CSCI 544: Applied Natural Language Processing

Dependency Parsing

Xuezhe Ma (Max)

USC University of Southern California

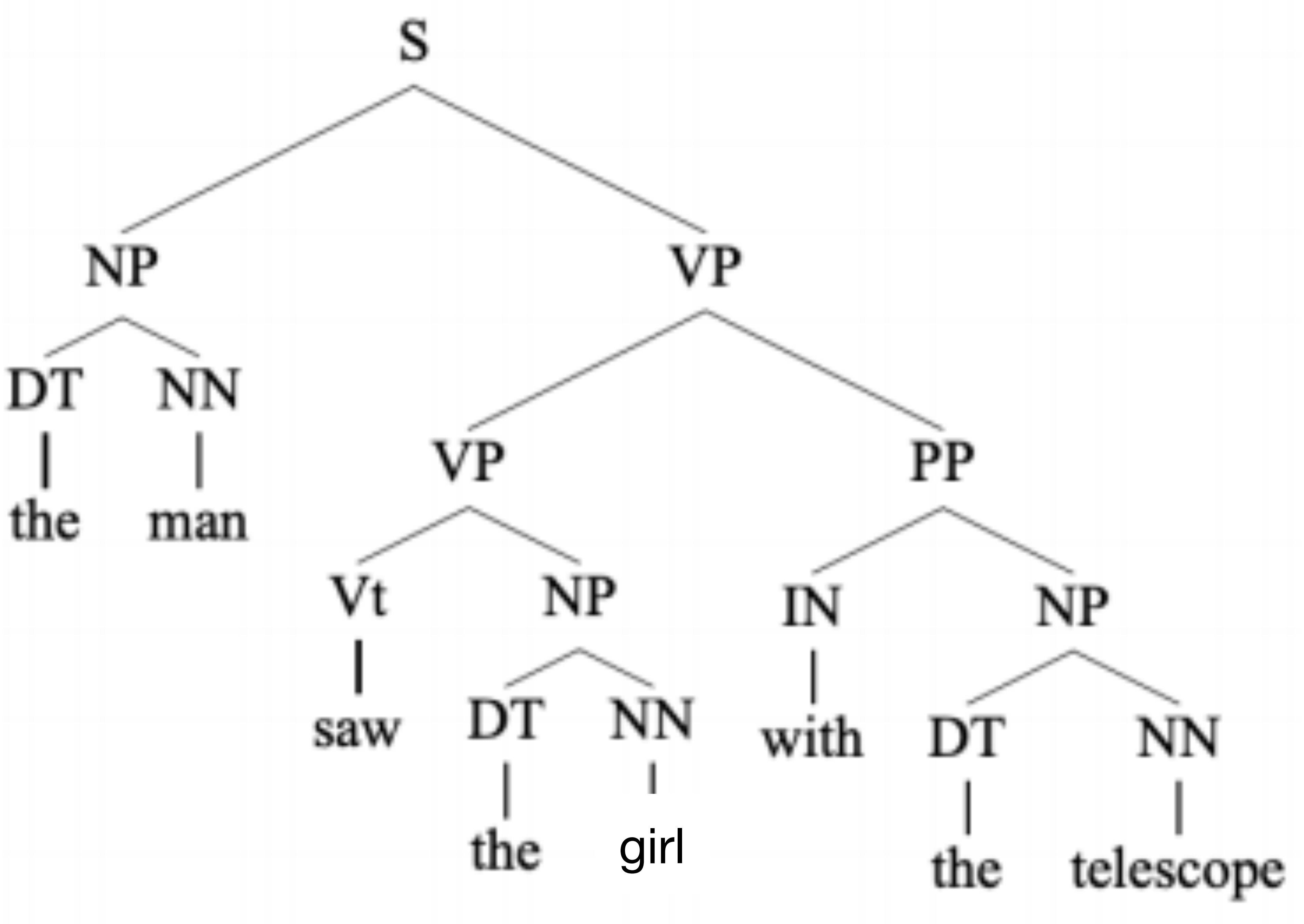
Logistic Points

- **GPU Resources:**
  - AWS Educate
  - $100 credits for each student

Recap: Constituency Structure

- **Starting units:** words are given a category: part-of-speech tags
  - N = noun, V = verb, DT = determiner
- **Phrases:** words combine into phrases with categories
  - NP = noun phrase, VP = verb phrase, S = sentence
  - Phrases can combine into bigger phrases recursively

The man saw the girl with the telescope



Recap: Probabilistic Context-free Grammar

- **A context free grammar (CFG) $G = (N, \Sigma, R, S)$ where:**
  - N is a set of non-terminal symbols
    - Phrasal categories: S, NP, VP, …
    - Part-of-speech: DT, NN, Vi, … (pre-terminals)
  - Σ is a set of terminal symbols: the, man, sleeps, …
  - R is a set of rules of the form $X \to Y_1 Y_2 \ldots Y_n$, for $n \geq 0$, $X \in N$, $Y_i \in (N \cup \Sigma)$
    - Examples: S -> NP VP, NP -> DT NN, NN -> man
  - $S \in N$ is a distinguished start symbol
- **Probabilistic PCFG**
  - A context free grammar (CFG) $G = (N, \Sigma, R, S)$ with probability assigned to each rule

Recap: The CKY Algorithm

- Base case definition: for all $i = 1 \ldots n$, for $X \in N$

$$\pi[i, i, X] = q(X \rightarrow w_i)$$

  (note: define $q(X \rightarrow w_i) = 0$ if $X \rightarrow w_i$ is not in the grammar)

- Recursive definition: for all $i = 1 \ldots n$, $j = (i+1) \ldots n$, $X \in N$,

$$\pi(i, j, X) = \max_{\substack{X \rightarrow Y Z \in R, \\ s \in \{i \ldots (j-1)\}}} \left(q(X \rightarrow Y Z) \times \pi(i, s, Y) \times \pi(s+1, j, Z) \right)$$

Q: Running time?

$O(n^3 |R|)$

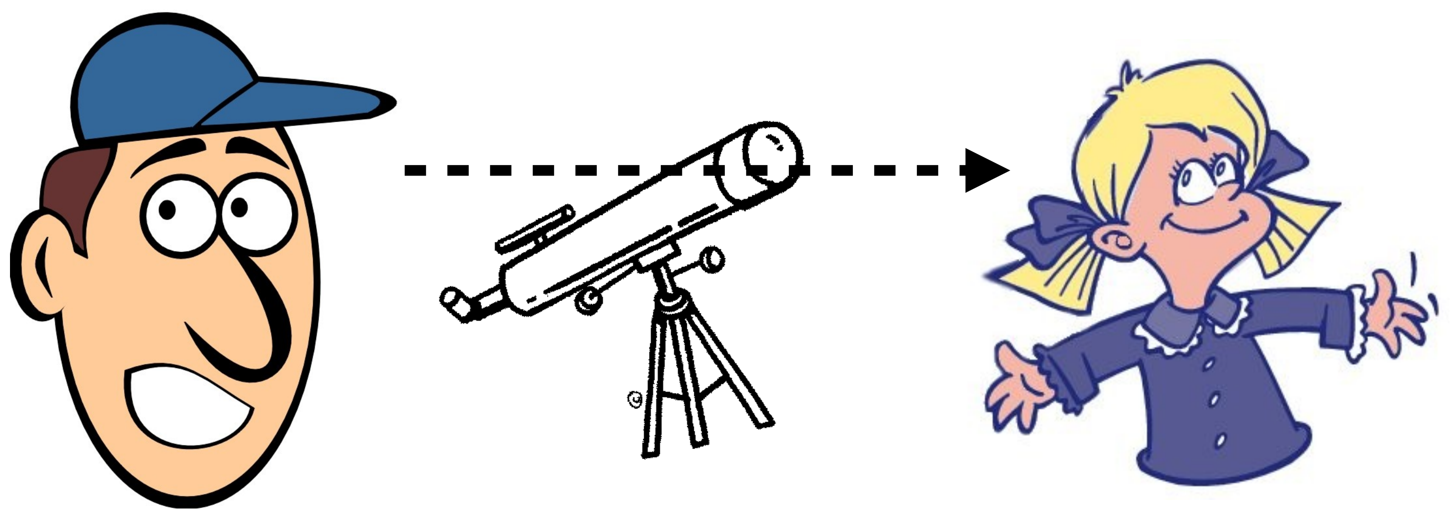
Overview

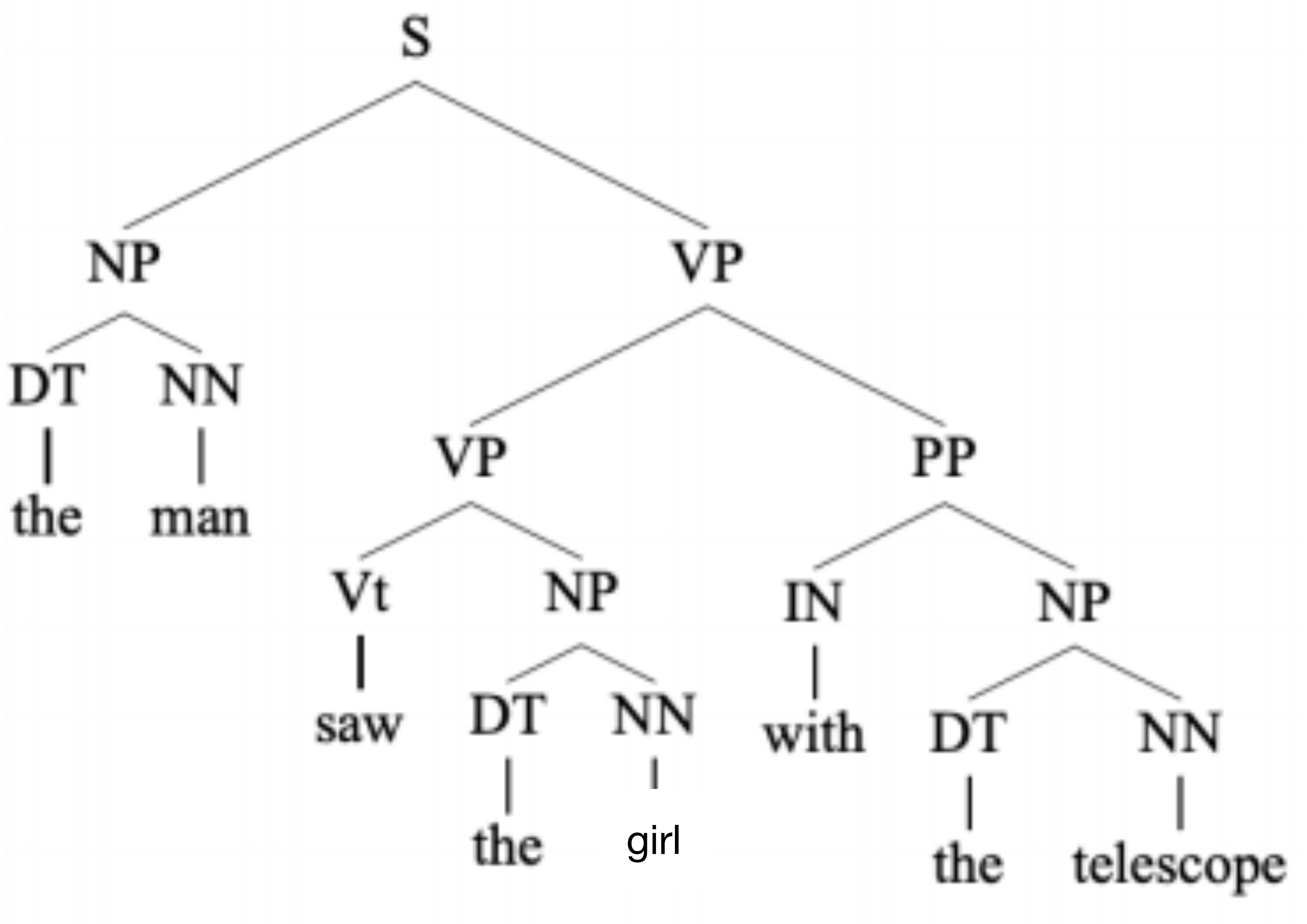
- **Constituency Parsing**
  - Constituency Structure
  - Context-free Grammar (CFG) & Probabilistic Context-free Grammar (PCFG)
  - The CKY algorithm
  - Lexicalized PCFGs
- **Dependency Parsing**
  - Dependency Structure
  - Graph-based Dependency Parsing
  - Transition-based Dependency Parsing

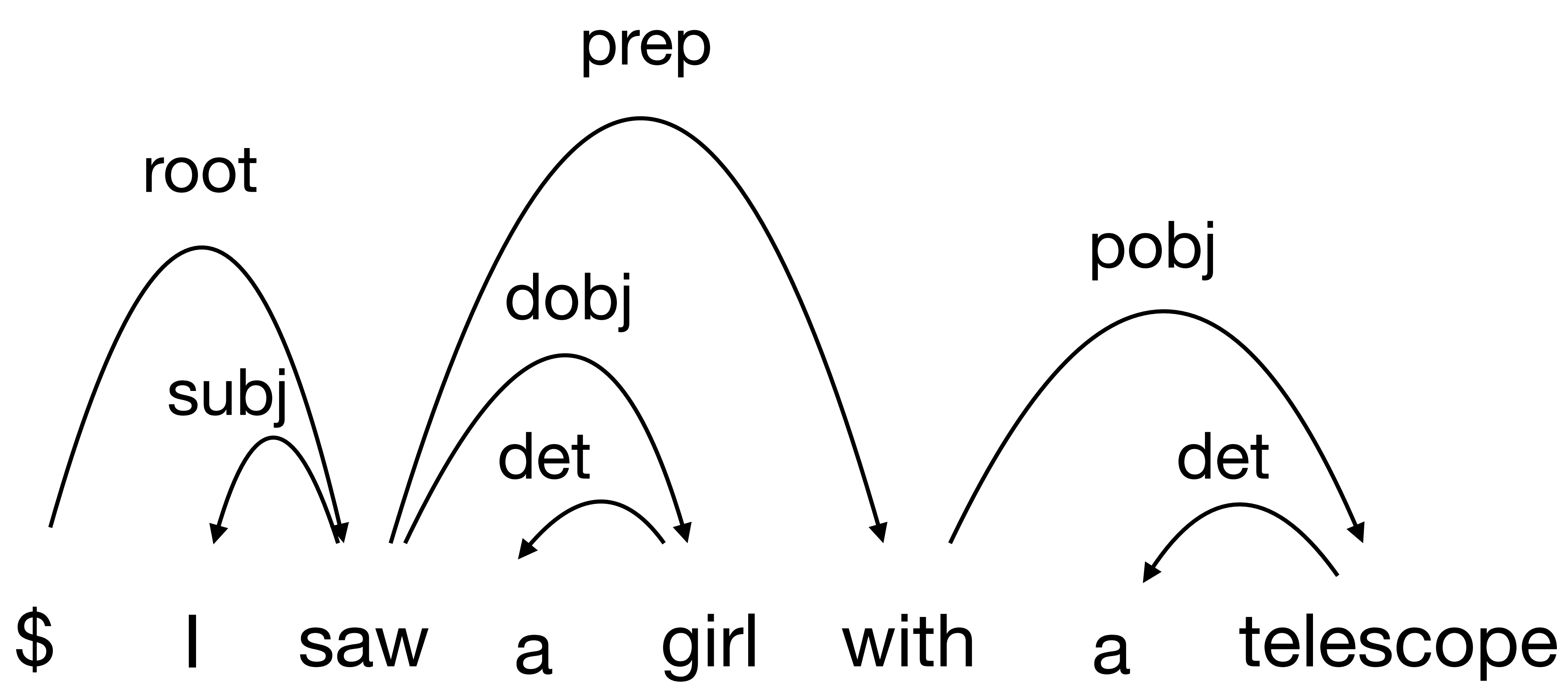
Dependency Parsing

Constituency vs. Dependency

The man saw the girl with the telescope

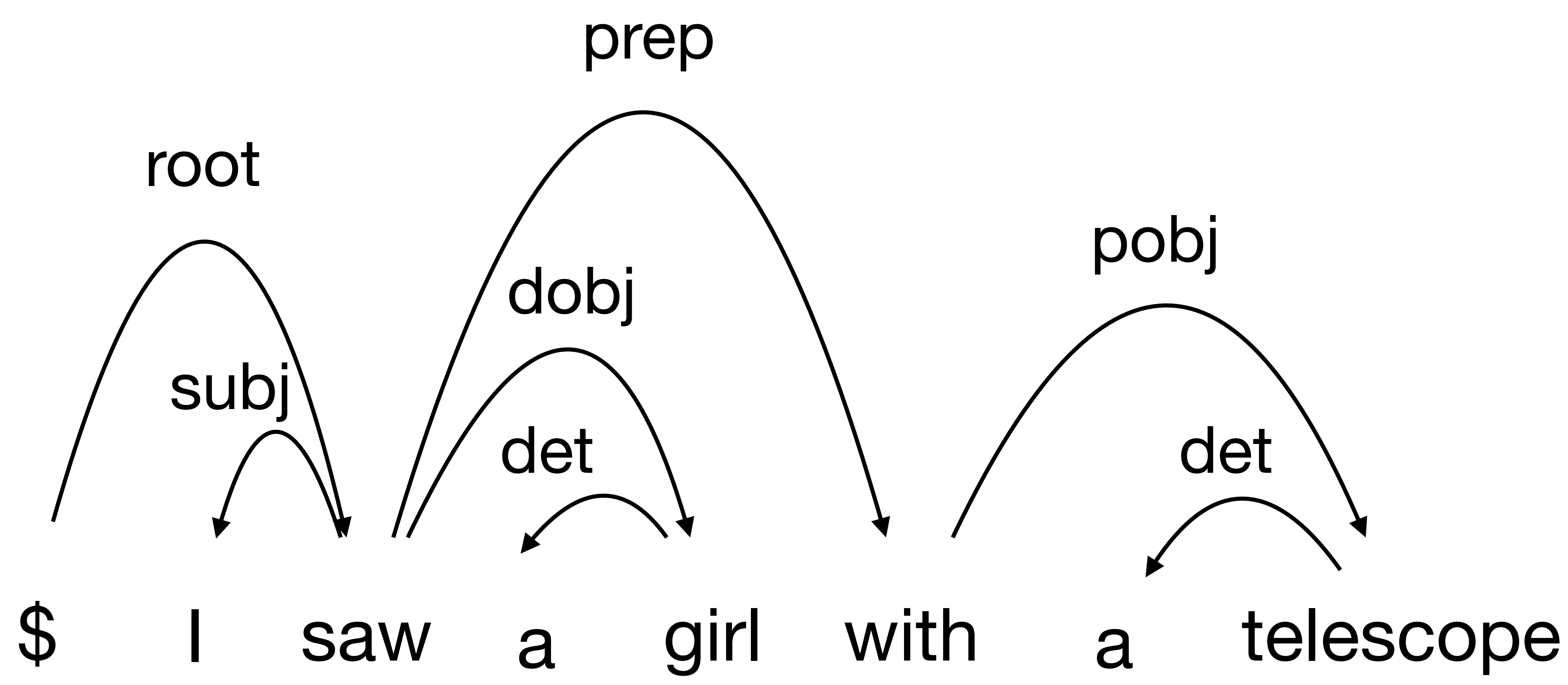




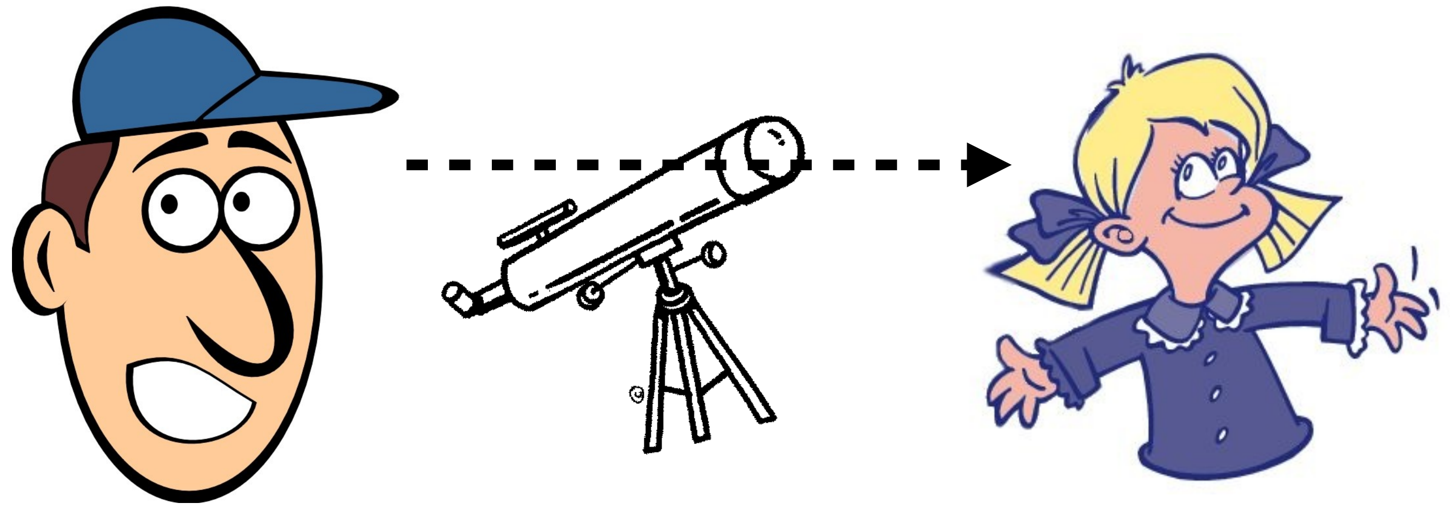


Dependency Structure

- **The basic idea:**
  - Syntactic structure consists of lexical items, linked by binary asymmetric relations called dependencies.
- **In the words of Lucien Tesniere** [Tesniere1959]:
  - The sentence is an organized whole, the constituent elements of which are *words* [1.2]. Every word that belongs to a sentence ceases by itself to be isolated as in the dictionary. Between the word and its neighbors, the mind perceives *connection*, the totality of which forms the structure of the sentence [1.3]. The structural connections establish *dependency* relations between the words. Each connection in principle unites a *superior* term and an *inferior* term [2.1]. The superior term receives the name *governor*, and the inferior term receives the name *subordinate*.

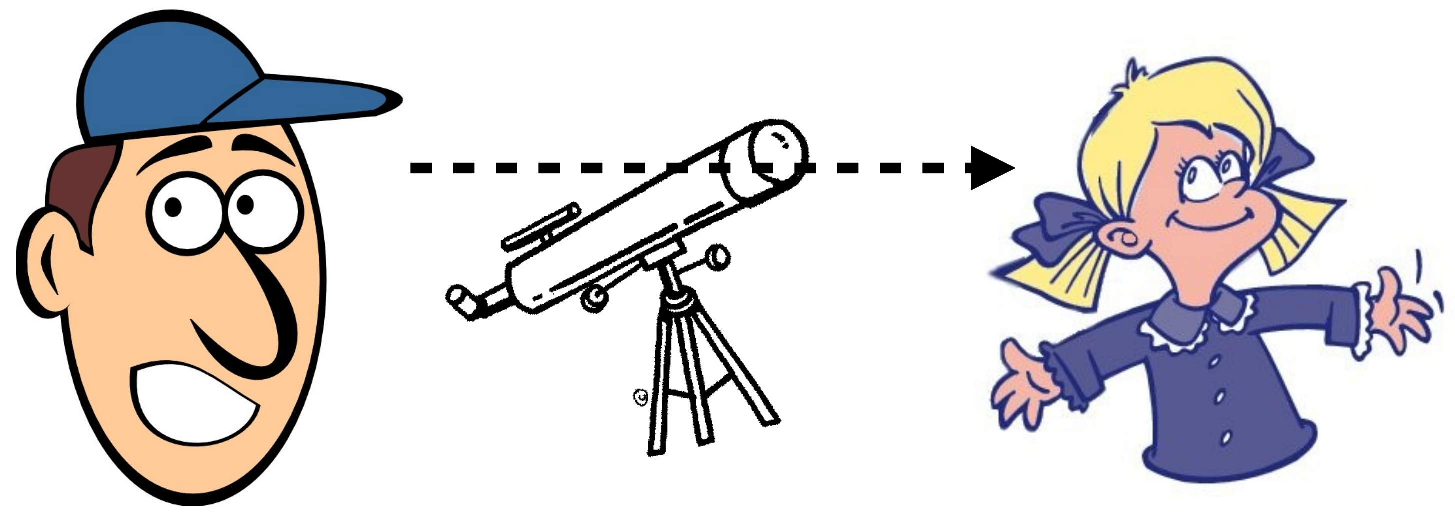


Dependency Structure



$ I saw a girl with a telescope

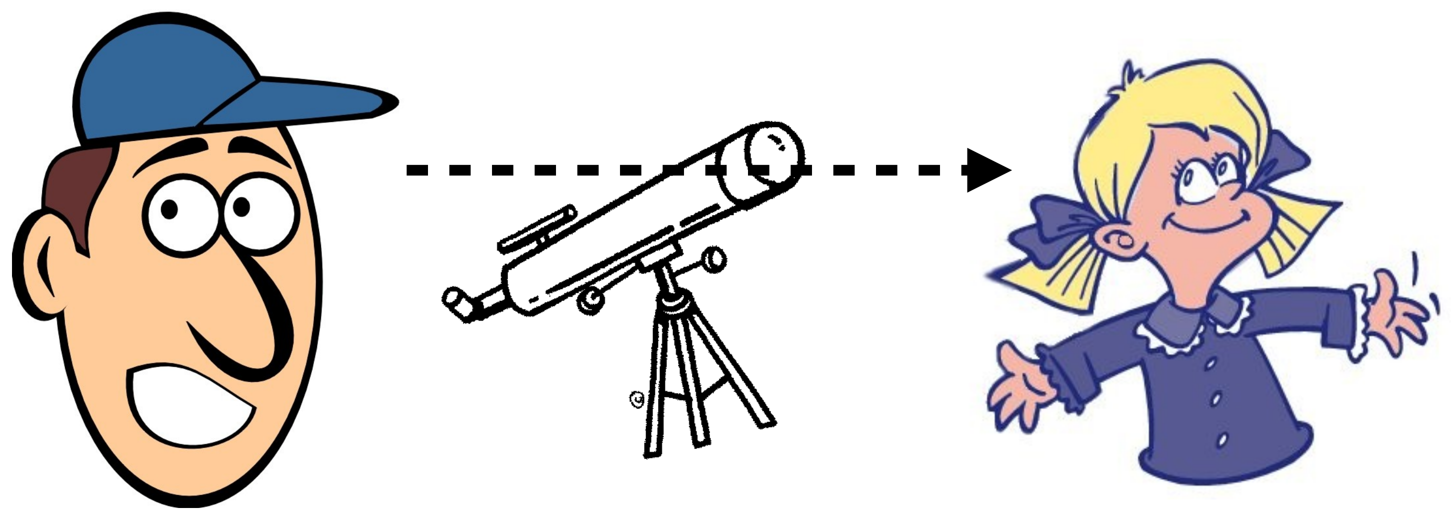
Dependency Structure

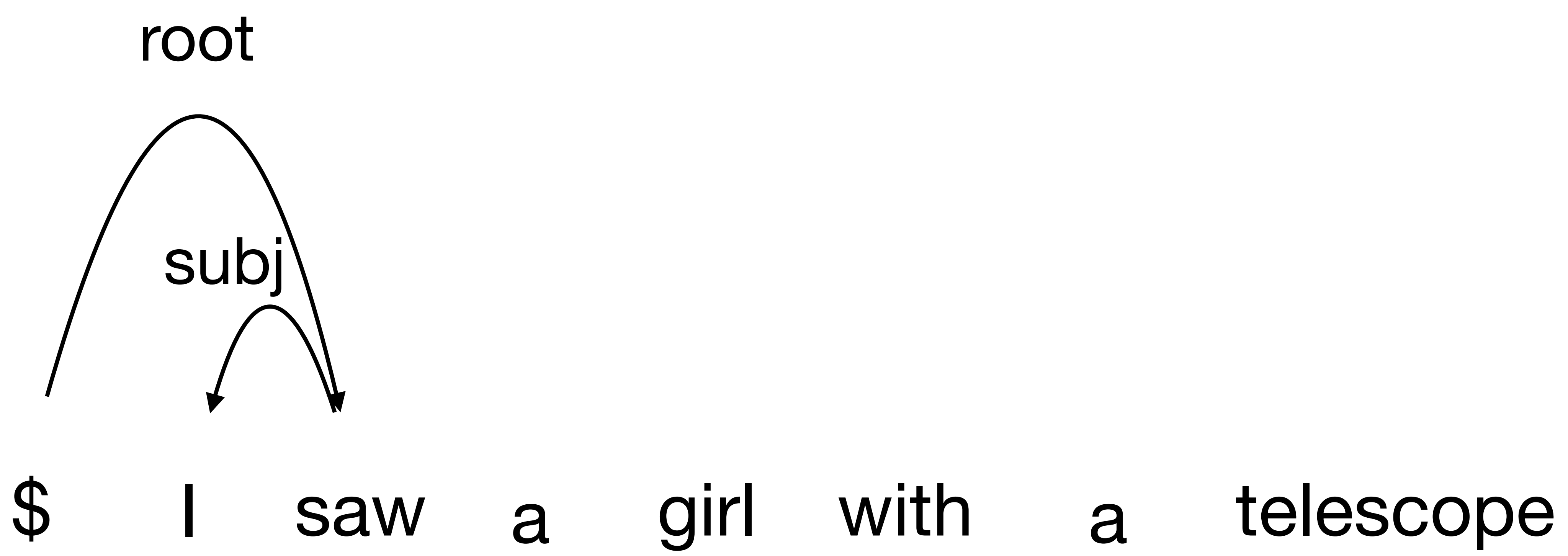


root

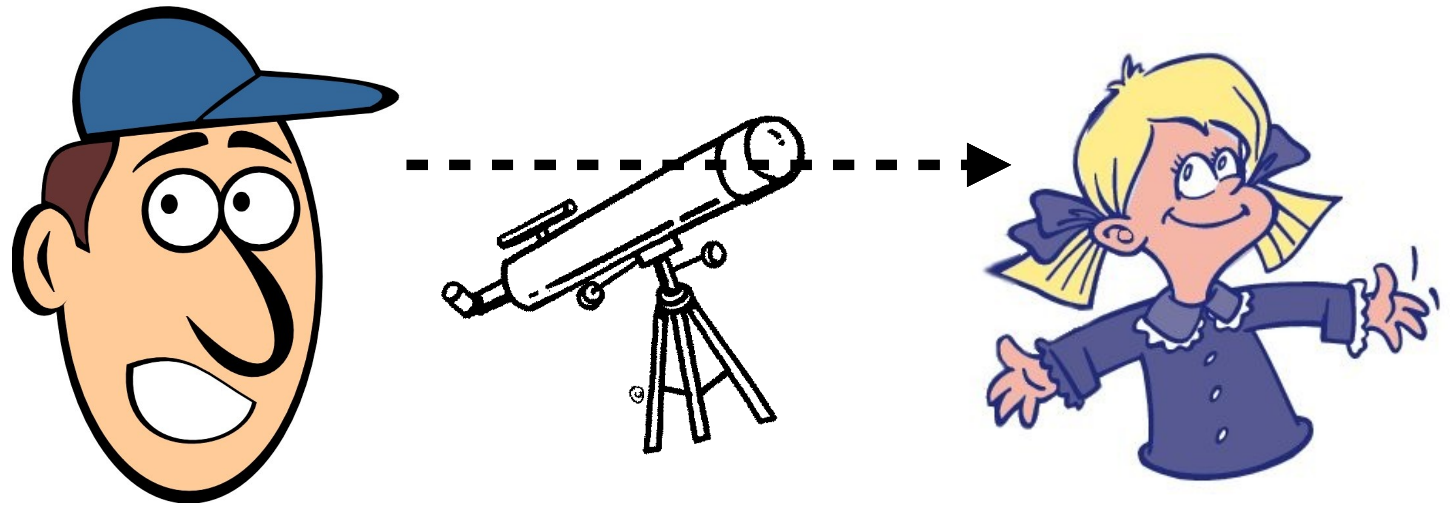
$ I saw a girl with a telescope

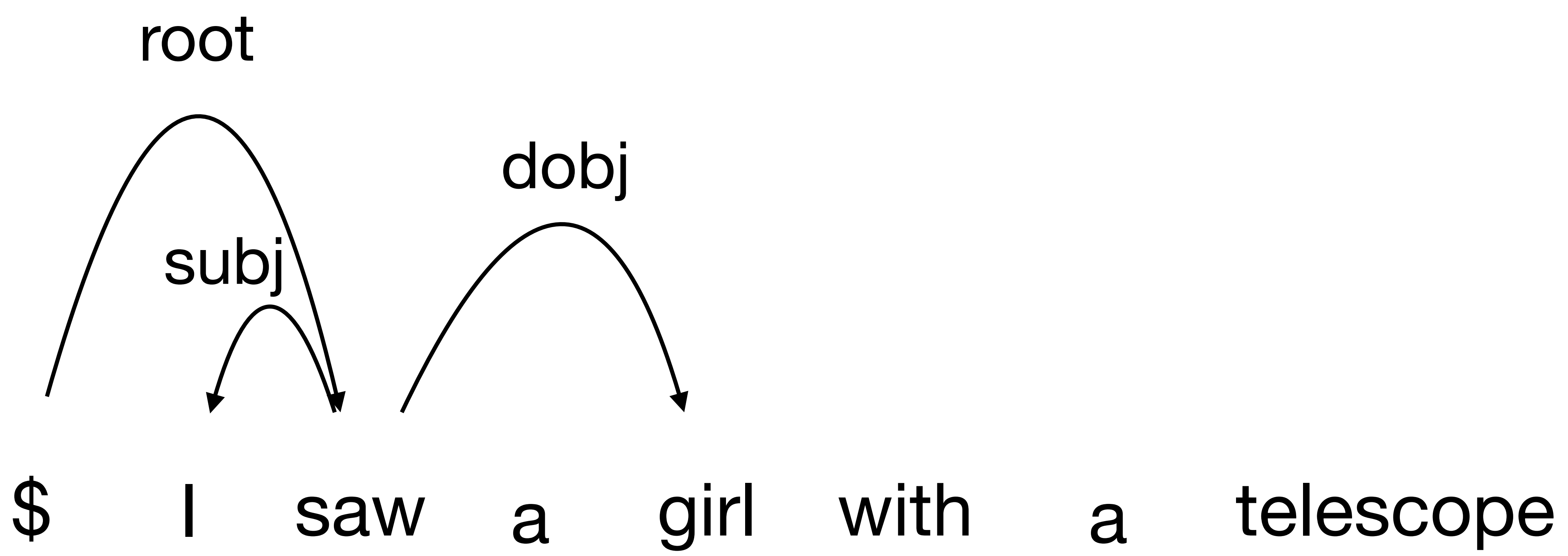
Dependency Structure



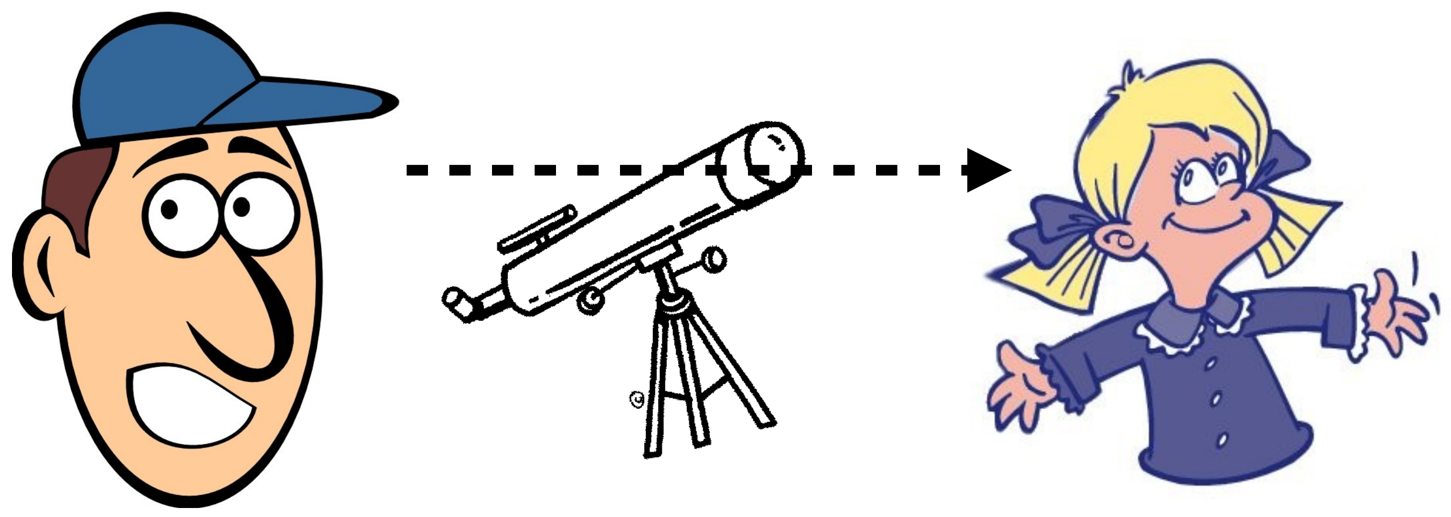


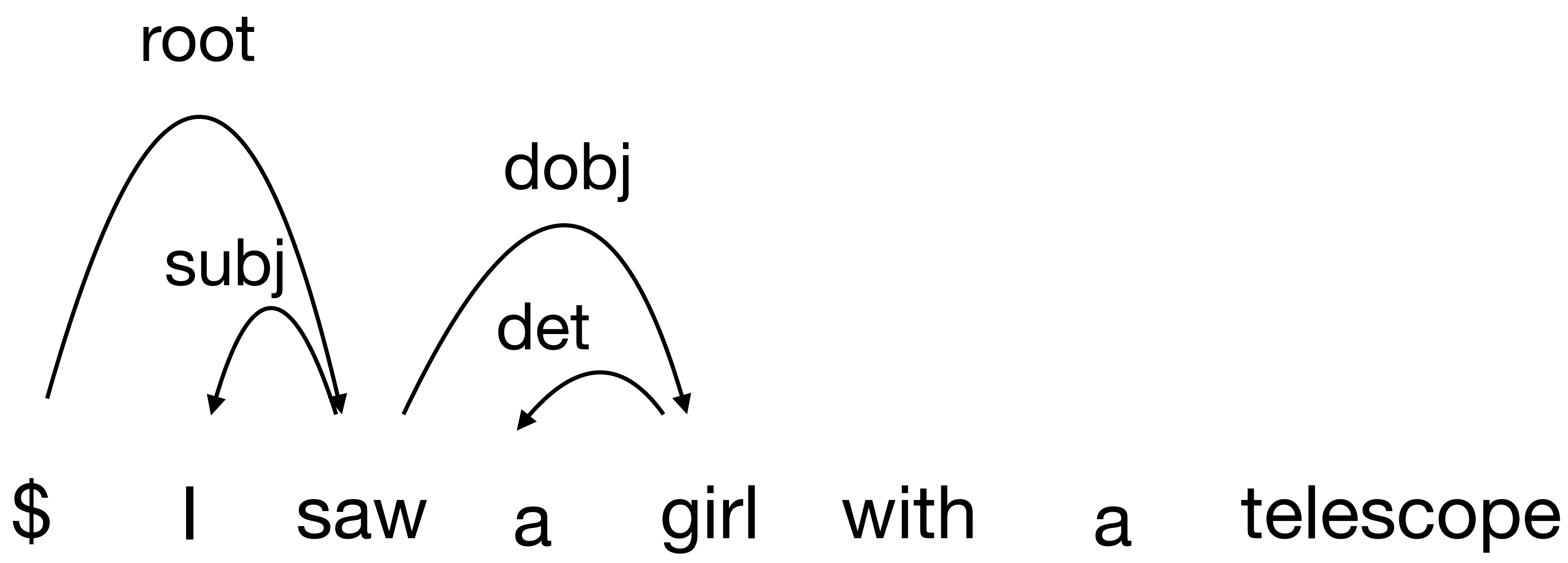
Dependency Structure



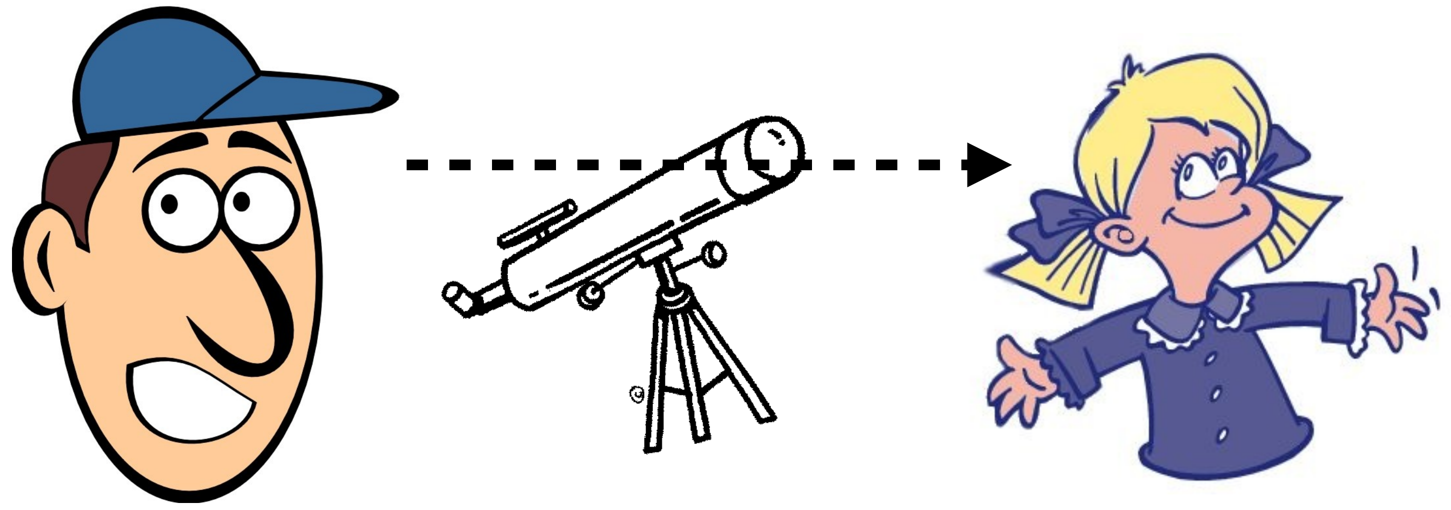


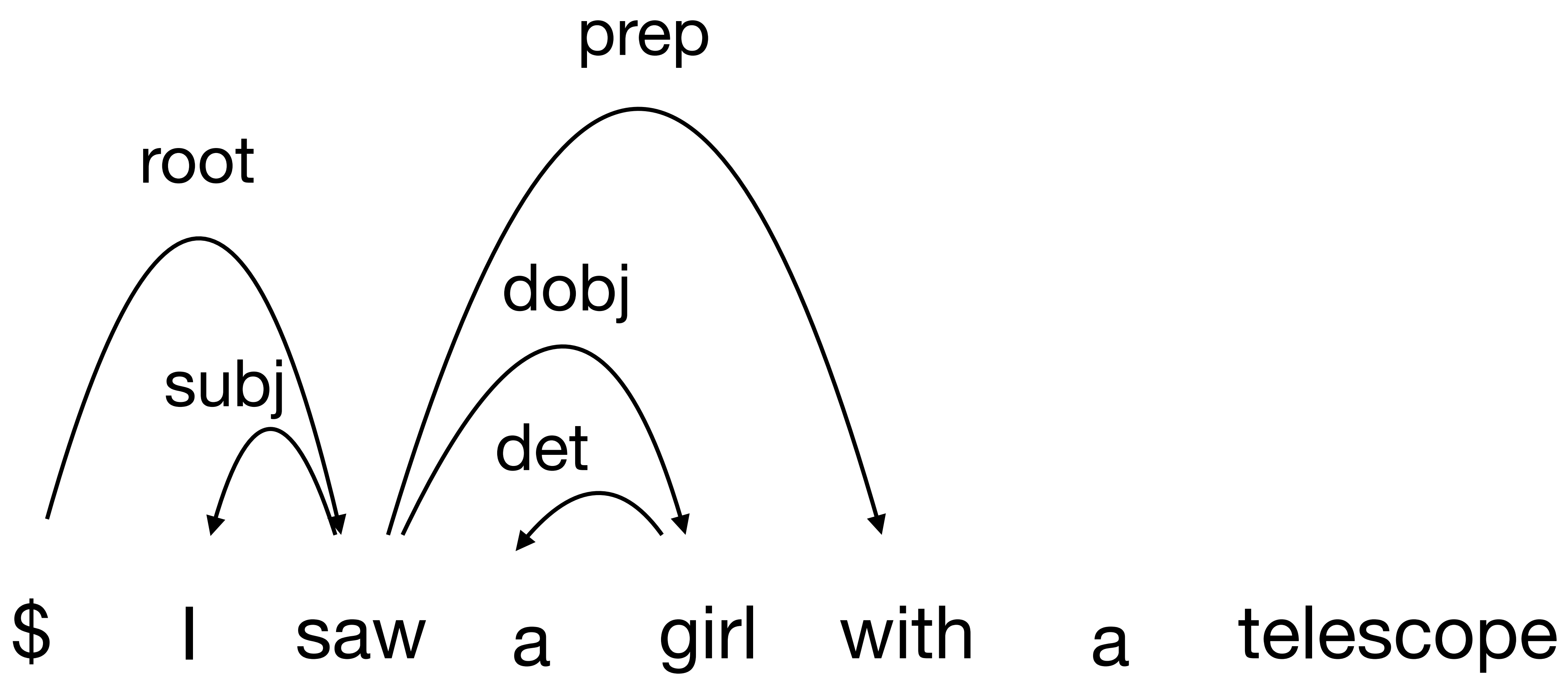
Dependency Structure



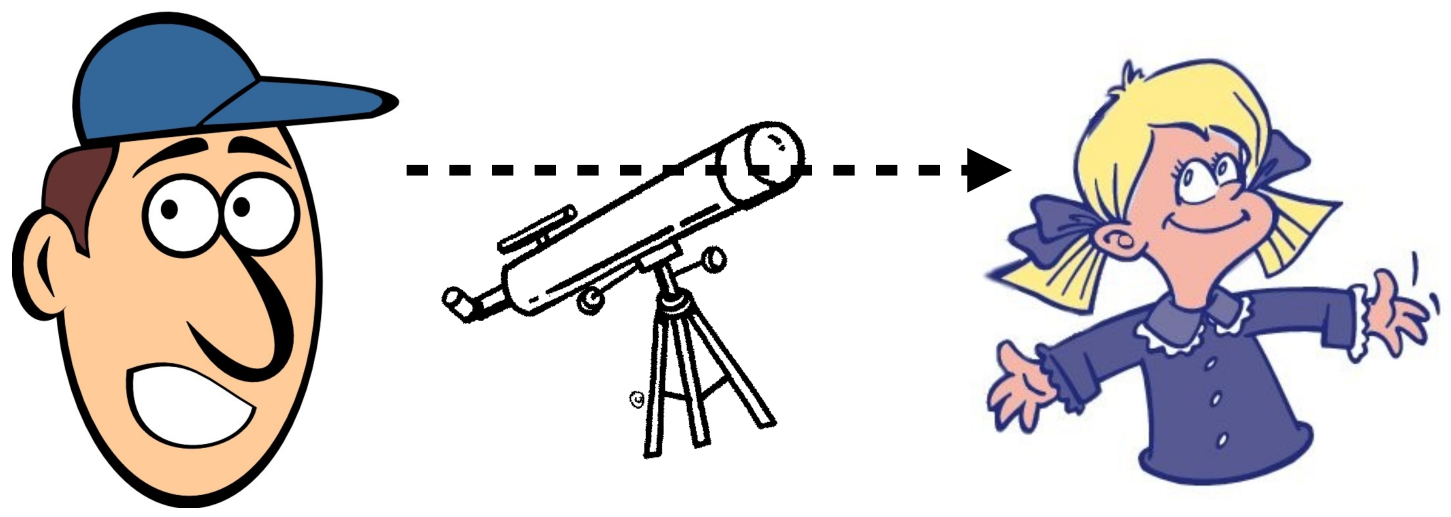


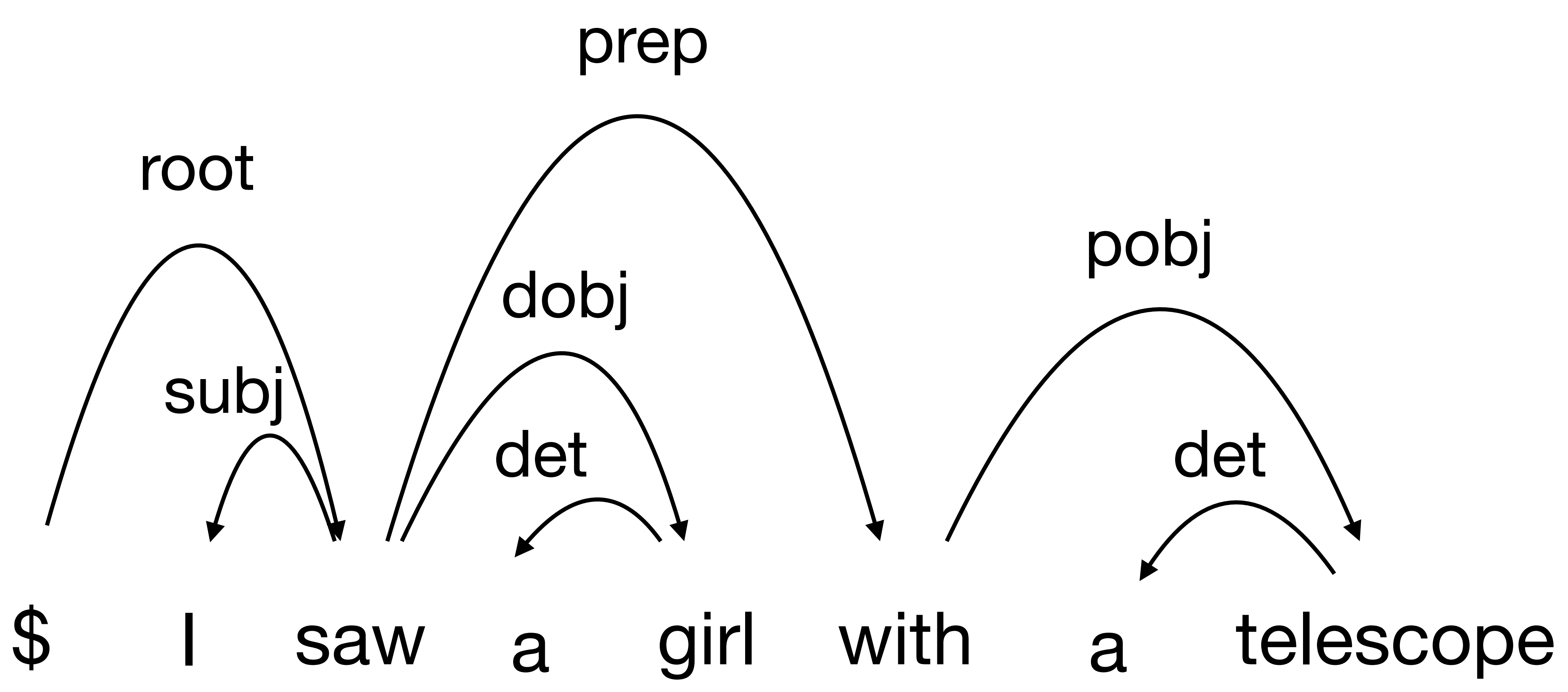
Dependency Structure





Dependency Structure





Terminology

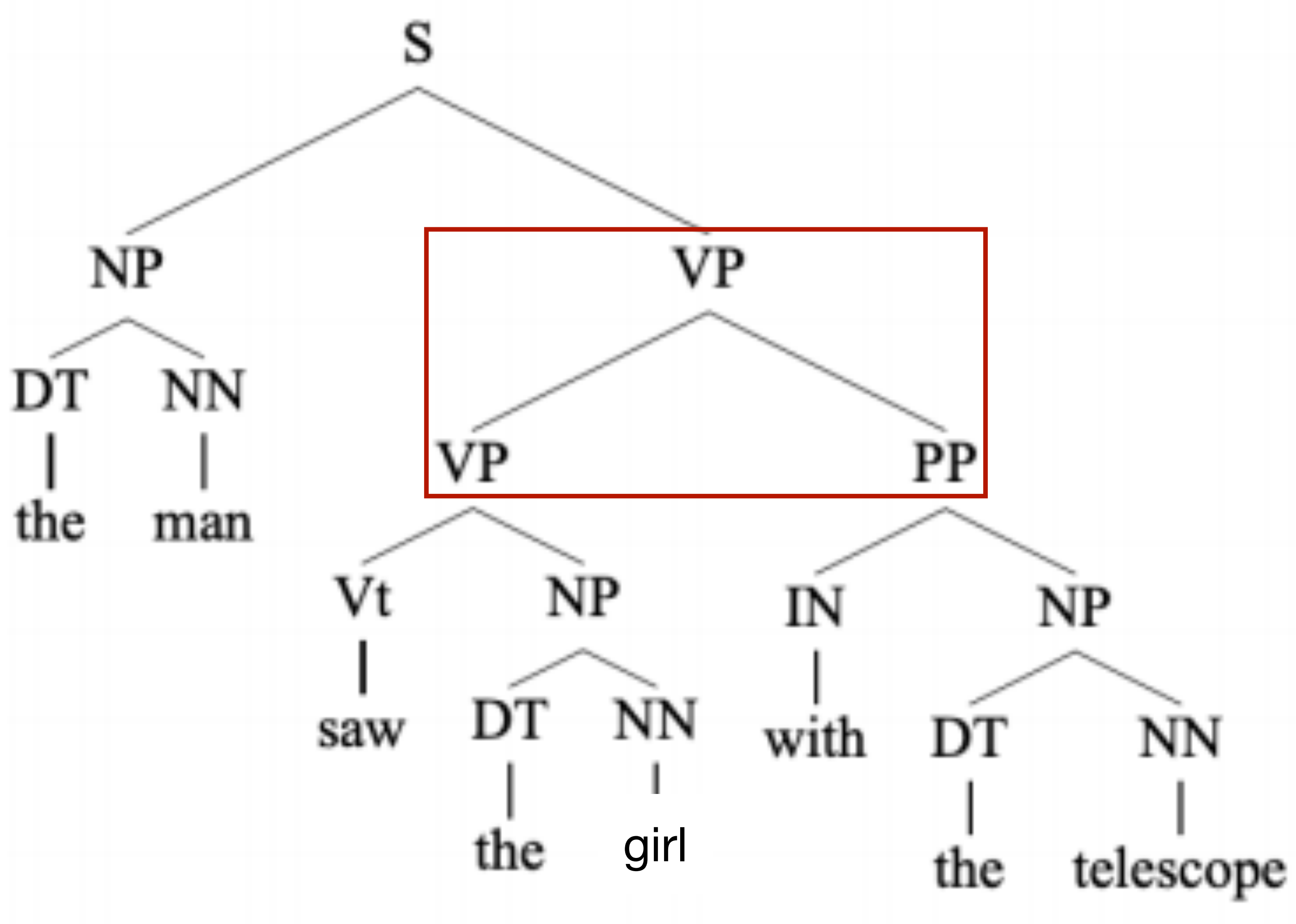
Superior	Inferior
Head	Dependent
Governor	Modifier
Regent	Subordinate
⋮	⋮

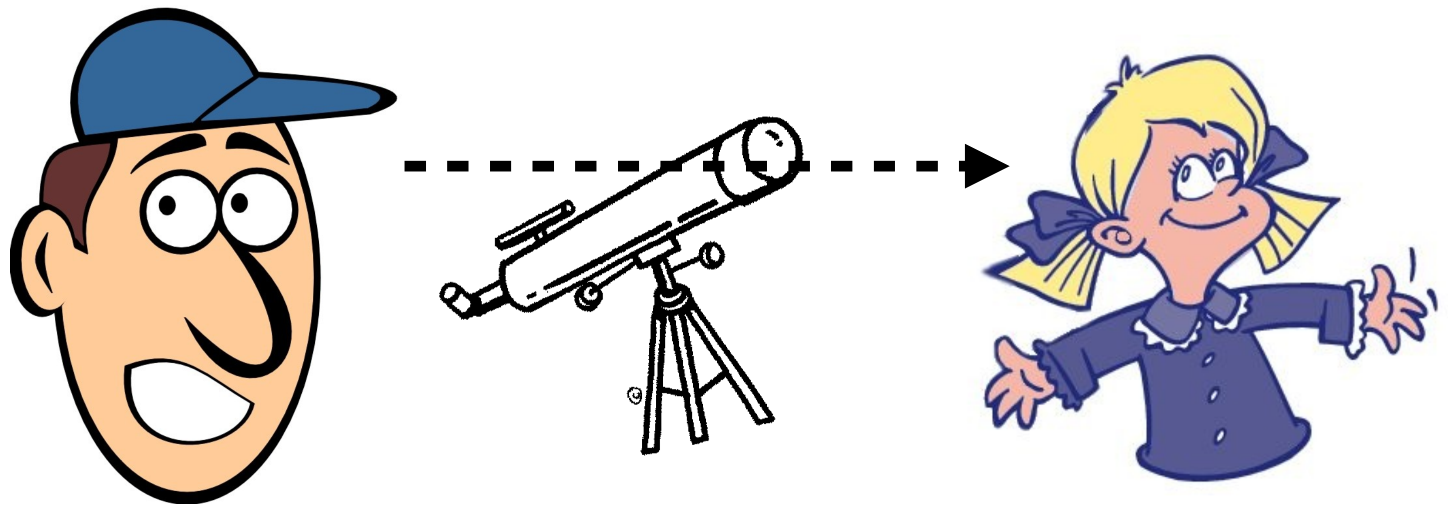
Terminology

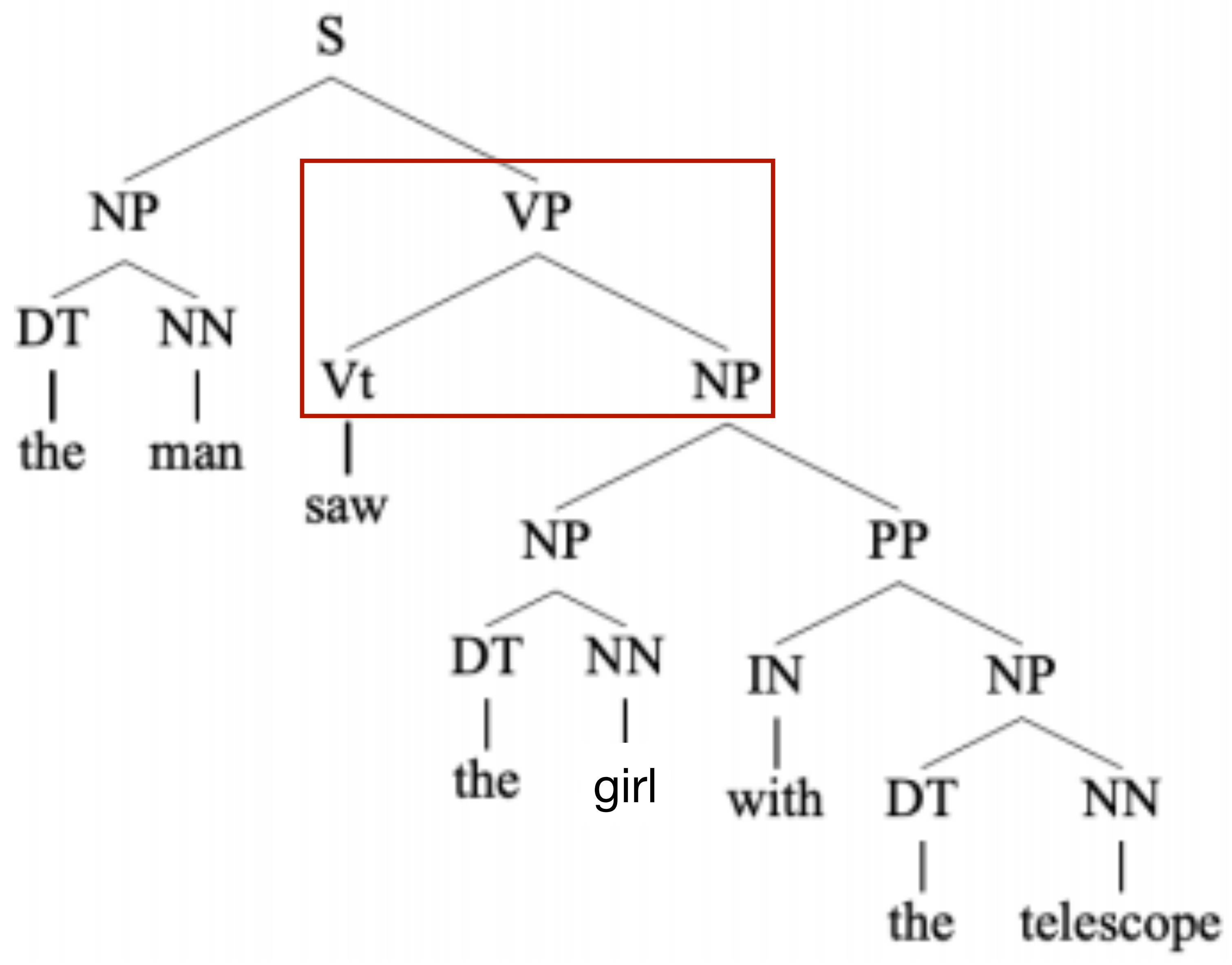
Superior	**Inferior**
Head	Dependent
Governor	Modifier
Regent	Subordinate
⋮	⋮

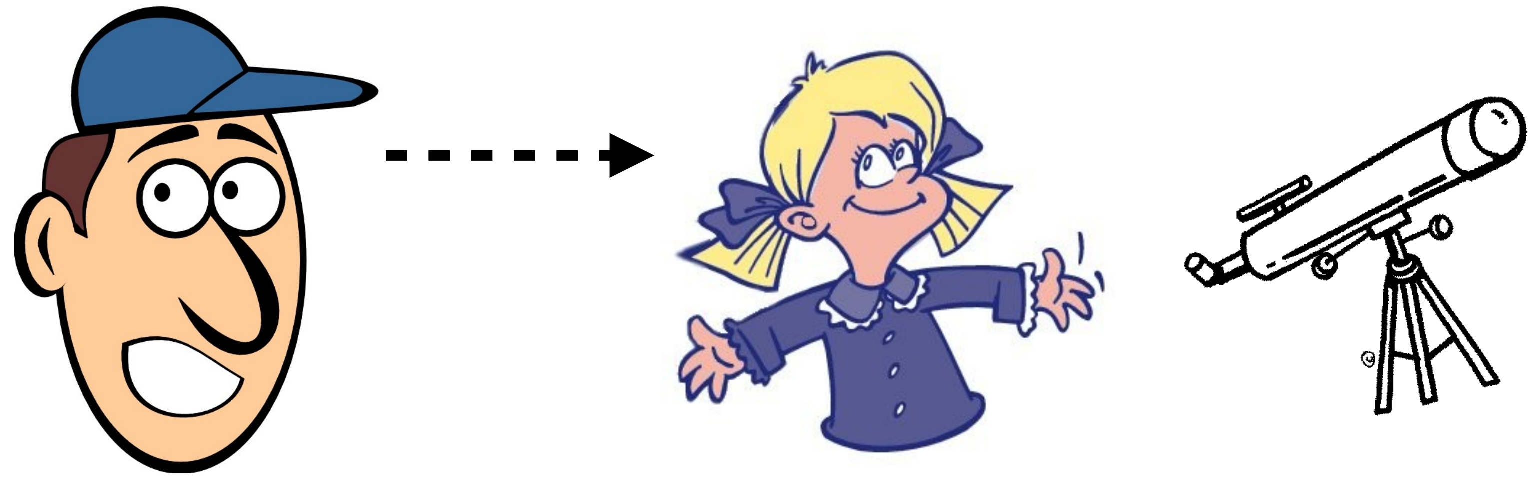
Constituency vs. Dependency

The man saw the girl with the telescope

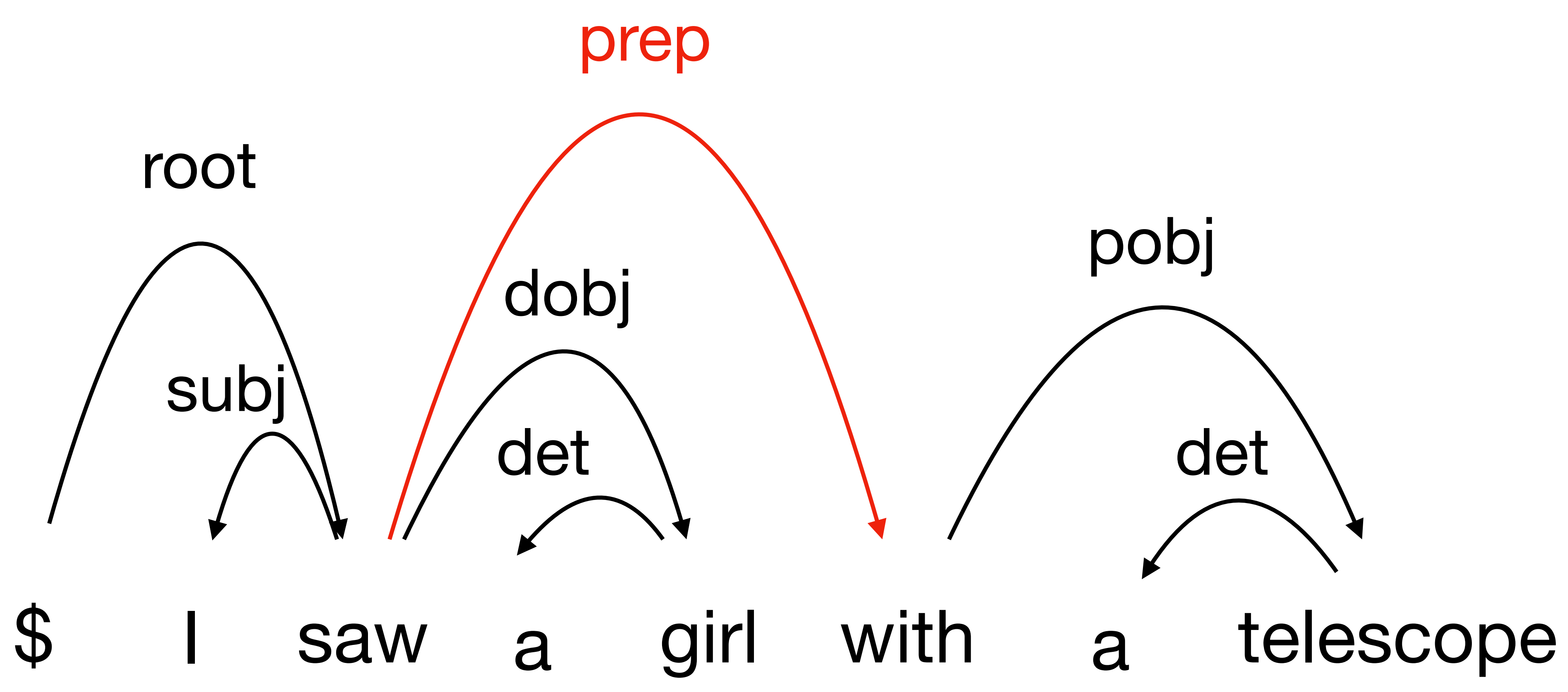


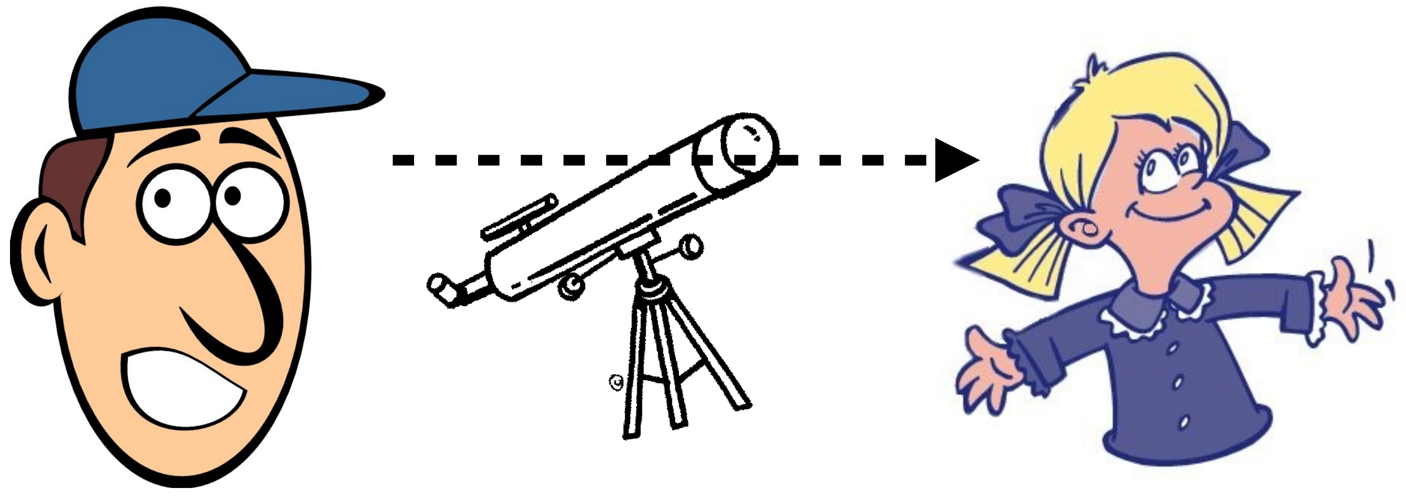


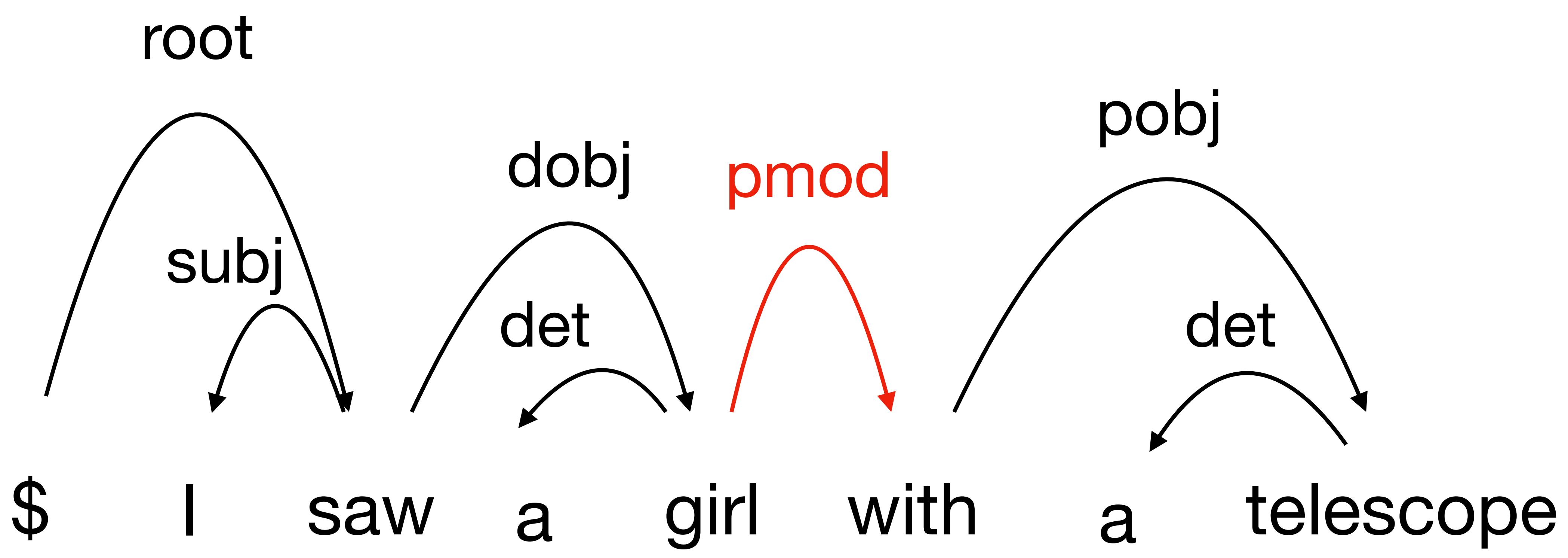


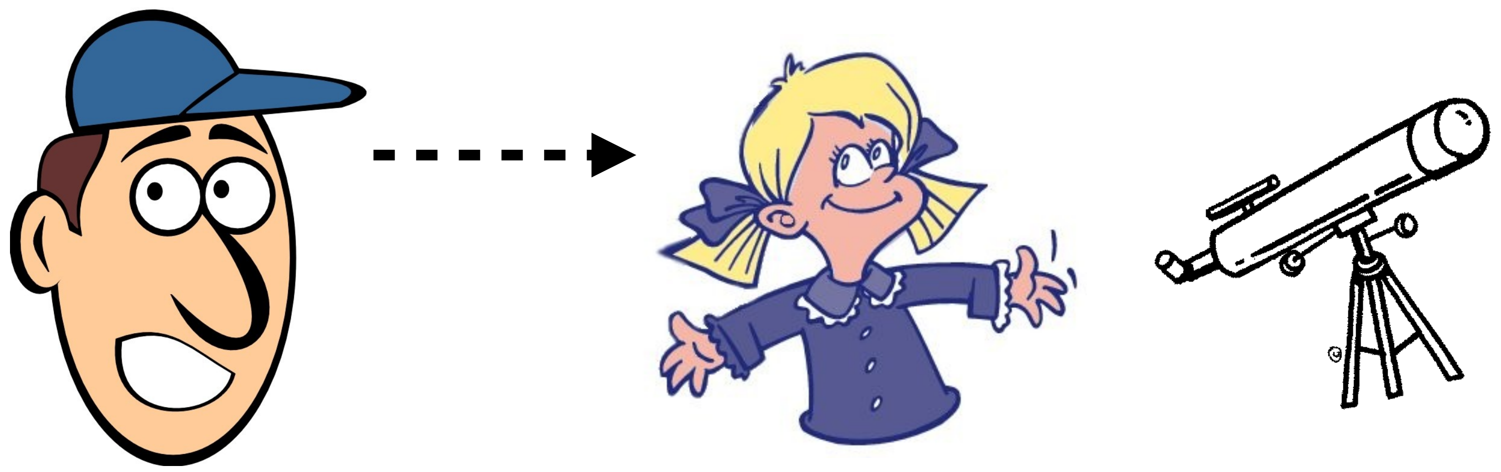


Constituency vs. Dependency









Constituency vs. Dependency

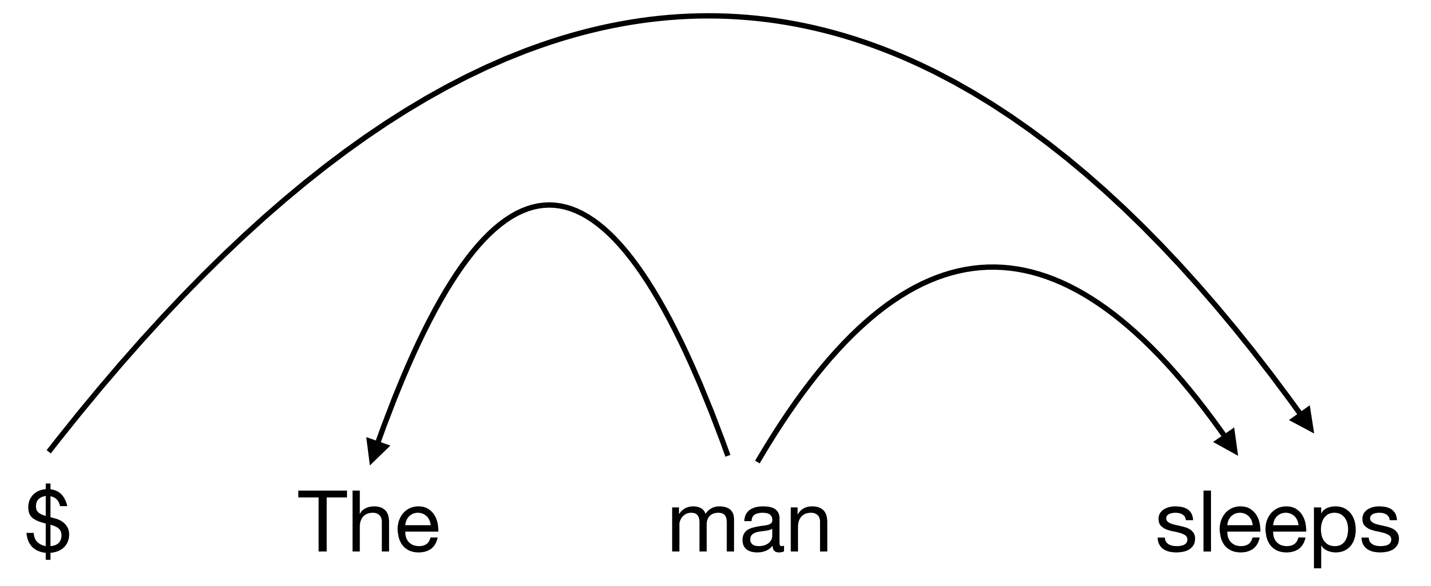
- **Dependency structures explicitly represent**
  - Head-dependent relations (directed arcs)
  - Functional categories (arc labels)
- **Constituent structures explicitly represent**
  - Phrases (non-terminal nodes)
  - Structural categories (non-terminal symbols)

Some Theoretical Frameworks

- Word Grammar (WG) [Hudson 1984, Hudson 1990, Hudson 2007]
- Functional Generative Description (FGD) [Sgall et al. 1986]
- Dependency Unification Grammar (DUG)
  [Hellwig 1986, Hellwig 2003]
- Meaning-Text Theory (MTT) [Mel'čuk 1988, Milićević 2006]
- (Weighted) Constraint Dependency Grammar ([W]CDG)
  [Maruyama 1990, Menzel and Schröder 1998, Schröder 2002]
- Functional Dependency Grammar (FDG)
  [Tapanainen and Järvinen 1997, Järvinen and Tapanainen 1998]
- Topological/Extensible Dependency Grammar ([T/X]DG)
  [Duchier and Debusmann 2001, Debusmann et al. 2004]

A Formal Definition of Dependency Structures

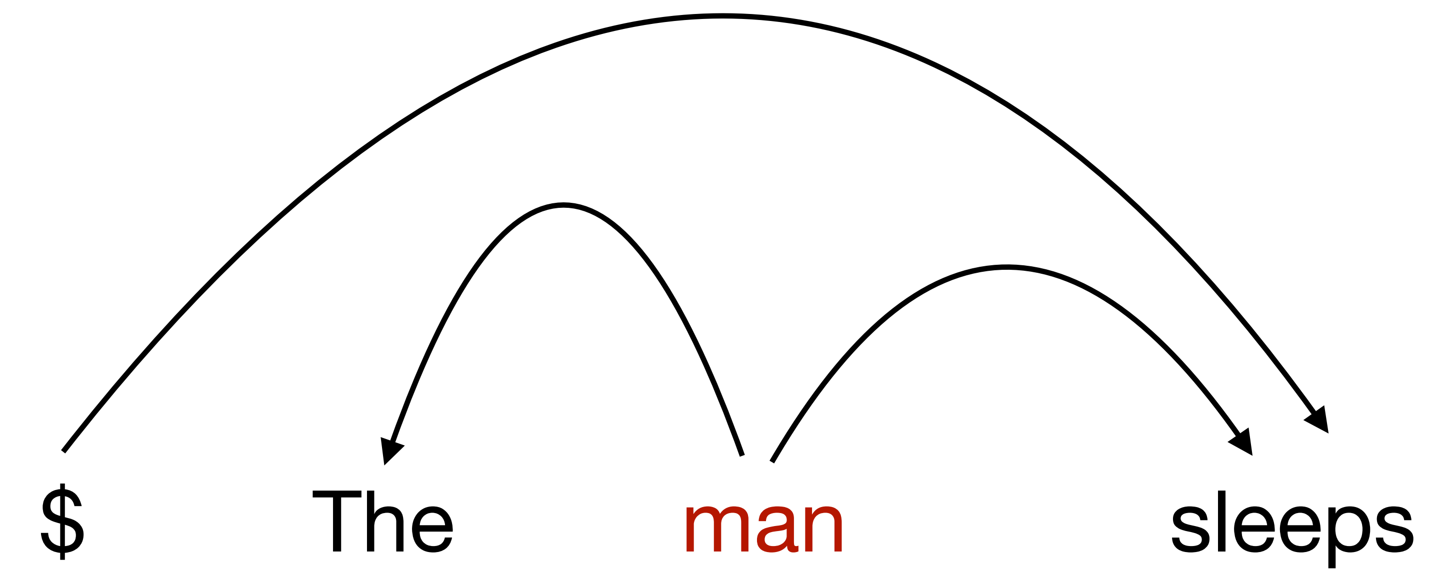
- **A dependency structure can be defined as a directed graph G, consisting of**
  - A set of nodes V
  - A set of directed arcs E (directed edges)
  - A linear precedence order $<$ on V (word order)



Is this directed graph a valid dependency structure?

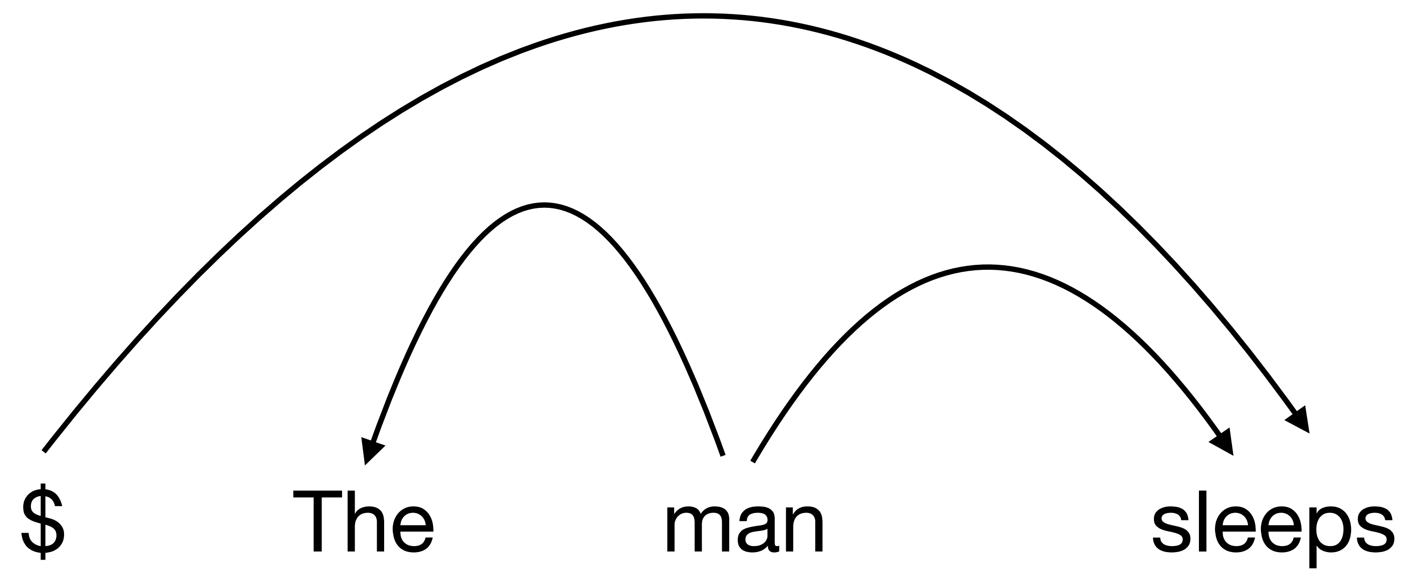
A Formal Definition of Dependency Structures

- **A dependency structure can be defined as a directed graph G, consisting of**
  - A set of V of nodes
  - A set of E of directed arcs (directed edges)
  - A linear precedence order $<$ on V (word order)
- **Formal Conditions of Dependency Structures**
  - G is connected: there exists a directed path from the root to every other node



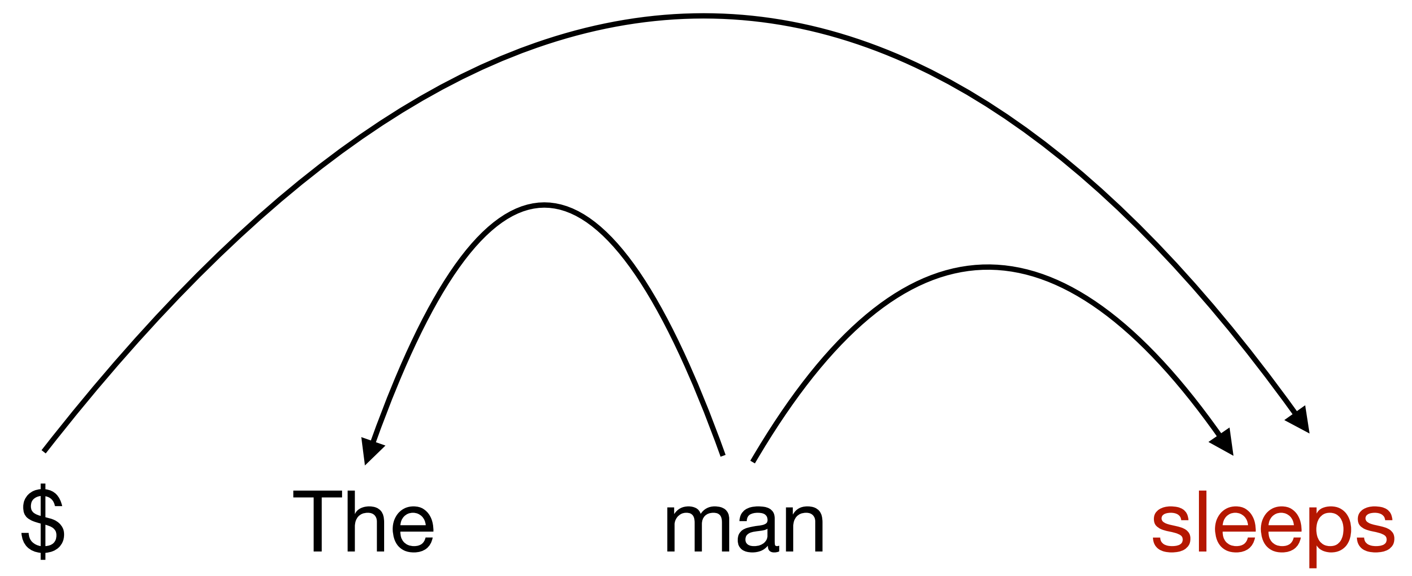
A Formal Definition of Dependency Structures

