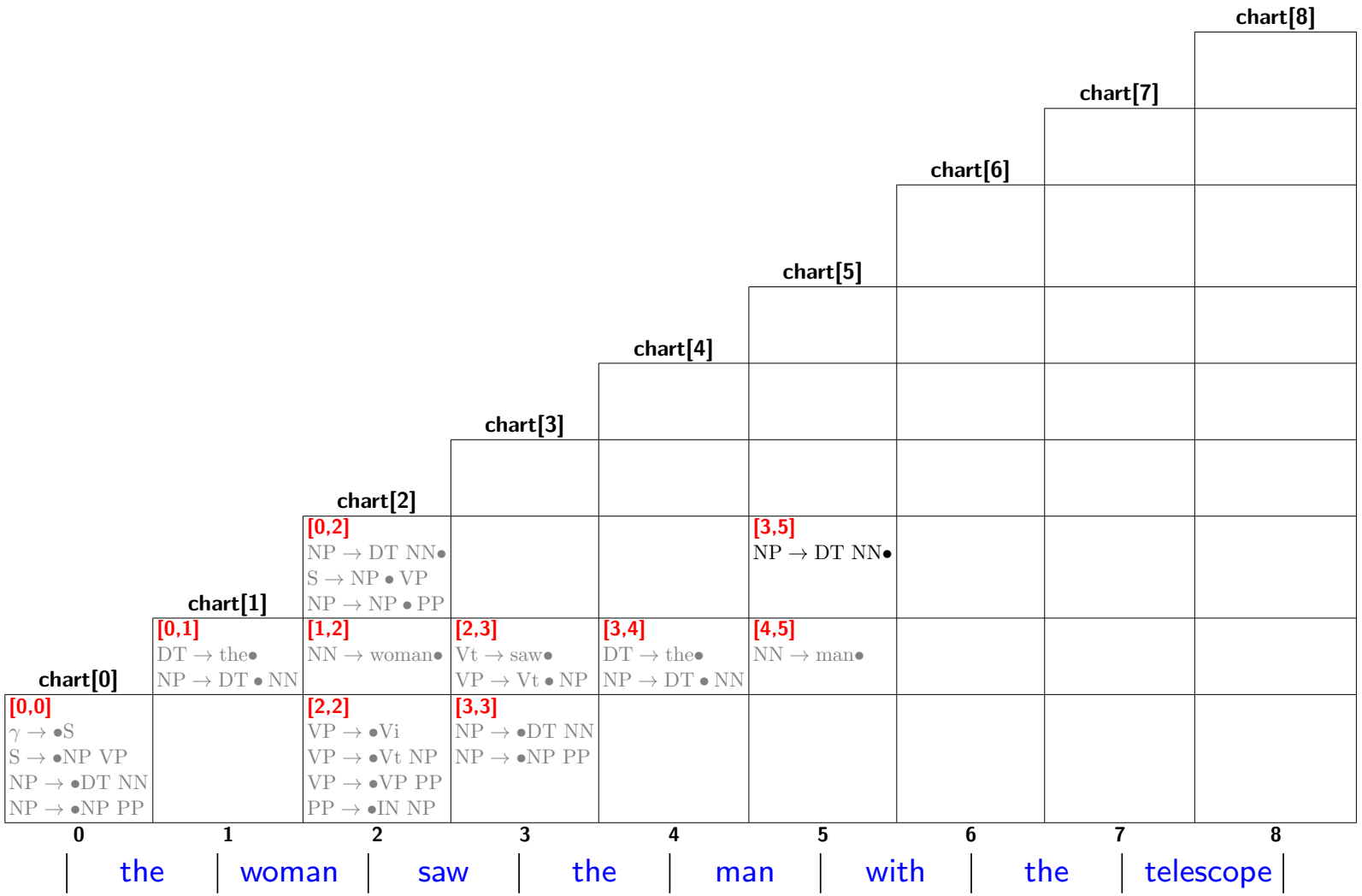
Earley Algorithm



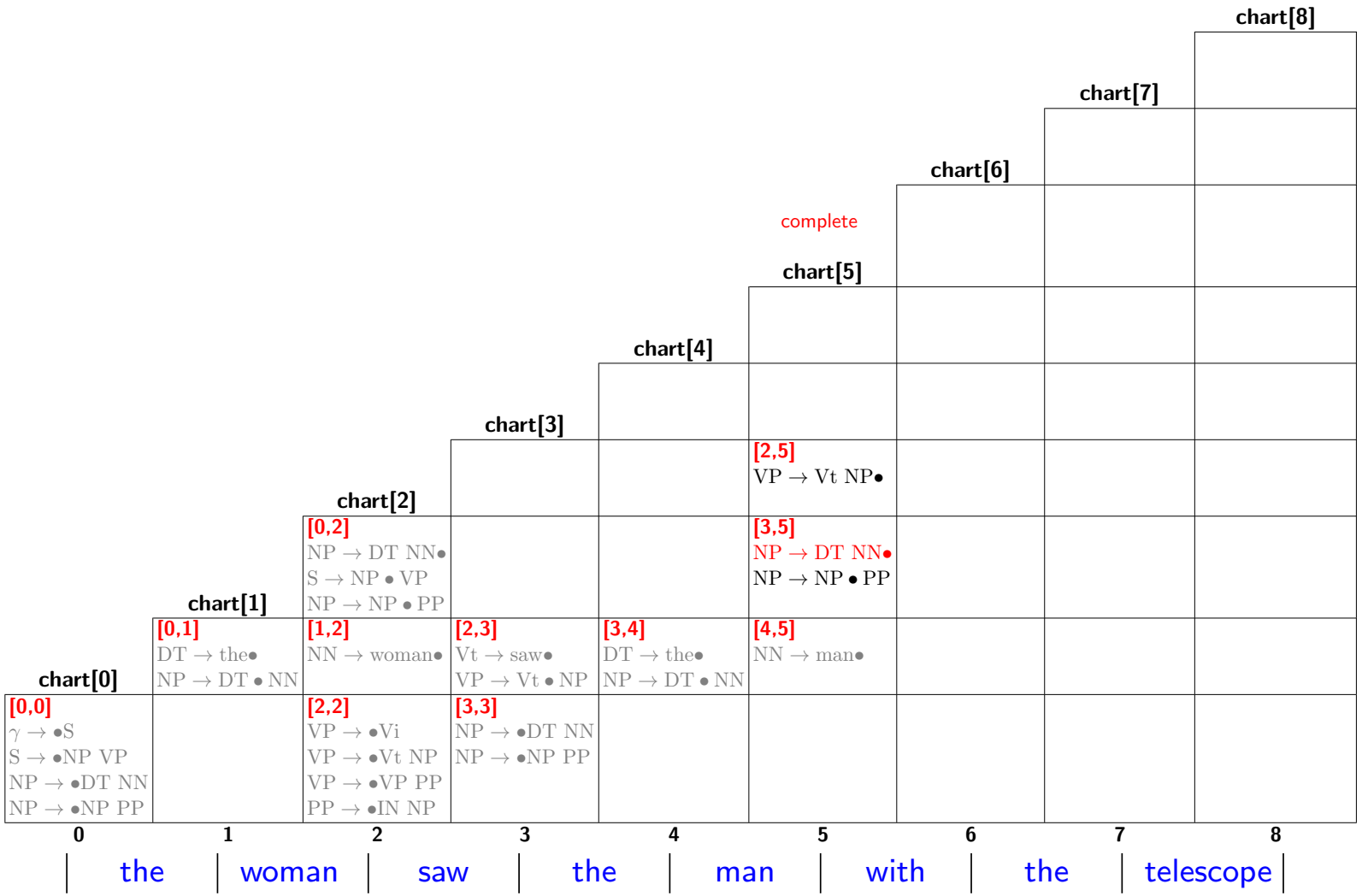
Earley Algorithm



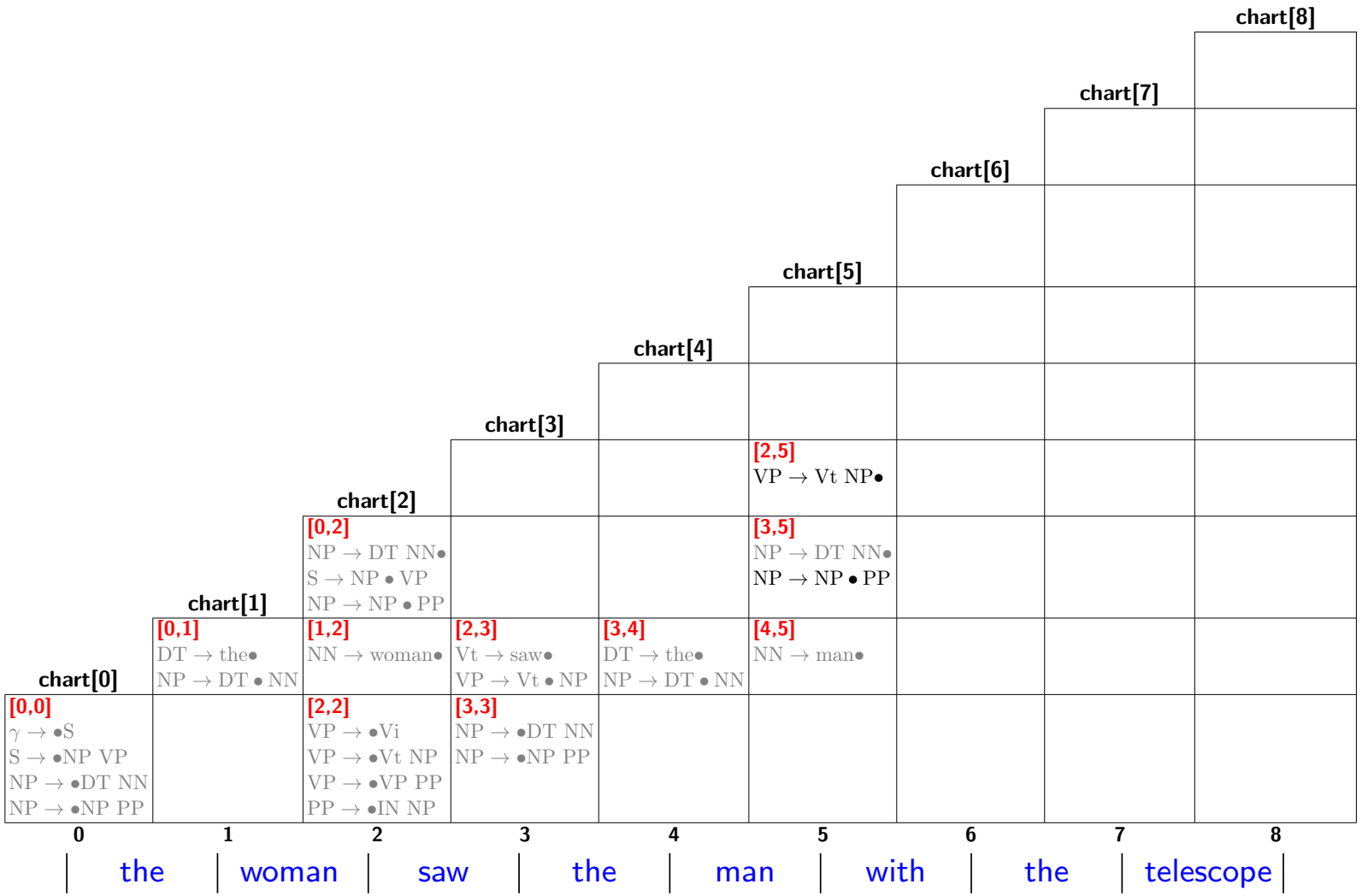
Earley Algorithm



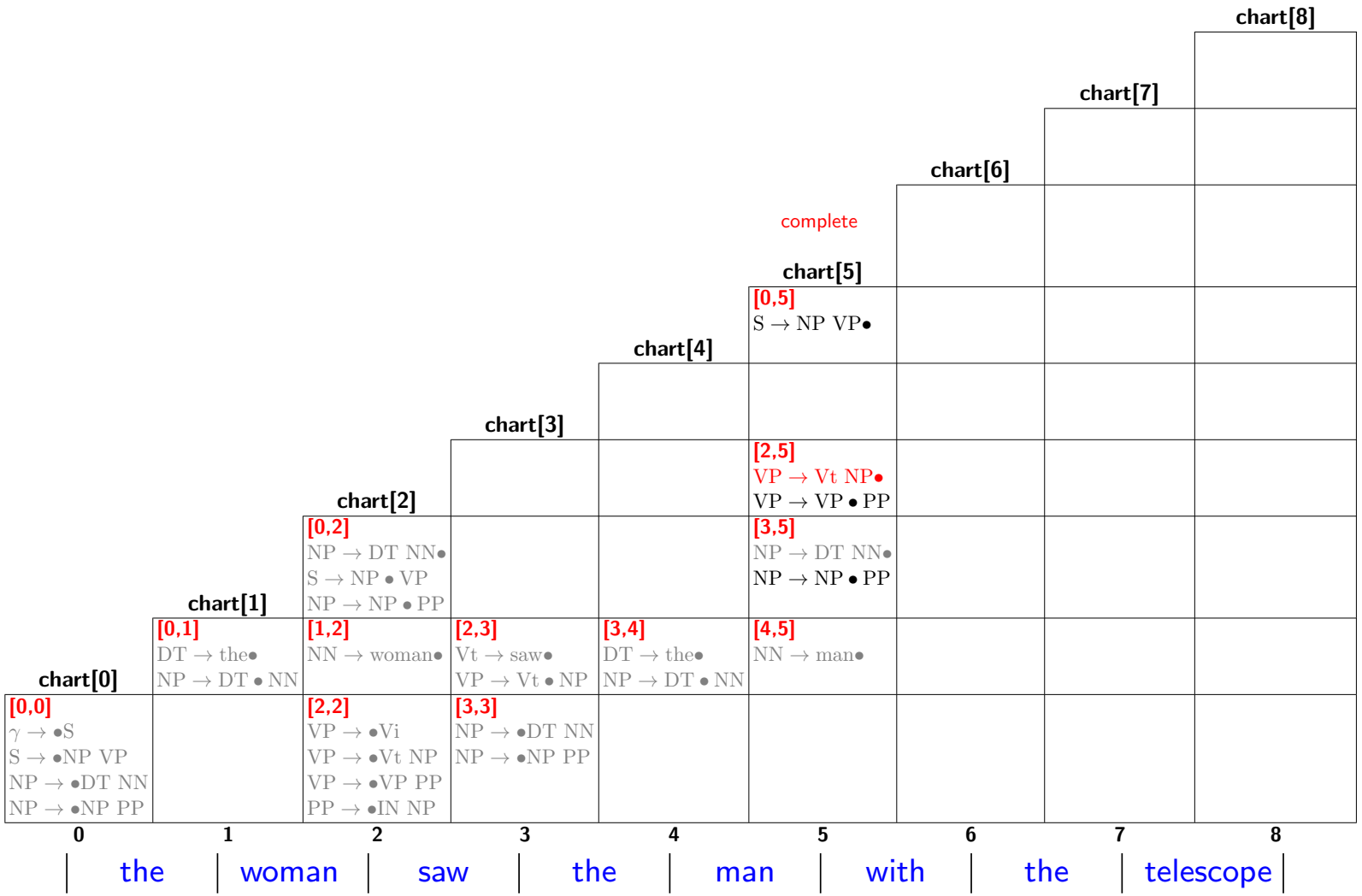
Earley Algorithm



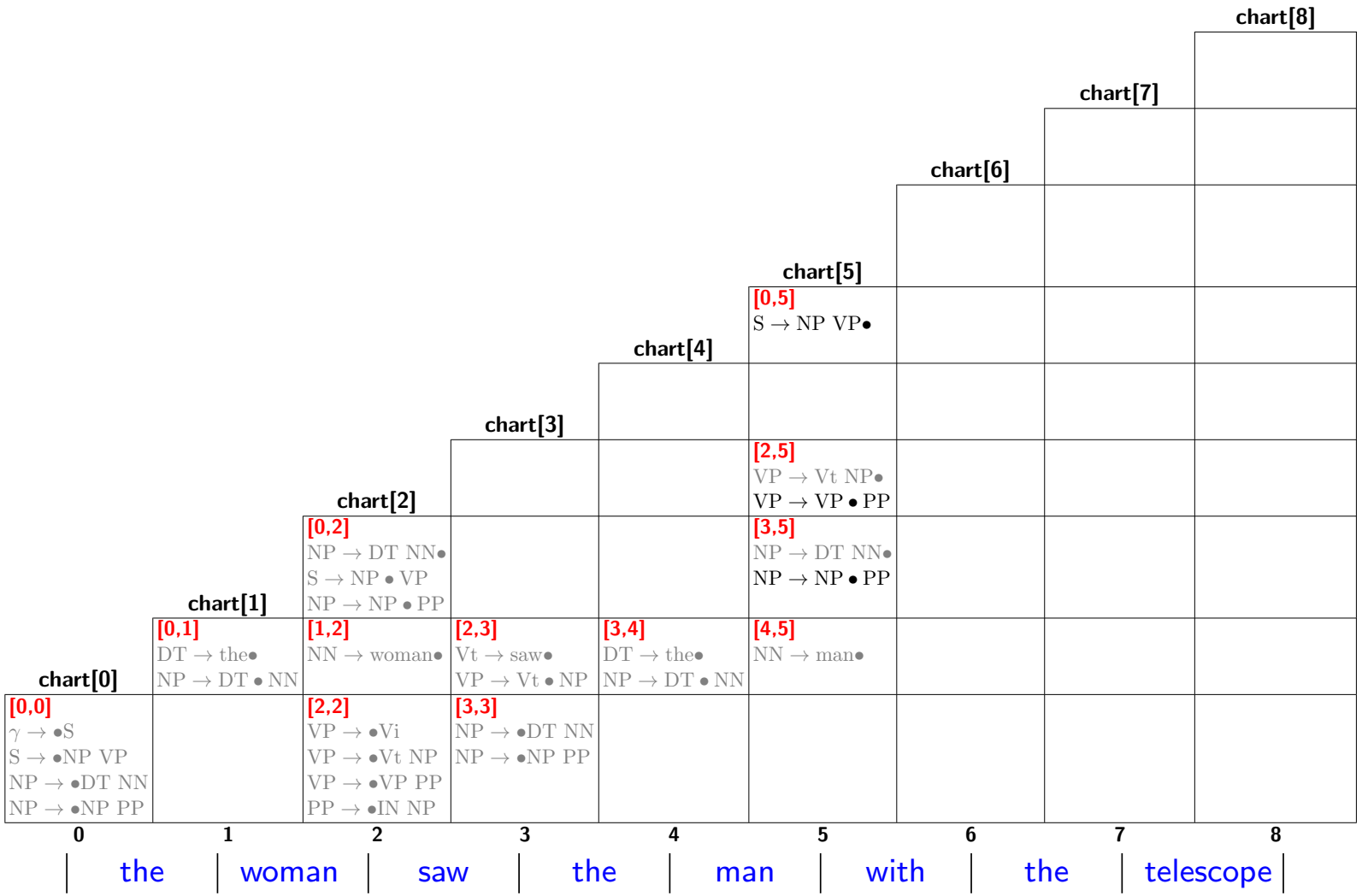
Earley Algorithm



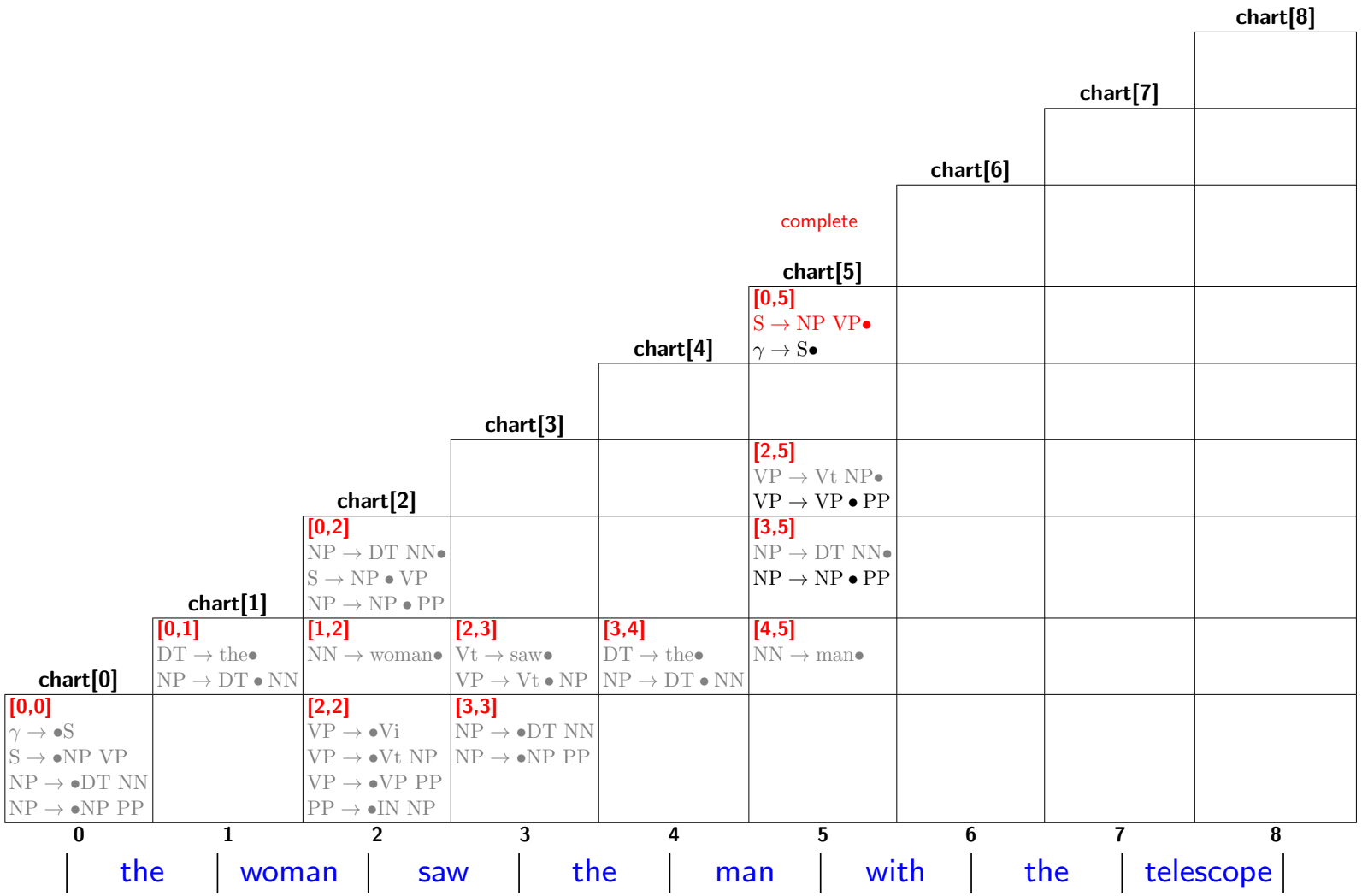
Earley Algorithm



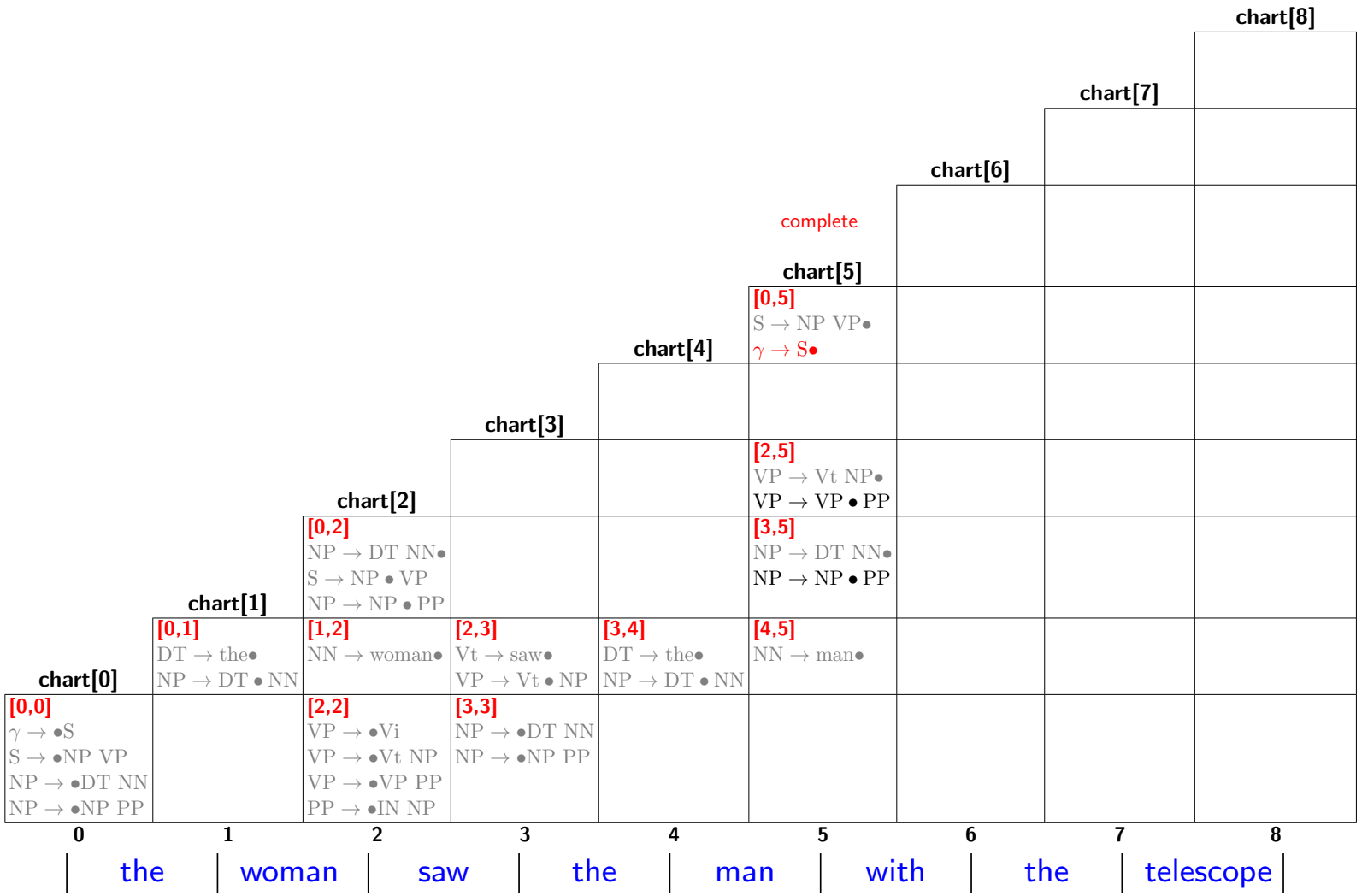
Earley Algorithm



