Lecture 11: Parsing II

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Last Time

- Chomsky Hierarchy and Grammar
- Parsing Approaches for Context-Free Grammar (CFG)
  - Top-down Approach
  - Bottom-up Approach
- Parsing Algorithms
  - Shift-reduce Parsing
  - Chart Parsing

Today's Class

- Probabilistic Context-Free Grammar (PCFG)
- Lexicalized PCFG
- Dependency Syntax
- Dependency Parsing
- Parsing Resources

Statistical Parsing

- Statistical parsing uses a probabilistic model of syntax in order to assign probabilities to each parse tree.
- Provides principled approach to resolving syntactic ambiguity.
- Allows supervised learning of parsers from tree-banks of parse trees provided by human linguists.
- Also allows unsupervised learning of parsers from raw text, but the accuracy of such parsers has been limited.

Probabilistic Context Free Grammar (PCFG)

- A PCFG is a probabilistic version of a CFG where each production has a probability.
- Probabilities of all productions rewriting a given non-terminal must add to 1, defining a distribution for each non-terminal.

$$\sum_{a} P(A -> \alpha) = 1$$

- String generation is now probabilistic where production probabilities are used to non-deterministically select a production for rewriting a given non-terminal.

PCFG

- Assumption 1: Place invariance
- Assumption 2: Context-free
- Assumption 3: Ancestor-free

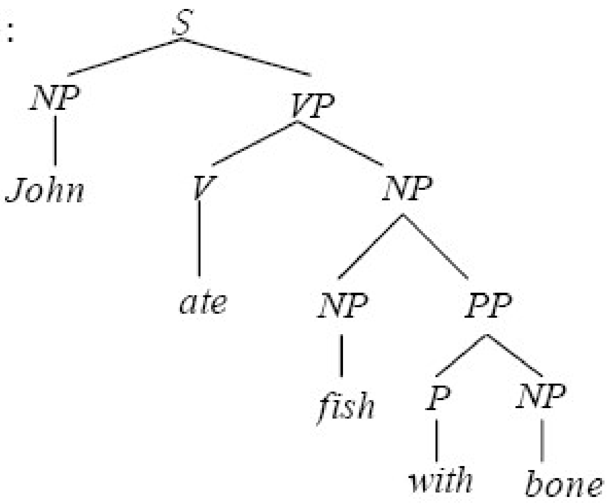
- The parse tree probability is the production of the probability of all applied parsing rules

Simple PCFG Example

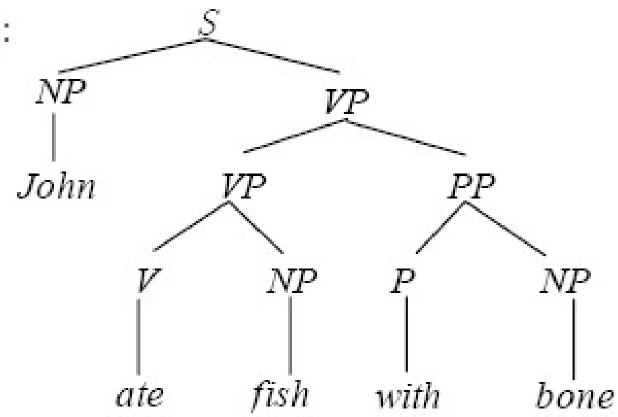
- Assume productions for each node are chosen independently.
- Probability of derivation is the product of the probabilities of its productions.
- Resolve ambiguity by picking most probable parse tree.

$sentence$ = "*John ate fish with bone*"

t_1:



t_2:



$S \rightarrow NP\ VP$	1.0	$NP \rightarrow NP\ PP$	0.4
$PP \rightarrow P\ NP$	1.0	$NP \rightarrow John$	0.1
$VP \rightarrow V\ NP$	0.7	$NP \rightarrow bone$	0.18
$VP \rightarrow VP\ PP$	0.3	$NP \rightarrow star$	0.04
$P \rightarrow with$	1.0	$NP \rightarrow fish$	0.18
$V \rightarrow ate$	1.0	$NP \rightarrow telescope$	0.1

$$P(t_1) = 1.0 \times 0.1 \times 0.7 \times 1.0 \times 0.4 \times 0.18 \times 1.0 \times 1.0 \times 0.18$$
$$= 0.0009072$$

$$P(t_2) = 1.0 \times 0.1 \times 0.3 \times 0.7 \times 1.0 \times 0.18 \times 1.0 \times 1.0 \times 0.18$$
$$= 0.0006804$$

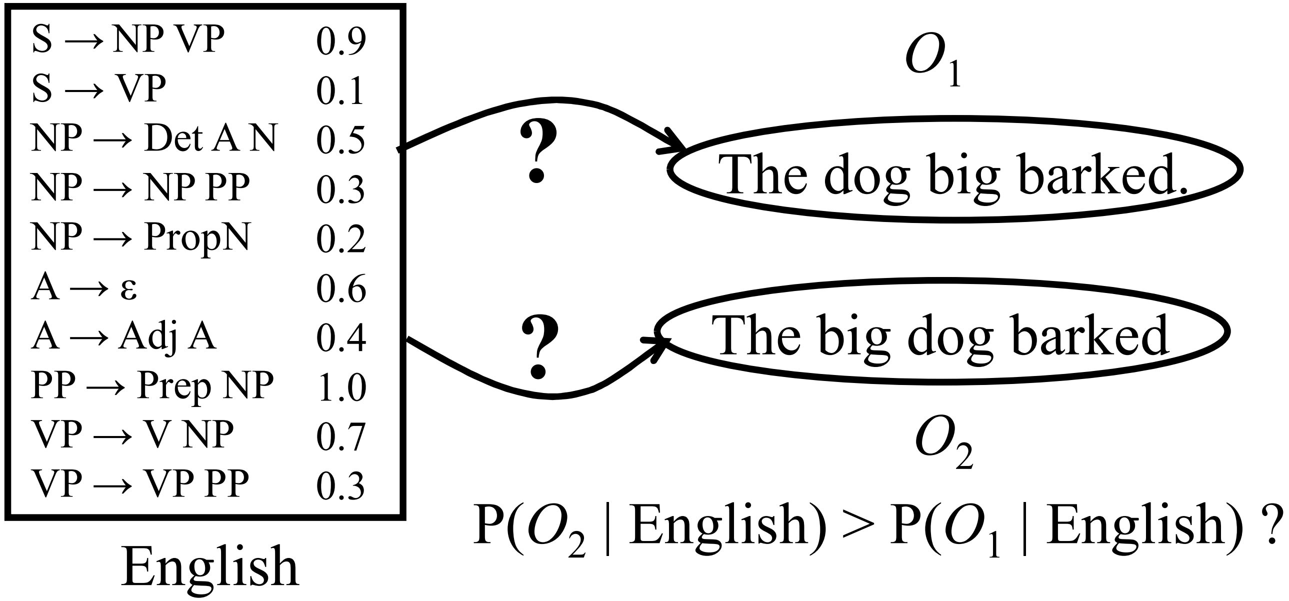
$$P(sentence) = P(t_1) + P(t_2) = 0.0015876$$

Three PCFG Tasks

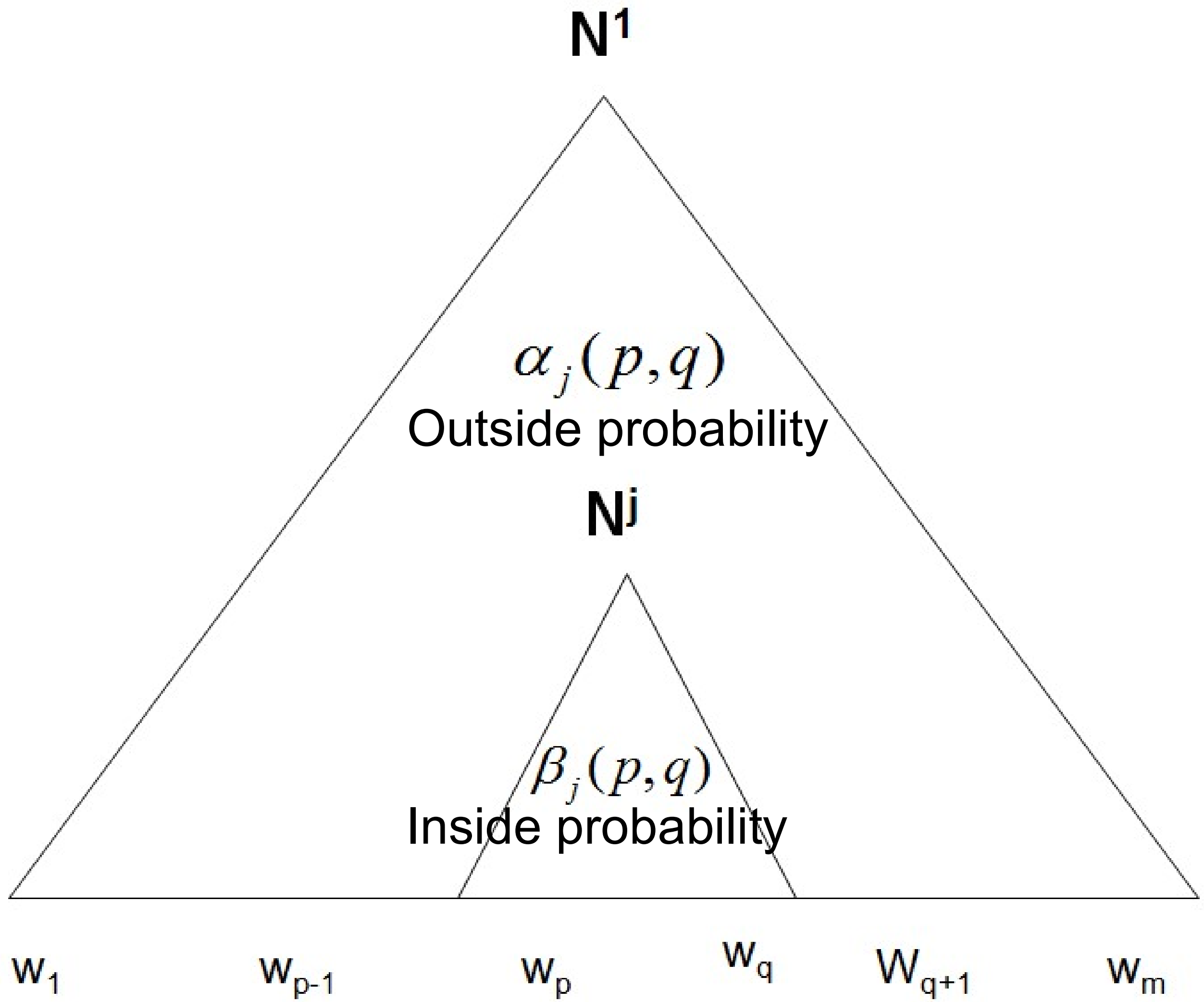
- Observation likelihood: To classify and order sentences. P(W|G) for sentence $W=w_1w_2…w_n$
  - Inside Algorithm
- Most likely derivation: To determine the most likely parse tree for a sentence.
  - Viterbi Algorithm
- Maximum likelihood training: To train a PCFG to fit empirical training data, i.e. maximize P(W|G)

PCFG: Observation Likelihood

- There is an analog to Forward algorithm for HMMs called the Inside algorithm for efficiently determining how likely a string is to be produced by a PCFG.



