Integrated CCG Parsing and Supertagging

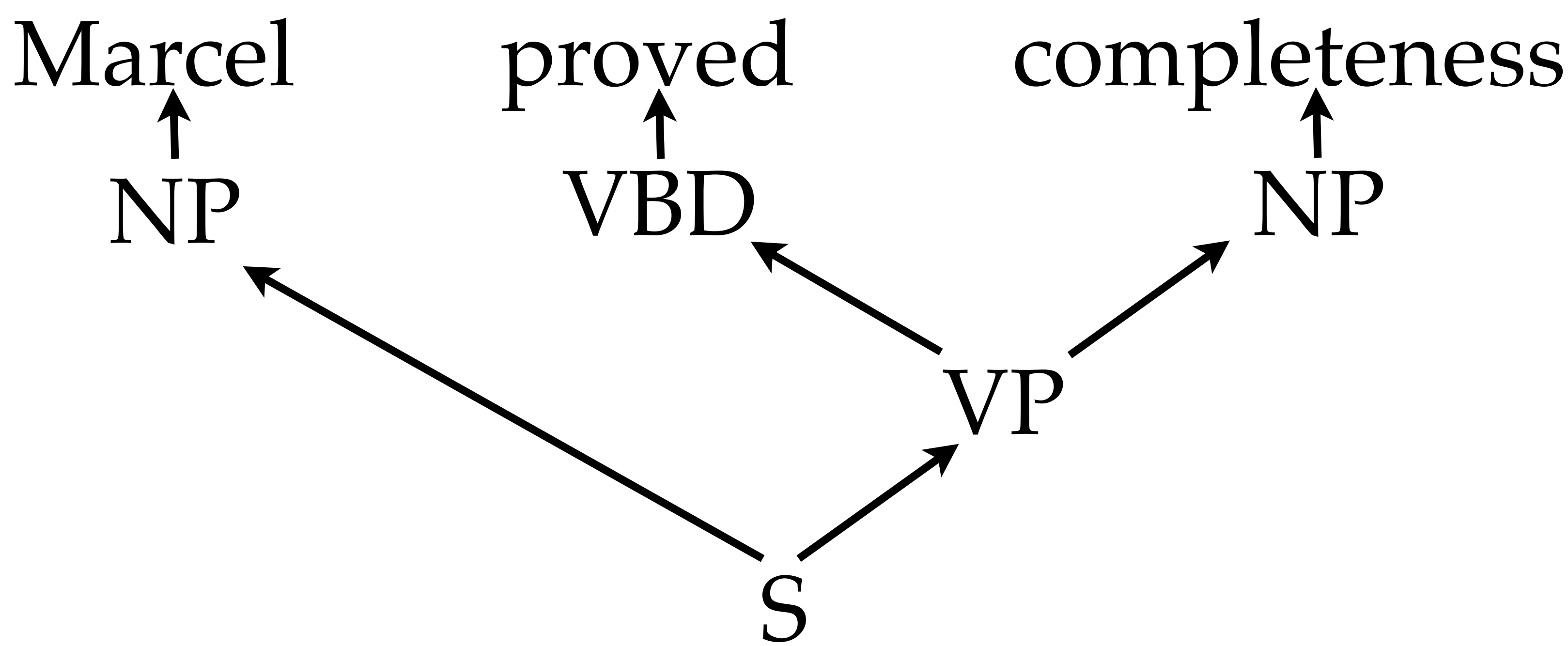
Michael Auli
(University of Edinburgh; graduating spring 2012)
joint work with
Adam Lopez (Johns Hopkins University)

Parsing

Parsing

Marcel proved completeness

Parsing



Parsing

Combinatory Categorial Grammar (CCG; Steedman 2000)

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lexicalized, binary branching, CKY-parseable

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Parsing

$$\frac{\text{Marcel}}{NP} \qquad \frac{\text{proved}}{(S\backslash NP)/NP} \qquad \frac{\text{completeness}}{NP}$$

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Parsing

$$
\dfrac{\text{Marcel}}{NP} \quad \dfrac{\text{proved}}{(S\backslash NP)/\color{red}{NP}} \quad \dfrac{\text{completeness}}{\color{red}{NP}}
$$

$$
\dfrac{(S\backslash NP)/\color{red}{NP} \quad \color{red}{NP}}{\mathrm{S\backslash NP}}>
$$

Combinatory Categorial Grammar (CCG; Steedman 2000)

lexicalized, binary branching, CKY-parseable

Parsing

$$\begin{array}{ccc} \text{Marcel} & \text{proved} & \text{completeness} \\ \hline NP & (S\backslash NP)/{\color{red}NP} & {\color{red}NP} \\ \cline{2-3} & \multicolumn{2}{c}{\mathrm{S}\backslash\mathrm{NP} \quad >} \end{array}$$

Combinatory Categorial Grammar (CCG; Steedman 2000)

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Parsing

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Combinatory Categorial Grammar (CCG; Steedman 2000)

lexicalized, binary branching, CKY-parseable

Parsing

time flies like an arrow

Parsing

$$
\begin{array}{ccccc}
\underline{\text{time}} & \underline{\text{flies}} & \underline{\text{like}} & \underline{\text{an}} & \underline{\text{arrow}} \\
NP & S\backslash NP & ((S\backslash NP)\backslash(S\backslash NP))/NP & NP/NP & NP
\end{array}
$$

Parsing

time	flies	like	an	arrow
NP	$S\backslash NP$	$((S\backslash NP)\backslash(S\backslash NP))/NP$	NP/NP	NP
N/N	NP	PP/NP	$(NP\backslash NP)/N$	$NP\backslash NP$
N/S	$(S\backslash NP)/PP$	$(NP\backslash NP)/NP$	$((S\backslash NP)\backslash(S\backslash NP))/N$	N/N
$(S\backslash NP)\backslash(S\backslash NP)$	$(S\backslash NP)/S$	$(S/S)/NP$	$(S\backslash S)/N$	N/S
$NP\backslash NP$	$(S\backslash NP)/NP$	$((S\backslash NP)/(S\backslash NP))/S$	NP	$(\mathrm{S}\backslash\mathrm{NP})\backslash(\mathrm{S}\backslash\mathrm{NP})$
$(S\backslash NP)/NP$	$((S\backslash NP)/PP)/NP$	$(PP/PP)/NP$	$(N/N)/(N/N)$	$\mathrm{S}\backslash\mathrm{NP}$
...	$(S\backslash NP)/S$	PP/S	...	...
	...	...		

Parsing

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$(S\backslash NP)/NP$	$((S\backslash NP)/PP)/NP$	$(PP/PP)/NP$	$(N/N)/(N/N)$	S\NP
...	$(S\backslash NP)/S$	PP/S	...	...
	...	...		

Over 22 tags per word! (Clark & Curran 2004)

Hard parsing task

Supertagging

Supertagging

time flies like an arrow

Supertagging

$$\frac{\text{time}}{NP} \quad \frac{\text{flies}}{S\backslash NP} \quad \frac{\text{like}}{((S\backslash NP)\backslash(S\backslash NP))/NP} \quad \frac{\text{an}}{NP/NP} \quad \frac{\text{arrow}}{NP}$$

Supertagging

time	flies	like	an	arrow
NP	$S\backslash NP$	$((S\backslash NP)\backslash(S\backslash NP))/NP$	NP/NP	NP

$$\text{an arrow: } NP/NP \;\; NP \xrightarrow{>} \mathrm{NP}$$

$$\text{like an arrow: } ((S\backslash NP)\backslash(S\backslash NP))/NP \;\; \mathrm{NP} \xrightarrow{>} \mathrm{(S\backslash NP)\backslash(S\backslash NP)}$$

$$\text{flies like an arrow: } S\backslash NP \;\; \mathrm{(S\backslash NP)\backslash(S\backslash NP)} \xrightarrow{<} \mathrm{S\backslash NP}$$

$$\text{time flies like an arrow: } NP \;\; \mathrm{S\backslash NP} \xrightarrow{<} \mathrm{S}$$

Overview

- The Problem with Pipeline Models
- Decoding Integrated Models
  with Loopy Belief Propagation and Dual Decomposition (ACL 2011)
- Training Integrated Models
  with Softmax-Margin using Exact and Approximate Loss Functions (EMNLP 2011)

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			NP	
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		S\NP		

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$$\dfrac{NP/NP \quad NP}{\mathrm{NP}} >$$

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...	...	$((S\backslash NP)\backslash(S\backslash NP))/NP$		
		....		

Adaptive Supertagging

Clark & Curran (2004)

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- Algorithm:
  - Run supertagger.
  - Return tags with posterior higher than some alpha.
  - Parse by combining tags (CKY).
  - If parsing succeeds, stop.
  - If parsing fails, lower alpha and repeat.

Adaptive Supertagging

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- Algorithm:
  - Run supertagger.
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  - If parsing succeeds, stop.
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- Q: are parses returned in early rounds suboptimal?

Answer...

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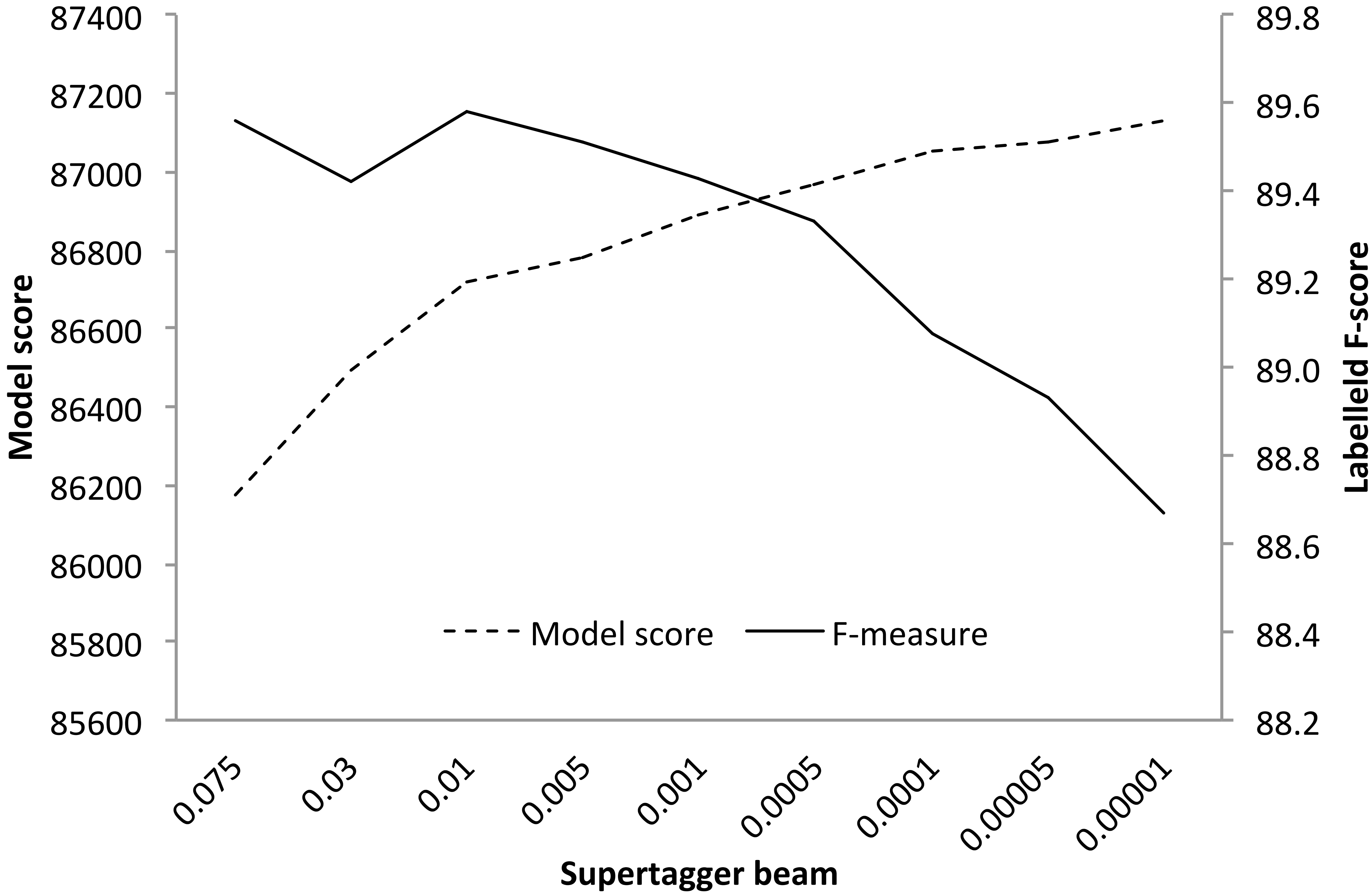
- Oracle parsing (Huang 2008):
  - With tight beam: 94.35
  - With loose beam: **97.65**
  - With gold-supertags: 97.73

Answer...

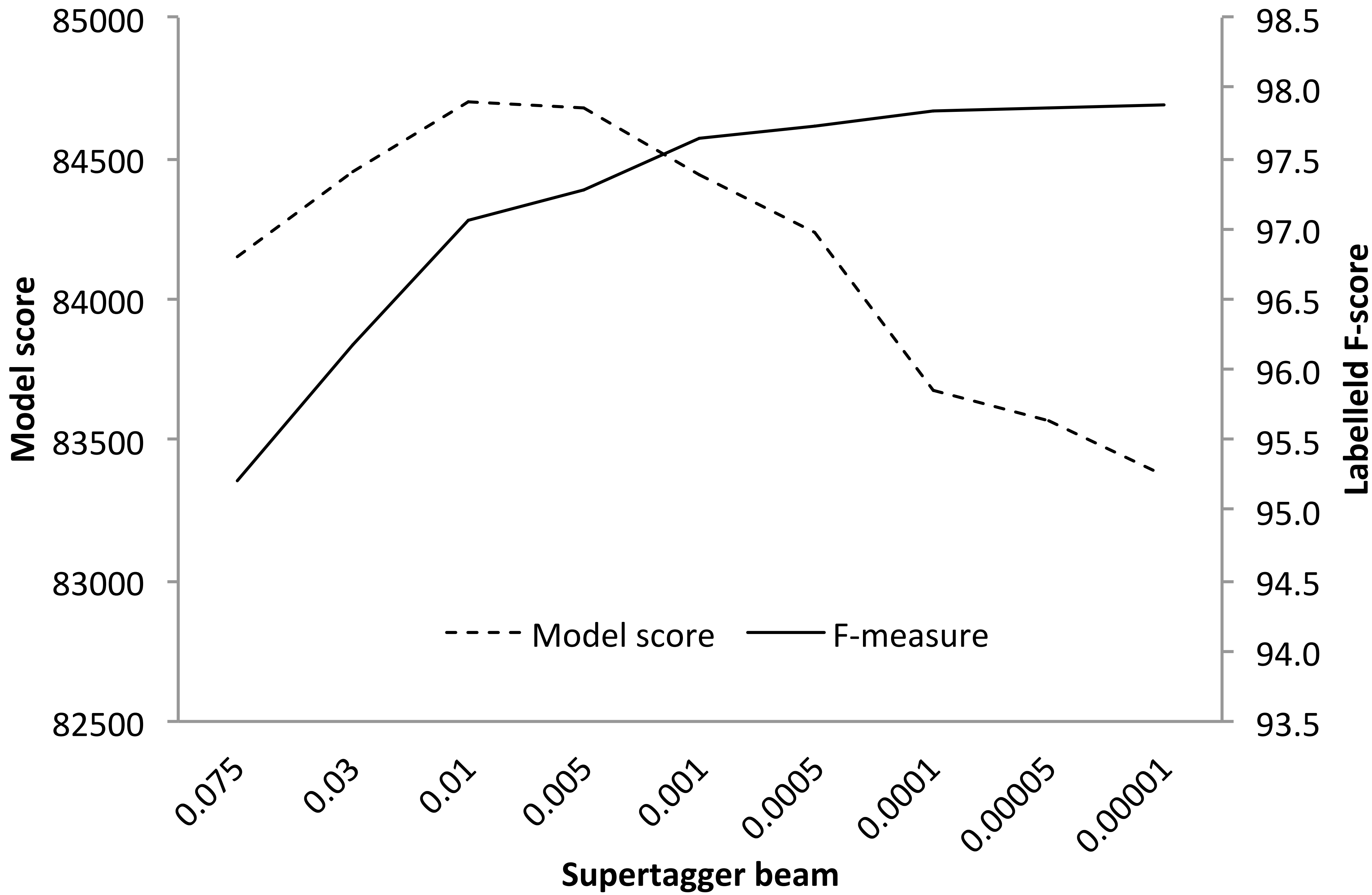
- Oracle parsing (Huang 2008):
  - With tight beam: 94.35
  - With loose beam: **97.65**
  - With gold-supertags: 97.73
- Standard parsing task (Clark & Curran 2007):
  - With tight beam: 87.38 (labeled F-measure)
  - With loose beam: 87.36

Parsing



Note: only sentences parsable at all beam settings.

Oracle Parsing



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- Supertagger keeps parser from making serious errors.
- But it also occasionally prunes away useful parses.

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- Supertagger keeps parser from making serious errors.
- But it also occasionally prunes away useful parses.
- Why not combine supertagger and parser into one?

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Integrated Model

- Supertagger & parser are undirected log-linear models.
- **Idea**: combine their features into one model.
- **Problem**: Exact computation of marginal or maximum quantities becomes very expensive because parsing and tagging submodels must agree on the tag sequence.

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Intersection of a regular and context-free language

(Bar-Hillel et al. 1964)

Integrated Model

$\mathrm{A} \rightarrow \mathrm{B} \;\; \mathrm{C} \qquad O(Gn^3)$

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\begin{array}{ccc}
\underline{\text{Marcel}} & \underline{\text{proved}} & \underline{\text{completeness}} \\
NP & (S\backslash NP)/NP & NP \\
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\hline
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Intersection of a regular and context-free language

(Bar-Hillel et al. 1964)

Integrated Model

$$A \rightarrow B \quad C \qquad O(Gn^3)$$

$${}_{q}A_{r} \rightarrow {}_{q}B_{s} \ {}_{s}C_{r} \qquad O(G^3n^3)$$

$$\begin{array}{ccc} \underline{\text{Marcel}} & \underline{\text{proved}} & \underline{\text{completeness}} \\ {}_{<s>}NP_{(S\backslash NP)/NP} & {}_{NP}(S\backslash NP)/NP_{NP} & {}_{(S\backslash NP)/NP}\,NP_{</s>} \end{array}$$

$$\underline{\qquad\qquad {}_{NP}\,S\backslash NP_{</s>} \qquad\qquad} >$$

$$\underline{\qquad\qquad\qquad\qquad\qquad\qquad} <$$

$${}_{<s>}\,S_{</s>}$$

Intersection of a regular and context-free language

(Bar-Hillel et al. 1964)

Approximate Algorithms

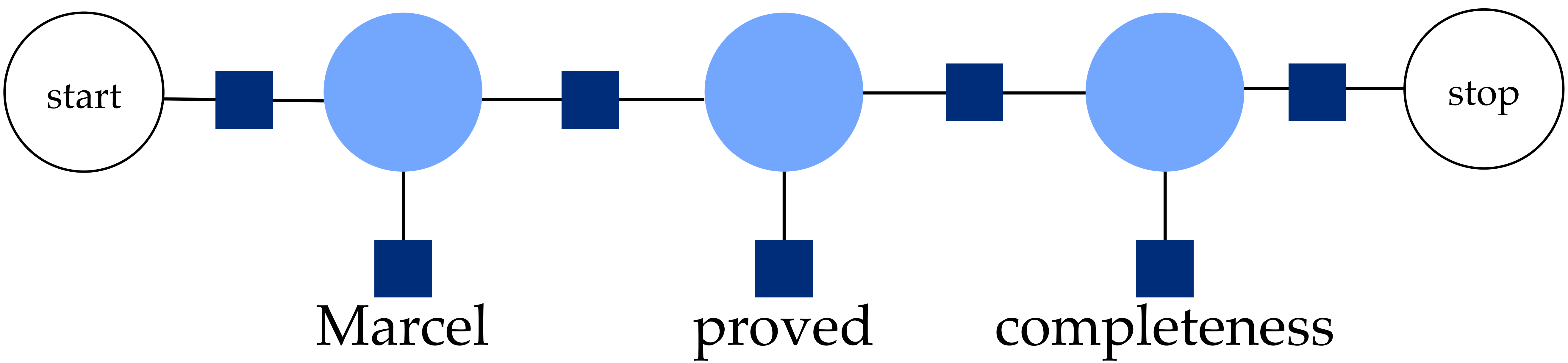
- Loopy belief propagation: approximate calculation of marginals. (Pearl 1988; Smith & Eisner 2008)
- Dual decomposition: exact (sometimes) calculation of maximum. (Dantzig & Wolfe 1960; Komodakis et al. 2007; Koo et al. 2010)

Belief Propagation

Belief Propagation

Forward-backward is belief propagation (Smyth et al. 1997)

Belief Propagation



Forward-backward is belief propagation (Smyth et al. 1997)

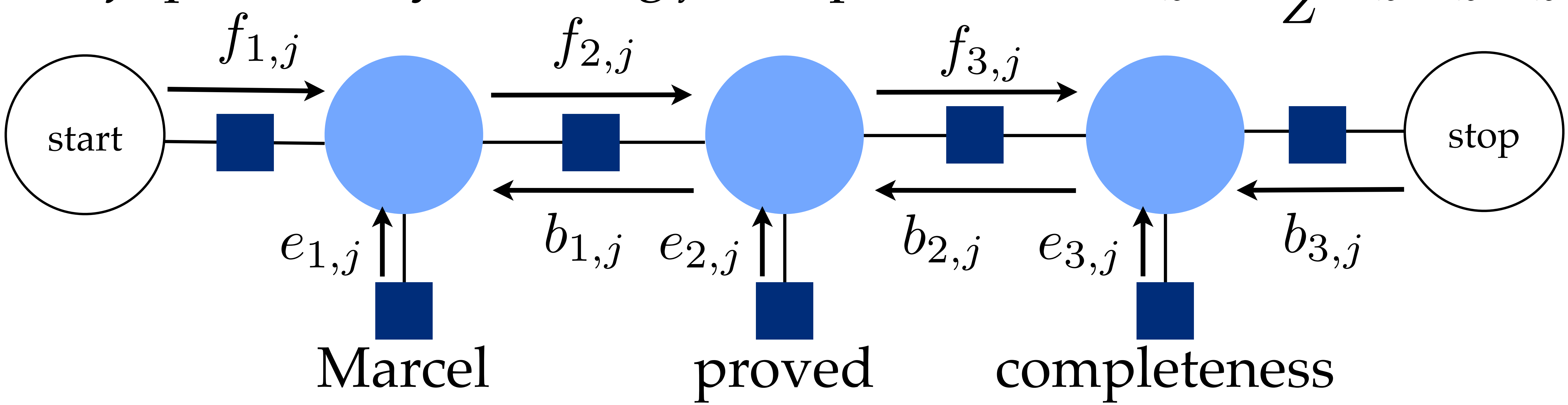
Belief Propagation

emission message: $e_{i,j}$

forward message: $f_{i,j} = \sum_{j'} f_{i-1,j'} e_{i-1,j'} t_{j',j}$

backward message: $b_{i,j} = \sum_{j'} b_{i+1,j'} e_{i+1,j'} t_{j,j'}$

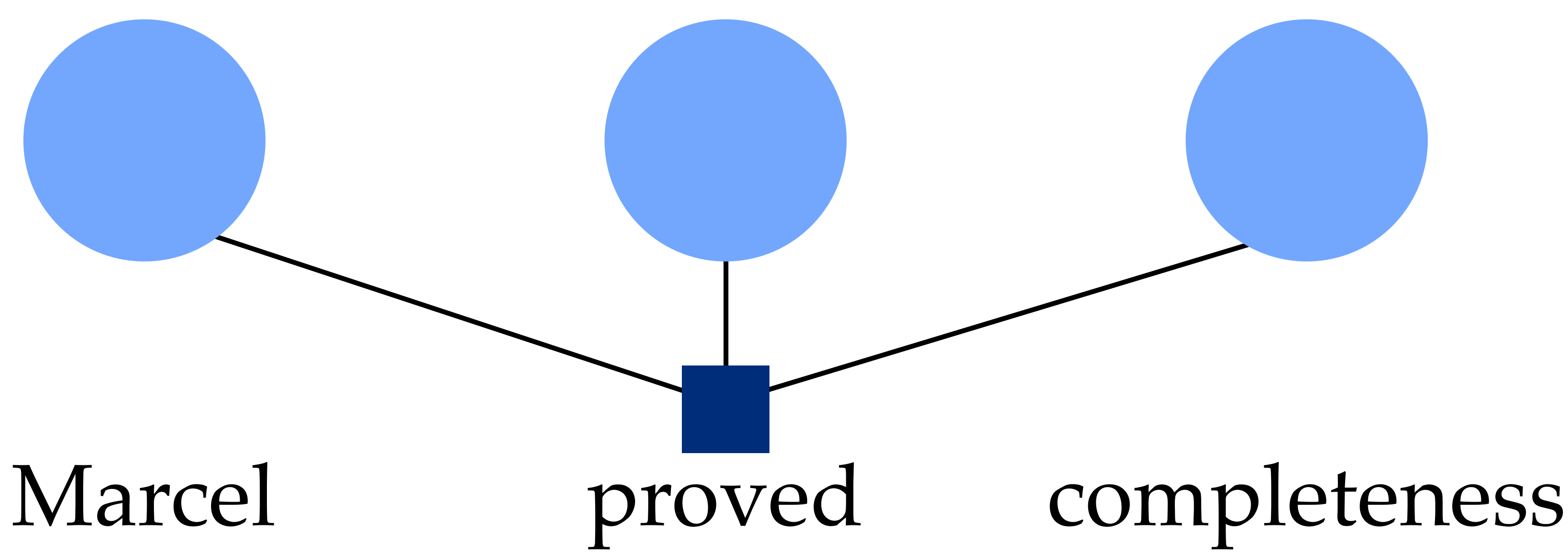
belief (probability) that tag *j* is at position *i*: $p_{i,j} = \frac{1}{Z} f_{i,j} e_{i,j} b_{i,j}$



Forward-backward is belief propagation (Smyth et al. 1997)

Belief Propagation

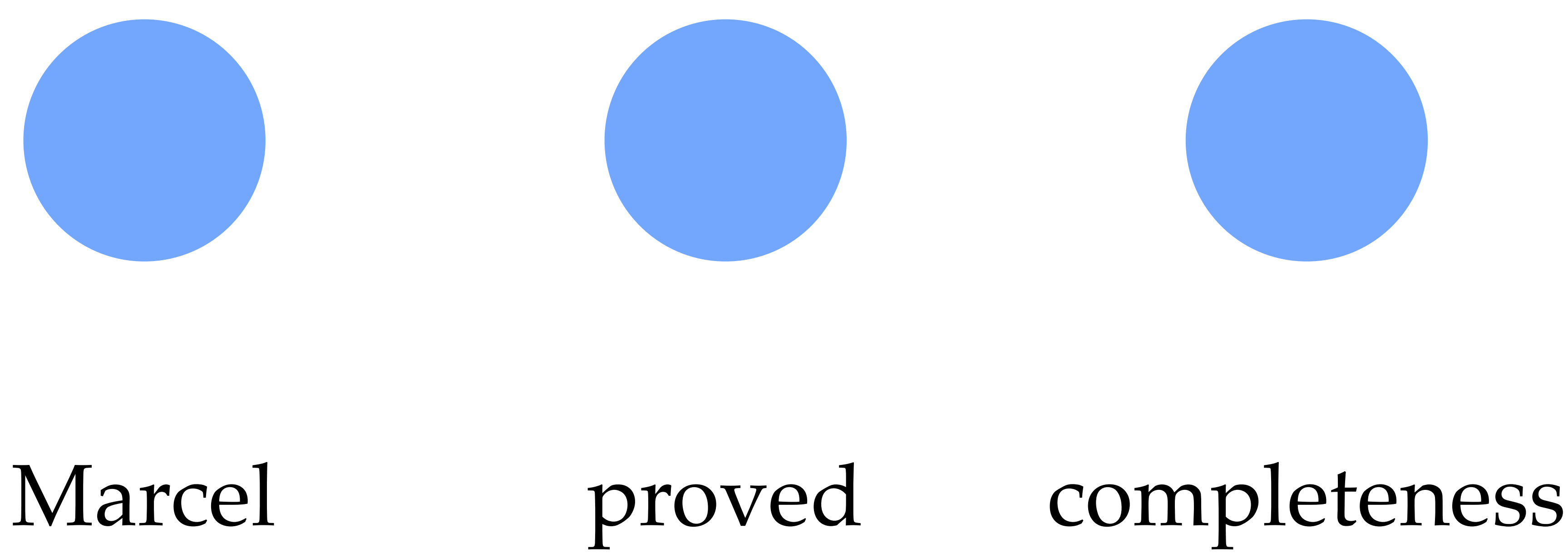
Notational convenience: one factor describes whole distribution over supertag sequence...