- **A dependency structure can be defined as a directed graph G, consisting of**
  - A set of V of nodes
  - A set of E of directed arcs (directed edges)
  - A linear precedence order $<$ on V (word order)
- **Formal Conditions of Dependency Structures**
  - G is connected: there exists a directed path from the root to every other node
  - G is acyclic: no cycles like $A \to B, B \to C, C \to A$



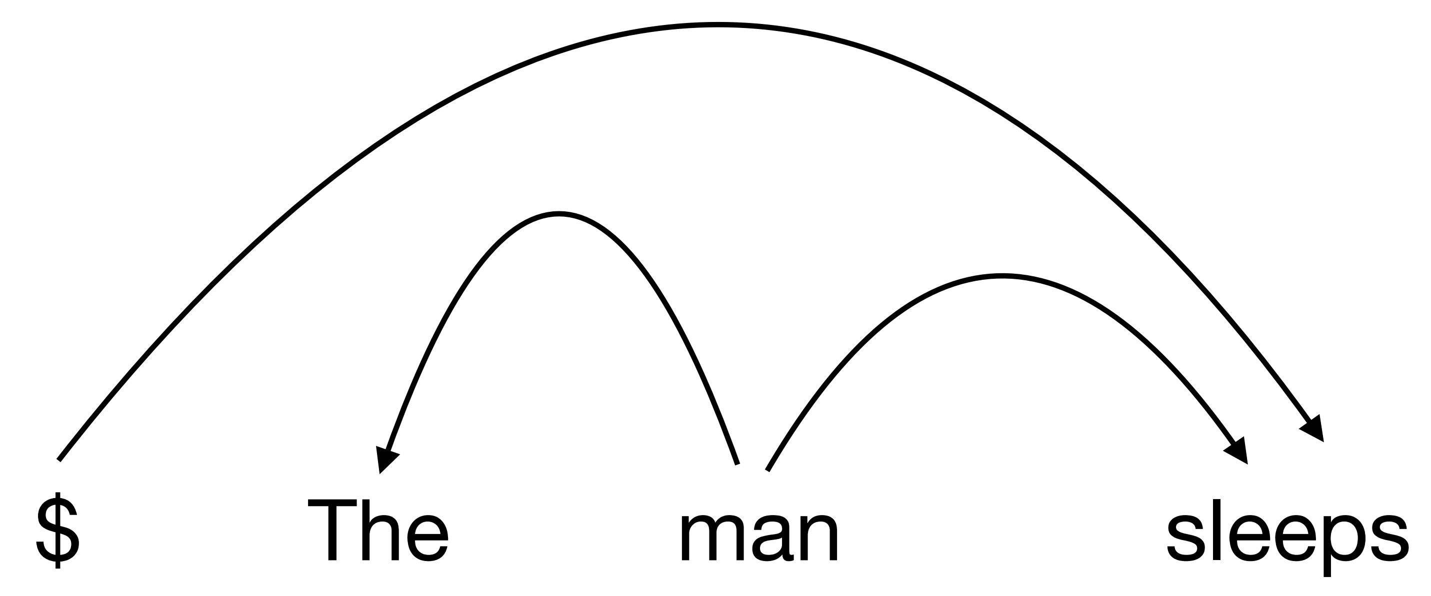
A Formal Definition of Dependency Structures

- **A dependency structure can be defined as a directed graph G, consisting of**
  - A set of V of nodes
  - A set of E of directed arcs (directed edges)
  - A linear precedence order $<$ on V (word order)
- **Formal Conditions of Dependency Structures**
  - G is connected: there exists a directed path from the root to every other node
  - G is acyclic: no cycles like $A \to B, B \to C, C \to A$
  - G obeys the single-head constraint: each non-root node has only one head

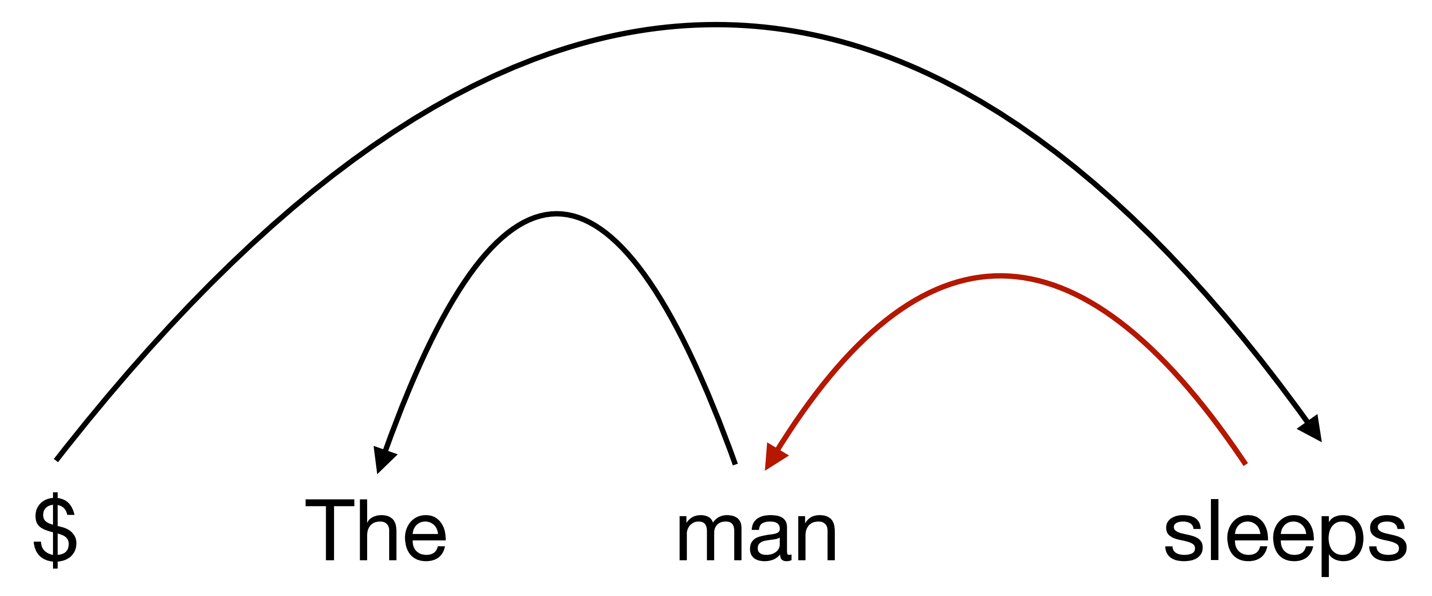


Dependency Structures: An Example

Invalid

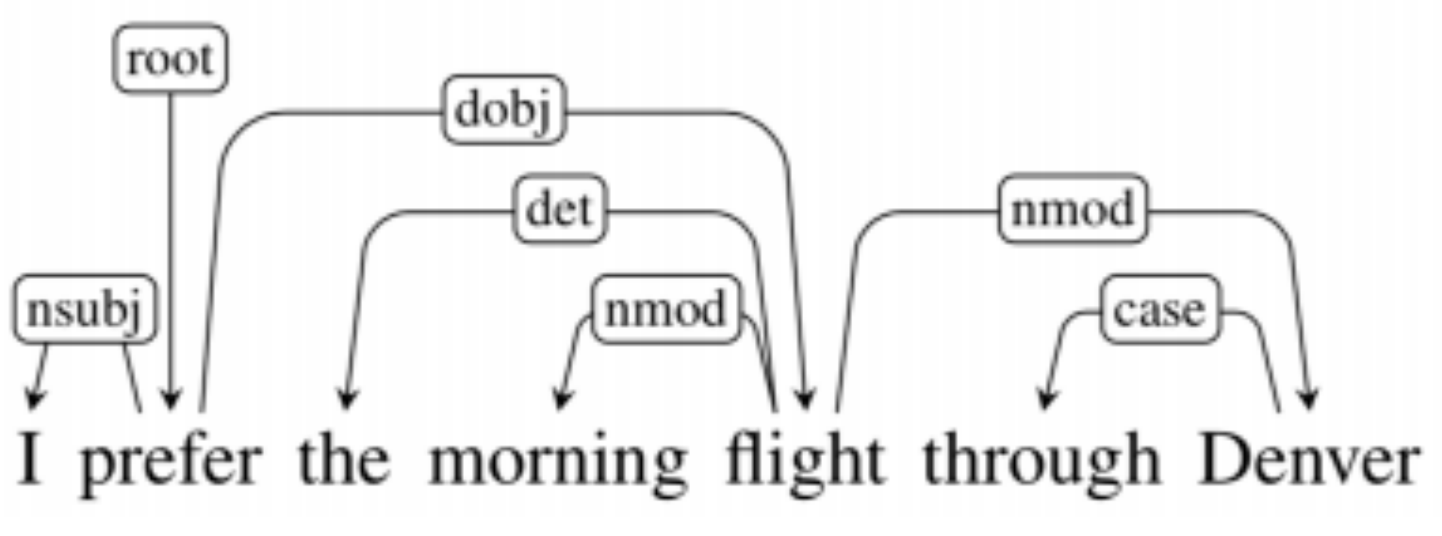


Valid

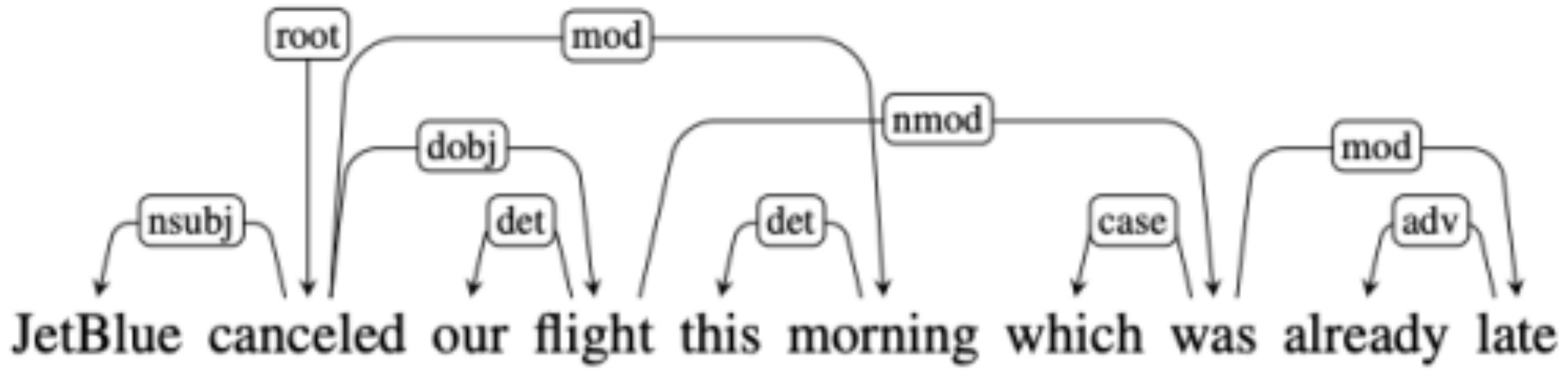


Additional Constraint: Projectivity

- **Definition of projectivity: there are no crossing dependency when the words are laid out in their linear order, with all arcs above the words**



projective



non-projective

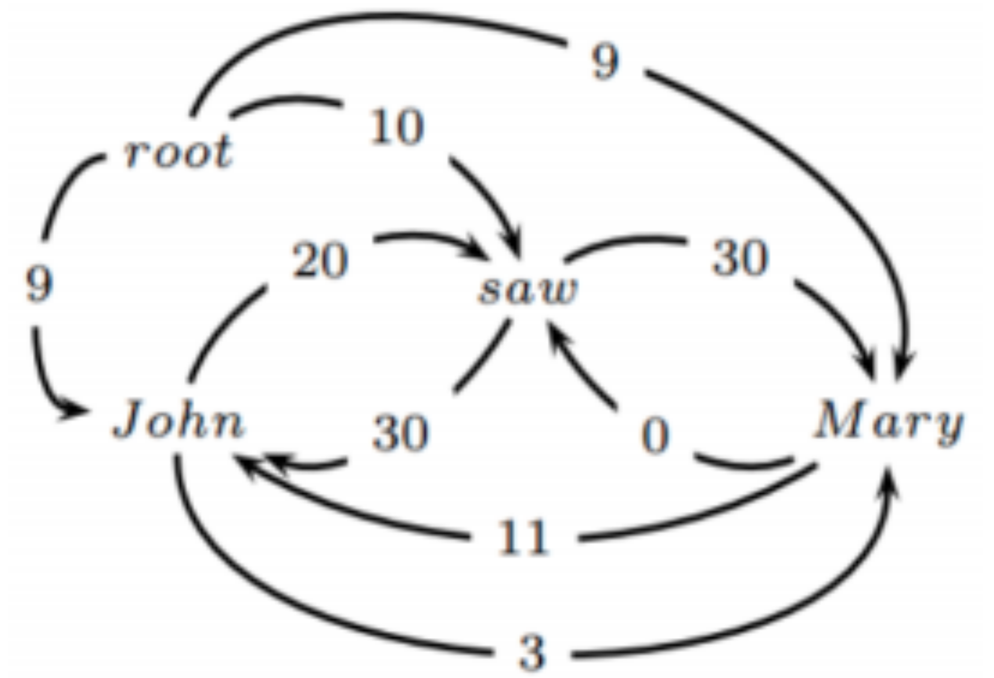
Non-projectivity arises due to long distance dependencies or in languages with flexible word order.

We will first consider projective parsing

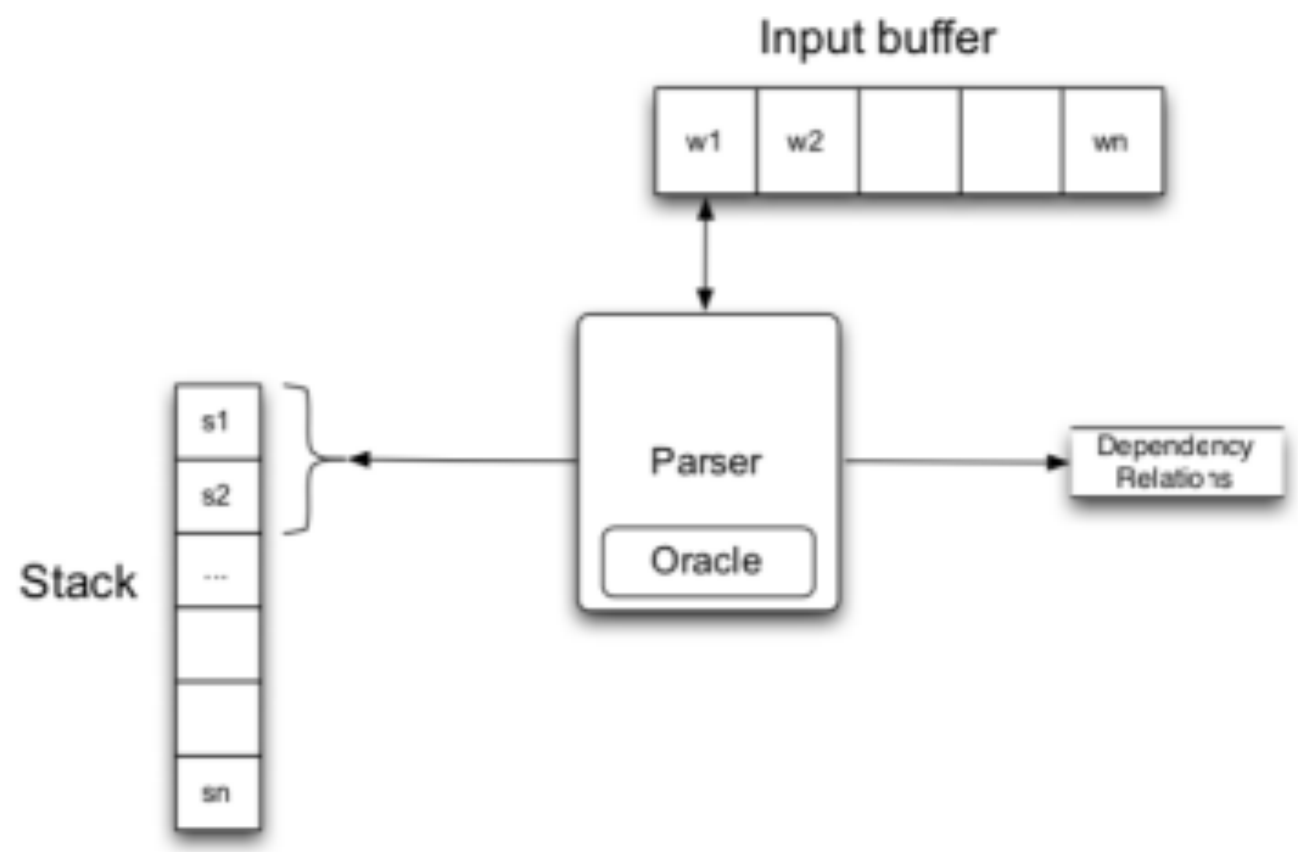
Dataset	# Sentences	(%) Projective
English	39,832	99.9
Chinese	16,091	100.0
Czech	72,319	76.9
German	38,845	72.2

Two Families of Dependency Parsing Algorithms

- **Graph-based Dependency Parsing**
  - Learning: Induce a model for scoring an entire dependency graph for a sentence
  - Parsing: Find the highest-scoring dependency graph



- **Transition-based Dependency Parsing**
  - Learning: Induce a model for predicting the next state transition, given the transition history
  - Parsing: Construct the optimal transition sequence



Graph-based Dependency Parsing

Graph-based Dependency Parsing

- The General Problem
  - We have an input sentence x
  - We have a set valid dependency structures $\mathcal{T}(x)$
  - Aim is to provide a conditional probability $p(y \mid x),\ y \in \mathcal{T}(x)$

Log-linear Model: $$p(y \mid x) = \frac{\exp(v \cdot f(x, y))}{\sum_{y' \in \mathcal{T}(x)} \exp(v \cdot f(x, y'))}$$

How to simplify the feature function $f(x, y)$?