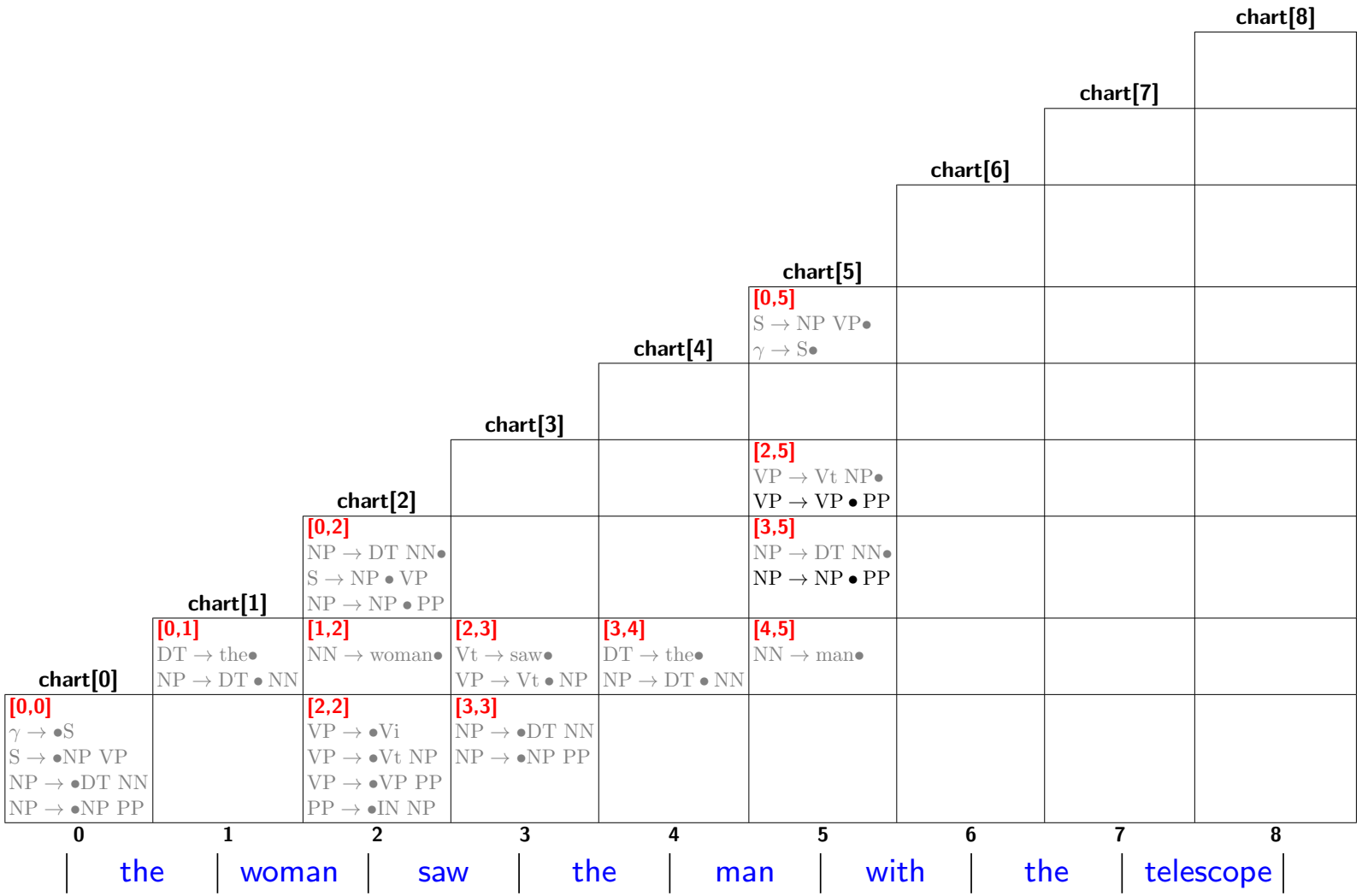
Earley Algorithm



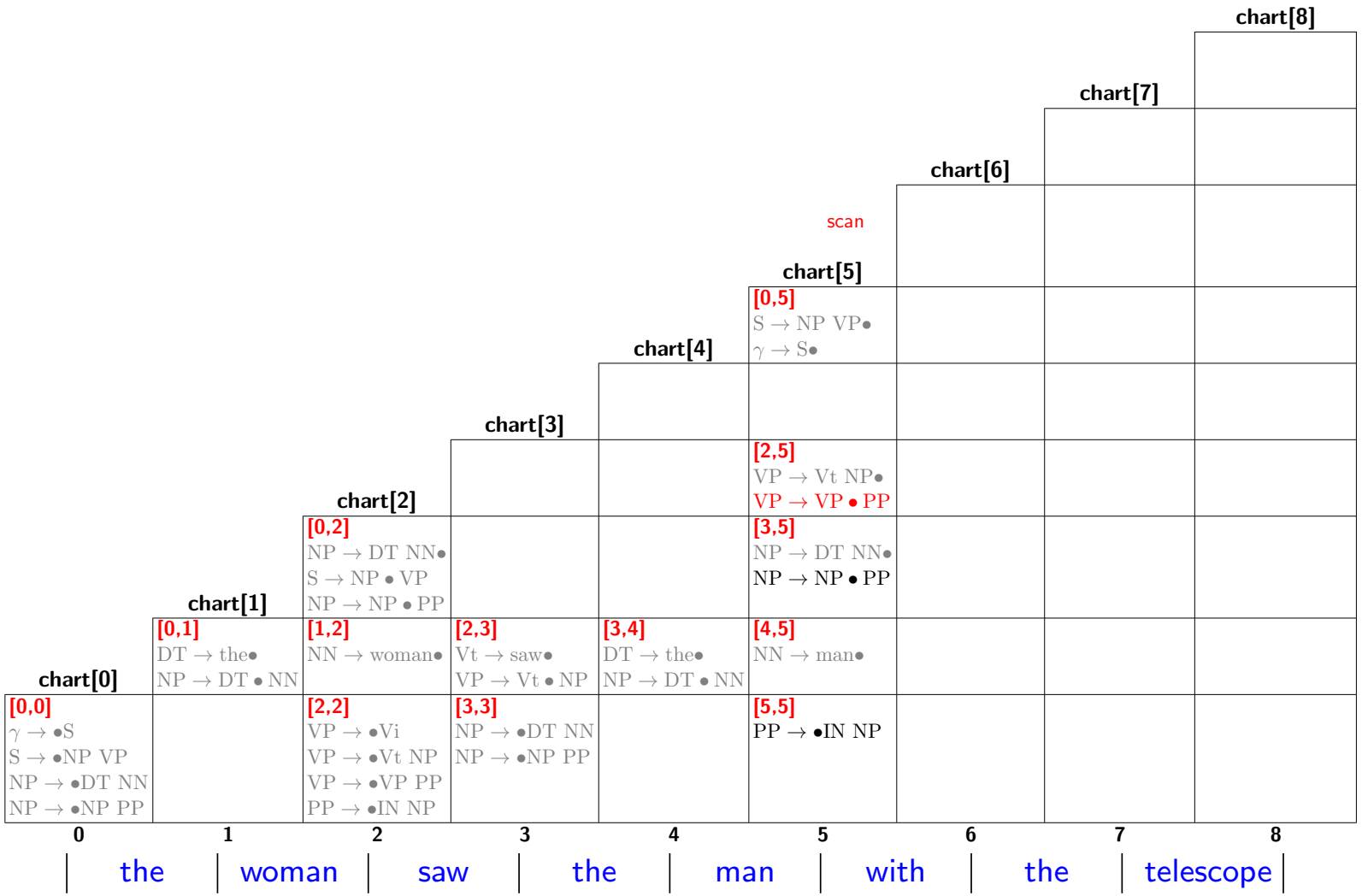
Earley Algorithm



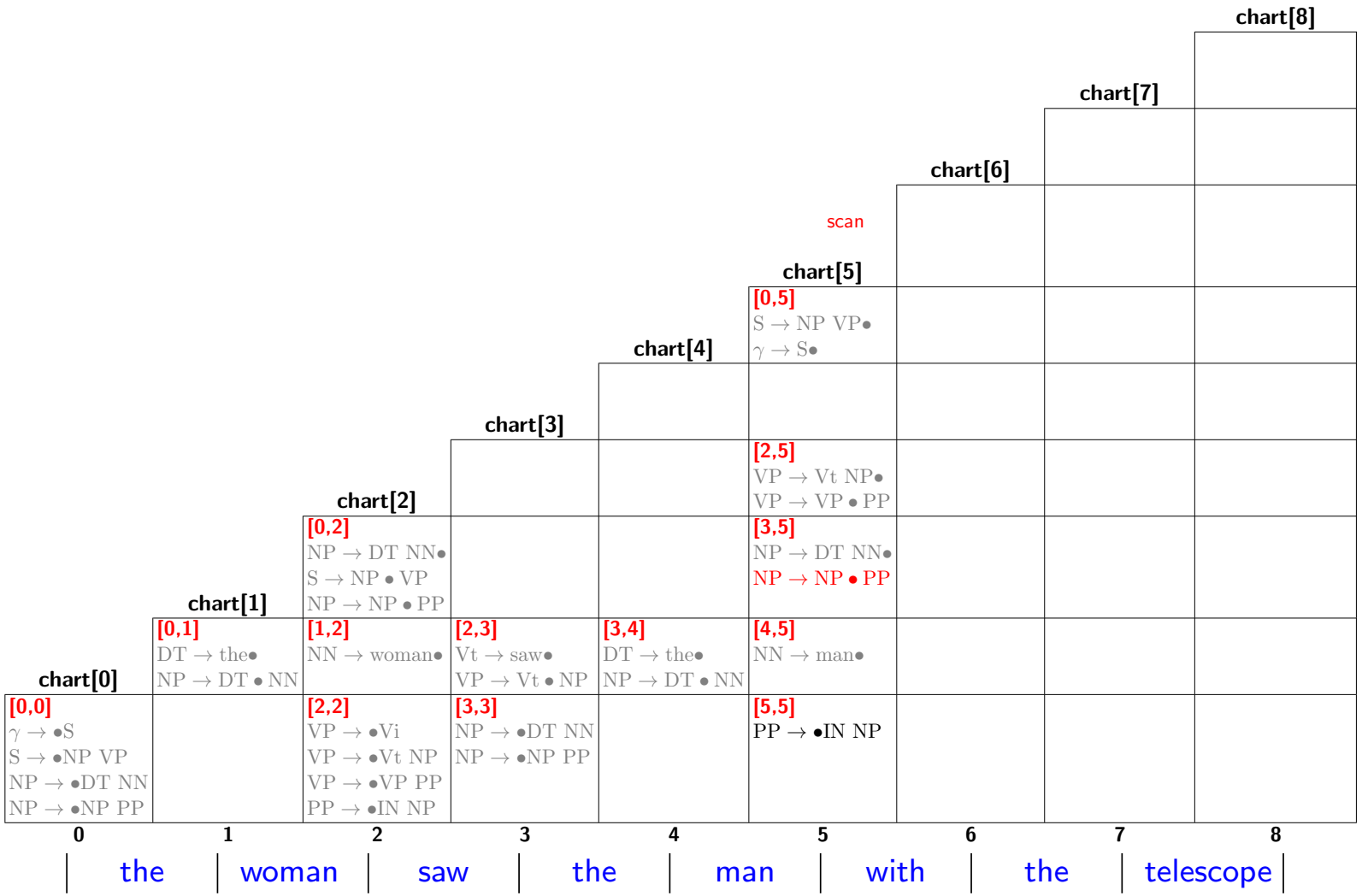
Earley Algorithm



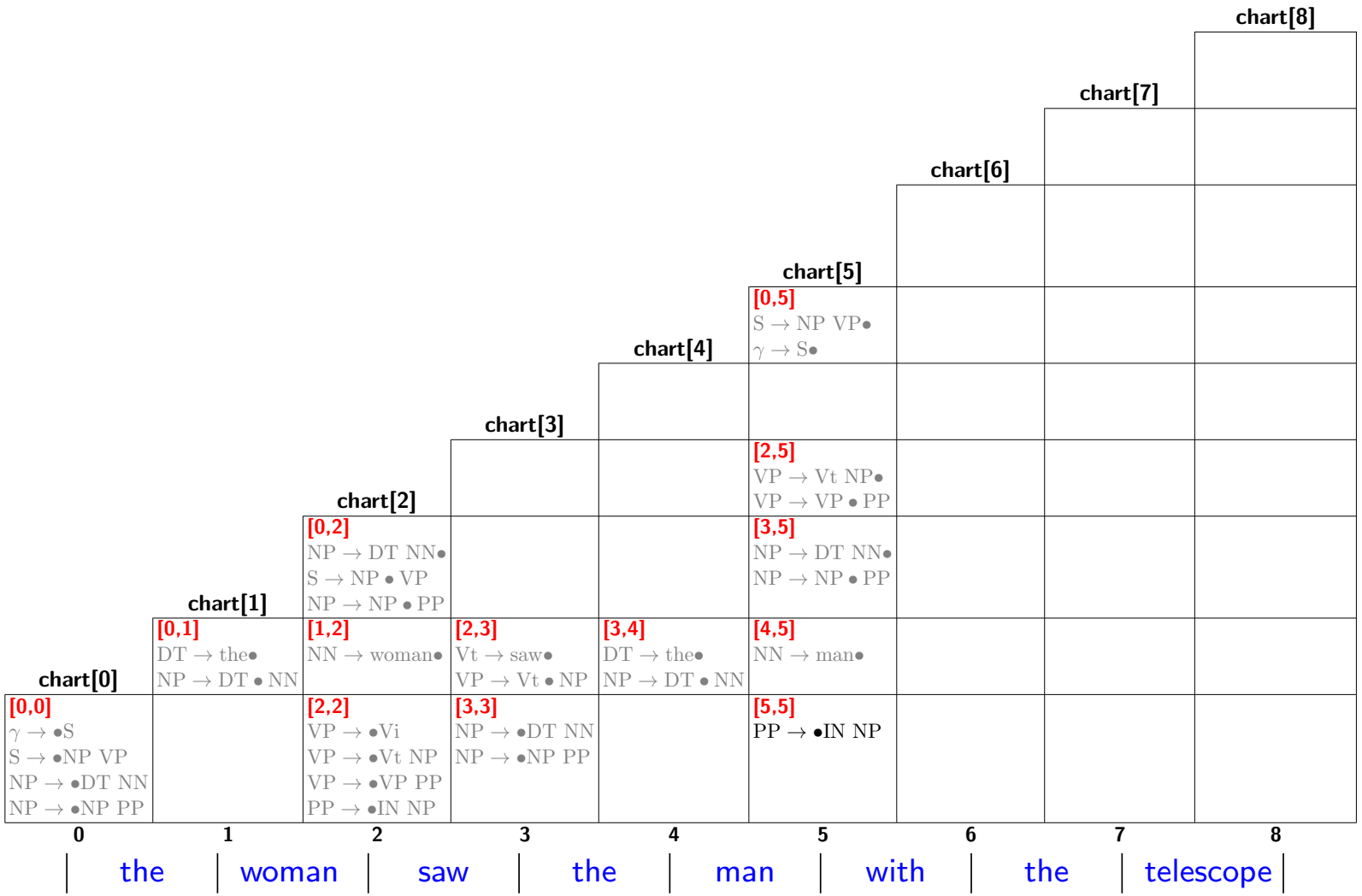
Earley Algorithm



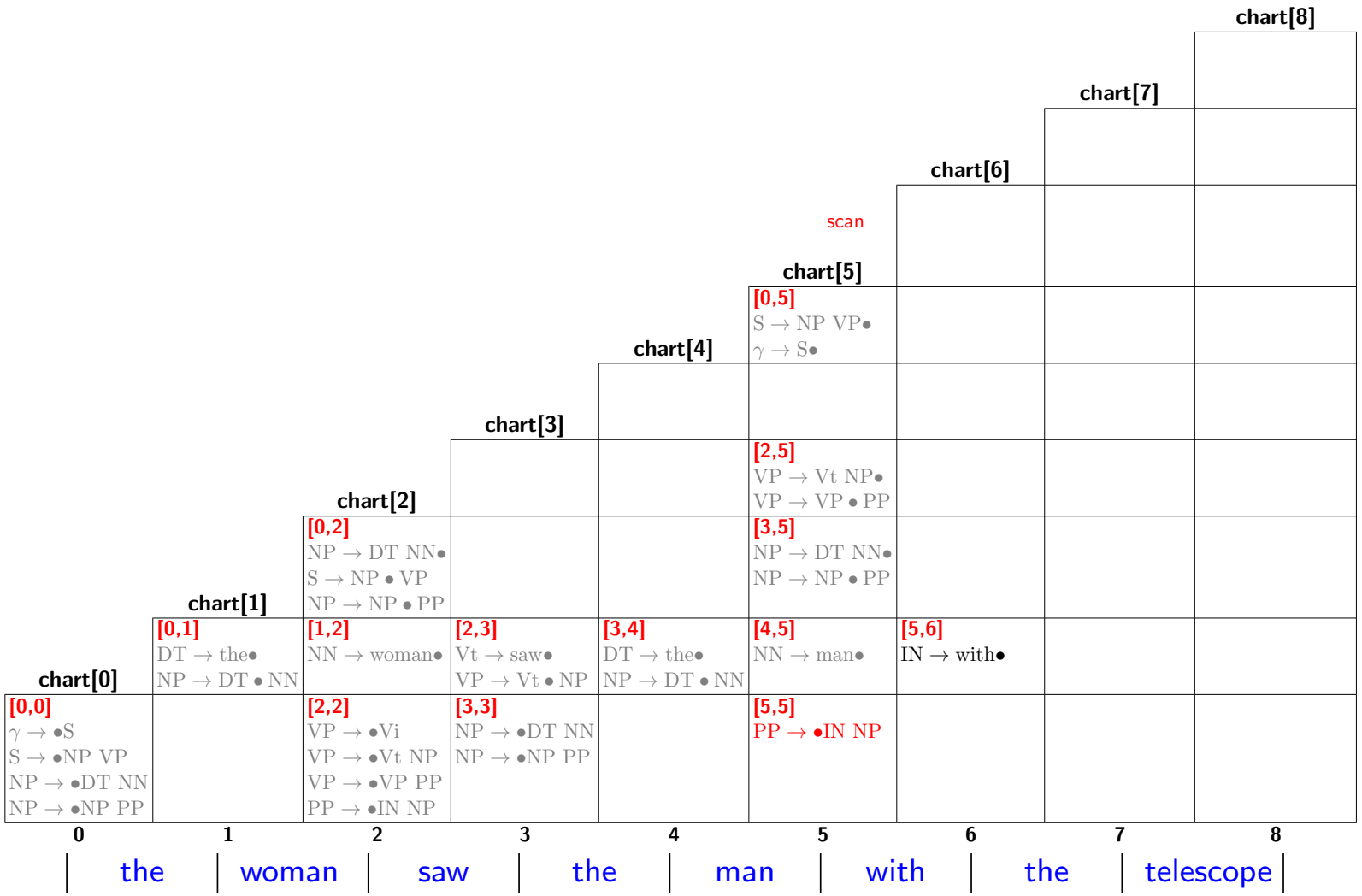
Earley Algorithm



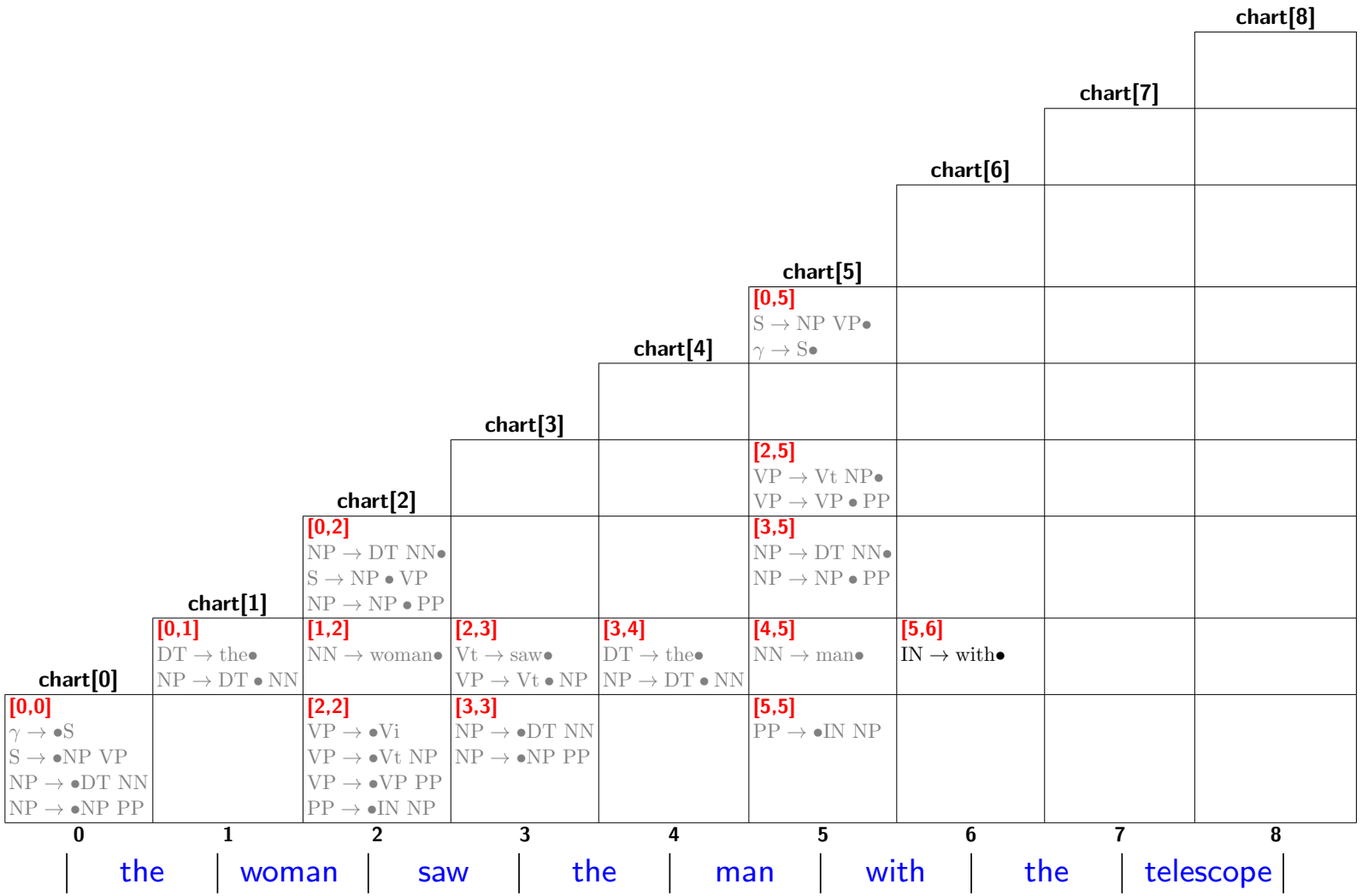
Earley Algorithm



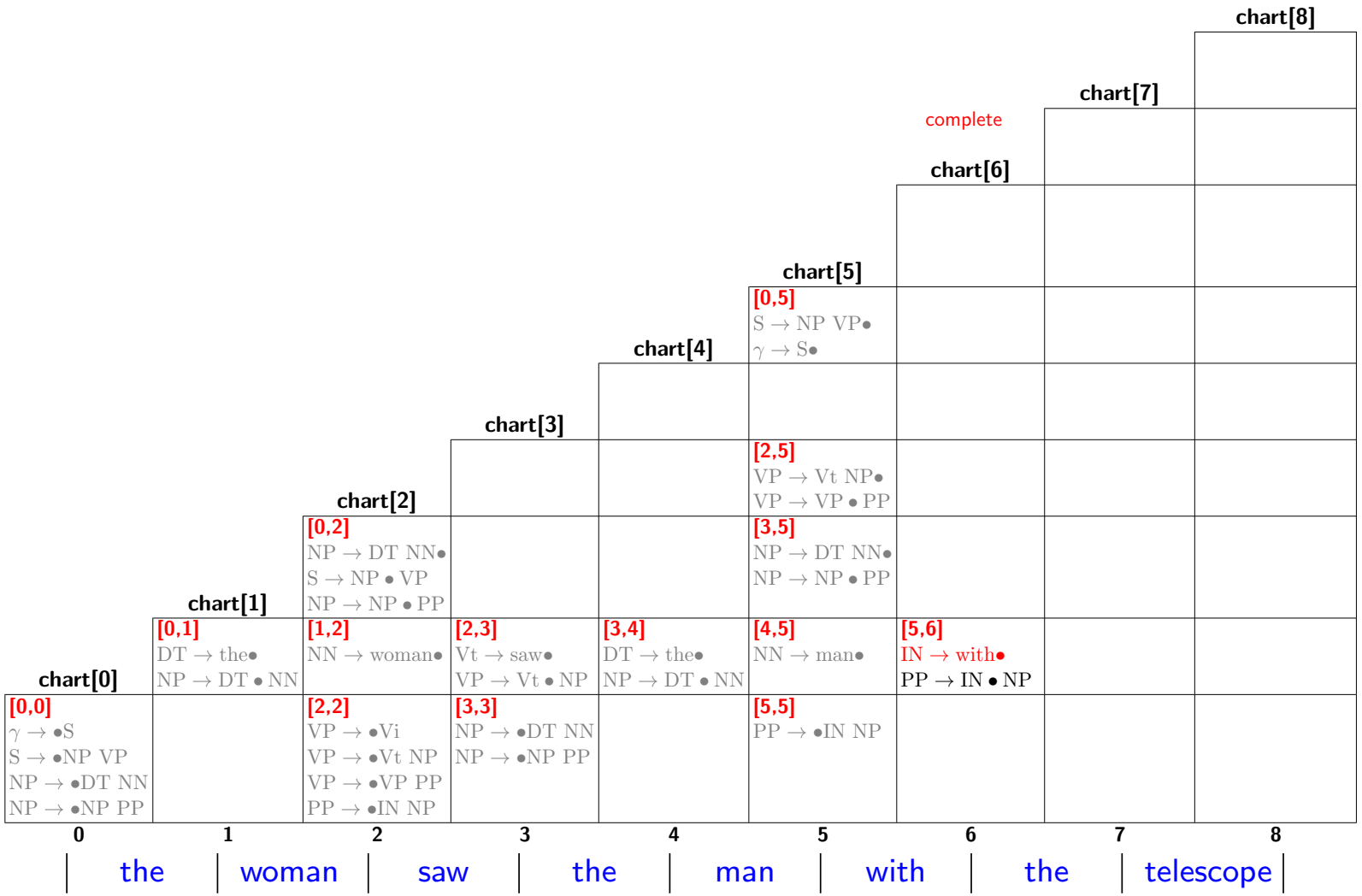
Earley Algorithm



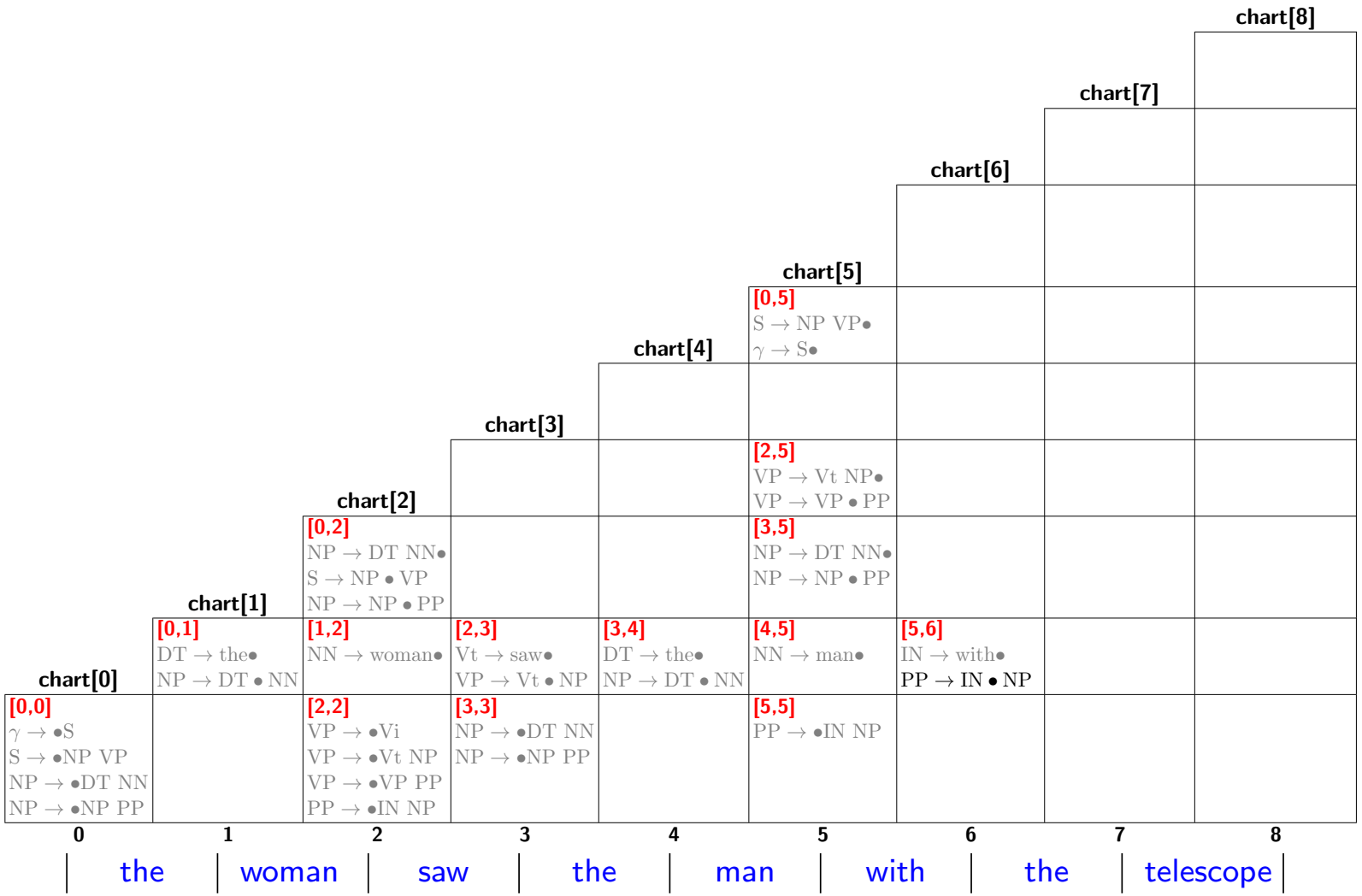