Notation



N^1
$\alpha_j(p,q)$
Outside probability
N^j
$\beta_j(p,q)$
Inside probability
w_1
w_{p-1}
w_p
w_q
W_{q+1}
w_m

Inside and Outside Probability

- Inside probability: total probability of generating words $w_p \ldots w_q$ from non-terminal N^j.

$$\beta_j(p,q) = P(w_{pq} \mid N^j_{pq})$$

- Outside probability: total probability of beginning with the start symbol N^1 and generating N^j_{pq} and all the words outside $w_p \ldots w_q$

$$\alpha_j(p,q) = P(w_{1(p-1)}, N^j_{pq}, w_{(q+1)m})$$

- When p>q,

$$\alpha_j(p,q) = \beta_j(p,q) = 0$$

Probabilistic CKY Algorithm

- Revised CKY with probabilistic information
- Set and maintain production probability during transfer grammar rule to CNF
- Each cell provide a probability for each non-terminal
- Cell[i,j] ： the most likely parsing contains all of Non-terminals which covers Word_{i+1} to Word_{j} and its probability

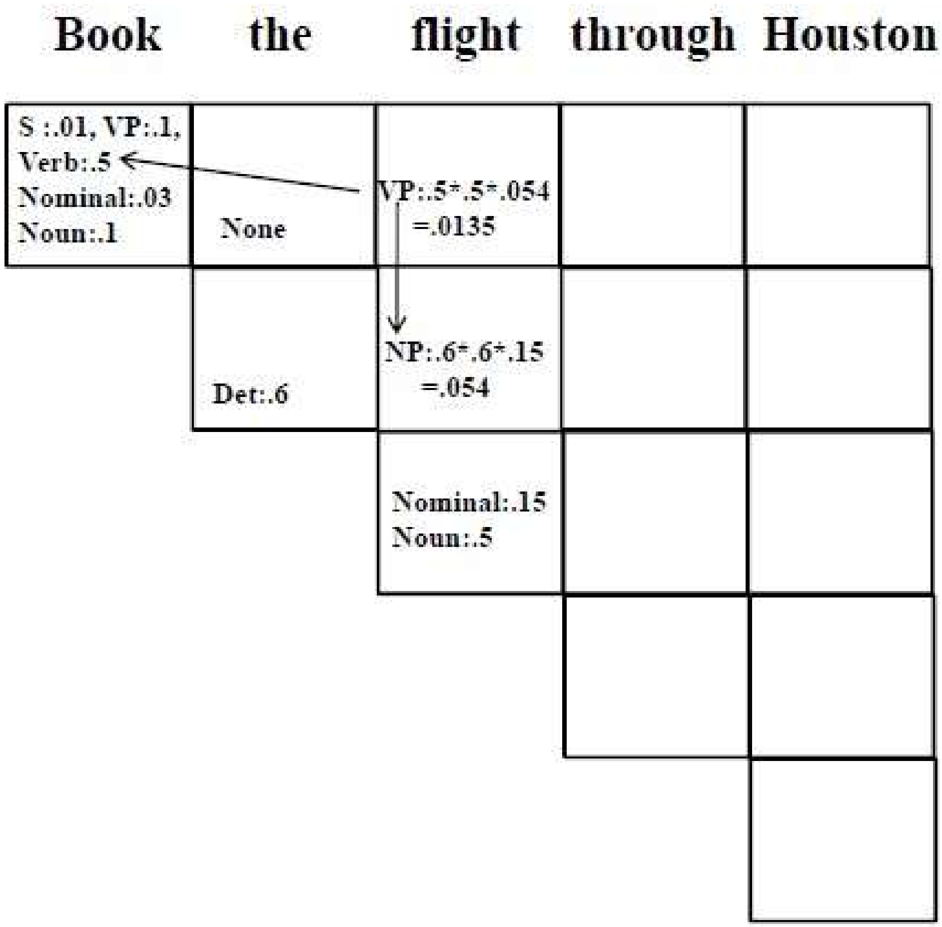
Probabilistic CKY Algorithm

Original Grammar		Chomsky Normal Form	
S → NP VP	0.8	S → NP VP	0.8
S → Aux NP VP	0.1	S → X1 VP	0.1
		X1 → Aux NP	1.0
S → VP	0.1	S → book | include | prefer 0.01 0.004 0.006	
		S → Verb NP	0.05
		S → VP PP	0.03
NP → Pronoun	0.2	NP → I | he | she | me 0.1 0.02 0.02 0.06	
NP → Proper-Noun	0.2	NP → Houston | NWA 0.16 .04	
NP → Det Nominal	0.6	NP → Det Nominal	0.6
Nominal → Noun	0.3	Nominal → book | flight | meal | money 0.03 0.15 0.06 0.06	
Nominal → Nominal Noun	0.2	Nominal → Nominal Noun	0.2
Nominal → Nominal PP	0.5	Nominal → Nominal PP	0.5
VP → Verb	0.2	VP → book | include | prefer 0.1 0.04 0.06	
VP → Verb NP	0.5	VP → Verb NP	0.5
VP → VP PP	0.3	VP → VP PP	0.3
PP → Prep NP	1.0	PP → Prep NP	1.0

Probabilistic CKY Algorithm

Book	the	flight	through	Houston
S :.01, VP:.1, Verb:.5 Nominal:.03 Noun:.1	None			
	Det:.6	NP:.6*.6*.15 =.054		
		Nominal:.15 Noun:.5		

Probabilistic CKY Algorithm



Probabilistic CKY Algorithm

Book	the	flight	through	Houston
S :.01, VP:.1, Verb:.5 Nominal:.03 Noun:.1	None	S:.05*.5*.054 =.00135 VP:.5*.5*.054 =.0135		
	Det:.6	NP:.6*.6*.15 =.054		
		Nominal:.15 Noun:.5		

Probabilistic CKY Algorithm

Book	the	flight	through	Houston
S :.01, VP:.1, Verb:.5 Nominal:.03 Noun:.1	None	S:.05*.5*.054 =.00135 VP:.5*.5*.054 =.0135	None	
	Det:.6	NP:.6*.6*.15 =.054	None	
		Nominal:.15 Noun:.5	None	
			Prep:.2	

Probabilistic CKY Algorithm

Book	the	flight	through	Houston
S :.01, VP:.1, Verb:.5 Nominal:.03 Noun:.1	None	S:.05*.5*.054 =.00135 VP:.5*.5*.054 =.0135	None	
	Det:.6	NP:.6*.6*.15 =.054	None	
		Nominal:.15 Noun:.5	None	
			Prep:.2	PP:1.0*.2*.16 =.032
				NP:.16 PropNoun:.8

Probabilistic CKY Algorithm

Book	the	flight	through	Houston
S :.01, VP:.1, Verb:.5 Nominal:.03 Noun:.1	None	S:.05*.5*.054 =.00135 VP:.5*.5*.054 =.0135	None	
	Det:.6	NP:.6*.6*.15 =.054	None	
		Nominal:.15 Noun:.5	None	Nominal: .5*.15*.032 =.0024
			Prep:.2	PP:1.0*.2*.16 =.032
				NP:.16 PropNoun:.8

Probabilistic CKY Algorithm

Book	the	flight	through	Houston
S :.01, VP:.1, Verb:.5 Nominal:.03 Noun:.1	None	S:.05*.5*.054 =.00135 VP:.5*.5*.054 =.0135	None	
	Det:.6	NP:.6*.6*.15 =.054	None	NP:.6*.6* .0024 =.000864
		Nominal:.15 Noun:.5	None	Nominal: .5*.15*.032 =.0024
			Prep:.2	PP:1.0*.2*.16 =.032
				NP:.16 PropNoun:.8

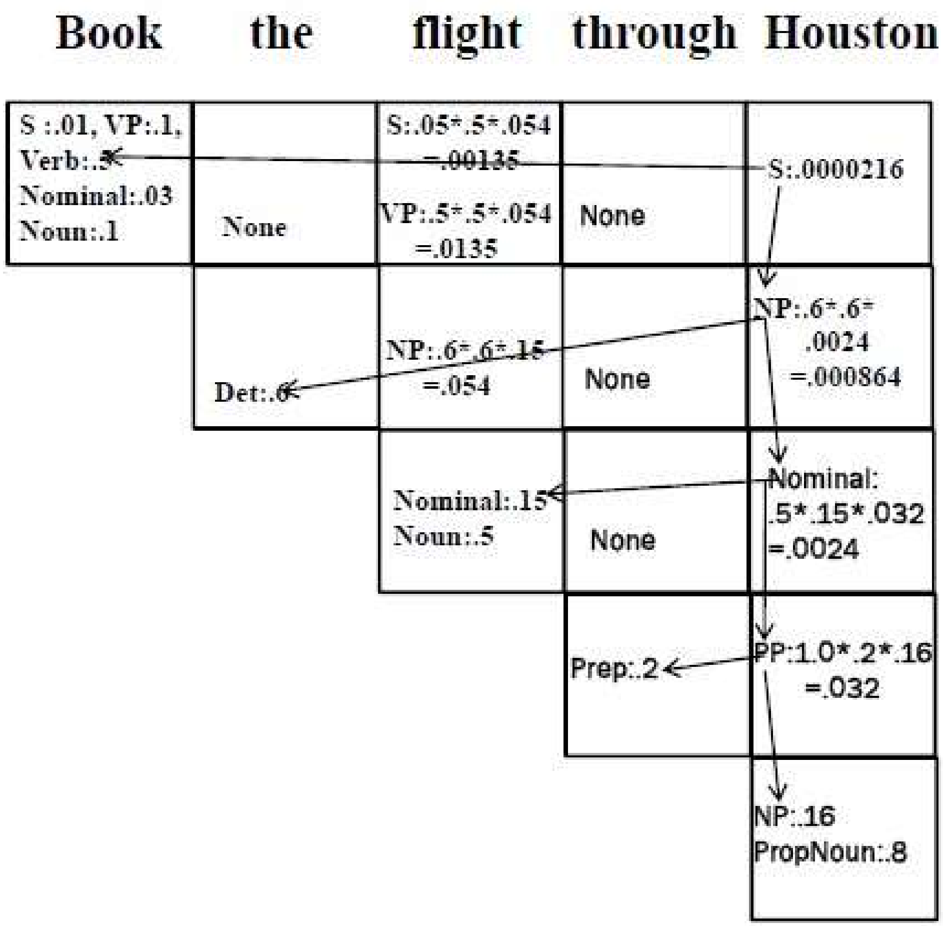
Probabilistic CKY Algorithm

Book	the	flight	through	Houston
S :.01, VP:.1, Verb:.5 Nominal:.03 Noun:.1	None	S:.05*.5*.054 =.00135 VP:.5*.5*.054 =.0135	None	S:.05*.5* .000864 =.0000216
	Det:.6	NP:.6*.6*.15 =.054	None	NP:.6*.6* .0024 =.000864
		Nominal:.15 Noun:.5	None	Nominal: .5*.15*.032 =.0024
			Prep:.2	PP:1.0*.2*.16 =.032
				NP:.16 PropNoun:.8

Probabilistic CKY Algorithm

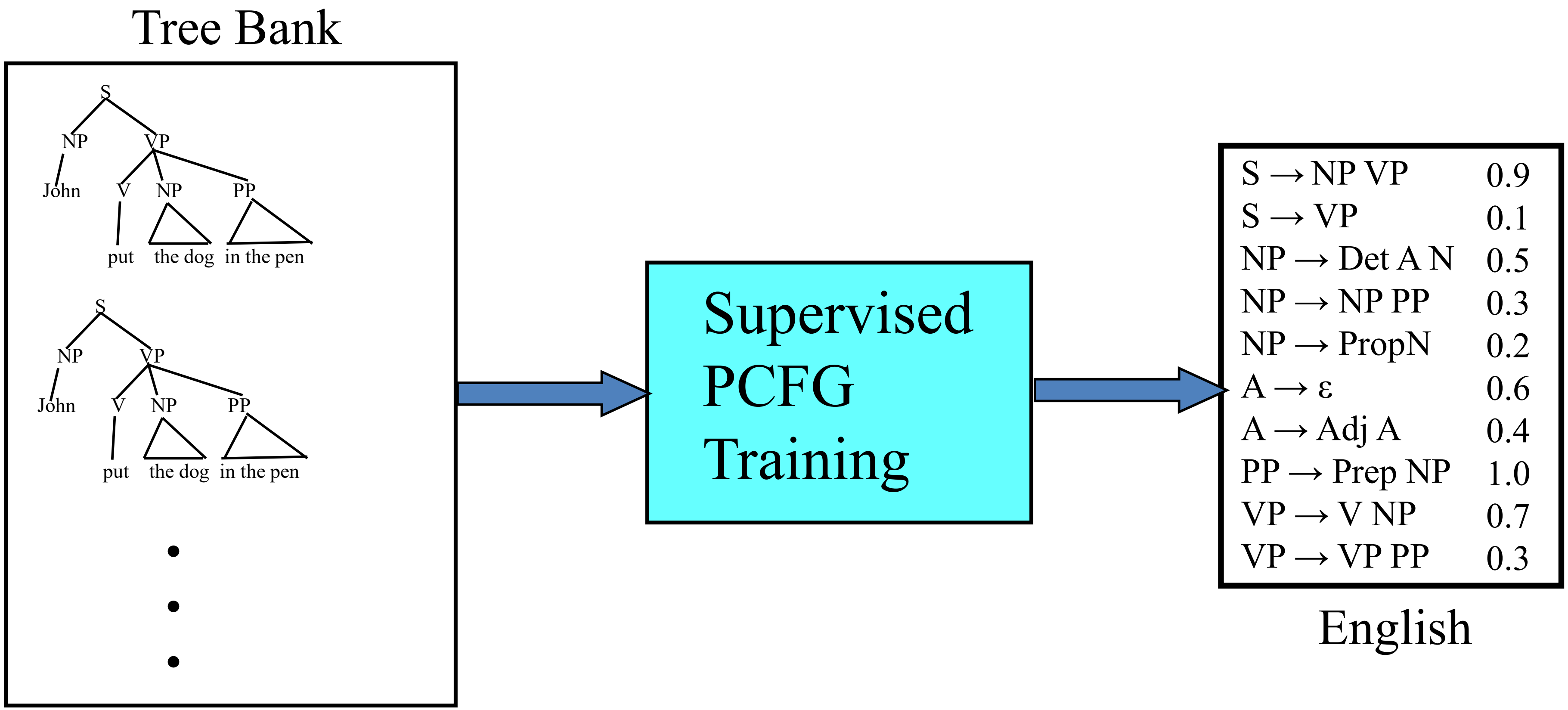
Book	the	flight	through	Houston
S :.01, VP:.1, Verb:.5 Nominal:.03 Noun:.1	None	S:.05*.5*.054 =.00135 VP:.5*.5*.054 =.0135	None	S:.03*.0135* .032 =.00001296 S:.0000216
	Det:.6	NP:.6*.6*.15 =.054	None	NP:.6*.6* .0024 =.000864
		Nominal:.15 Noun:.5	None	Nominal: .5*.15*.032 =.0024
			Prep:.2	PP:1.0*.2*.16 =.032
				NP:.16 PropNoun:.8

Probabilistic CKY Algorithm



PCFG: Supervised Training

- If parse trees are provided for training sentences, a grammar and its parameters can be estimated directly from counts accumulated from the tree-bank (with appropriate smoothing).