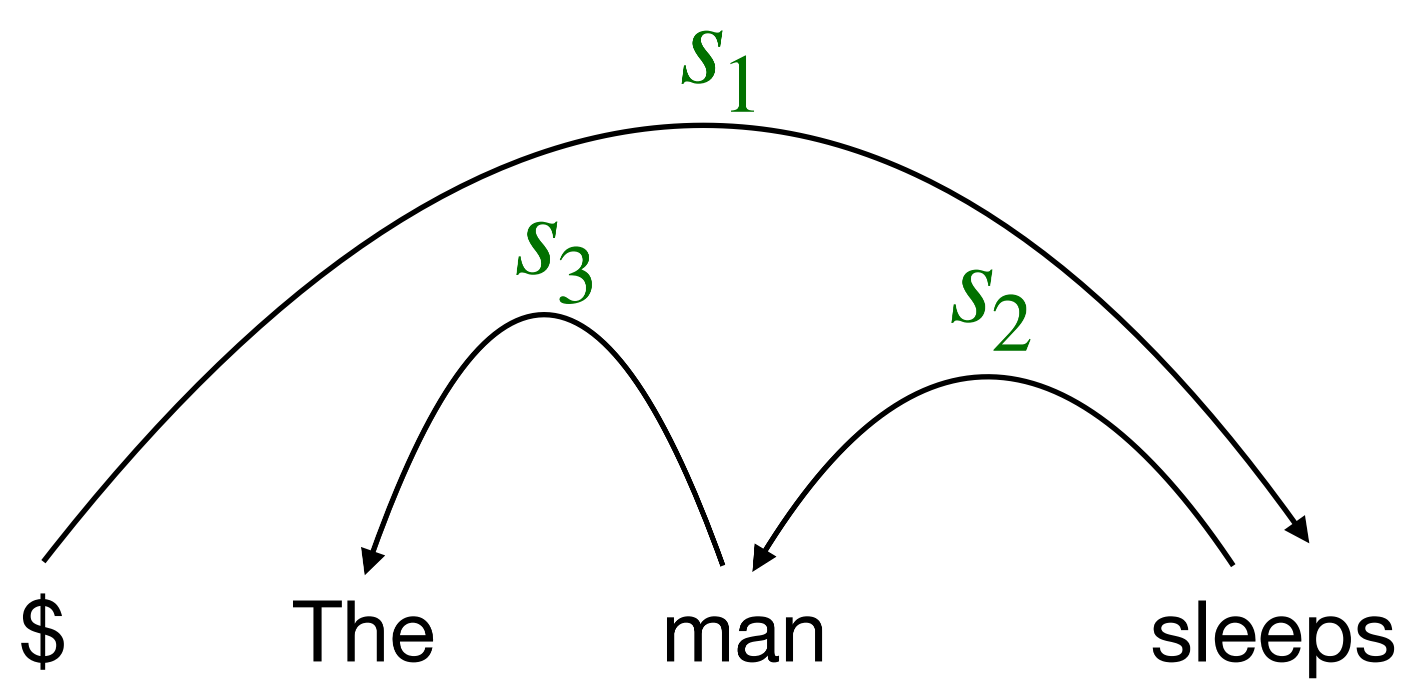
First-order Model

- **Factorize $f(x, y)$ into each edge of y**

$$p(y \mid x) = \frac{\exp(v \cdot f(x, y))}{\sum_{y' \in \mathcal{T}(x)} \exp(v \cdot f(x, y'))} \qquad f(x, y) = \sum_{e \in y} f(x, e)$$

the score of an edge

$$\exp(v \cdot f(x, y)) = \exp(v \cdot \sum_{e \in y} f(x, e)) = \prod_{e \in y} \exp(\boxed{v \cdot f(x, e)})$$



First-order Model

- **Factorize $f(x, y)$ into each edge of y**

$$p(y \,|\, x) = \frac{\exp(v \cdot f(x, y))}{\sum_{y' \in \mathcal{T}(x)} \exp(v \cdot f(x, y'))} \qquad f(x, y) = \sum_{e \in y} f(x, e)$$

- **Two standard problems:**
  - Learning: $\sum_{y' \in \mathcal{T}(x)} \exp(v \cdot f(x, y'))$
  - Parsing: $\arg\max_{y' \in \mathcal{T}(x)} \exp(v \cdot f(x, y'))$

First-order Projective Parsing Algorithm

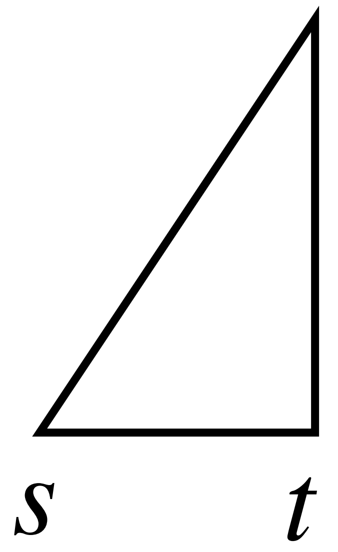
- **Cubic Parsing Algorithm** [Eisner, 1996]
- **Projective Parse Trees only**
  - $\mathcal{T}(x)$ only contains projective trees
- **Define a dynamic programming table**
  - $\pi[s, t, d, c] =$ maximum probability of a dependency graph spanning words $s, \ldots, t$ inclusive, with direction $d \in \{\rightarrow, \leftarrow\}$, and completeness $c \in \{0,1\}$

- **Our goal is to calculate** $\max_{y \in \mathcal{T}(x)} p(y \mid x) = \pi[0, n, \rightarrow, 1]$

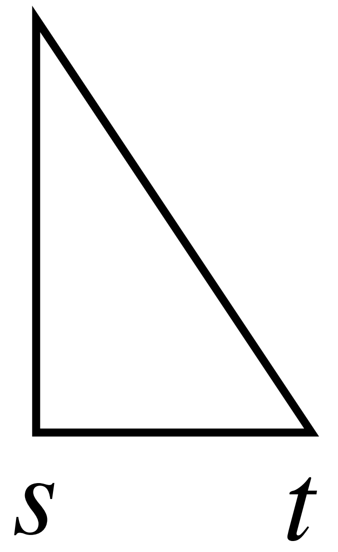
First-order Projective Parsing Algorithm

complete items

$\pi[s, t, \rightarrow, 1]$ dependency graphs from word s to t, with s as the root



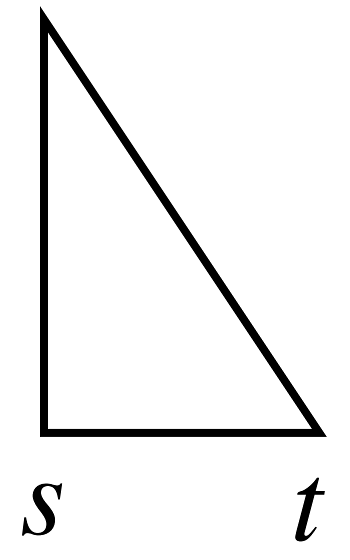
$\pi[s, t, \leftarrow, 1]$ dependency graphs from word s to t, with t as the root



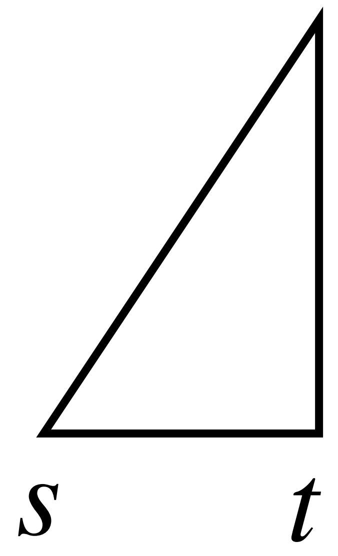
First-order Projective Parsing Algorithm

complete items

$\pi[s, t, \rightarrow, 1]$ dependency graphs from word s to t, with s as the root



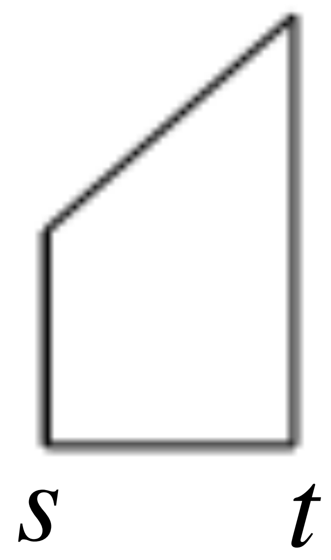
$\pi[s, t, \leftarrow, 1]$ dependency graphs from word s to t, with t as the root



incomplete items

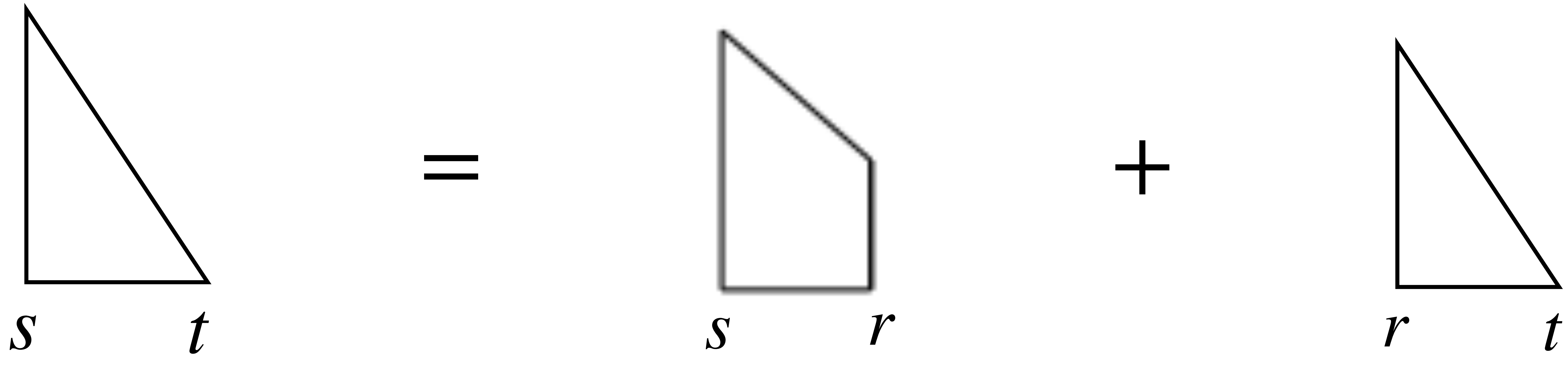
$\pi[s, t, \rightarrow, 0]$ dependency graphs from word s to t, with s as the root and an edge $s \rightarrow t$

$\pi[s, t, \leftarrow, 0]$ dependency graphs from word s to t, with t as the root and an edge $s \leftarrow t$

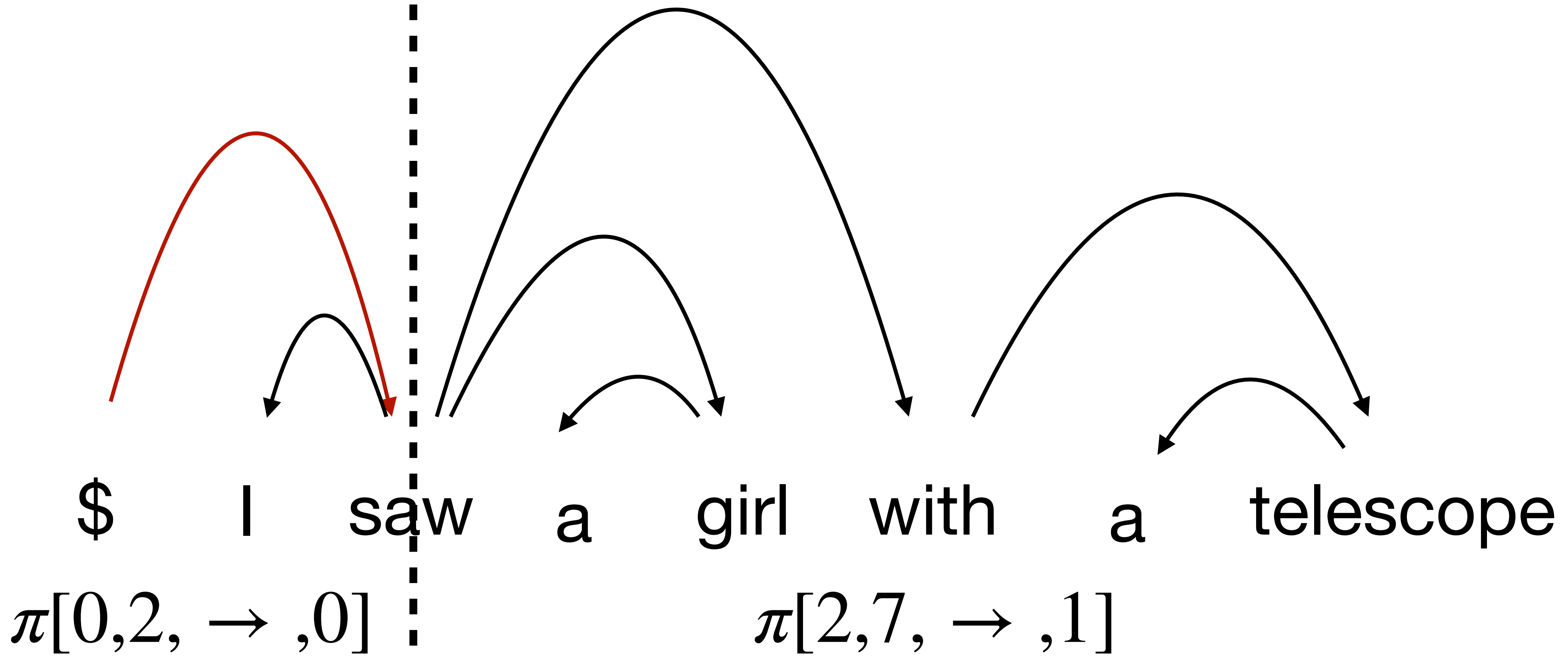


First-order Projective Parsing Algorithm

- **Dynamic programming derivations**

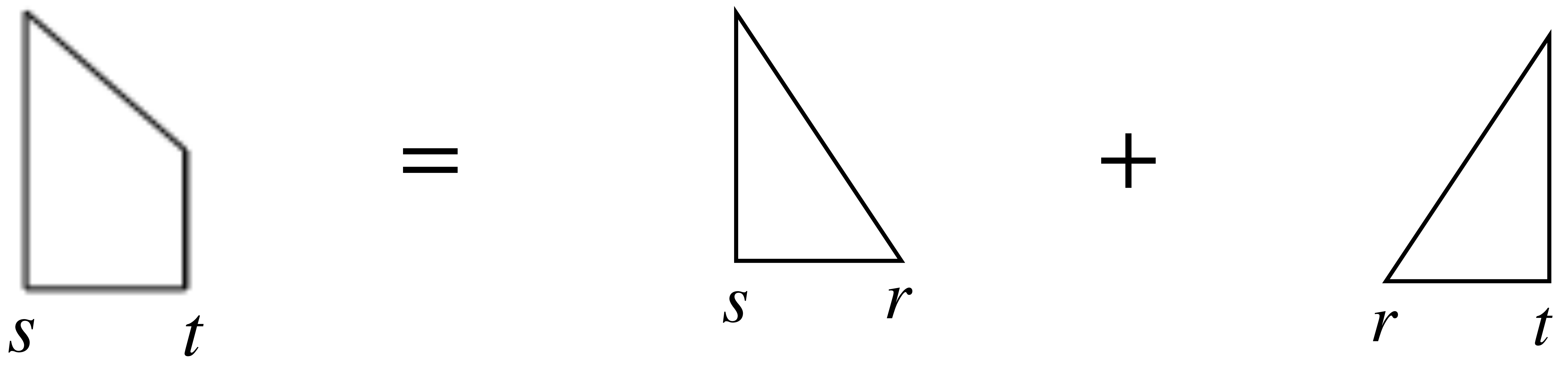


$$\pi[s, t, \rightarrow, 1] \quad = \quad \max_{s<r\leq t} \pi[s, r, \rightarrow, 0] + \pi[r, t, \rightarrow, 1]$$