Earley Algorithm



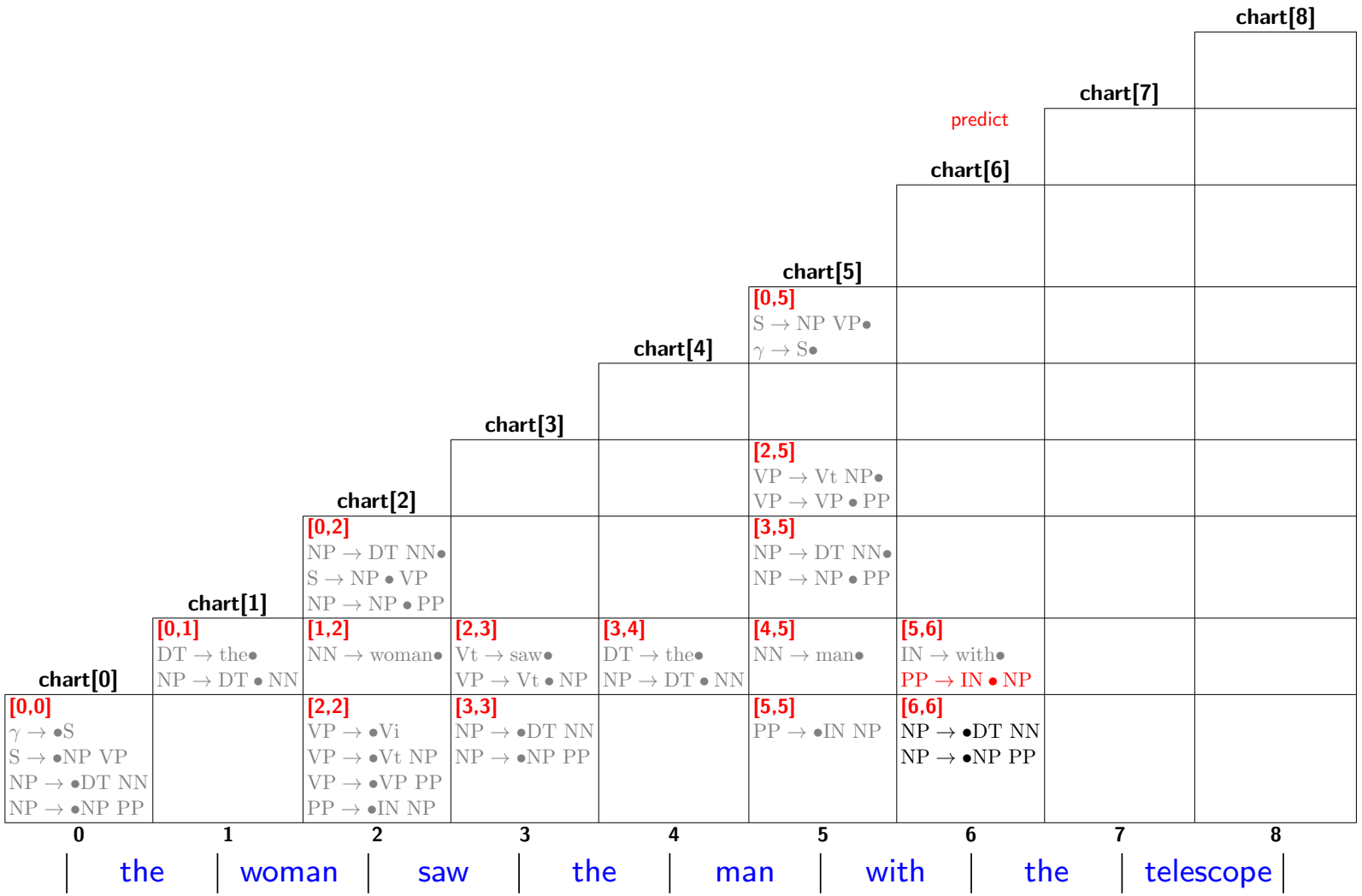
Earley Algorithm



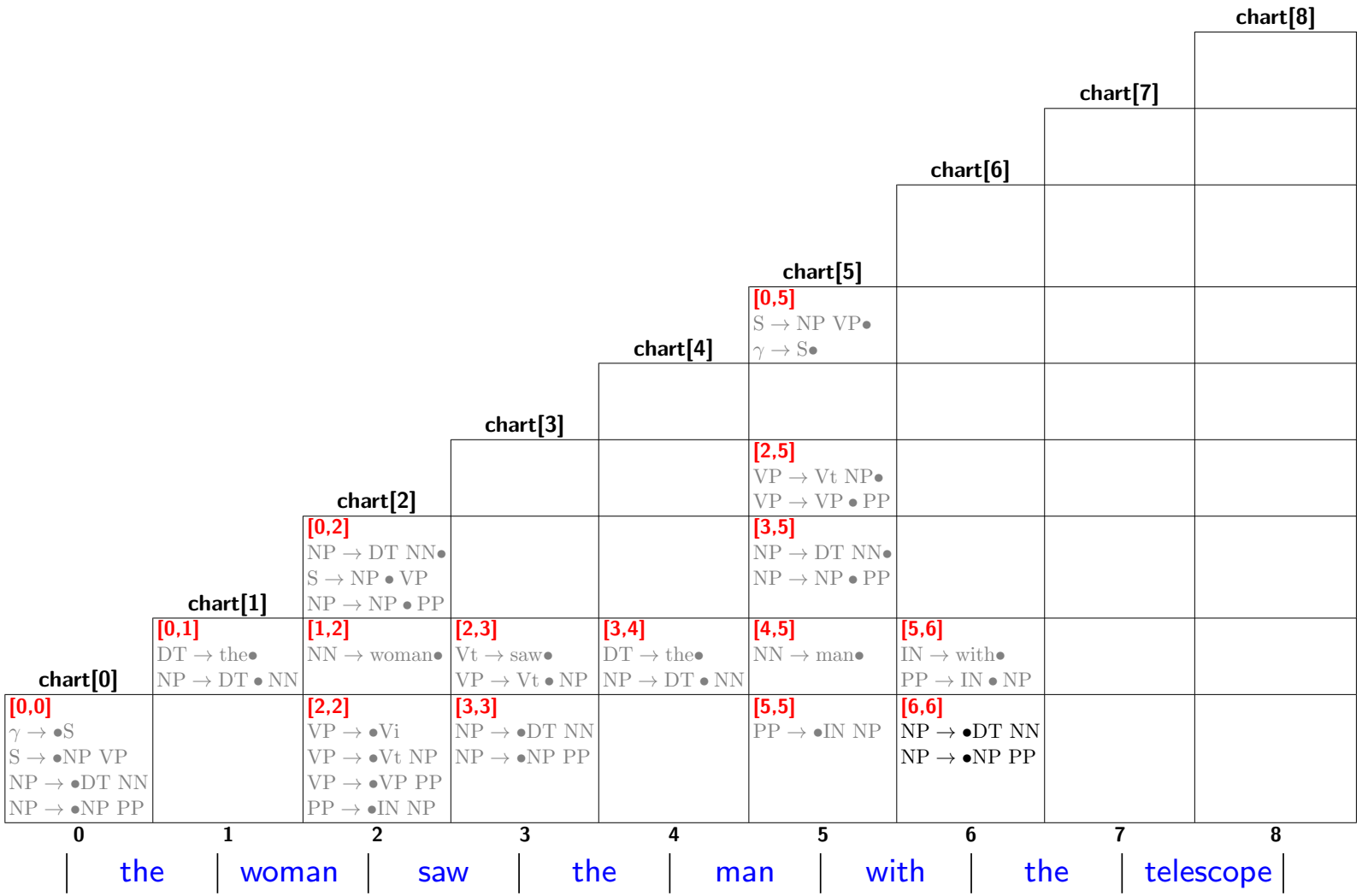
Earley Algorithm



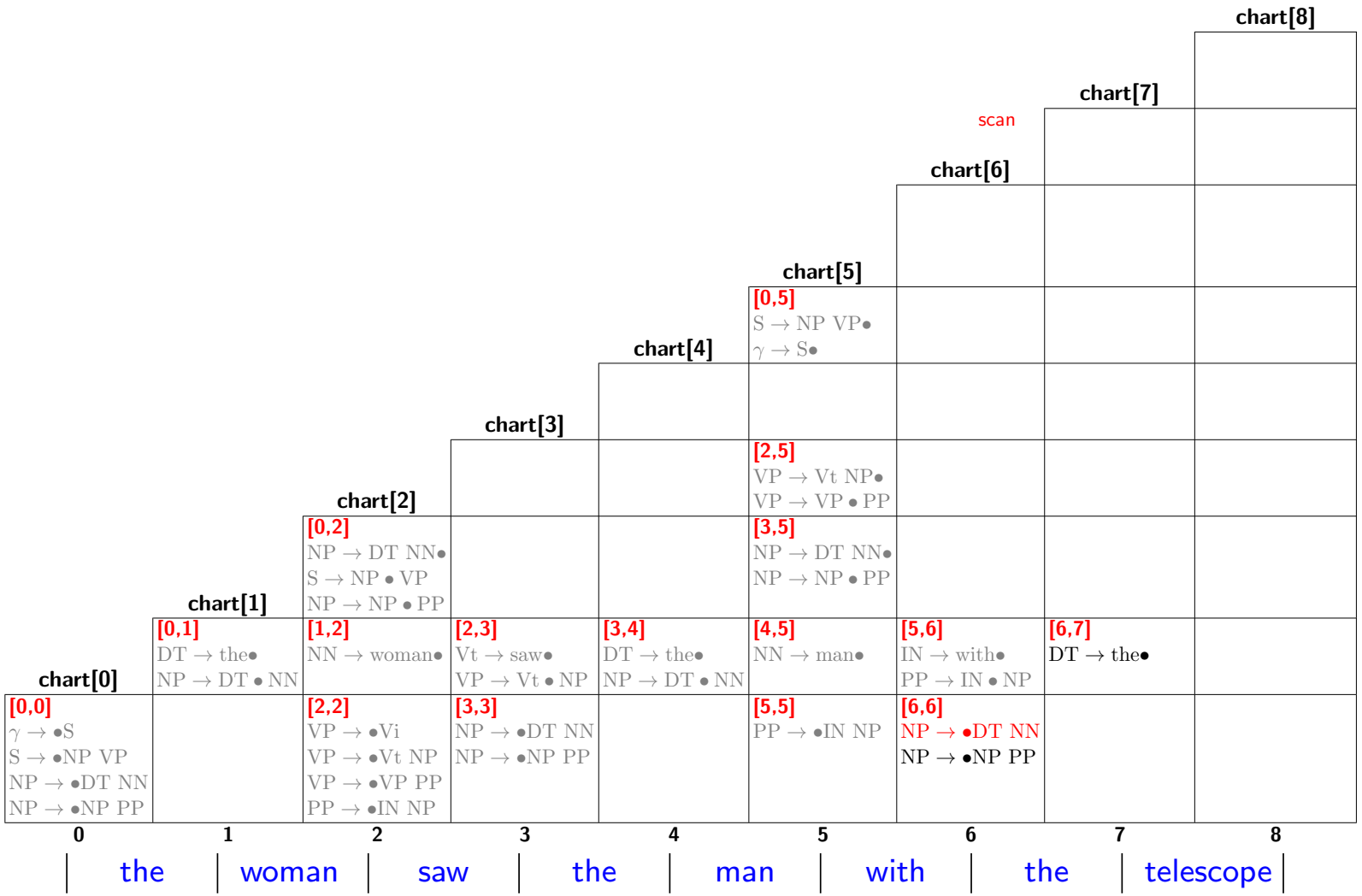
Earley Algorithm



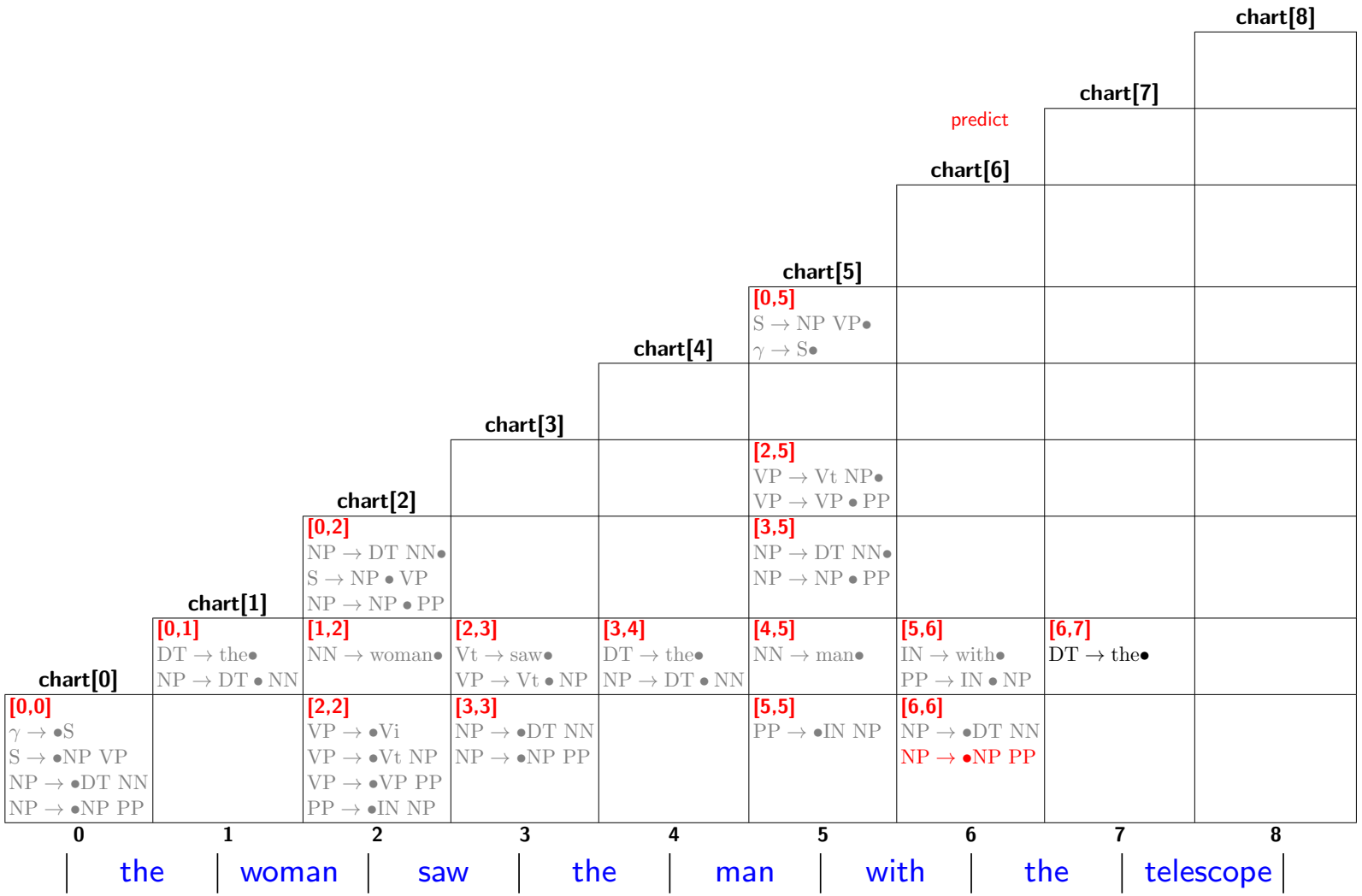
Earley Algorithm



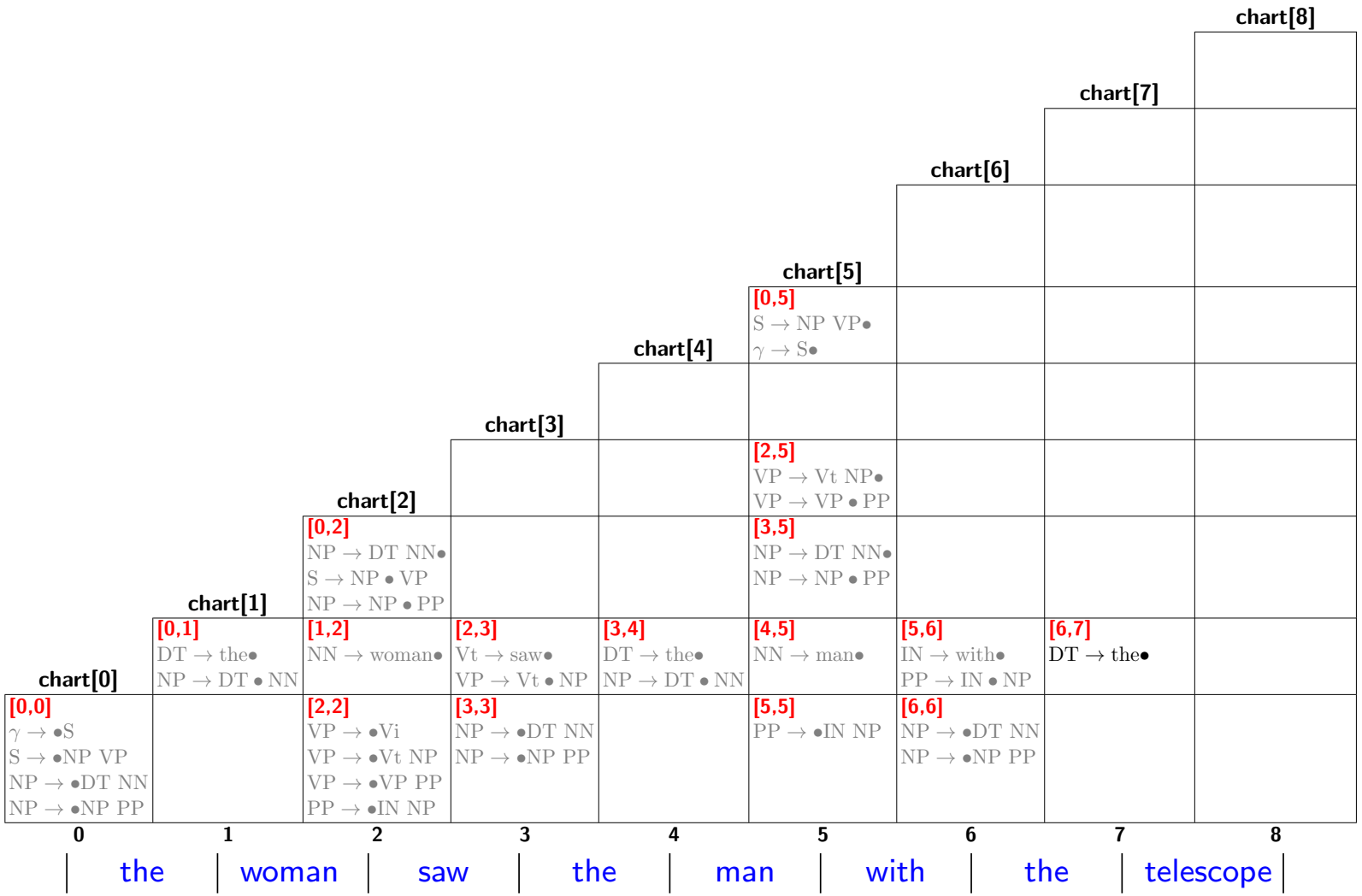
Earley Algorithm



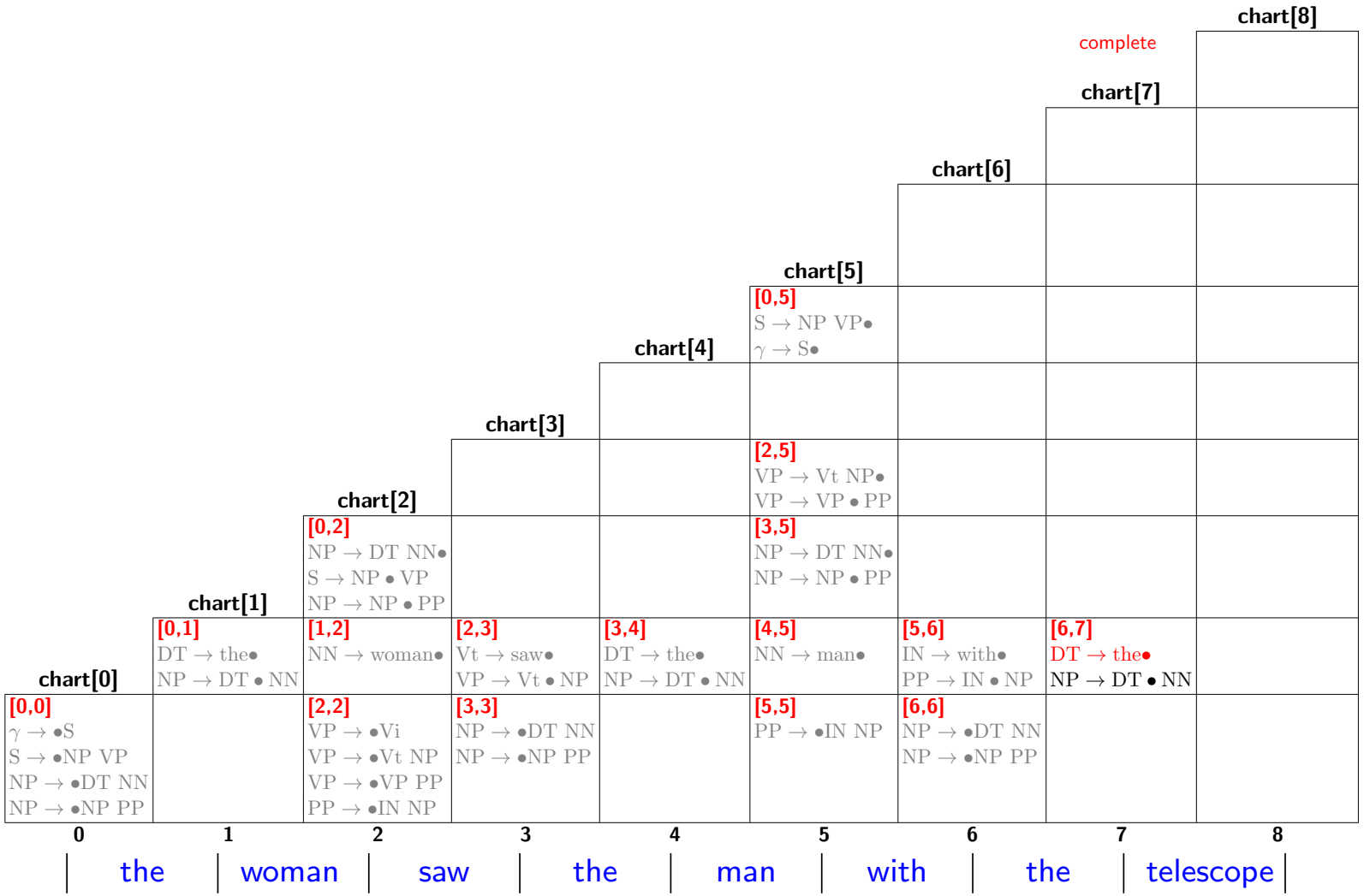
Earley Algorithm



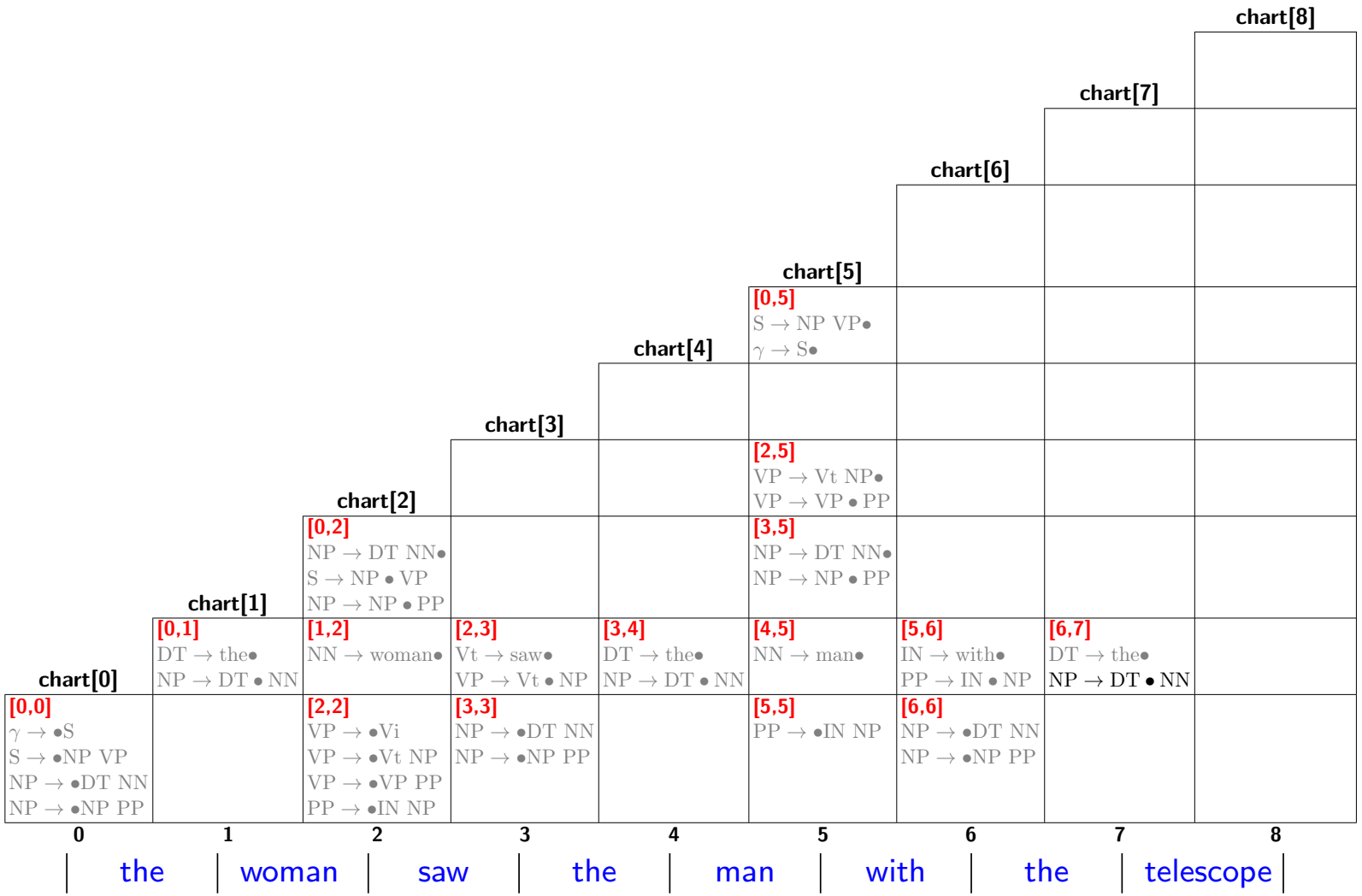