Estimating Production Probabilities

- Set of production rules can be taken directly from the set of rewrites in the treebank.
- Parameters can be directly estimated from frequency counts in the treebank.

$$P(\alpha \rightarrow \beta \mid \alpha) = \frac{\text{count}(\alpha \rightarrow \beta)}{\sum_{\gamma} \text{count}(\alpha \rightarrow \gamma)} = \frac{\text{count}(\alpha \rightarrow \beta)}{\text{count}(\alpha)}$$

PCFG: Maximum Likelihood Training

- Given a set of sentences, induce a grammar that maximizes the probability that this data was generated from this grammar.
- Assume the number of non-terminals in the grammar is specified.
- Only need to have an unannotated set of sequences generated from the model. Does not need correct parse trees for these sentences. In this sense, it is unsupervised.

PCFG: Maximum Likelihood Training

Training Sentences

John ate the apple
A dog bit Mary
Mary hit the dog
John gave Mary the cat.
•
•
•

PCFG Training

S → NP VP	0.9
S → VP	0.1
NP → Det A N	0.5
NP → NP PP	0.3
NP → PropN	0.2
A → ε	0.6
A → Adj A	0.4
PP → Prep NP	1.0
VP → V NP	0.7
VP → VP PP	0.3

English

Inside-Outside Algorithm

- The **Inside-Outside algorithm** is a version of EM for unsupervised learning of a PCFG.
  - Analogous to Baum-Welch (forward-backward) for HMMs
- Given the number of non-terminals, construct all possible CNF productions with these non-terminals and observed terminal symbols.
- Use EM to iteratively train the probabilities of these productions to locally maximize the likelihood of the data.
- Experimental results are not impressive, but recent work imposes additional constraints to improve unsupervised grammar learning.

Summary of PCFG

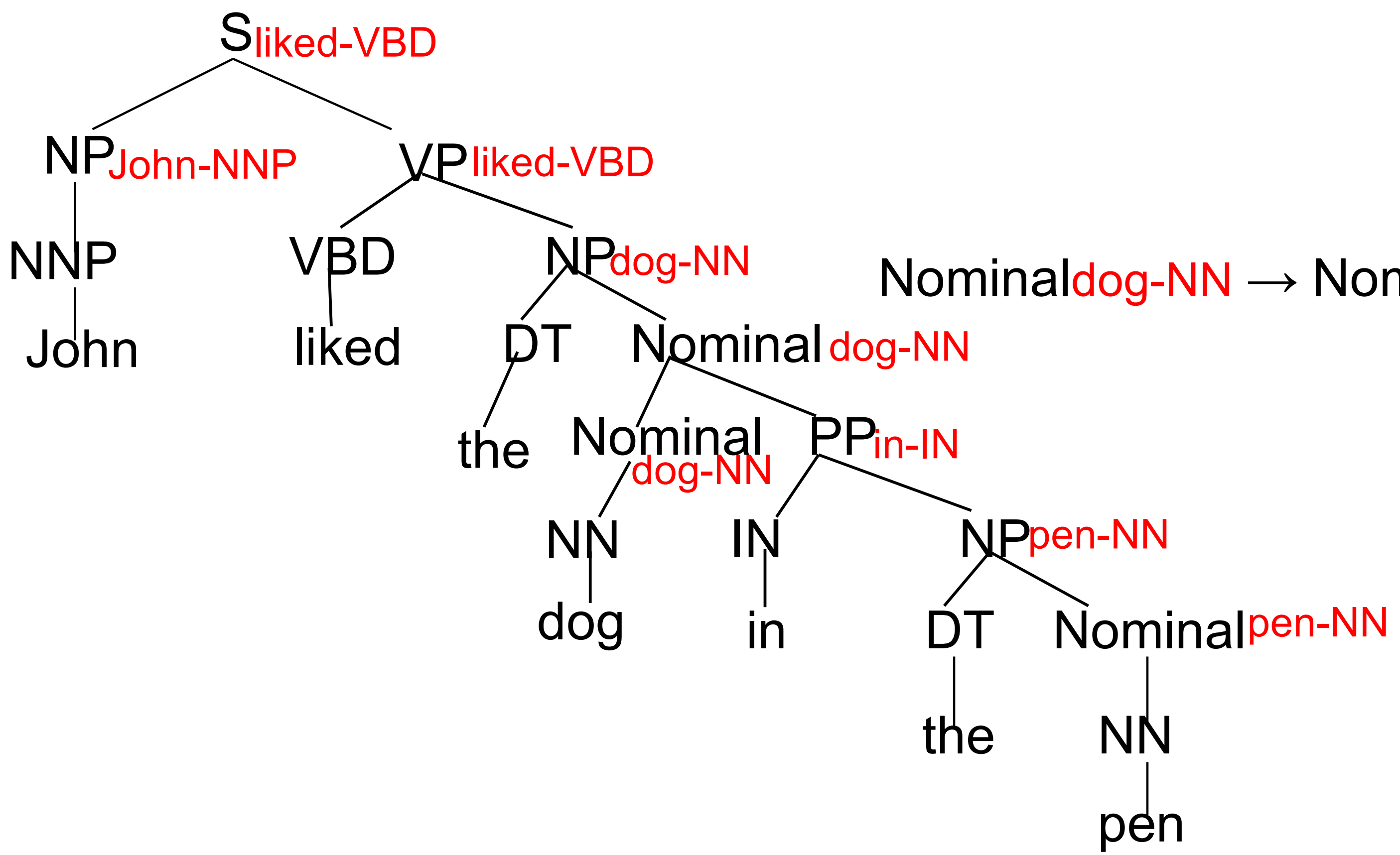
- Pros
  - Disambiguation of structurally different parses
  - Speed syntactic analysis by eliminate low probability structures
  - Improve the robust of analyzer by use of low probabilities
  - Helpful to grammar induction
- Cons
  - Since probabilities of productions do not rely on specific words or concepts, only general structural disambiguation is possible
  - cannot resolve syntactic ambiguities that require semantics to resolve, e.g. ate with fork vs. meatballs.

Lexicalized PCFG

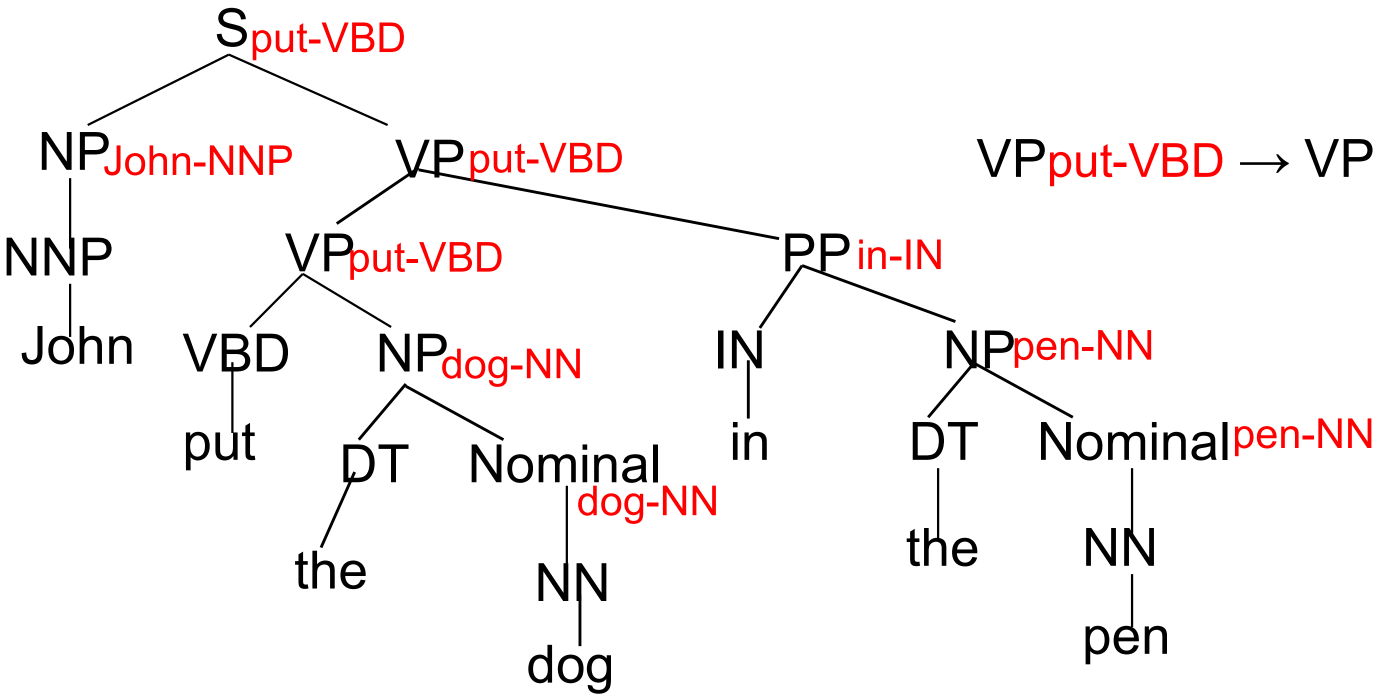
- PCFGs must be lexicalized, i.e. productions must be specialized to specific words by including their head-word in their LHS non-terminals
- Each non-terminal is associated to headword *w*
- Syntactic phrases usually have a word in them that is most "central" to the phrase.
- Process Rule
  - Head of a VP is the main verb
  - Head of an NP is the main noun
  - Head of a PP is the preposition
  - Head of a sentence is the head of its VP

Lexicalized Productions

- Specialized productions can be generated by including the head word and its POS of each non-terminal as part of that non-terminal's symbol



$\text{Nominal}_{\text{dog-NN}} \rightarrow \text{Nominal}_{\text{dog-NN}}\ \text{PP}_{\text{in-IN}}$



$$VP_{put\text{-}VBD} \rightarrow VP_{put\text{-}VBD}\ PP_{in\text{-}IN}$$

Parameterizing Lexicalized Productions

- Accurately estimating parameters on such a large number of very specialized productions requires enormous amounts of treebank data.
- Need some way of estimating parameters for lexicalized productions that makes reasonable independence assumptions so that accurate probabilities for very specific rules can be learned.

Collins' Parser

- Collins' (1999) parser assumes a simple generative model of lexicalized productions.
- Models productions based on context to the left and the right of the head daughter.
  - LHS → $L_n L_{n-1} \ldots L_1 H\ R_1 \ldots R_{m-1} R_m$
- First generate the head (H) and then repeatedly generate left (L_i) and right (R_i) context symbols until the symbol STOP is generated.