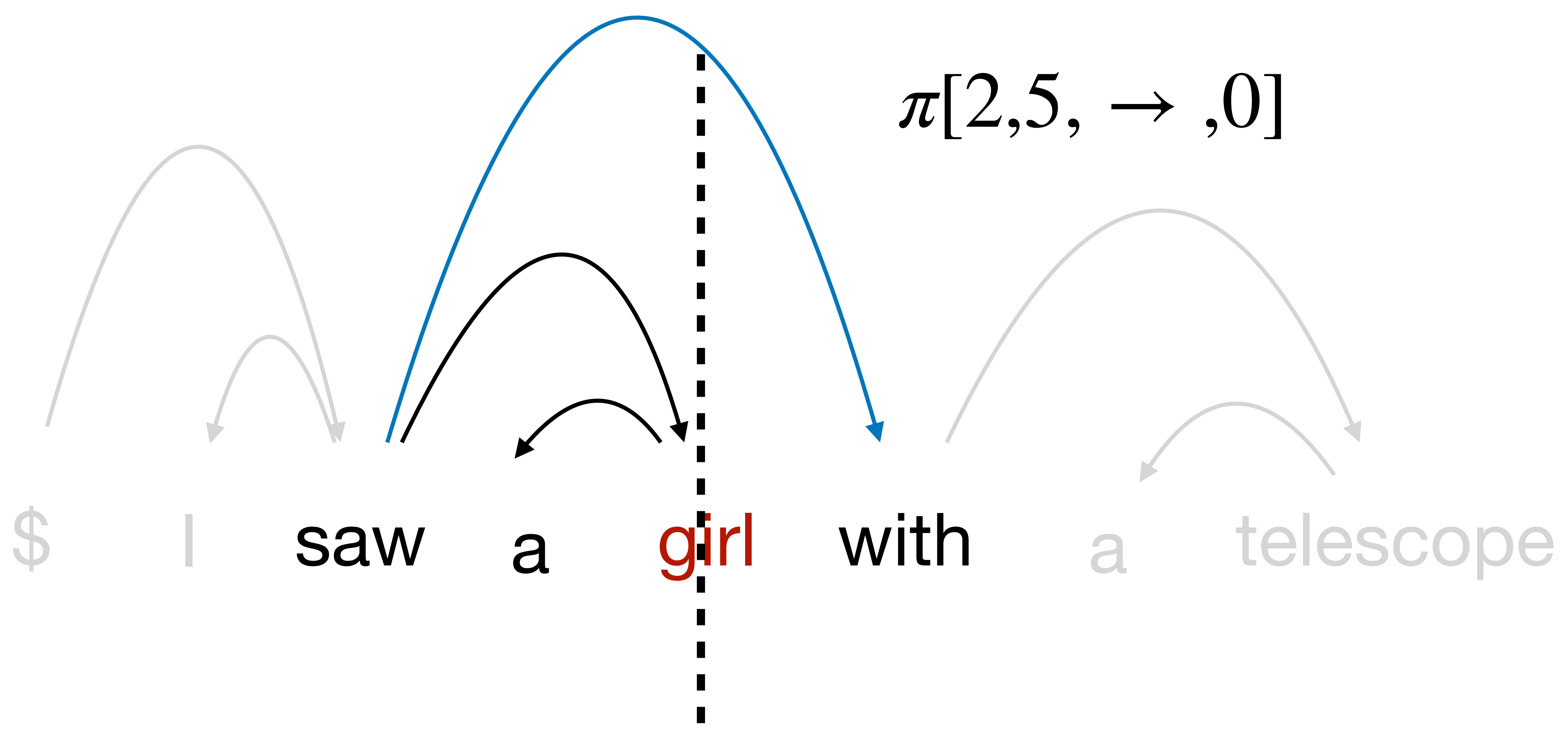


First-order Projective Parsing Algorithm

- **Dynamic programming derivations**



$$\pi[s, t, \rightarrow, 0] = \max_{s \le r < t} \left(\pi[s, r, \rightarrow, 1] + \pi[r+1, t, \leftarrow, 1] + s(s \rightarrow t) \right)$$



$\pi[2,5, \rightarrow, 0]$

First-order Projective Parsing Algorithm

Initialization: $C[s][s][d][c] = 0.0 \quad \forall s, d, c$

for $k : 1..n$

  for $s : 1..n$

    $t = s + k$

    if $t > n$ then break

    % First: create incomplete items

    $C[s][t][\leftarrow][0] = \max_{s \leq r < t} \; (C[s][r][\rightarrow][1] + C[r+1][t][\leftarrow][1] + s(t, s))$

    $C[s][t][\rightarrow][0] = \max_{s \leq r < t} \; (C[s][r][\rightarrow][1] + C[r+1][t][\leftarrow][1] + s(s, t))$

    % Second: create complete items

    $C[s][t][\leftarrow][1] = \max_{s \leq r < t} \; (C[s][r][\leftarrow][1] + C[r][t][\leftarrow][0])$

    $C[s][t][\rightarrow][1] = \max_{s < r \leq t} \; (C[s][r][\rightarrow][0] + C[r][t][\rightarrow][1])$

  end for

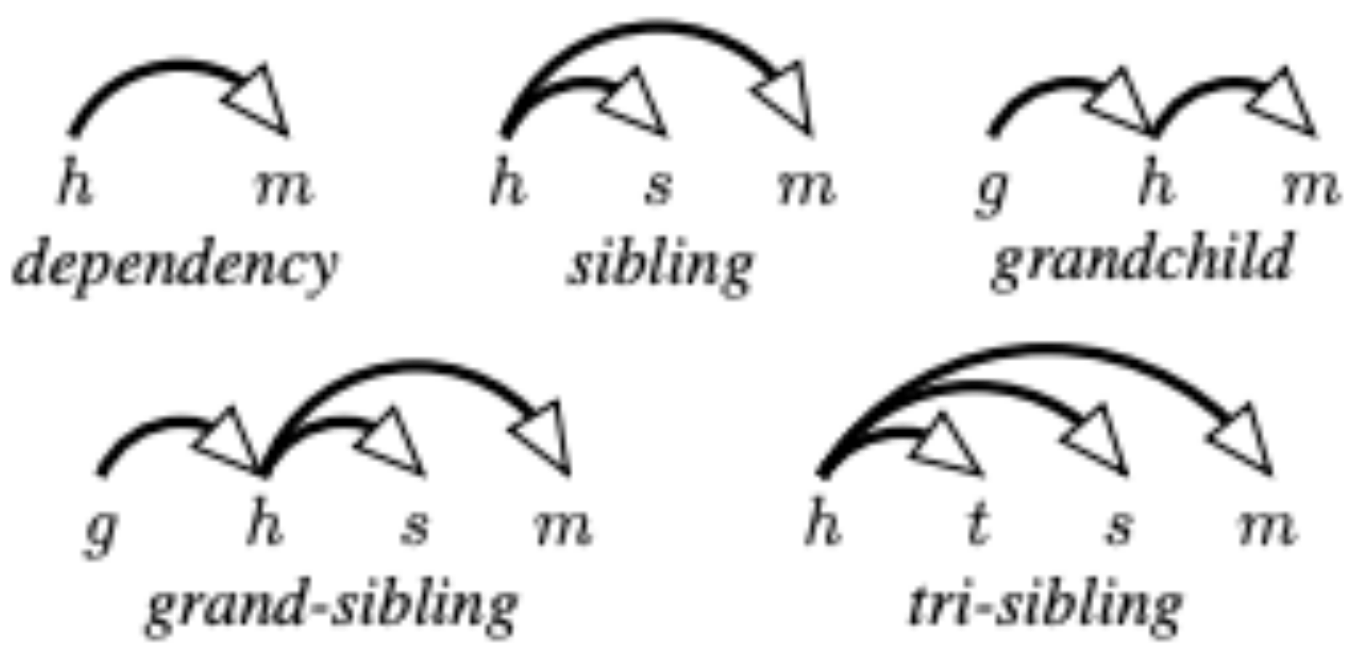
end for

Running time:
$O(n^3)$

Higher-order Parsing

- **First-order: factorizing features into each edge**
- **Higher-order: factorizing features into more complex components**

$$f(x,y) = \sum_{p \in y} f(x,p)$$

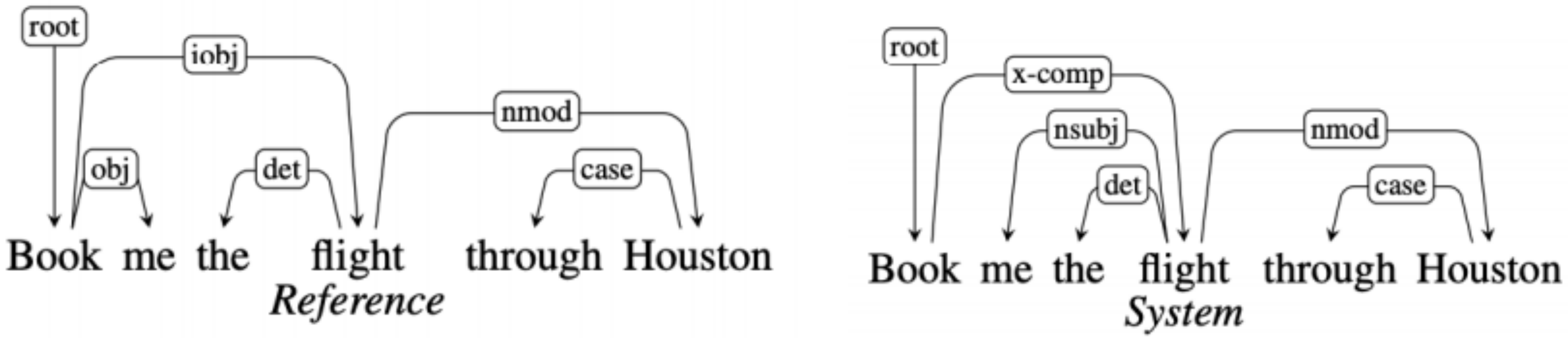


Non-projective Parsing

- **Two standard problems:**
  - Learning: $\sum_{y' \in \mathcal{T}(x)} \exp(v \cdot f(x, y'))$
  - Parsing: $\arg \max_{y' \in \mathcal{T}(x)} \exp(v \cdot f(x, y'))$
- **First-order Model:**
  - Learning: Matrix-Tree Theorem [Koo et al., 2007]
  - Parsing: Maximum Spanning Tree algorithm [McDonald, 2005]
- **High-order Models: NP-hard**

Evaluation Dependency Parsing

- **Unlabeled Attachment Score (UAS)**
  - Percentage of words that have been assigned the corrected head
- **Labeled Attachment Score (LAS)**
  - Percentage of words that have been assigned the correct head & label
- **Root Accuracy (RA)**
  - Accuracy of the root dependencies



UAS = 5/6 LAS = 4/6 RA = 1/1

Parsing Exeriments

- **Penn Treebank**

	UAS	Complexity
1st-proj	91.8	$O(n^3)$
1st-non-proj	91.7	$O(n^3)$
2nd-proj	92.4	$O(n^3)$
3nd-proj	93.0	$O(n^4)$
4nd-proj	93.4	$O(n^5)$

Transition-based Dependency Parsing

Transition-based Parsing

- **Basic Ideas**
  - Define a transition system for dependency parsing
  - Learn a machine learning model for scoring possible transitions
  - Parse by searching for the optimal transition sequence

Transition-based Parsing

- **The Arc-standard Transition System**
  - Three data structures, a stack σ, a buffer β and a set α
  - A configuration consists of
    1. A *stack* σ consisting of a sequence of words, e.g.,

       $$\sigma = [\text{root}_0, \text{I}_1, \text{live}_2]$$

    2. A *buffer* β consisting of a sequence of words, e.g.,

       $$\beta = [\text{in}_3, \text{New}_4, \text{York}_5, \text{city}_6, ._7]$$

    3. A set α of *labeled dependencies*, e.g.,

       $$\alpha = \{\{1 \rightarrow^{nsubj} 2\}, \{6 \rightarrow^{nn} 5\}$$

  - Initial configuration: $\sigma = [\$],\ \beta = [w_1, \ldots, w_n],\ \alpha = \{\,\}$
  - Three types of transition actions: LEFT-ARC, RIGHT-ARC, SHIFT
  - A terminal configuration: $\sigma = [\$],\ \beta = []$

The Arc-standard System

The Initial Configuration

$$\sigma = [\mathsf{root}_0], \quad \beta = [\mathsf{I}_1, \mathsf{live}_2, \mathsf{in}_3, \mathsf{New}_4, \mathsf{York}_5, \mathsf{city}_6, ._7], \quad \alpha = \{\}$$

The Arc-standard System

- The **shift action** takes the first word in the buffer, and adds it to the end of the stack

$$\sigma = [\text{root}_0], \quad \beta = [\text{I}_1, \text{live}_2, \text{in}_3, \text{New}_4, \text{York}_5, \text{city}_6, ._7], \quad \alpha = \{\}$$

SHIFT

$$\Downarrow$$

$$\sigma = [\text{root}_0, \text{I}_1], \quad \beta = [\text{live}_2, \text{in}_3, \text{New}_4, \text{York}_5, \text{city}_6, ._7], \quad \alpha = \{\}$$

$$\sigma = [\text{root}_0, \text{I}_1], \quad \beta = [\text{live}_2, \text{in}_3, \text{New}_4, \text{York}_5, \text{city}_6, ._7], \quad \alpha = \{\}$$

SHIFT

$$\Downarrow$$

$$\sigma = [\text{root}_0, \text{I}_1, \text{live}_2], \quad \beta = [\text{in}_3, \text{New}_4, \text{York}_5, \text{city}_6, ._7], \quad \alpha = \{\}$$

The Arc-standard System

- The LEFT-ARC action takes the top two words on the stack, and adds a dependency between them in the left direction, and removes the modifier word from the stack

$$\sigma = [\text{root}_0, \text{I}_1, \text{live}_2], \quad \beta = [\text{in}_3, \text{New}_4, \text{York}_5, \text{city}_6, ._7], \quad \alpha = \{\}$$

$$\text{LEFT-ARC}^{nsubj}$$

$$\Downarrow$$

$$\sigma = [\text{root}_0, \text{live}_2], \quad \beta = [\text{in}_3, \text{New}_4, \text{York}_5, \text{city}_6, ._7], \quad \alpha = \{\{2 \rightarrow^{nsubj} 1\}\}$$

The Arc-standard System

- The RIGHT-ARC action takes the top two words on the stack, and adds a dependency between them in the right direction, and removes the modifier word from the stack

$$\sigma = [\text{root}_0, \text{live}_2, \text{in}_3], \quad \beta = [._7], \quad \alpha = \{\{2 \rightarrow^{nsubj} 1\},\}$$

$$\text{RIGHT-ARC}^{prep}$$

$$\Downarrow$$

$$\sigma = [\text{root}_0, \text{live}_2], \quad \beta = [._7], \quad \alpha = \{\{2 \rightarrow^{nsubj} 1\}, \{2 \rightarrow^{prep} 3\}\}$$

The Arc-standard System

- **Each projective dependency graph is mapped to a sequence of actions**

Action	σ	β	$h \xrightarrow{l} d$
Shift	[root$_0$]	[I$_1$,live$_2$, in$_3$, New$_4$, York$_5$, city$_6$, .$_7$]	
Shift	[root$_0$, I$_1$]	[live$_2$, in$_3$, New$_4$, York$_5$, city$_6$, .$_7$]	
Left-Arc^{nsubj}	[root$_0$, I$_1$, live$_2$]	[in$_3$, New$_4$, York$_5$, city$_6$, .$_7$]	$2 \xrightarrow{nsubj} 1$
Shift	[root$_0$, live$_2$]	[in$_3$, New$_4$, York$_5$, city$_6$, .$_7$]	
Shift	[root$_0$, live$_2$, in$_3$]	[New$_4$, York$_5$, city$_6$, .$_7$]	
Shift	[root$_0$, live$_2$, in$_3$, New$_4$]	[York$_5$, city$_6$, .$_7$]	
Shift	[root$_0$, live$_2$, in$_3$, New$_4$, York$_5$]	[city$_6$, .$_7$]	
Left-Arc^{nn}	[root$_0$, live$_2$, in$_3$, New$_4$, York$_5$, city$_6$]	[.$_7$]	$6 \xrightarrow{nn} 5$
Left-Arc^{nn}	[root$_0$, live$_2$, in$_3$, New$_4$, city$_6$]	[.$_7$]	$6 \xrightarrow{nn} 4$
Right-Arc^{pobj}	[root$_0$, live$_2$, in$_3$, city$_6$]	[.$_7$]	$3 \xrightarrow{pobj} 6$
Right-Arc^{prep}	[root$_0$, live$_2$, in$_3$]	[.$_7$]	$2 \xrightarrow{prep} 3$
Shift	[root$_0$, live$_2$]	[.$_7$]	
Right-Arc^{punct}	[root$_0$, live$_2$, .$_7$]	[]	$2 \xrightarrow{punct} 7$
Right-Arc^{root}	[root$_0$, live$_2$]	[]	$0 \xrightarrow{root} 2$
Terminal	[root$_0$]	[]	

Transition-based Parsing: Learning

- **How to decide which transition actions to take?**
  - Learn a machine learning model, e.g. a classifier
  - We can design features based on the current configuration: parsing history

1. A *stack* σ consisting of a sequence of words, e.g.,

$$\sigma = [\text{root}_0, \text{I}_1, \text{live}_2]$$

2. A *buffer* β consisting of a sequence of words, e.g.,

$$\beta = [\text{in}_3, \text{New}_4, \text{York}_5, \text{city}_6, ._7]$$

3. A set α of *labeled dependencies*, e.g.,

$$\alpha = \{\{1 \rightarrow^{nsubj} 2\}, \{6 \rightarrow^{nn} 5\}$$

Transition-based Parsing: Parsing

- **No Exact Parsing Algorithm**
  - Greedy search or beam search
  - Linear time complexity
  - Comparable performance with graph-based parsing algorithms

Reading Materials

- **Comparison and Integration of graph-based and transition-based dependency parsers**
  - McDonald and Nivre, 2011