Earley Algorithm



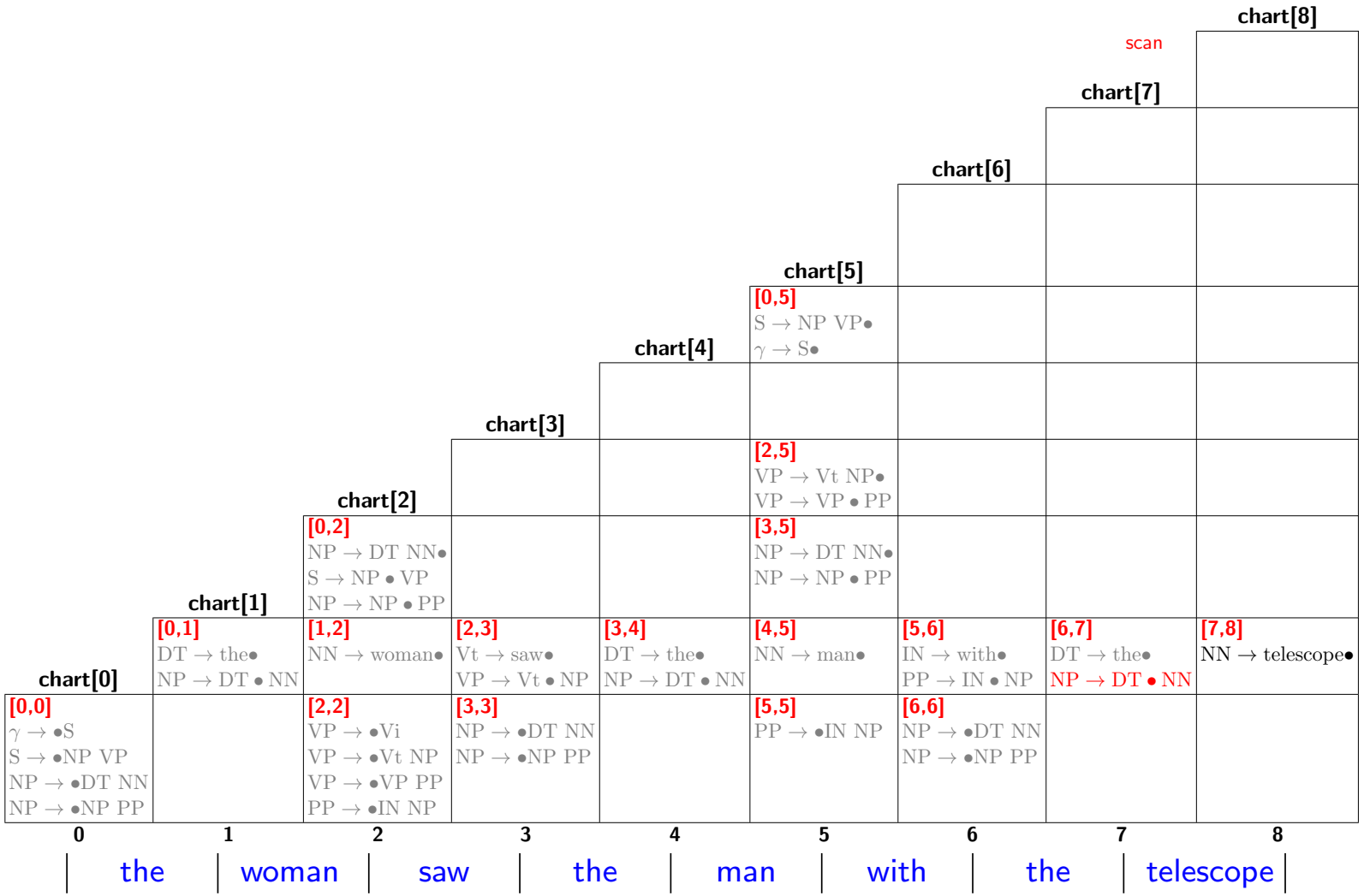
Earley Algorithm



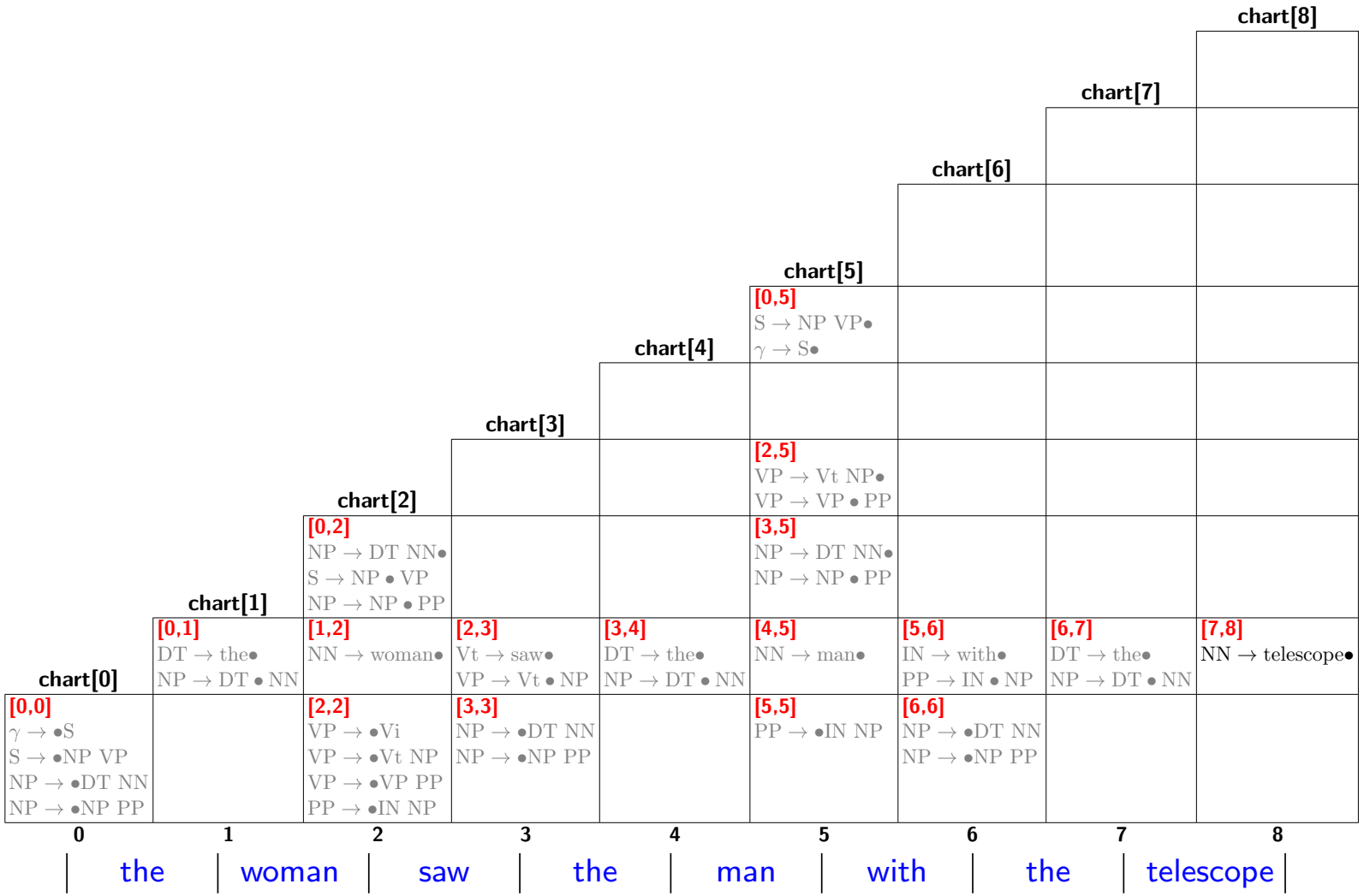
Earley Algorithm



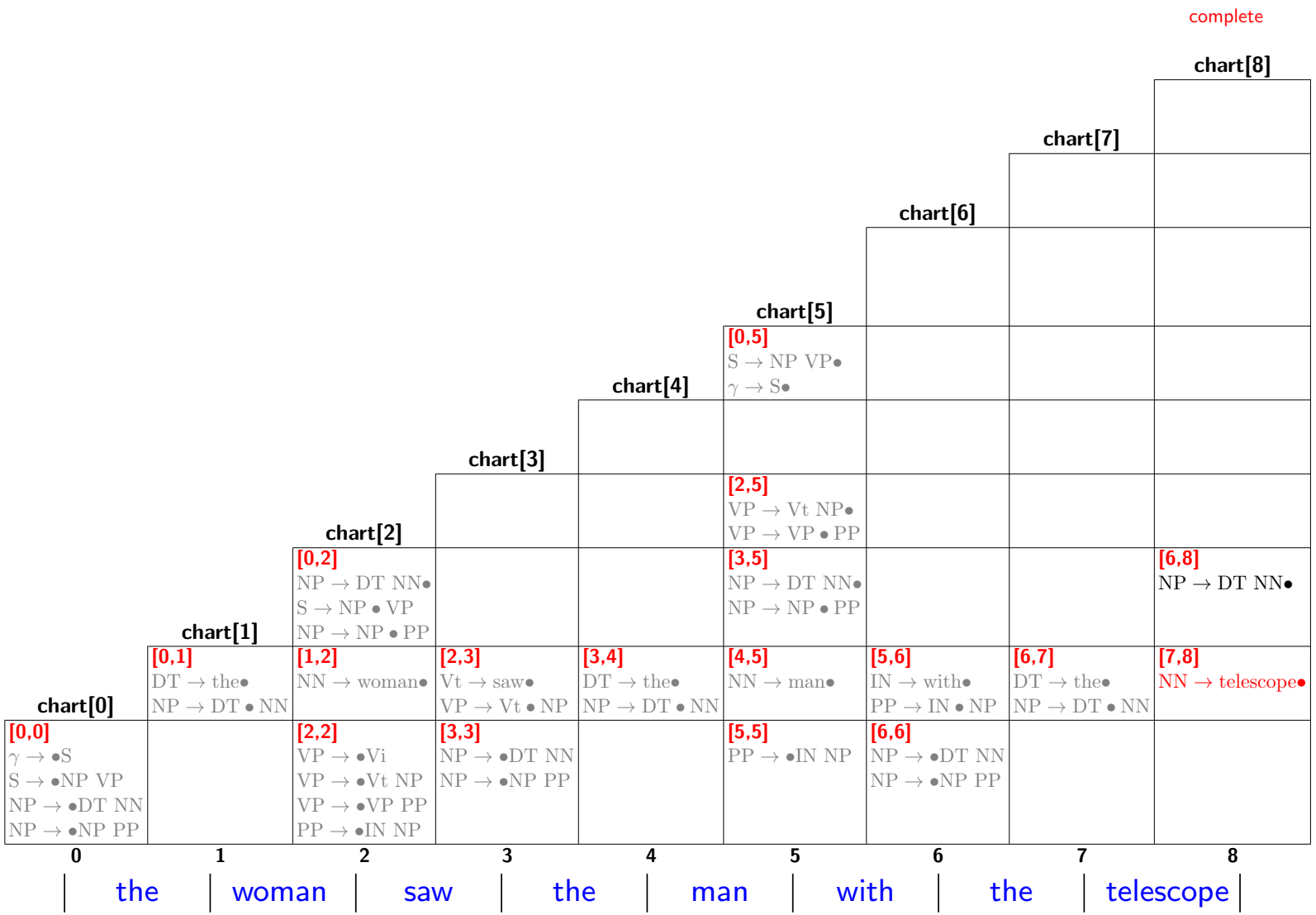
Earley Algorithm



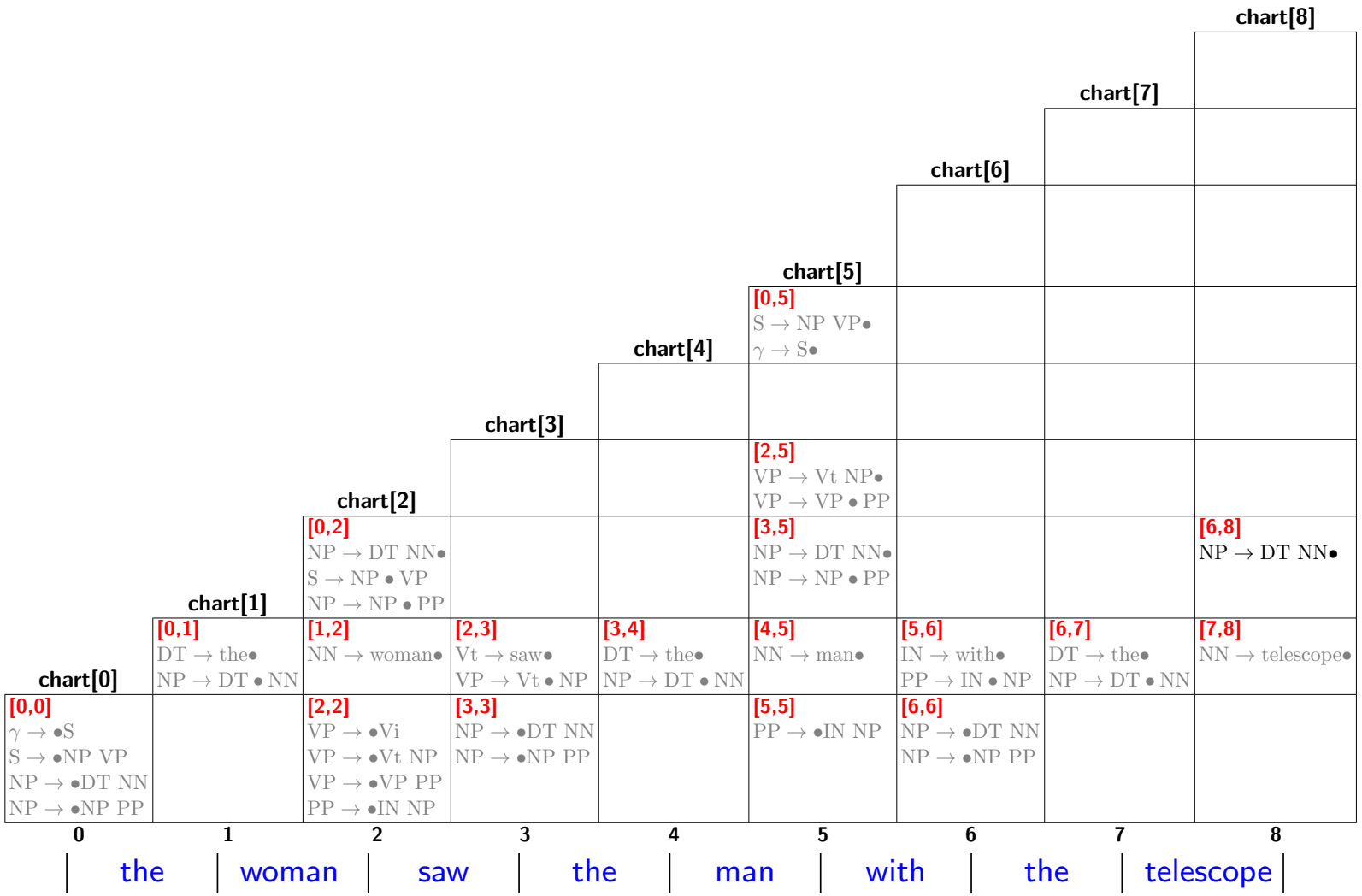
Earley Algorithm



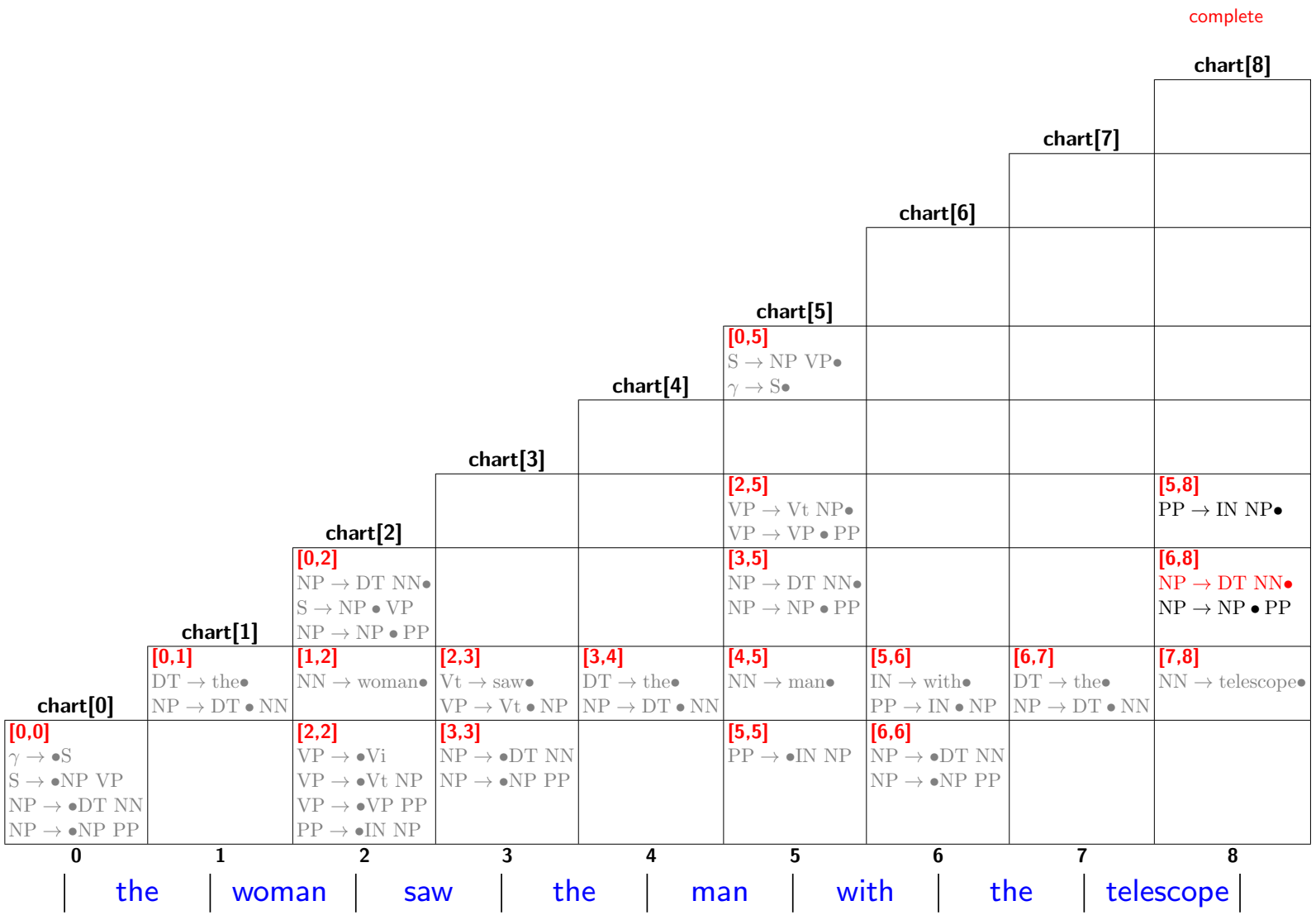
Earley Algorithm



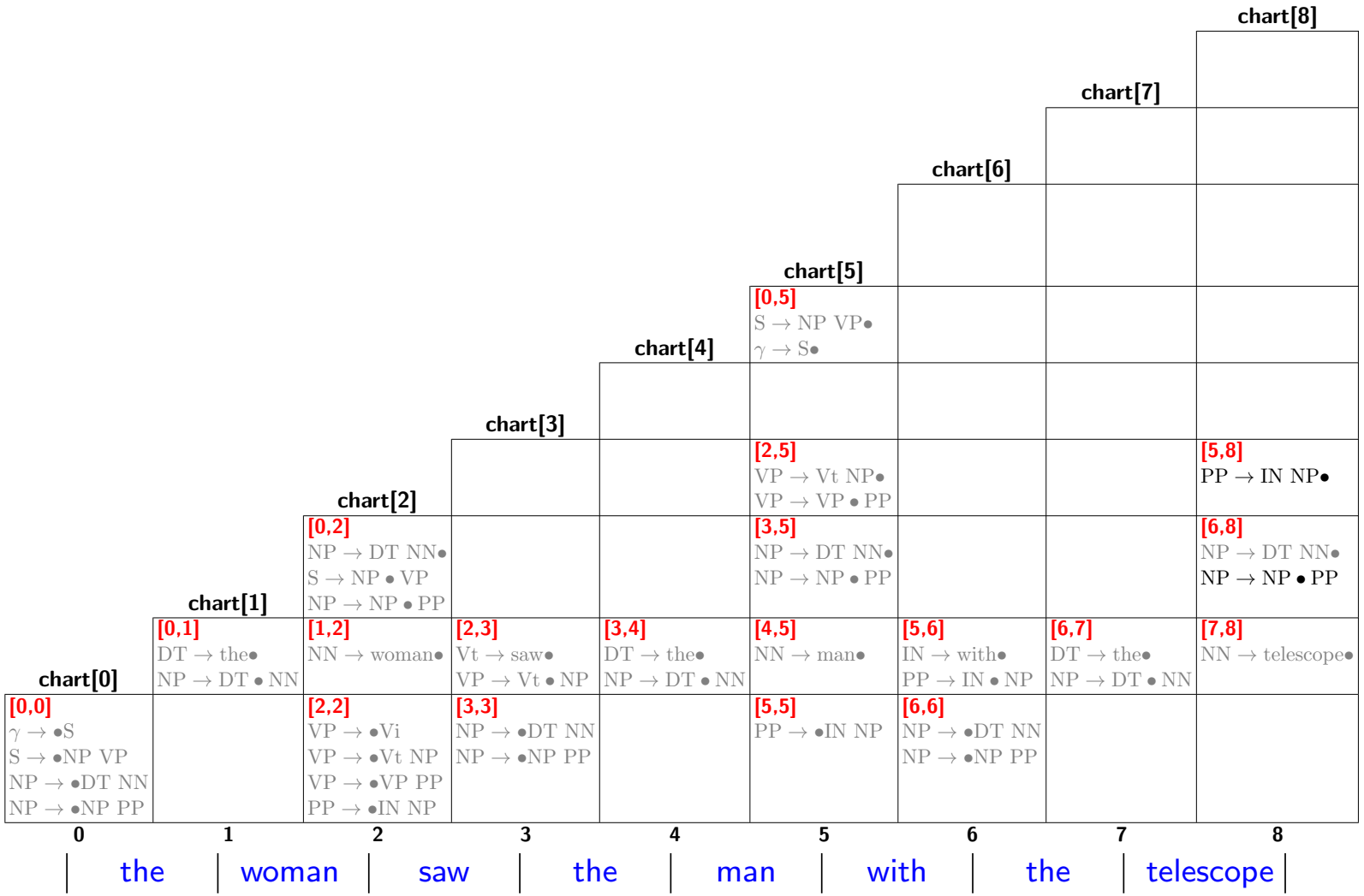
Earley Algorithm



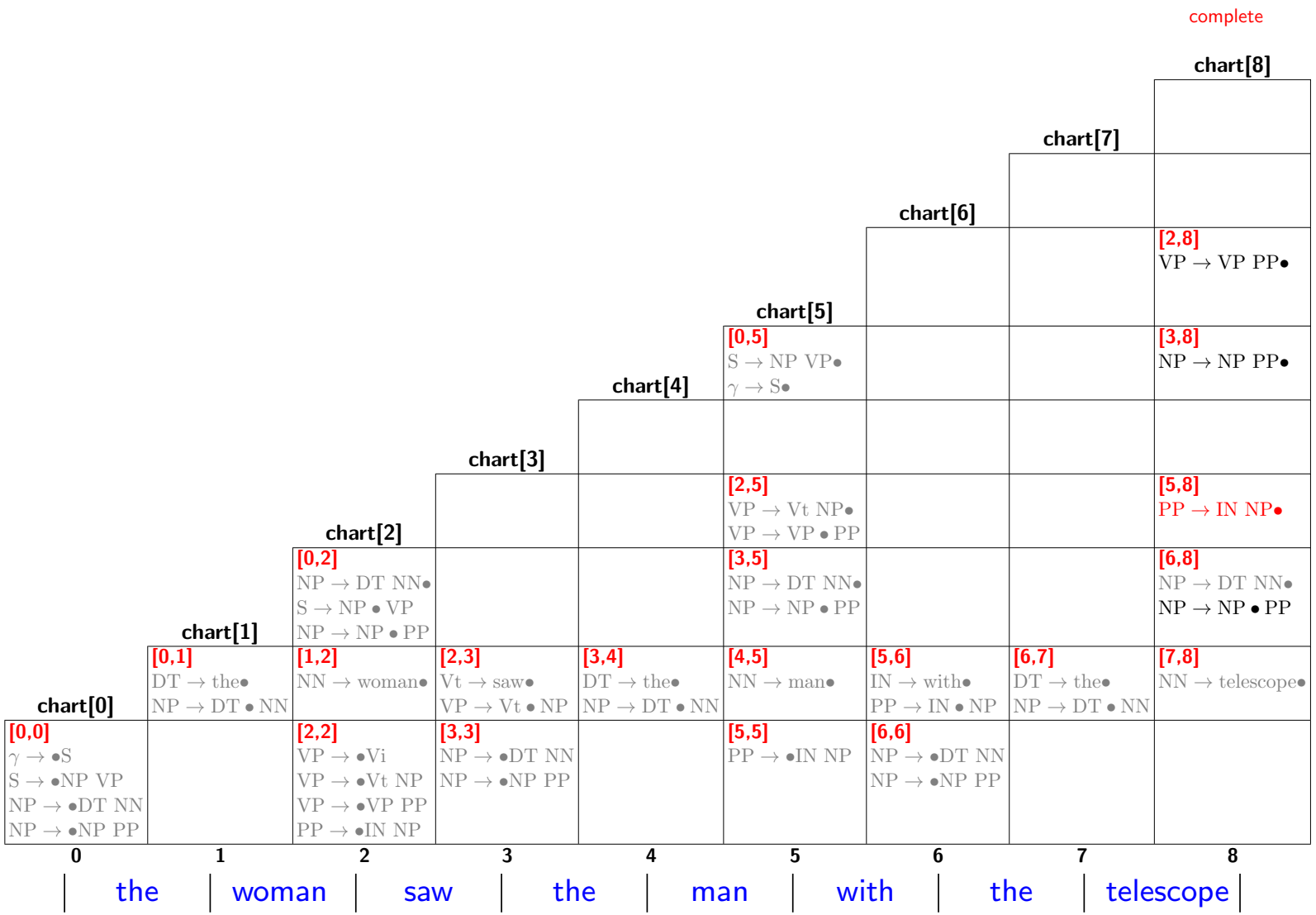