Sample Production

VPput-VBD → VBDput-VBD NPdog-NN PPin-IN

VPput-VBD → STOP VBDput-VBD NPdog-NN PPin-IN STOP

L_1 H R_1 R_2 R_3

P_L(STOP | VPput-VBD) * P_H(VBD | VPput-VBD)*
P_R(NPdog-NN | VPput-VBD)*
P_R(PPin-IN | VPput-VBD) * P_R(STOP | VPput-VBD)

Estimating Production Generation Parameters

- Estimate P_H, P_L, and P_R parameters from treebank data.

$$P_R(\text{PPin-IN} \mid \text{VPput-VBD}) = \frac{\text{Count(PPin-IN right of head in a VPput-VBD production)}}{\text{Count(symbol right of head in a VPput-VBD)}}$$

$$P_R(\text{NPdog-NN} \mid \text{VPput-VBD}) = \frac{\text{Count(NPdog-NN right of head in a VPput-VBD production)}}{\text{Count(symbol right of head in a VPput-VBD)}}$$

- Smooth estimates by linearly interpolating with simpler models conditioned on just POS tag or no lexical info.

$$\begin{aligned} smP_R(\text{PPin-IN} \mid \text{VPput-VBD}) = {} & \lambda_1 P_R(\text{PPin-IN} \mid \text{VPput-VBD}) \\ & + (1-\lambda_1)\,(\lambda_2 P_R(\text{PPin-IN} \mid \text{VPVBD}) + \\ & (1-\lambda_2)\, P_R(\text{PPin-IN} \mid \text{VP})) \end{aligned}$$

Parsing Evaluations Metrics

- PARSEVAL metrics measure the fraction of the constituents that match between the computed and human parse trees. If *P* is the system's parse tree and *T* is the human parse tree (the "gold standard"):
  - ***Recall*** = (# correct constituents in *P*) / (# constituents in *T*)
  - ***Precision*** = (# correct constituents in *P*) / (# constituents in *P*)
- ***Labeled Precision*** and ***labeled recall*** require getting the non-terminal label on the constituent node correct to count as correct.
- F_1 is the harmonic mean of precision and recall.

Summary of Probabilistic Parsing

- Statistical models such as PCFGs allow for probabilistic resolution of ambiguities.
- PCFGs can be easily learned from treebanks.
- Lexicalization and non-terminal splitting are required to effectively resolve many ambiguities.
- Current statistical parsers are quite accurate but not yet at the level of human-expert agreement.

Dependency

- Syntactic structure consists of lexical items, linked by binary asymmetric relations called dependencies.
- [Tesniere 1959]

> The sentence is an *organized whole*, the constituent elements of which are *words*. 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 *connections*, the totality of which forms the structure of the sentence. The structural connections establish *dependency* relations between the words. Each connection in principle unites a *superior* term and an *inferior* term. The superior term receives the name *governor*. The inferior term receives the name *subordinate*.

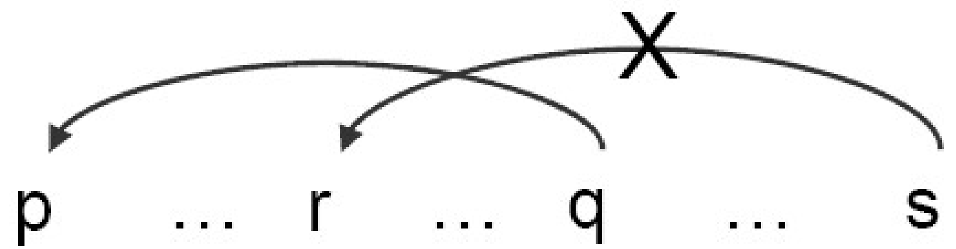
Robinson’s axiom

(a) one and only one element is independent;

(b) all others depend directly on some element;

(c) no element depends directly on more than one other; and

(d) (non-crossing constraint): if ***A*** depends directly to ***B*** and some element ***C*** intervenes between them (in linear order of string), then ***C*** depends directly on ***A*** or on ***B*** or to some other intervening element.



(e) An element cannot have dependents lying on the other side of its own governor.(Huang, Changning)

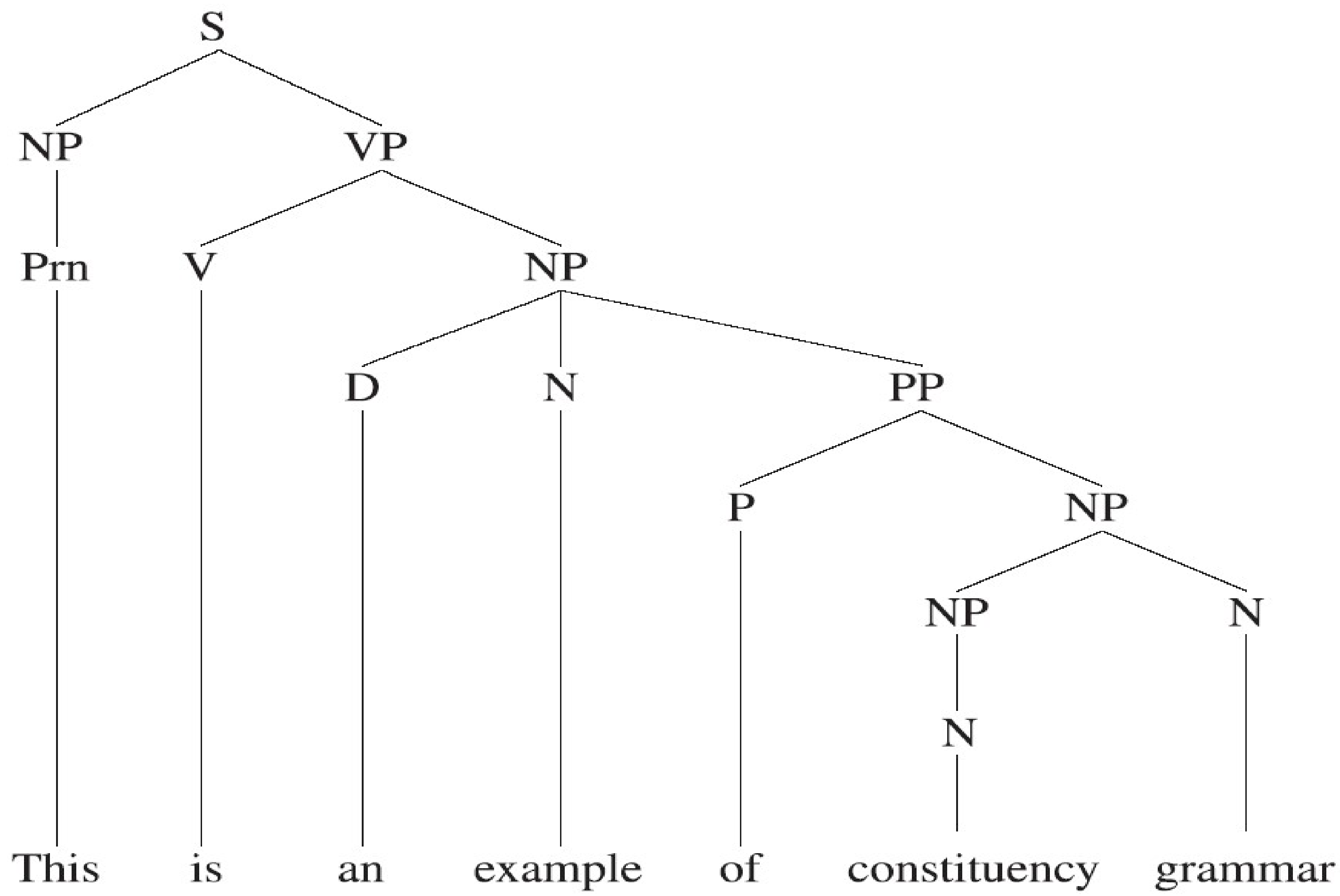
Element:

- Head (Superior, Head, Governor, Regent, 核心词)
  - Plays the role in determining the behavior of the pair.
- Dependent (Inferior, Modifier, Subordinate,从属词)
  - Modifier, object or complement
  - Pre-dependent, post-dependent
- Link – the relation (Arc)
  - Close to semantic relation
  - With Dependency Type

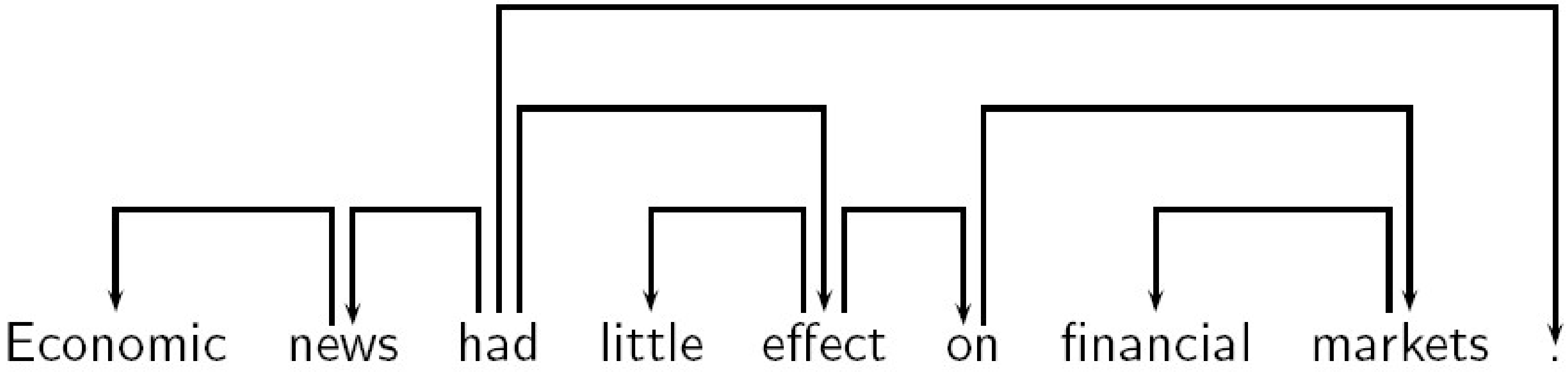
Typical Dependency Types

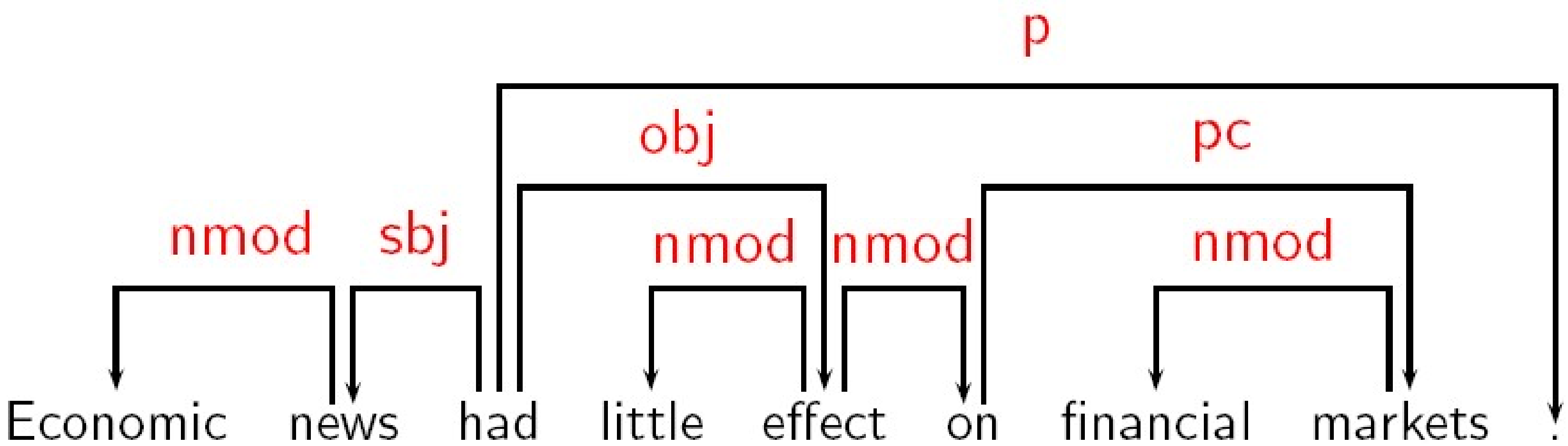
	Dependency Description	Example
	Adjective and its adverbial modifier	极其/d 惨痛/a *greatly painful*
ADV	Predicate and its adverbial modifier in which the predicate serves as head	沉重/ad 打击/v *heavily strike*
AN	Noun and its adjective modifier	合法/a 收入/n *lawful incoming*
CMP	Predicate and its complement in which the predicate serves as head	医治/v 无效/v *ineffectively treat*
NJX	Juxtaposition structure	公正/a 合理/a *fair and reasonable*
NN	Noun and its nominal modifier	人身/n 安全/n *personal safety*
SBV	Predicate and its subject	财产/n 转移/v *property transfer*
VO	Predicate and its object in which the predicate serves as head	转换/v 机制/n *change mechanism*
VV	Serial verb constructions which indicates that there are serial actions	跟踪/v 报导/v *trace and report*
OT	Others	

Phrase Structure



Dependency Structure





The Comparison

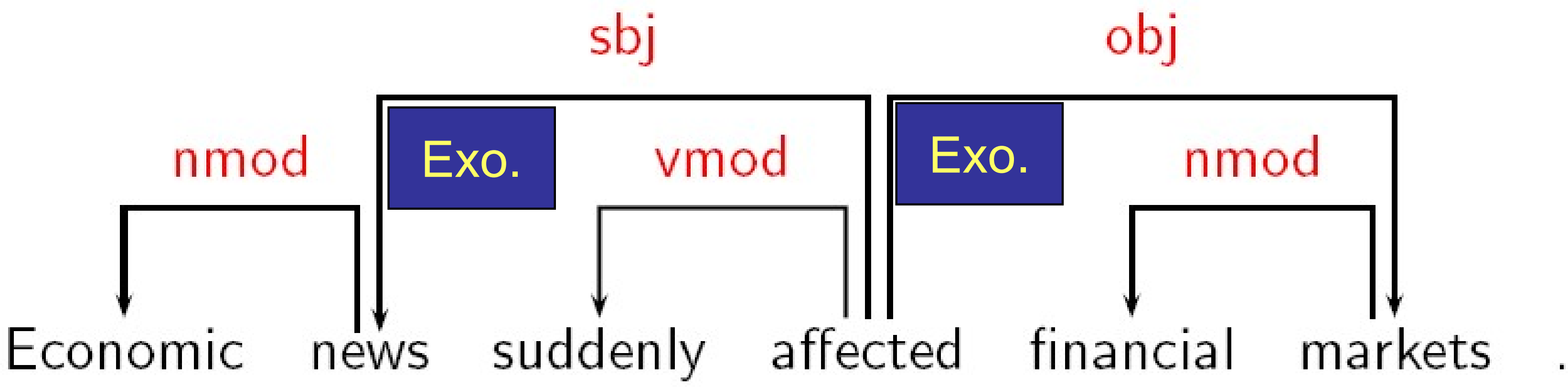
	Phrase structure	Dependency structure
word relation	phrasal constitution	head-dependent
categories	syntactic functional	syntactic structural
new node (Y/N)	multiple nodes per word	one node per word
operation	waiting for complete phrase	word-at-a-time

Some Theoretical Frameworks

- Word Grammar (WG) [Hudson 1984, Hudson 1990]
- Functional Generative Description (FGD) [Sgall et al. 1986]
- Dependency Unification Grammar (DUG)
  - [Hellwig 1986, Hellwig 2003]
- Meaning-Text Theory (MTT) [Melcuk 1988]
- (Weighted) Constraint Dependency Grammar ([W]CDG)
  - [Maruyama 1990, Harper and Helzerman 1995,
  - Menzel and Schr ¨ oder 1998, Schr ¨ oder 2002]
- Functional Dependency Grammar (FDG)
  - [Tapanainen and Jarvinen 1997, Jarvinen and Tapanainen 1998]
- Topological/Extensible Dependency Grammar ([T/X]DG)
  - [Duchier and Debusmann 2001, Debusmann et al. 2004]

Examples

	Construction	Head	Dependent
outwards	Exocentric	Verb	Subject (sbj)
		Verb	Object (obj)
inwards	Endocentric	Verb	Adverbial (vmod)
		Noun	Attribute (nmod)



	Construction	Head	Dependent
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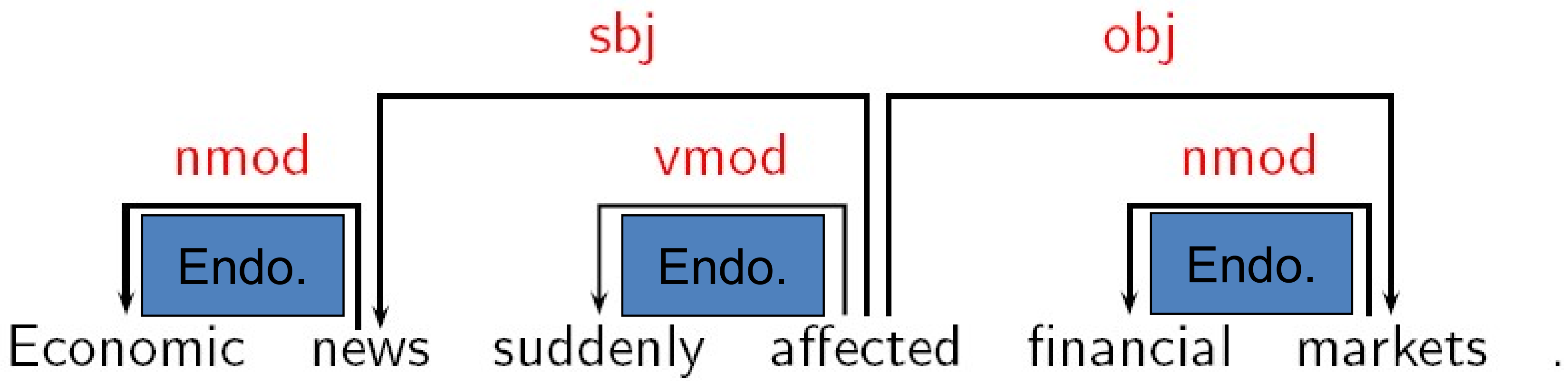
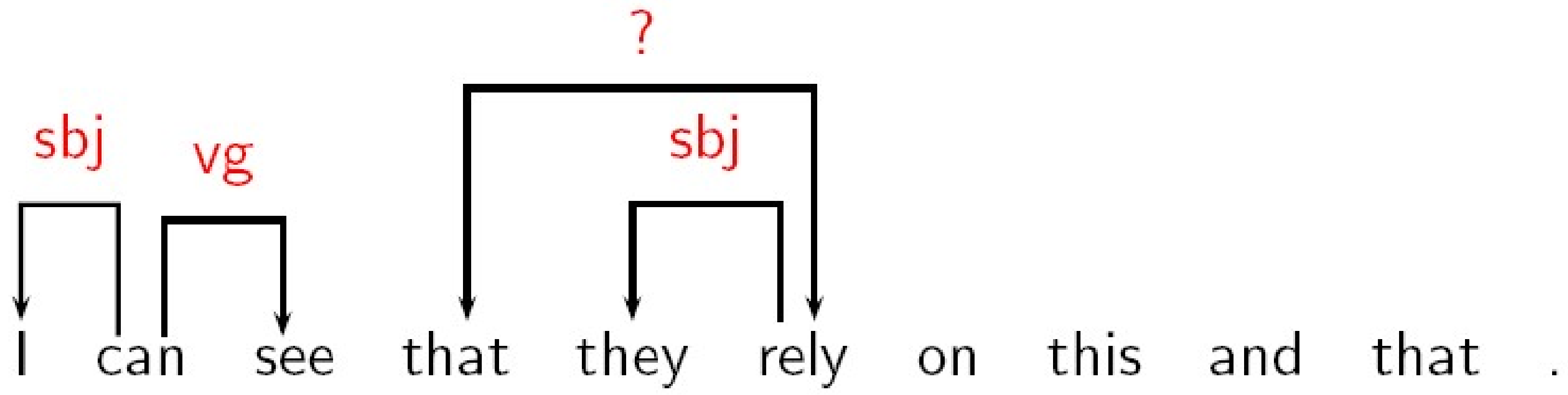
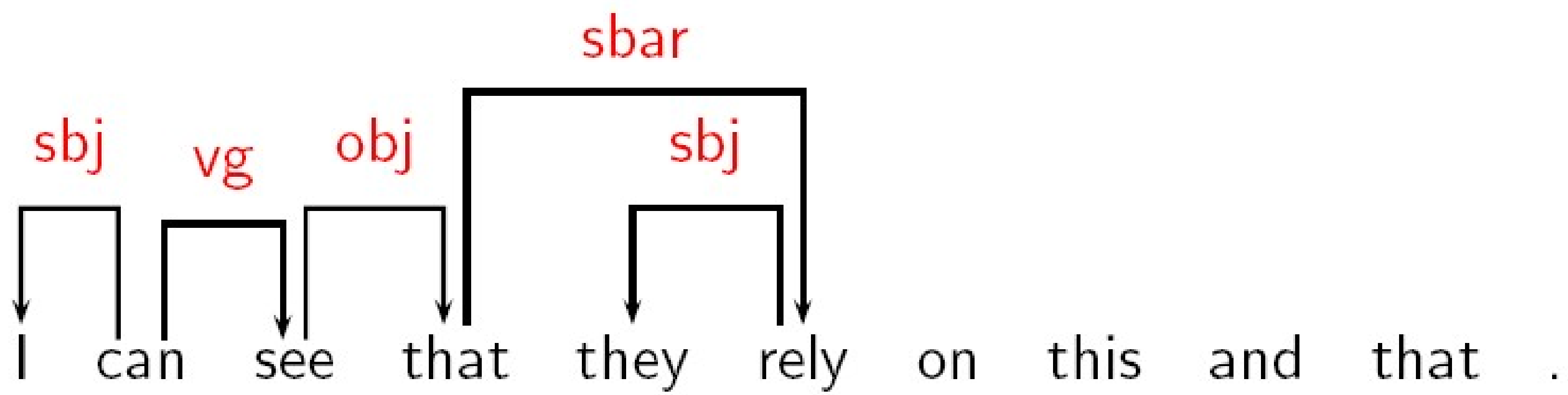


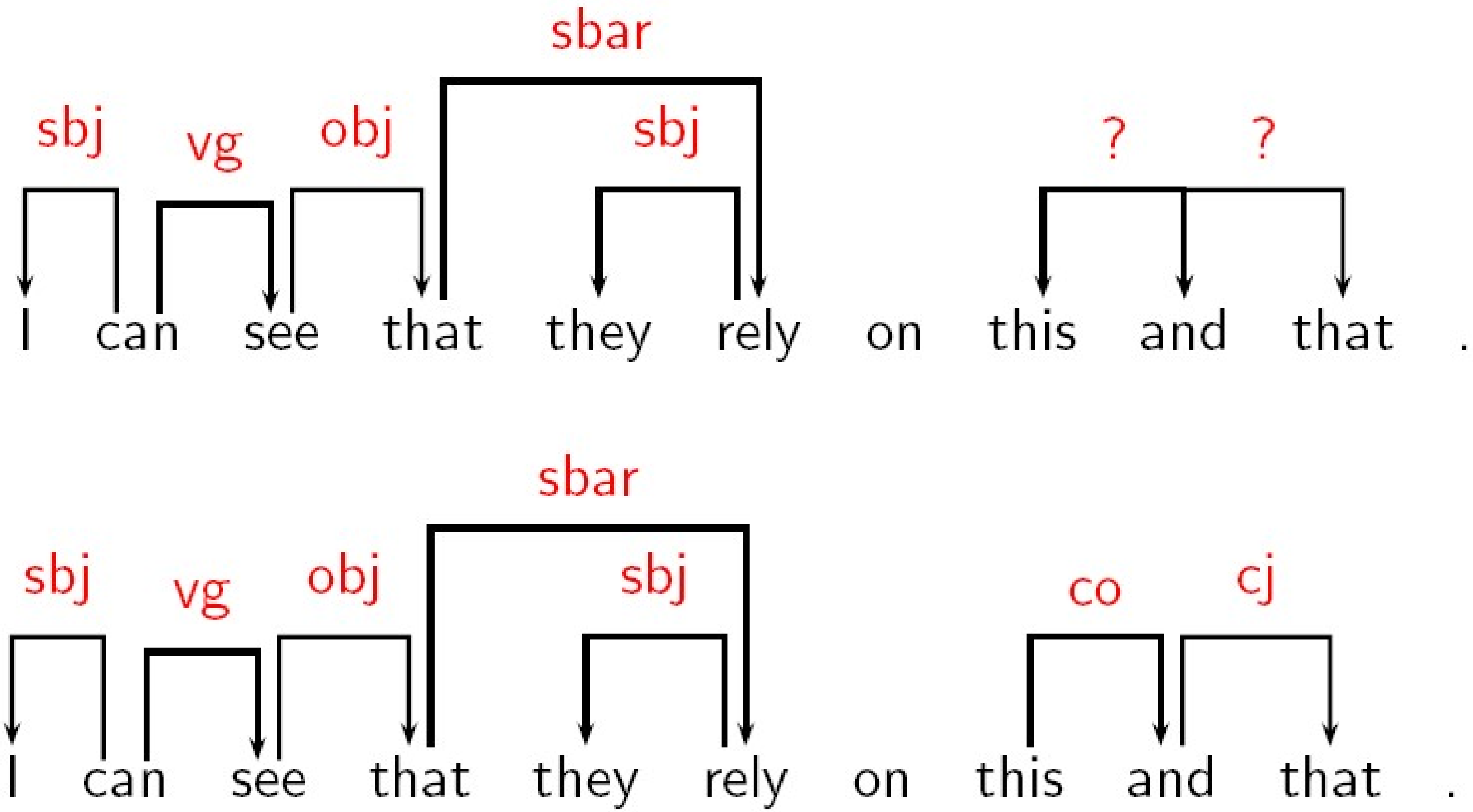
Tricky Cases

- Subordinate clauses (complementizer ↔ verb)