Belief Propagation

We can also do the same for the distribution over parse trees

(Case-factor diagrams: McAllester et al. 2008)



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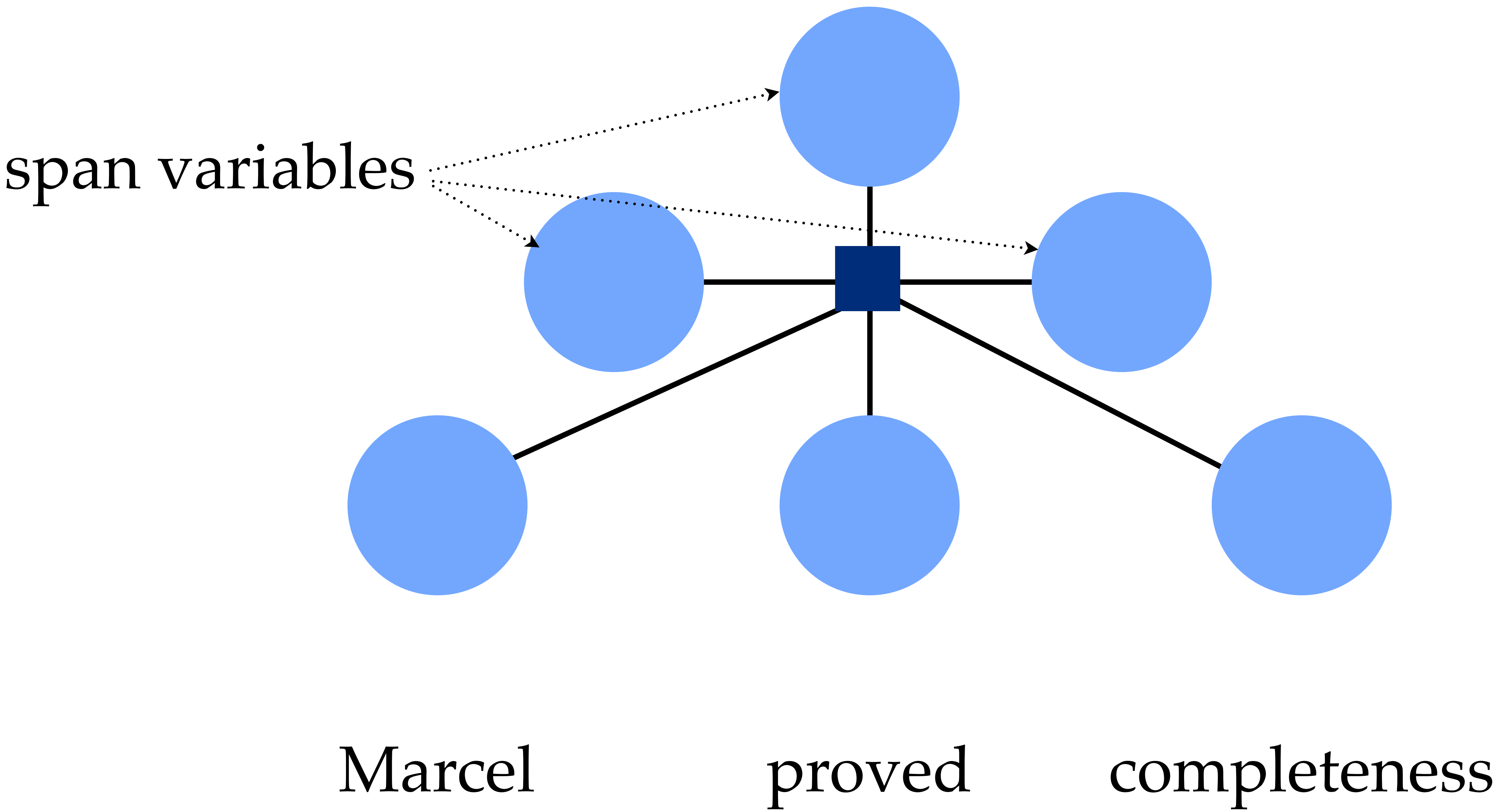

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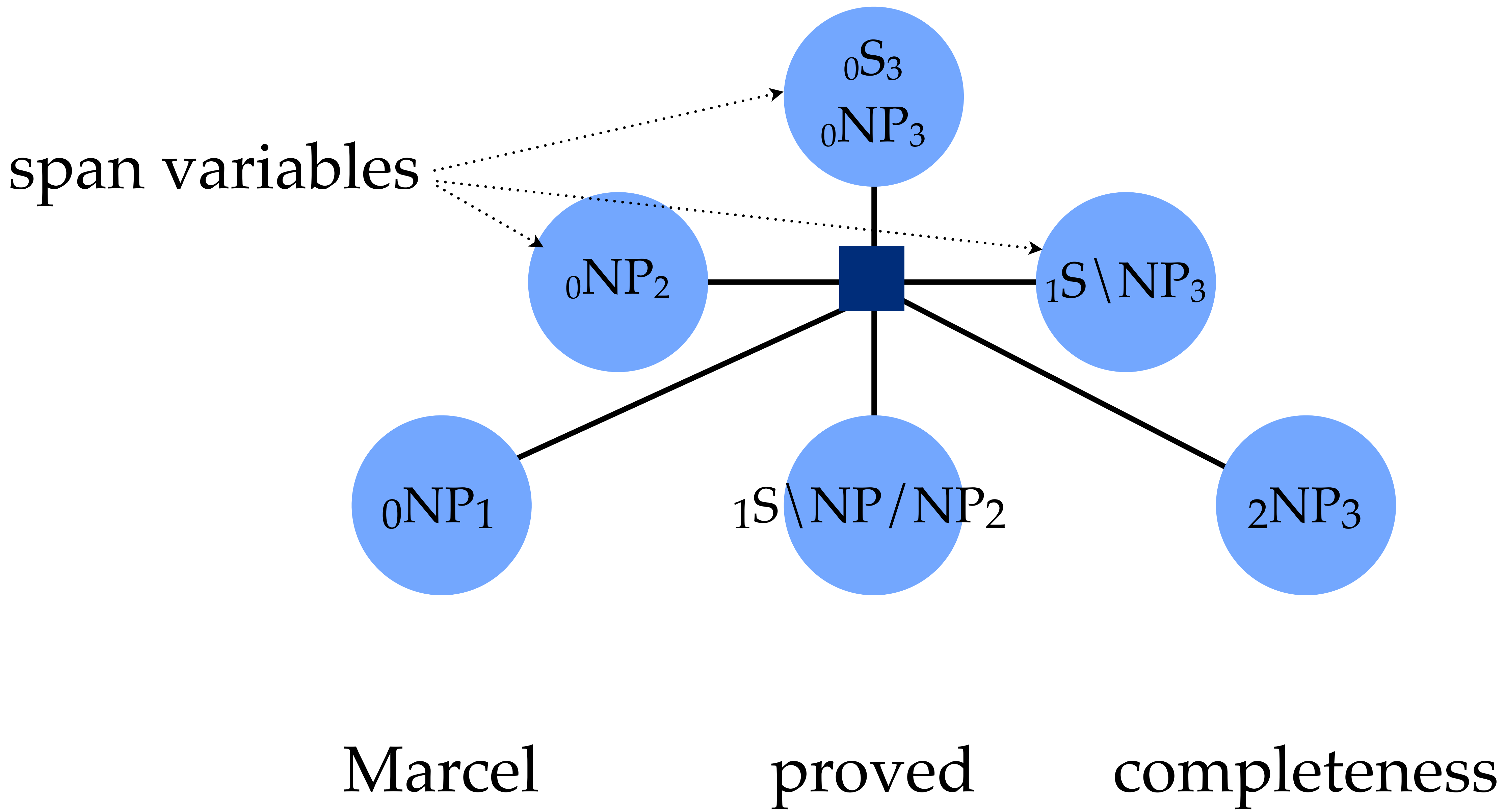

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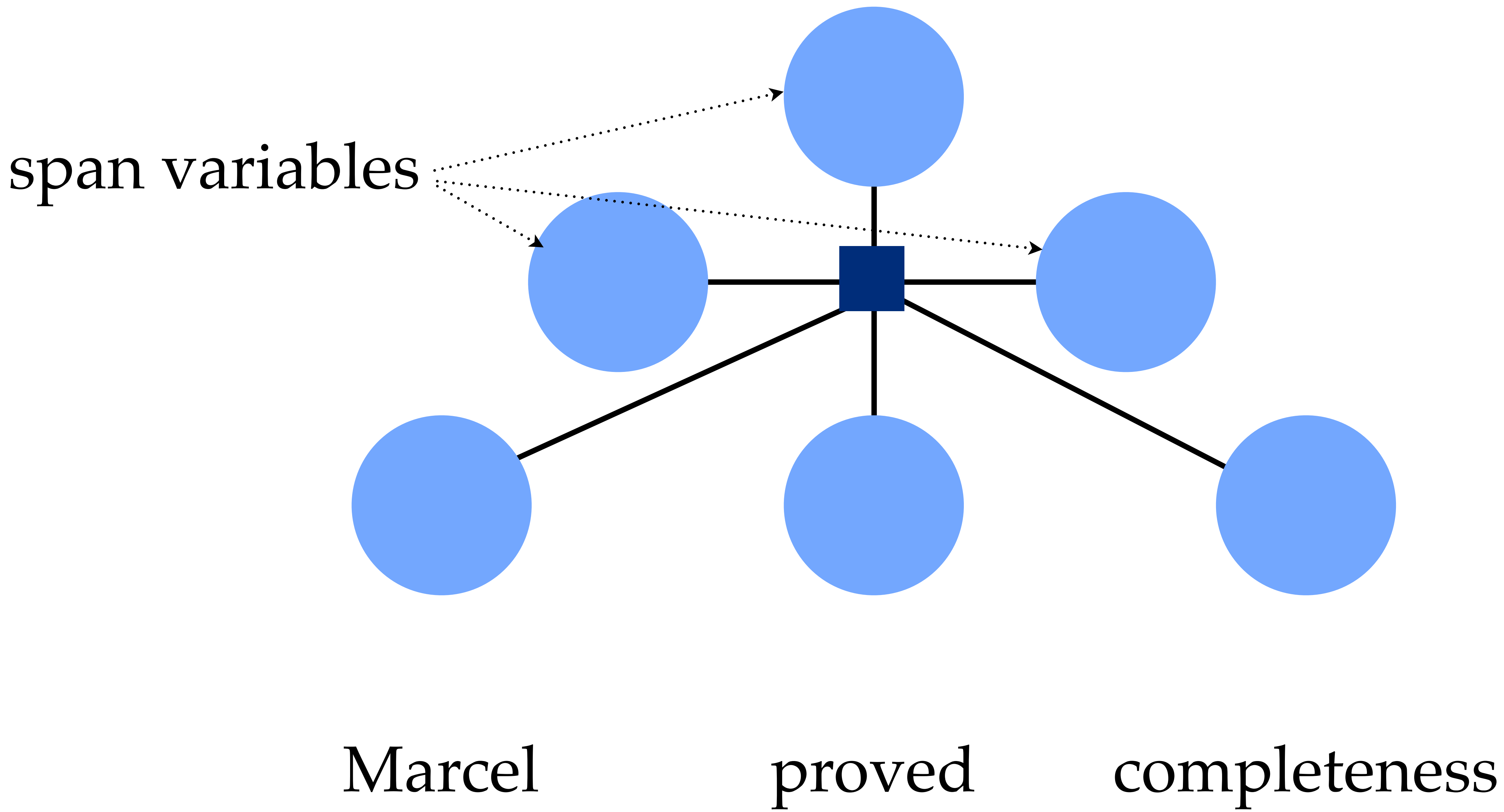
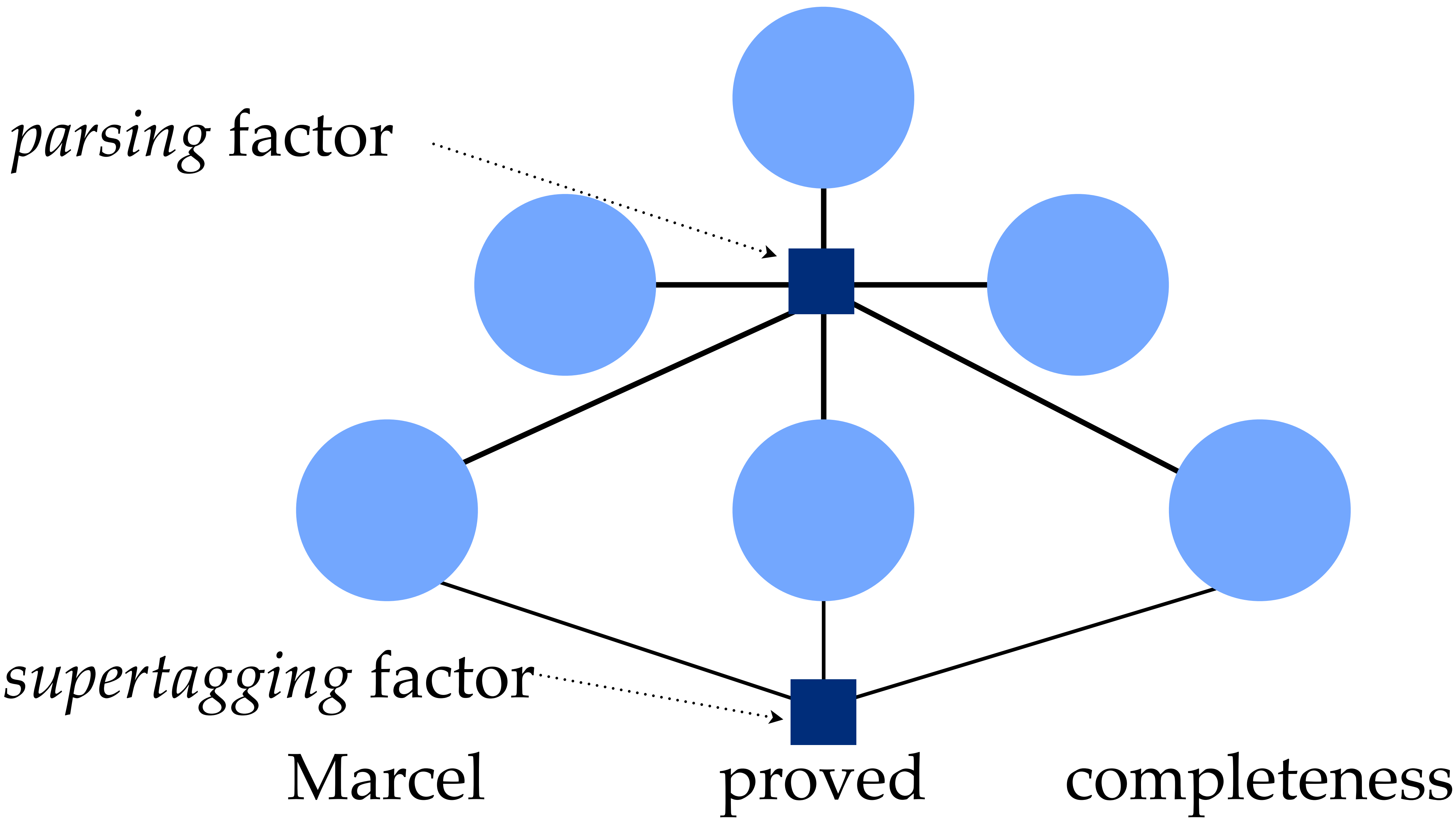


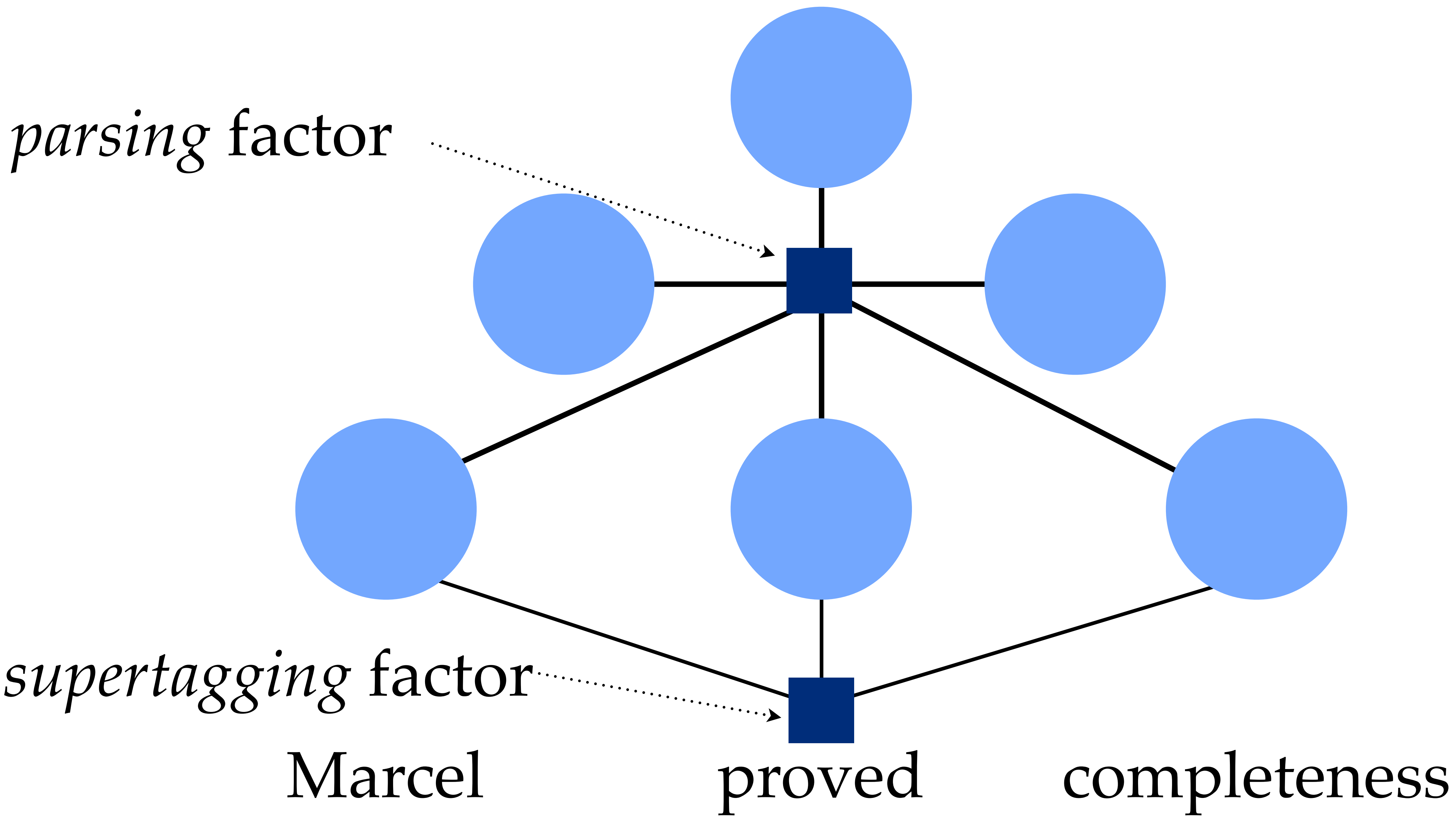
Inside-outside is belief propagation (Sato 2007)

Belief Propagation



Belief Propagation

Graph is not a tree!



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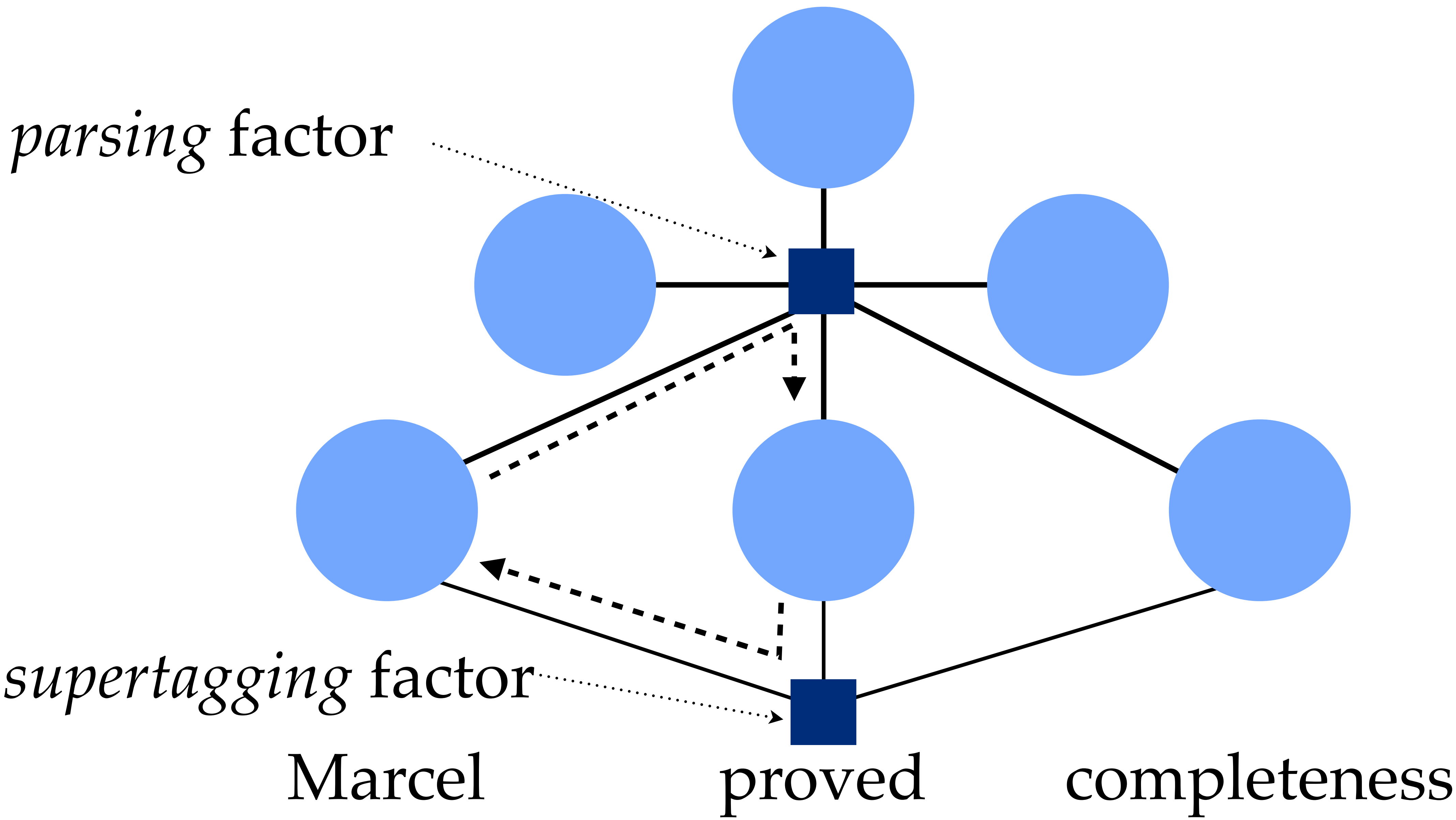

Loopy Belief Propagation

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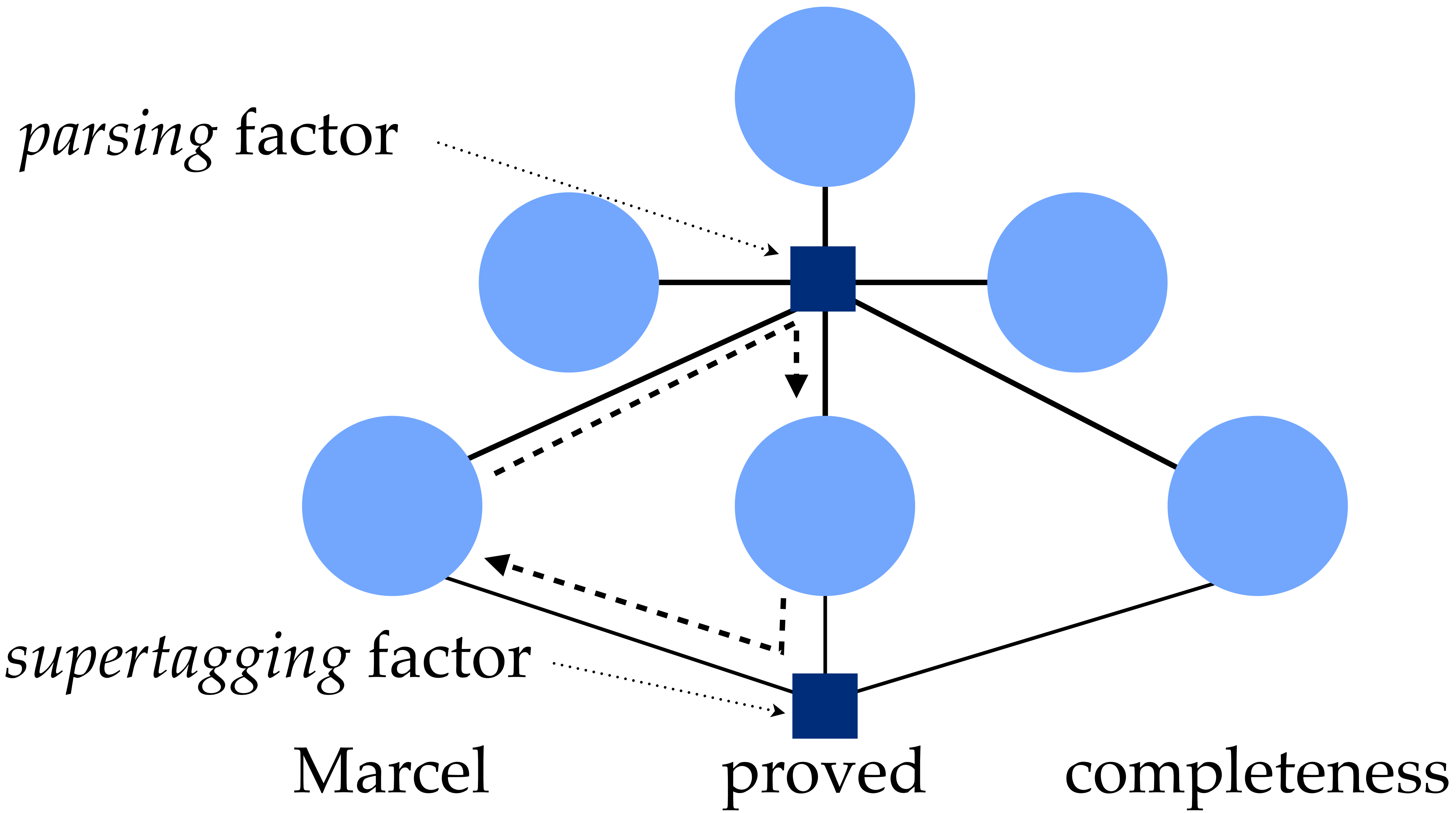