Earley Algorithm



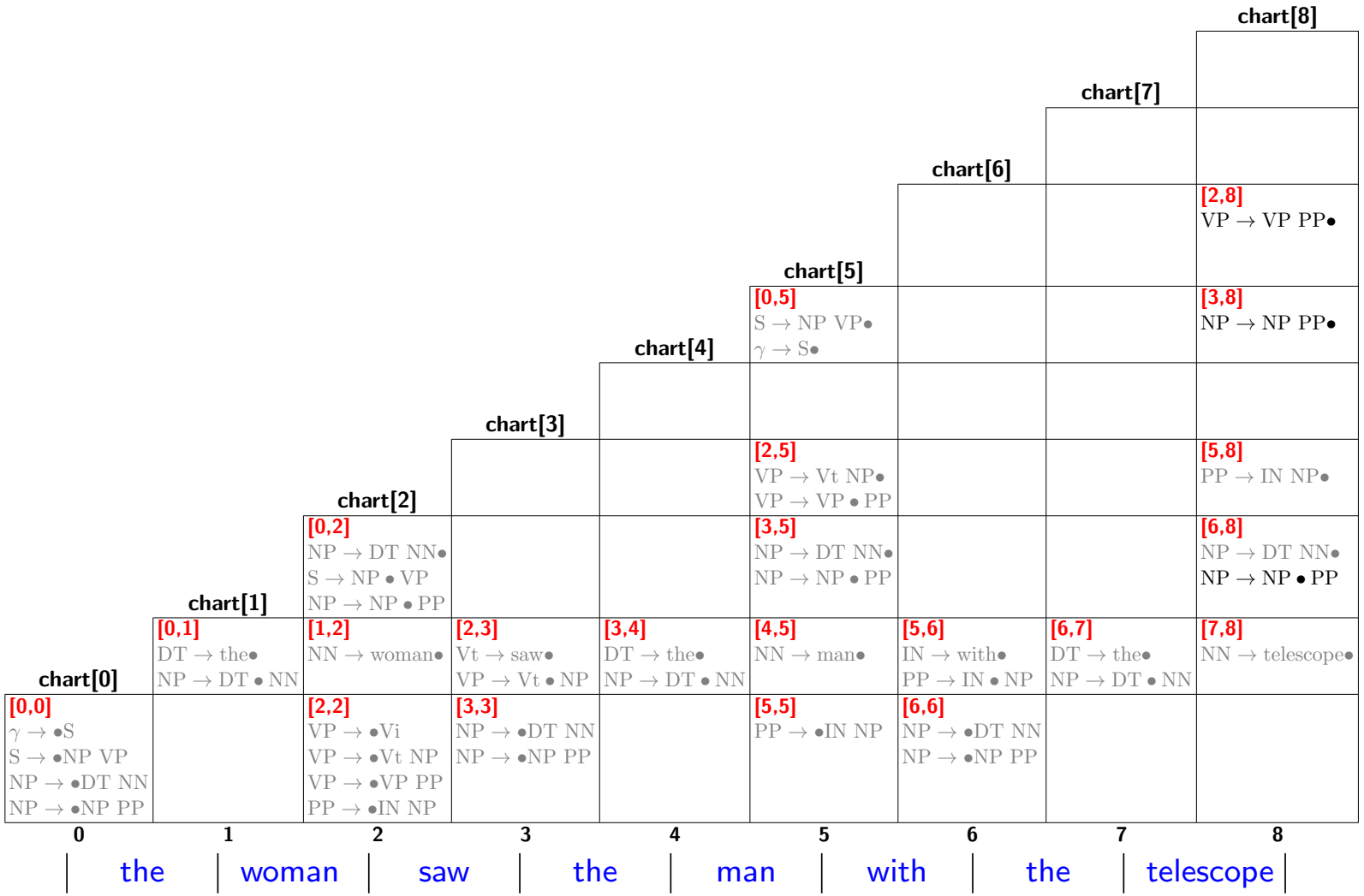
Earley Algorithm



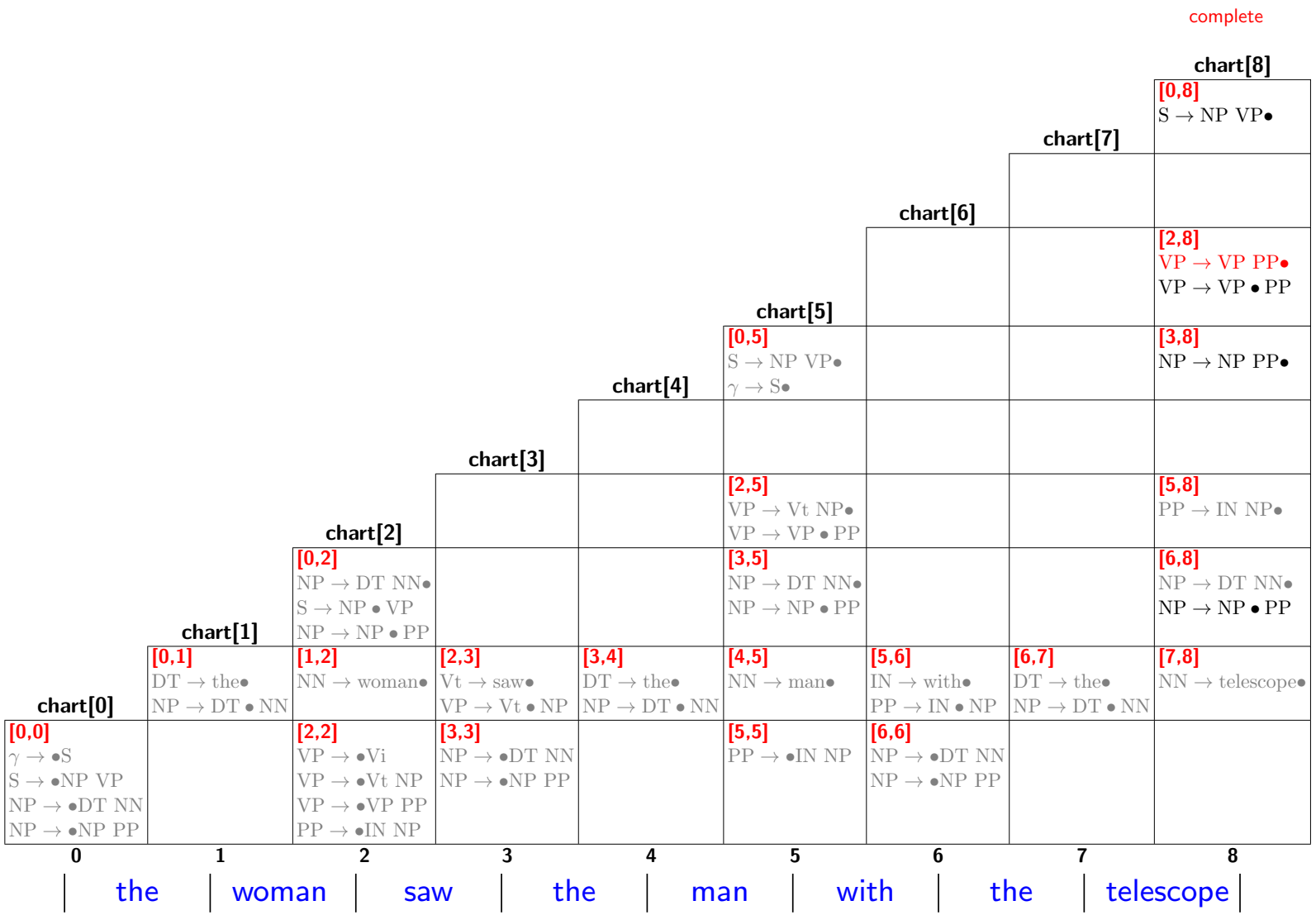
Earley Algorithm



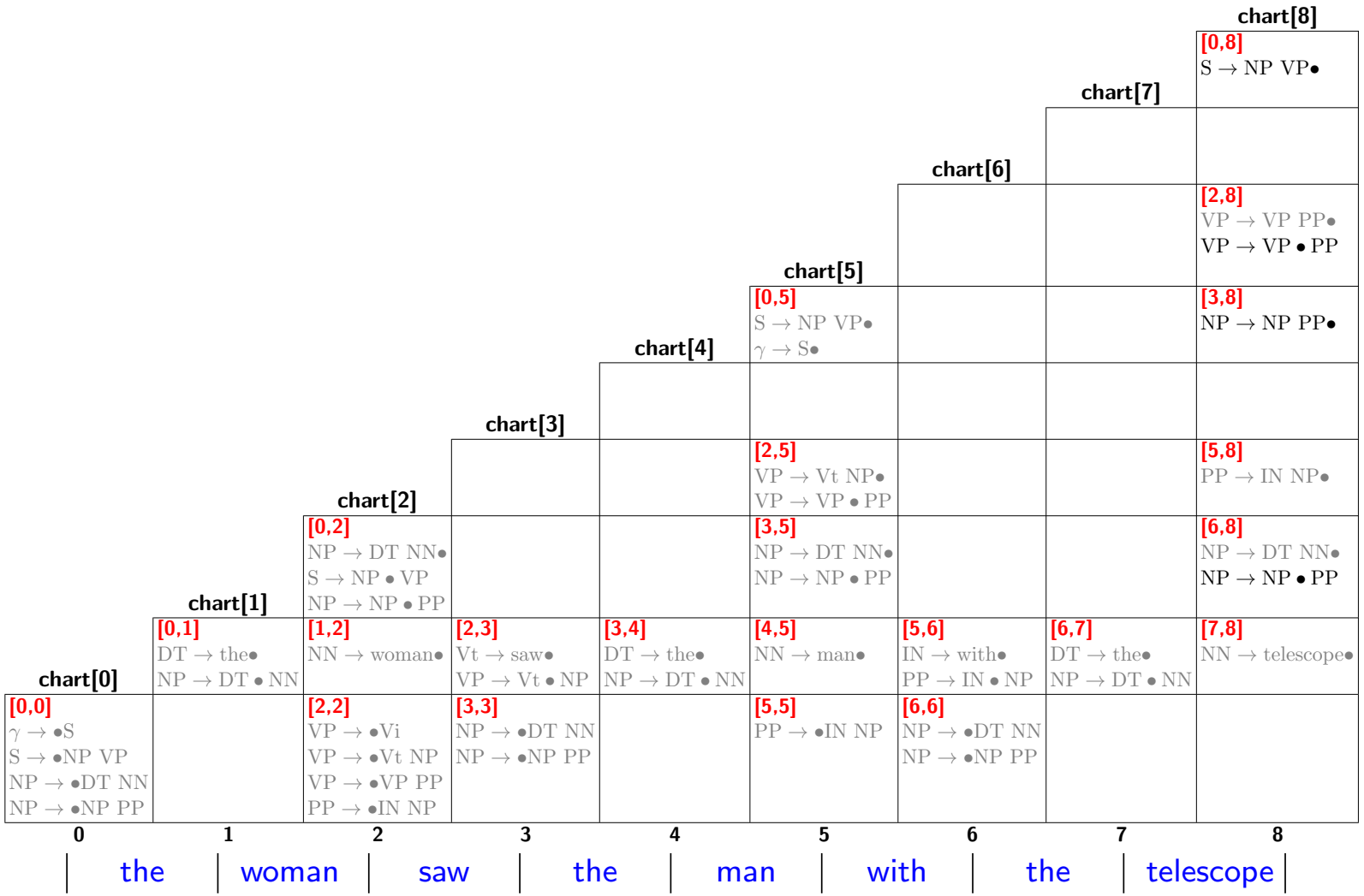
Earley Algorithm



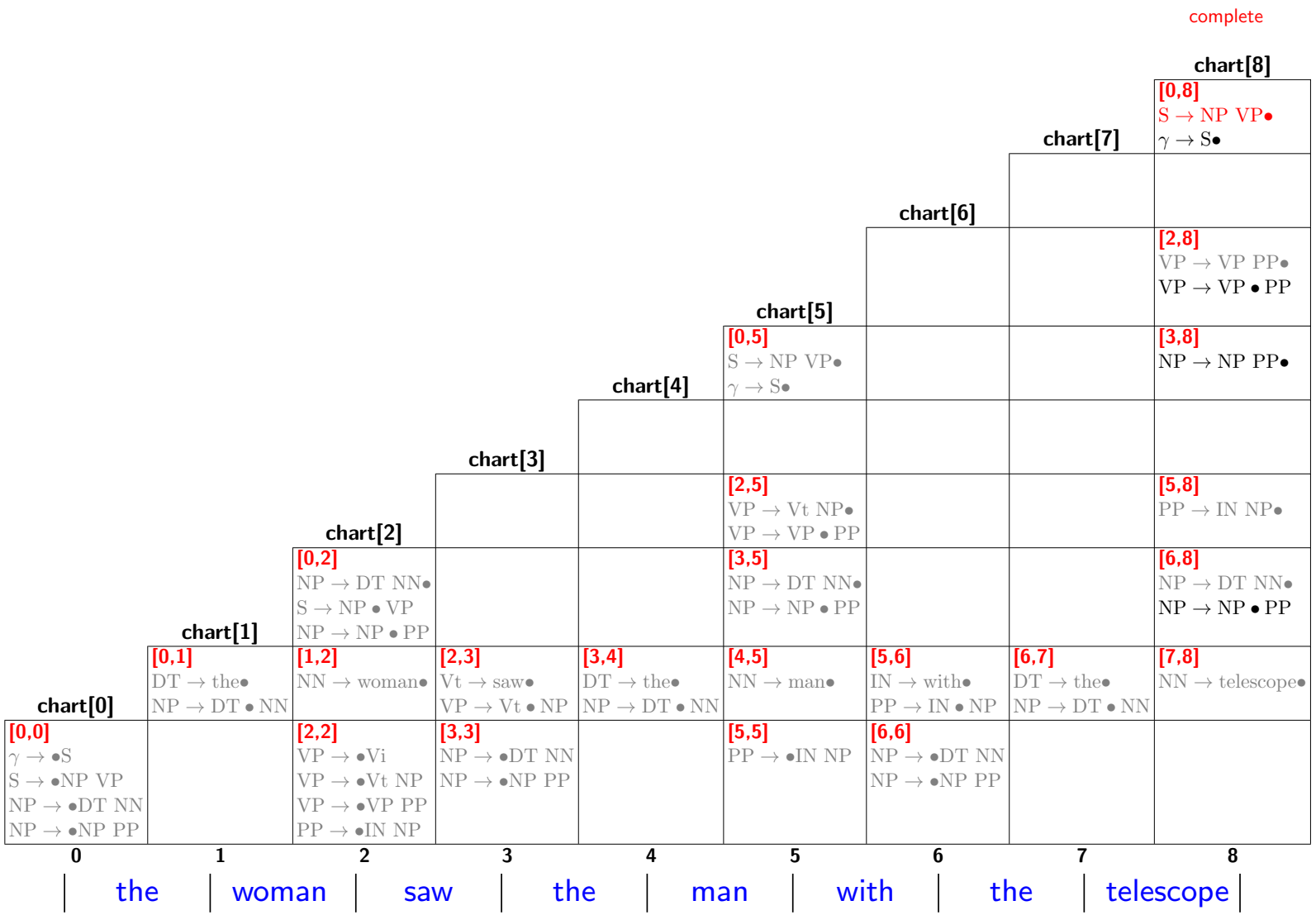
Earley Algorithm



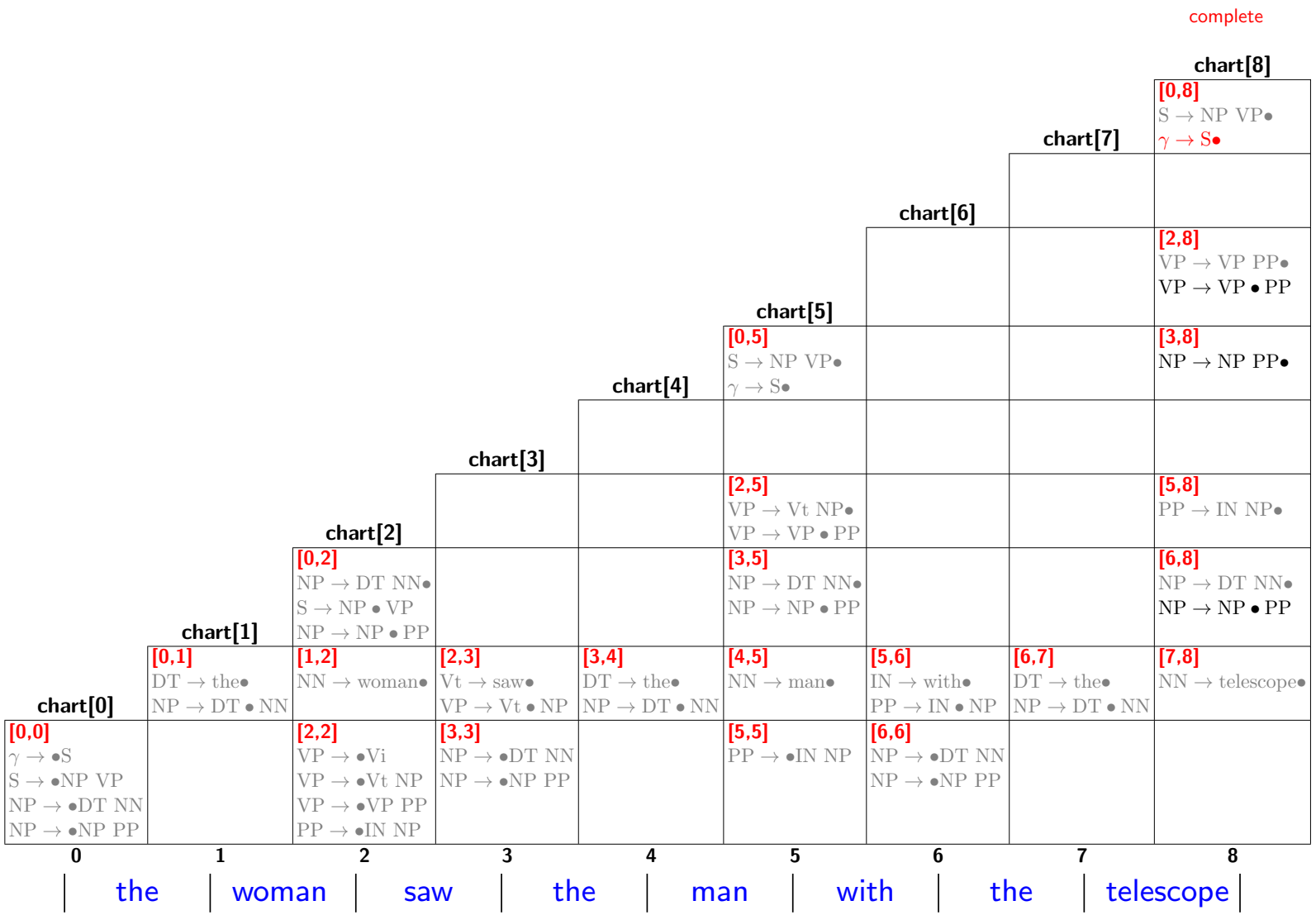
Earley Algorithm



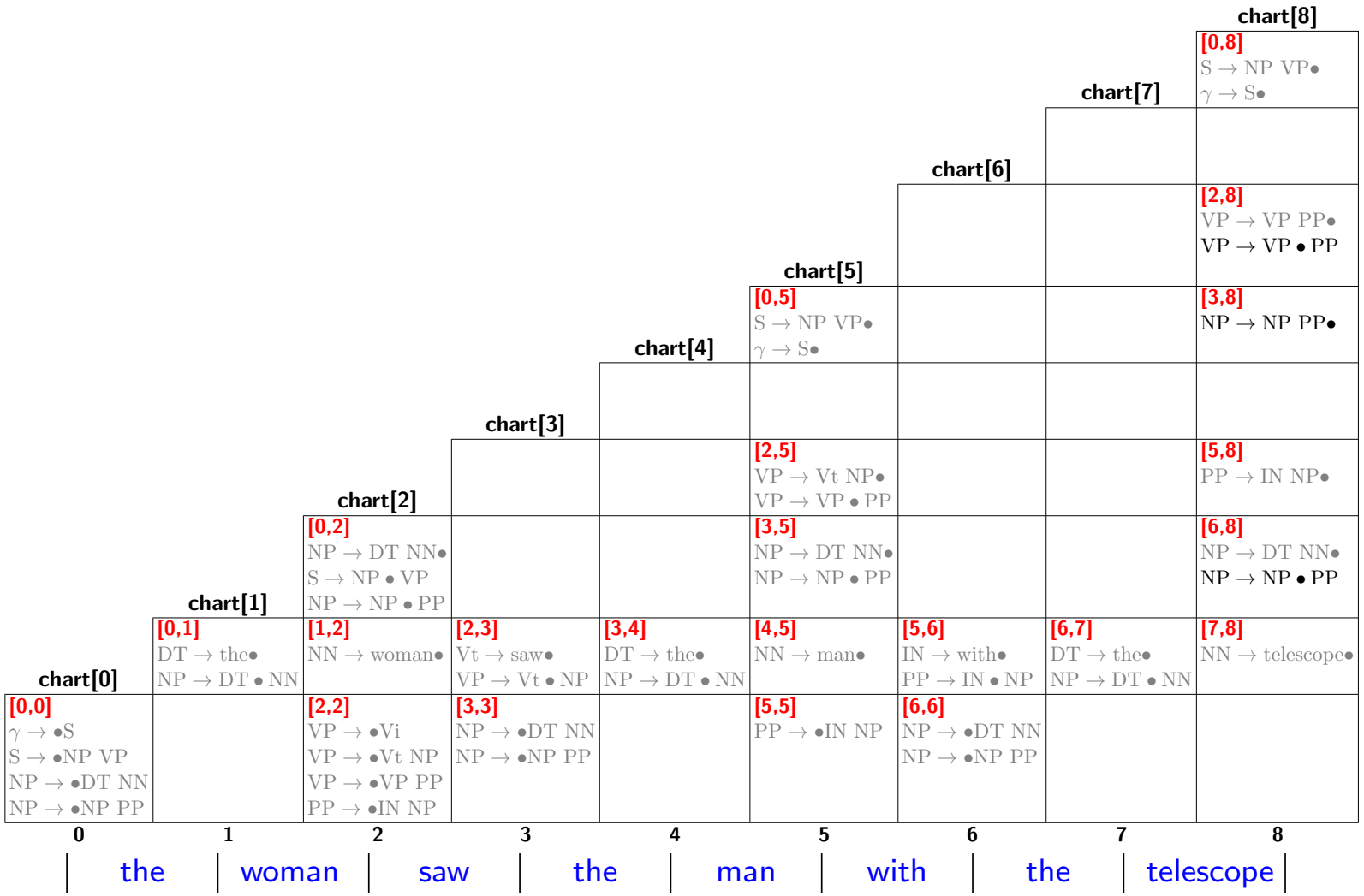
Earley Algorithm



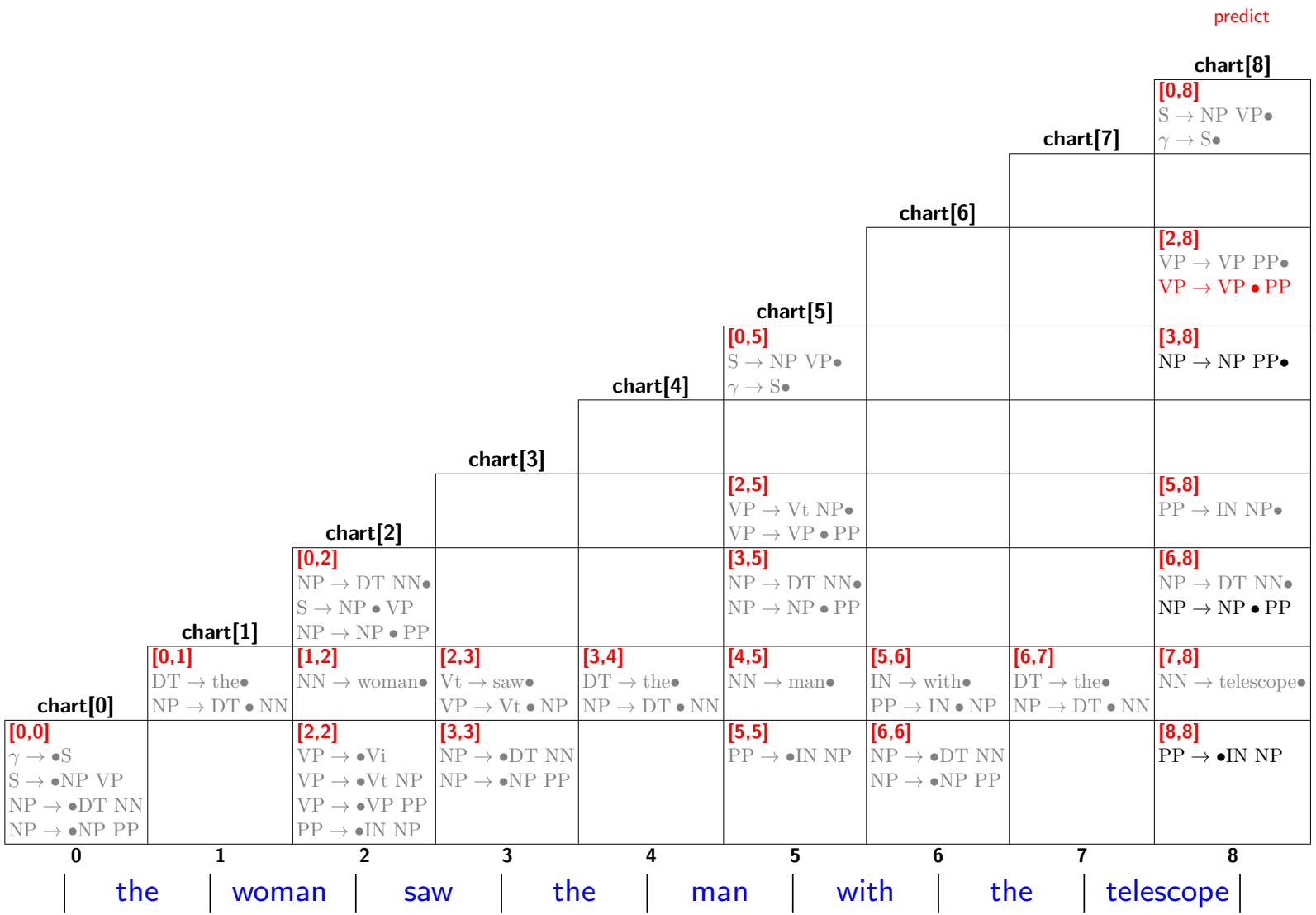
Earley Algorithm