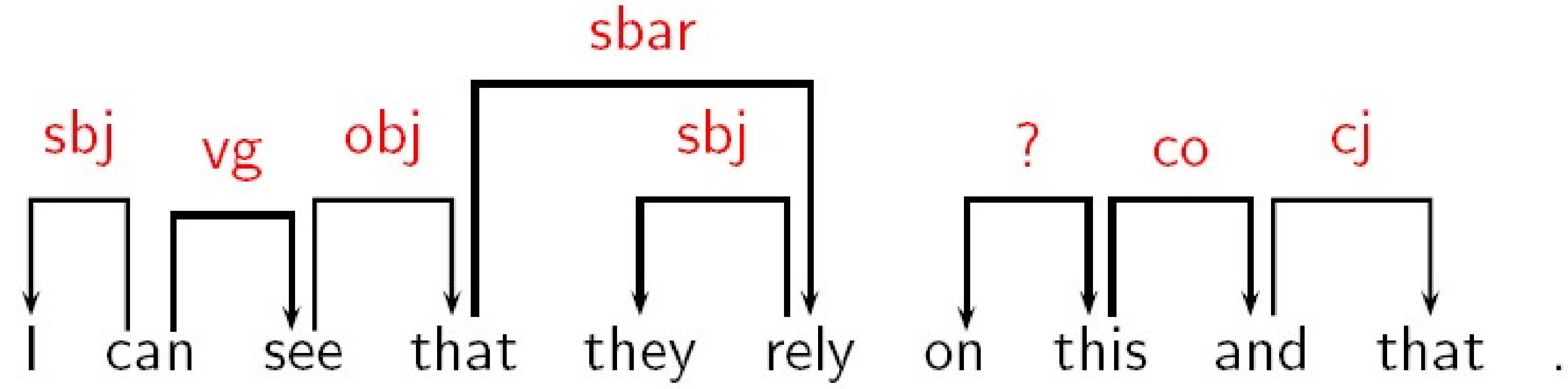


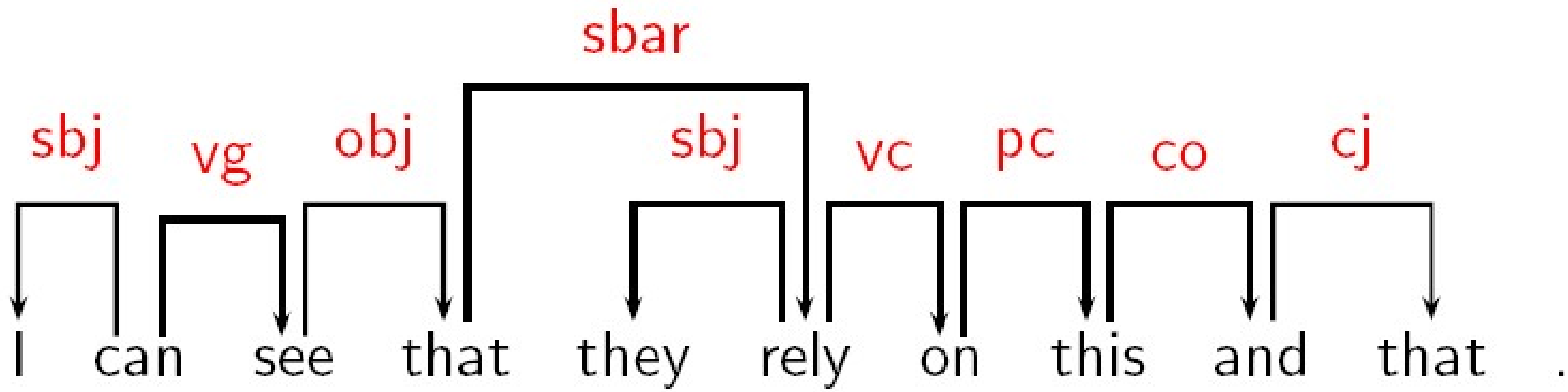


- Coordination (coordinator ↔ conjuncts)

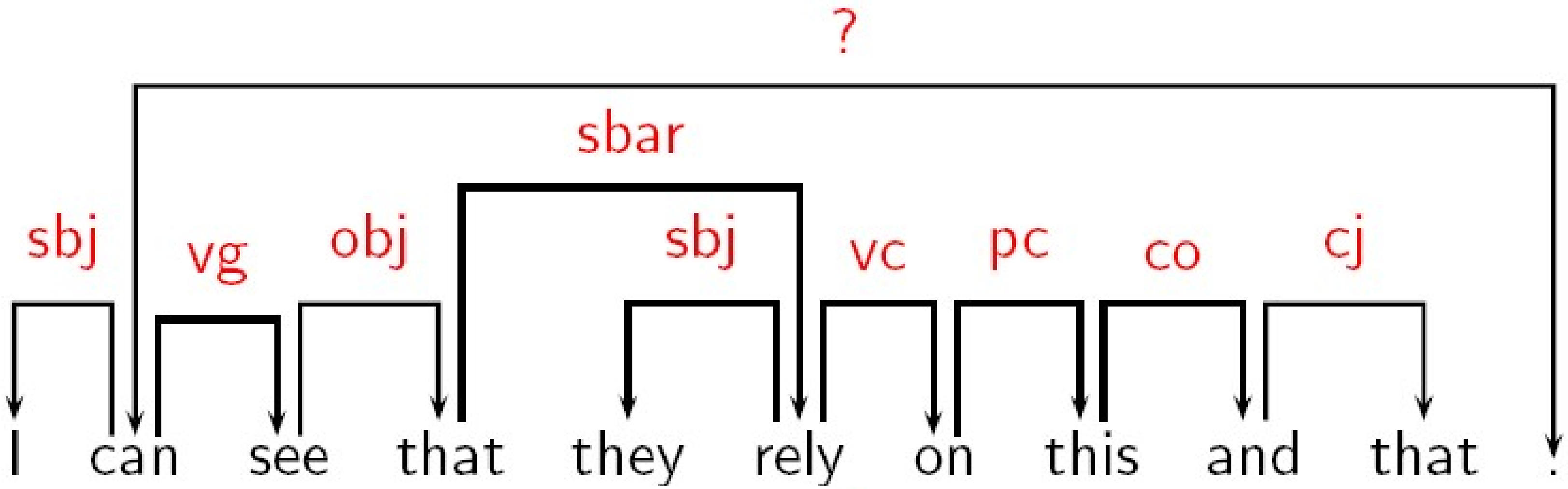


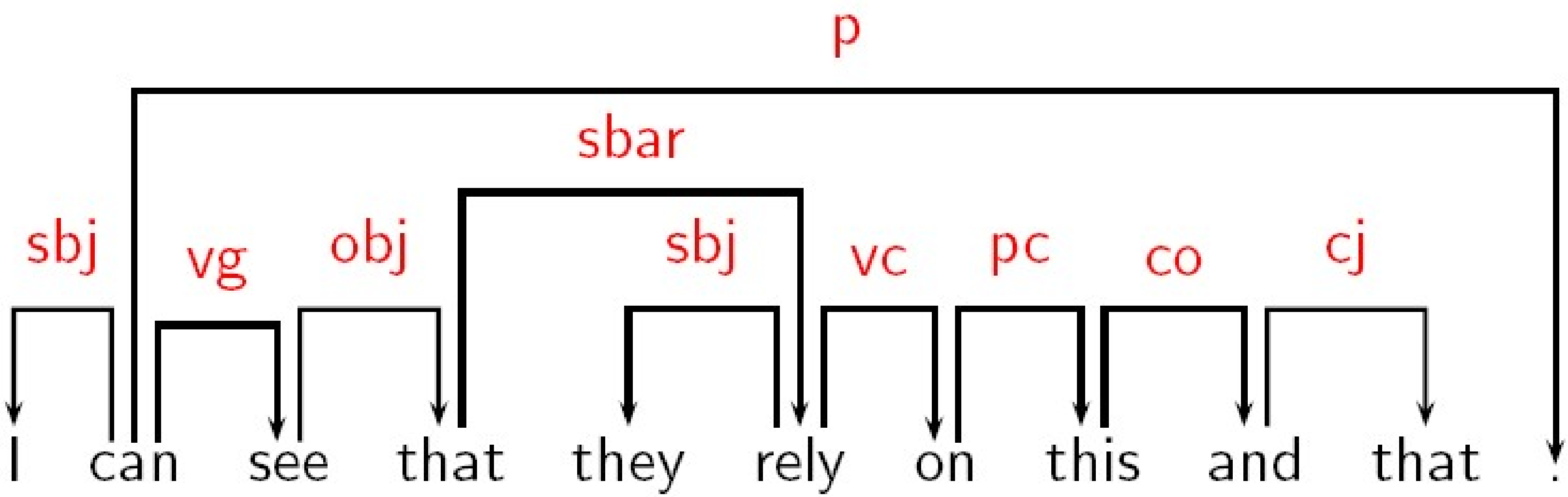
- Prepositional phrases (preposition ↔ nominal)





- Punctuation





Dependency parsing

- **Input**:

  Sentence $W = w_0, w_1, \ldots, w_n$ with w_0=*root*

- **Output**:

  Dependency graph $G = (V, A)$ for W where:

  – $V = \{0, 1, \ldots, n\}$ is the *vertex* set,

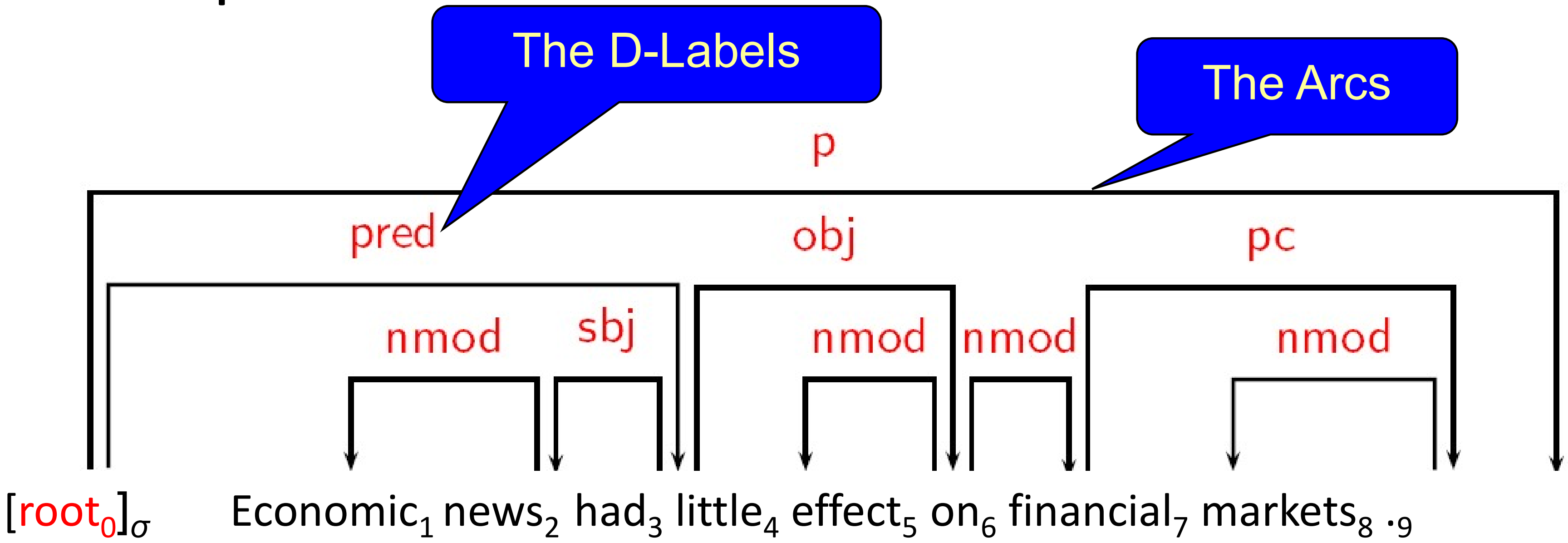
  – A is the *arc* set, i.e., $(i, j, k) \in A$ represents a dependency from w_i to w_j with label $l_k \in L$

Example

- Input:

[$\color{red}{\text{root}_0}$]$_\sigma$ Economic$_1$ news$_2$ had$_3$ little$_4$ effect$_5$ on$_6$ financial$_7$ markets$_8$.$_9$

- Output:



Approaches

- Grammar-based parsing
  - Context-free dependency grammar
  - Constraint dependency grammar
- Data-driven parsing
  - Transition-based models
  - Graph-based models

Context-free dependency grammar

- Basic idea
  - Dependency grammar as lexicalized context-free grammar
  - Standard context-free parsing algorithms (CKY, Earley, etc.)

- Recent developments:
  - Link Grammar [Sleator and Temperley 1991]
  - Earley-style parser with left-corner filtering
  - [Lombardo and Lesmo 1996]
  - Bilexical grammars [Eisner 1996, Eisner 2000]

Constraint Dependency Grammar

- Parsing as constraint satisfaction [Maruyama 1990]:
  - Grammar consists of a set of boolean constraints, i.e. logical formulas that describe well-formed dependency graphs.
  - Constraint propagation removes candidate graphs that contradict constraints (eliminative parsing).
- Recent developments:
  - Weighted Constraint Dependency Grammar [Menzel and Schr ¨ oder 1998, Foth et al. 2004]
  - Probabilistic Constraint Dependency Grammar [Harper and Helzerman 1995, Wang and Harper 2004]
  - Topological/Extensible Dependency Grammar [Duchier and Debusmann 2001, Debusmann et al. 2004]

Transition-based models

- Basic idea:
  - Define a transition system (state machine, MM) for mapping a sentence to its dependency graph.
  - Learning: Induce a model for predicting the next state transition, given the transition history.
  - Parsing: Construct the optimal transition sequence, given the induced model.

- Characteristics:
- Local training of a model for optimal transitions
- Greedy search/inference

Lexicalized Dependency Probabilistic Model

- Collins 1996
- Training: Retrieve the probability of any words with specific dependency through Maximal Likelihood Estimation.
- Parsing (Decoding): Search a dependency tree with the highest product of production probability of all dependent pairs

Probabilistic Dependency Model

- Eisner, 1996
- For each candidate dependency tree, *T*, its production probability is defined as the probability product of the production probability of each node in T

$$Gen(T) = \prod_{x \in T} Gen(x)$$

- Task of Parsing: Looking for the dependency tree with the highest production probability

Shift-Reduce Dependency Parsing

- Transitions:
  - Left-Arc$_k$:
    $$(\sigma|i,j|\beta, A) \Rightarrow (\sigma, j|\beta, A \cup \{(j, i, k)\})$$
  - Right-Arc$_k$:
    $$(\sigma|i,j|\beta, A) \Rightarrow (\sigma, i|\beta, A \cup \{(i, j, k)\})$$
  - Shift:
    $$(\sigma, i|\beta, A) \Rightarrow (\sigma|i, \beta, A)$$
- Preconditions:
  - Left-Arc$_k$:
    $$\neg[i = 0]$$
    $$\neg\exists i' \exists k' [(i', i, k') \in A]$$
  - Right-Arc$_k$:
    $$\neg\exists i' \exists k' [(i', j, k') \in A]$$

Example: Shift-Reduce Parsing - 1

$[\text{root}_0]_\sigma$ $[\text{Economic}_1\ \text{news}_2\ \text{had}_3\ \text{little}_4\ \text{effect}_5\ \text{on}_6\ \text{financial}_7\ \text{markets}_8\ ._9]_\beta$

We have nothing in the configuration.
Just shift to first word

2

[root$_0$ Economic$_1$]$_\sigma$ [news$_2$ had$_3$ little$_4$ effect$_5$ on$_6$ financial$_7$ markets$_8$.$_9$]$_\beta$

Shift

We have one word in the configuration. Now to search the in/out arcs …

3

nmod

$[\text{root}_0]_\sigma$ Economic_1 $[\text{news}_2$ had_3 little_4 effect_5 on_6 financial_7 markets_8 $._9]_\beta$

$\text{Left-Arc}_{\text{nmod}}$

A left-arc is found. Include the dependent in current configuration …

4

nmod

$[\text{root}_0\ \text{Economic}_1\ \text{news}_2]_\sigma\ [\text{had}_3\ \text{little}_4\ \text{effect}_5\ \text{on}_6\ \text{financial}_7\ \text{markets}_8\ ._9]_\beta$

Shift

Current configuration is self-contained. Now shift is required to include the next word …

5

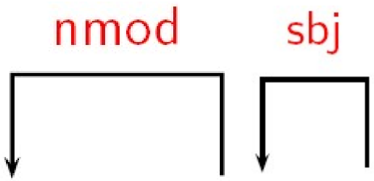
nmod sbj

[root$_0$]$_\sigma$ Economic$_1$ news$_2$ [had$_3$ little$_4$ effect$_5$ on$_6$ financial$_7$ markets$_8$.$_9$]$_\beta$

Left-Arc$_{sbj}$

But the next word holds a *SBJ* left arc to word *news*.
The configuration is reduced to empty again.

6



[root$_0$ Economic$_1$ news$_2$ had$_3$]$_\sigma$ [little$_4$ effect$_5$ on$_6$ financial$_7$ markets$_8$.$_9$]$_\beta$

Shift

The *SBJ* left arc creates a new configuration. We now shift to the next word.

7

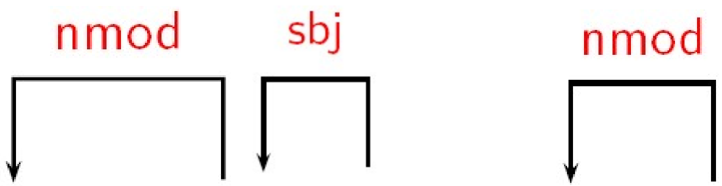
nmod sbj

$[\text{root}_0\ \text{Economic}_1\ \text{news}_2\ \text{had}_3\ \text{little}_4]_\sigma\ \text{effect}_5\ \text{on}_6\ \text{financial}_7\ \text{markets}_8\ ._9]_\beta$

Shift

The next word holds no valid arc with current configuration. Then we continue to shift.

8

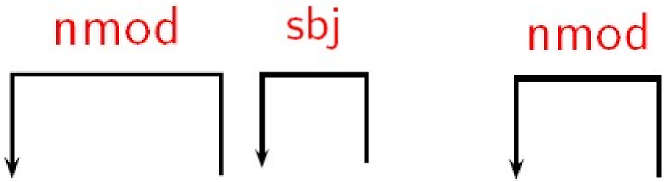


[root$_0$ Economic$_1$ news$_2$ had$_3$]$_\sigma$ little$_4$ [effect$_5$ on$_6$ financial$_7$ markets$_8$.$_9$]$_\beta$

Left-Arc$_{nmod}$

Now a NMOD left arc is found. The current configuration is reduced to previous one.

9

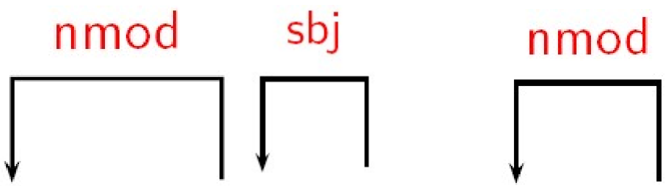


[root$_0$ Economic$_1$ news$_2$ had$_3$ little$_4$ effect$_5$]$_\sigma$ [on$_6$ financial$_7$ markets$_8$.$_9$]$_\beta$

Shift

The valid NMOD left arc is included in the current configuration. Shift to next word.

10



[root$_0$ Economic$_1$ news$_2$ had$_3$ little$_4$ effect$_5$ on$_6$]$_\sigma$ [financial$_7$ markets$_8$.$_9$]$_\beta$

Shift

The word on should hold an arc to its neighbors. It is not word effect. So we continue to shift.

11

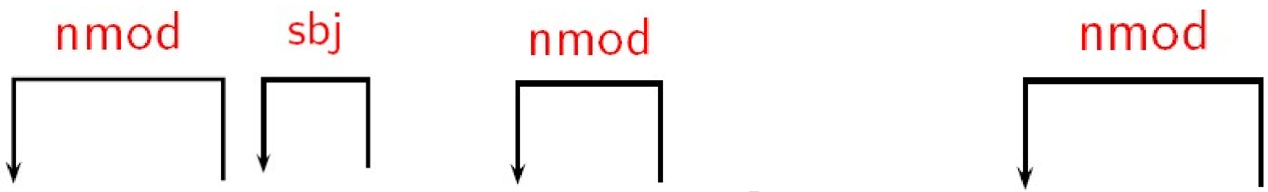
nmod sbj nmod

[root$_0$ Economic$_1$ news$_2$ had$_3$ little$_4$ effect$_5$ on$_6$ financial$_7$]$_\sigma$ [markets$_8$.$_9$]$_\beta$

Shift

We include the new word in the configuration. However, the arc from *on* to *financial* is not valid. Shift but reduce to previous configuration.

12

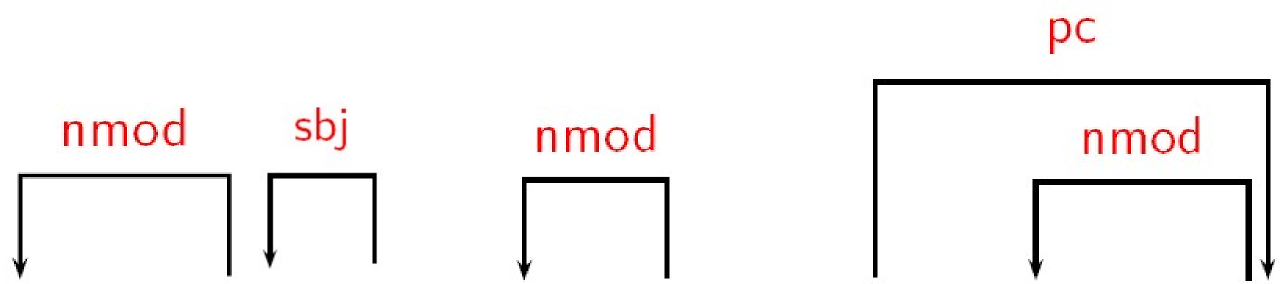


[root$_0$ Economic$_1$ news$_2$ had$_3$ little$_4$ effect$_5$ on$_6$]$_\sigma$ financial$_7$ [markets$_8$.$_9$]$_\beta$

New NMOD left arc is found. The remaining word is punctuation. Stop shifting. Search right arc.

Left-Arc$_{nmod}$

13

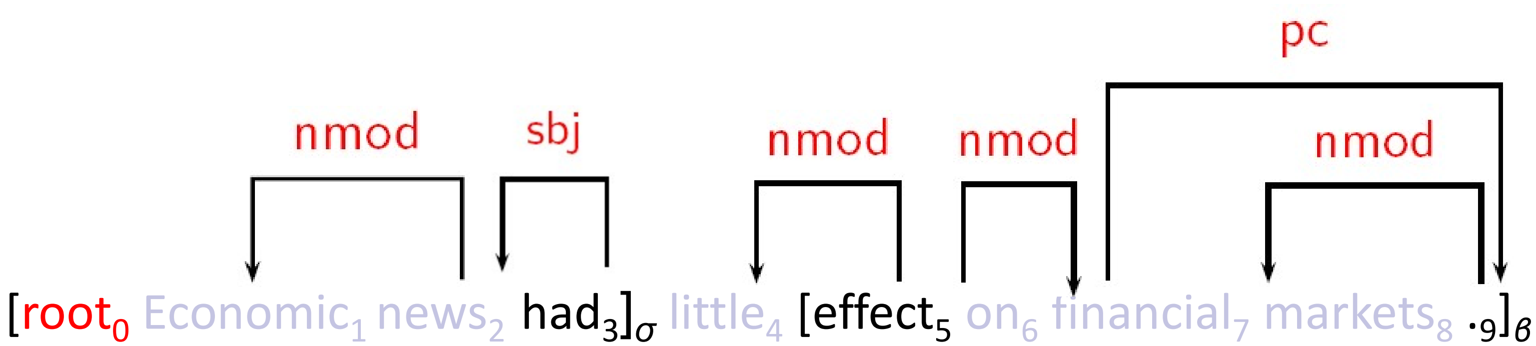


[root_0 Economic_1 news_2 had_3 little_4 $\text{effect}_5]_\sigma$ [on_6 financial_7 markets_8 $._9]_\beta$

Right-Arc_{pc}

A PC right arc is found from *on* to *markets*. Reduce configuration. Continue searching right arc.

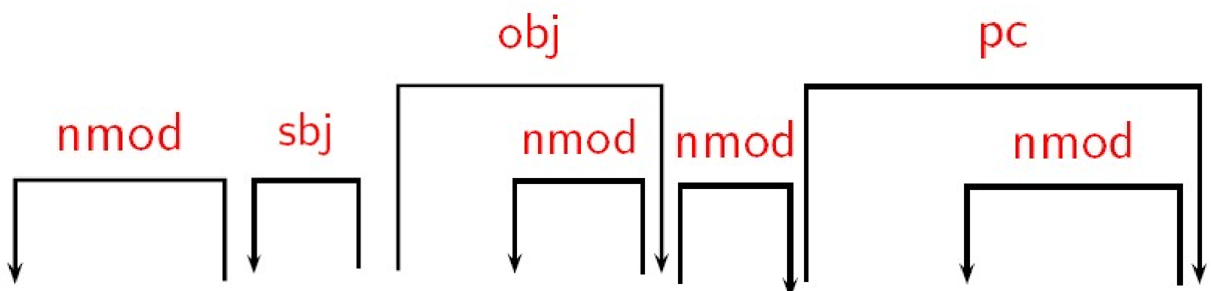
14



Right-Arc$_{nmod}$

A PC right arc is found from *effect* to *on*. Reduce configuration. Continue searching right arc.

15

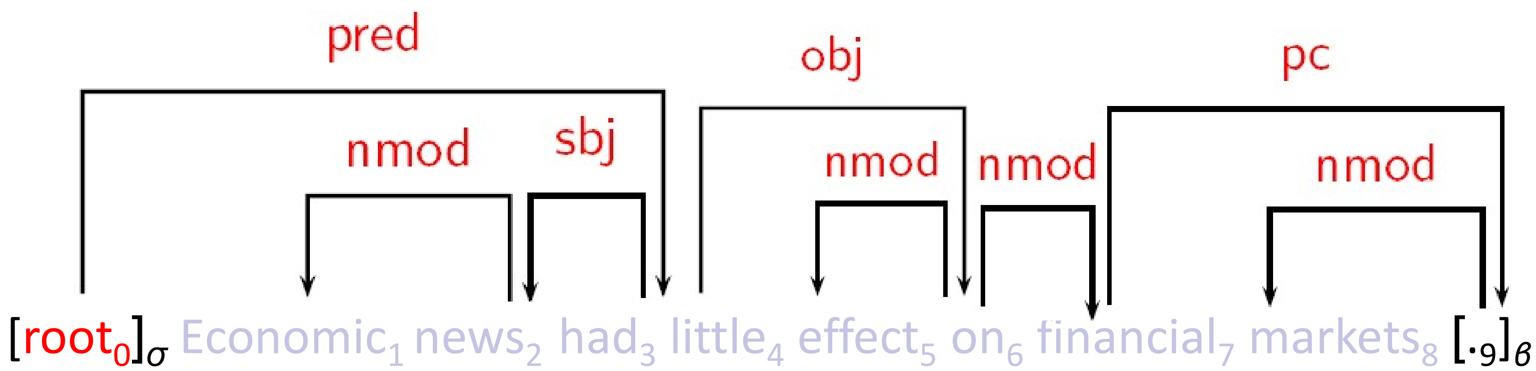


[root_0]$_\sigma$ Economic_1 news_2 [had_3 little_4 effect_5 on_6 financial_7 markets_8 $._9$]$_\beta$

A PC right arc is found from *had* to *effect*. Reduce configuration. Continue searching right arc.

Right-Arc$_{obj}$

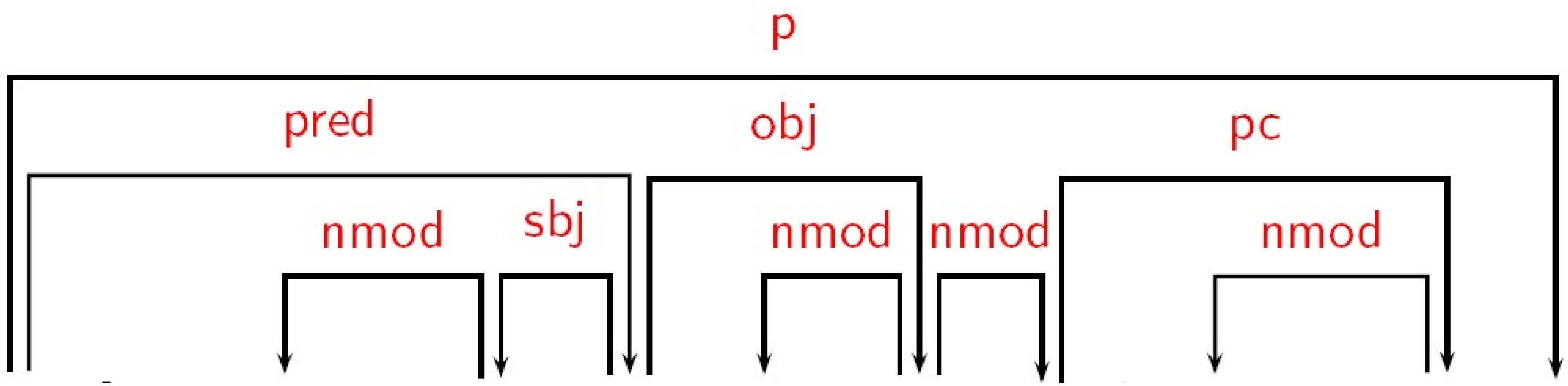
16



A PC right arc is found from *root* to *had*. Reduce configuration. Continue searching right arc.

Right-Arc$_{pred}$

17

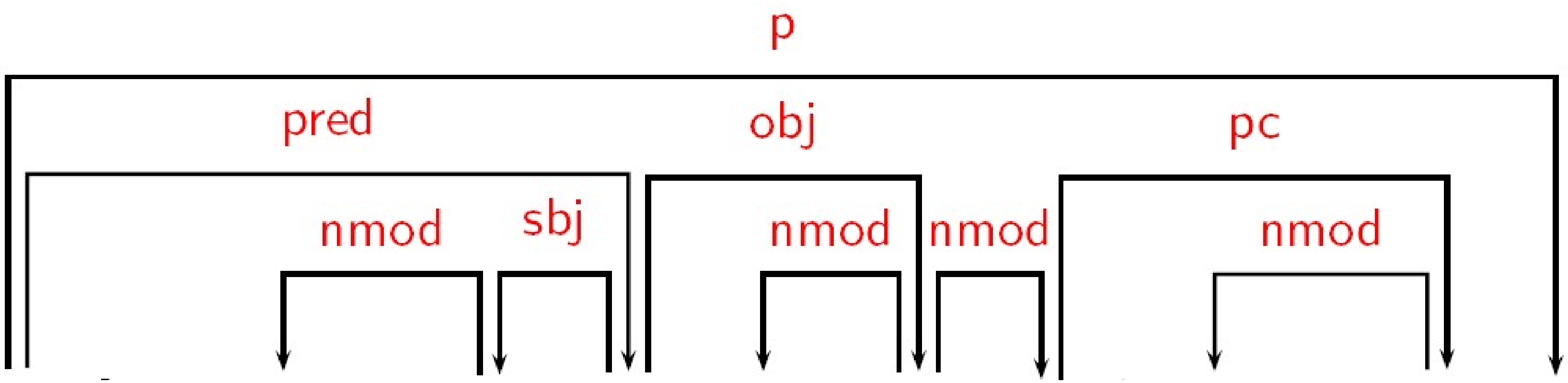


$[]_{\sigma}$ $[\text{root}_0]$ $_{\beta}$ Economic$_1$ news$_2$ had$_3$ little$_4$ effect$_5$ on$_6$ financial$_7$ markets$_8$.$_9$

Right-Arc$_p$

A PC right arc is found from *root* to *punctuation*. Reduce configuration. Continue searching right arc.

18

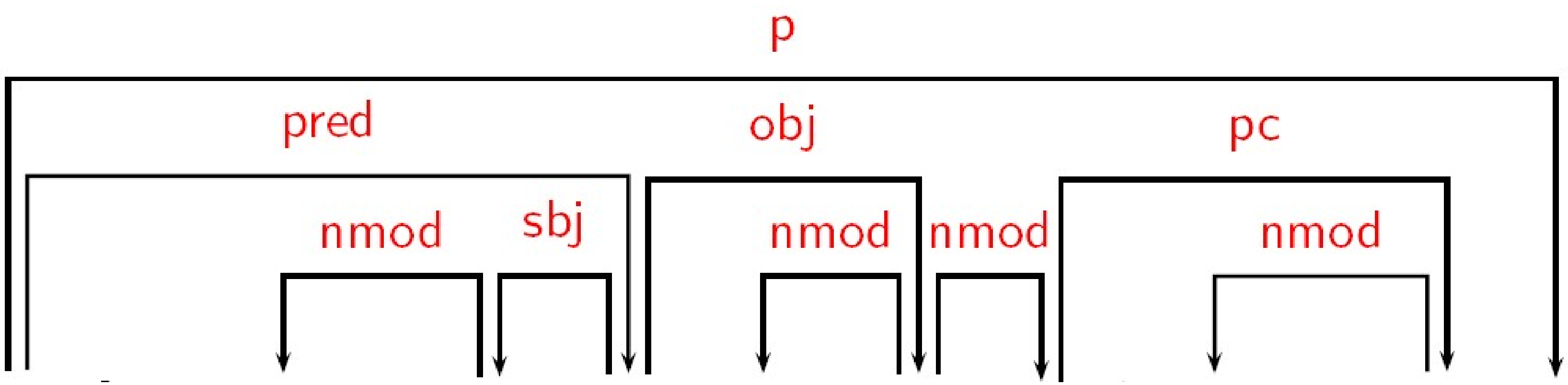


$[\text{root}_0]_\sigma$ Economic_1 news_2 had_3 little_4 effect_5 on_6 financial_7 markets_8 $._9$

Shift

No right arc is found. Remove the empty configuration.
Parsing over.

19



[root_0]$_\sigma$ Economic_1 news_2 had_3 little_4 effect_5 on_6 financial_7 markets_8 $._9$

Shift

Graph-based models

- Basic idea:
  - Define a space of candidate dependency graphs for a sentence.
  - Learning: Induce a model for *scoring* an entire dependency graph for a sentence.
  - Parsing: Find the highest-scoring dependency graph, given the induced model.

- Characteristics:
  - Global training of a model for optimal dependency graphs
  - Exhaustive search/inference

Treebanks

- English Penn Treebank: Standard corpus for testing syntactic parsing consists of 1.2 M words of text from the Wall Street Journal (WSJ).
- Typical to train on about 40,000 parsed sentences and test on an additional standard disjoint test set of 2,416 sentences.
- Chinese Penn Treebank: 100K words from the Xinhua news service.
- Other corpora existing in many languages, see the Wikipedia article “Treebank”

Parsing Resources

- Michael Collins 's Parser : English
  - http://people.csail.mit.edu/mcollins/code.html
- Dan Bikel 's Parser: English / Chinese / Arabic
  - http://www.cis.upenn.edu/~dbikel/software.html#stat-parser
- Stanford Parser: English / Chinese / German
  - http://www-nlp.stanford.edu/software/lex-parser.shtml
  - English / Chinese / German
- David Chiang's Parser: English / Chinese
  - http://www.isi.edu/~chiang/
- HIT IR Dependency Parser
  - http://ir.hit.edu.cn