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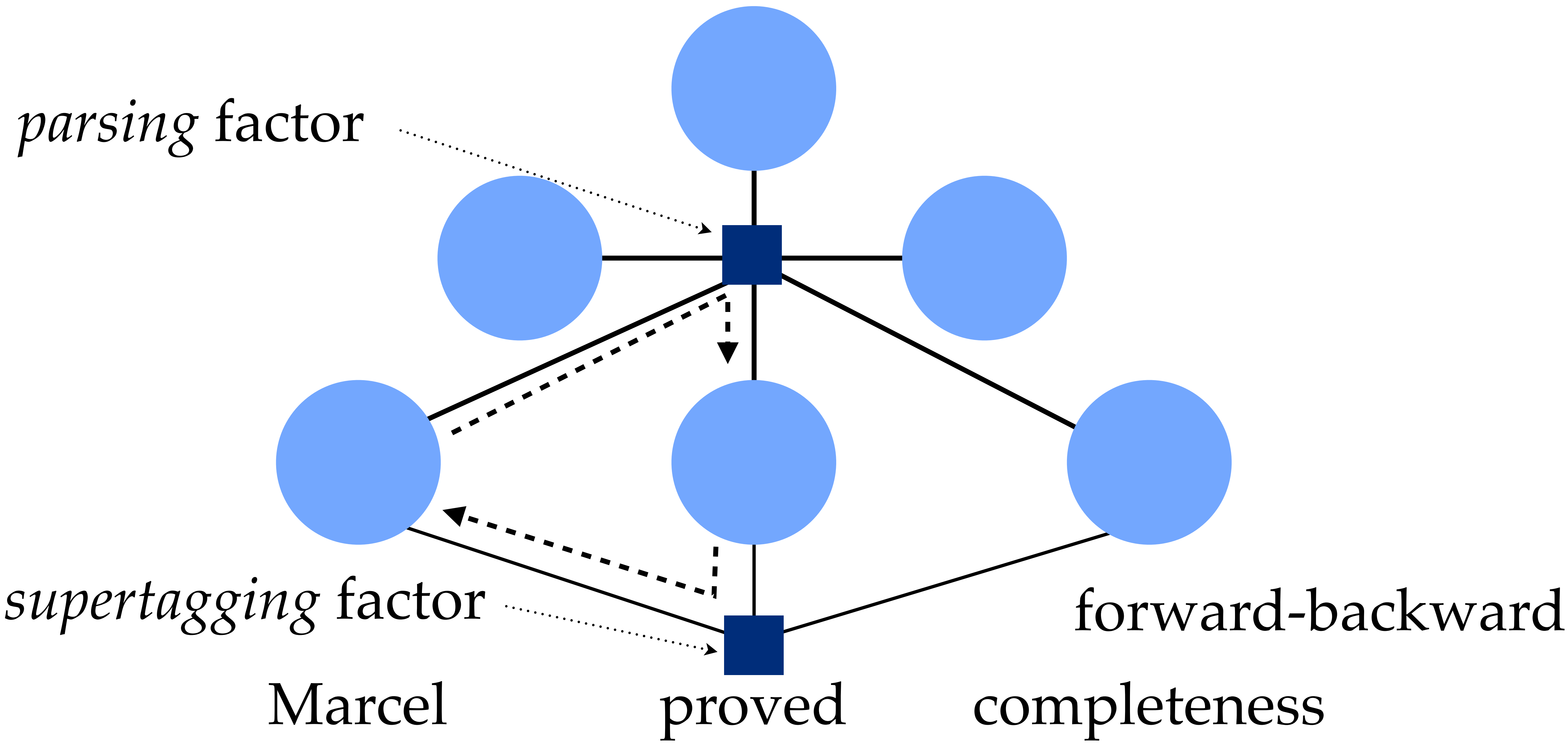

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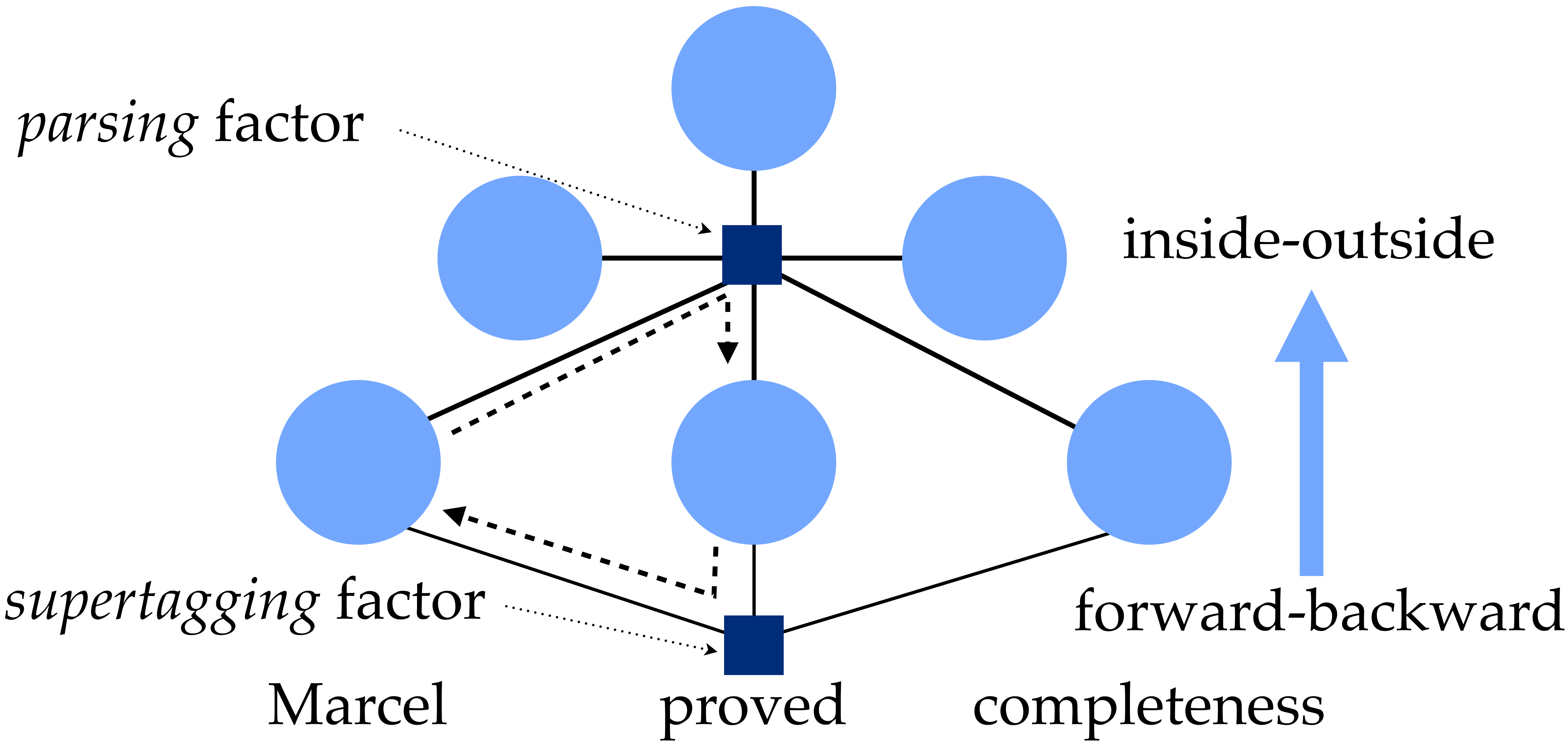

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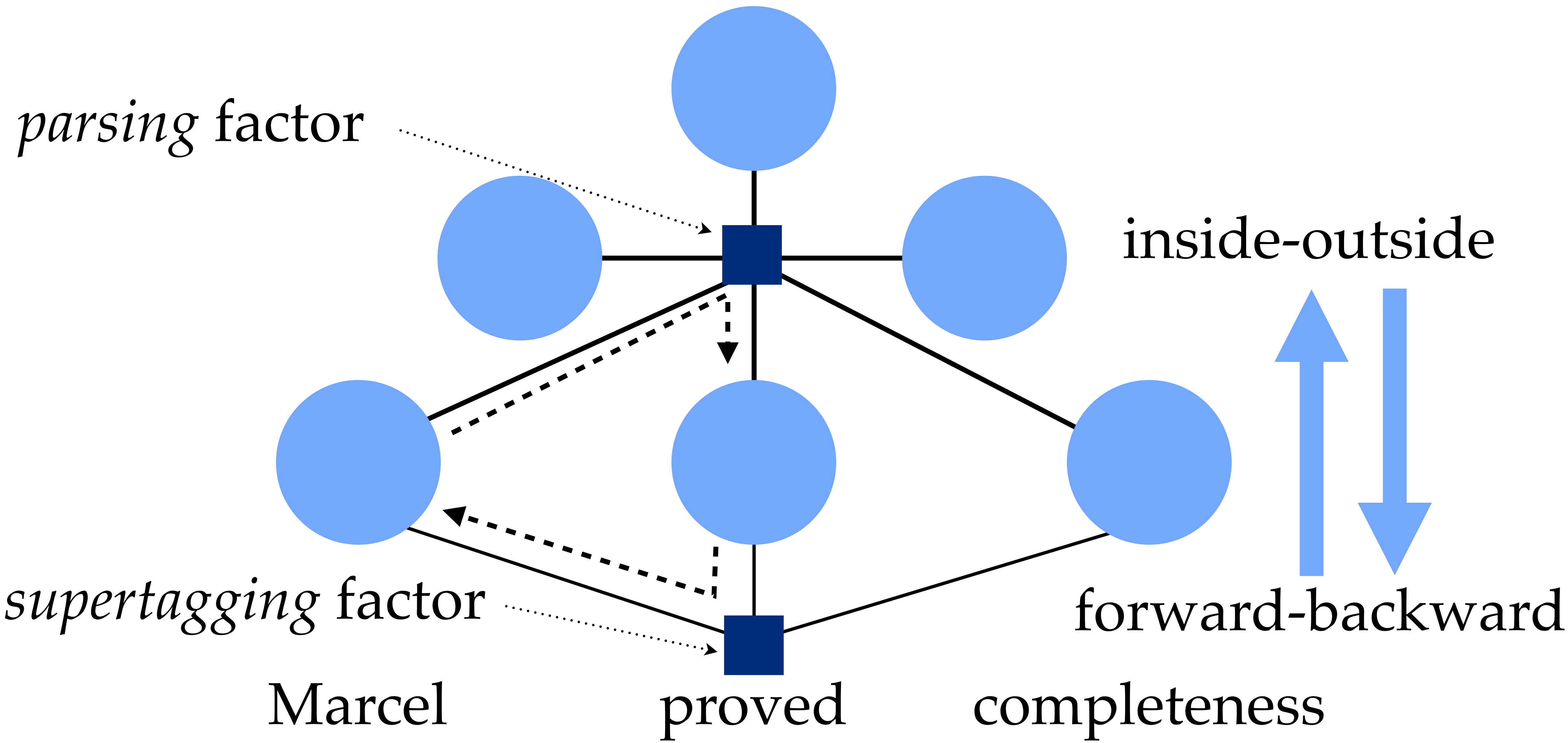

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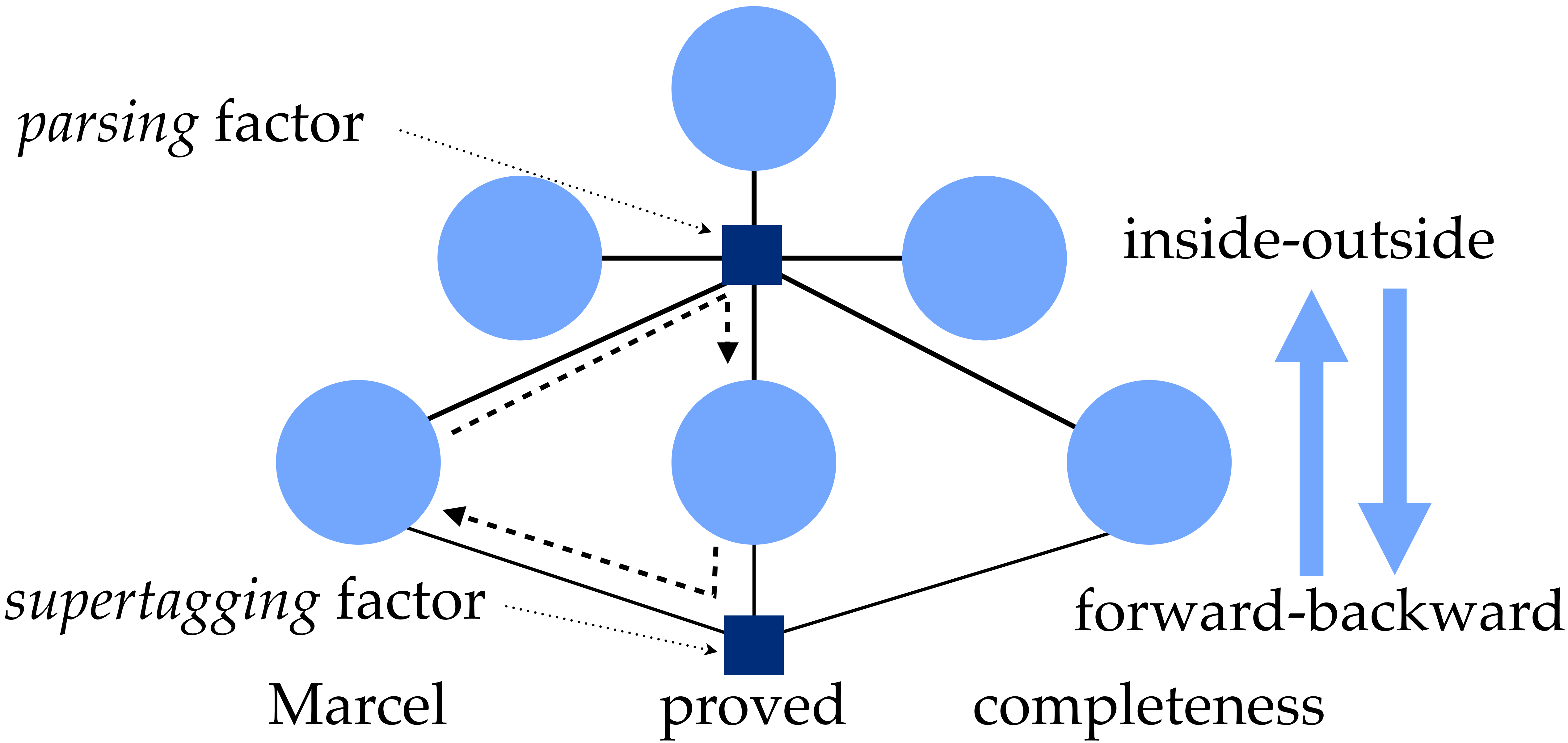

Converges to bounded approximate marginals (Yedidia et al. 2001)

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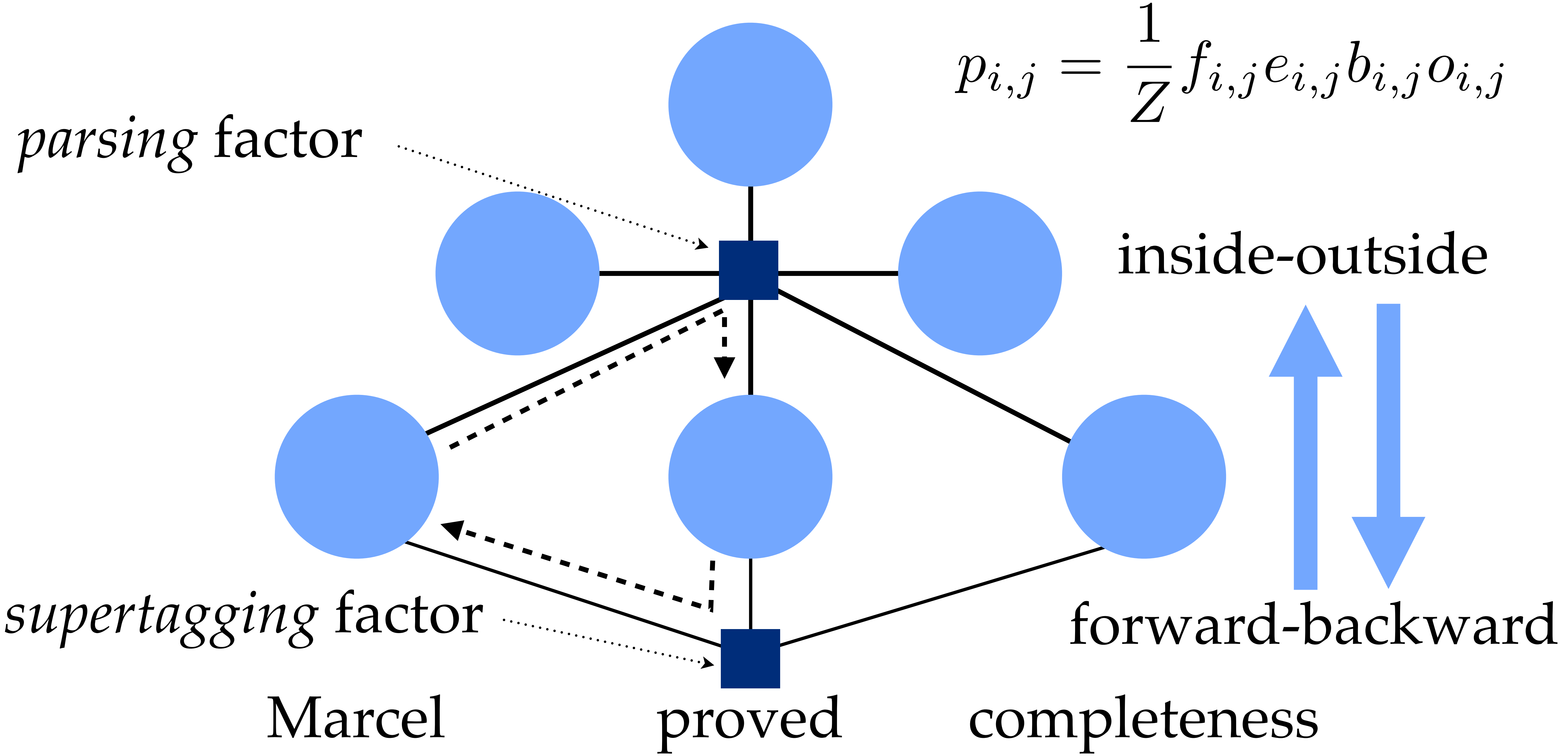

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Loopy Belief Propagation

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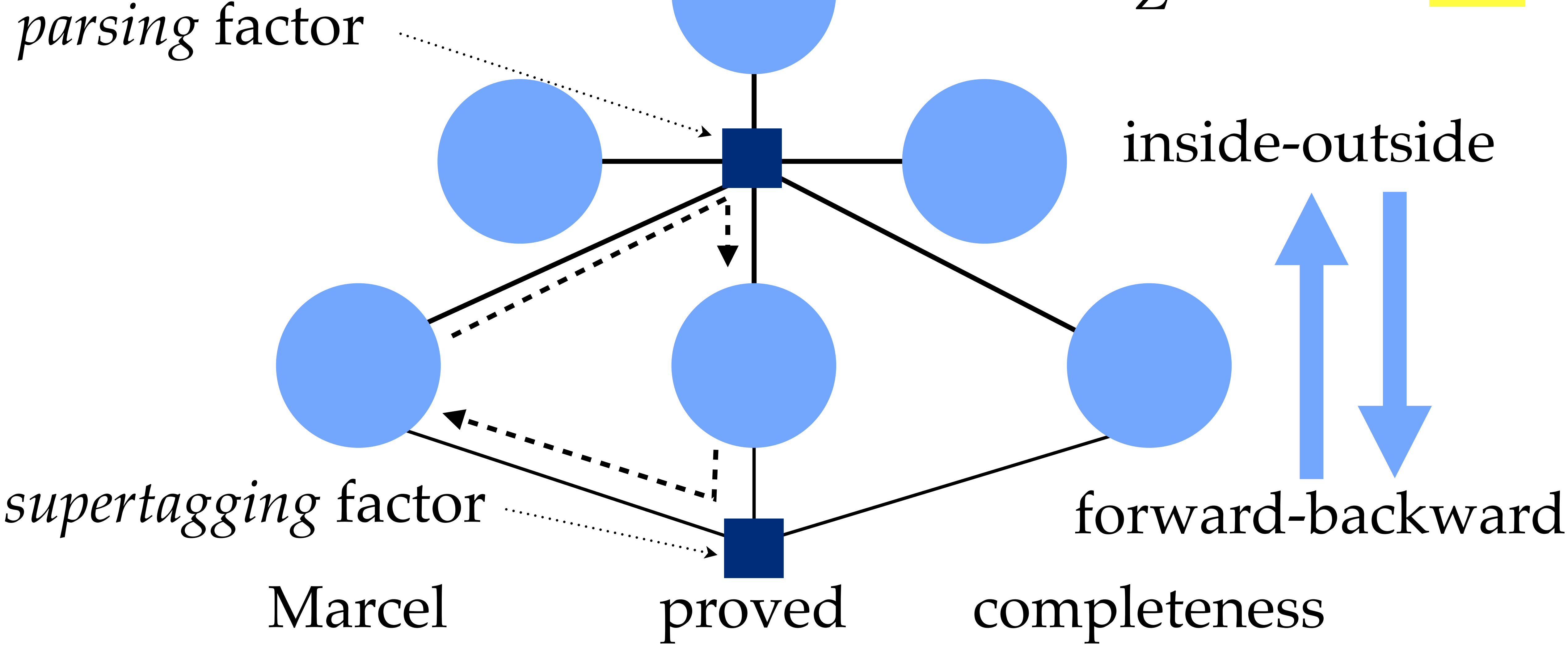
$$p_{i,j} = \frac{1}{Z} f_{i,j} e_{i,j} b_{i,j} o_{i,j}$$

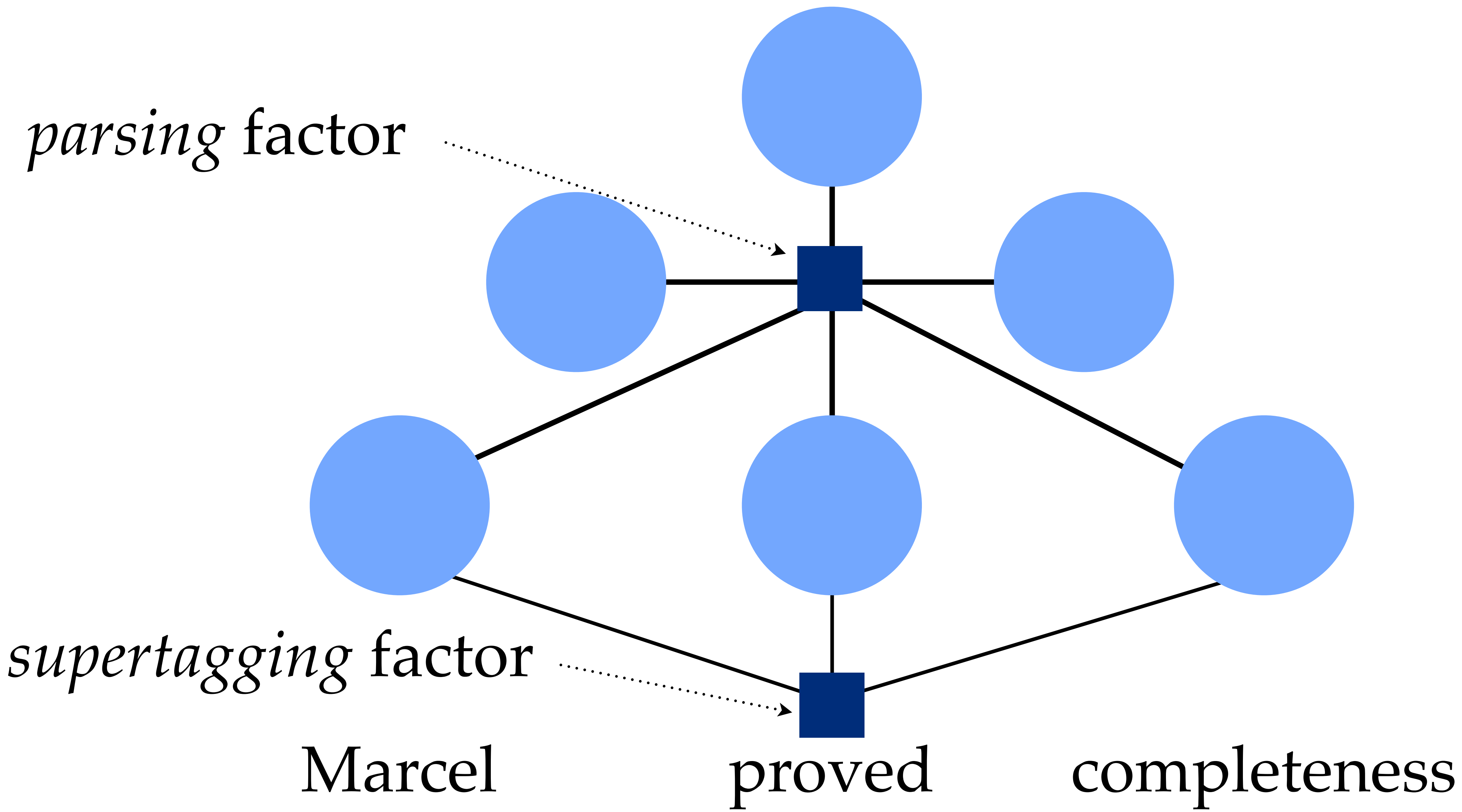


Converges to bounded approximate marginals (Yedidia et al. 2001)

Loopy Belief Propagation

- Computes approximate marginals.
- Complexity is additive: $O(Gn^3 + Gn)$ vs. $O(G^3n^3)$
- In training: use for gradient optimization (e.g. SGD).
- In decoding: compute minimum-risk parse (Goodman 1996).

Dual Decomposition



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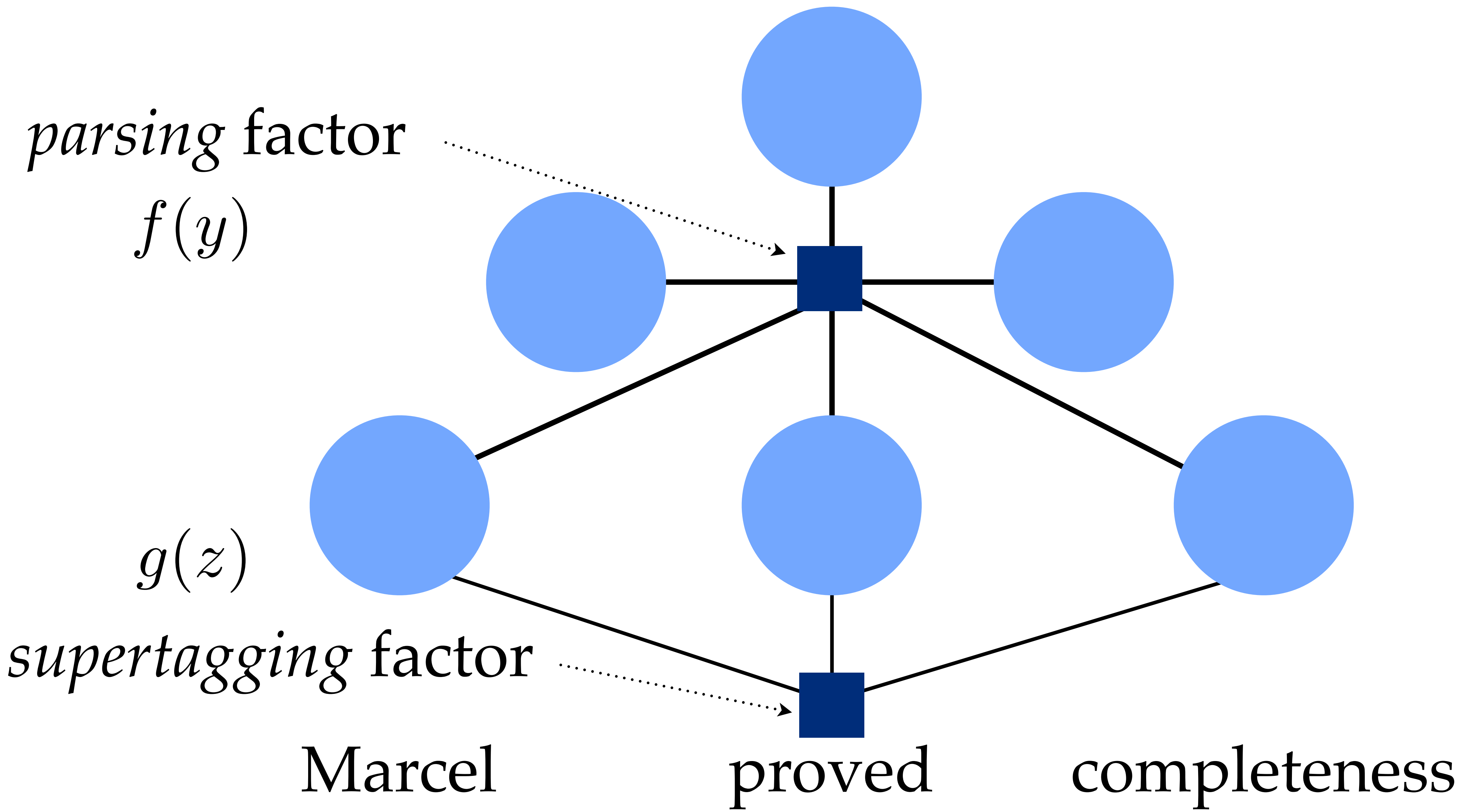
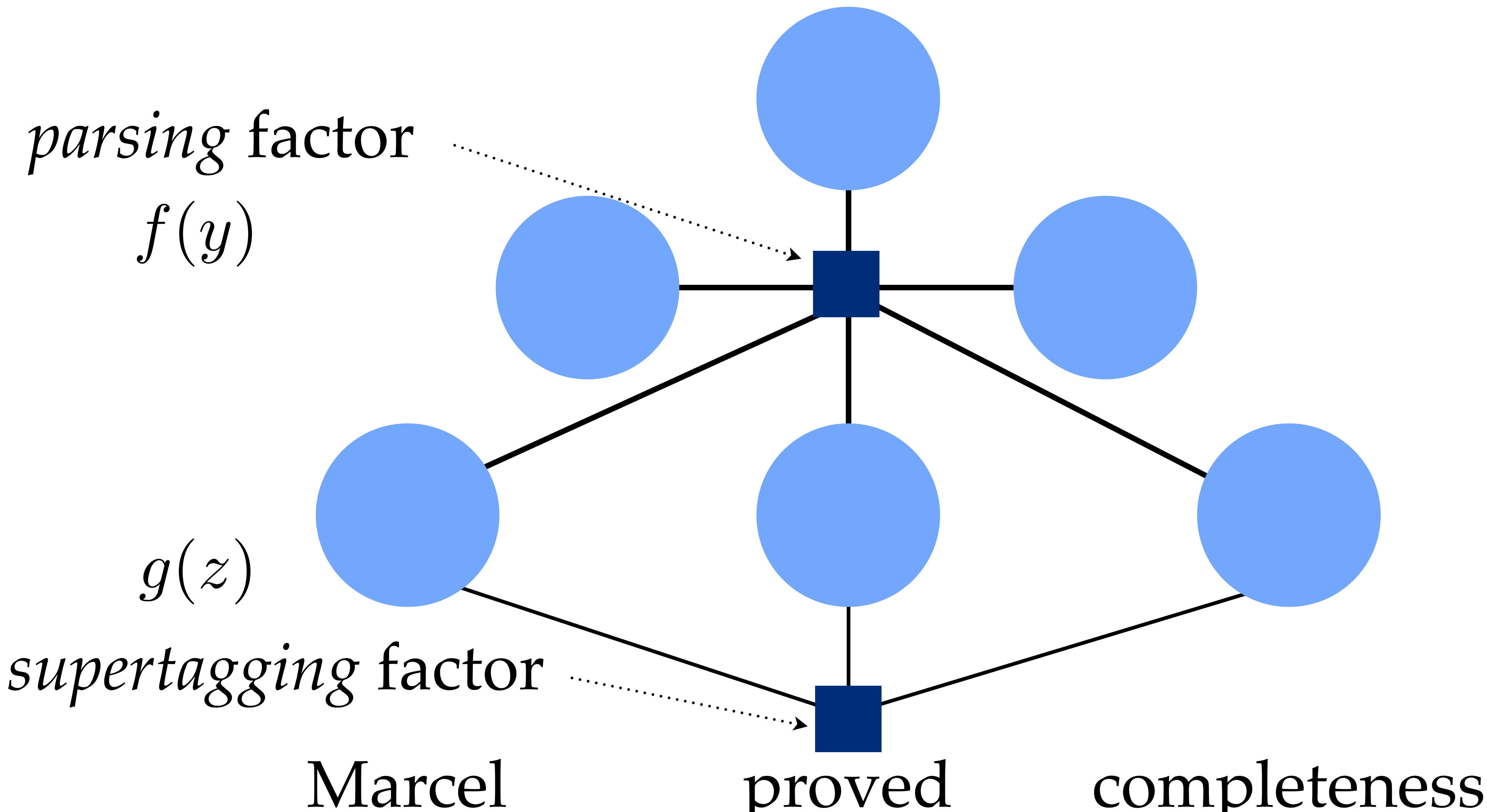


Dual Decomposition

$$\arg\max_{y,z} f(y) + g(z) \quad \text{s.t. } y(i,t) = z(i,t) \text{ for all } i, t$$



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$$L(u) = \max_{y} f(y) + \sum_{i,t} u(i,t) \cdot y(i,t)$$
$$+ \max_{z} g(z) - \sum_{i,t} u(i,t) \cdot z(i,t)$$

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relaxed original problem

$$+ \max_z g(z) - \sum_{i,t} u(i,t) \cdot z(i,t)$$

Dual Decomposition

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$$L(u) = \max_y f(y) + \sum_{i,t} u(i,t) \cdot y(i,t)$$

modified subproblem

$$+ \max_z g(z) - \sum_{i,t} u(i,t) \cdot z(i,t)$$

Dual Decomposition

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Dual objective: find assignment of $u(i,t)$ that minimizes $L(u)$

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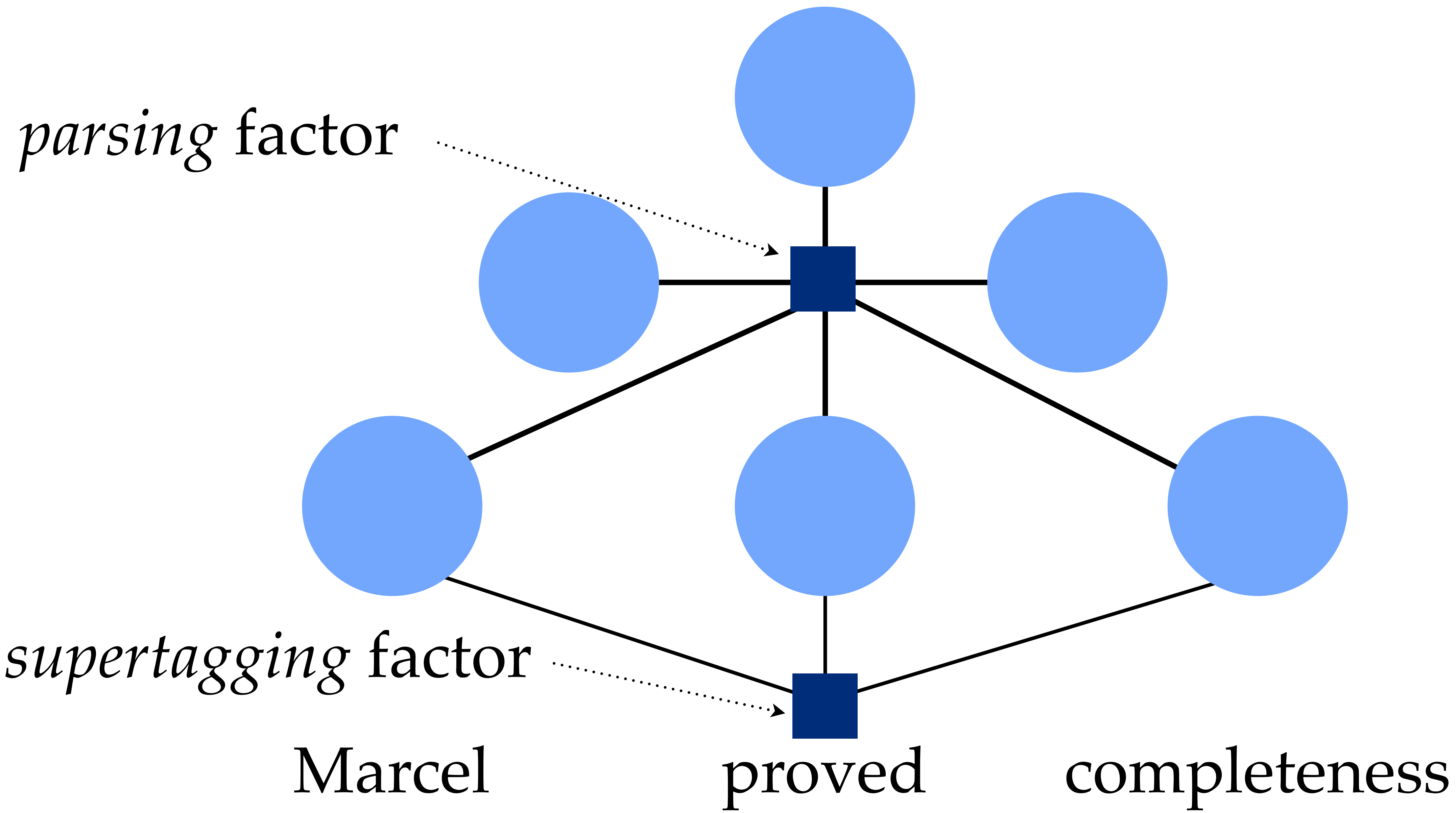
Dual objective: find assignment of $u(i,t)$ that minimizes $L(u)$

$$u(i,t) = u(i,t) + \alpha \cdot [y(i,t) - z(i,t)]$$ (Rush et al. 2010)

Solution provably solves original problem.

Dual Decomposition



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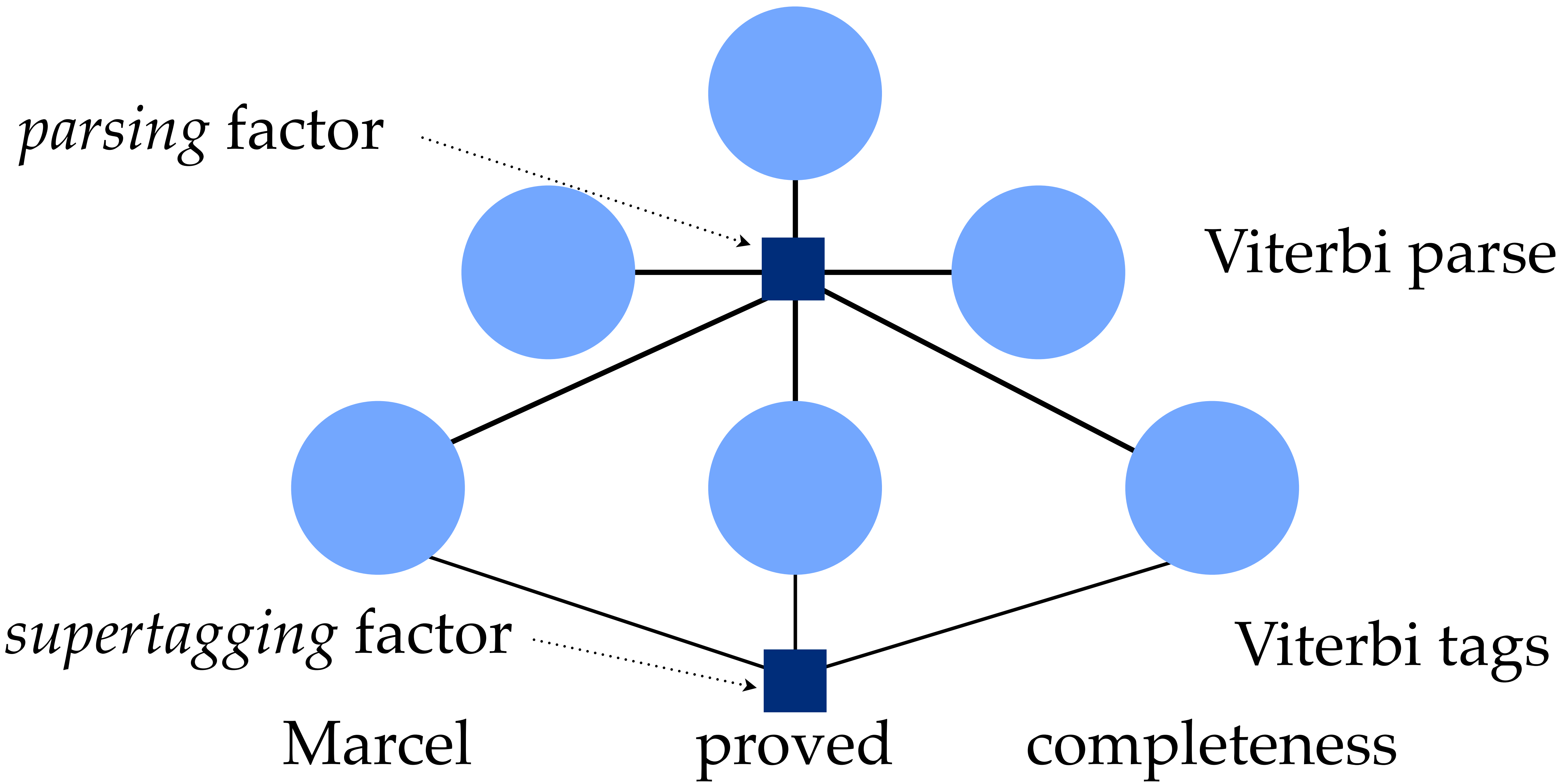

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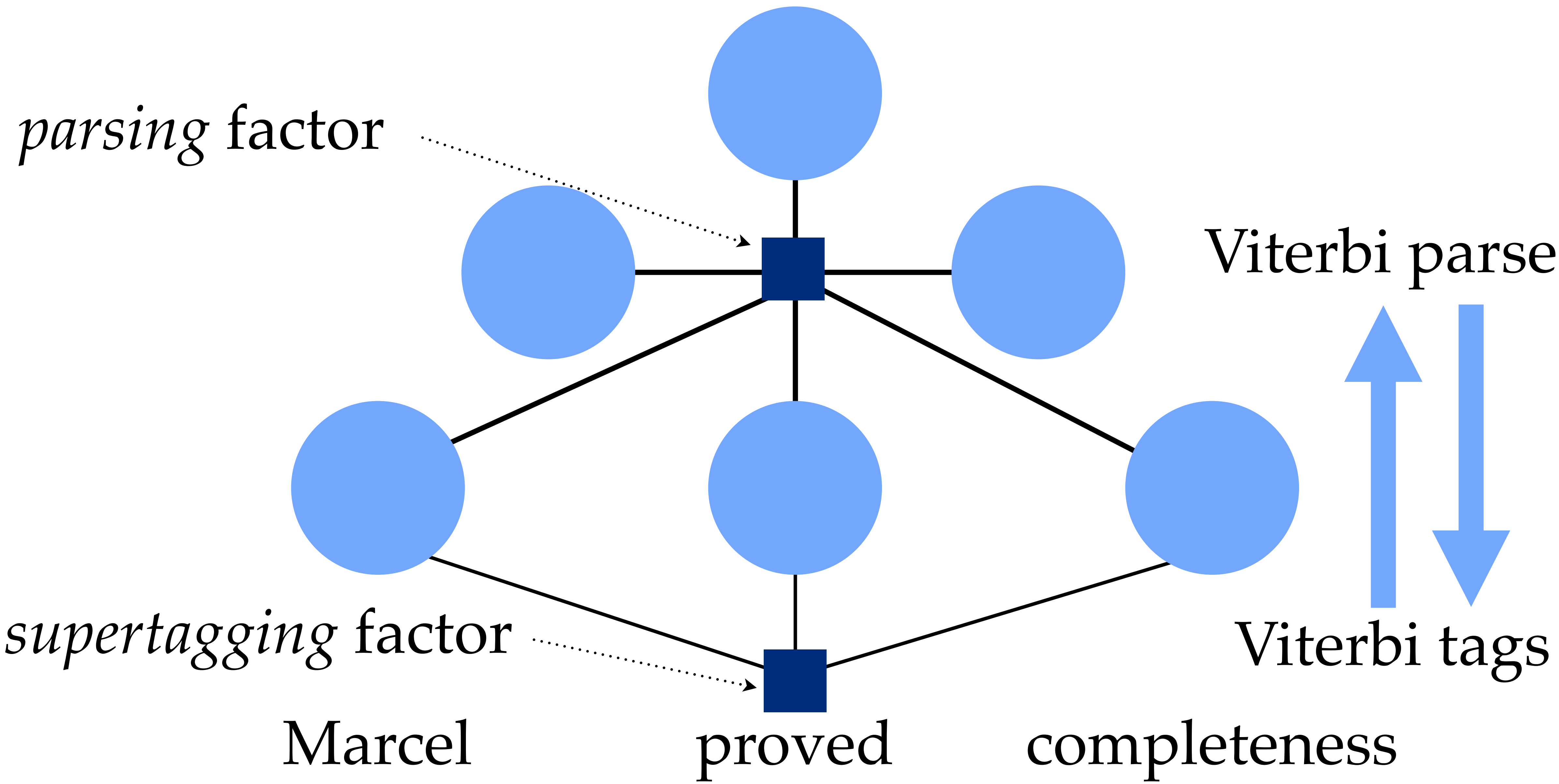


Dual Decomposition

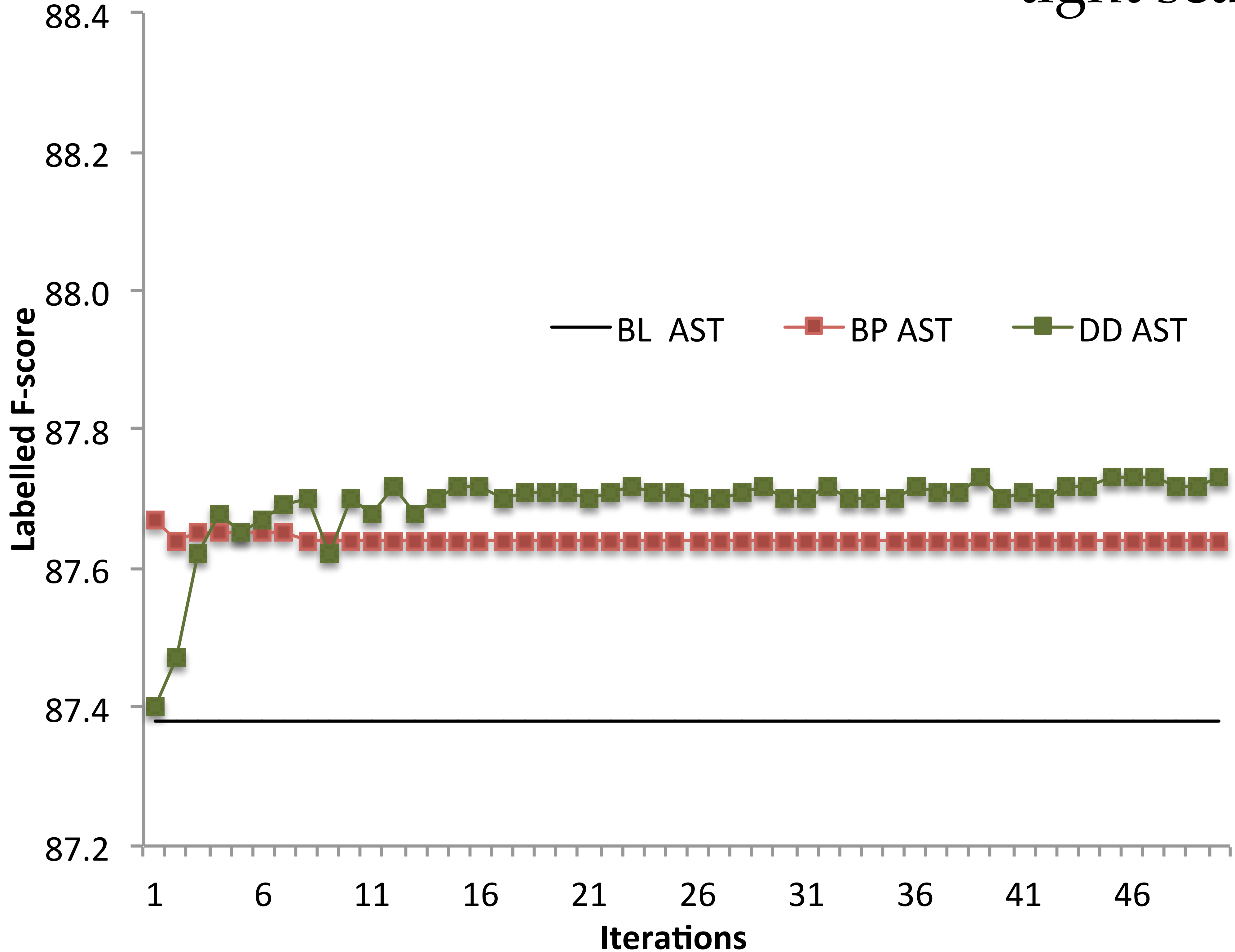
- Computes *exact* maximum, *if* it converges.
  - Otherwise: return best parse seen (approximation).
- Complexity is additive: $O(Gn^3 + Gn)$ vs. $O(G^3n^3)$
- In training: use with margin-based optimizers.
- In decoding: compute Viterbi parse.

Experiments

- Standard parsing task:
  - C&C Parser and supertagger (Clark & Curran 2007).
  - CCGBank standard train/dev/test splits.
  - Separate L-BFGS optimization for each submodel (pseudolikelihood: Besag 1975).
  - Approximate algorithms used to decode test set *only*.

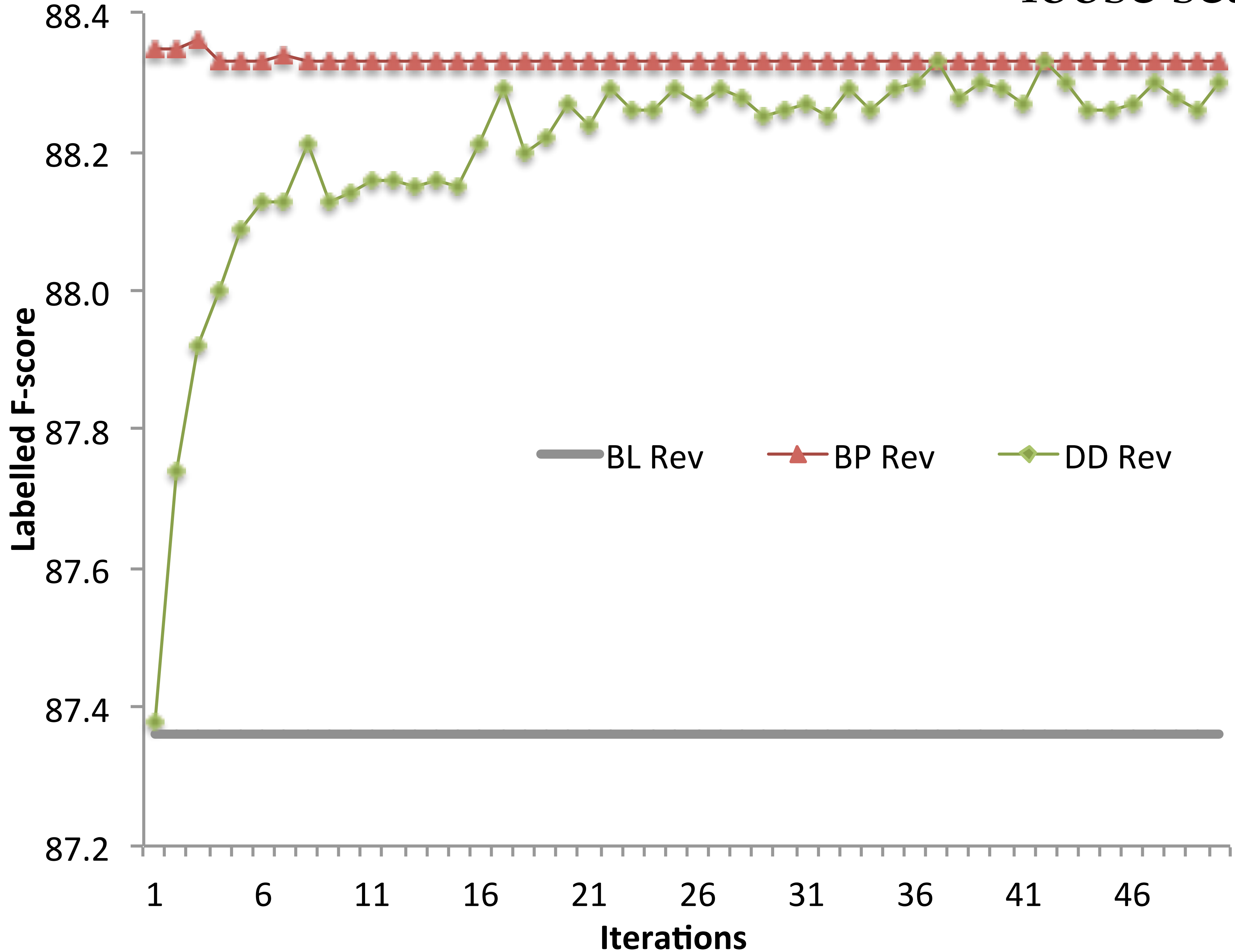
Experiments

tight search (AST)

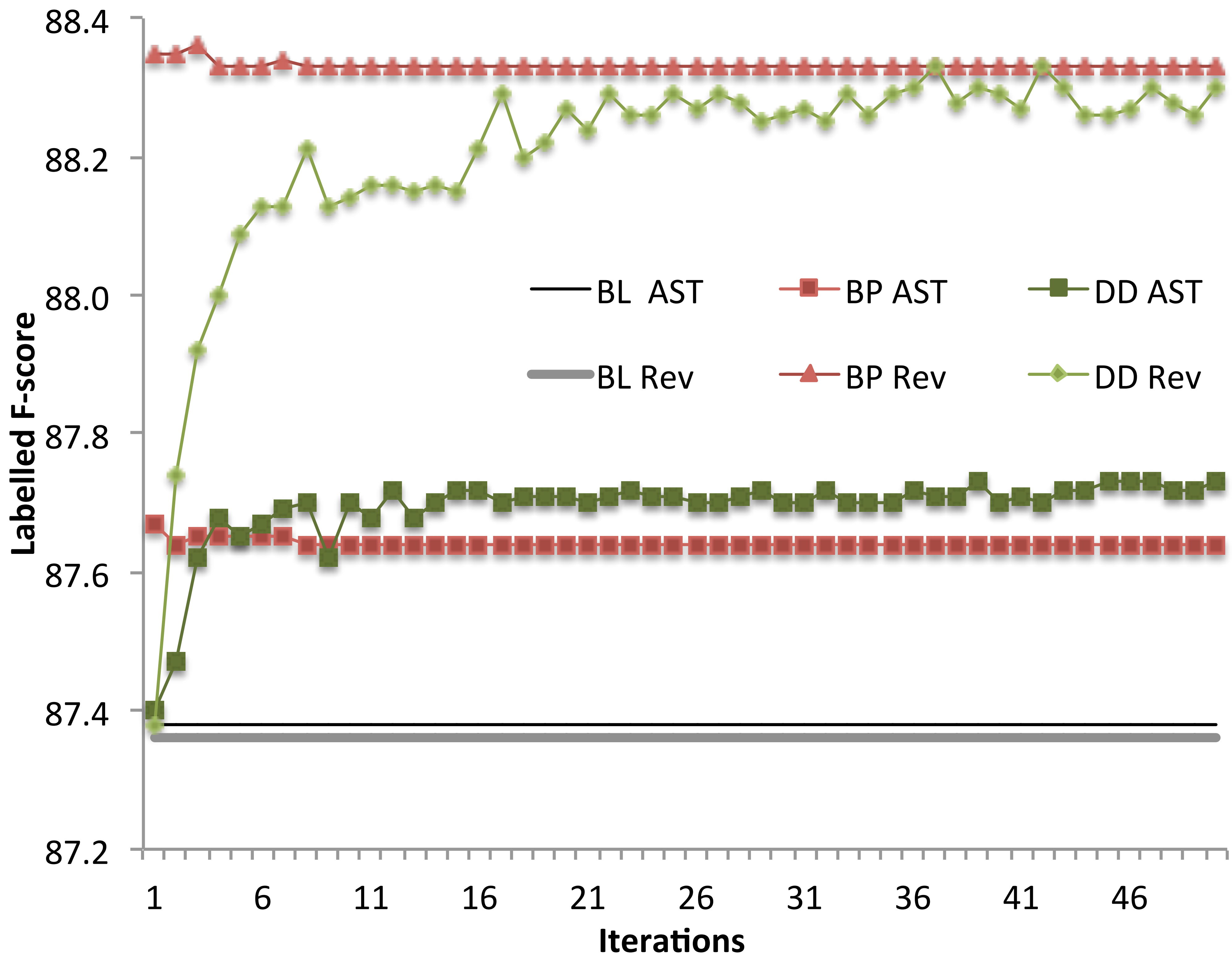


Experiments

loose search (Rev)



Experiments



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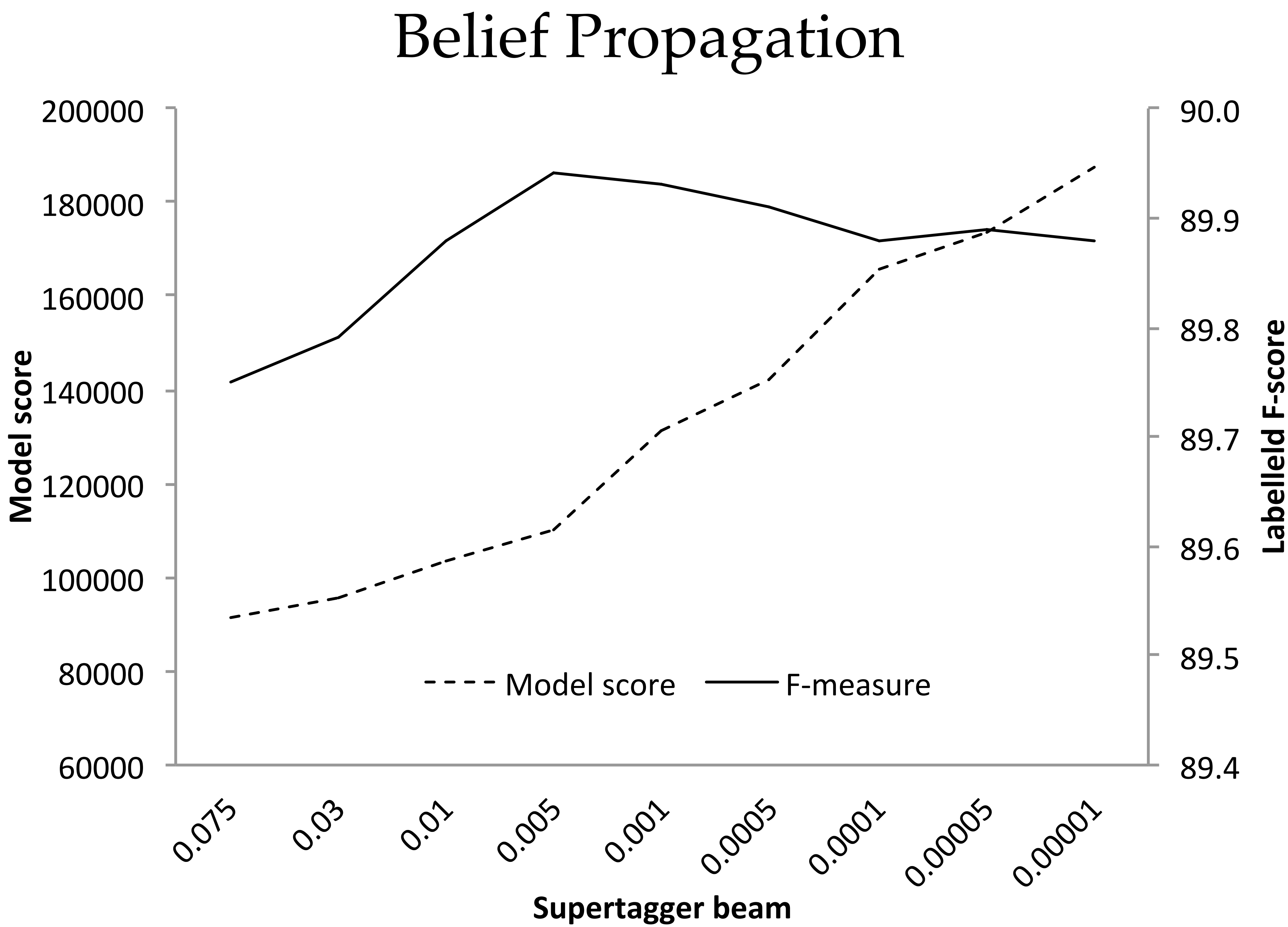
Best performance
in larger search space

Oracle Results Again



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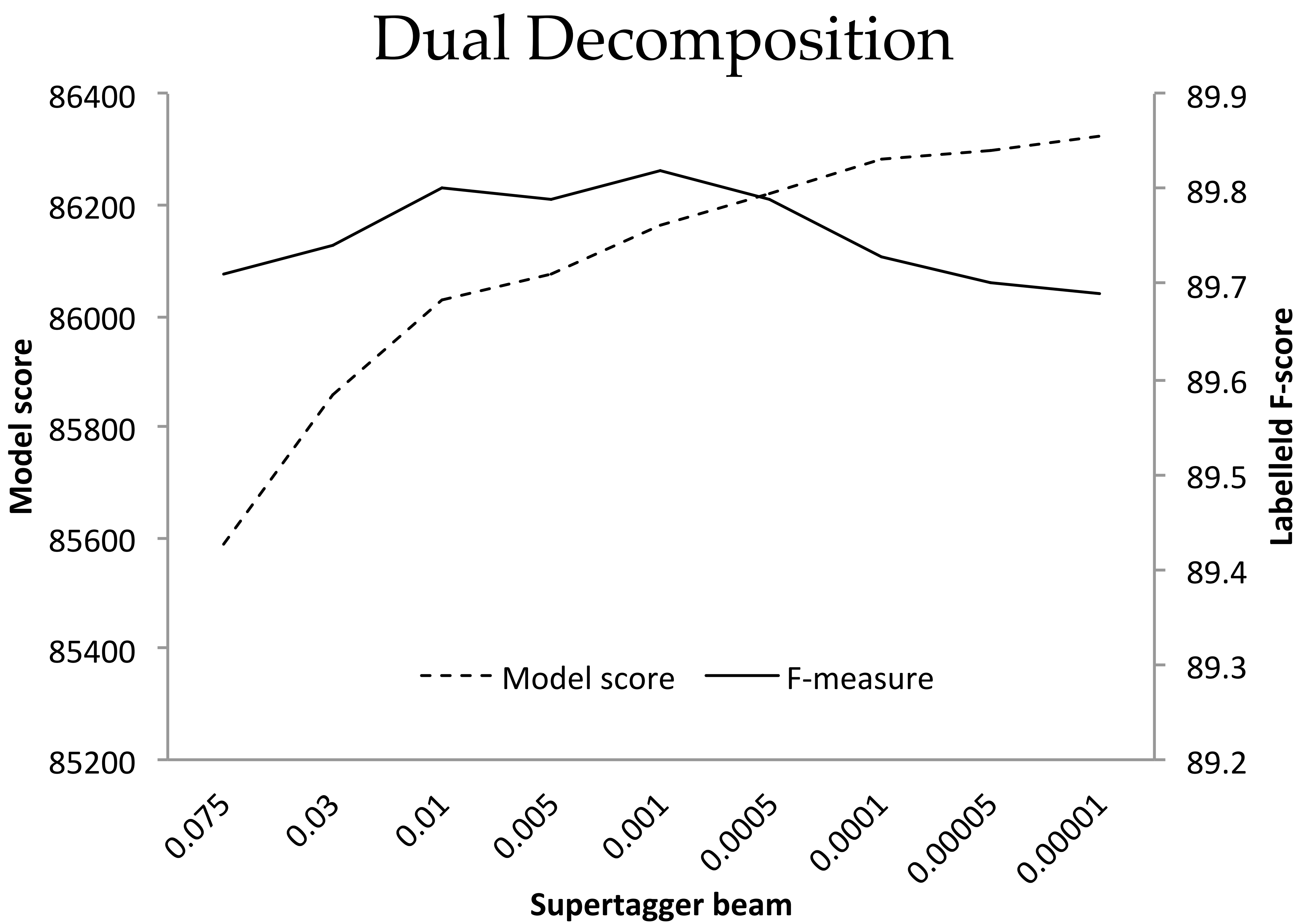

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  Better models can exploit larger search spaces.
- Accurate parsing possible in a combined model.

Overview

- The Problem with Pipeline Models
- Decoding Integrated Models
  with Loopy Belief Propagation and Dual Decomposition (ACL 2011)
- Training Integrated Models
  with Softmax-Margin using Exact and Approximate Loss Functions (EMNLP 2011)

Softmax-Margin

- Minimizes bound on expected risk (Gimpel & Smith, 2010).
- Allows optimization towards loss function.
- Retains probabilistic interpretation.
- Convex.
- Requires little change to existing Conditional Log-Likelihood (CLL) implementation.

Training Objectives

CLL: $$\min_{\theta} \sum_{i=1}^{m} \left[-\theta^{\mathsf{T}} f(x^{(i)}, y^{(i)}) + \log \sum_{y \in \mathcal{Y}(x^{(i)})} \exp\{\theta^{\mathsf{T}} f(x^{(i)}, y)\} \right]$$

Training Objectives

weights

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- Penalise high-loss outputs.
- Re-weight outcomes by *loss*.
- Loss function an *unweighted feature* -- if **decomposable.**

Parsing Metrics

Labelled, directed dependency recovery

(Clark & Hockenmaier, 2002)

$$
\begin{array}{ccc}
\text{Marcel} & \text{proved} & \text{completeness} \\
\hline
NP & (S\backslash NP)/NP & NP \\
\cline{2-3}
 & \multicolumn{2}{c}{S\backslash NP \quad >} \\
\hline
\multicolumn{3}{c}{S \quad <}
\end{array}
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$$f_1 + f_2 = \frac{2n_1}{d_1 + |y_1|} \oplus \frac{2n_2}{d_2 + |y_2|} = \frac{2(n_1 + n_2)}{d_1 + d_2 + |y_1| + |y_2|}$$

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$$\frac{\mathrm{NP} \quad \mathrm{S\backslash NP}}{\mathrm{S}} <$$

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F_1 $\qquad DecF1(y) = DecP(y) + DecR(y)$

(Taskar et al., 2004)

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efficient but *approximate!*

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Approximate Losses with CKY

items $A_{i,j}$

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time_1 flies_2 like_3 an_4 arrow_5

Approximate Losses with CKY

items $A_{i,j}$

target analysis

time_1 flies_2 like_3 an_4 arrow_5

Approximate Losses with CKY

items $A_{i,j}$

target analysis
correct dependencies
all dependencies

time$_1$ flies$_2$ like$_3$ an$_4$ arrow$_5$

Approximate Losses with CKY

items $A_{i,j}$

target analysis
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all dependencies

$((S\backslash NP)\backslash(S\backslash NP))/NP_{2,3}$

$NP_{0,1}$ $S\backslash NP_{1,2}$ $NP/NP_{3,4}$ $NP_{4,5}$

time$_1$ flies$_2$ like$_3$ an$_4$ arrow$_5$

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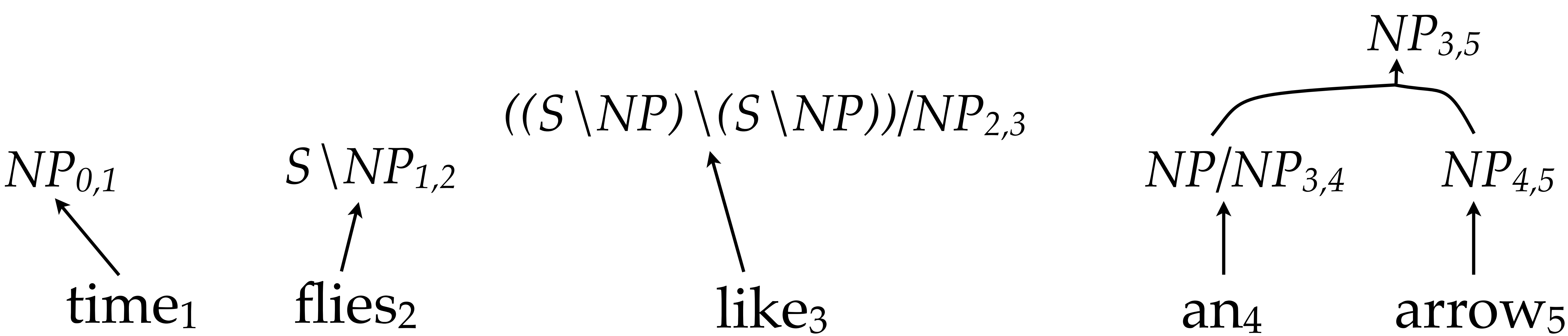

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$$NP_{3,5}$$

$$\mathrm{DecF_1}(1,1)$$

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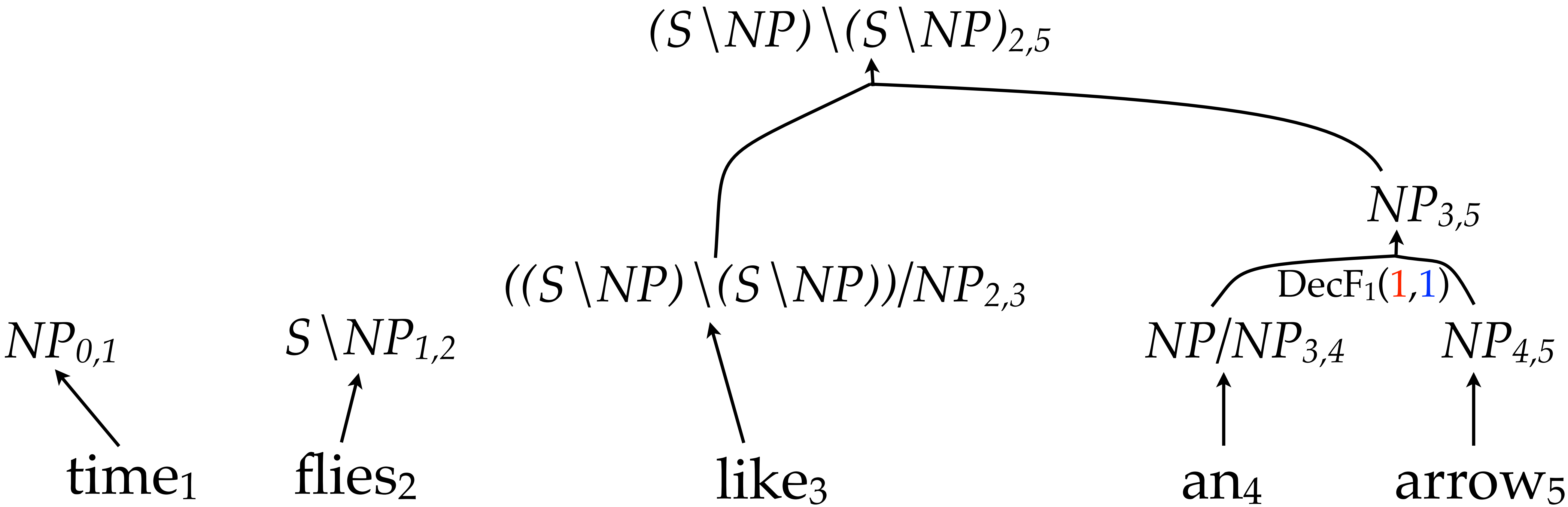

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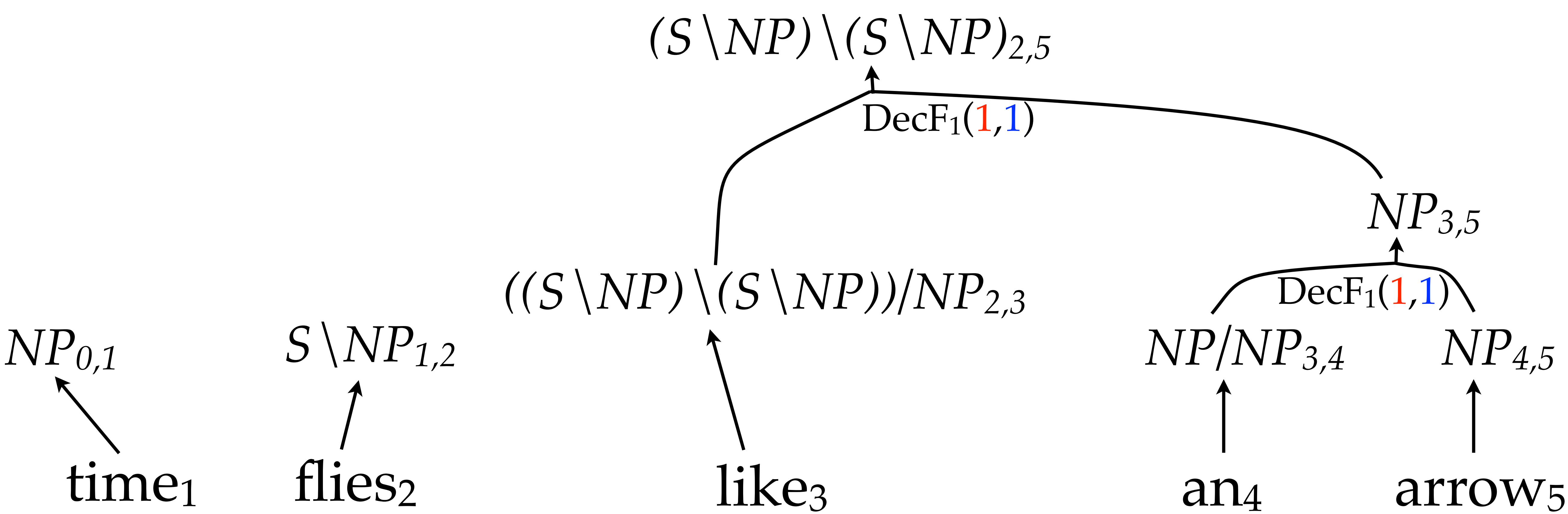

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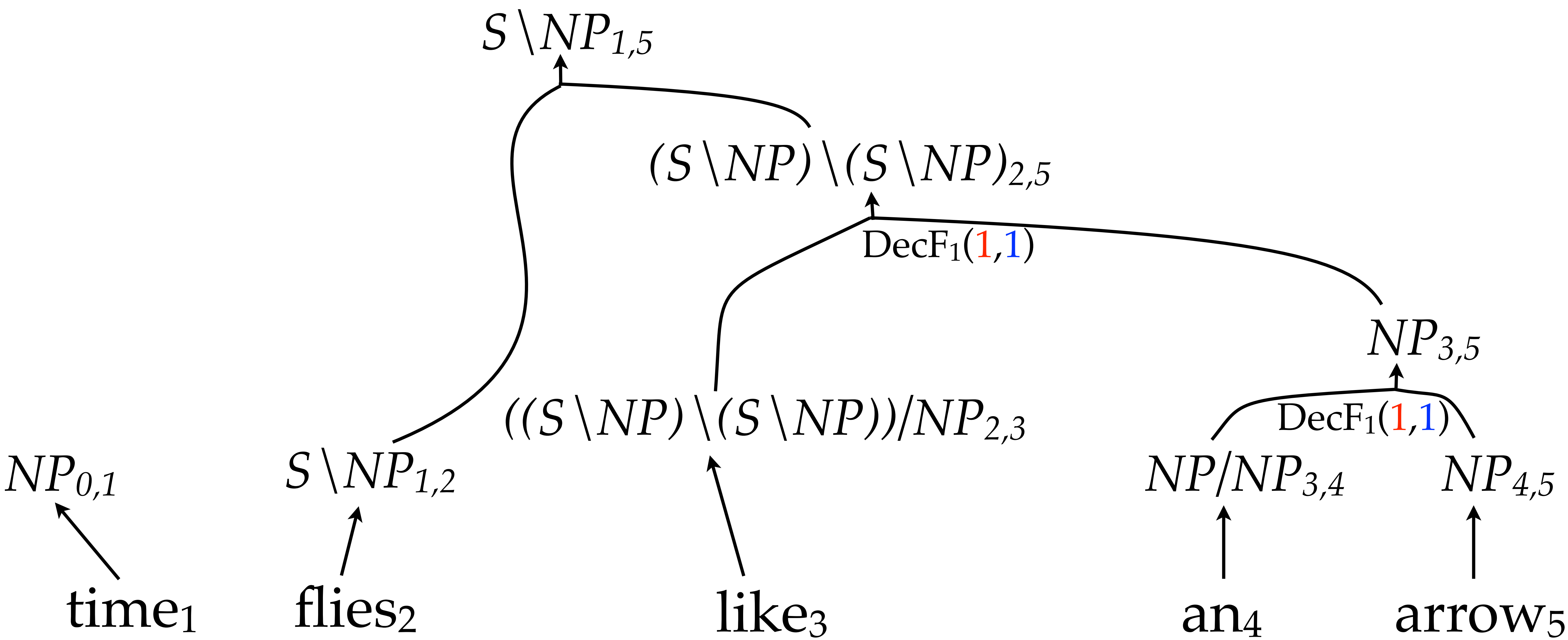

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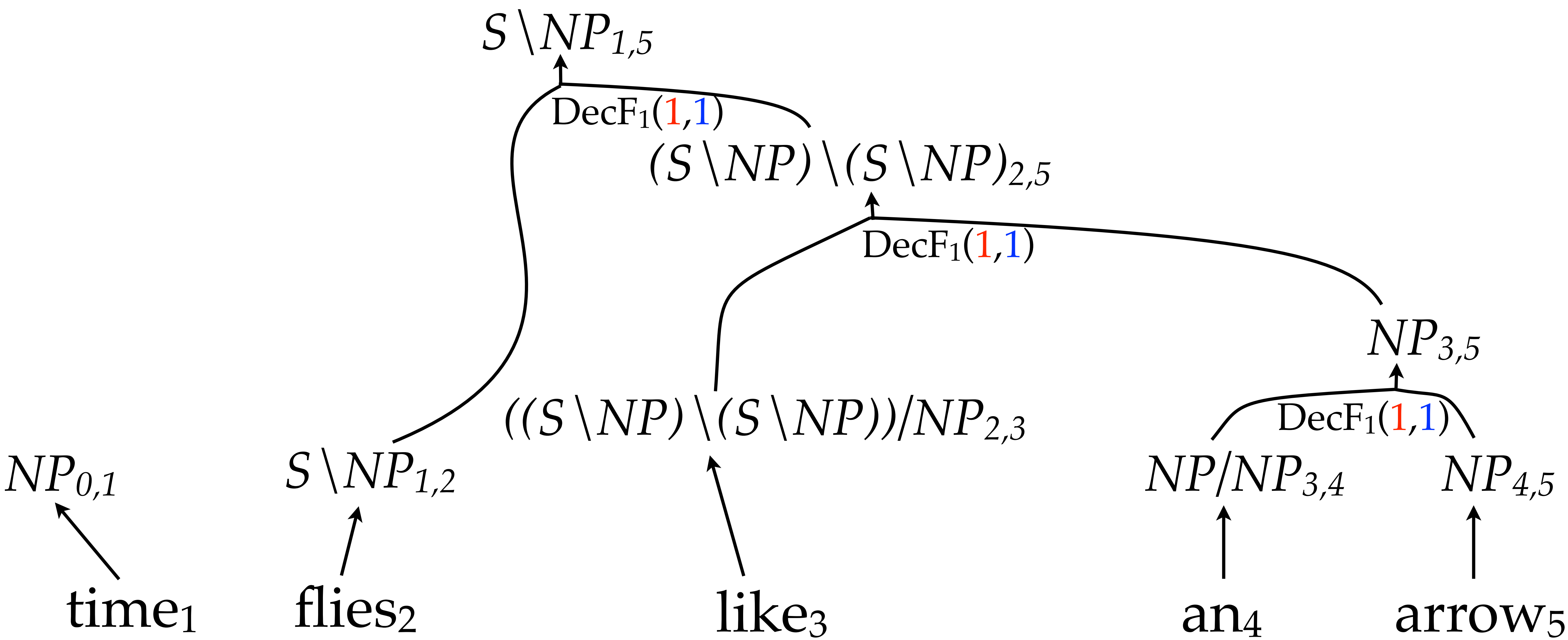

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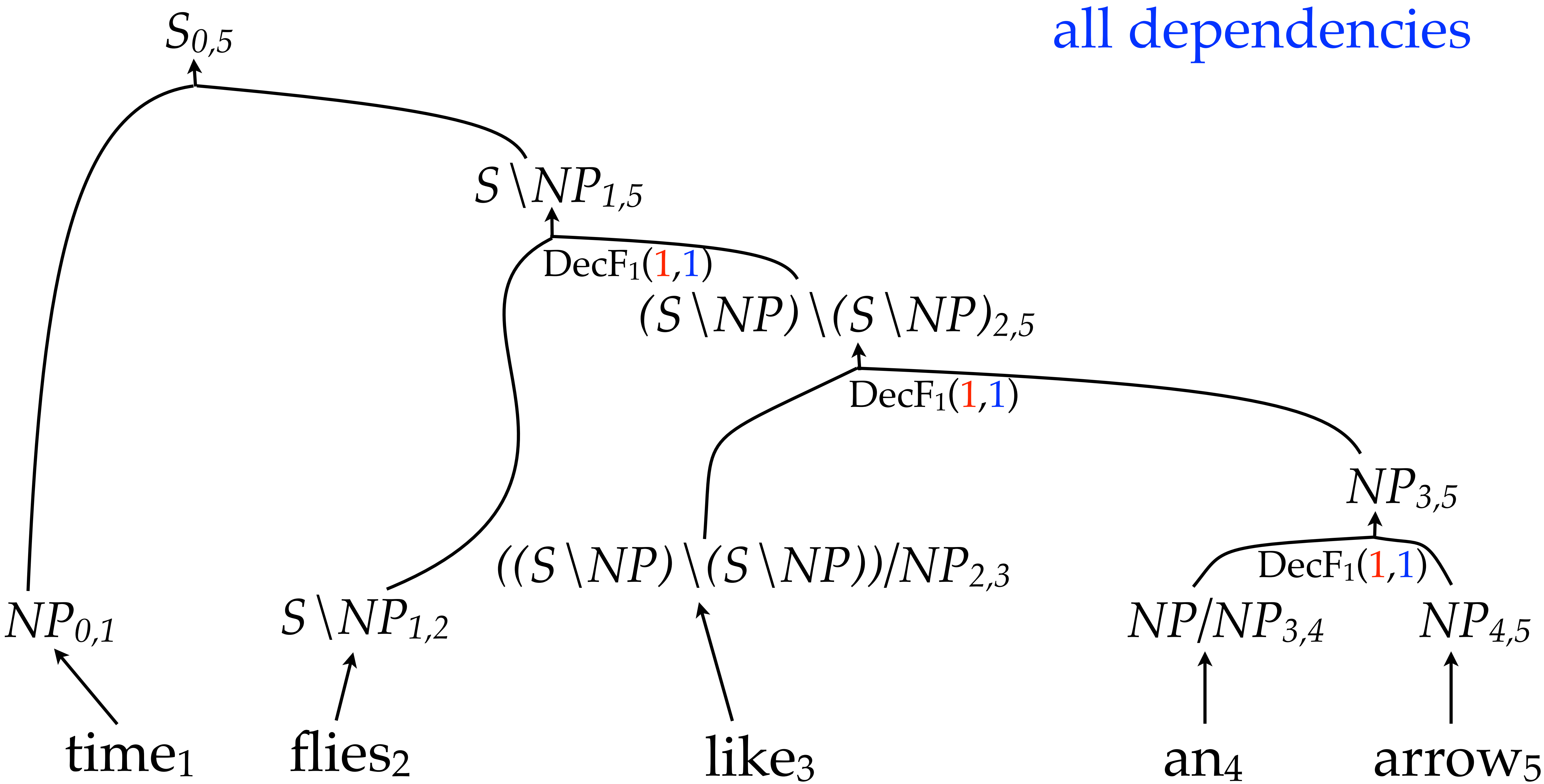

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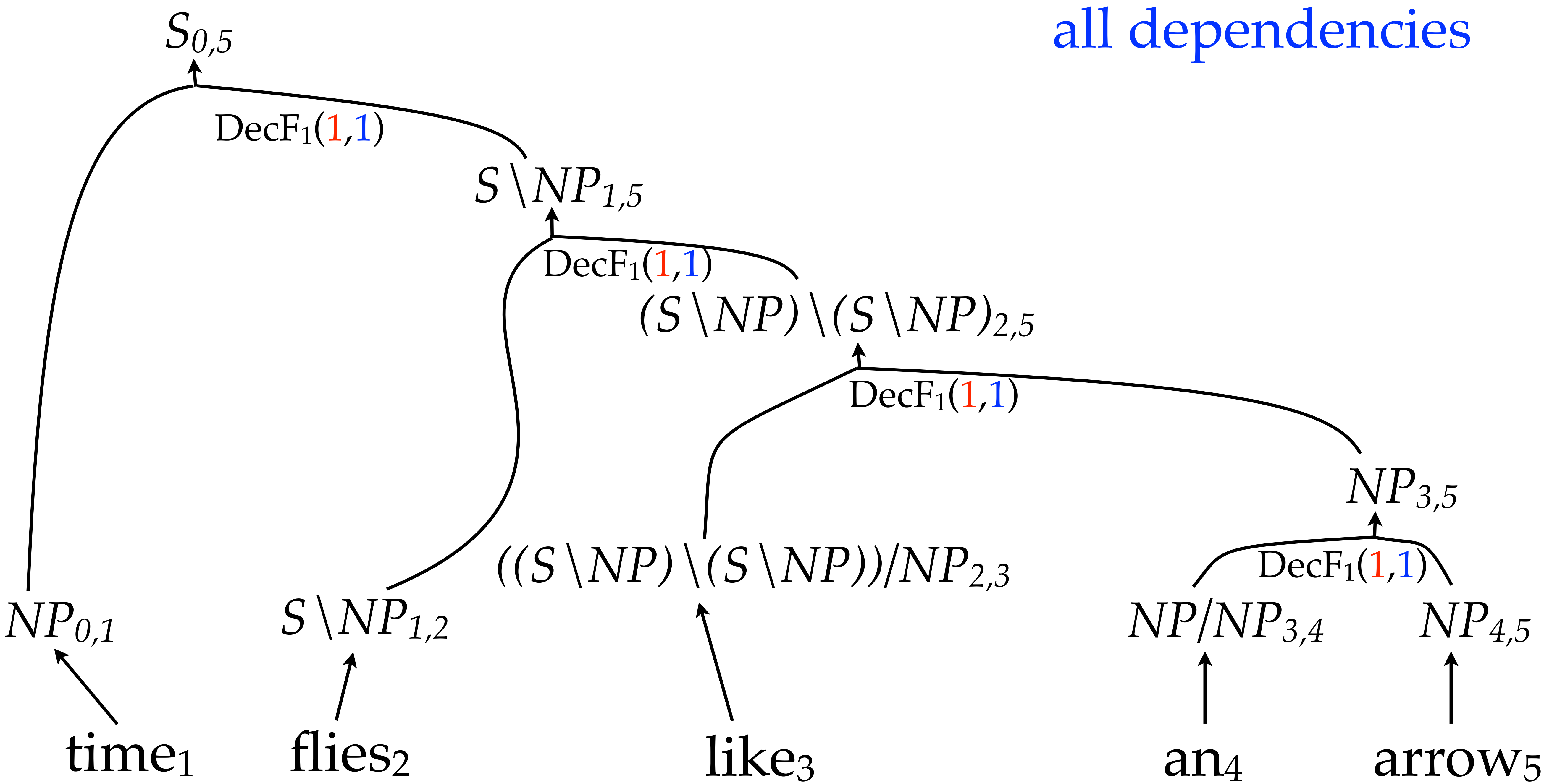

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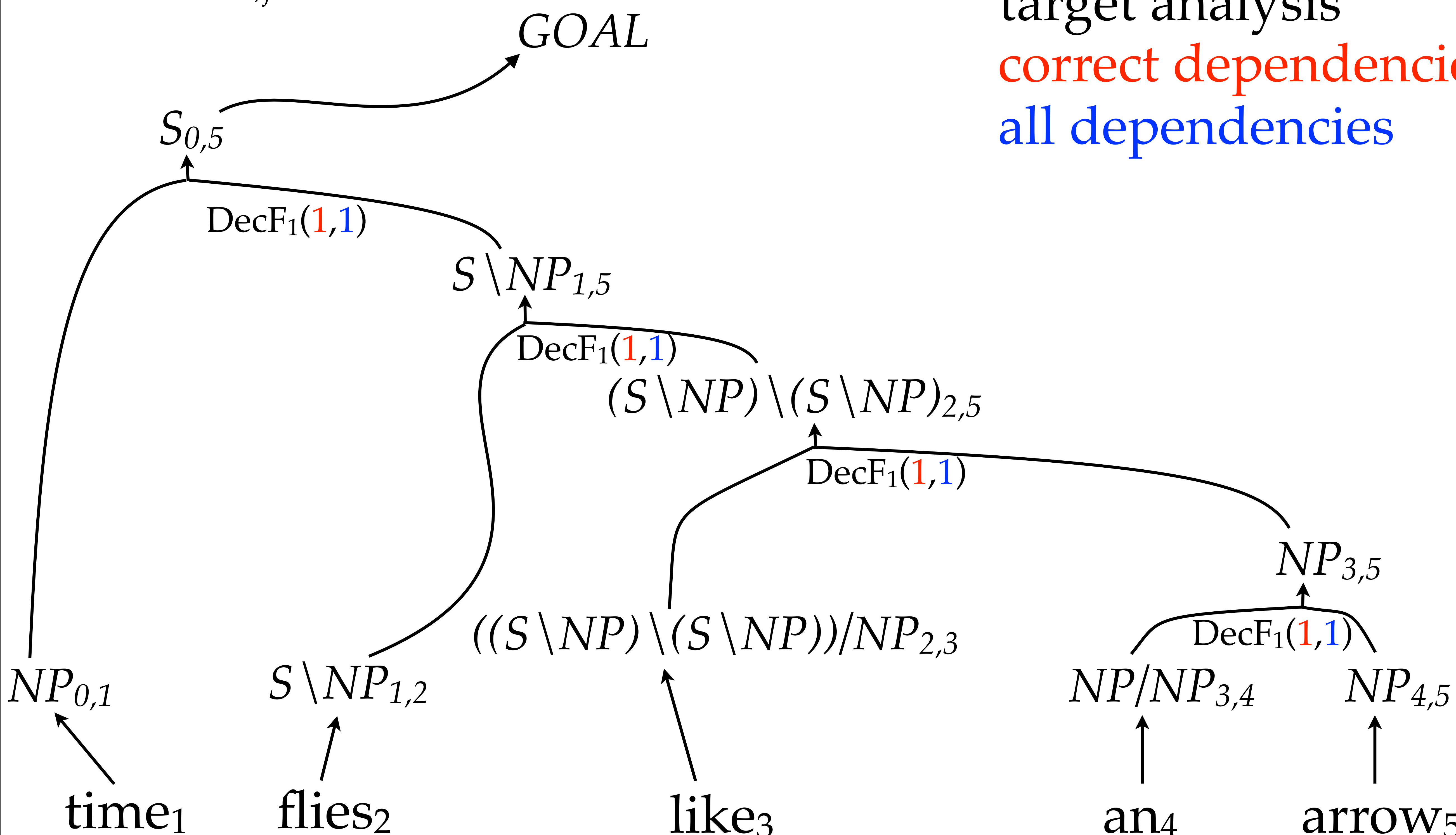

Approximate Losses with CKY

items $A_{i,j}$

another analysis
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all dependencies

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$(S\backslash NP)/NP_{2,3}$

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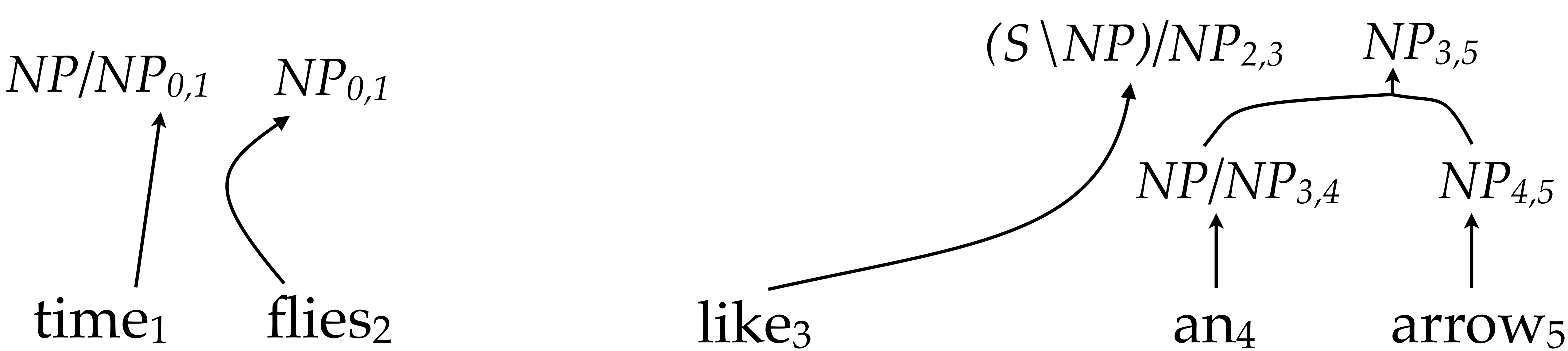

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$NP/NP_{0,1}$ $\quad NP_{0,1}$ $\quad (S\backslash NP)/NP_{2,3}$ $\quad NP_{3,5}$

$\mathrm{DecF}_1(1,1)$

$NP/NP_{3,4}$ $\quad NP_{4,5}$

time_1 $\quad \text{flies}_2$ $\quad \text{like}_3$ $\quad \text{an}_4$ $\quad \text{arrow}_5$

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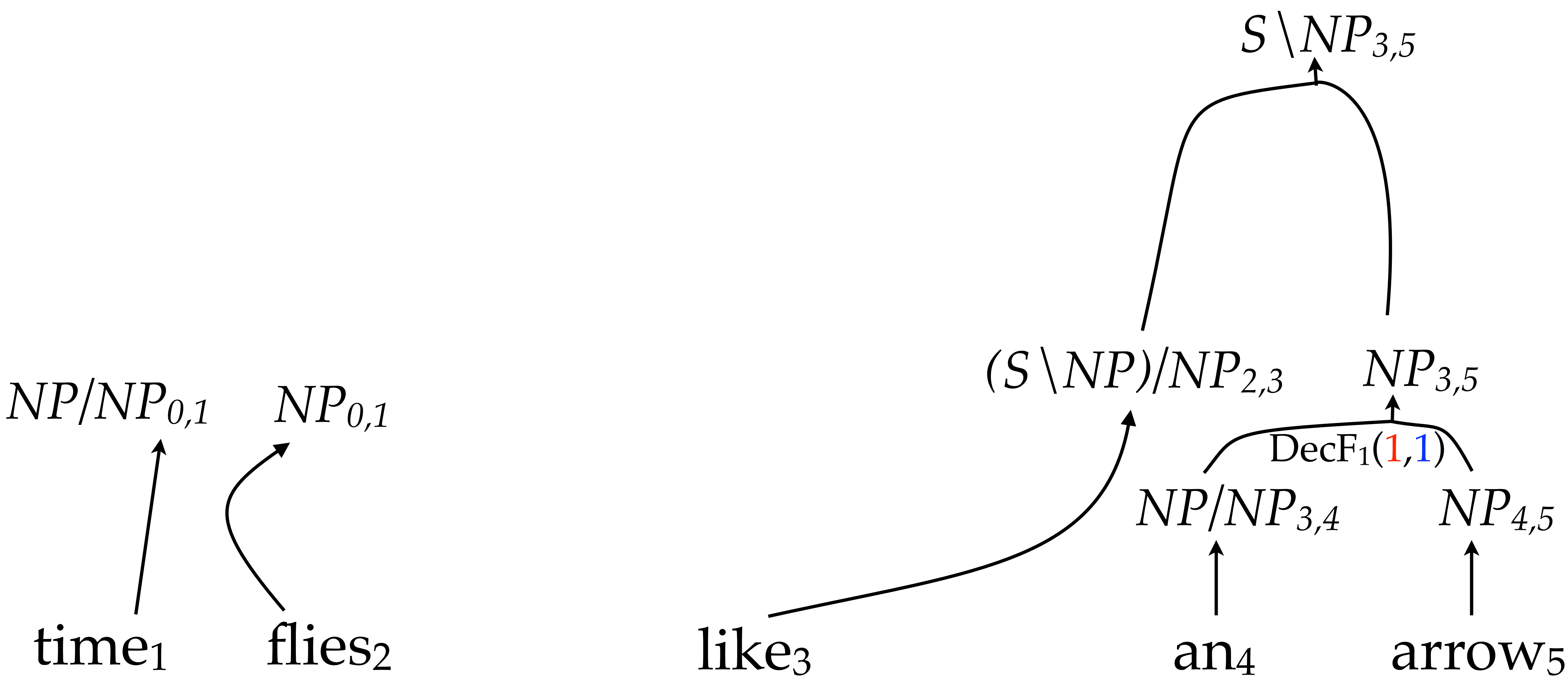

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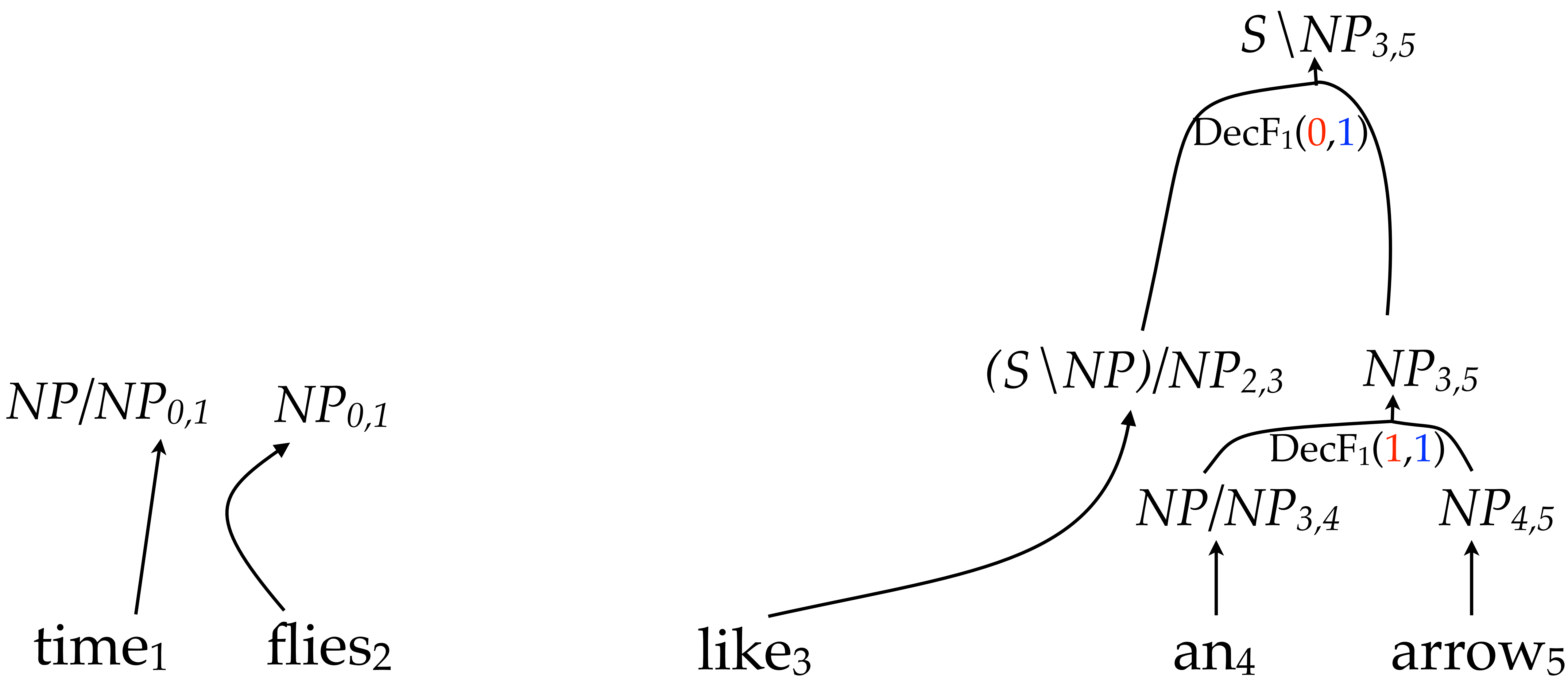

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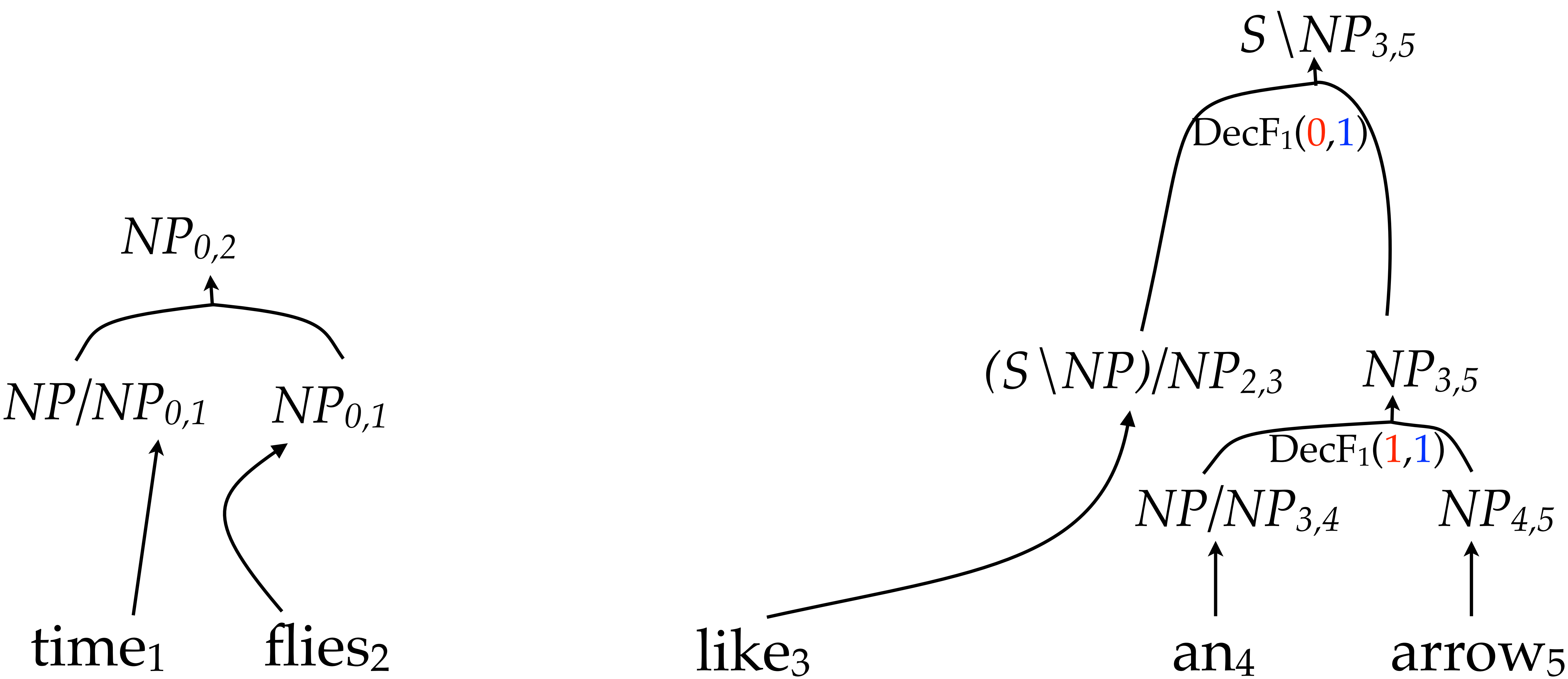

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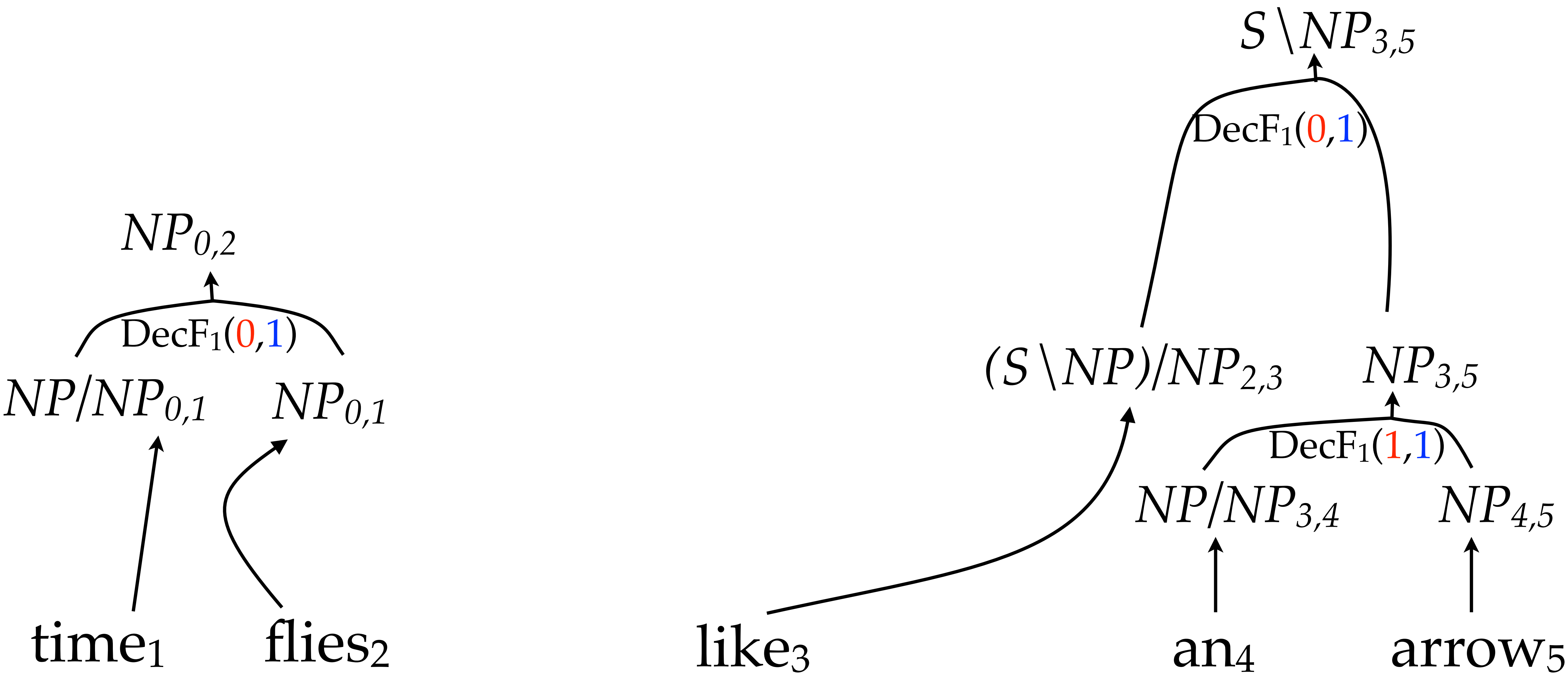

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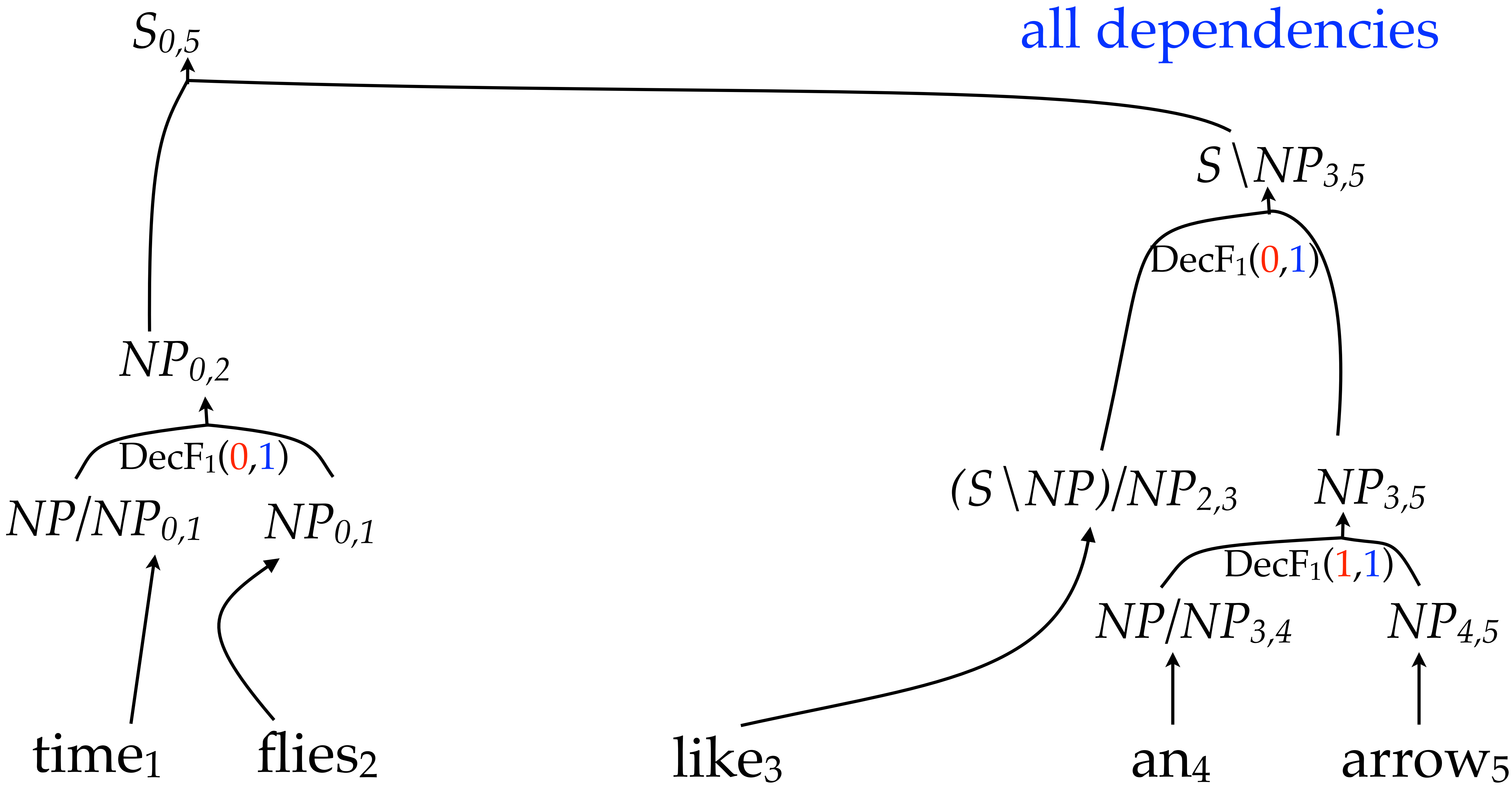

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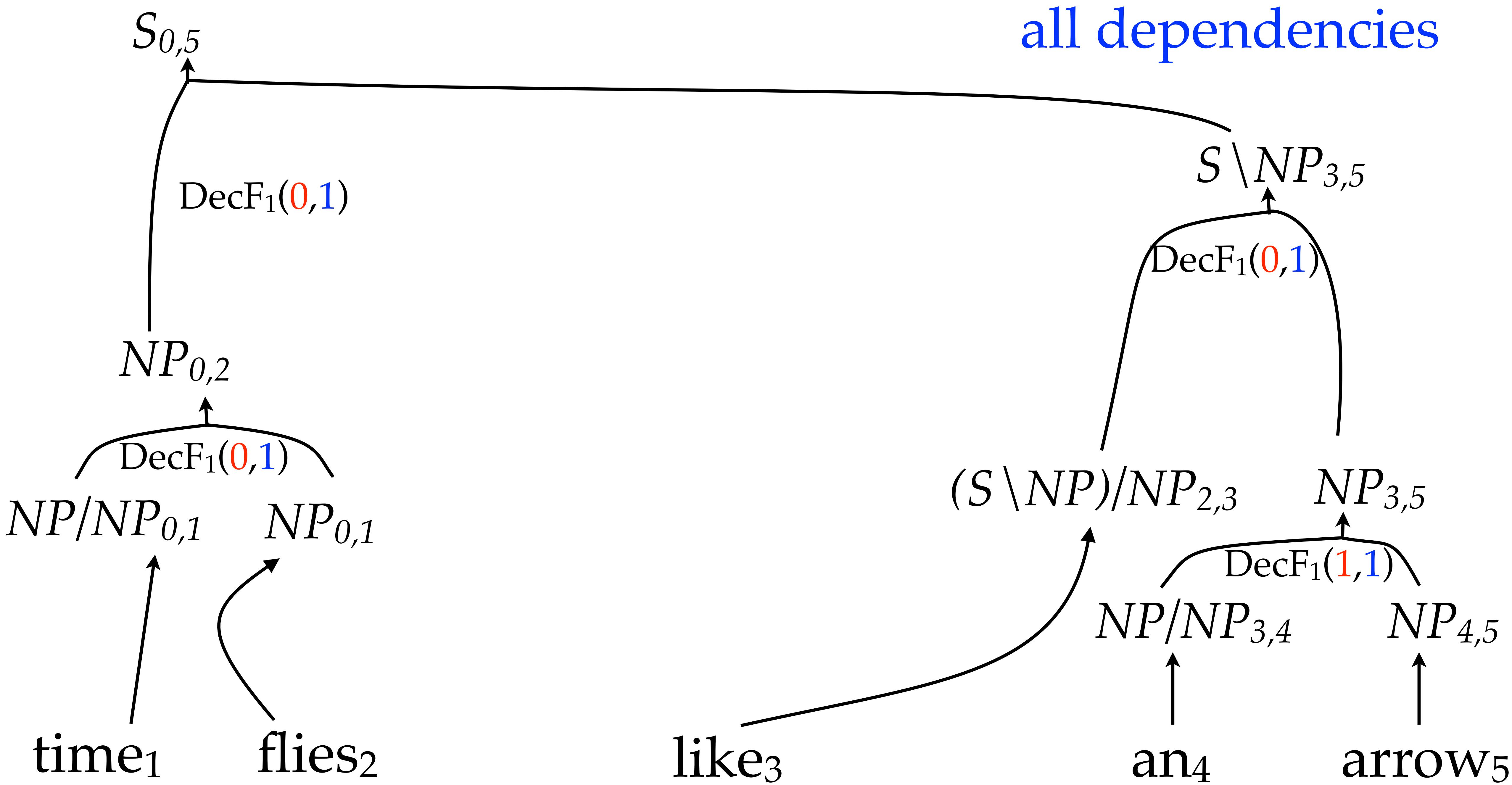

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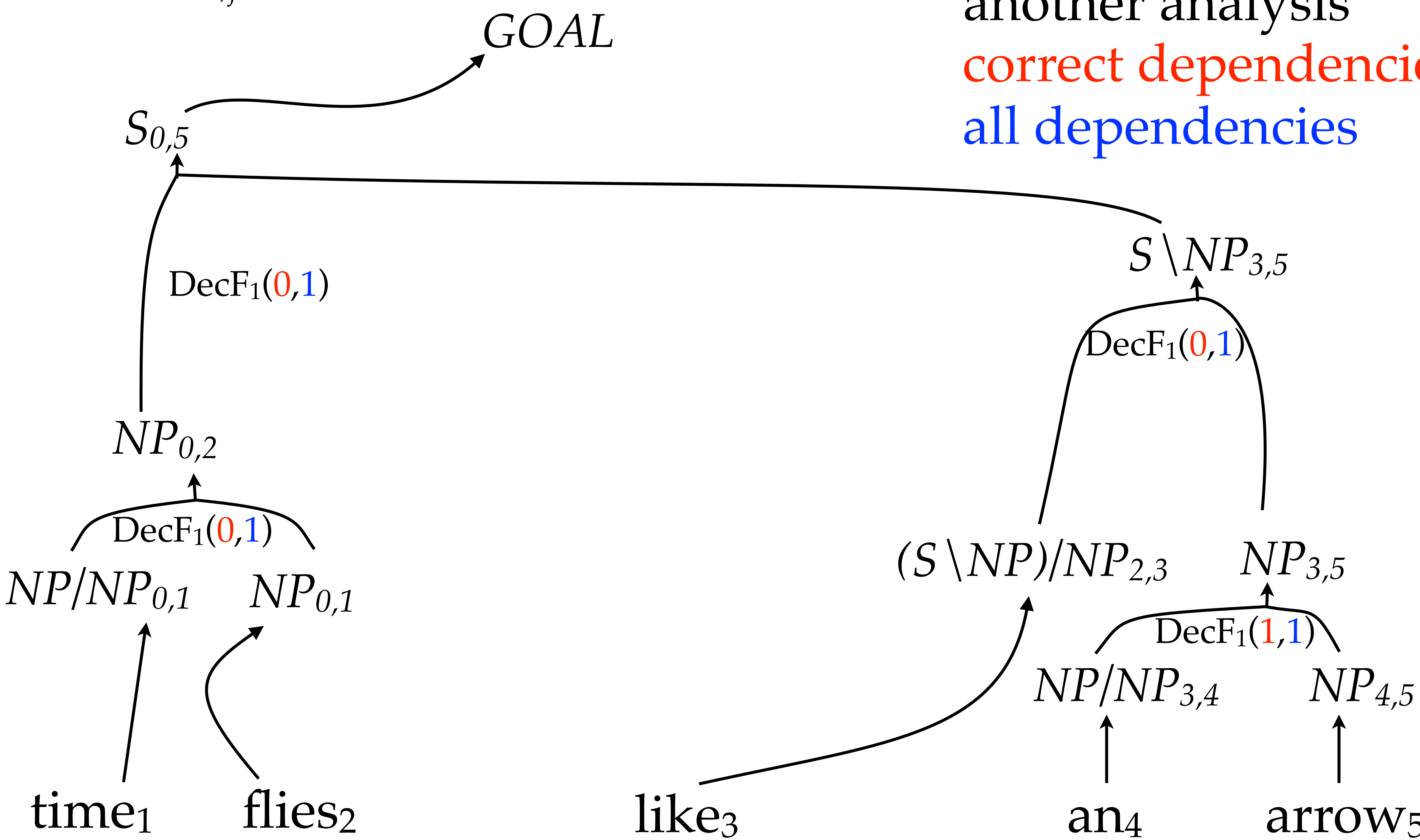

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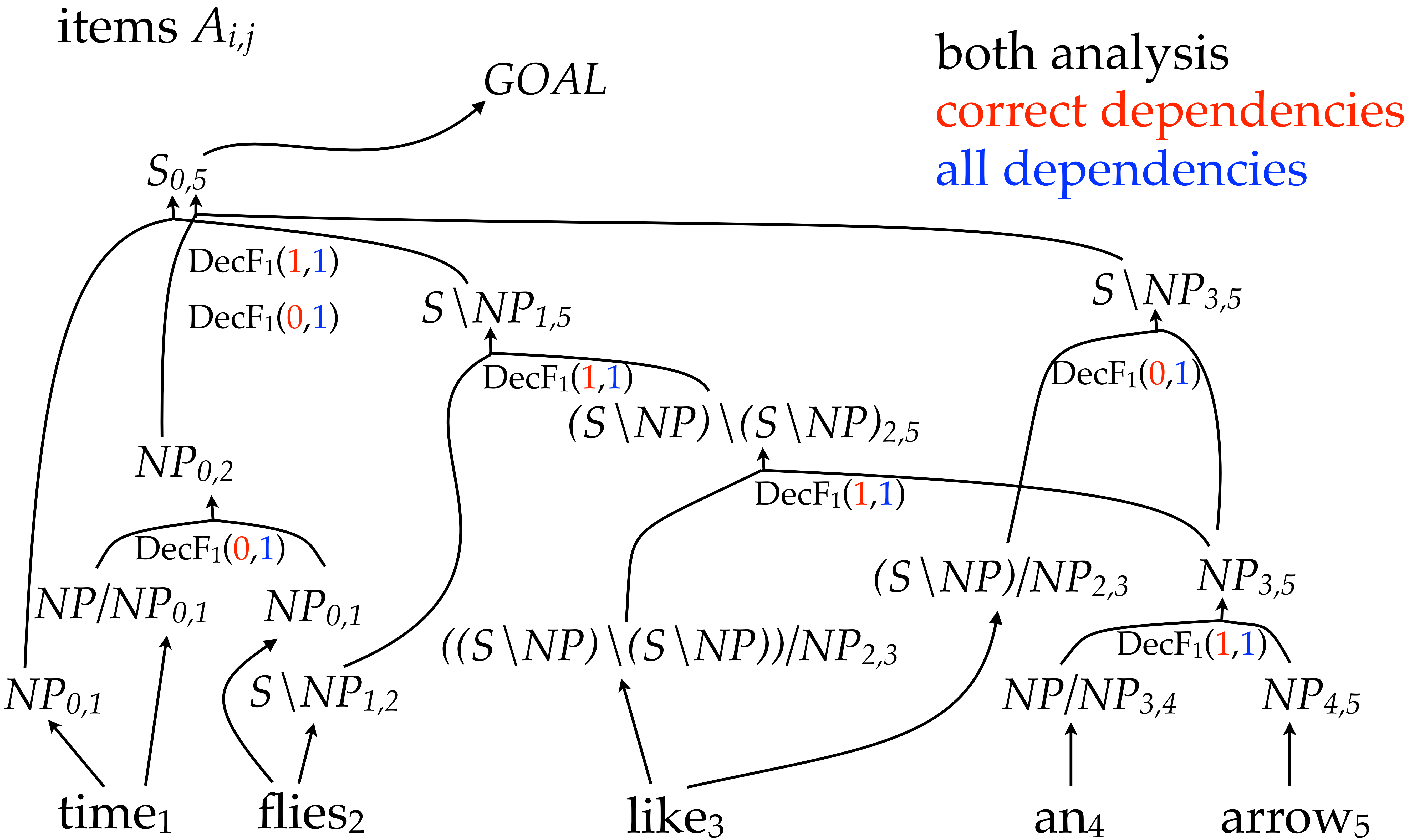

Approximate Losses with CKY

items $A_{i,j}$

both analysis
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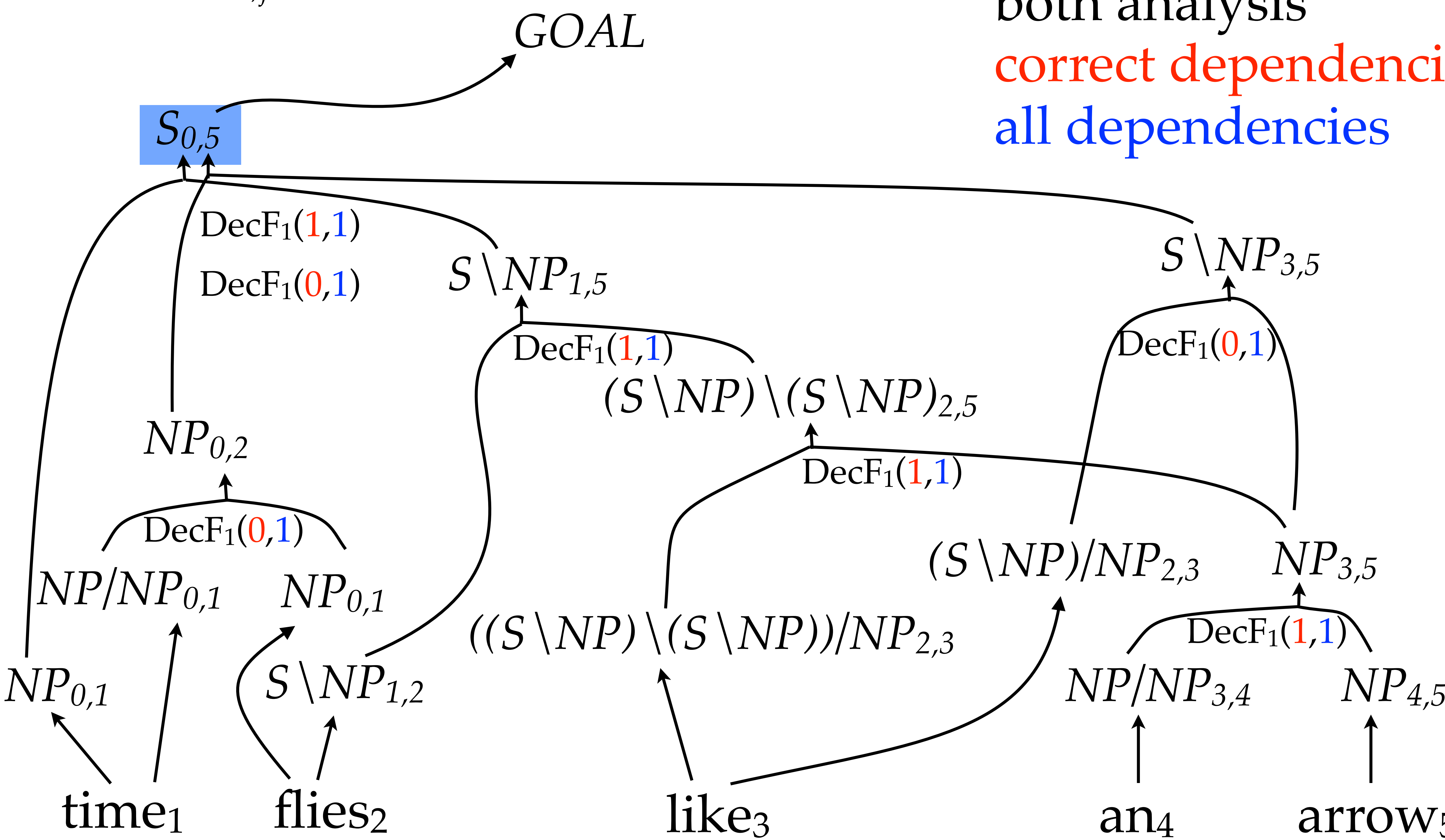

Exact Losses for Parsing

Precision $$P(y, y') = \frac{|y \cap y'|}{|y'|} = \frac{n}{d}$$

Recall $$R(y, y') = \frac{|y \cap y'|}{|y|} = \frac{n}{|y|}$$

F-measure $$F_1(y, y') = \frac{2PR}{P + R} = \frac{2|y \cap y'|}{|y| + |y'|} = \frac{2n}{d + |y|}$$

- Compute exact losses on sentence-level i.e. items $A_{i,j,n,d}$
- Treat F_1 as *non-local features* dependent on n, d

Exact Losses with State-Split CKY

items $A_{i,j,n,d}$

correct dependencies

all dependencies

time_1 flies_2 like_3 an_4 arrow_5

Exact Losses with State-Split CKY

items $A_{i,j,n,d}$

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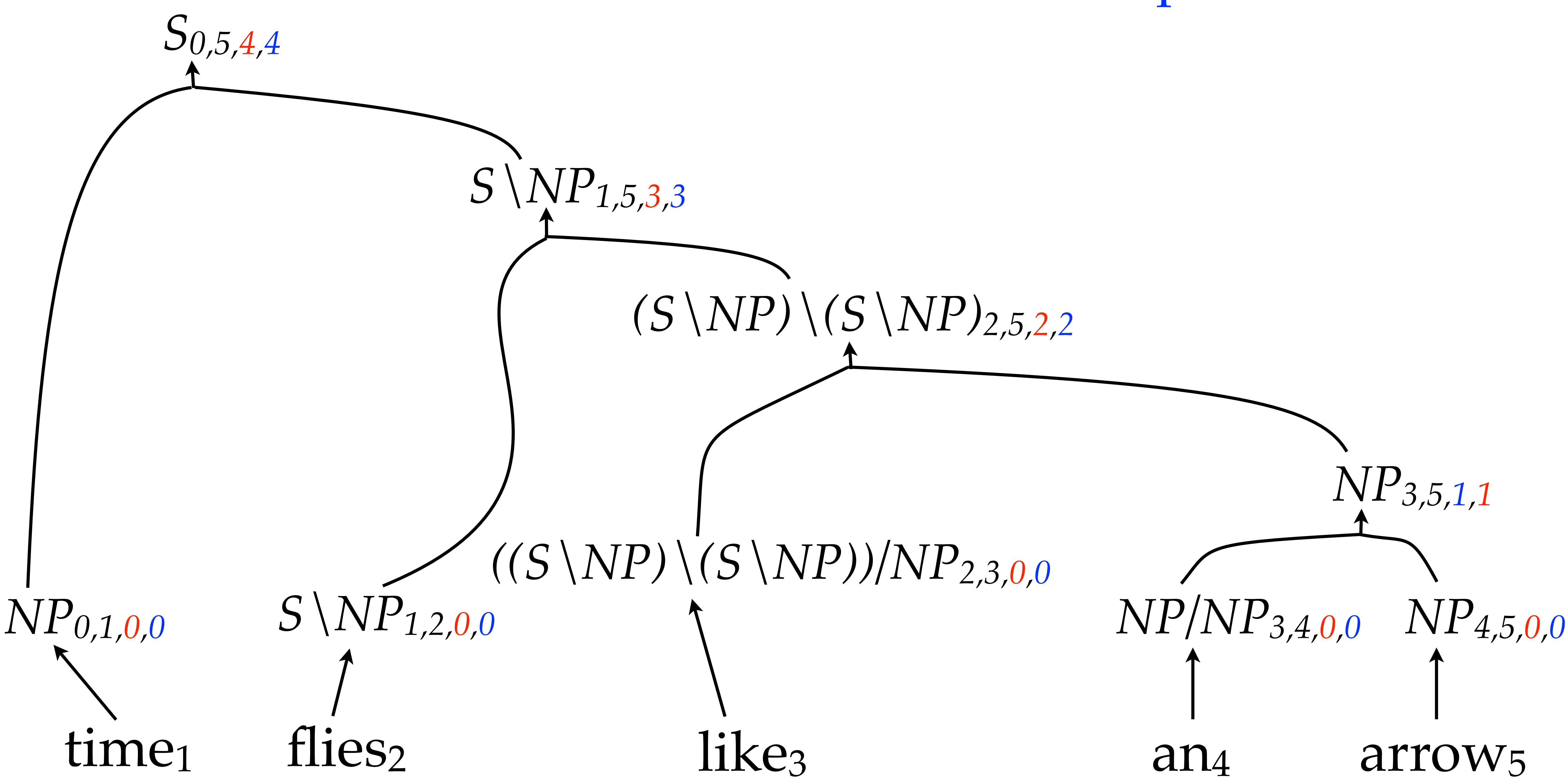

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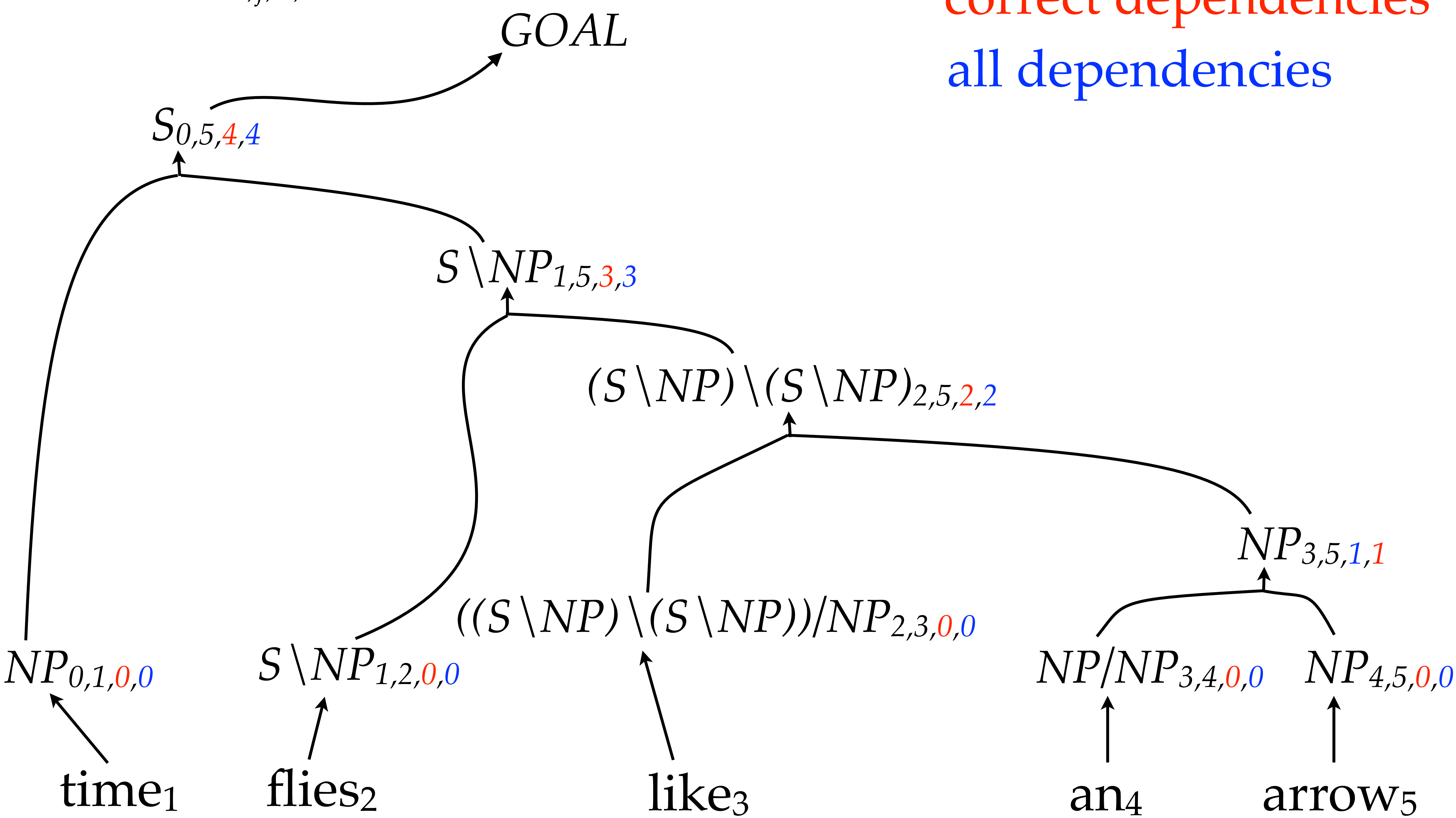

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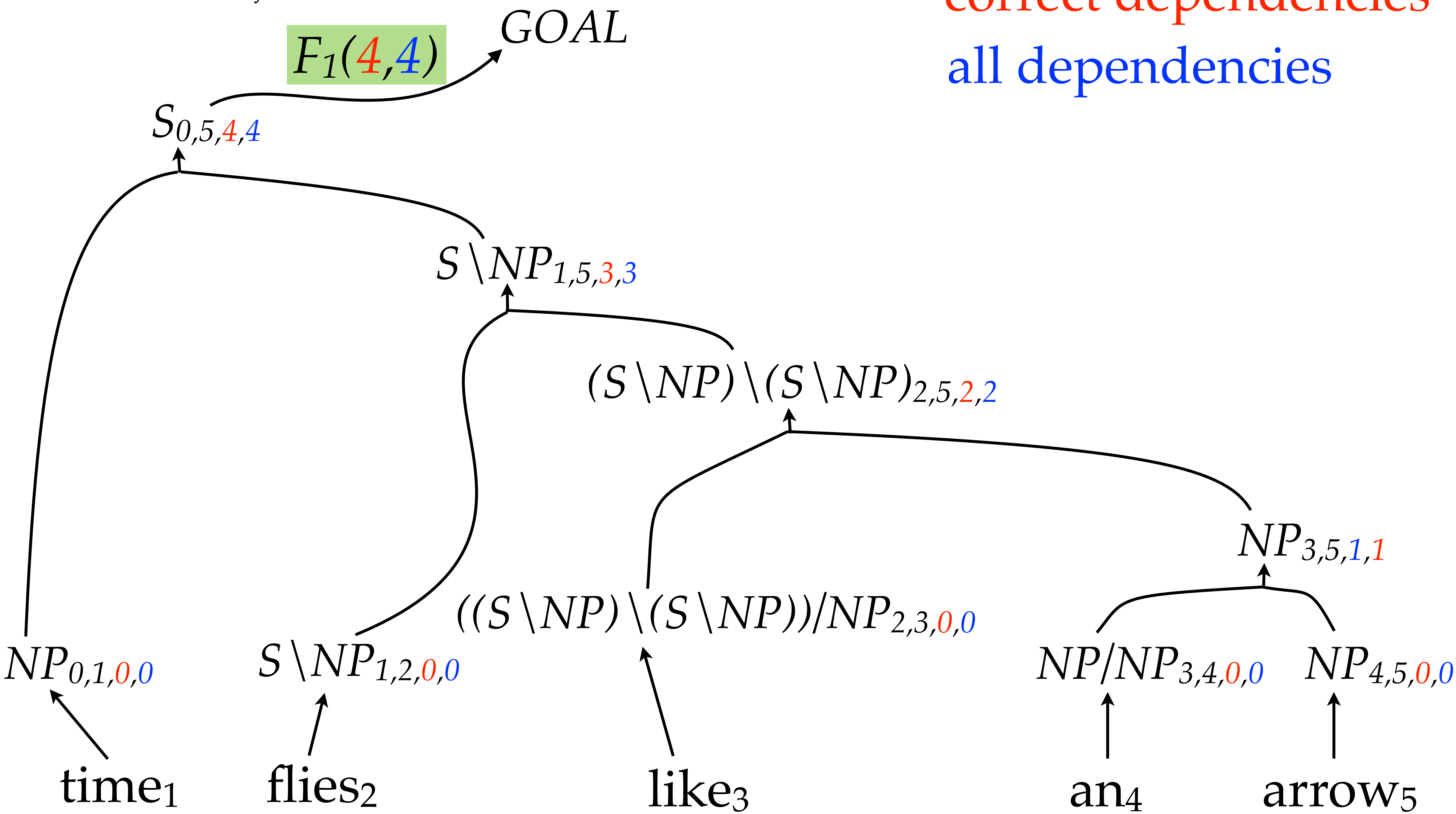

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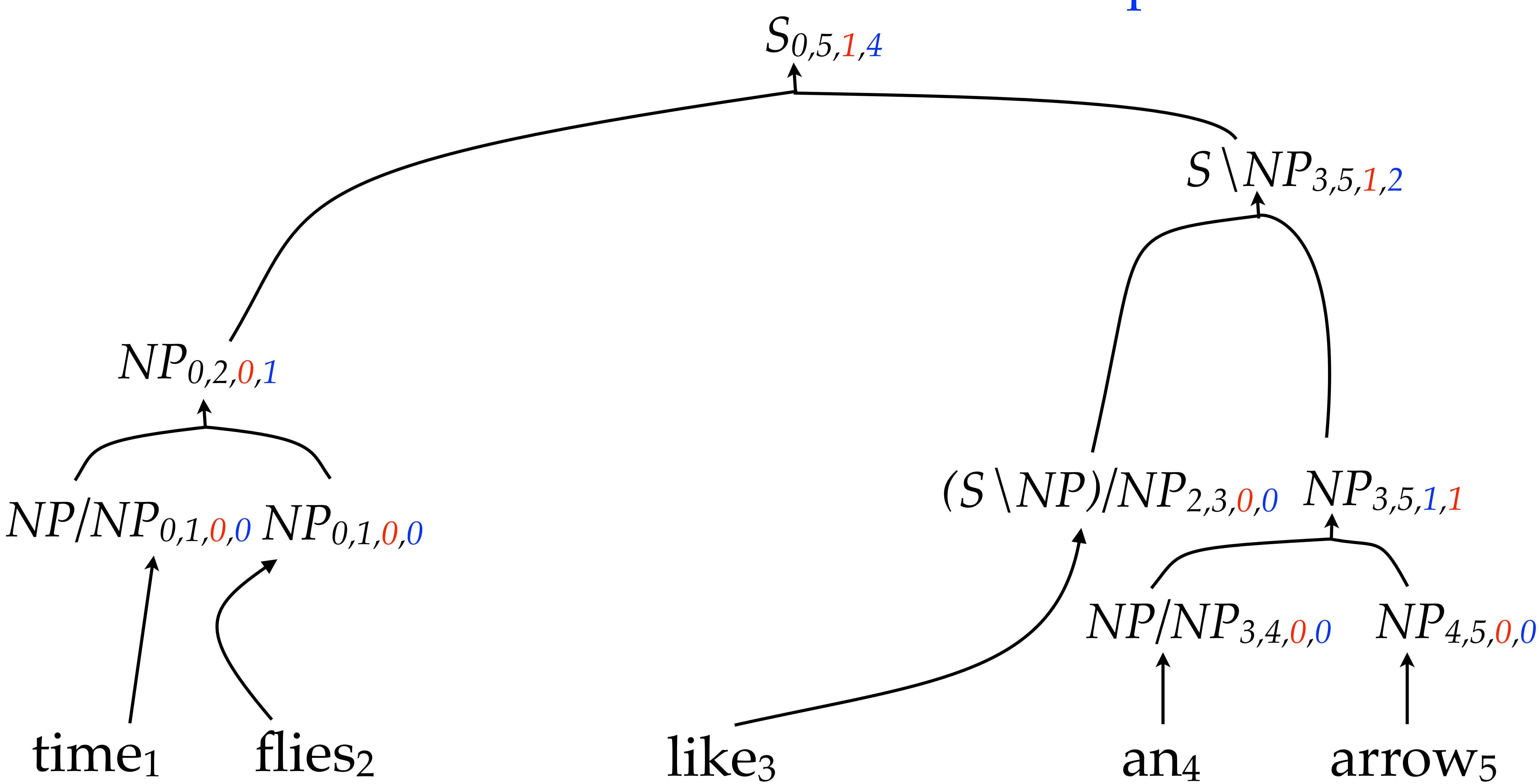

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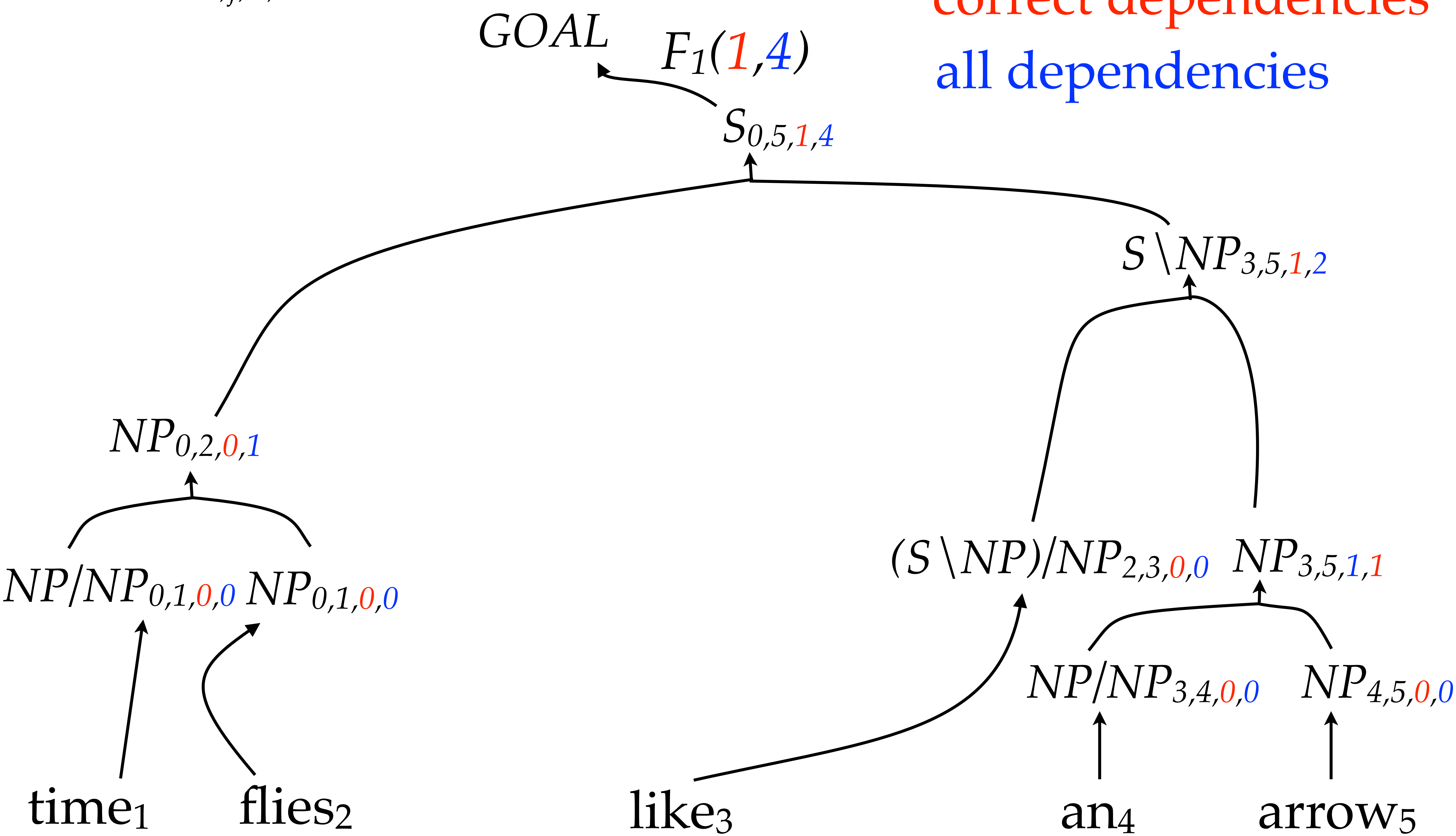
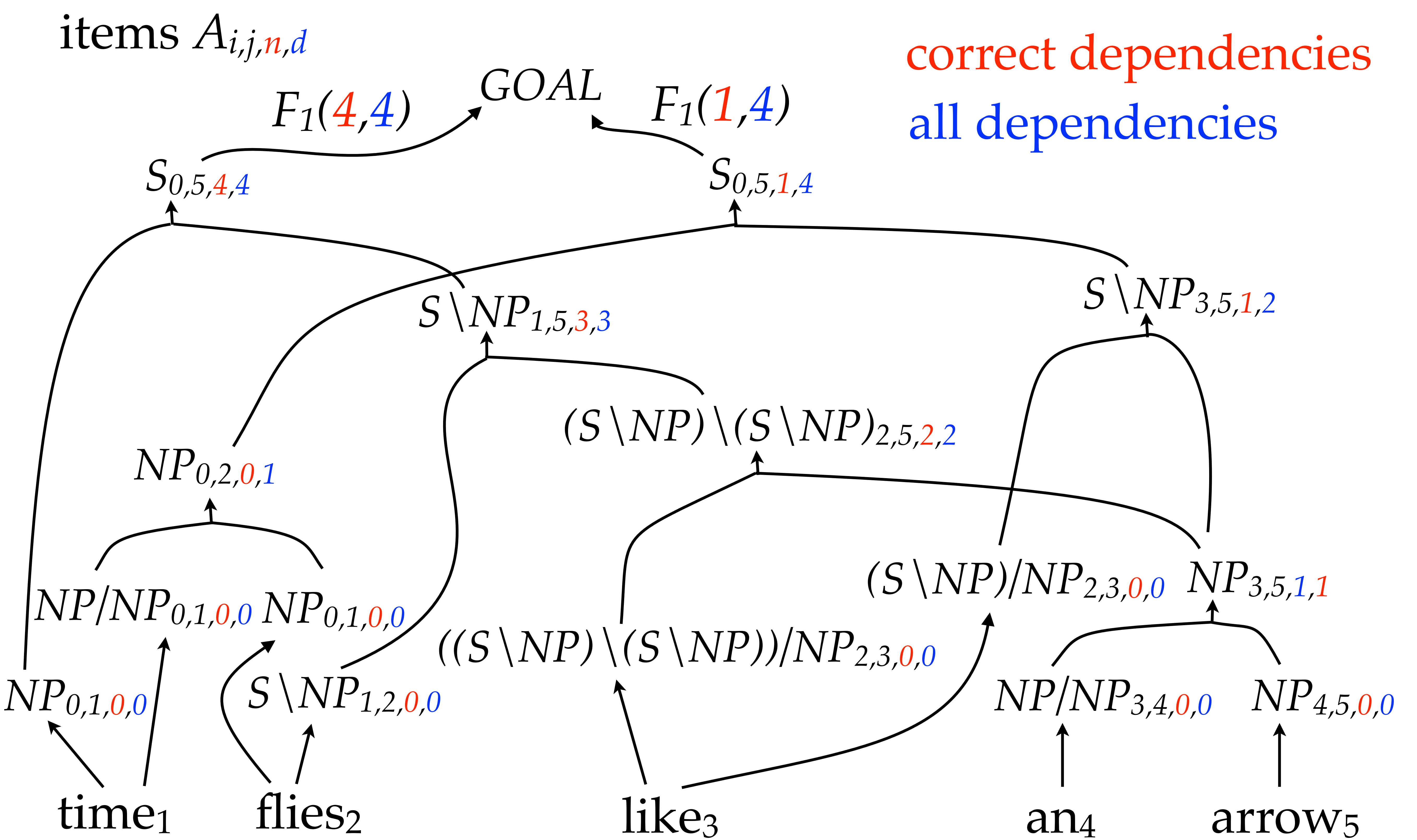
correct dependencies

all dependencies



Exact Losses with State-Split CKY

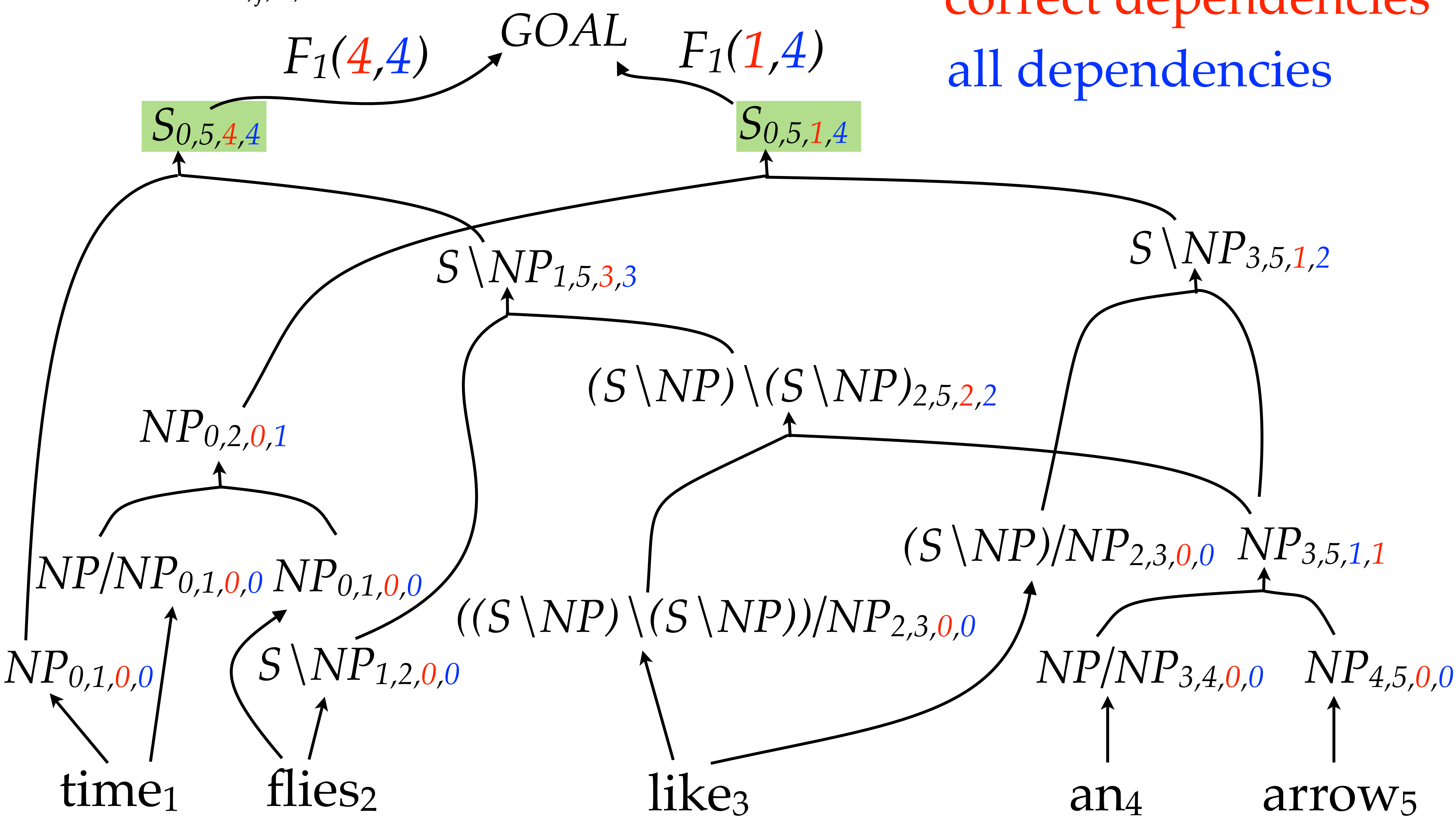


Exact Losses with State-Split CKY

items $A_{i,j,n,d}$

correct dependencies

all dependencies

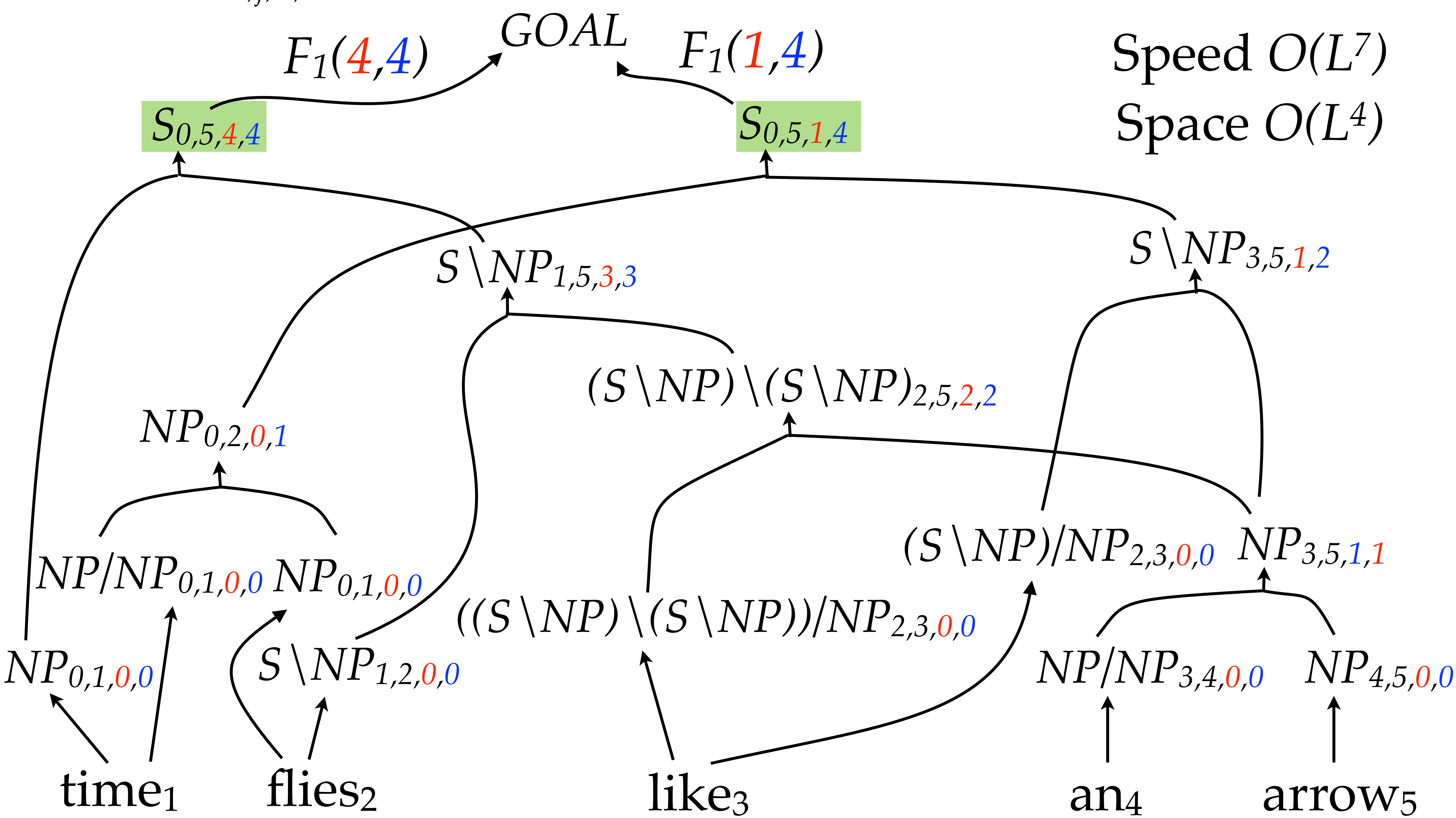


Exact Losses with State-Split CKY

items $A_{i,j,n,d}$

Speed $O(L^7)$

Space $O(L^4)$



Exact Losses with State-Split CKY

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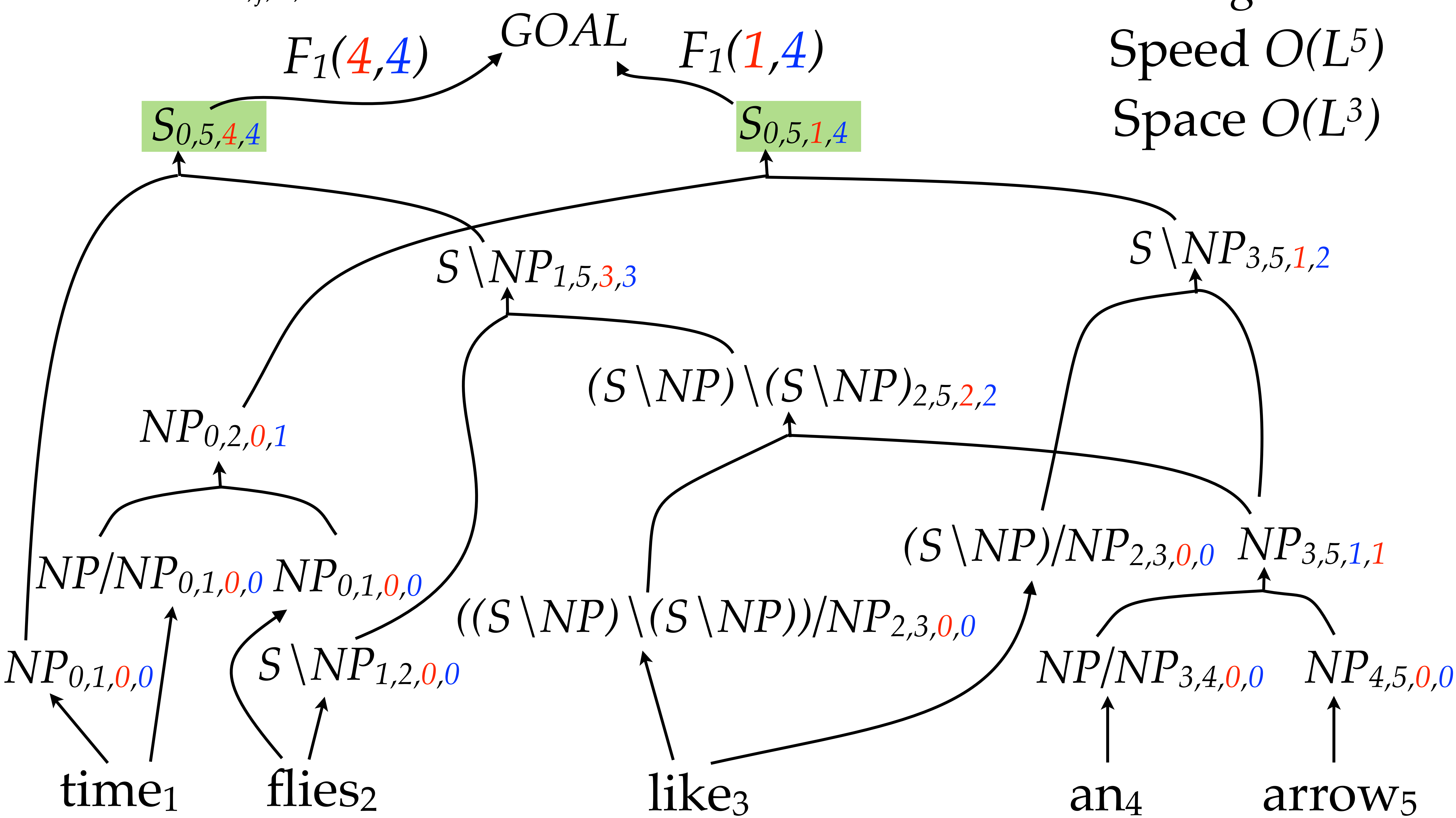

average case

Speed $O(L^5)$

Space $O(L^3)$

Experiments: Baseline + SMM

- Exact versus approximate loss functions on test:

Loss	Approx	Exact

Experiments: Baseline + SMM

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Precision	87.34	87.23

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F_1	87.69	87.71

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Loss	Approx	Exact
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Approximate loss functions very competitive!

Experiments: Baseline + SMM

- Results on test:
- CLL
  - tight beam: 87.73
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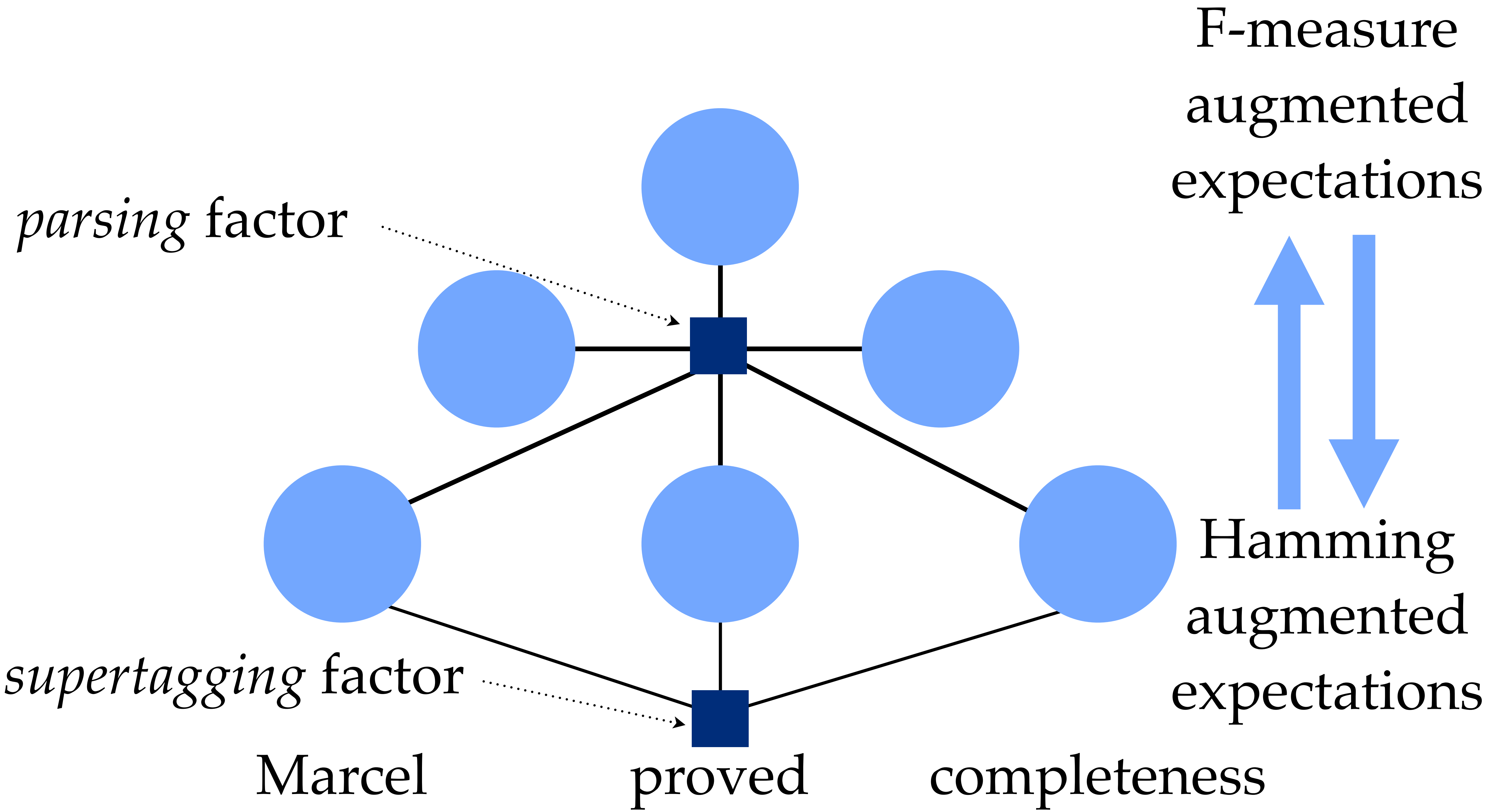
Best performance
in larger search space

Integrated Model + SMM



Experiments

- Results with integrated model using BP:

CLL	87.65

Experiments

- Results with integrated model using BP:

CLL	87.65
BP	88.86

Experiments

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CLL	87.65
BP	88.86
+ $DecF_1$	89.15

Experiments

- Results with integrated model using BP:

CLL	87.65	
BP	88.86	
+ DecF_1	89.15	parser loss
+ SA	**89.25**	Hamming loss

Experiments

- Auto-POS with integrated model using BP:

CLL	85.74
Petrov I-5	86.01

Fowler & Penn (2010)

Experiments

- Auto-POS with integrated model using BP:

CLL	85.74	
Petrov I-5	86.01	Fowler & Penn (2010)
BP	86.84	

Experiments

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Petrov 1-5	86.01	Fowler & Penn (2010)
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+ DecF_1	87.08	

Experiments

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CLL	85.74	
Petrov I-5	86.01	Fowler & Penn (2010)
BP	86.84	
+ $DecF_1$	87.08	parser loss
+ SA	**87.20**	Hamming loss

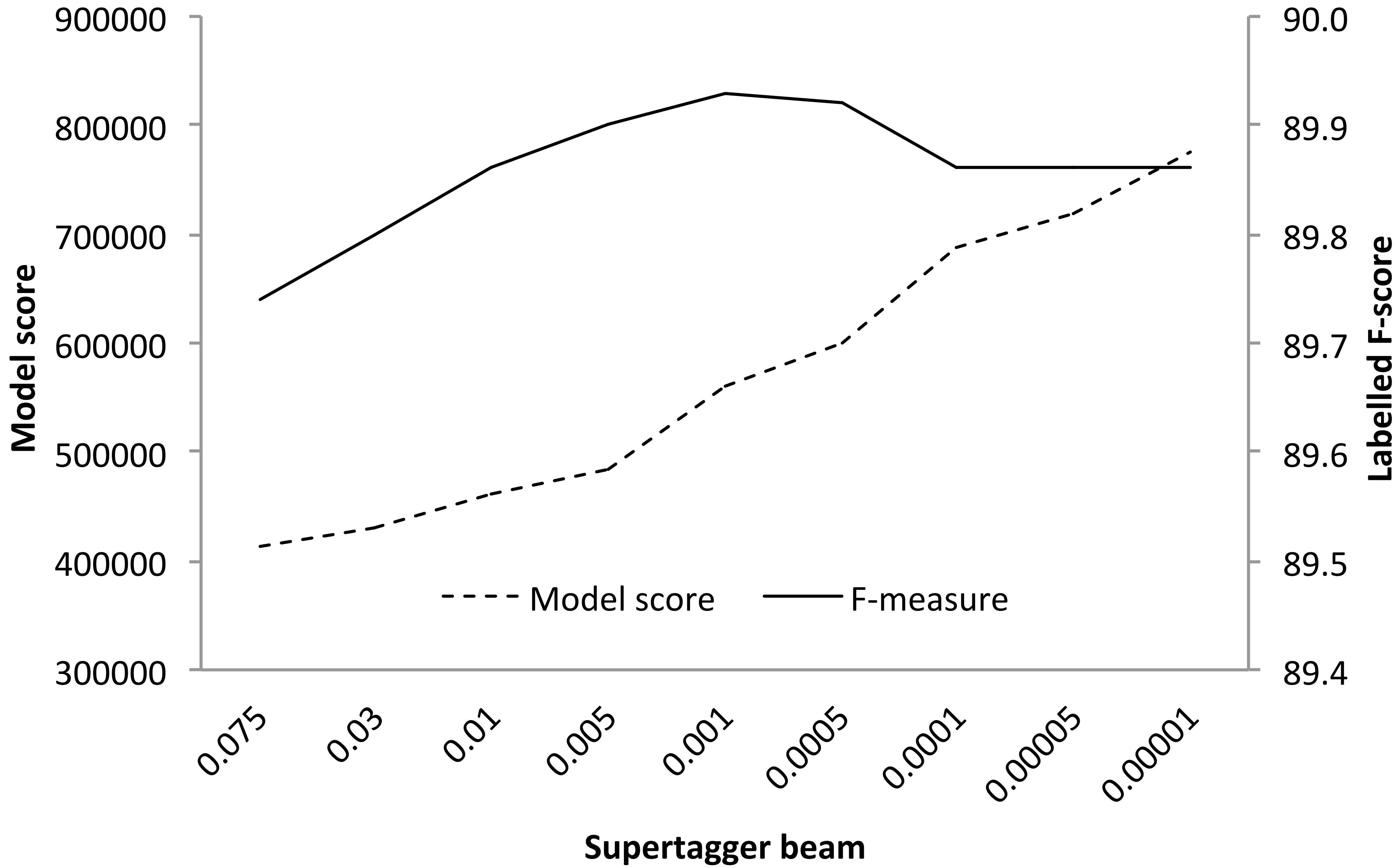
Experiments

- What is the performance when speed is important?
- Results with tight beam (AST):

	F_1	sent/sec	
CLL	87.73	65	
BP	88.20		
+ DecF_1	88.28	60	parser loss
+ SA	**88.46**		Hamming loss

Oracle Results Again

Belief Propagation



Conclusion

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- Methods are generally applicable.
- **Best reported results for CCG parsing (89.3)**

Future Directions

- Integration of POS sequence model.
- Combined models for grammar induction.
- Application to other grammar formalisms & problems.

Thanks!

Phil Blunsom
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