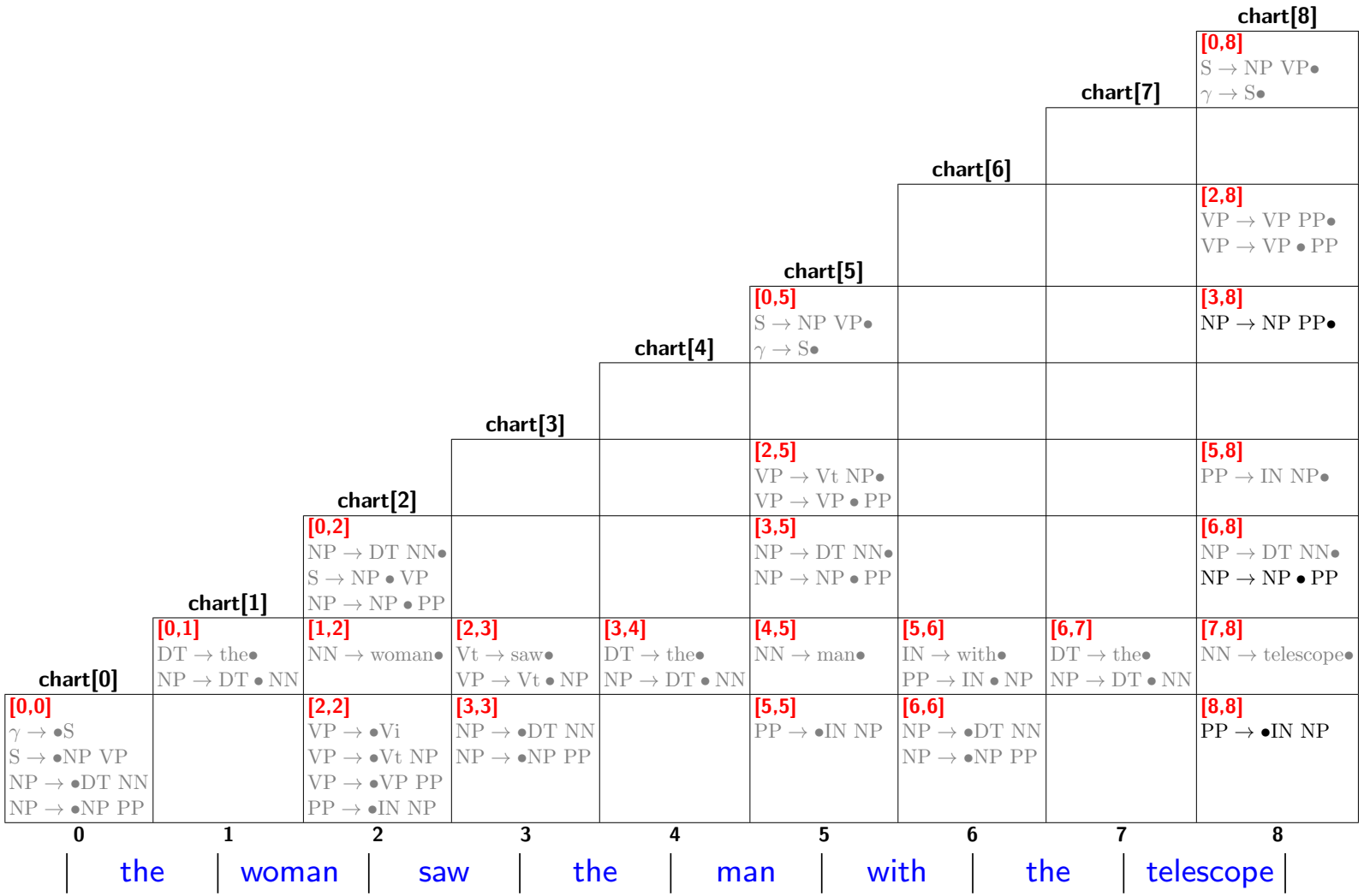
Earley Algorithm



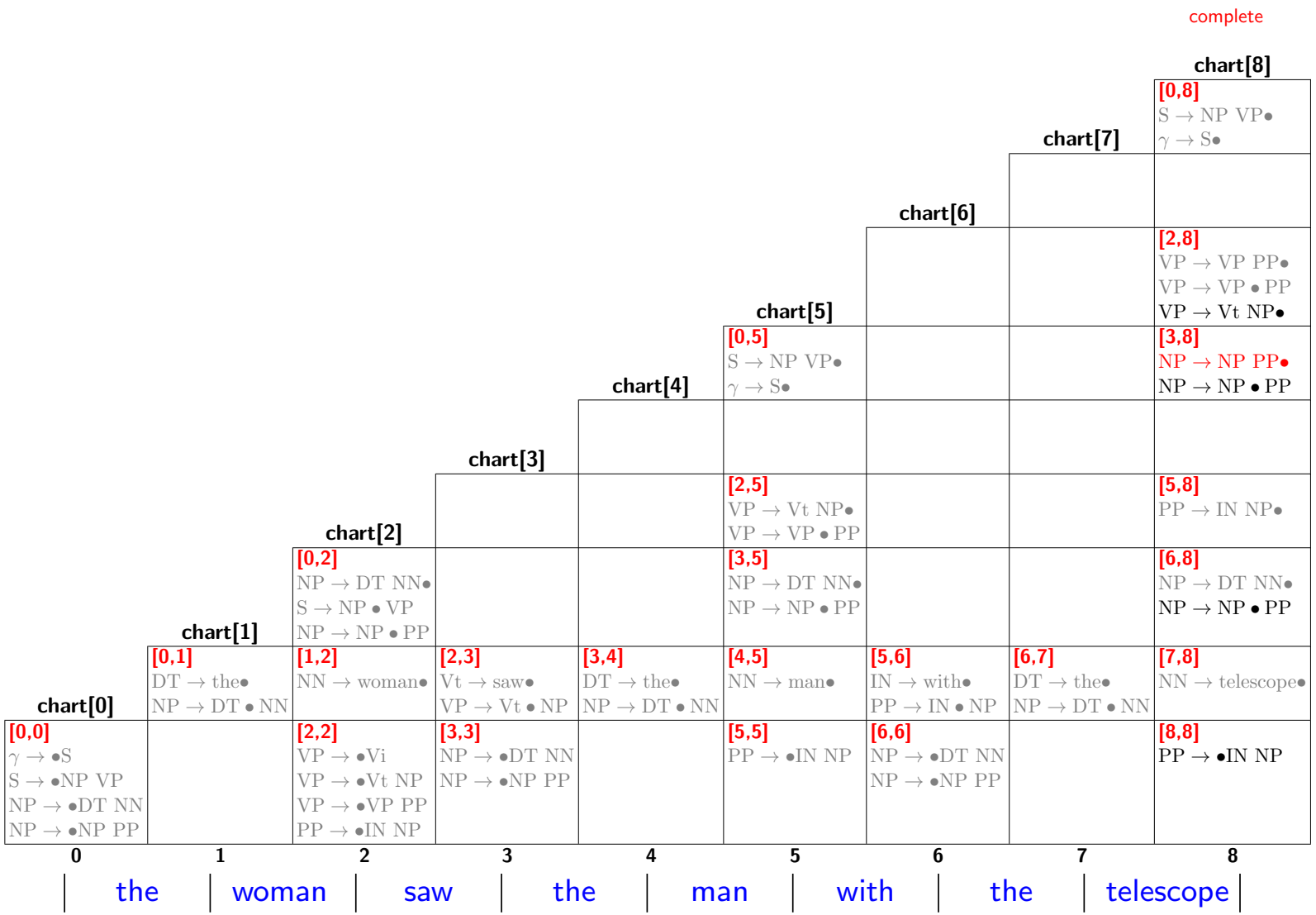
Earley Algorithm



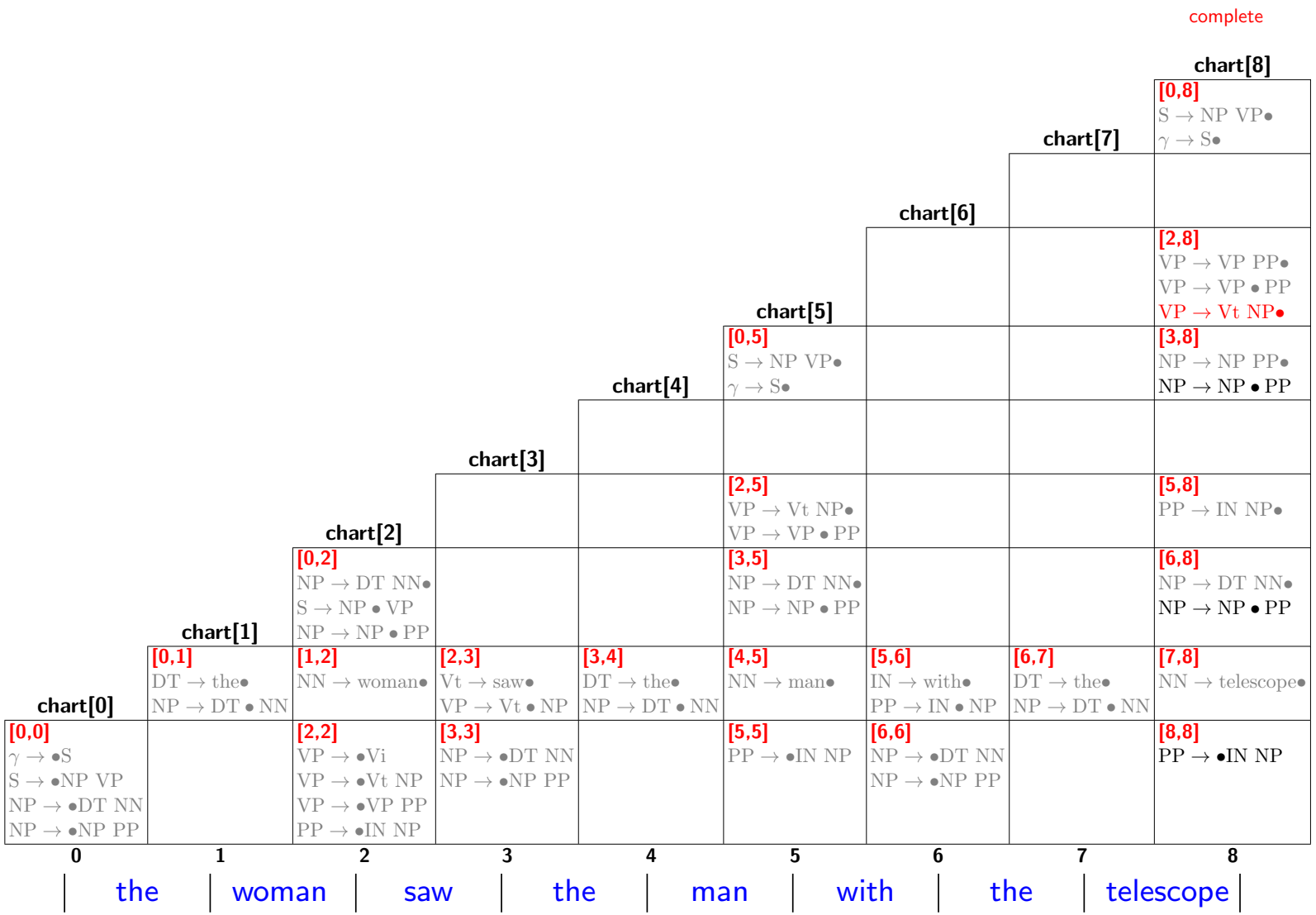
Earley Algorithm



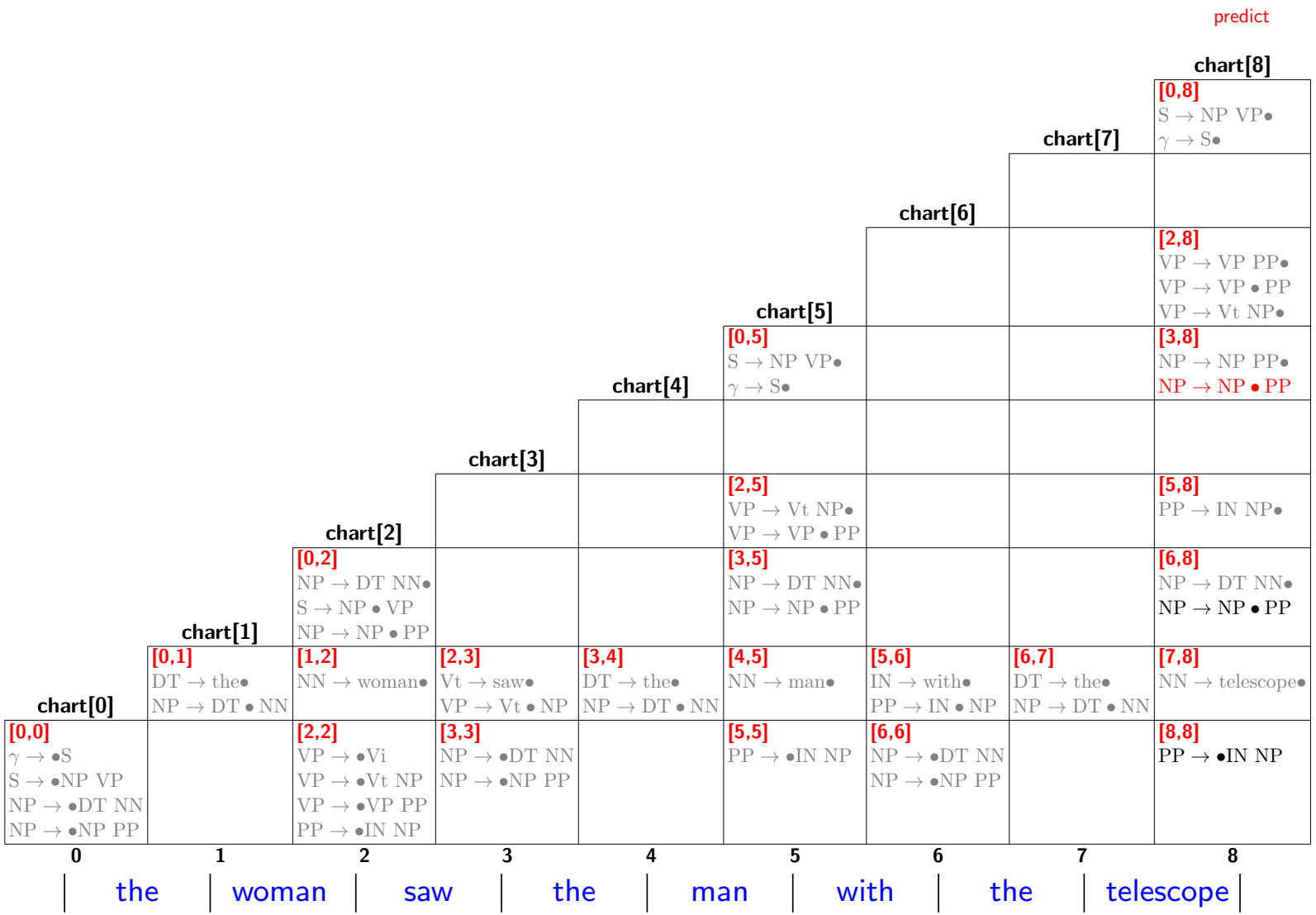
Earley Algorithm



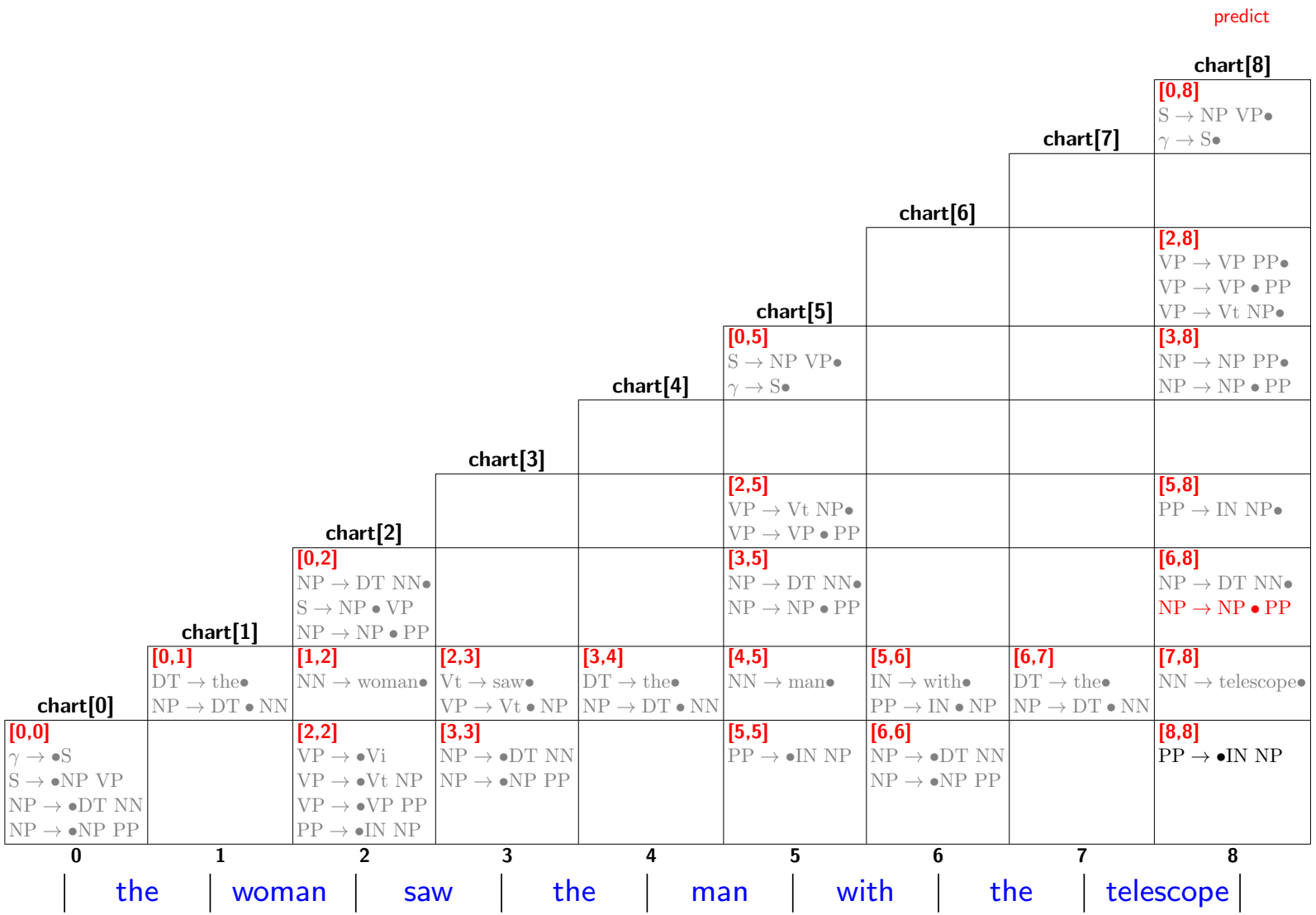
Earley Algorithm



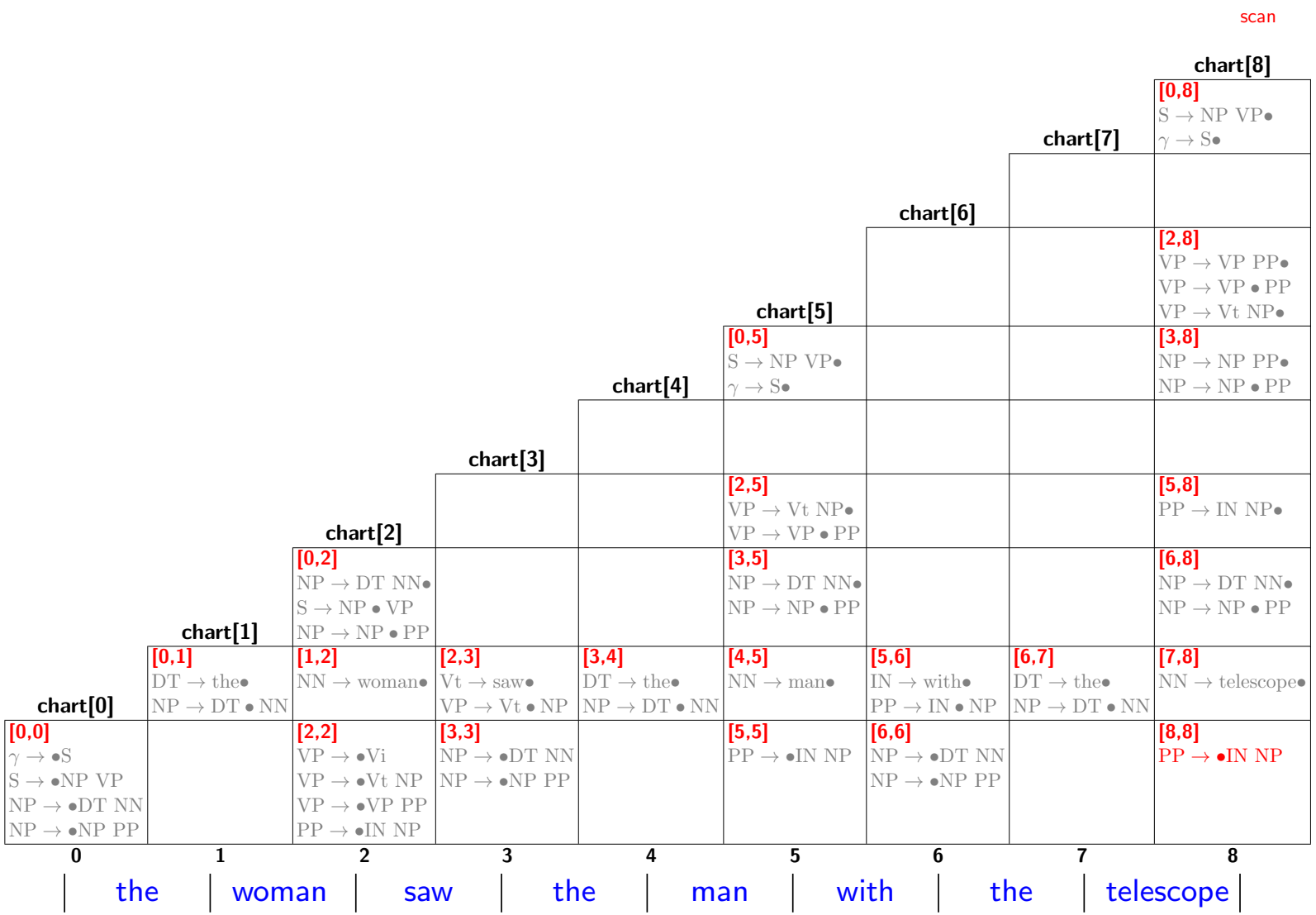
Earley Algorithm



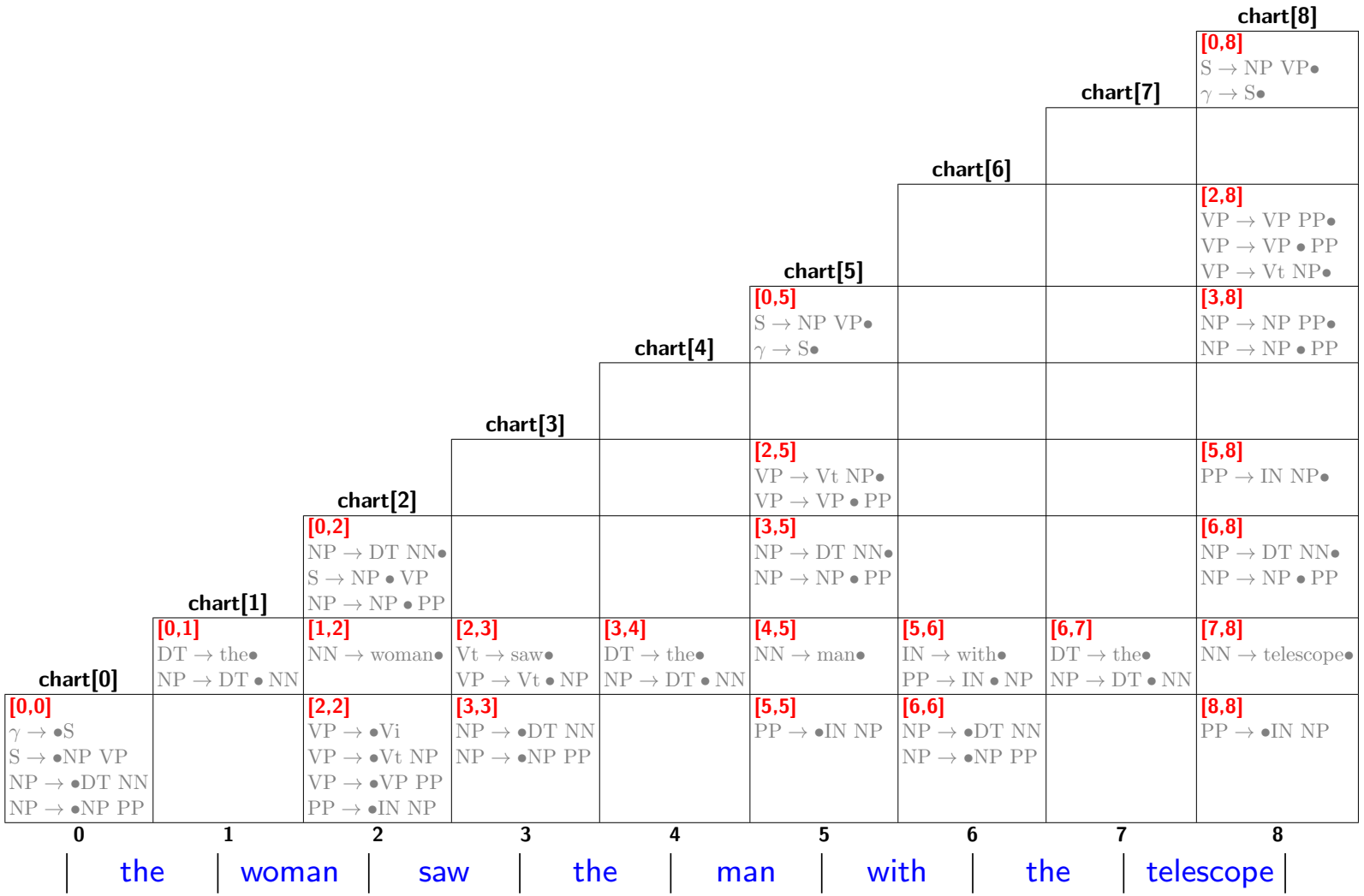
Earley Algorithm



Earley Algorithm



Earley Algorithm



CKY *vs* Earley

CKY

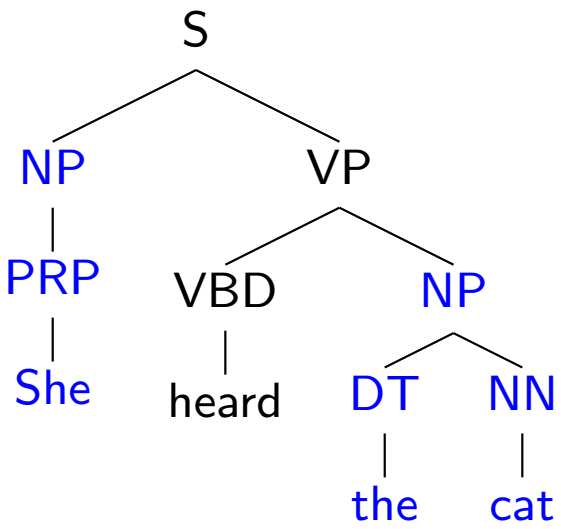
- Bottom-up
- Requires CNF
- Can compute all trees
- $\mathcal{O}(n^3)$
- Straightforward probabilistic version

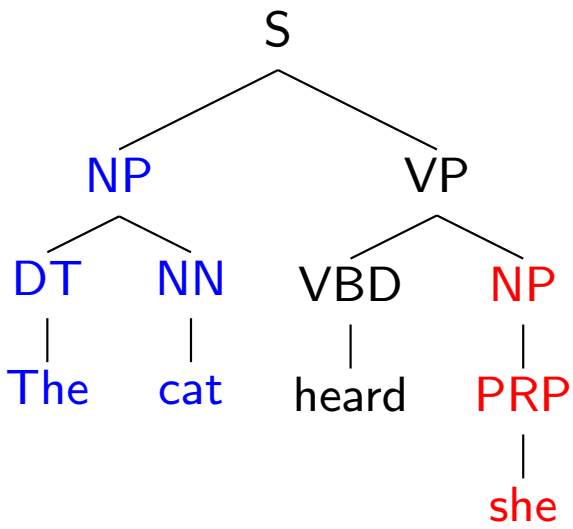
Earley

- 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* ?

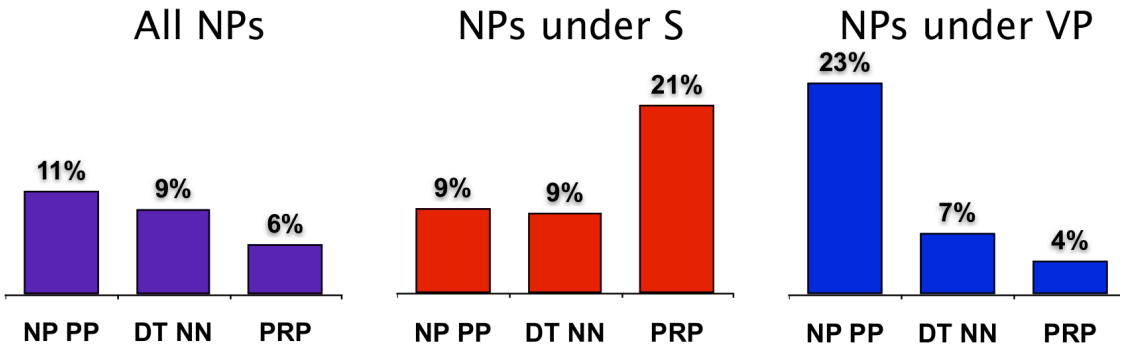
- Context-free means *independent of the context*, i.e, assumes that any expansion of a non-terminal is applicable, regardless of the context in which it occurs.





Natural Language is not Context-Free

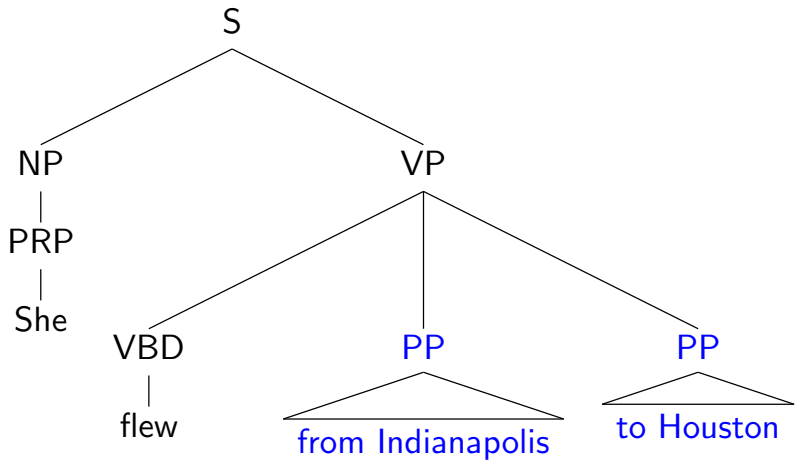
- NP expansion (for instance) is highly dependent on the parent of the NP

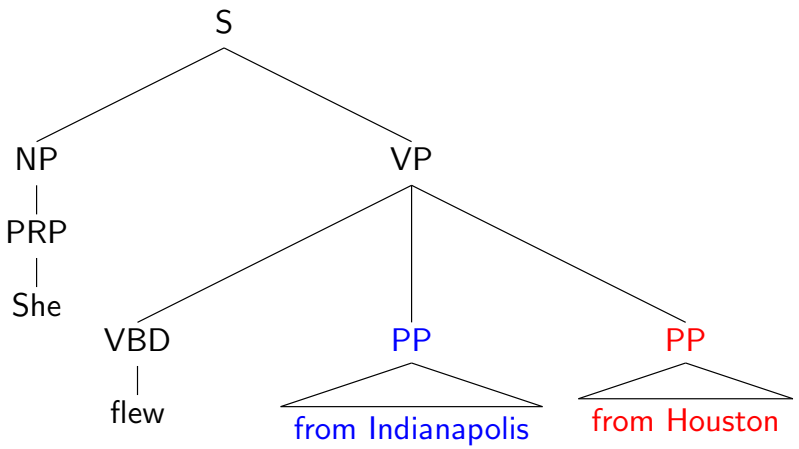


- Complete context independence is a too strong independence assumption for natural language.

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: