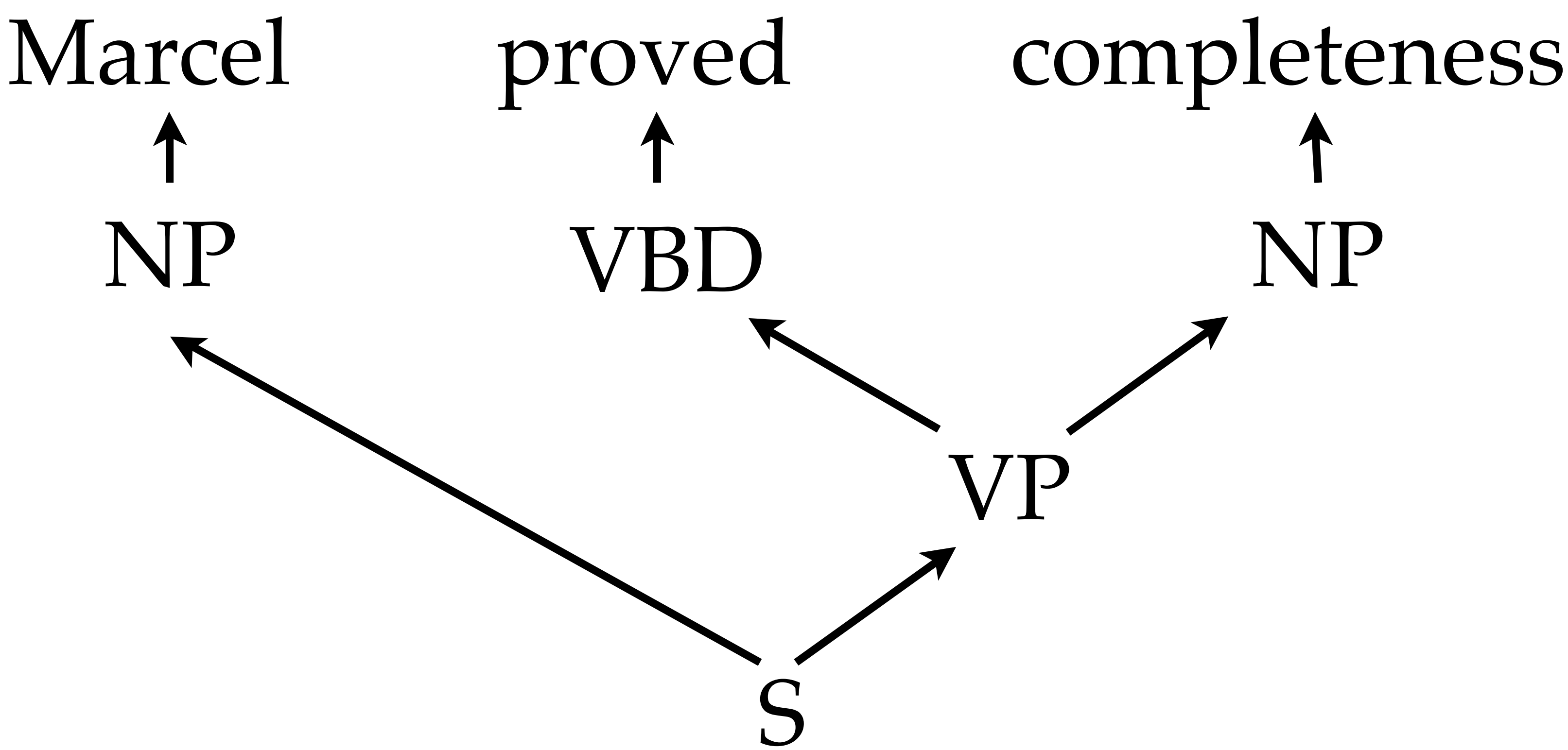
Integrated Supertagging and Parsing

Michael Auli
University of Edinburgh

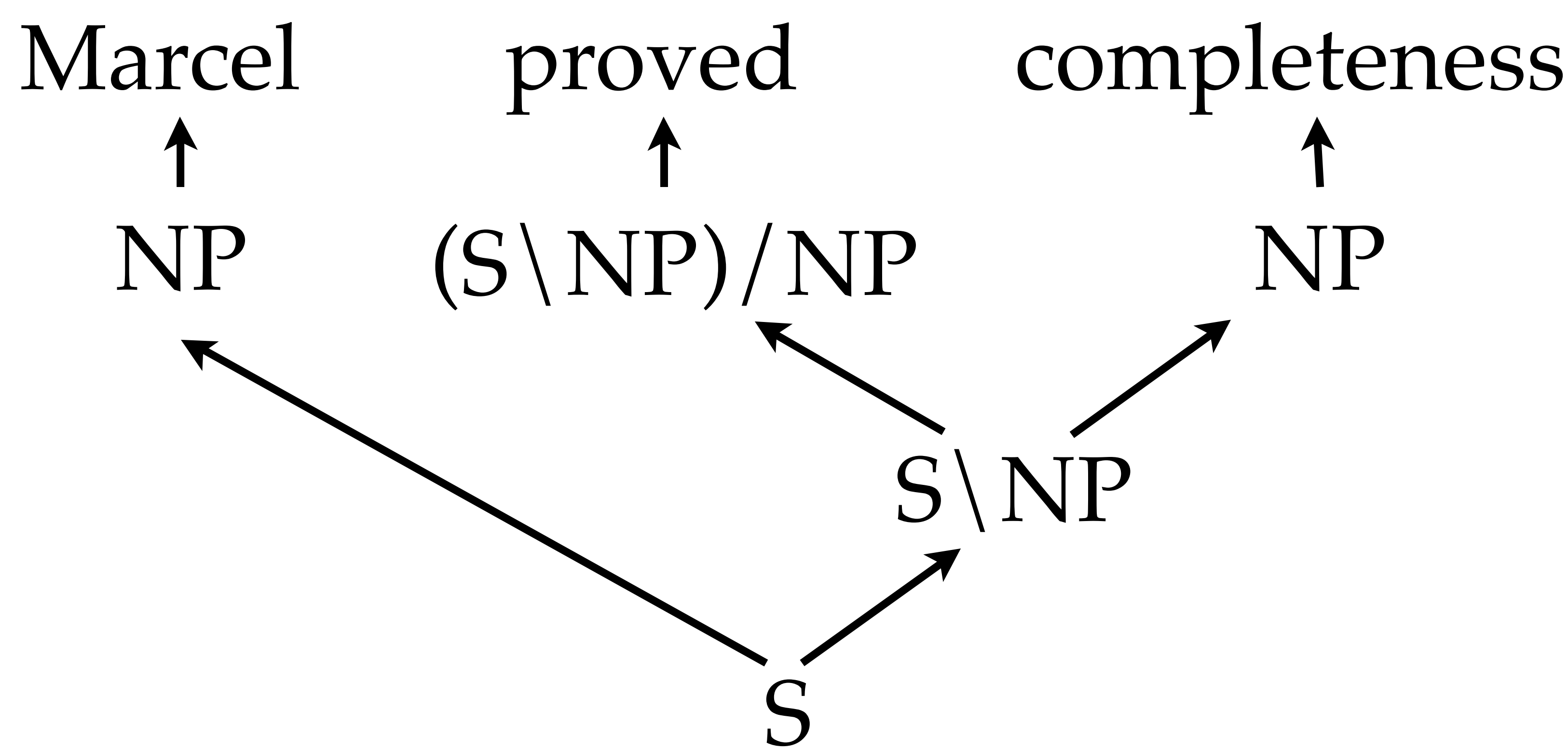
Parsing

Marcel proved completeness

Parsing

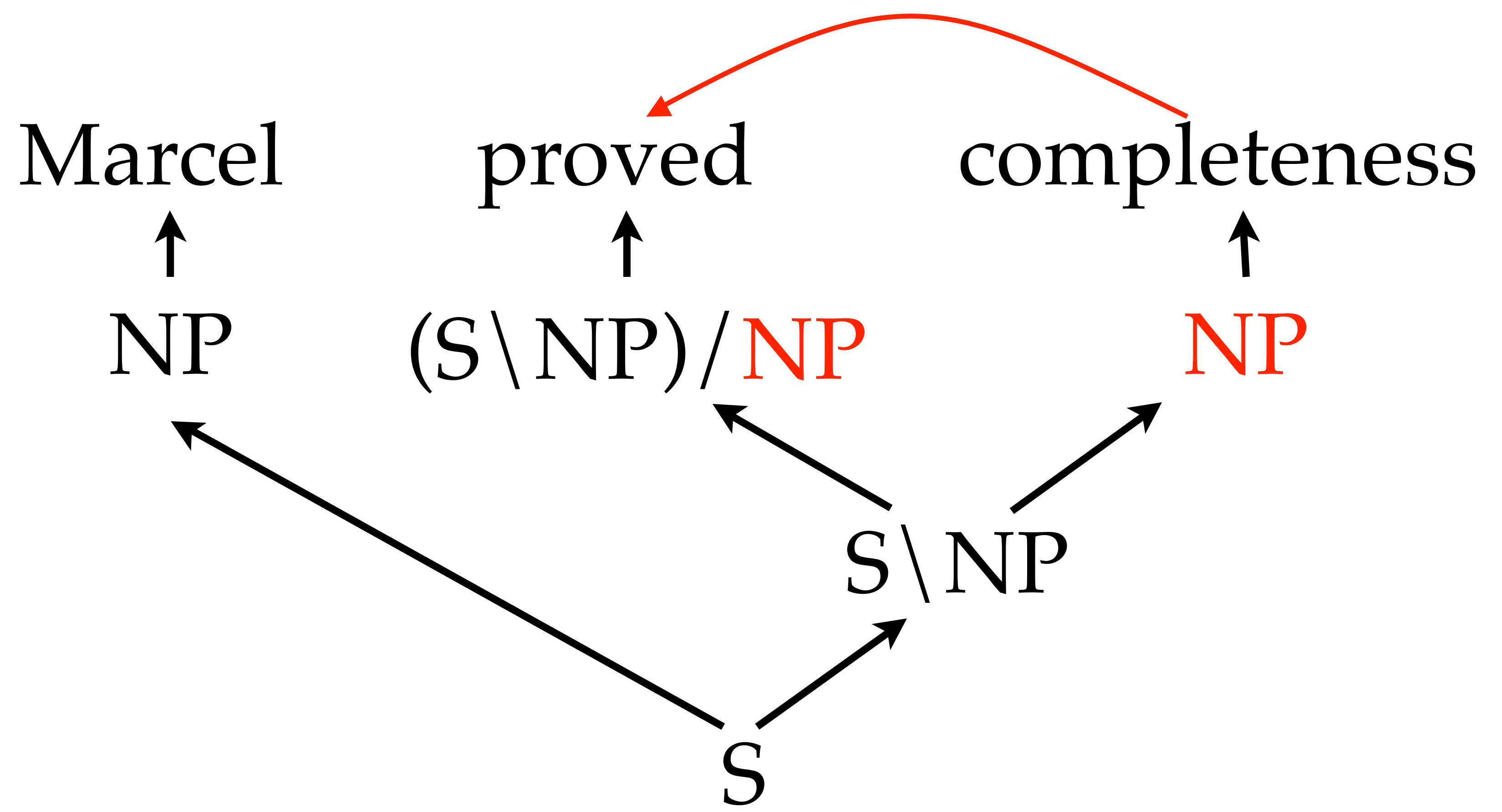


CCG Parsing



Combinatory Categorial Grammar (CCG; Steedman 2000)

CCG Parsing



<proved, (S\NP)/NP, completeness>

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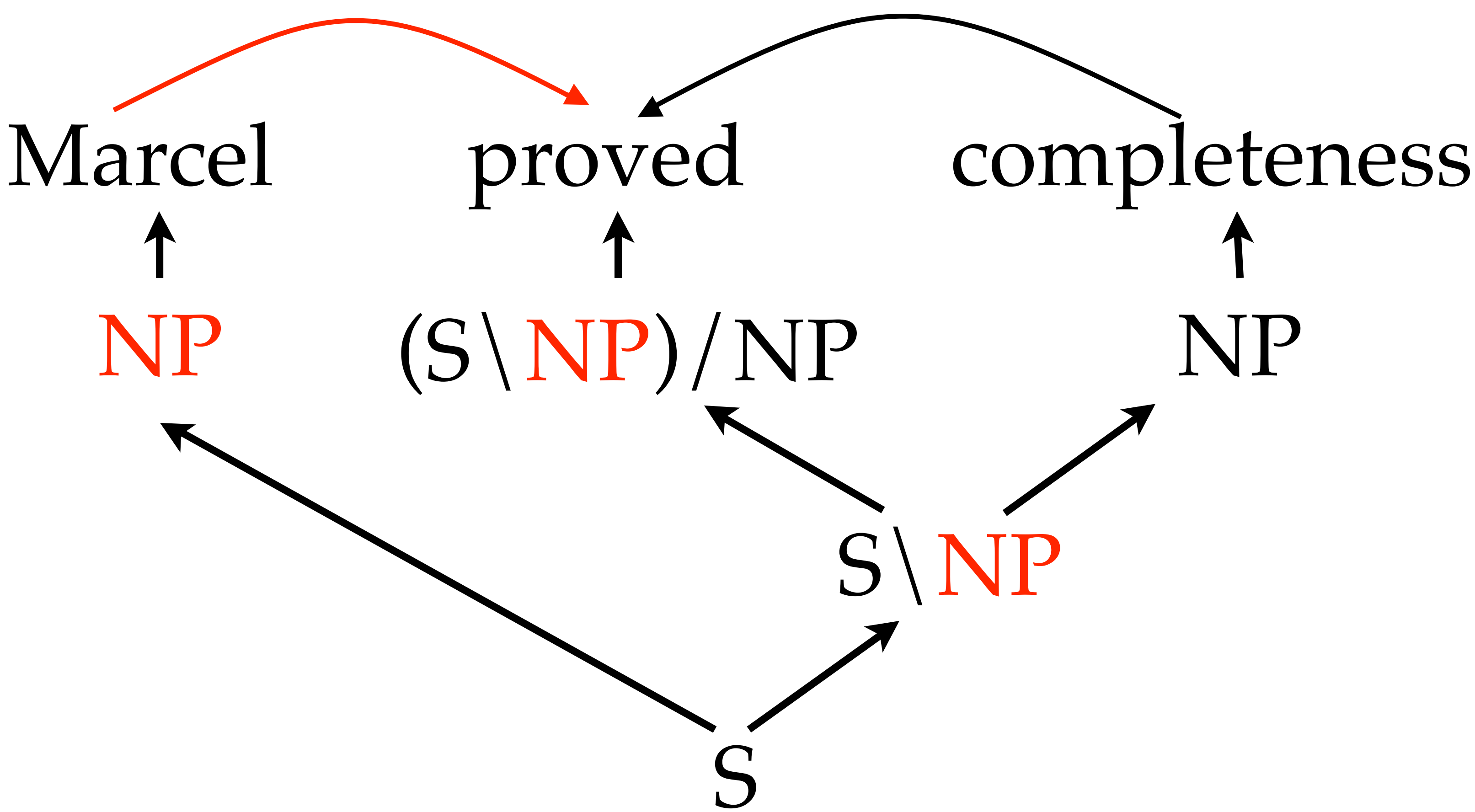

<proved, (S\NP)/NP, completeness>

<proved, (S\NP)/NP, Marcel>

Why CCG Parsing?

- MT: Can analyse nearly any span in a sentence
(Auli ’09; Mehay ‘10; Zhang & Clark 2011; Weese et. al. ’12)
e.g. “conjectured and proved completeness” $\vdash S\backslash NP$
- Composition of regular and context-free languages -- mirrors situation in syntactic MT (Auli & Lopez, ACL 2011)
- Transparent interface to semantics (Bos et al. 2004)
e.g. proved $\vdash (S\backslash NP)/NP : \lambda x.\lambda y.\mathit{proved'}\ xy$

CCG Parsing is hard!

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

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

Supertagging

Marcel proved completeness

Supertagging

Marcel	proved	completeness
NP	$(S\backslash NP)/NP$	NP

Supertagging

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Supertagging

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

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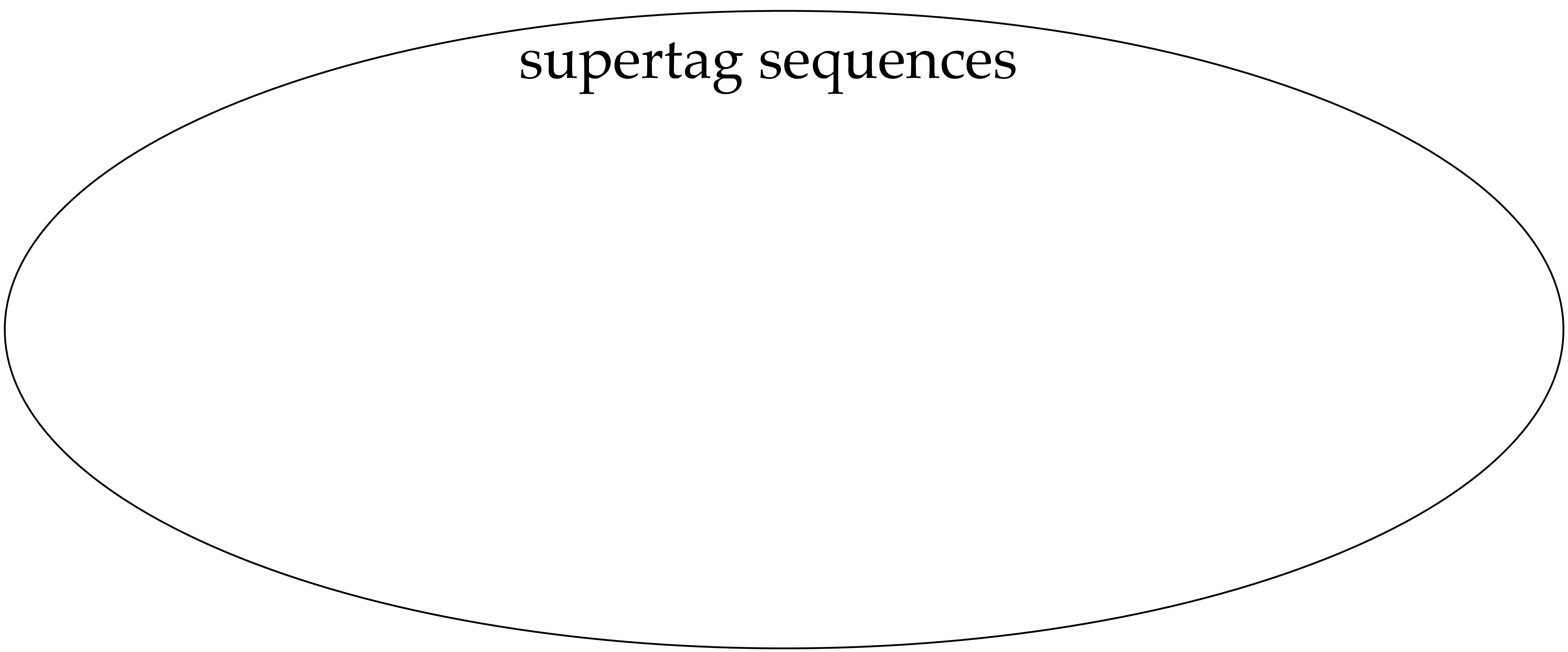

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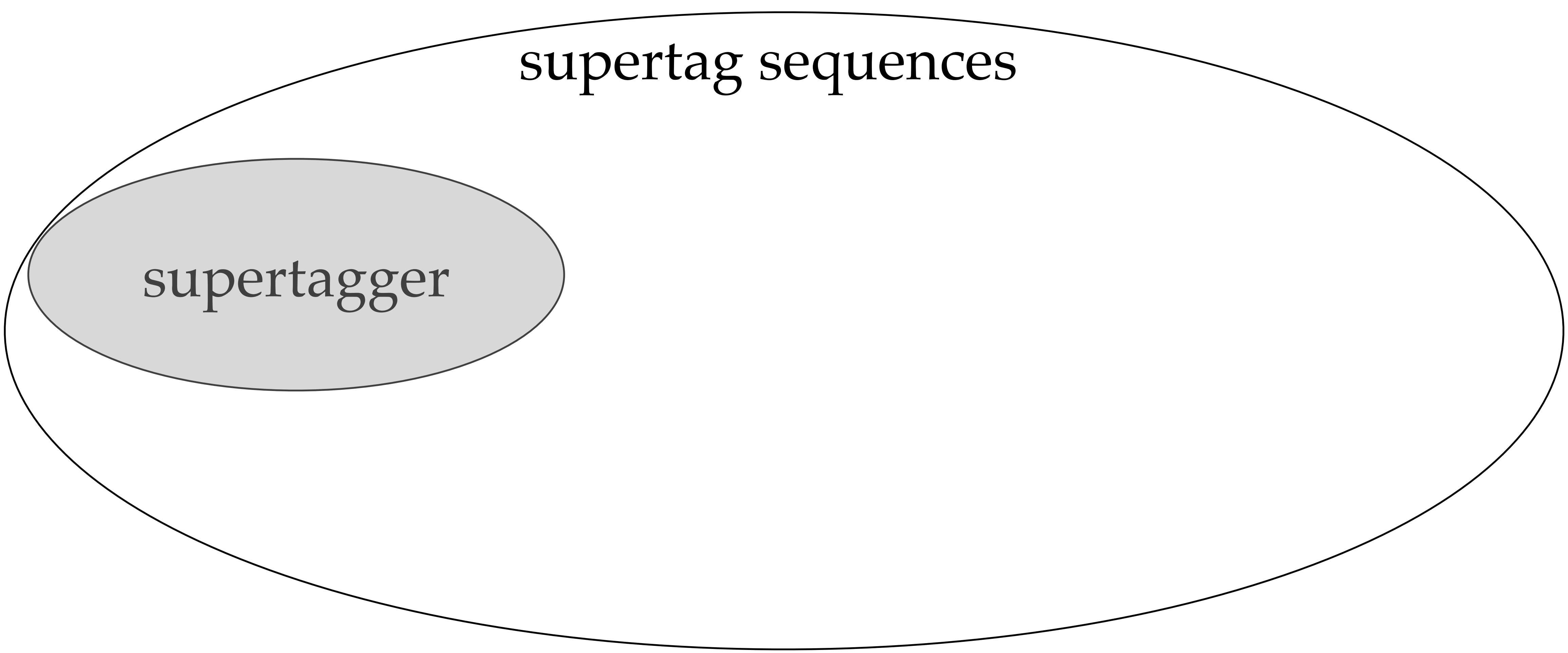

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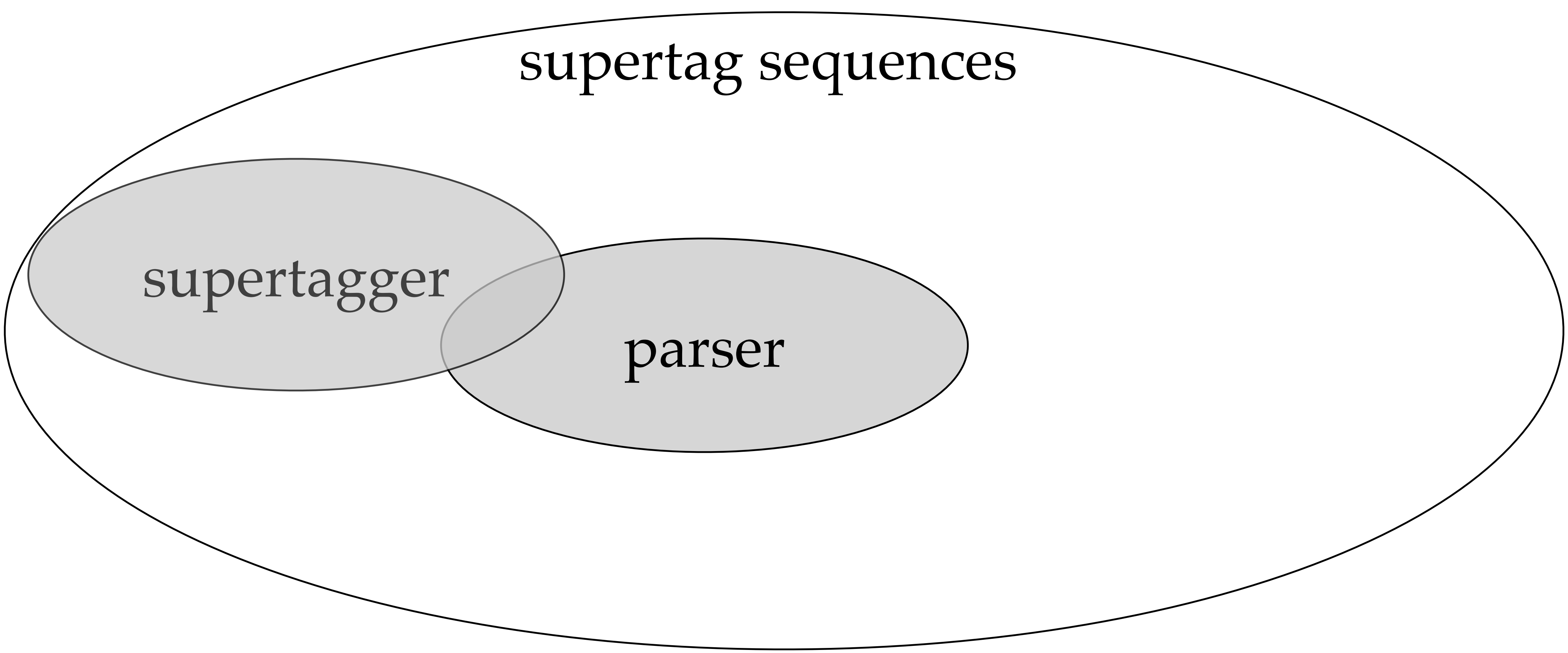

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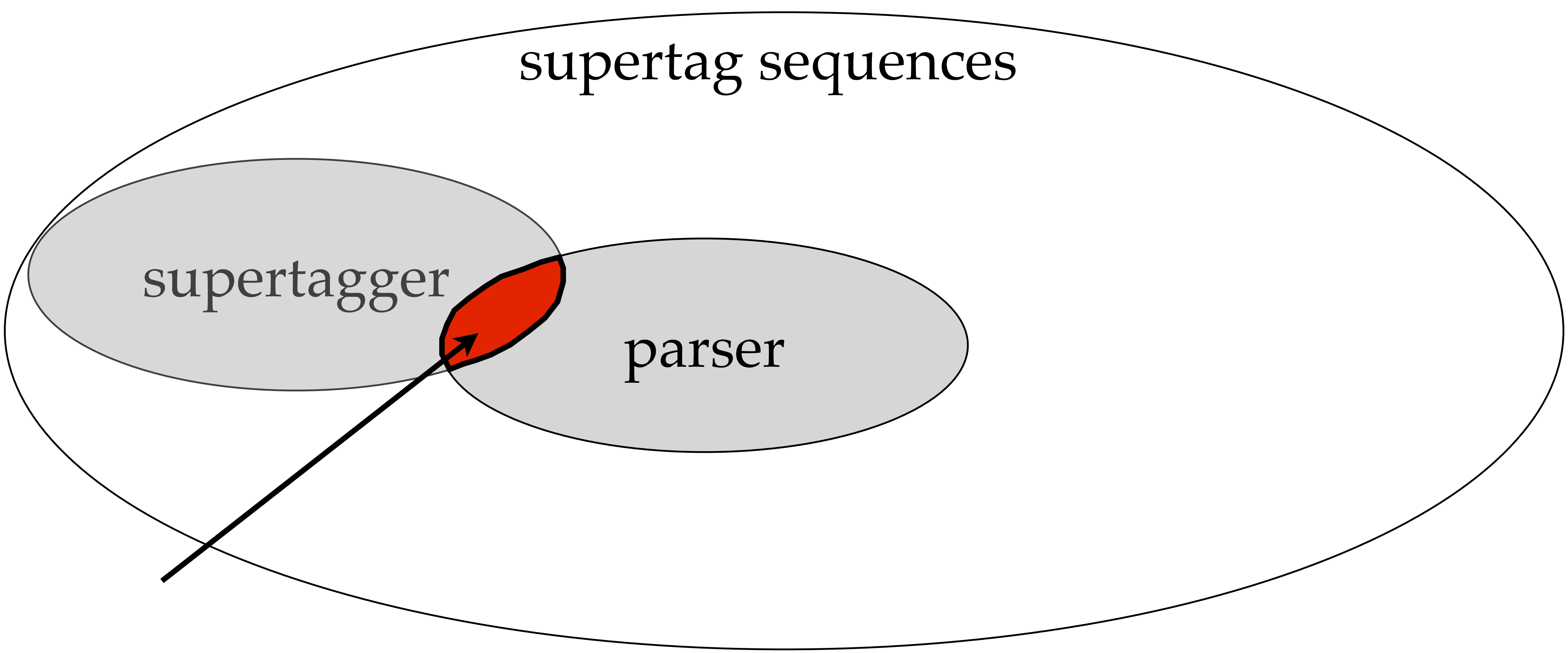

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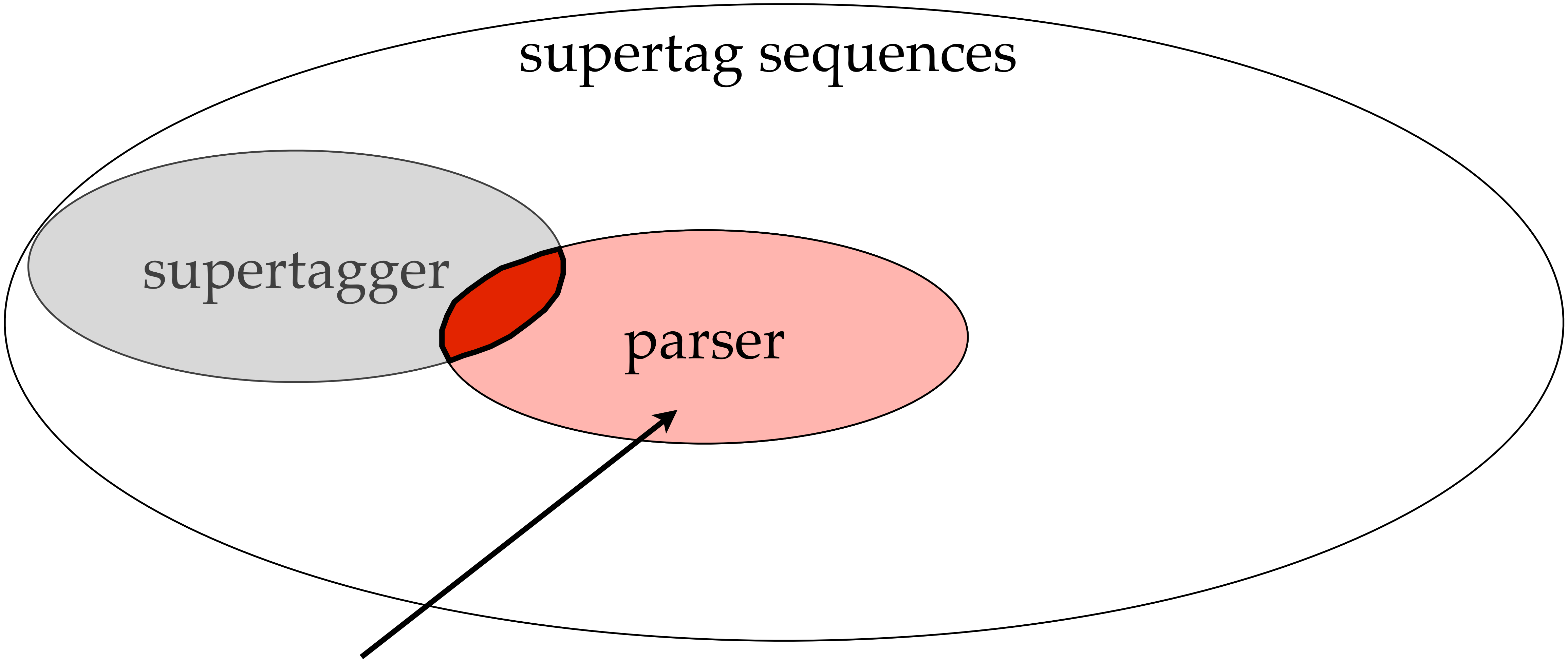

This talk

- Analysis of state-of-the-art approach
  Trade-off between efficiency and accuracy (ACL 2011a)
- Integrated supertagging and parsing
  with Loopy Belief Propagation and Dual Decomposition (ACL 2011b)
- Training the integrated model
  with Softmax-Margin towards task-specific metrics (EMNLP 2011)

Methods achieve **most accurate** CCG parsing results.

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Methods achieve

Adaptive Supertagging

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

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.
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- Algorithm:
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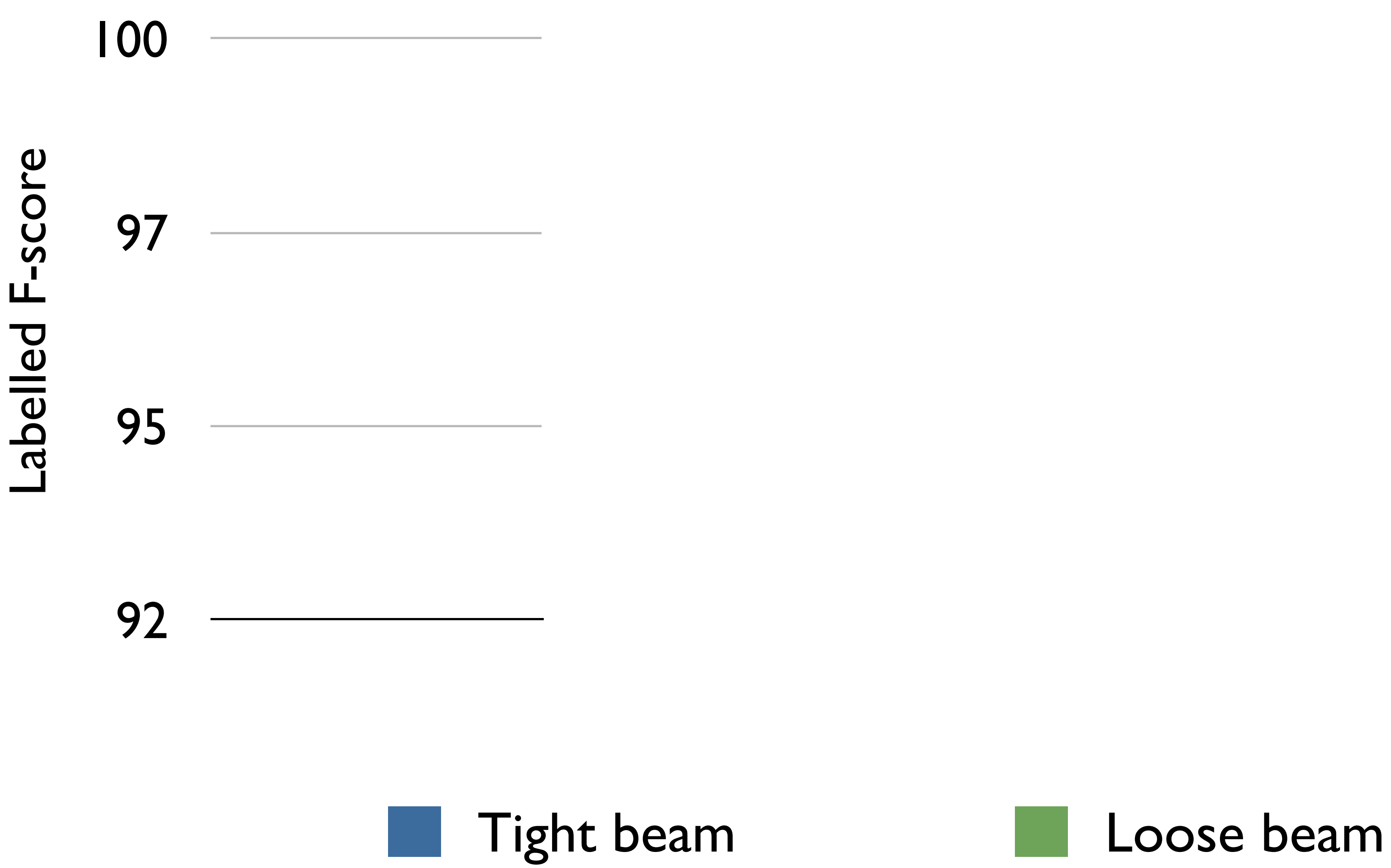
- **Q: are parses returned in early rounds suboptimal?**

Answer...

Oracle parsing
(Huang 2008)

Standard parsing
(Clark and Curran 2007)



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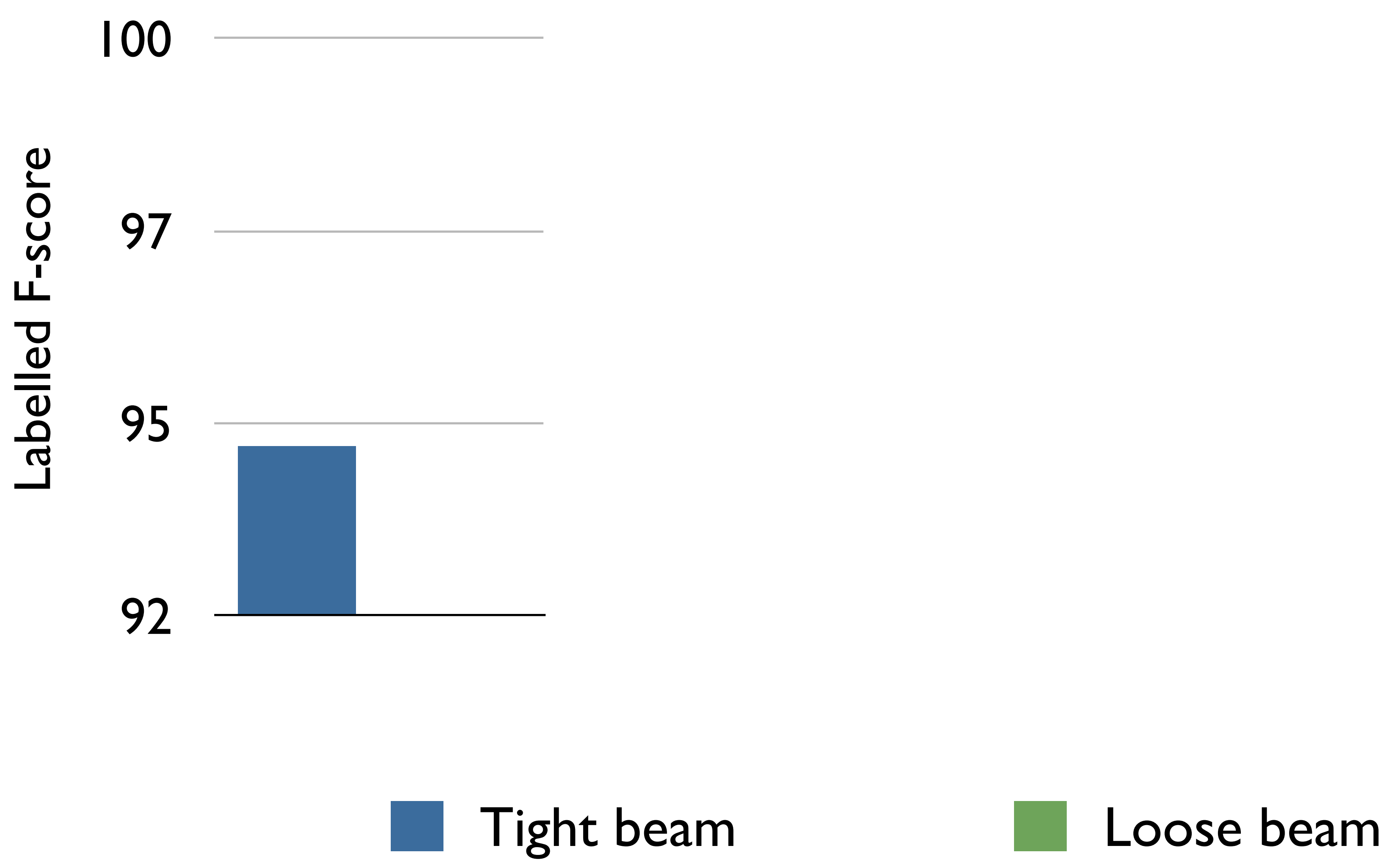

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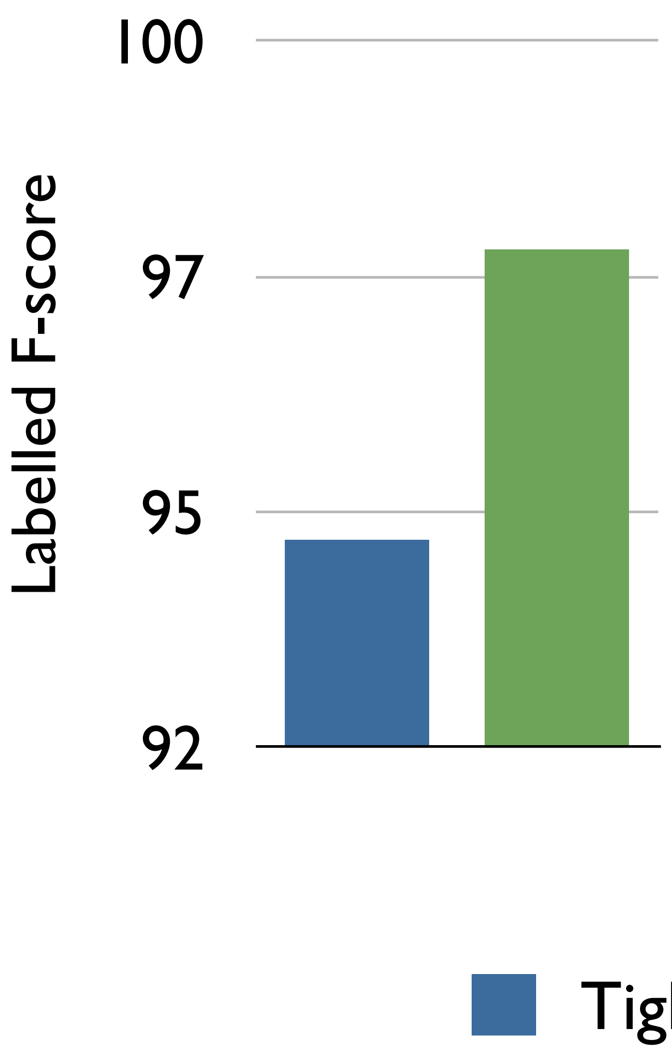

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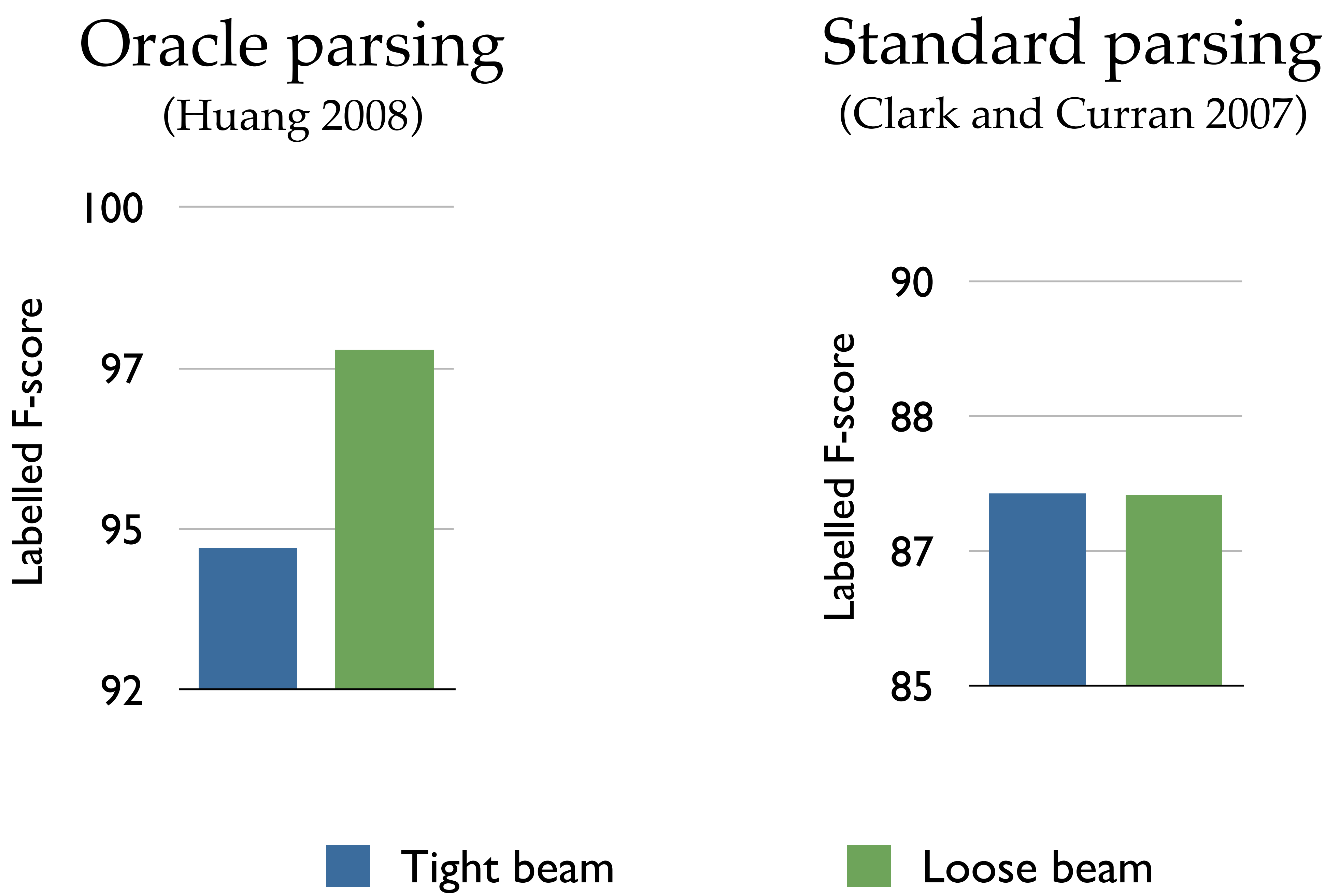
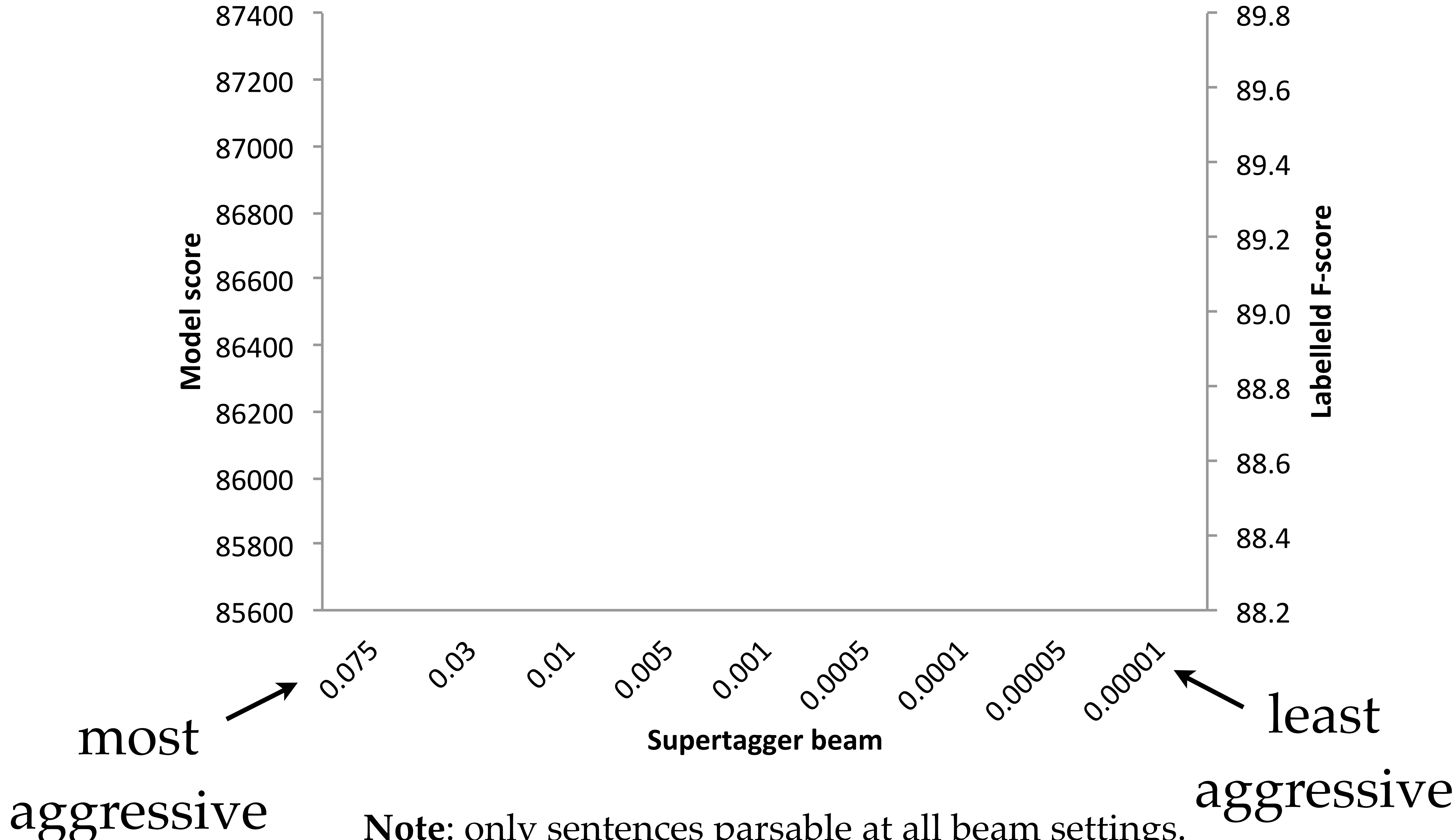


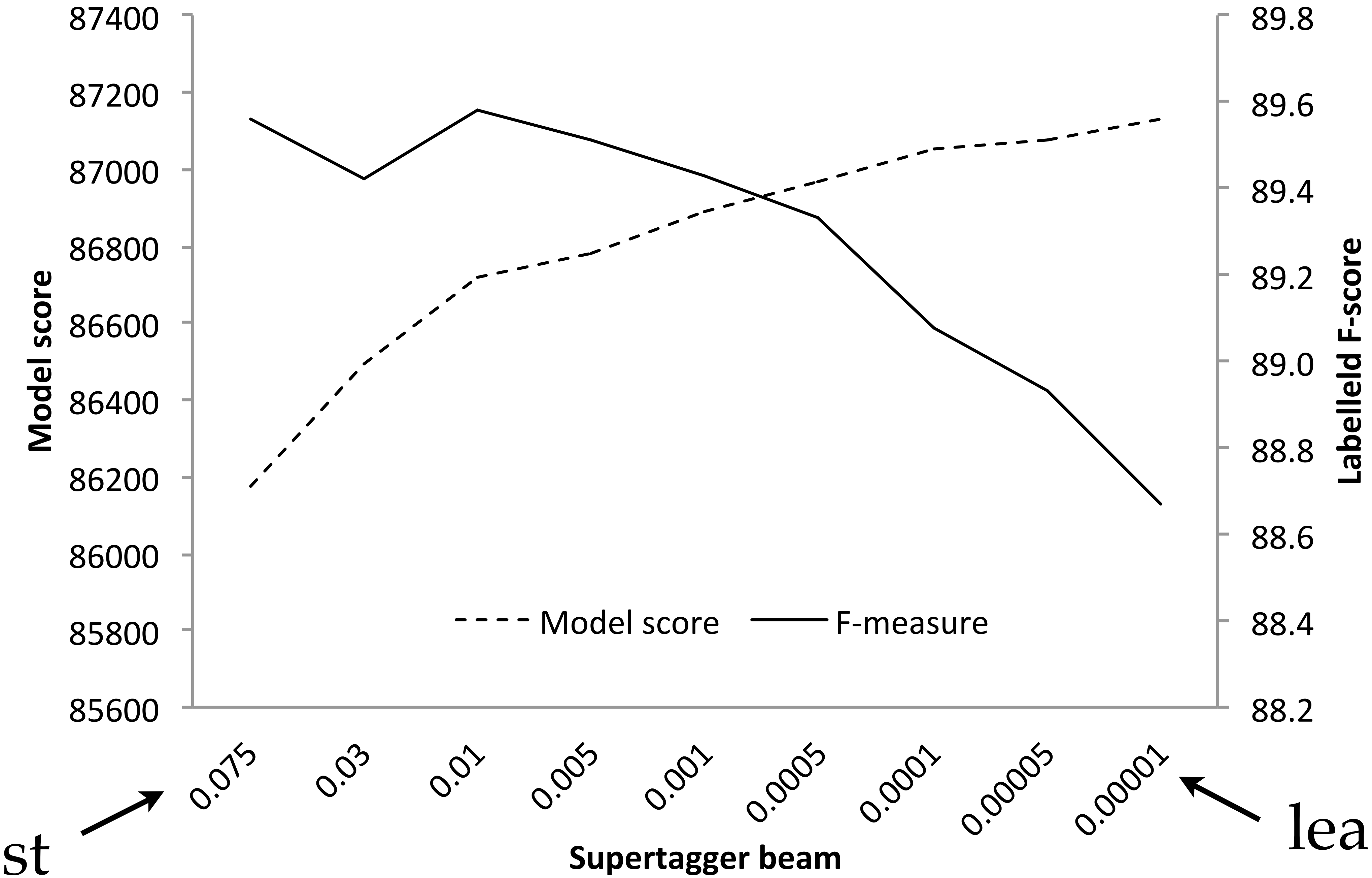
Oracle parsing
(Huang 2008)
Standard parsing
(Clark and Curran 2007)
Labelled F-score
100
97
95
92
90
88
87
85
Tight beam
Loose beam

Parsing



Note: only sentences parsable at all beam settings.

Parsing

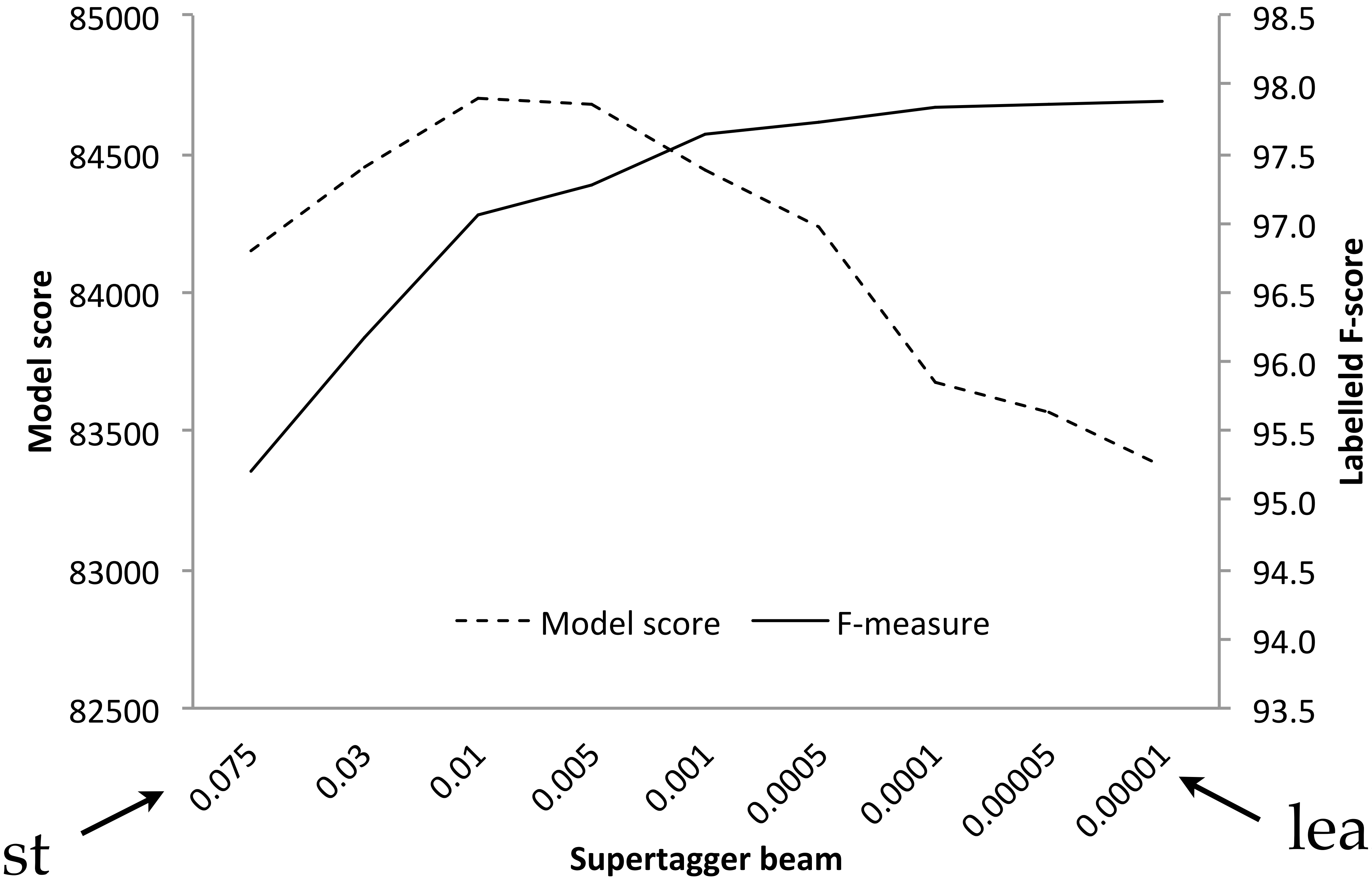


most aggressive

least aggressive

Note: only sentences parsable at all beam settings.

Oracle Parsing



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- Supertagger keeps parser from making serious errors.
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- Why not combine supertagger and parser into one?

Overview

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Integrated Model

- Supertagger & parser are 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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$\Downarrow$

new parsing problem: ${}_{q}\mathrm{B}_{s}\ {}_{s}\mathrm{C}_{r} \rightarrow {}_{q}\mathrm{A}_{r}$ $\quad O(G^3n^3)$

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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

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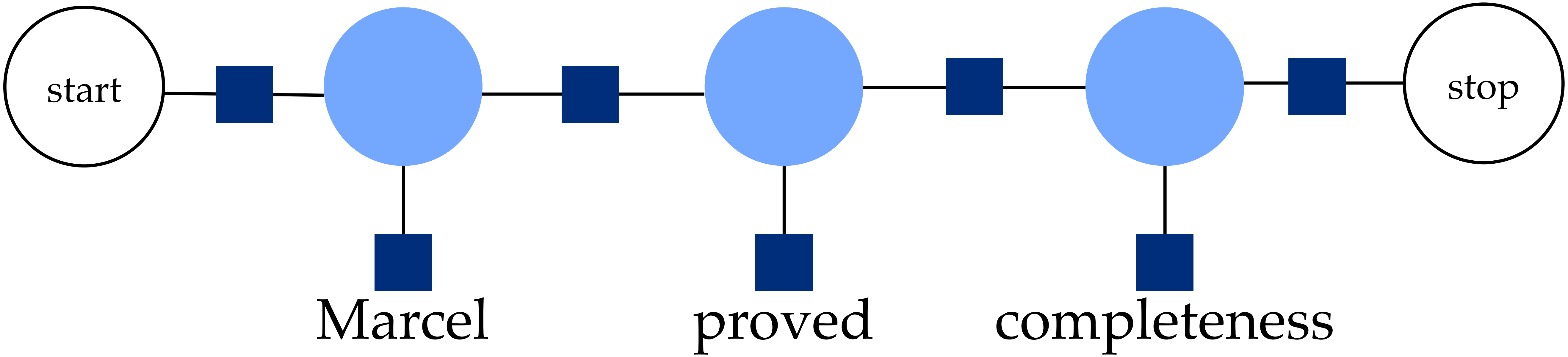
Forward-backward is belief propagation (Smyth et al. 1997)

Belief Propagation



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

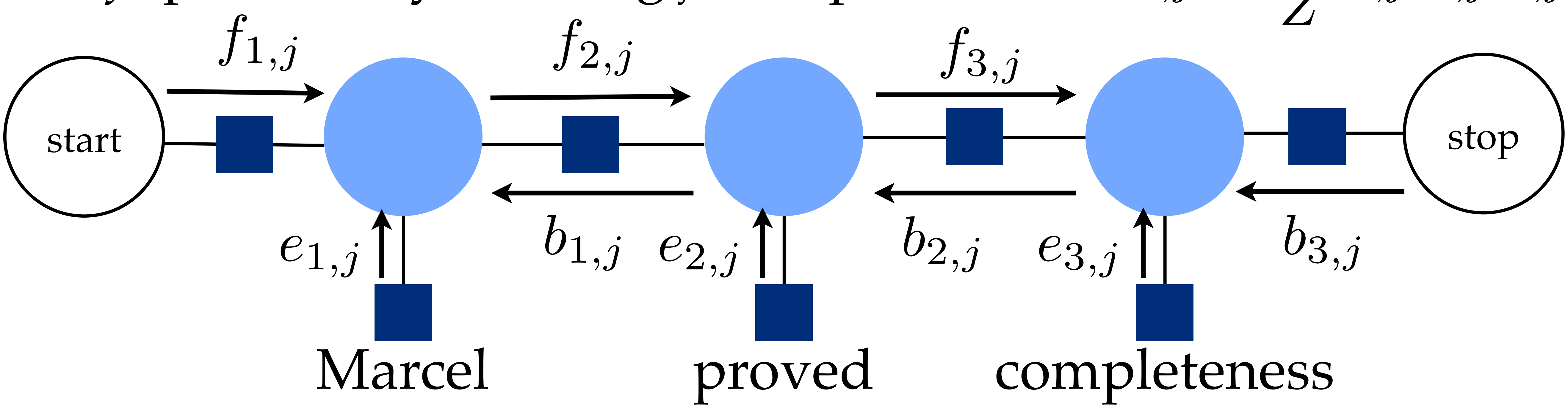
Belief Propagation

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



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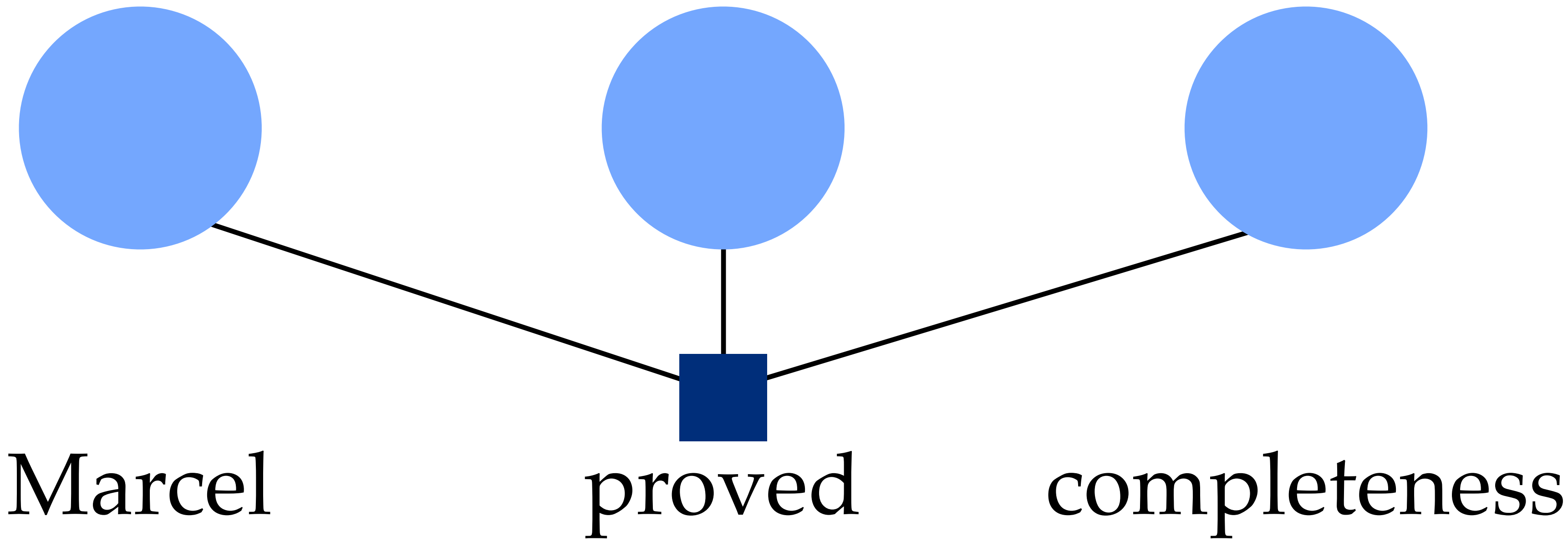
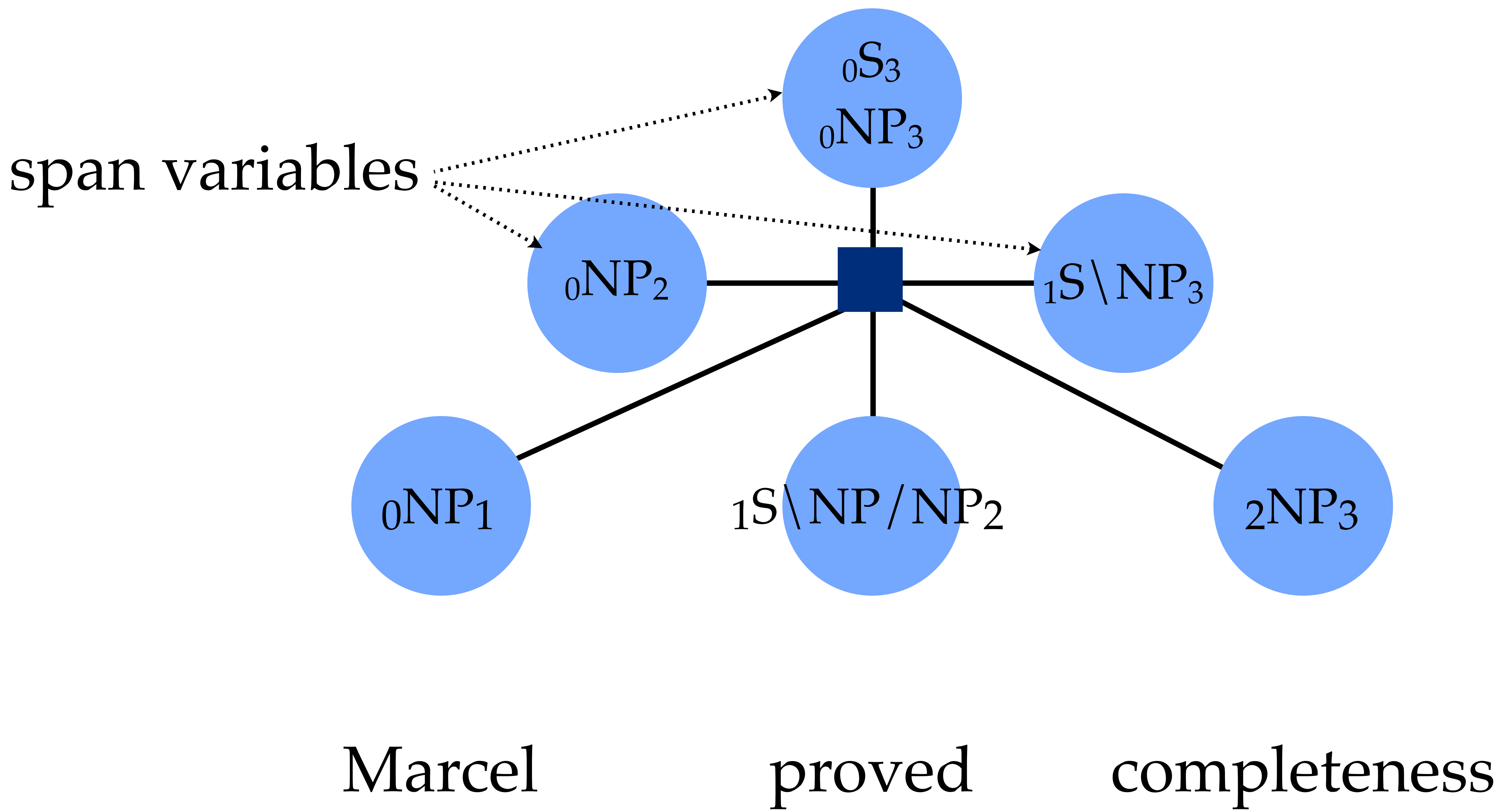
Belief Propagation

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



Belief Propagation

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



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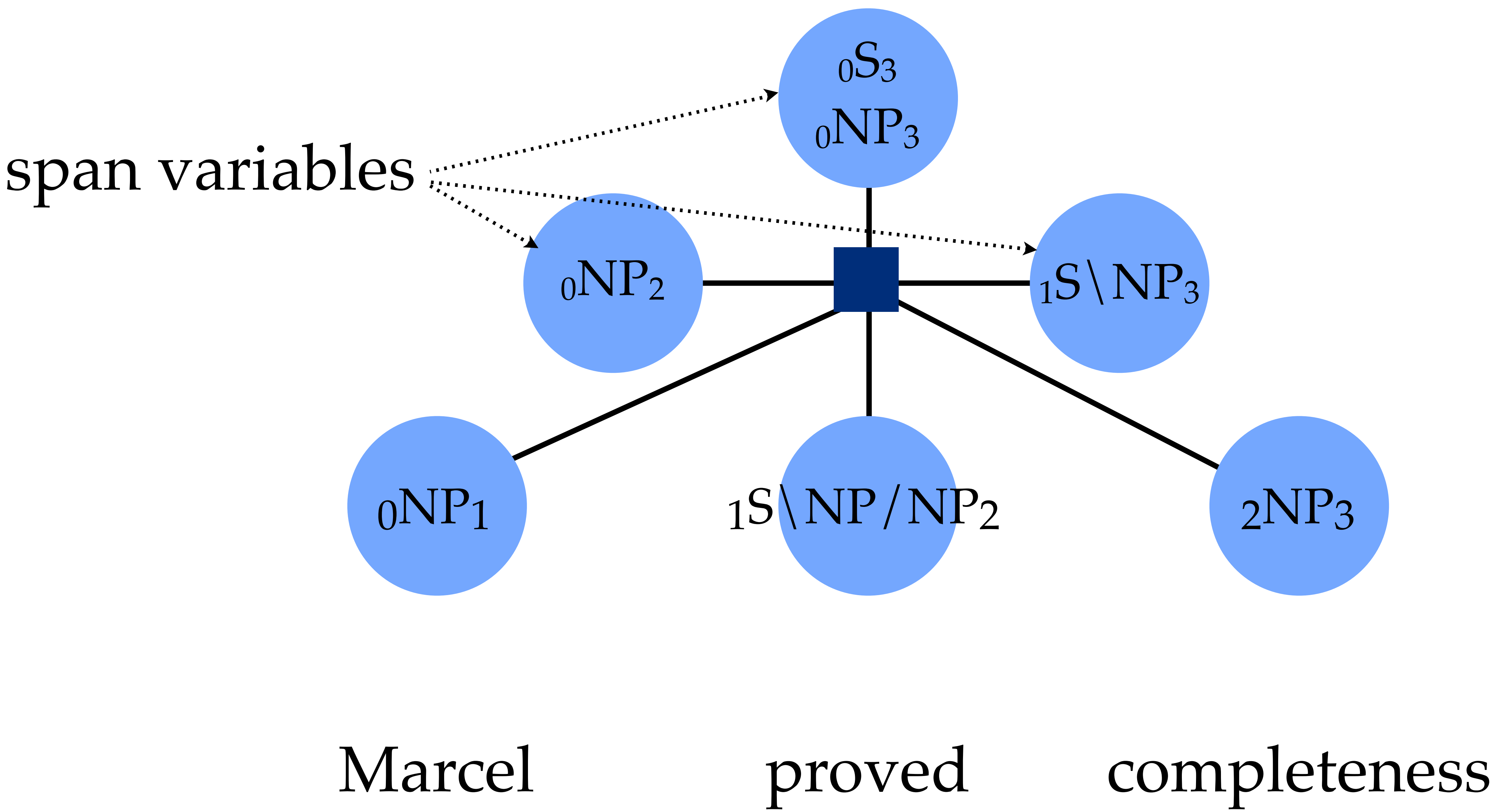
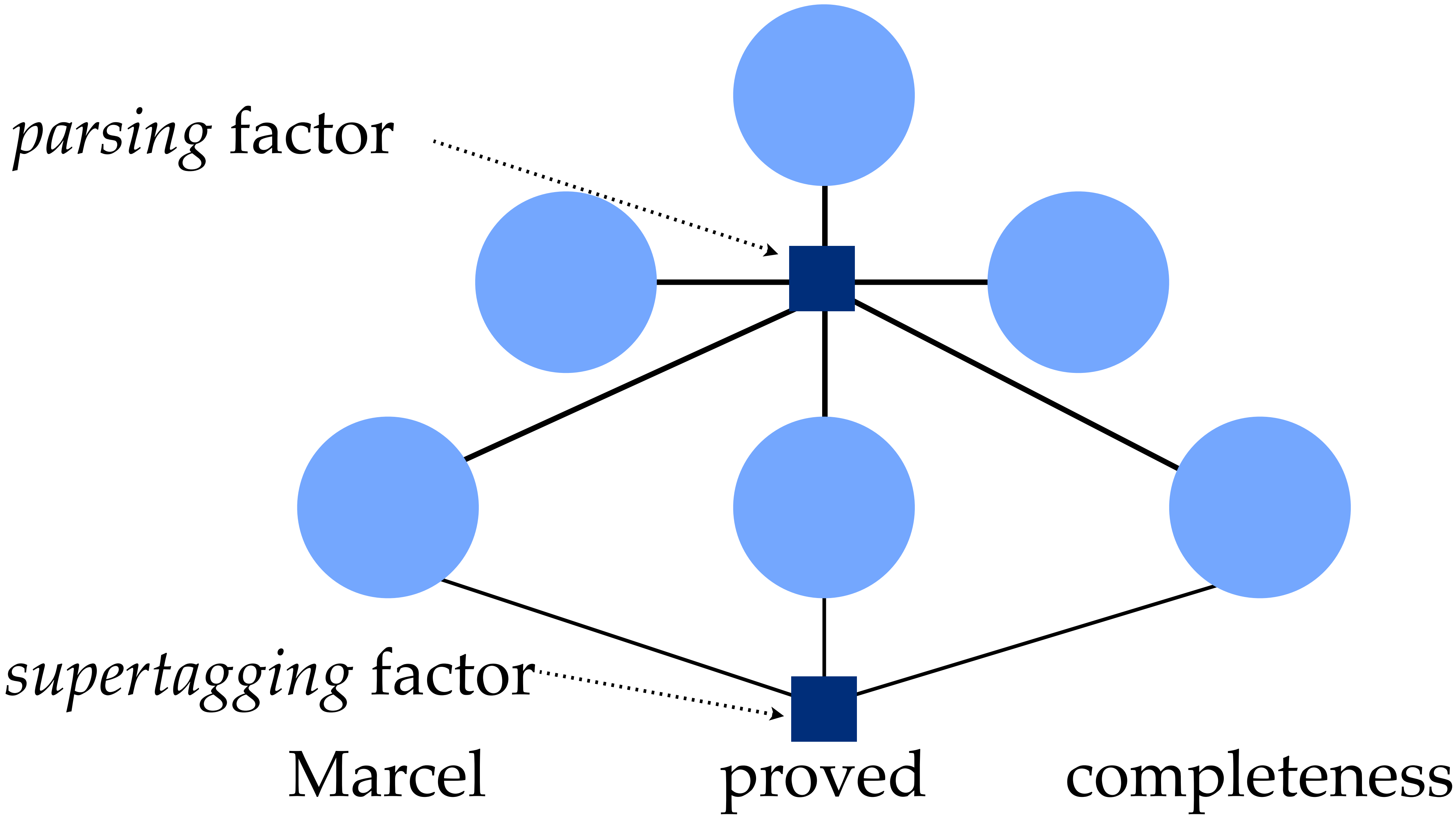


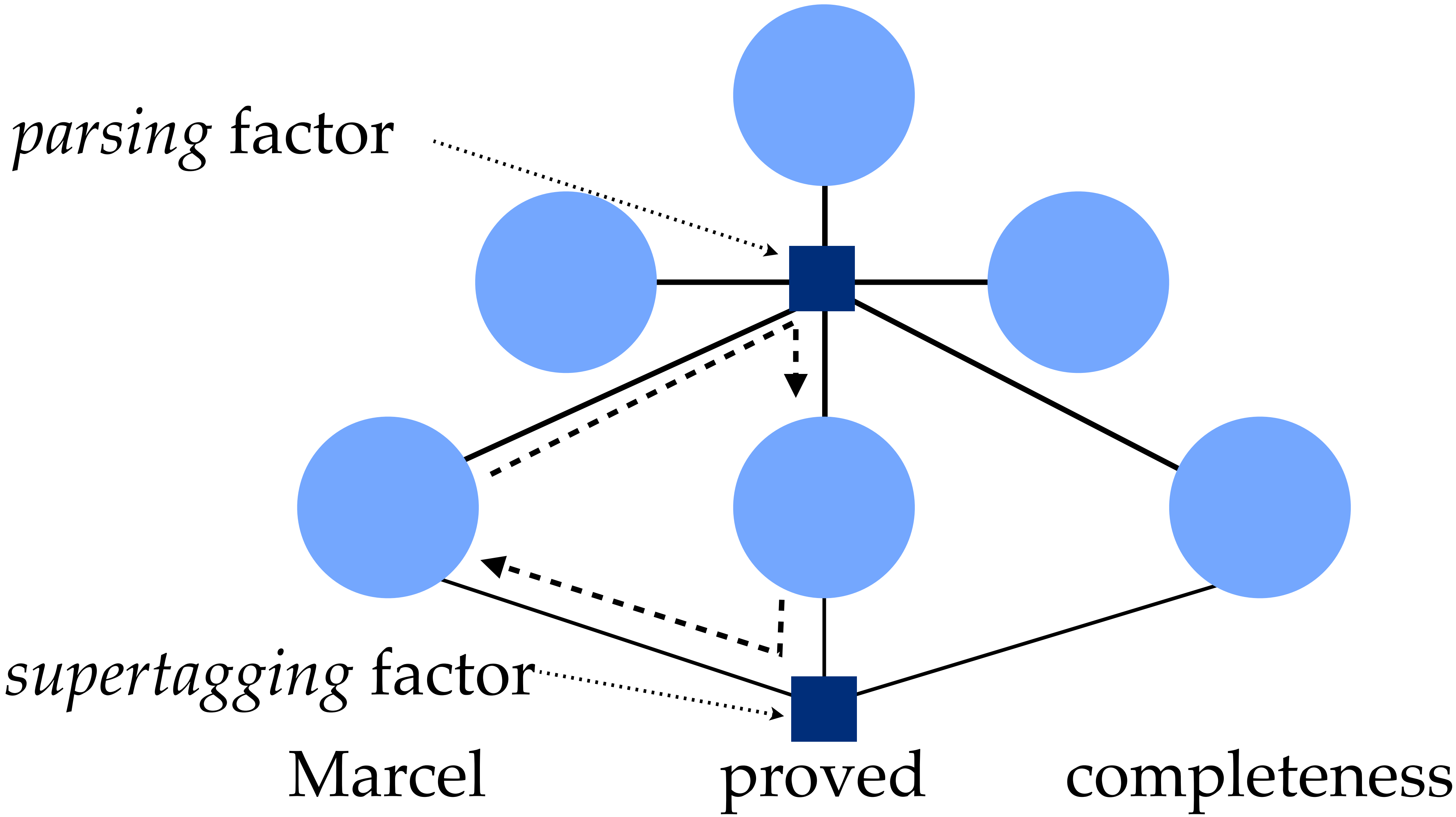
Inside-outside is belief propagation (Sato 2007)

Belief Propagation



Belief Propagation

Graph is not a tree!



Loopy Belief Propagation

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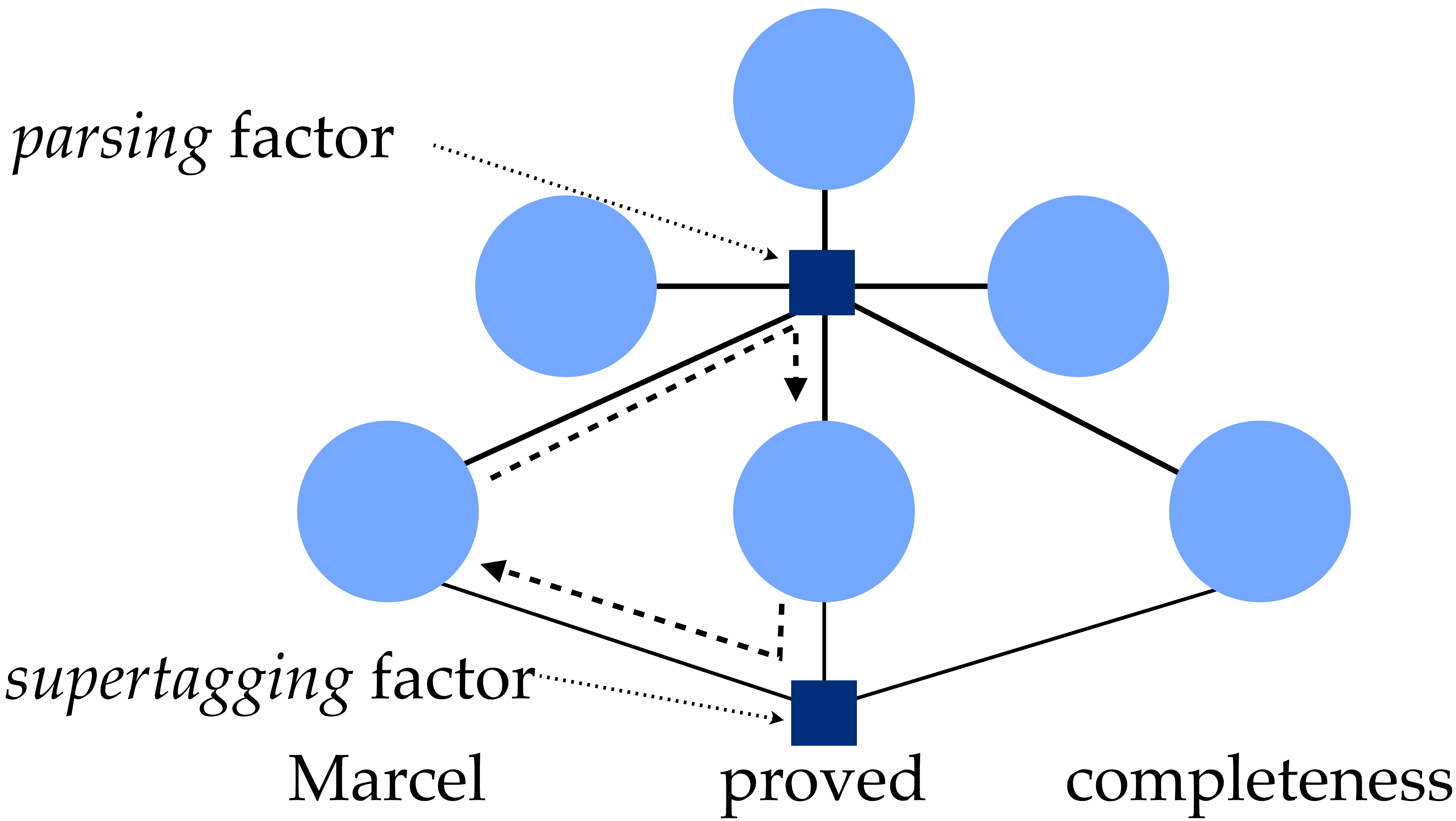

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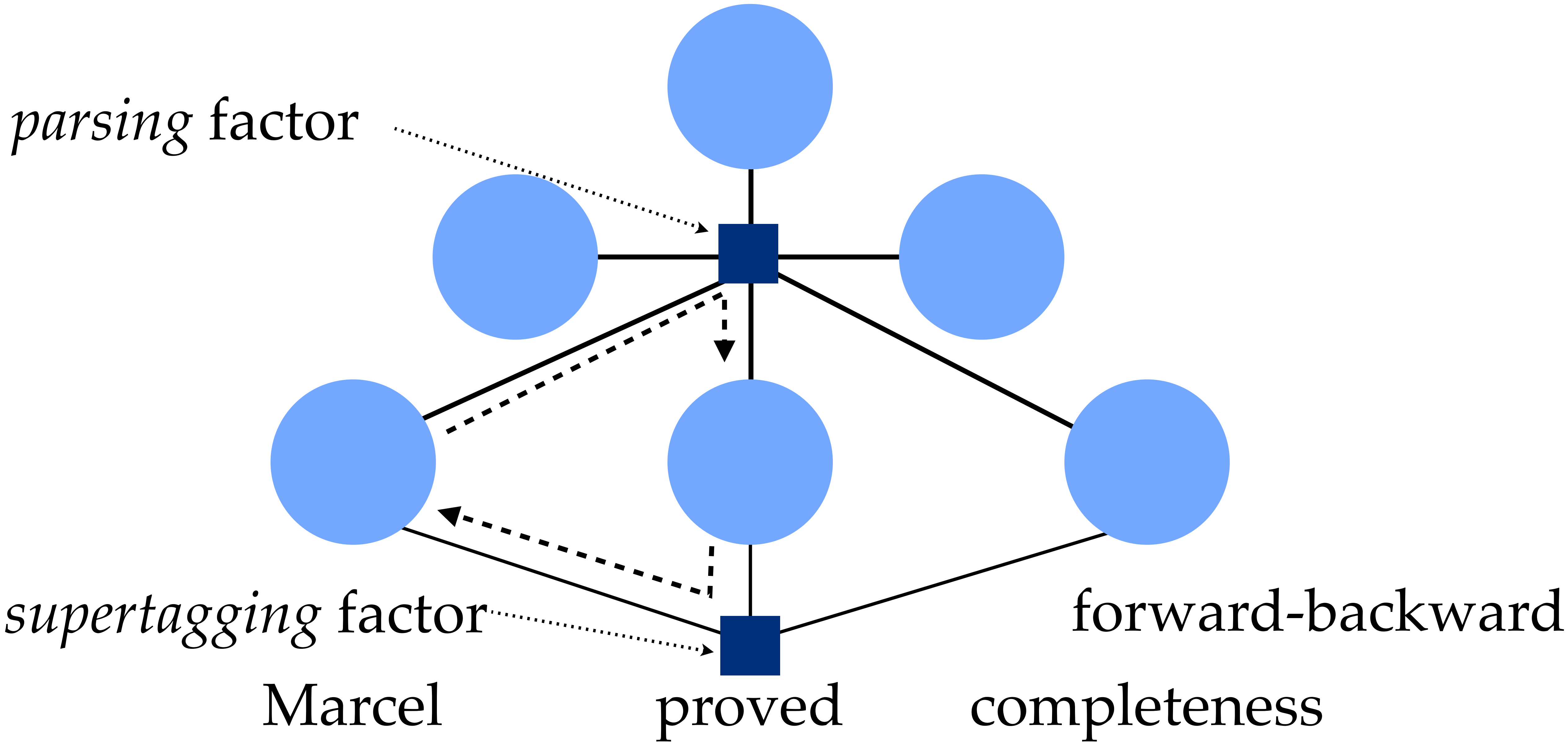

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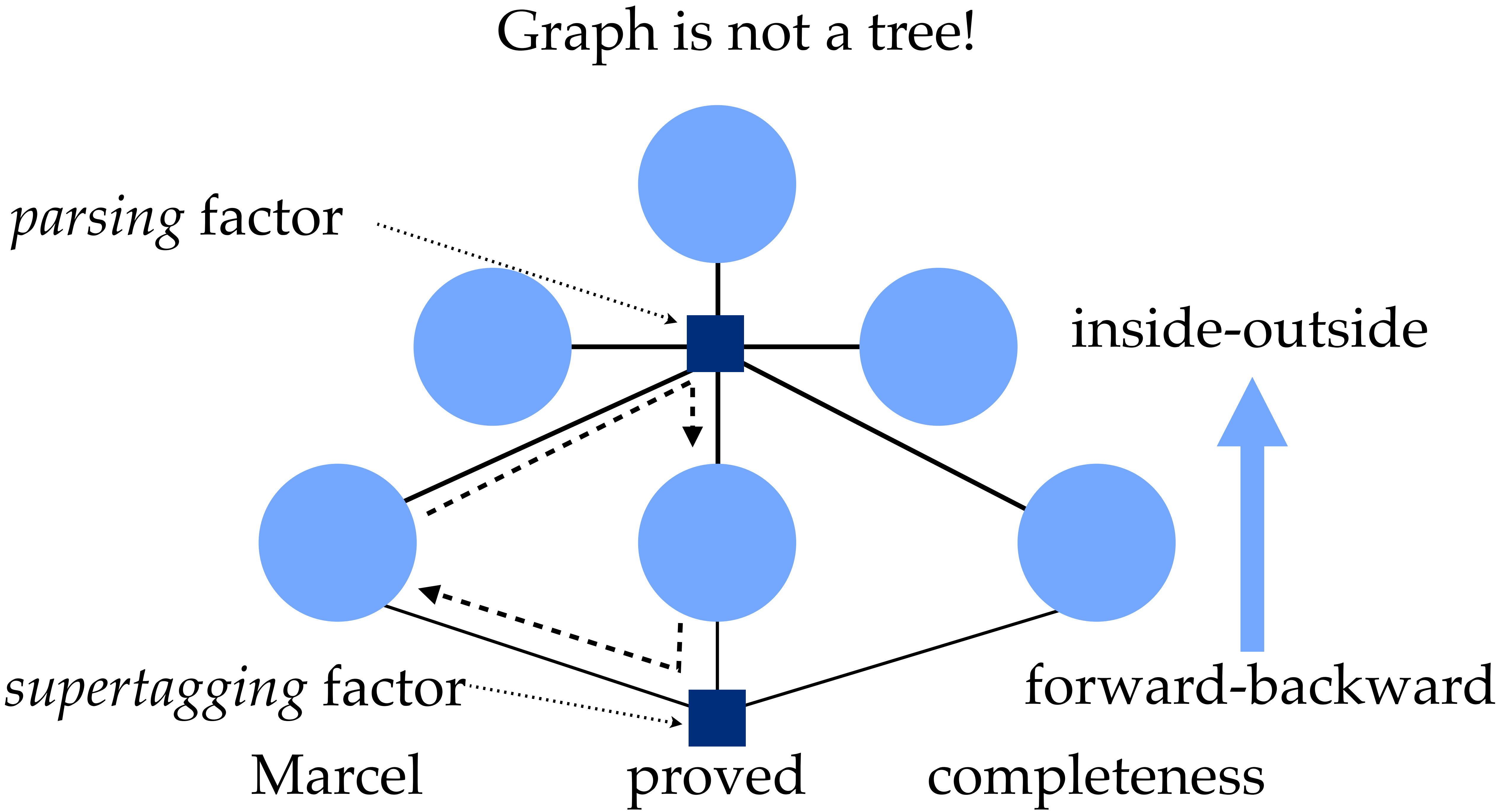

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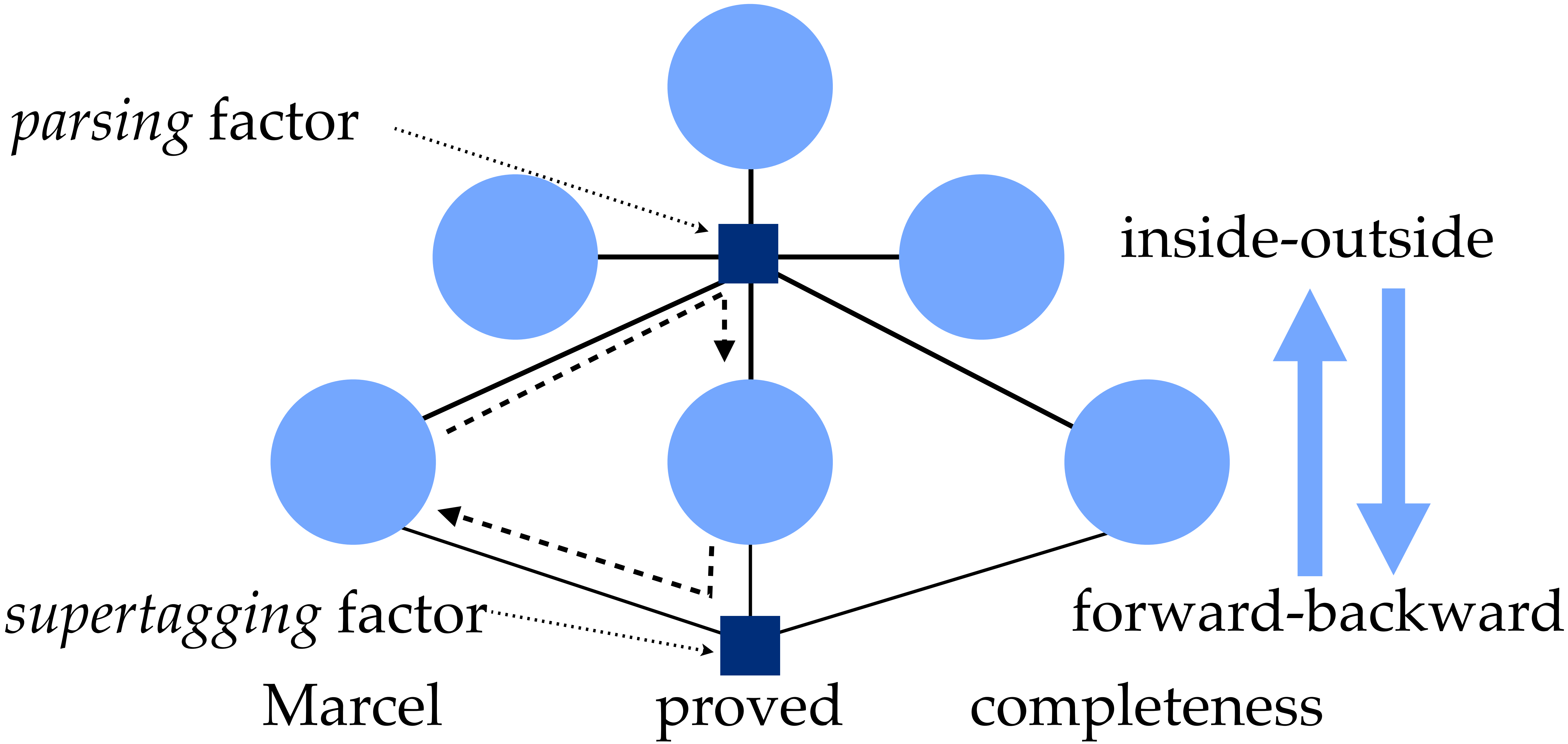
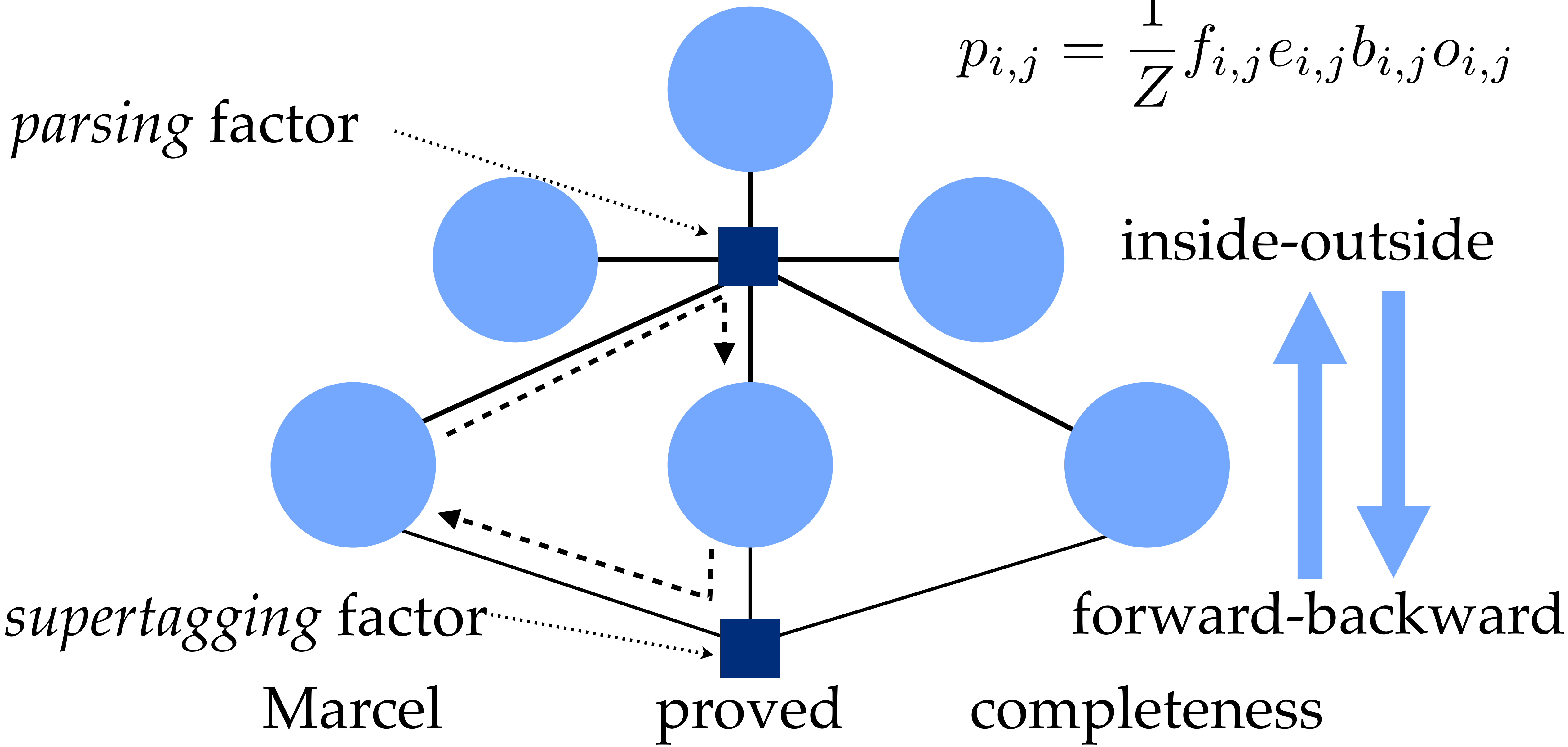


Loopy Belief Propagation

Graph is not a tree!

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



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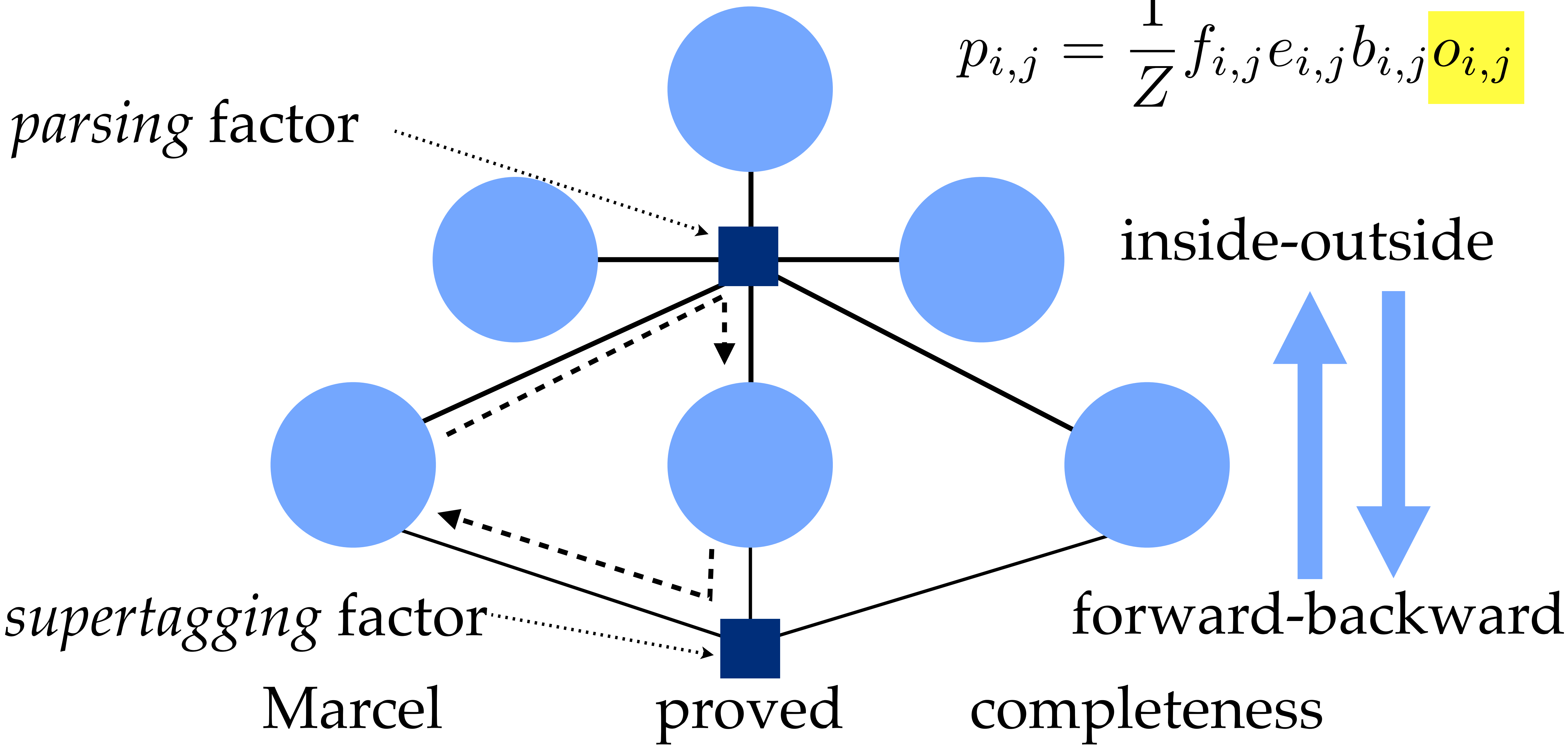
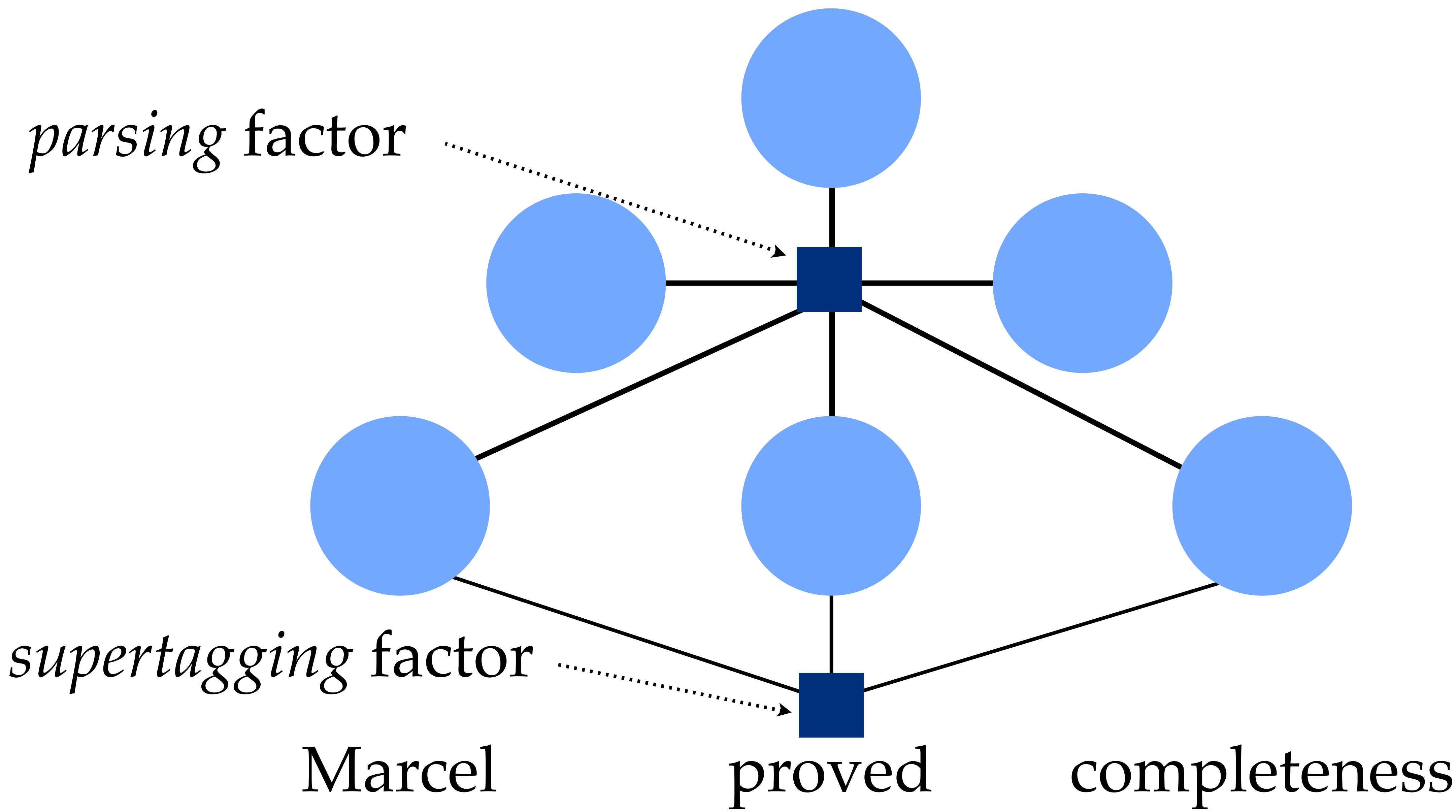


Loopy Belief Propagation

- Computes *approximate* marginals, no guarantees.
- Complexity is additive: $O(Gn^3 + Gn)$
- Used to compute minimum-risk parse (Goodman 1996).

Dual Decomposition



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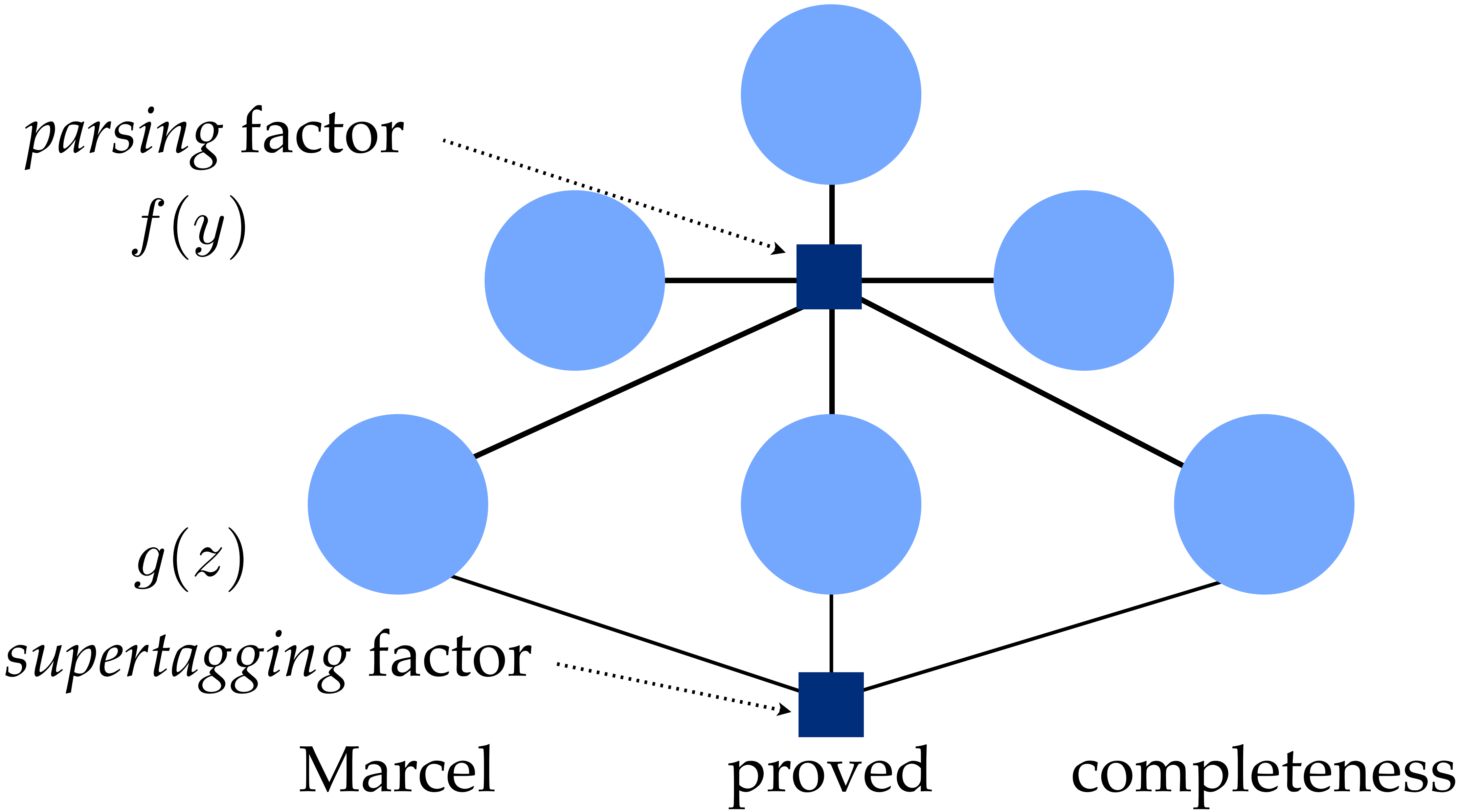
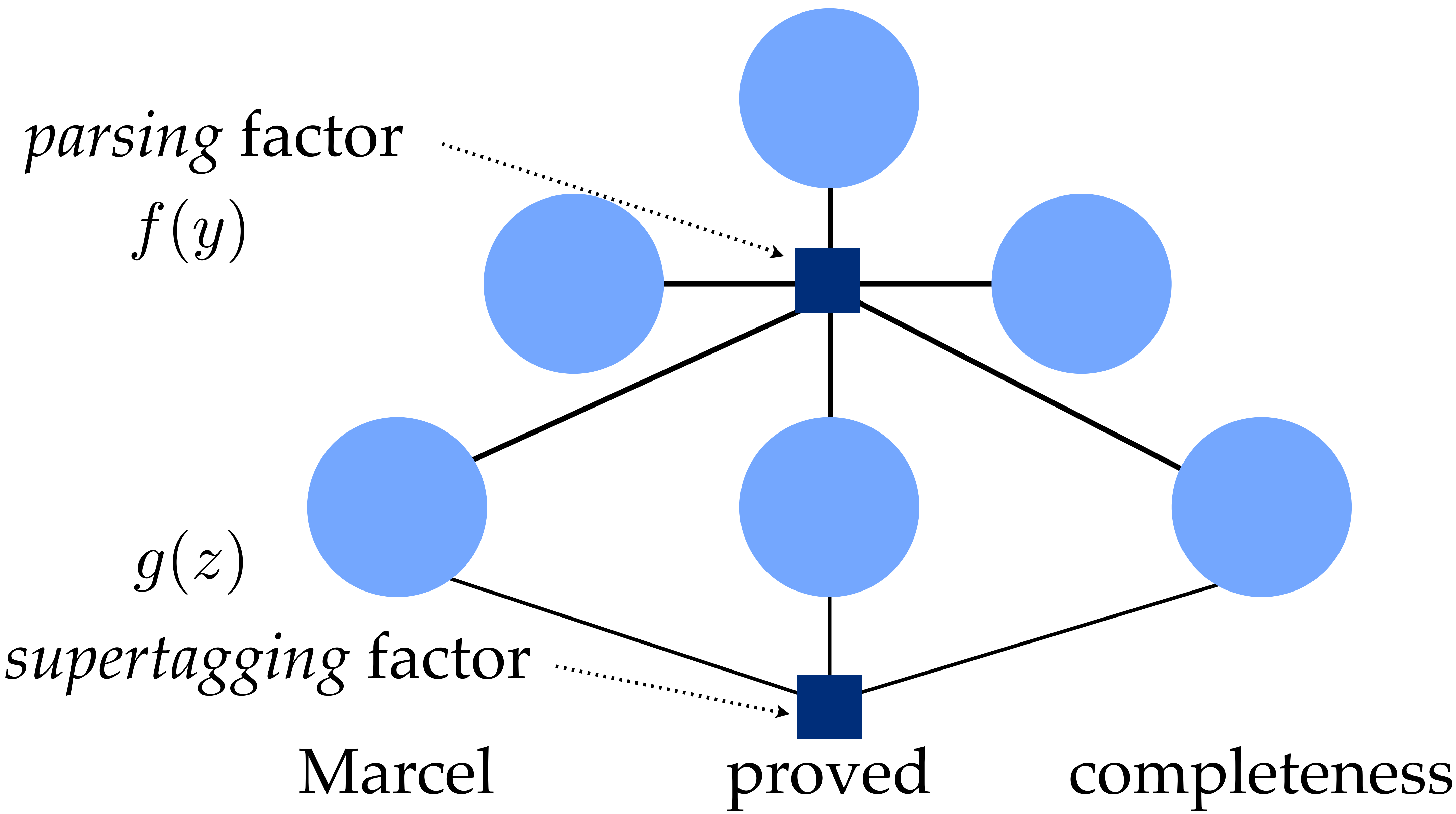


Dual Decomposition

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



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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

Dual Decomposition

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modified subproblem

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

Dual Decomposition

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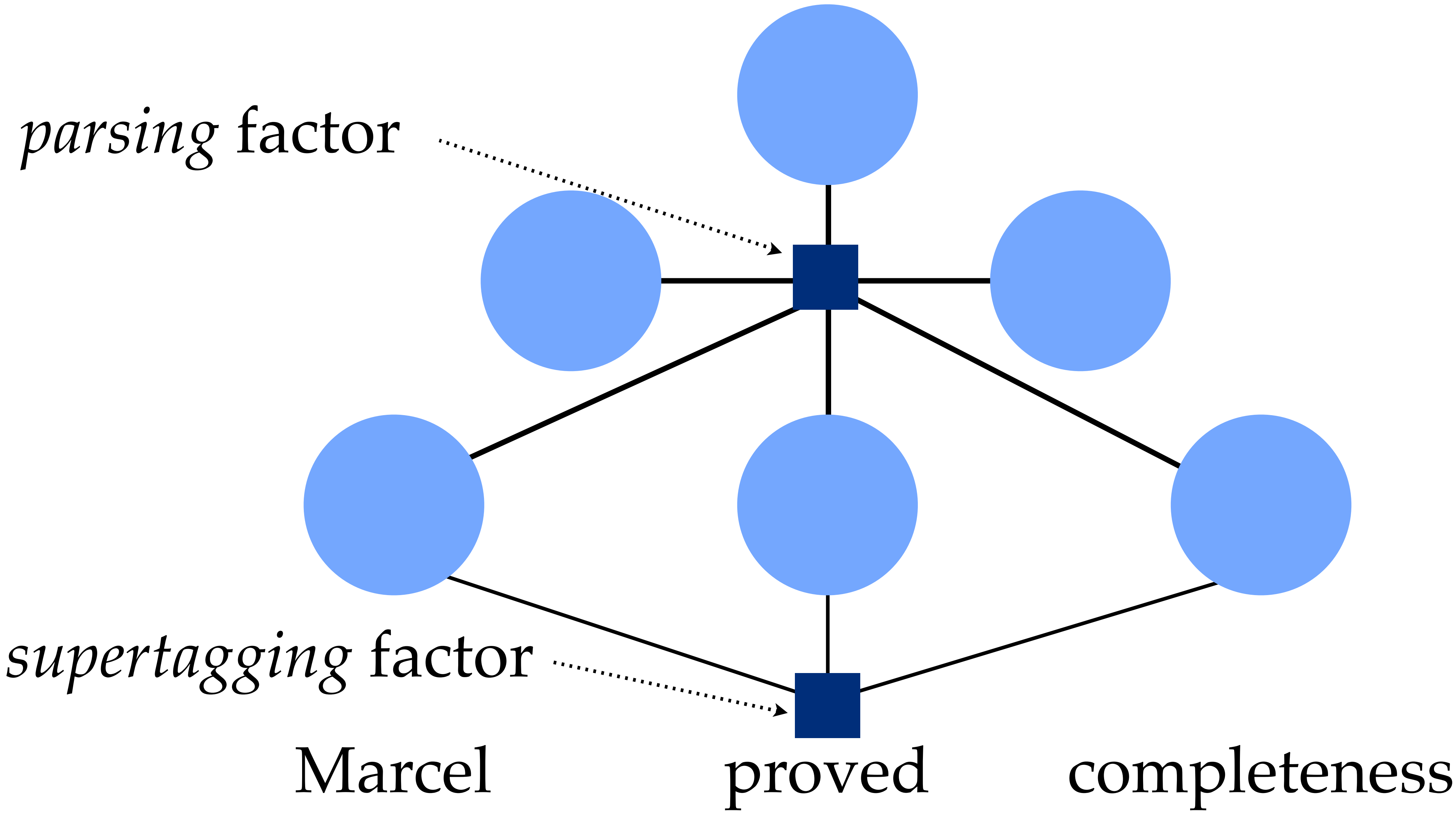
Dual objective: find assignment of $u(i,t)$ that minimises $L(u)$

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

Solution provably solves original problem.

Dual Decomposition



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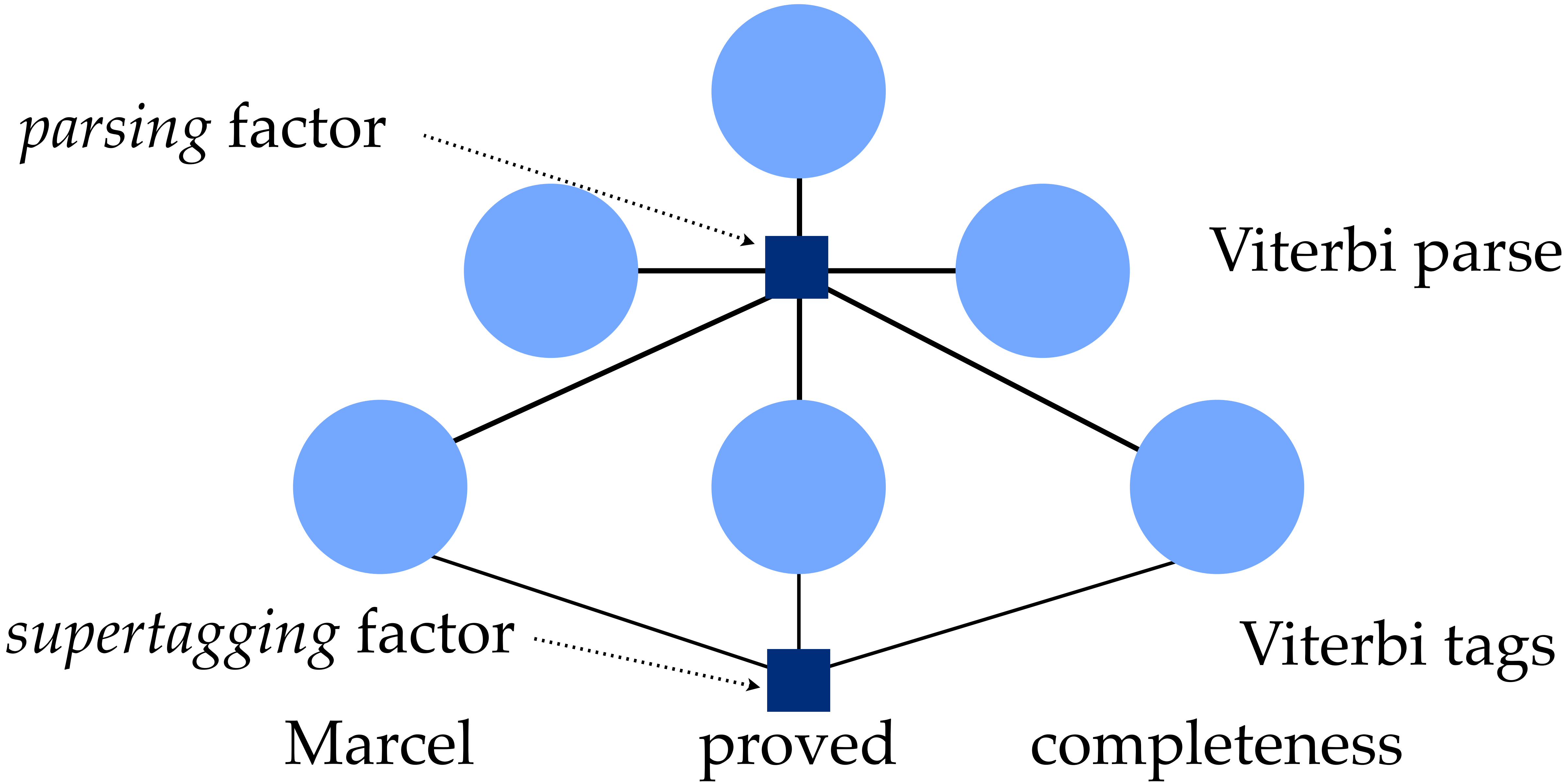
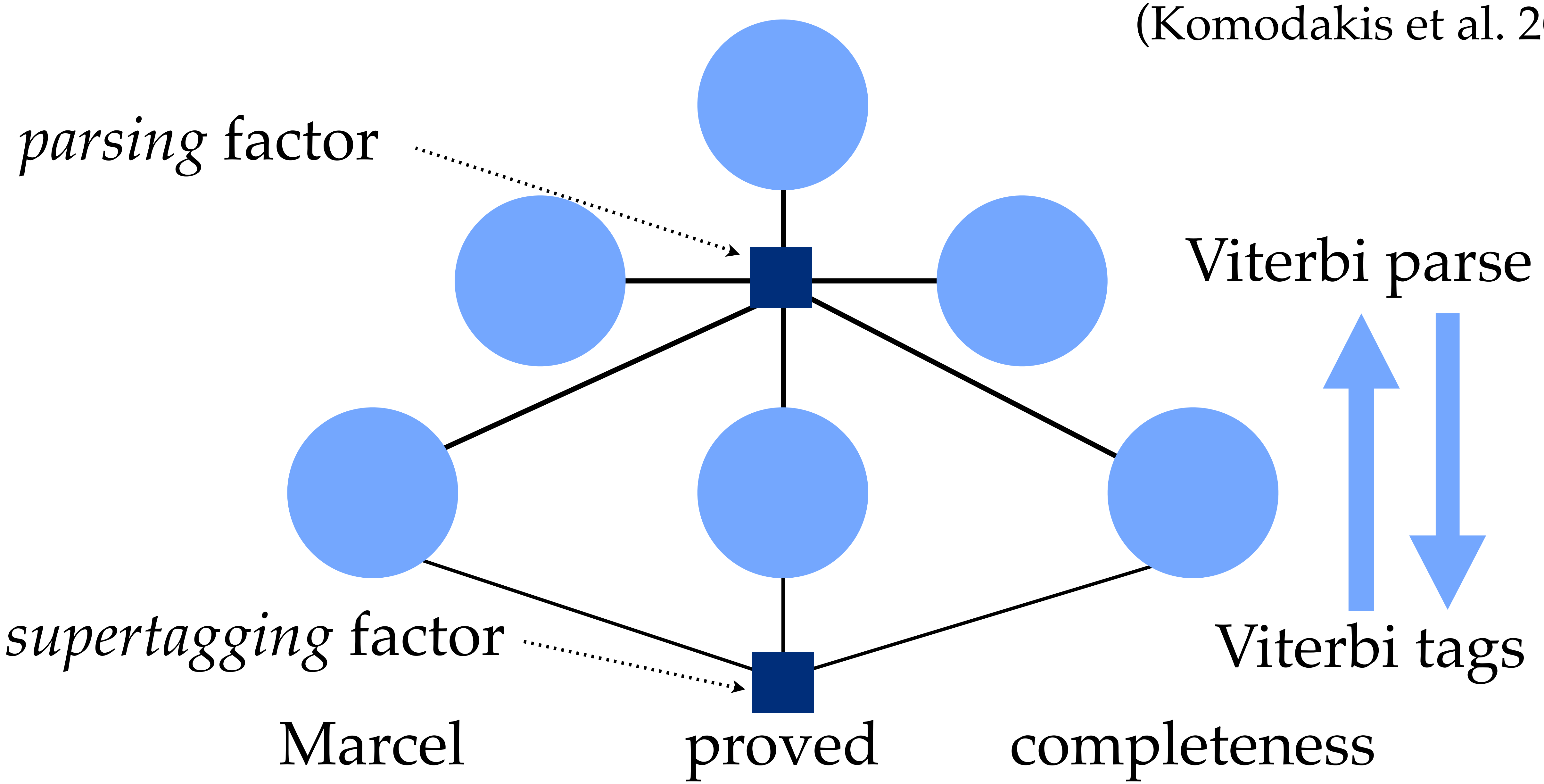


Dual Decomposition

"Message passing"
(Komodakis et al. 2007)



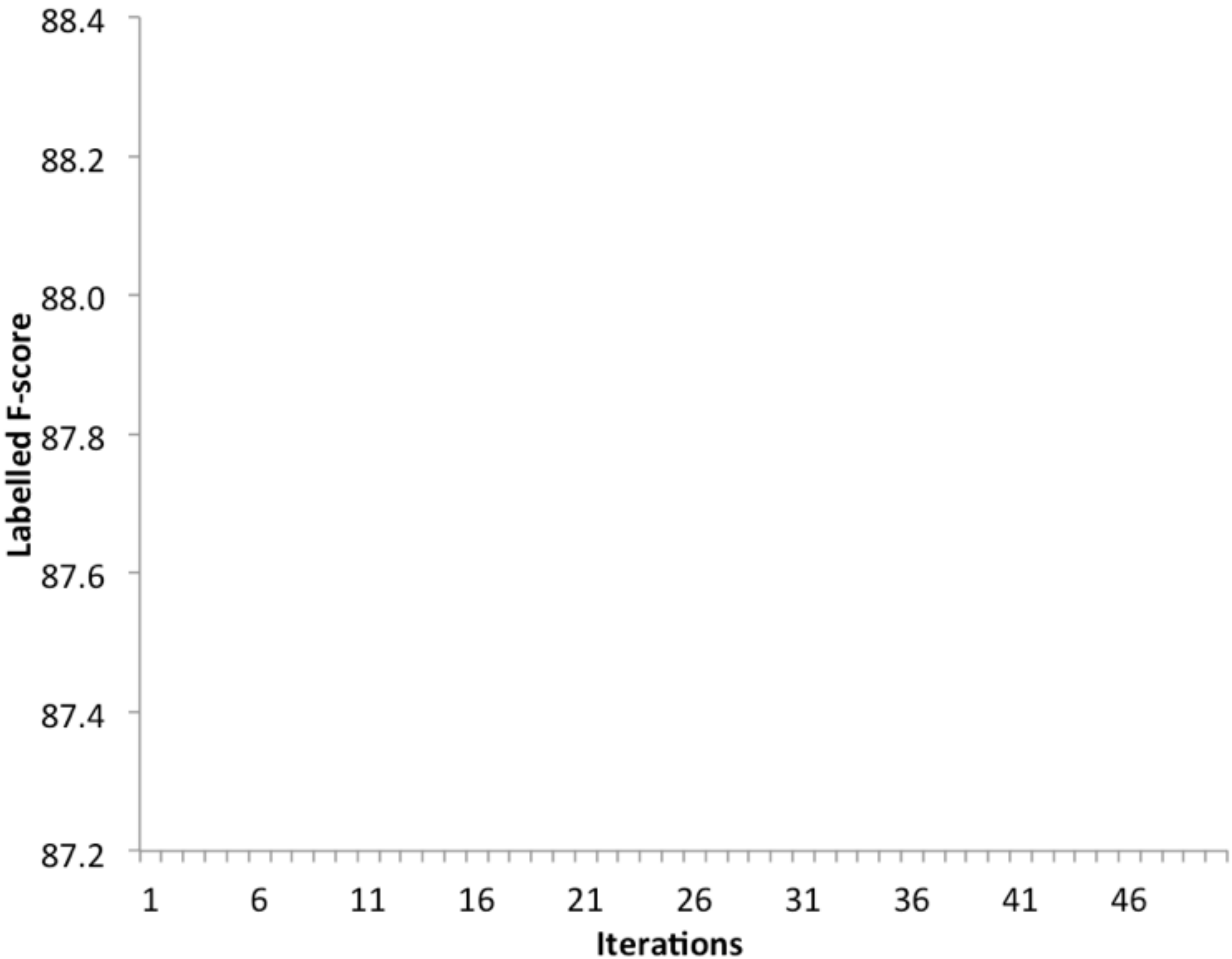
Dual Decomposition

- Computes *exact* maximum, *if* it converges.
  - Otherwise: return best parse seen (approximation).
- Complexity is additive: $O(Gn^3 + Gn)$
- Use to compute Viterbi solutions.

Experiments

- Standard parsing task:
    - C&C Parser and supertagger (Clark & Curran 2007).
    - CCGBank standard train/dev/test splits.
    - Piecewise optimisation (Sutton and McCallum 2005)
    - Approximate algorithms used to decode test set.

Experiments: Accuracy over time



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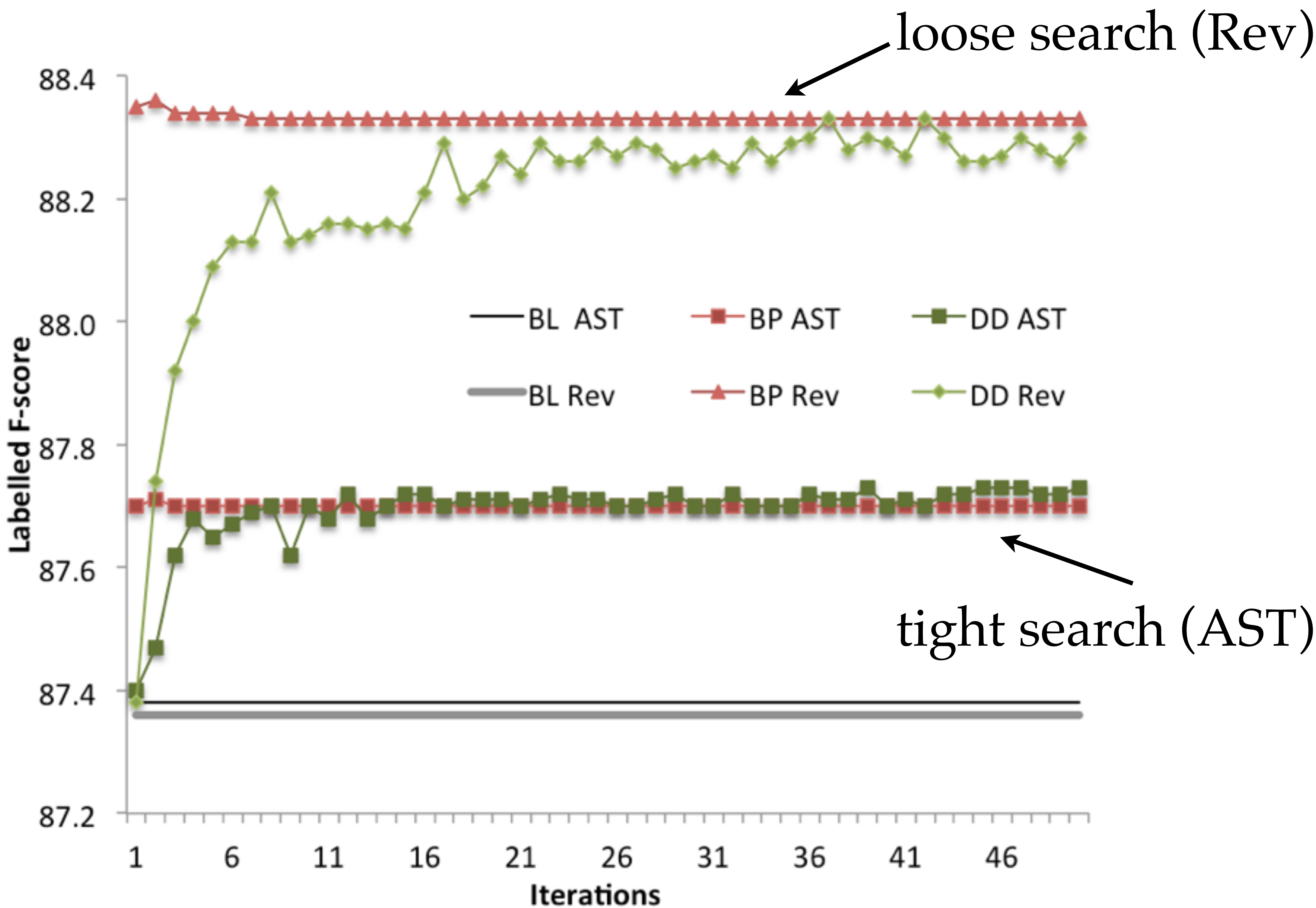

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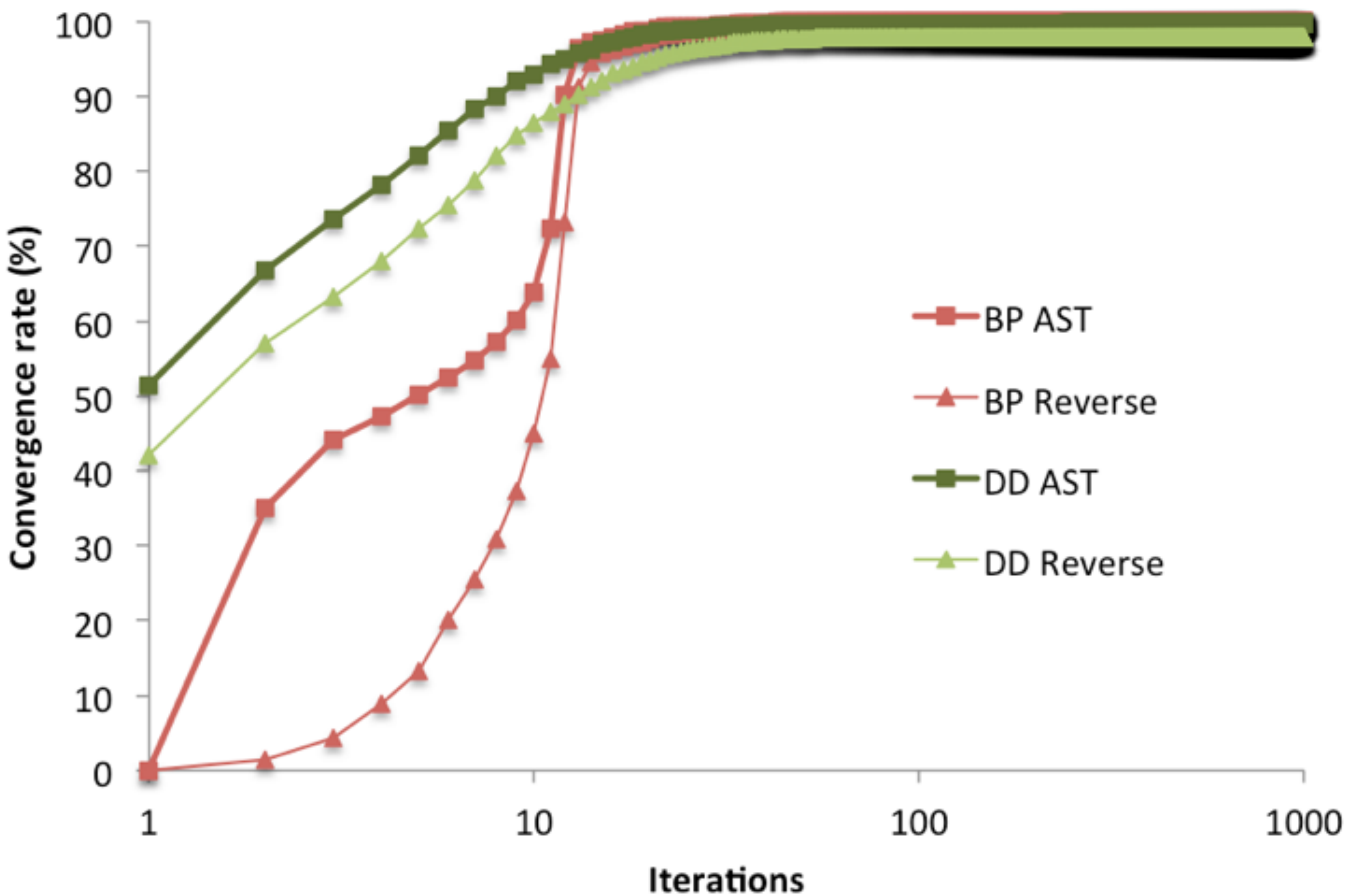
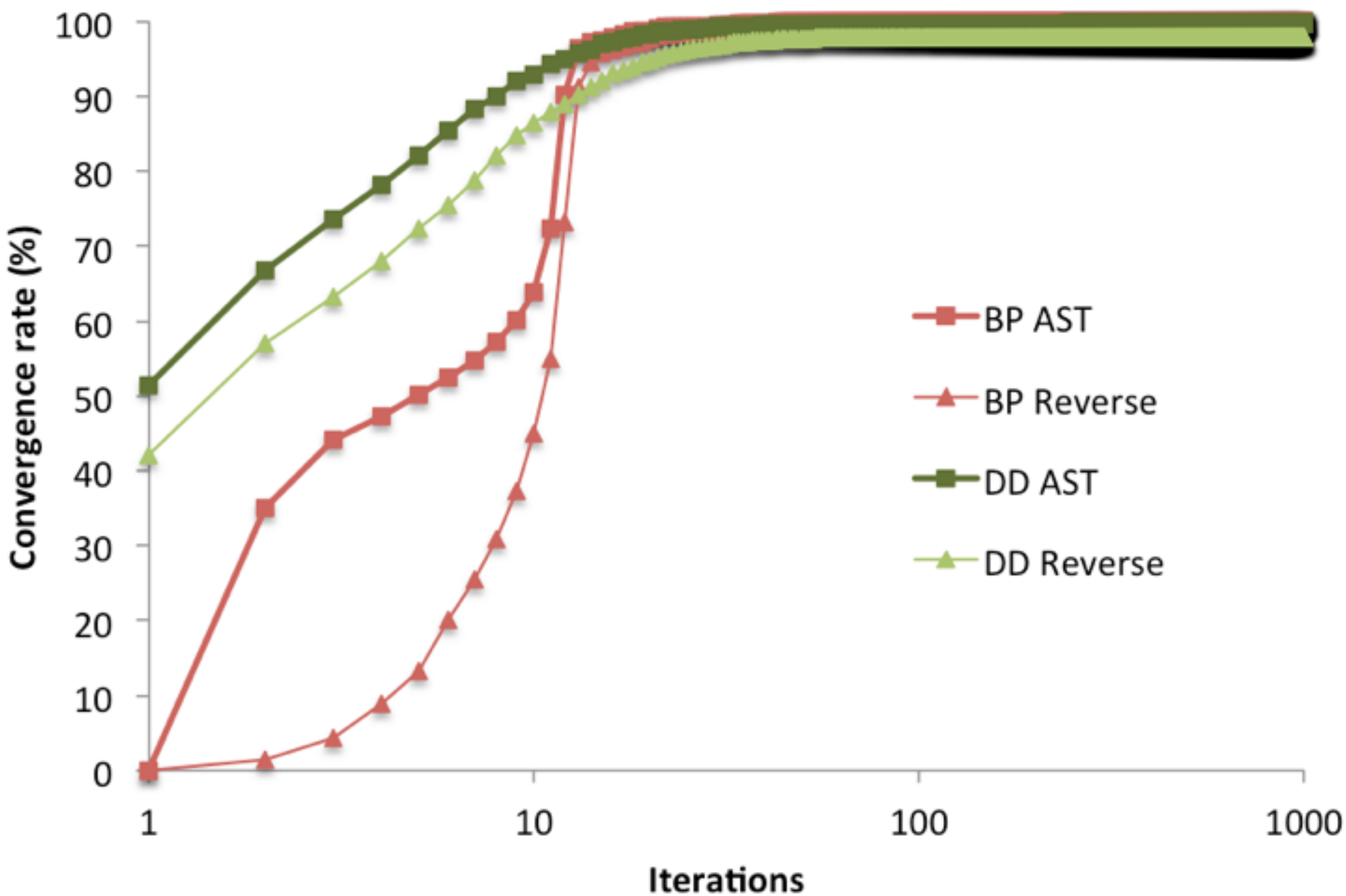


Experiments: Convergence



Dual decomposition exact in 99.7% of cases

What about belief propagation?

Experiments: BP Exactness

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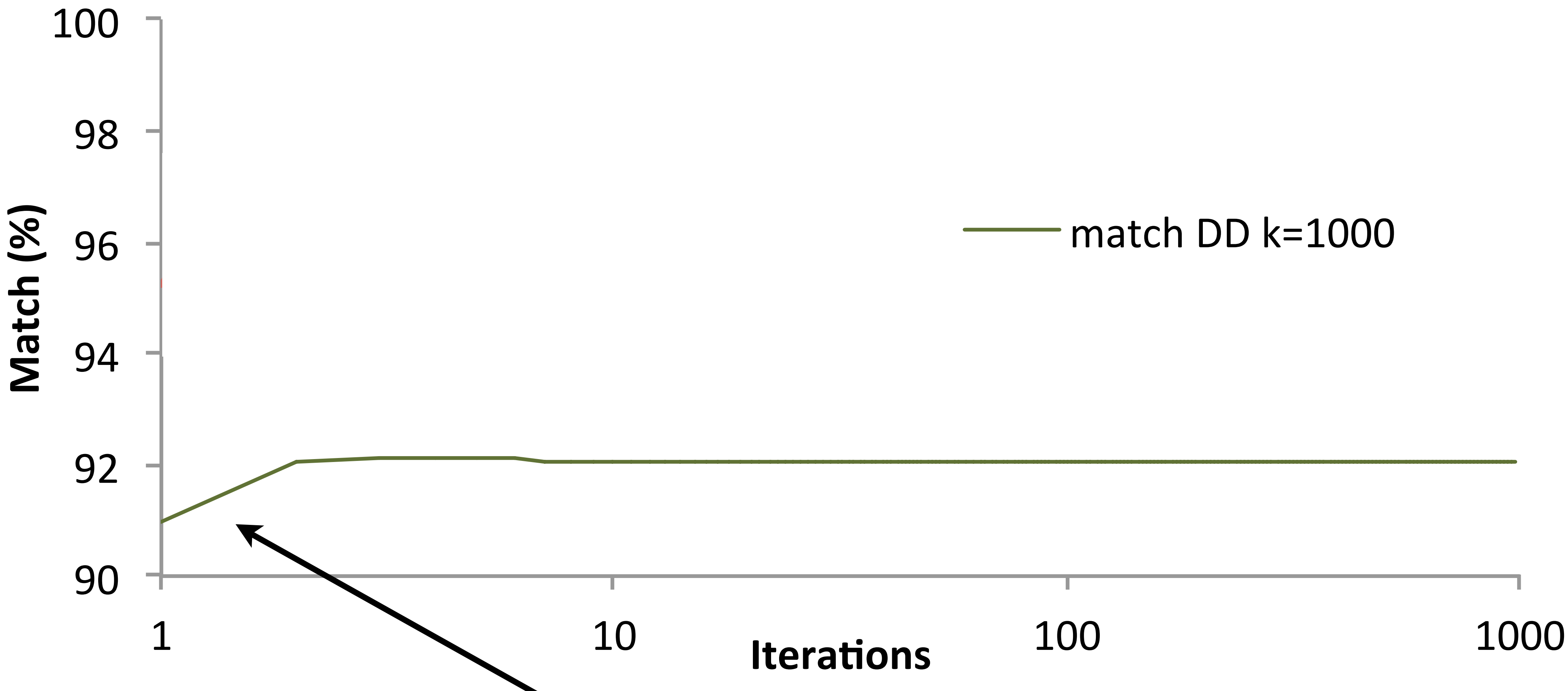
Experiments: BP Exactness

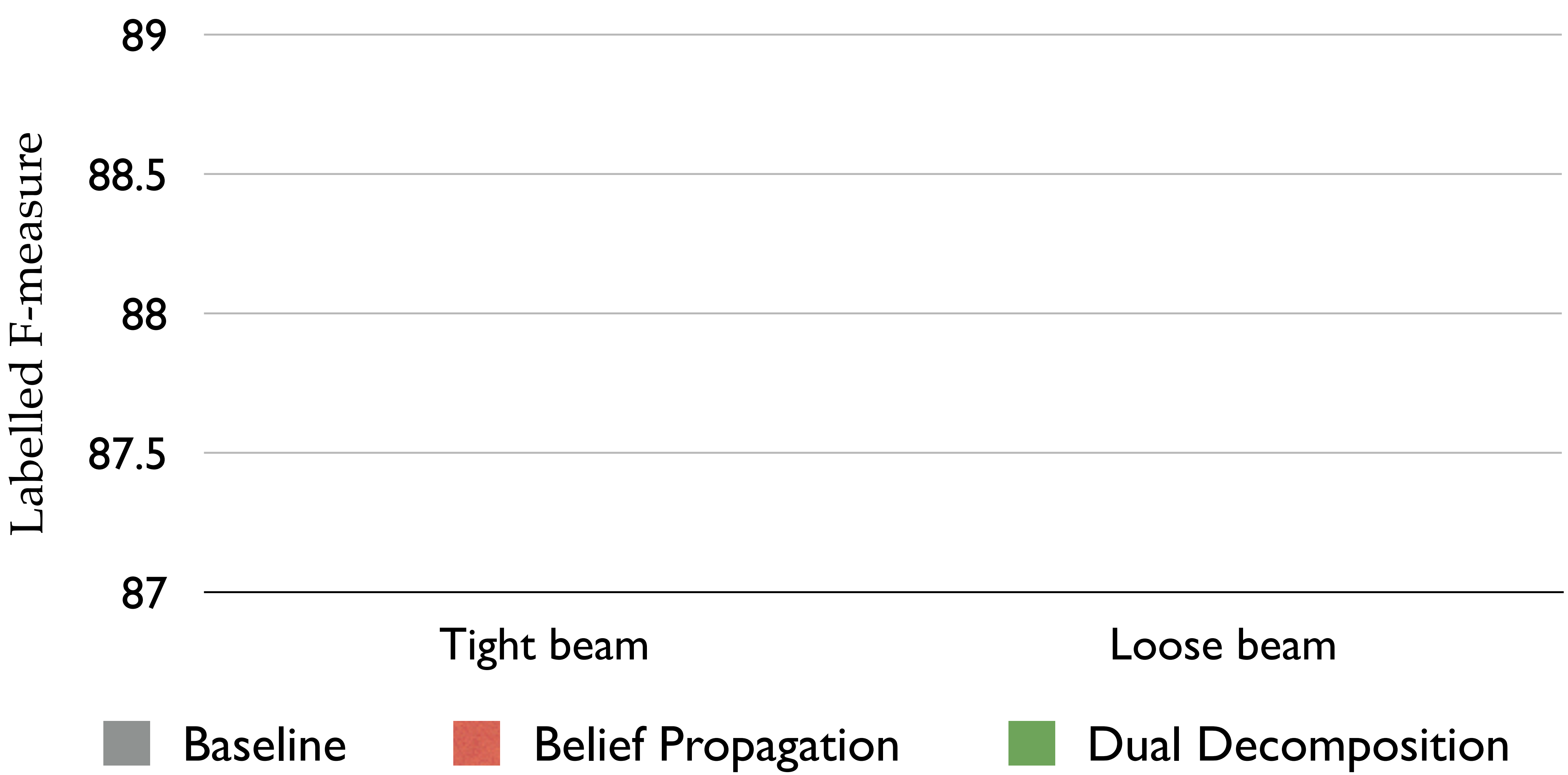


Instantly, 91% match final DD solutions!

Takes DD 15 iterations to reach same level.

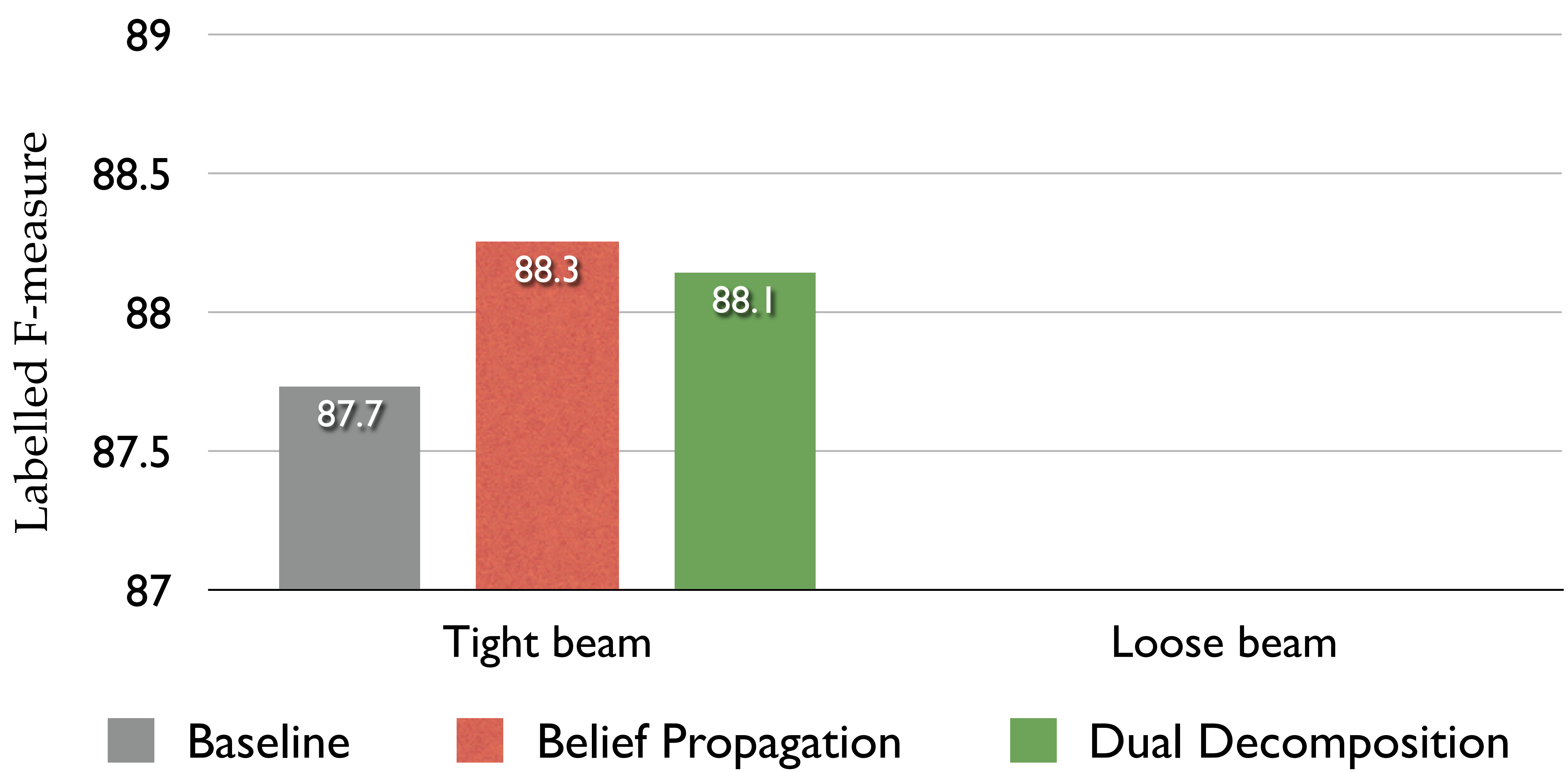
Experiments: Accuracy

Test set results



Experiments: Accuracy

Test set results



Experiments: Accuracy

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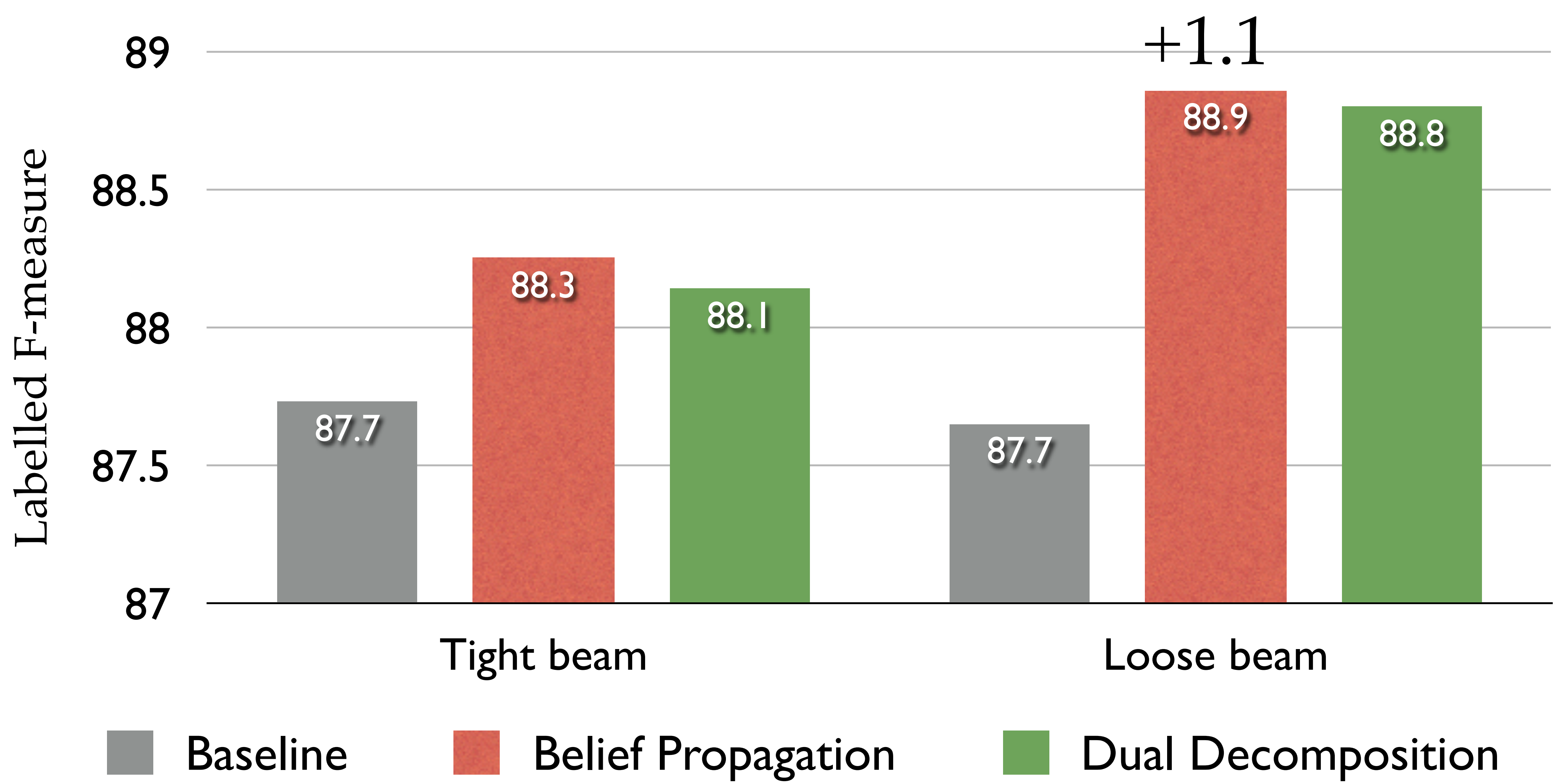
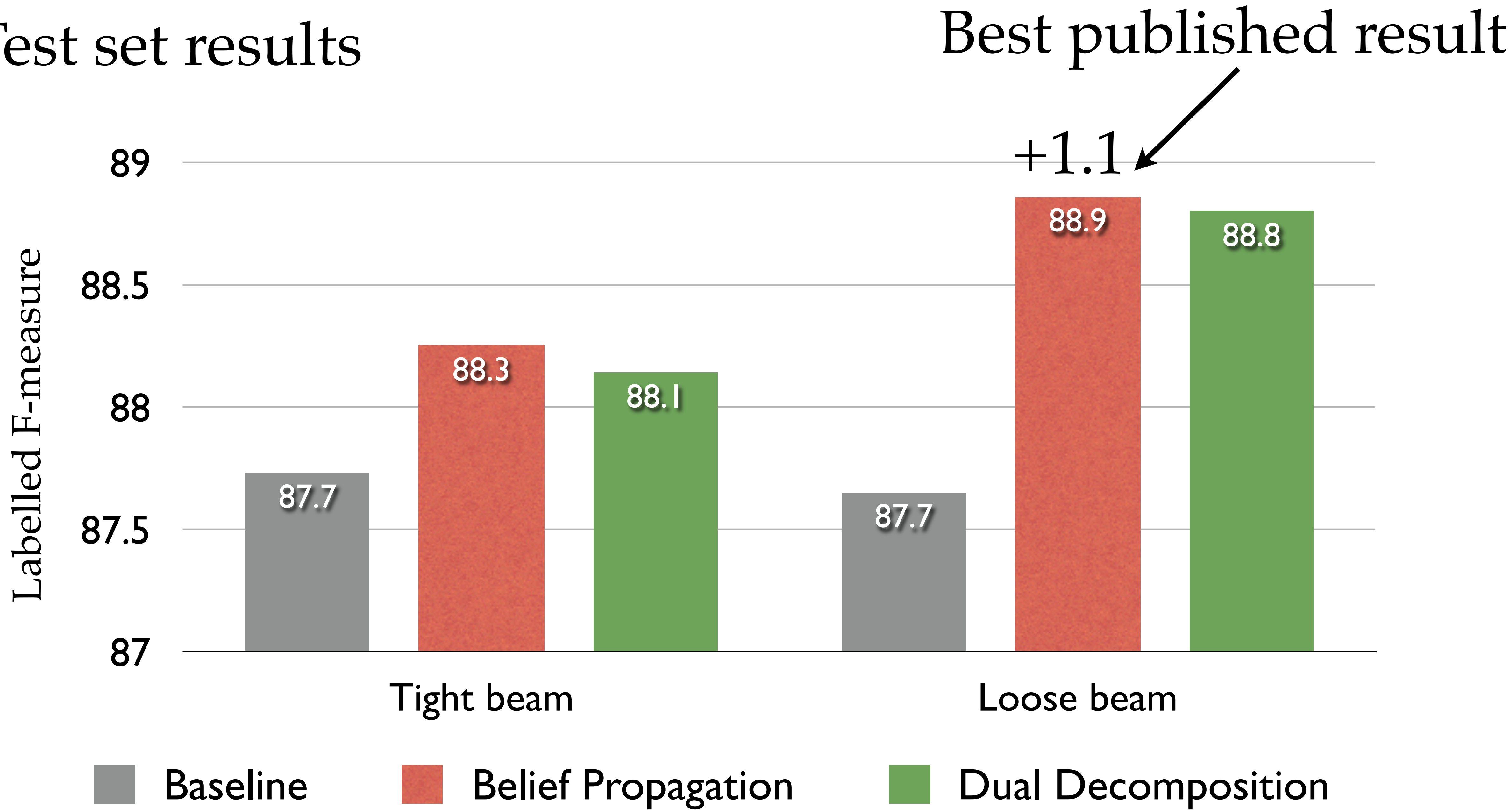


Note: BP accuracy after 1 iteration; DD accuracy after 25 iterations

Experiments: Accuracy

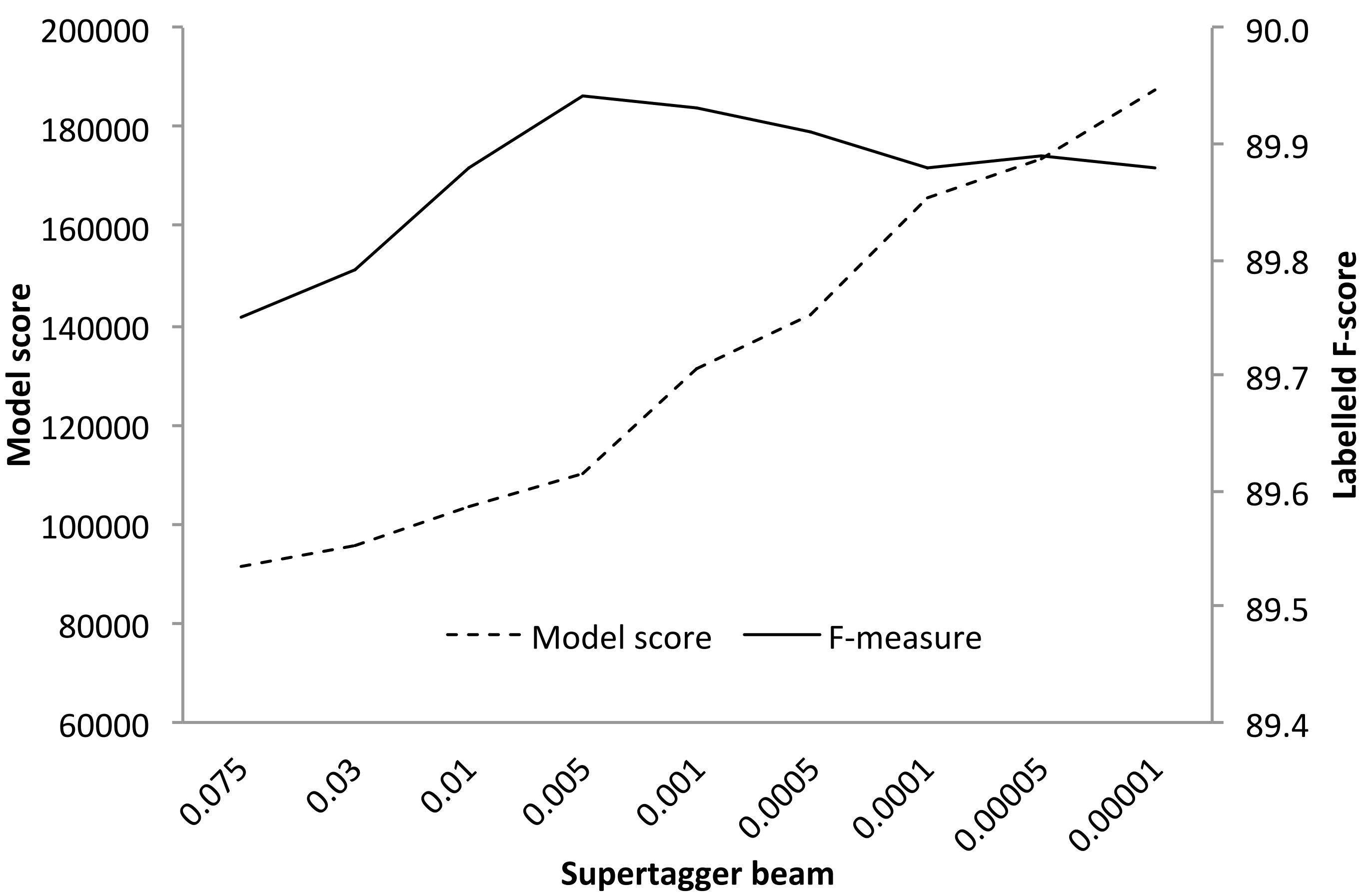
Test set results



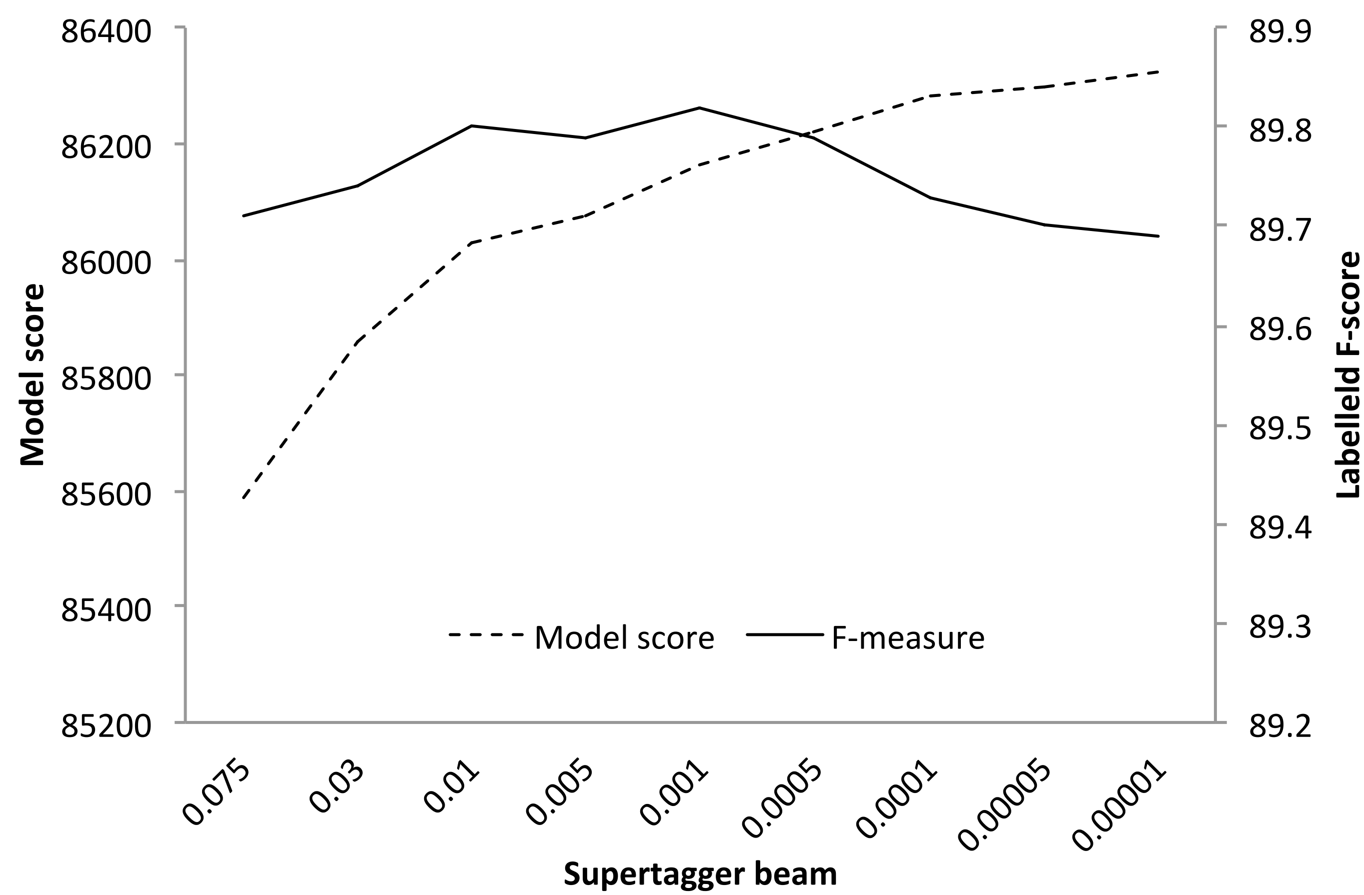
Note: BP accuracy after 1 iteration; DD accuracy after 25 iterations

Oracle Results Again

Belief Propagation



Dual Decomposition



Summary so far

- Supertagging efficiency comes at the cost of accuracy.
- Interaction between parser and supertagger can be exploited in an integrated model.
- Practical inference for complex integrated model.
- First empirical comparison between dual decomposition and belief propagation on NLP task.
- Loopy belief propagation is fast, accurate and exact.

Overview

- Analysis of state-of-the-art approach
  Trade-off between efficiency and accuracy (ACL 2011a)

- Integrated supertagging and parsing
  with Loopy Belief Propagation and Dual Decomposition (ACL 2011b)

- Training the integrated model
  with Softmax-Margin towards task-specific metrics (EMNLP 2011)

Overview

- Analysis of state-of-the-art approach
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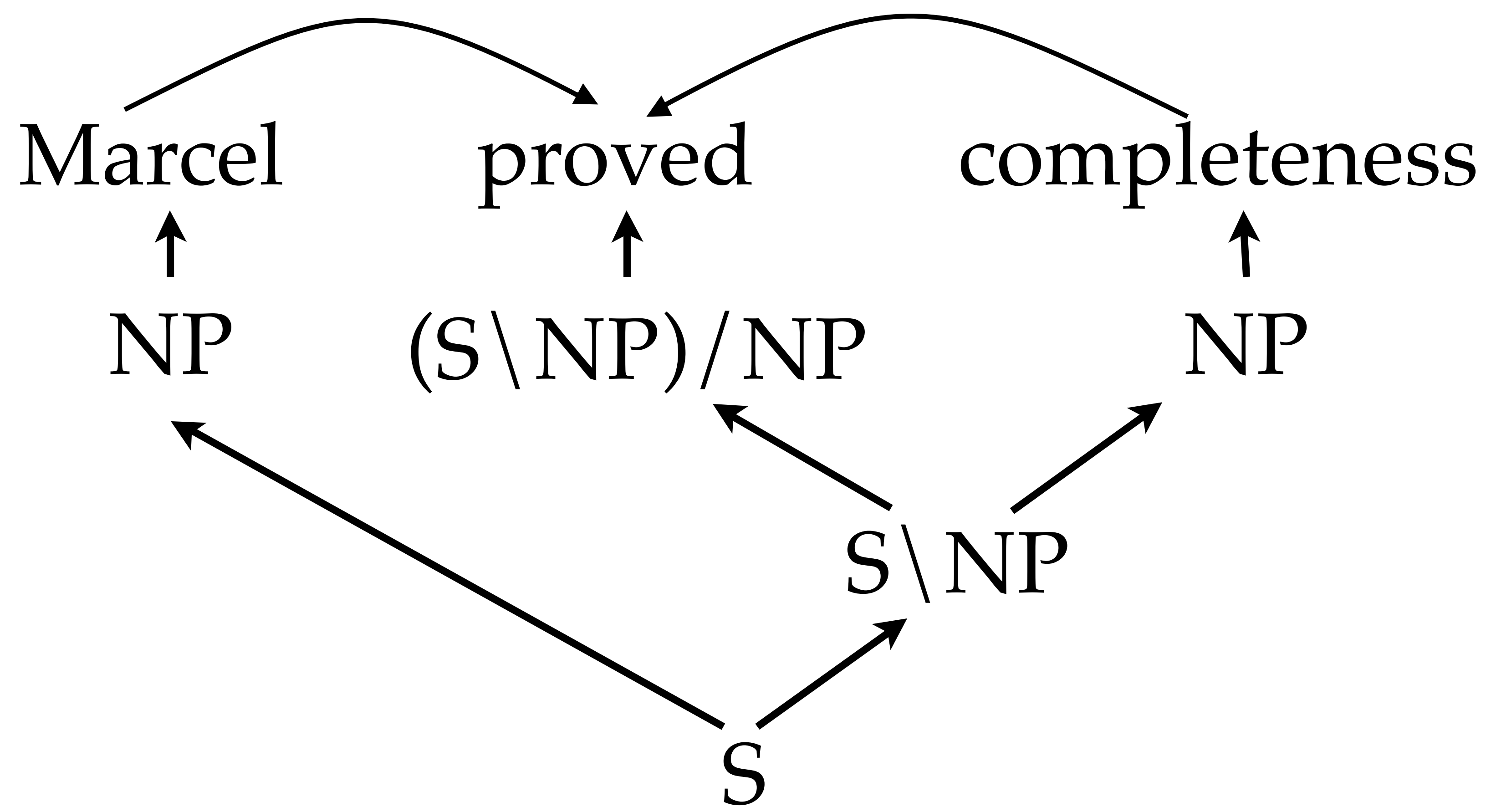
  with Softmax-Margin towards task-specific metrics (EMNLP 2011)

Training the Integrated Model

- So far optimised Conditional Log-Likelihood (CLL).
- Optimise towards task-specific metric e.g. F_1 such as in SMT (Och, 2003).
- Past work used approximations to Precision (Taskar et al. 2004).
- Contribution: Do it **exactly** and verify approximations.

Parsing Metrics

CCG: Labelled, directed dependency recovery
(Clark & Hockenmaier, 2002)



<proved, (S\NP)/NP, completeness>
<proved, (S\NP)/NP, Marcel>

Parsing Metrics

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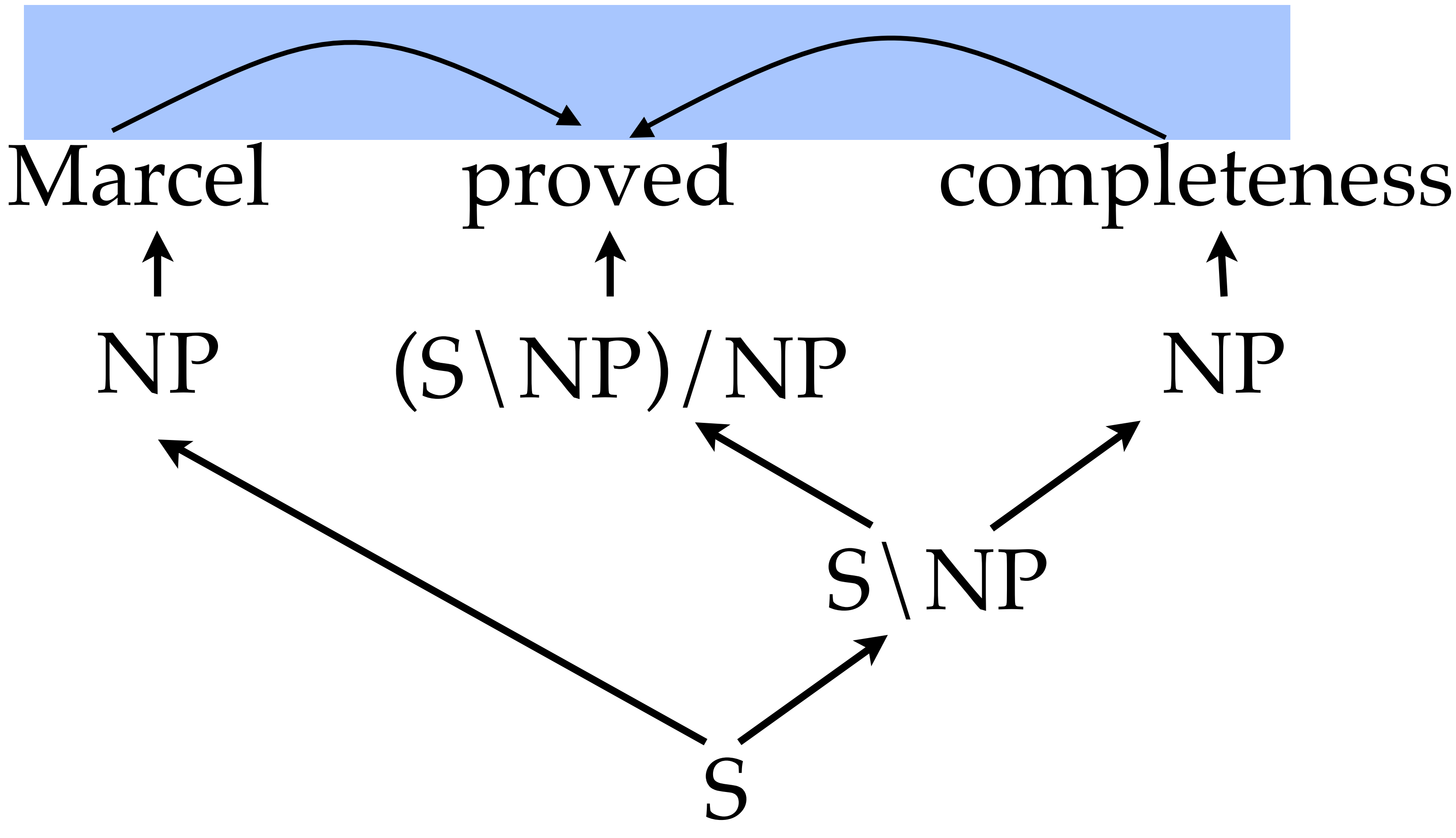

<proved, (S\NP)/NP, completeness>

<proved, (S\NP)/NP, Marcel>

} Evaluate this

Parsing Metrics

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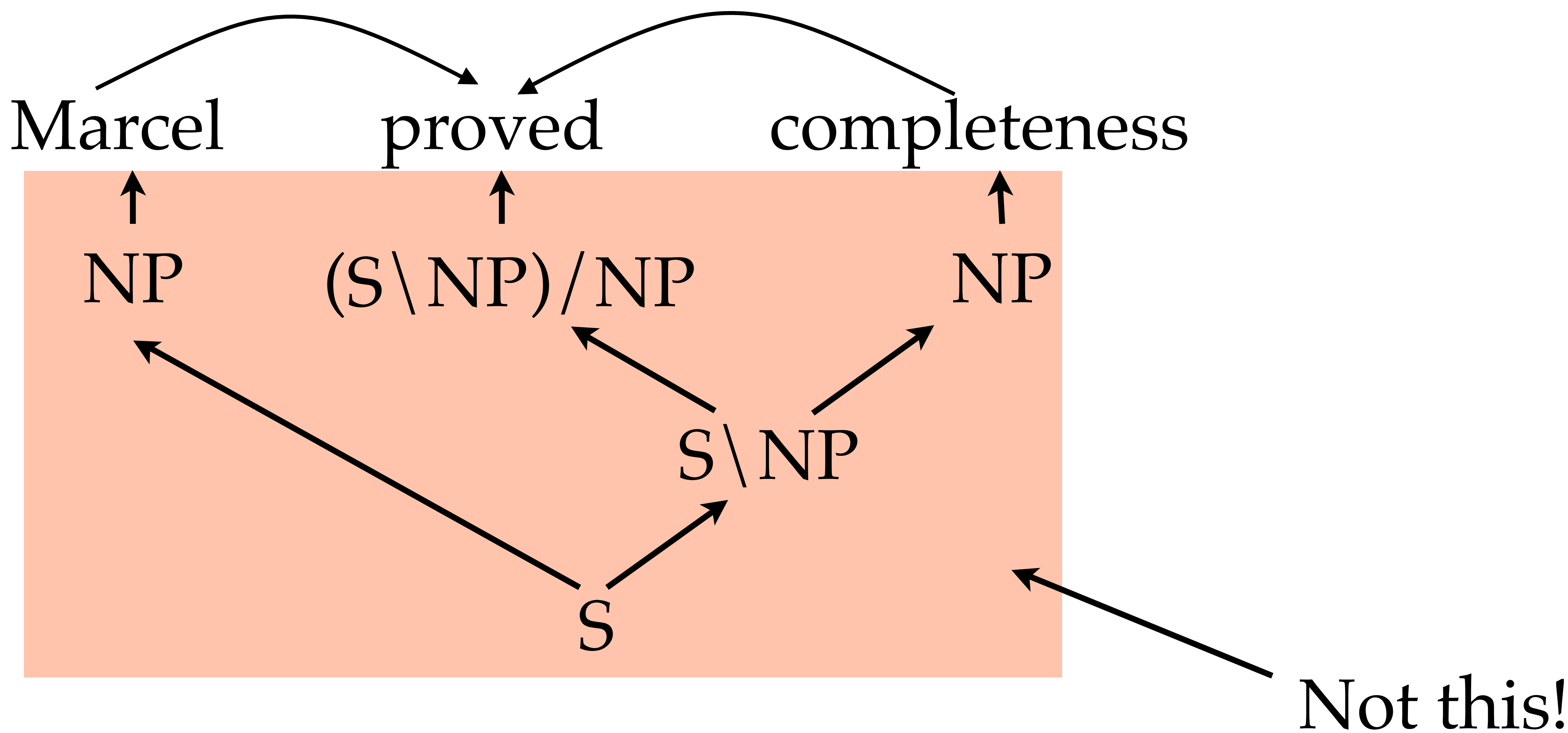

<proved, (S\NP)/NP, completeness>

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Parsing Metrics

y = dependencies in ground truth

y' = dependencies in proposed output

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Parsing Metrics

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

Softmax-Margin Training

(Sha & Saul, 2006; Povey & Woodland,2008; Gimpel & Smith, 2010)

- Discriminative.
- Probabilistic.
- Convex objective.
- Minimises bound on expected risk for a given loss function.
- Requires little change to existing CLL implementation.

Softmax-Margin Training

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

Softmax-Margin Training

training examples   weights   features   input   *true* output   possible outputs   *proposed* output

CLL:

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

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Softmax-Margin Training

training examples weights features input *true* output possible outputs *proposed* output

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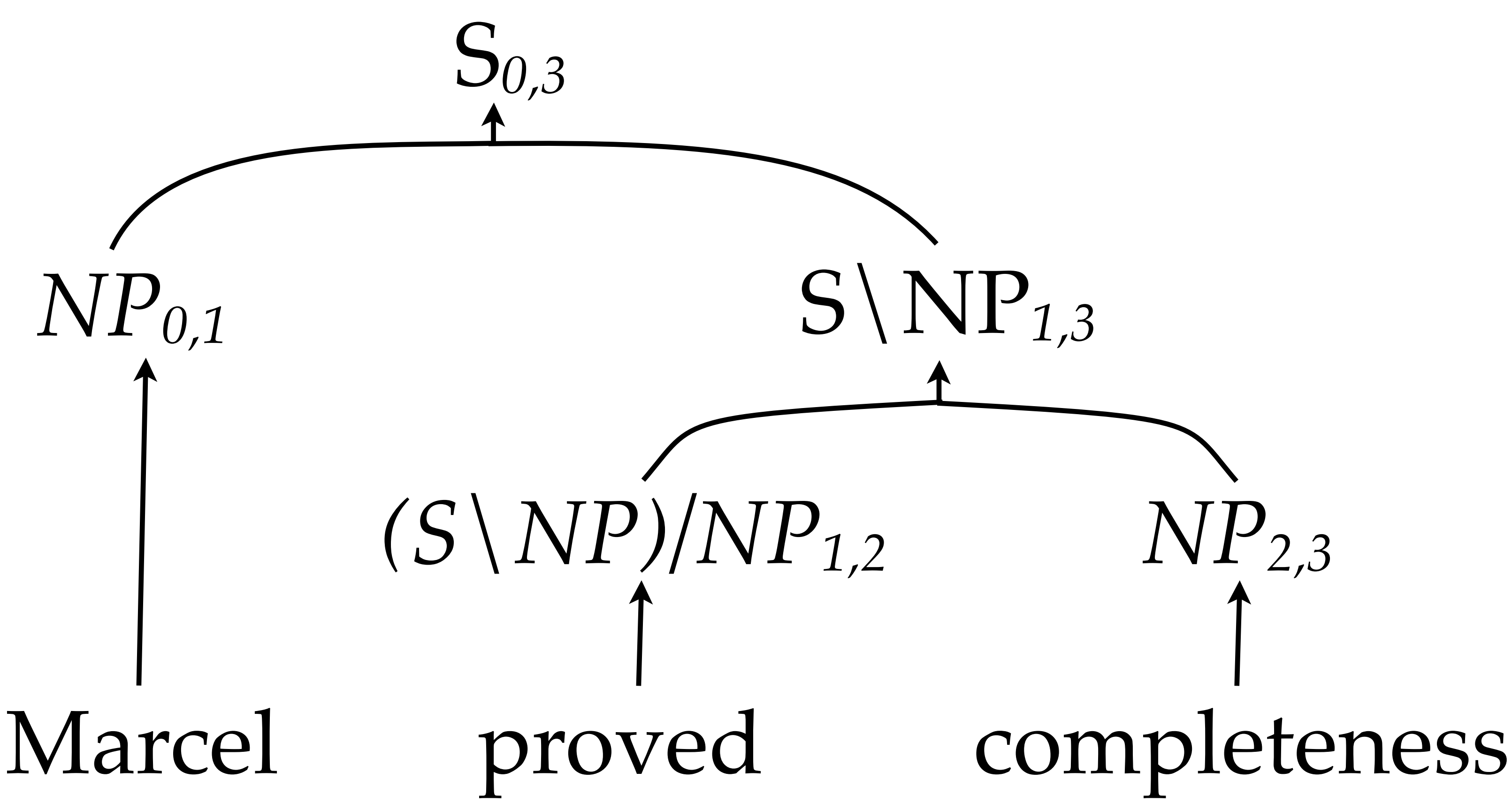
- Penalise high-loss outputs.
- Re-weight outcomes by *loss function.*
- Loss function an *unweighted feature* -- if **decomposable.**

Decomposability

- CKY assumes weights factor over substructures (node + children = substructure).
- A *decomposable* loss function must factor identically.



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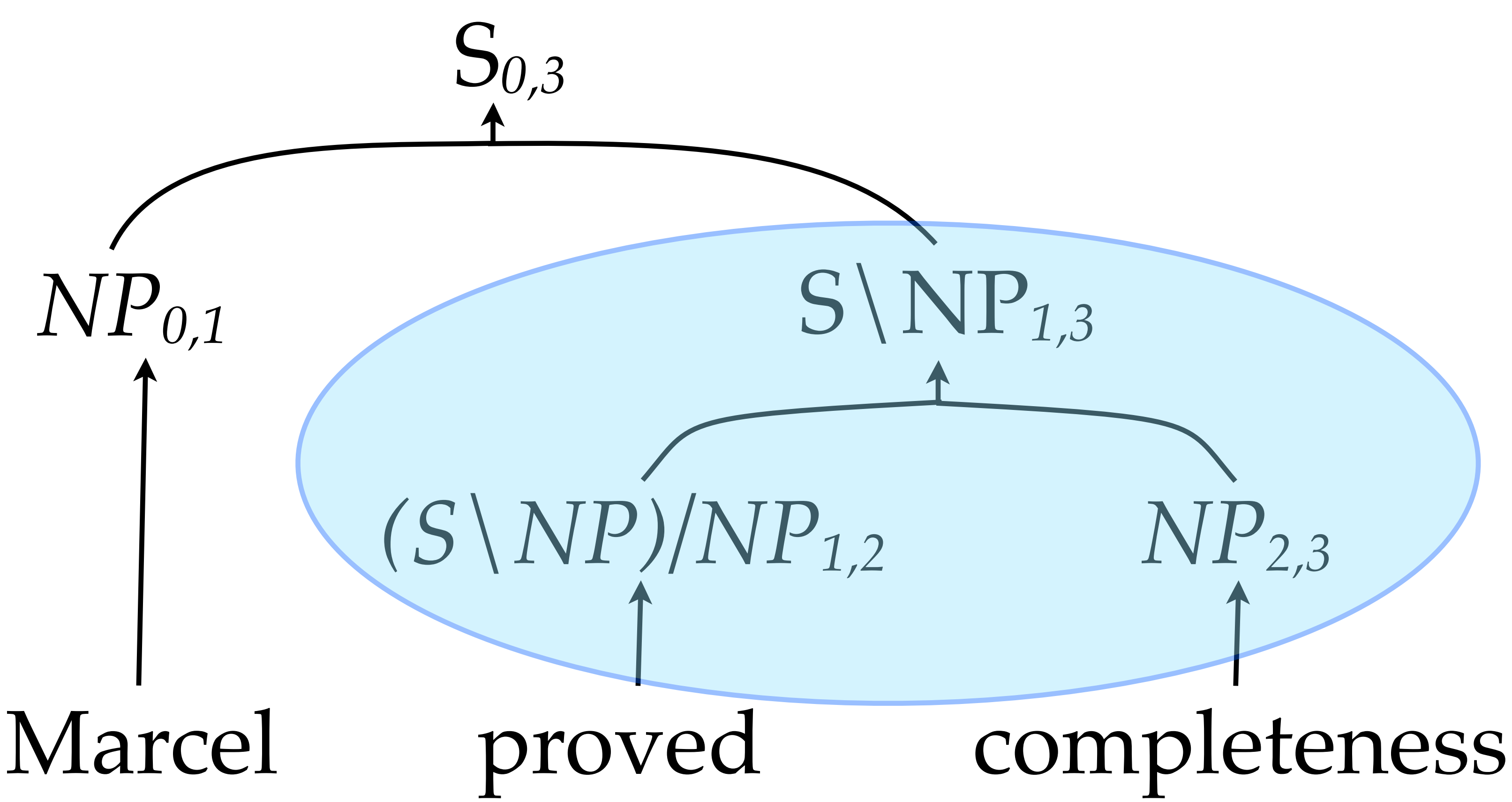

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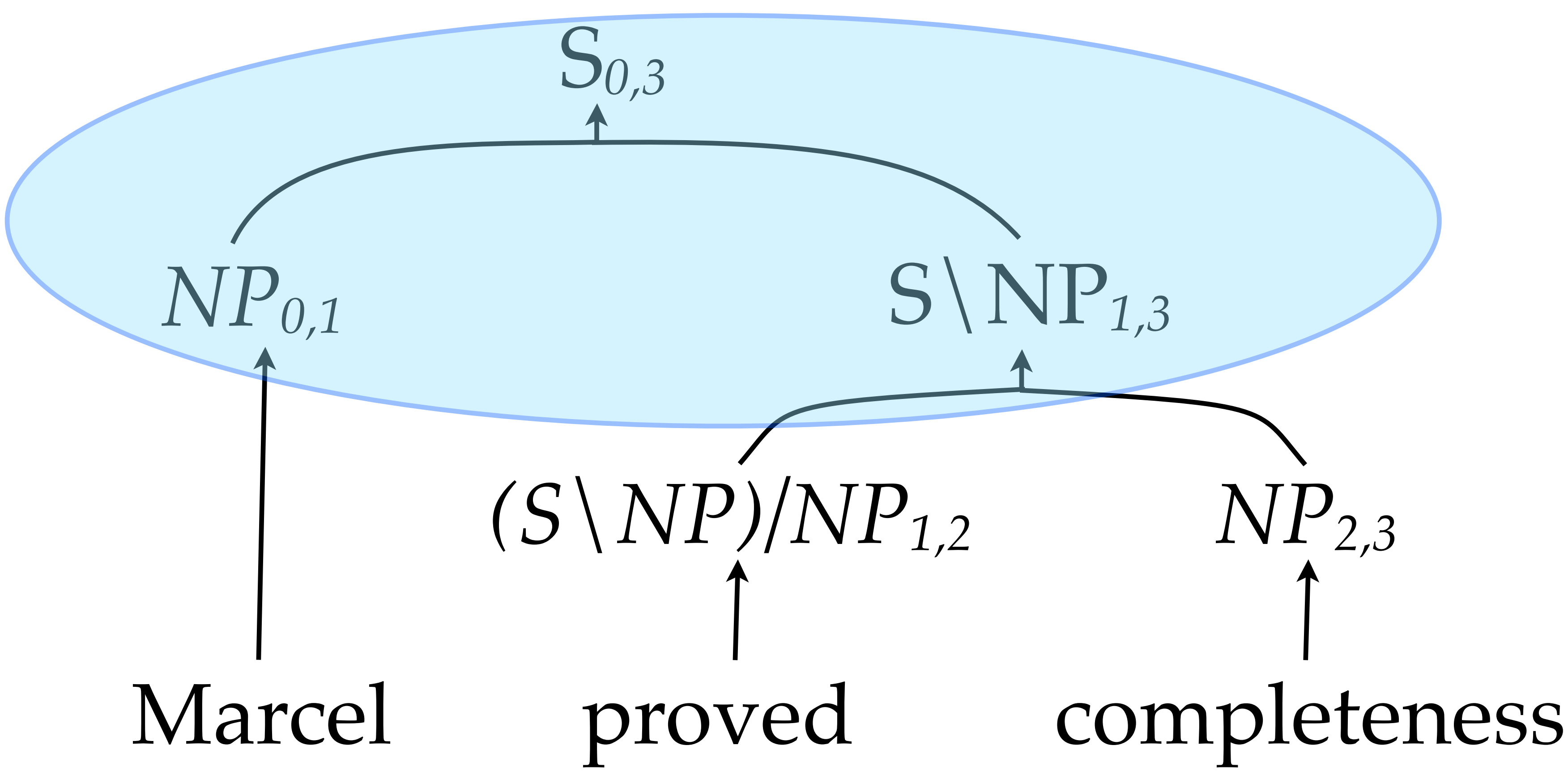
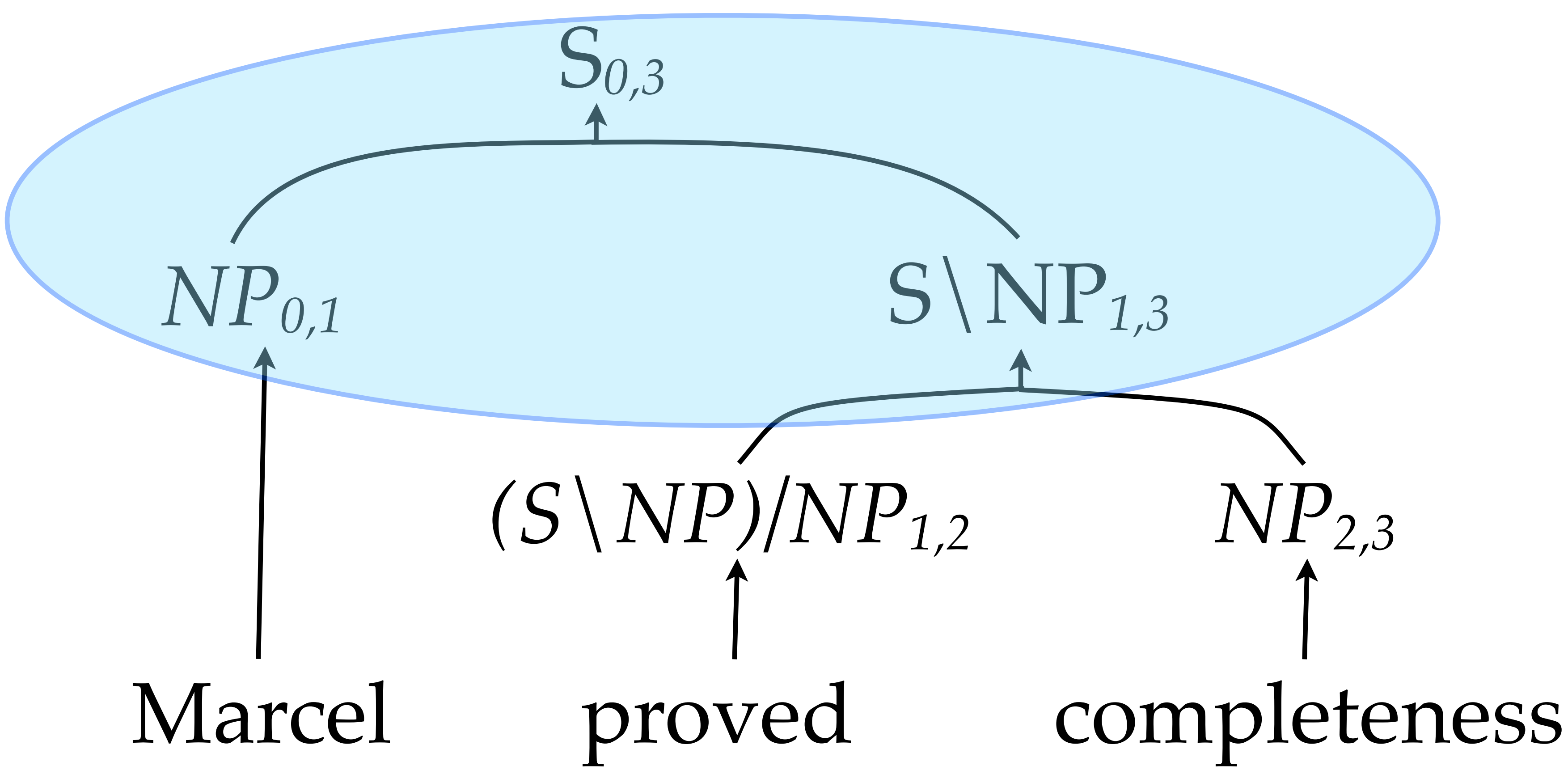


Decomposability

$|y \cap y'| = n$ correct dependencies returned

$|y'| = d$ all dependencies returned

$n = n_1 + n_2$



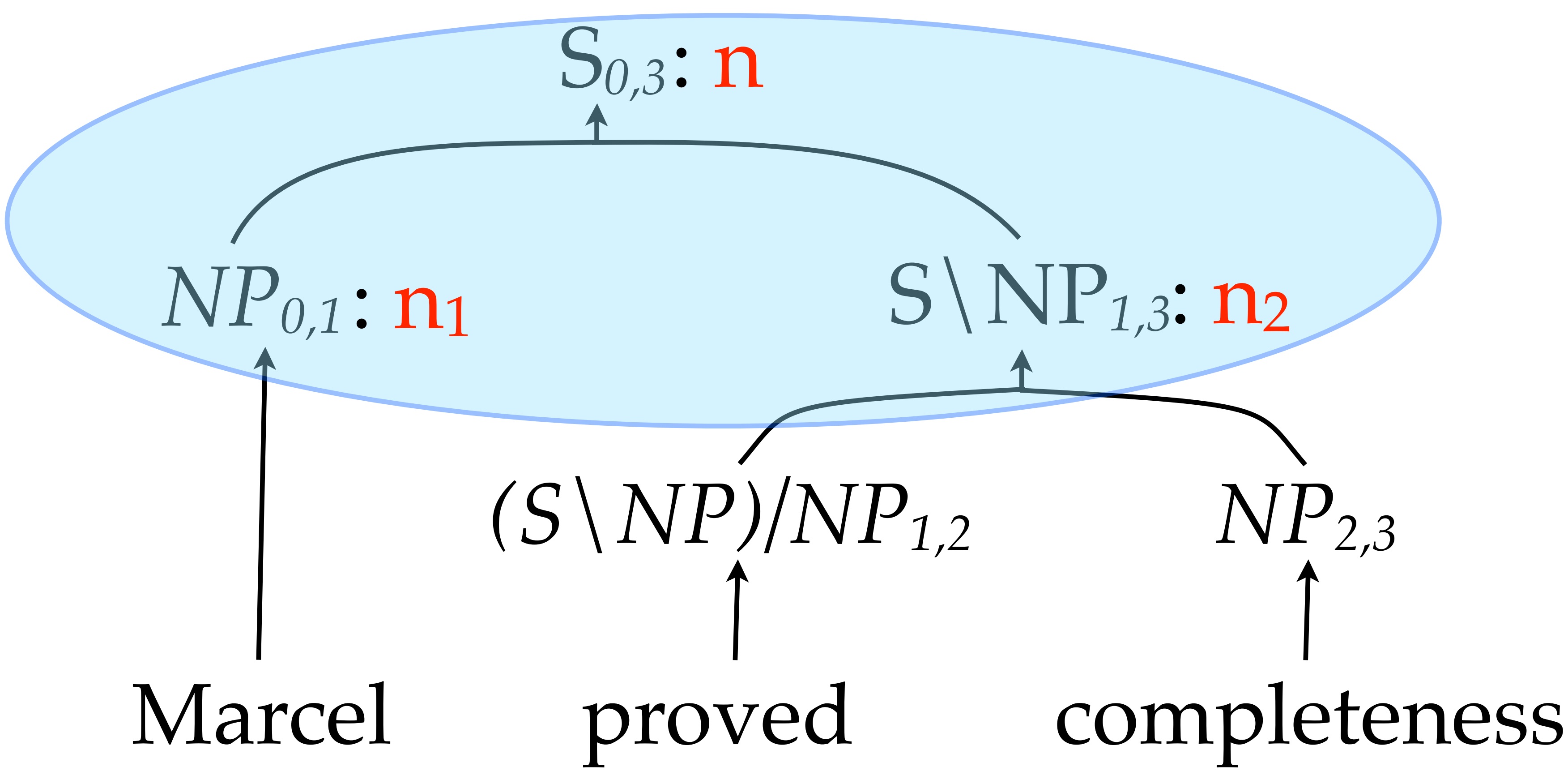
Decomposability

Correct dependency counts

$|y \cap y'| = n$ correct dependencies returned

$|y'| = d$ all dependencies returned

n = $n_1 + n_2$



Decomposability

F-measure

$$|y \cap y'| = n \quad \text{correct dependencies returned}$$

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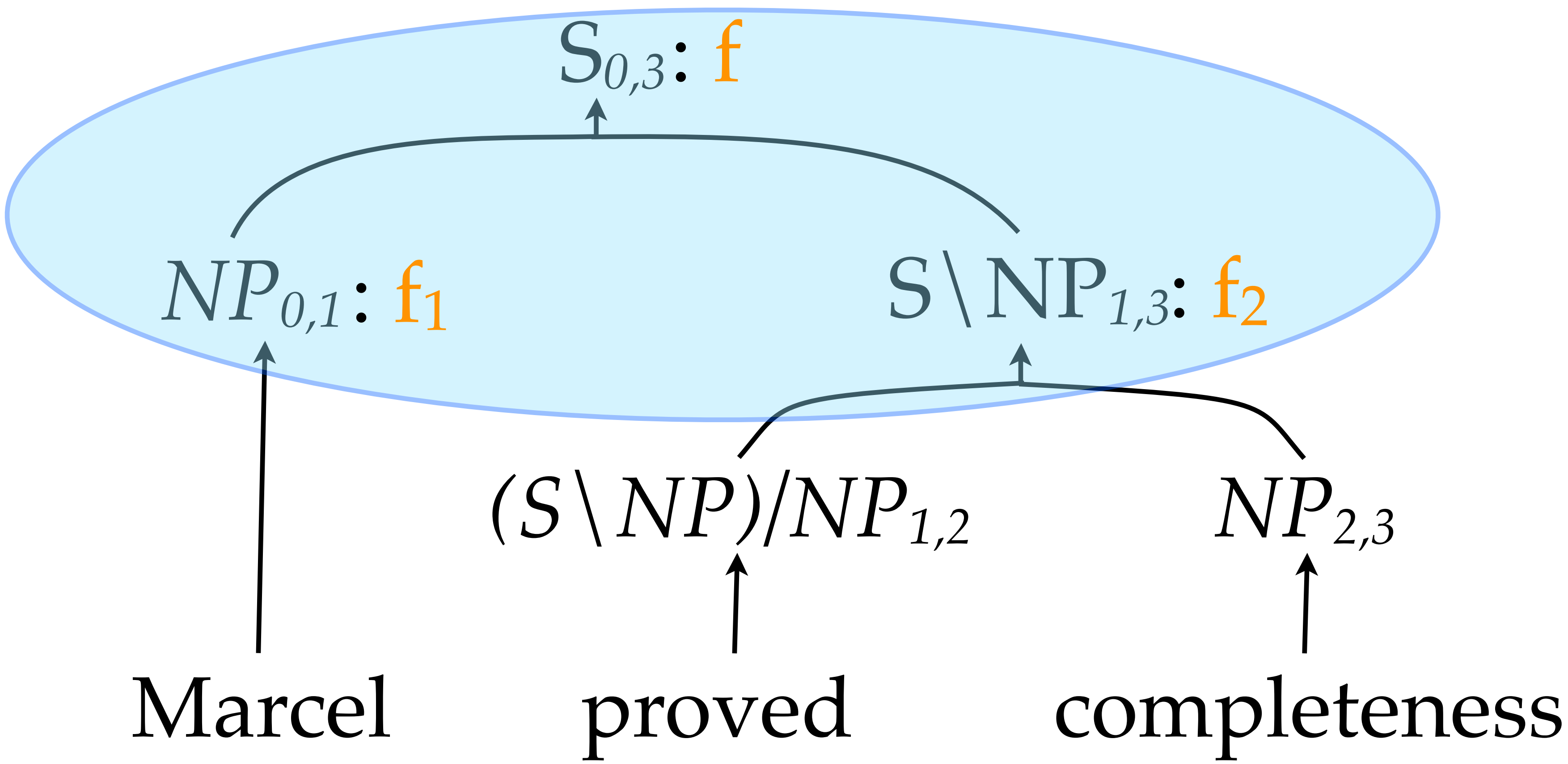

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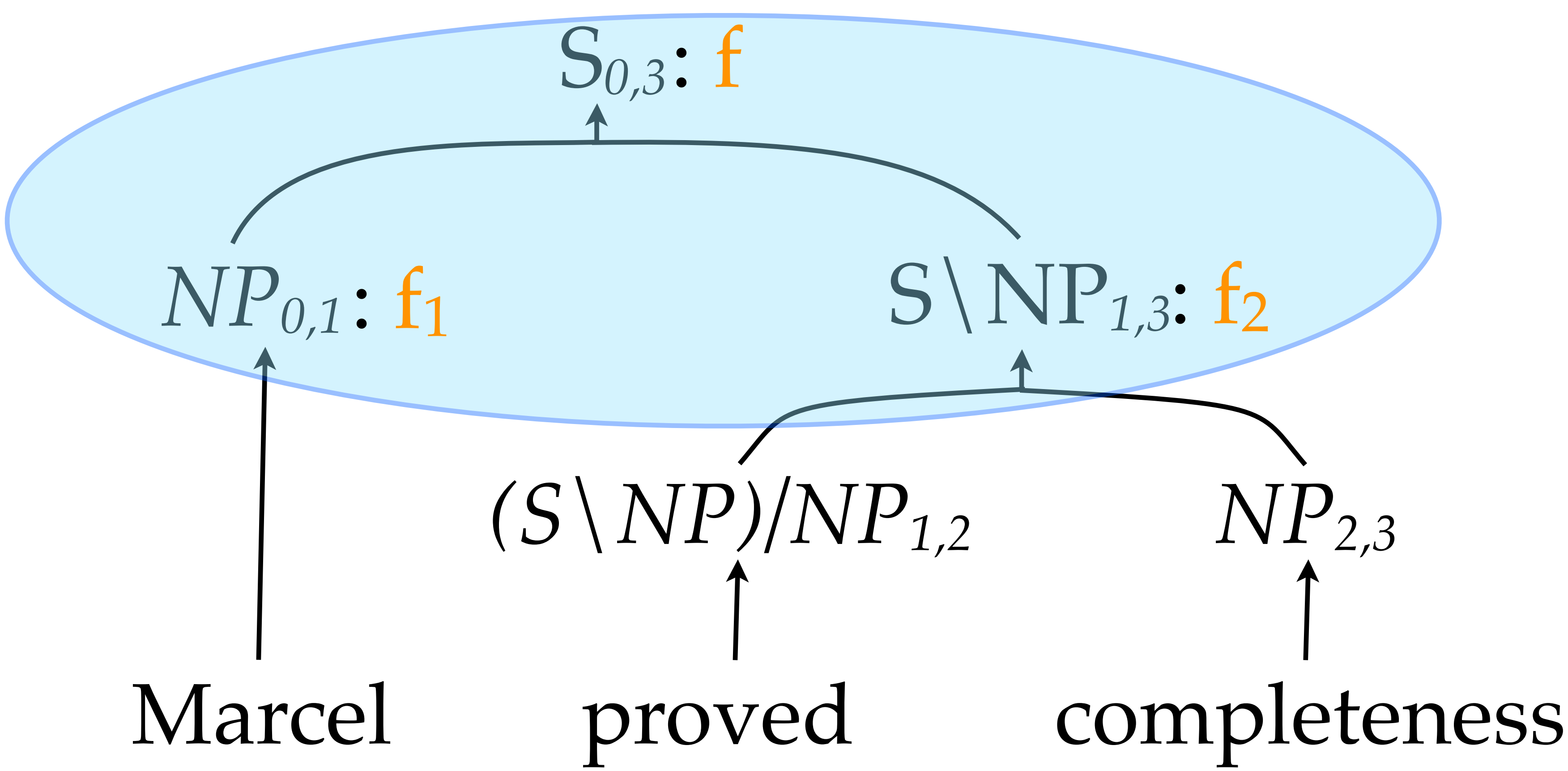
$f = f_1 \otimes f_2$



Decomposability

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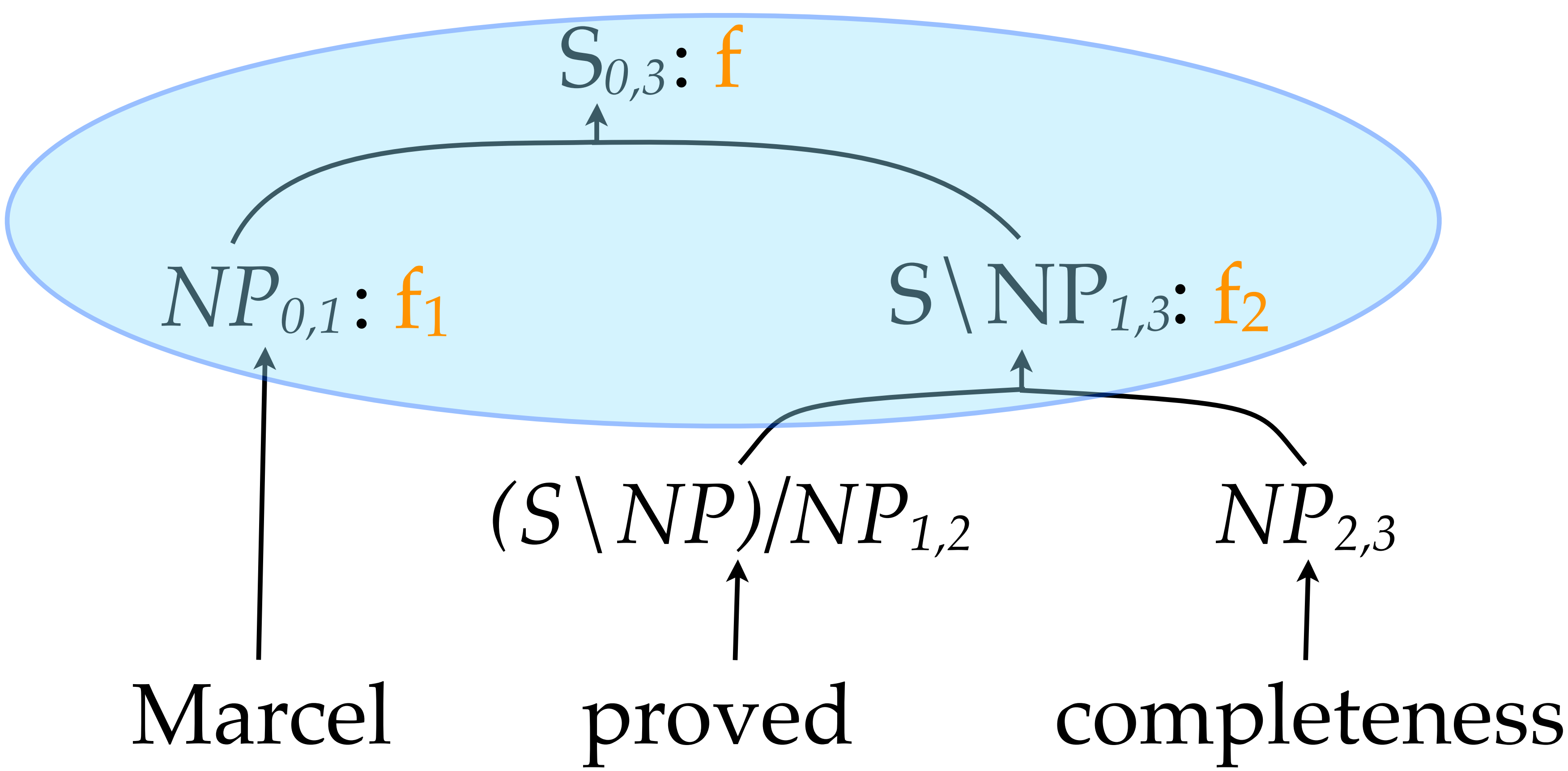
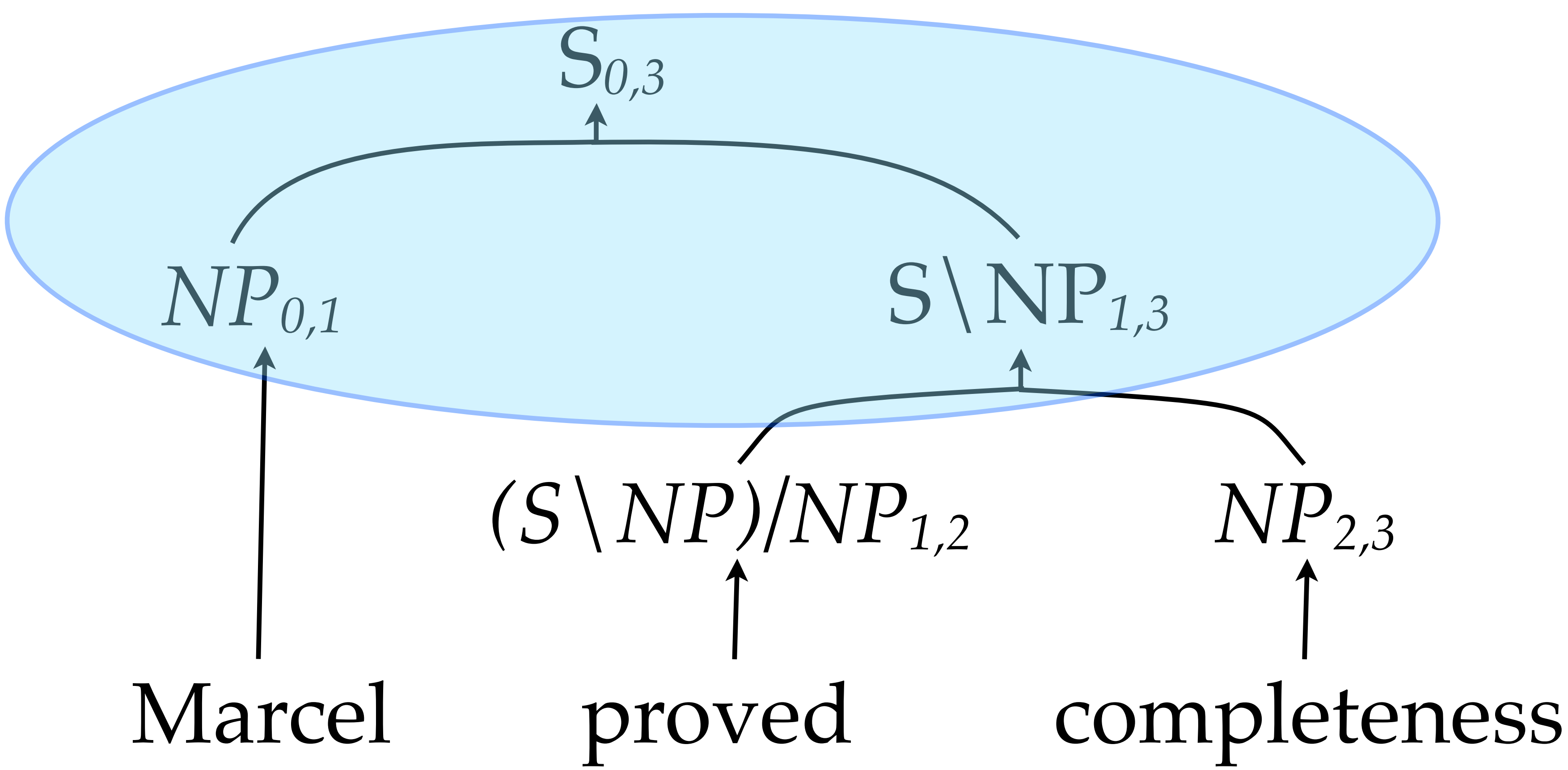
$\downarrow$

Approximations!



Approximate Loss Functions

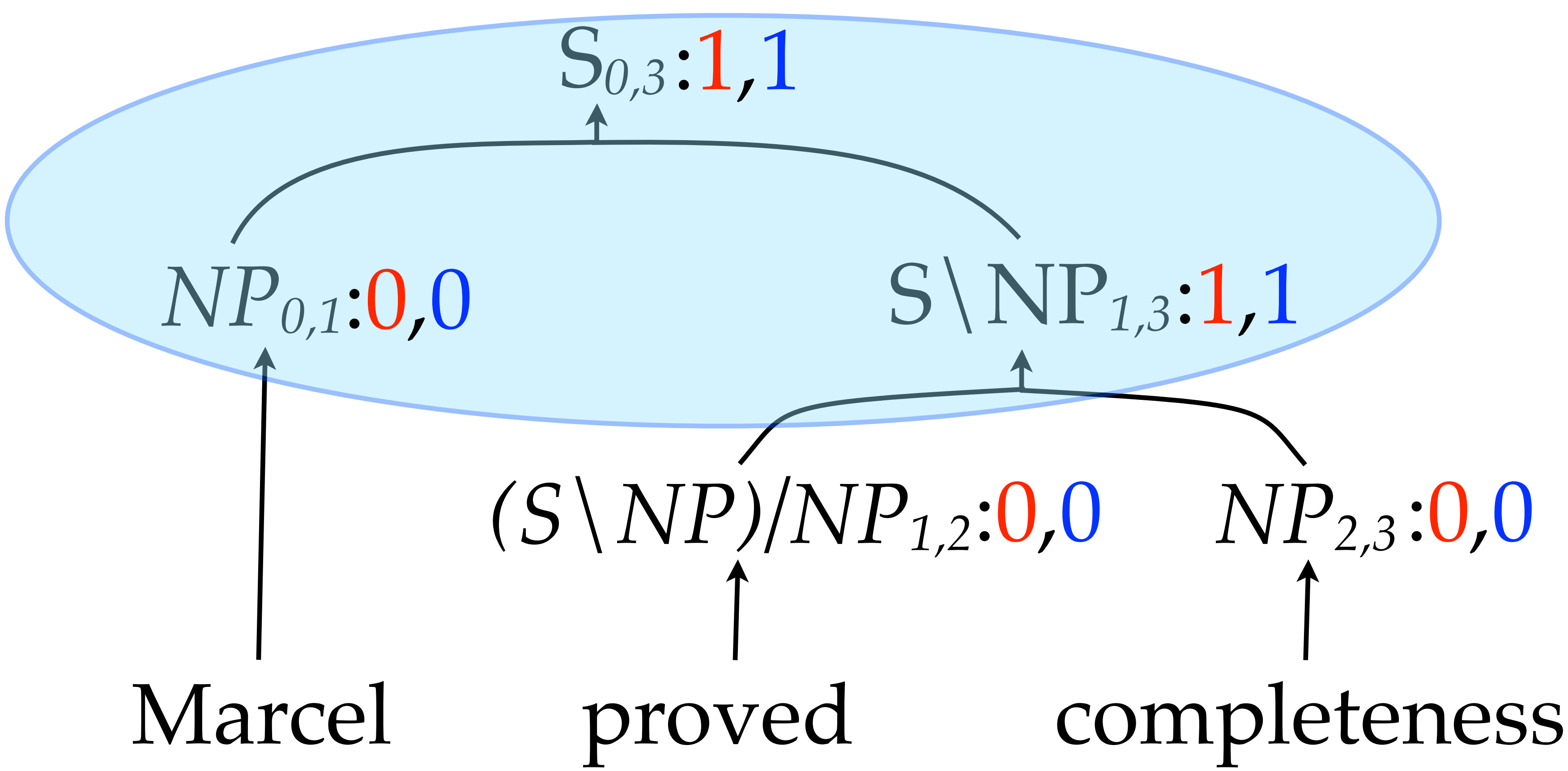


Approximate Loss Functions

for each substructure:

n_+ correct dependencies
d_+ all dependencies

c_+ gold dependencies



Approximate Loss Functions

for each substructure:

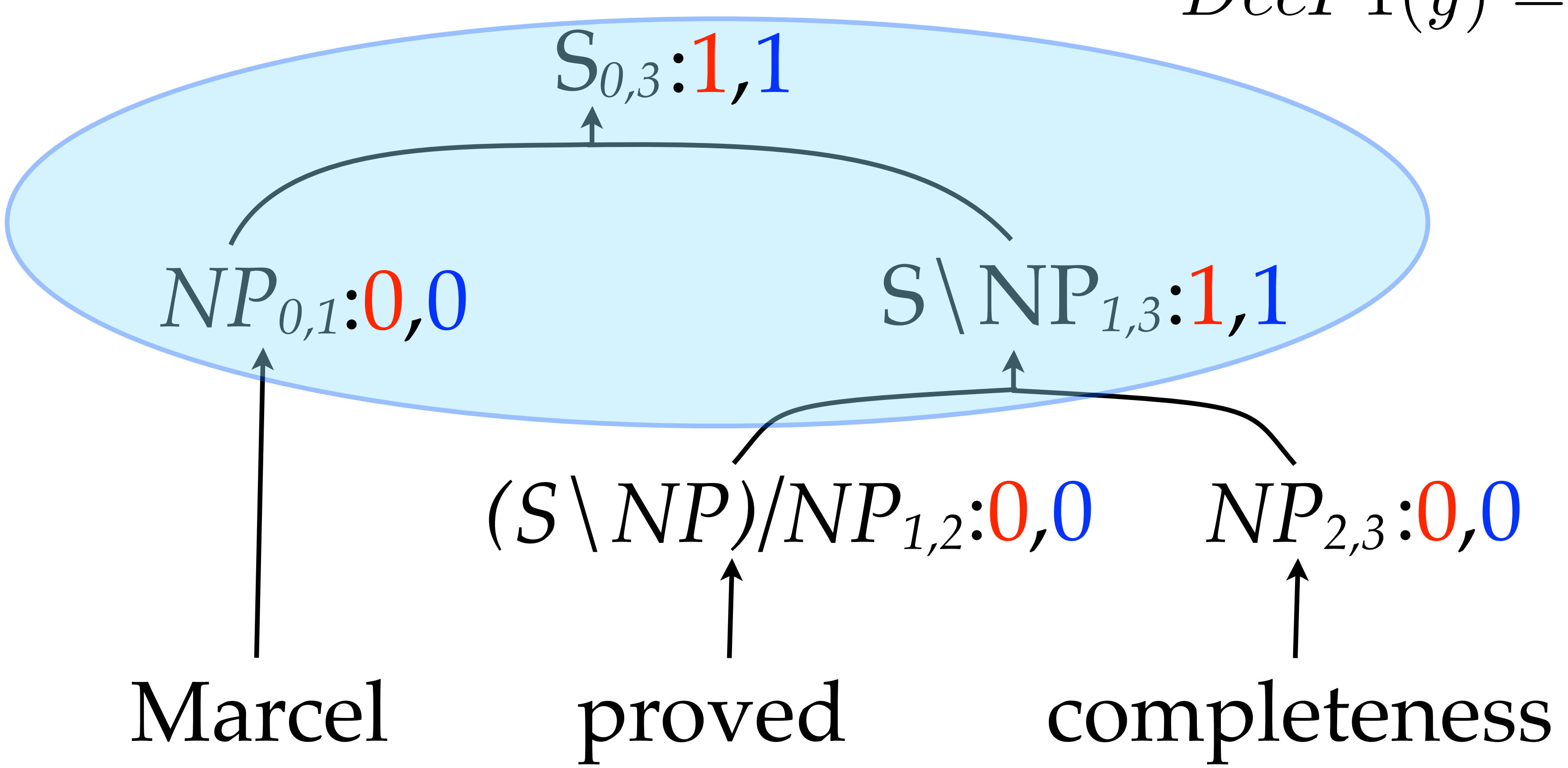
n_+ correct dependencies
d_+ all dependencies

c_+ gold dependencies

$$DecP(y) = \sum_{t \in T(y)} d_+(t) - n_+(t)$$

$$DecR(y) = \sum_{t \in T(y)} c_+(t) - n_+(t)$$

$$DecF1(y) = DecP(y) + DecR(y)$$



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

correct dependencies

all dependencies

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

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

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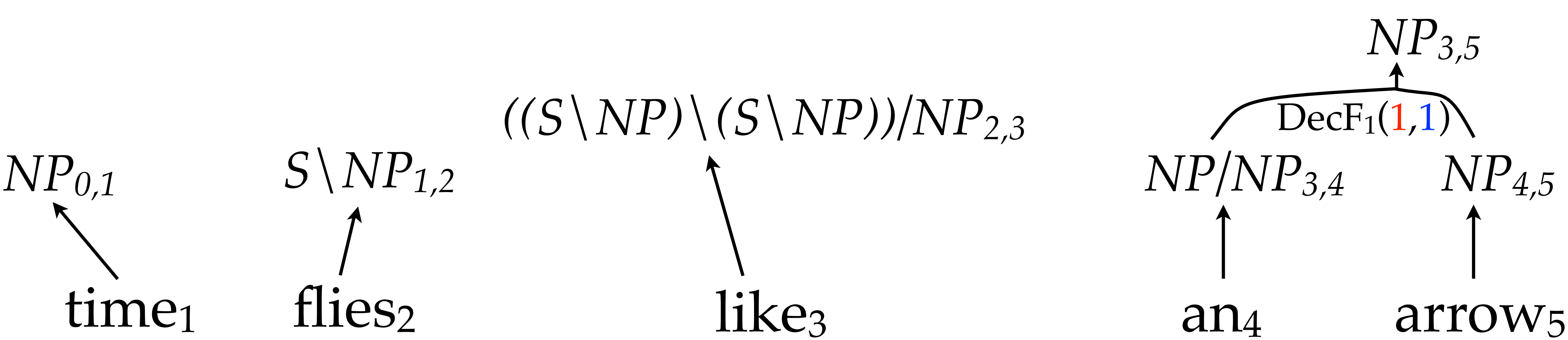

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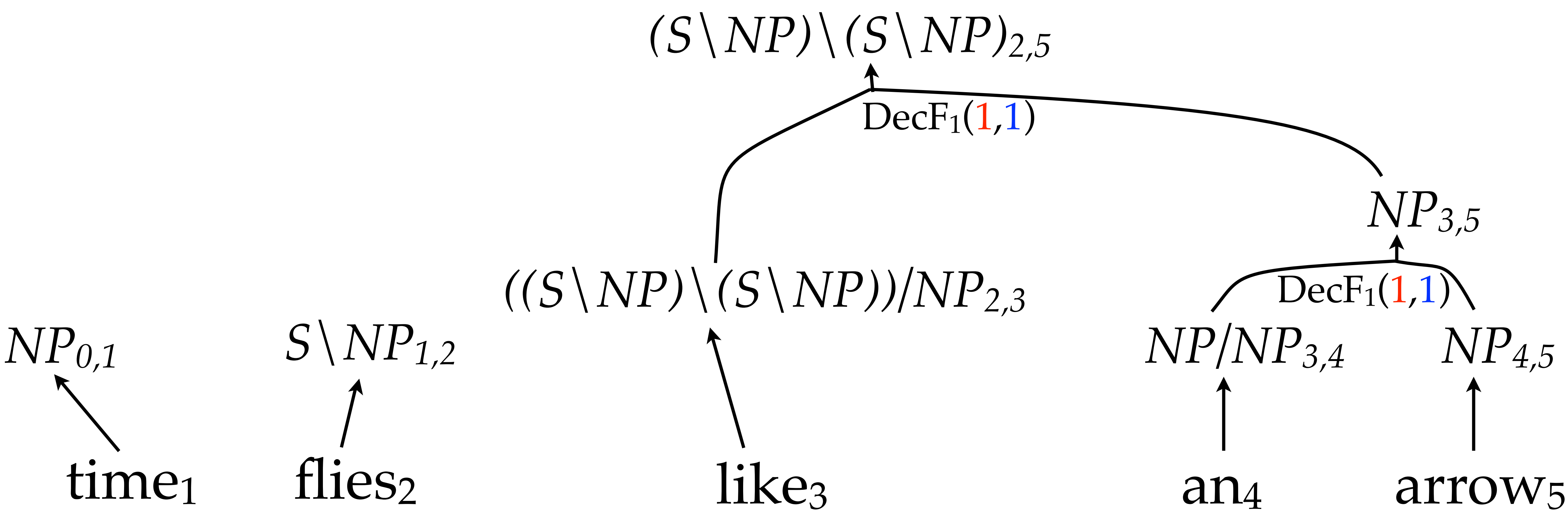

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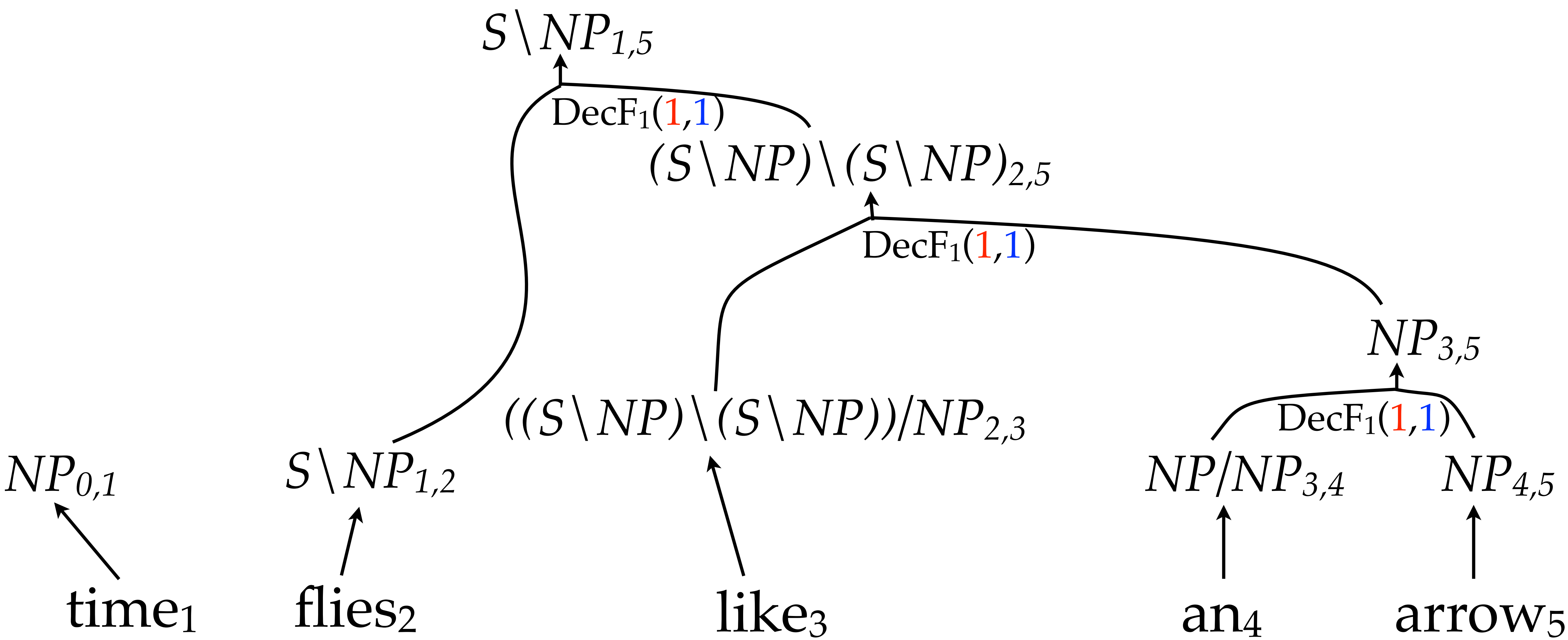

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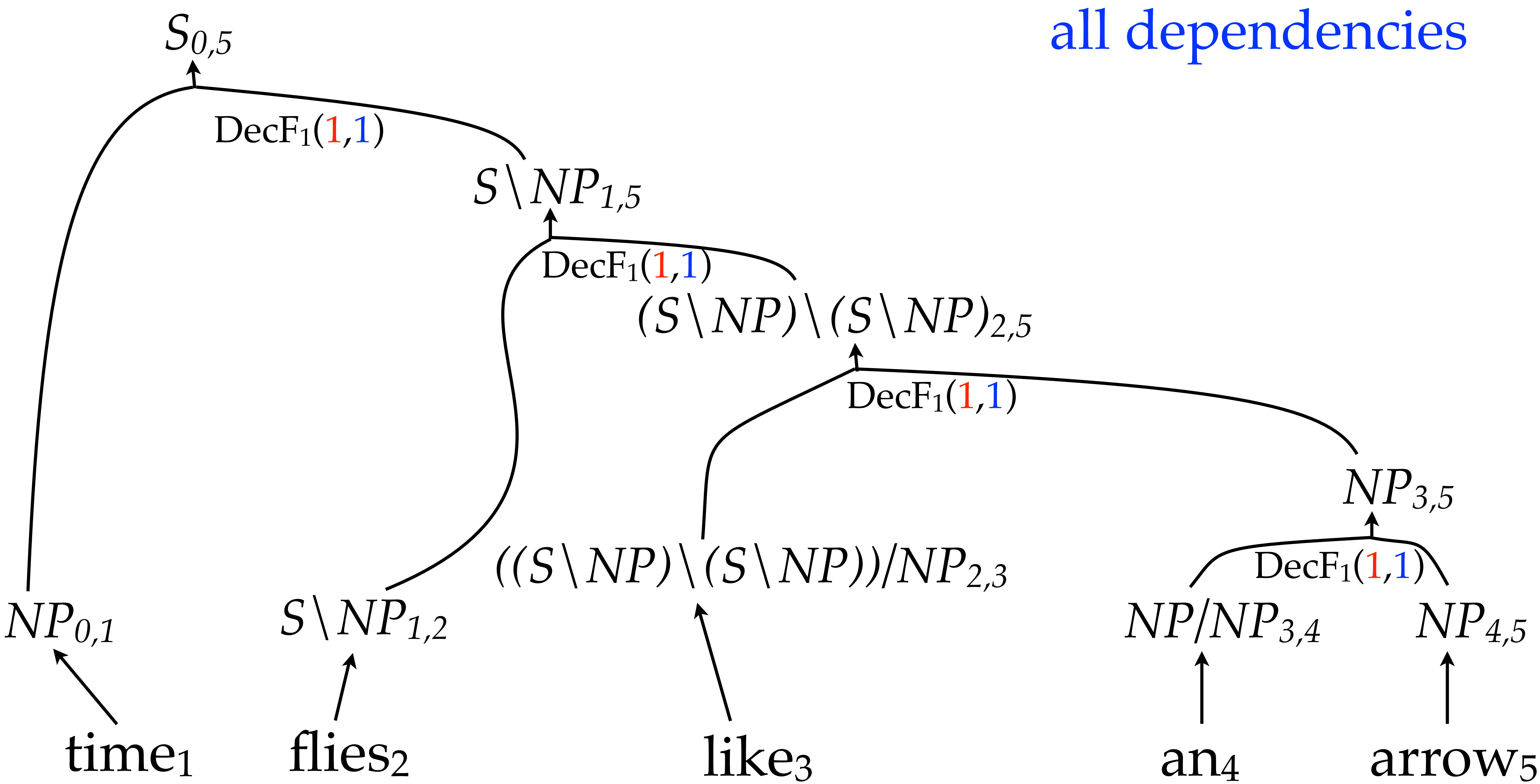

Approximate Losses with CKY

items $A_{i,j}$

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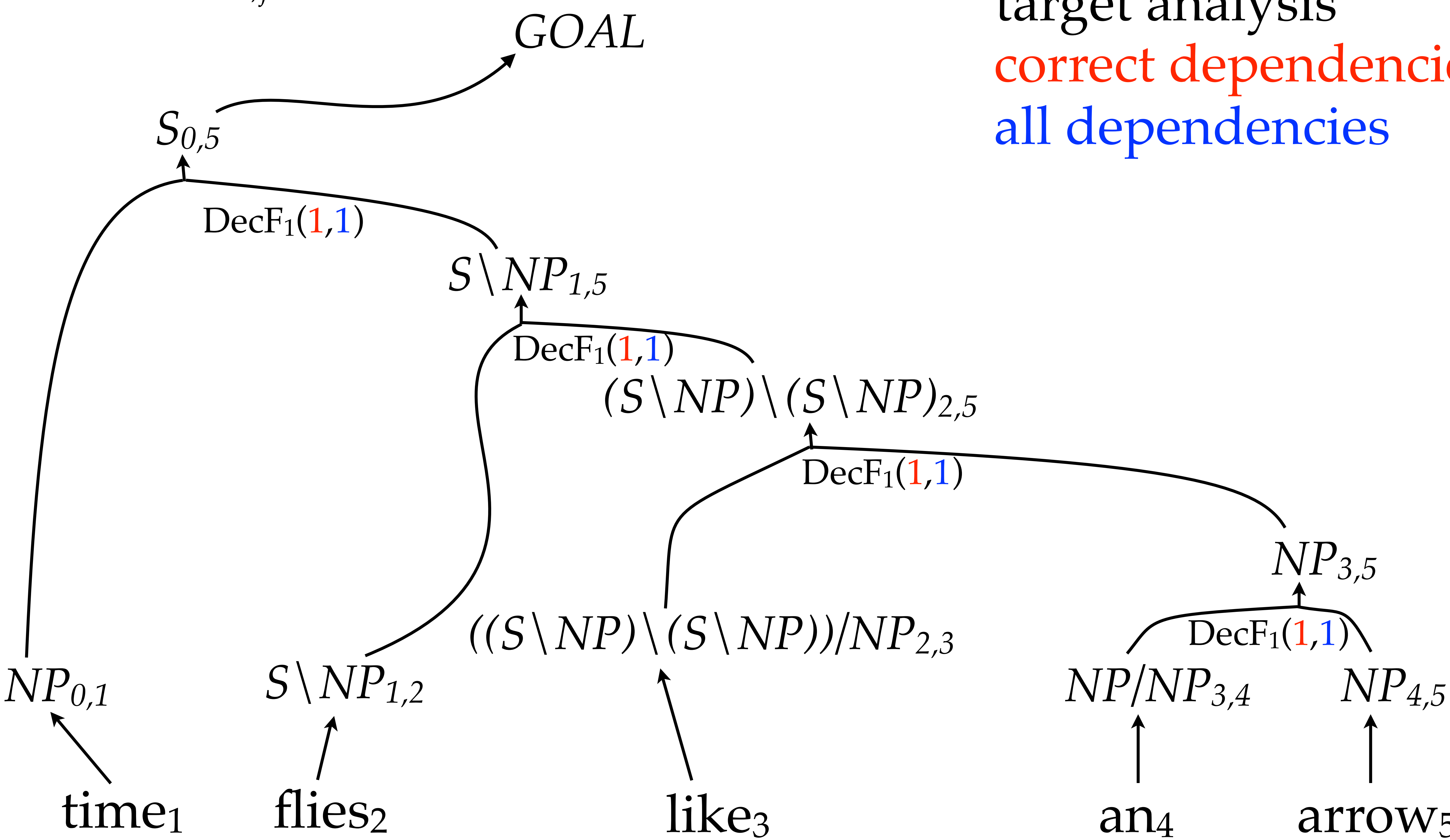


Approximate Losses with CKY

items $A_{i,j}$

another analysis
correct dependencies
all dependencies

time_1 flies_2 like_3 an_4 arrow_5

Approximate Losses with CKY

items $A_{i,j}$

another analysis
correct dependencies
all dependencies

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

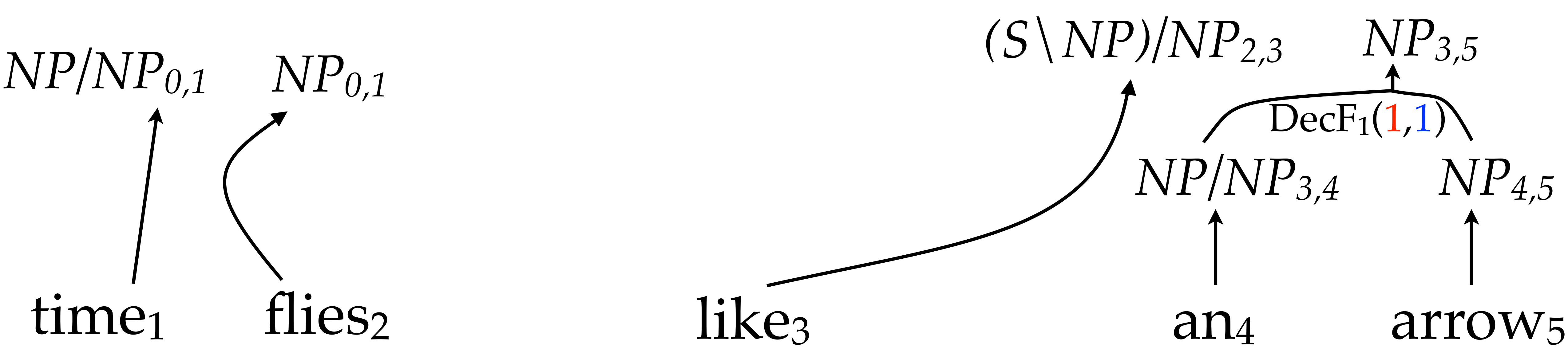
$NP/NP_{0,1}$ $NP_{0,1}$ $NP/NP_{3,4}$ $NP_{4,5}$

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

Approximate Losses with CKY

items $A_{i,j}$

another analysis
correct dependencies
all dependencies



Approximate Losses with CKY

items $A_{i,j}$

another analysis
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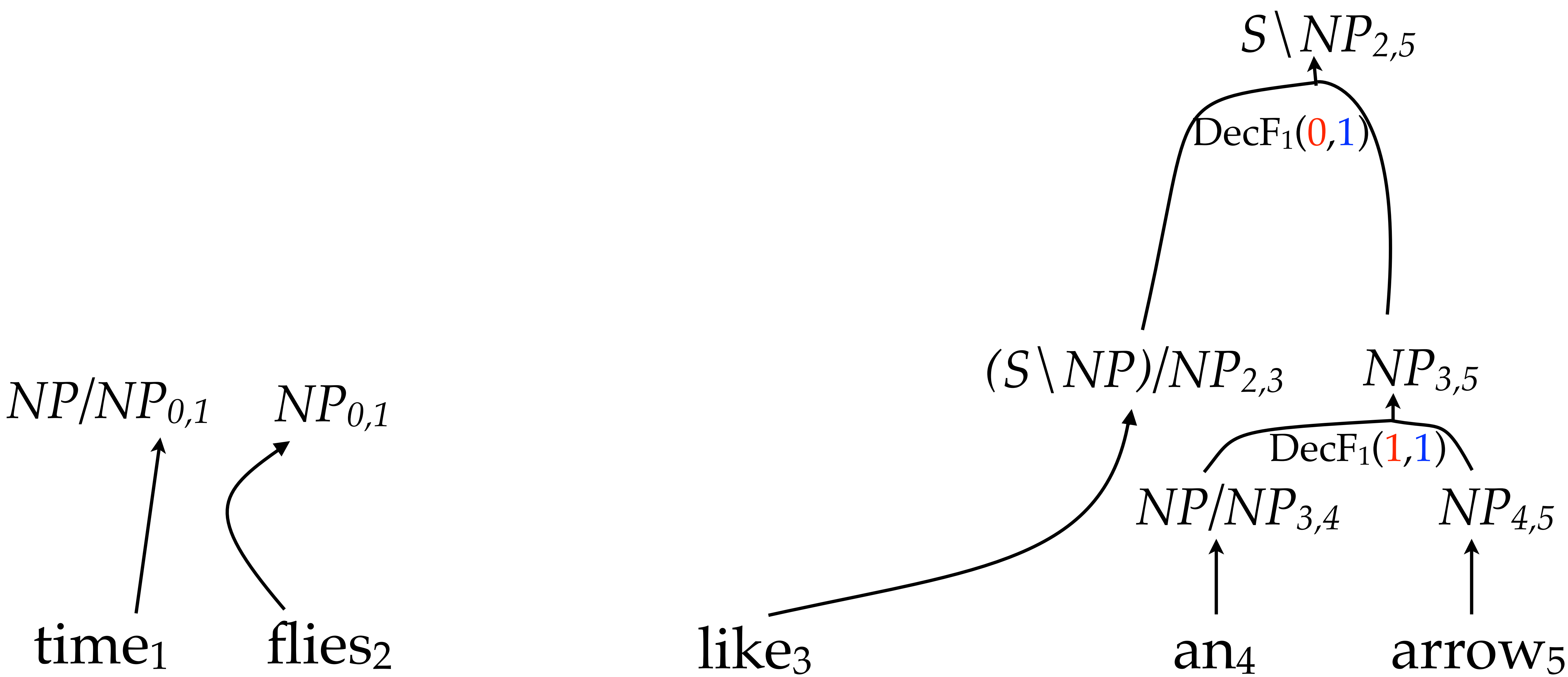

Approximate Losses with CKY

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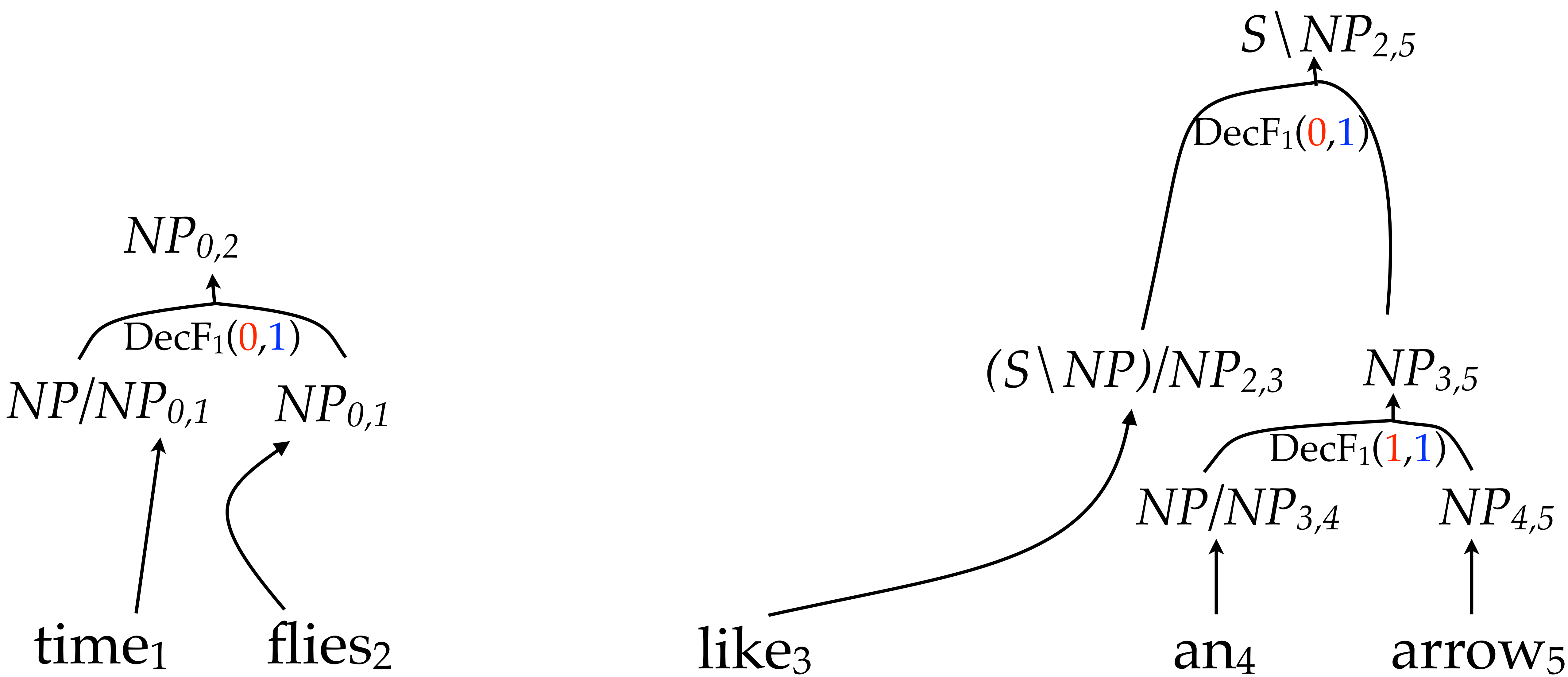

Approximate Losses with CKY

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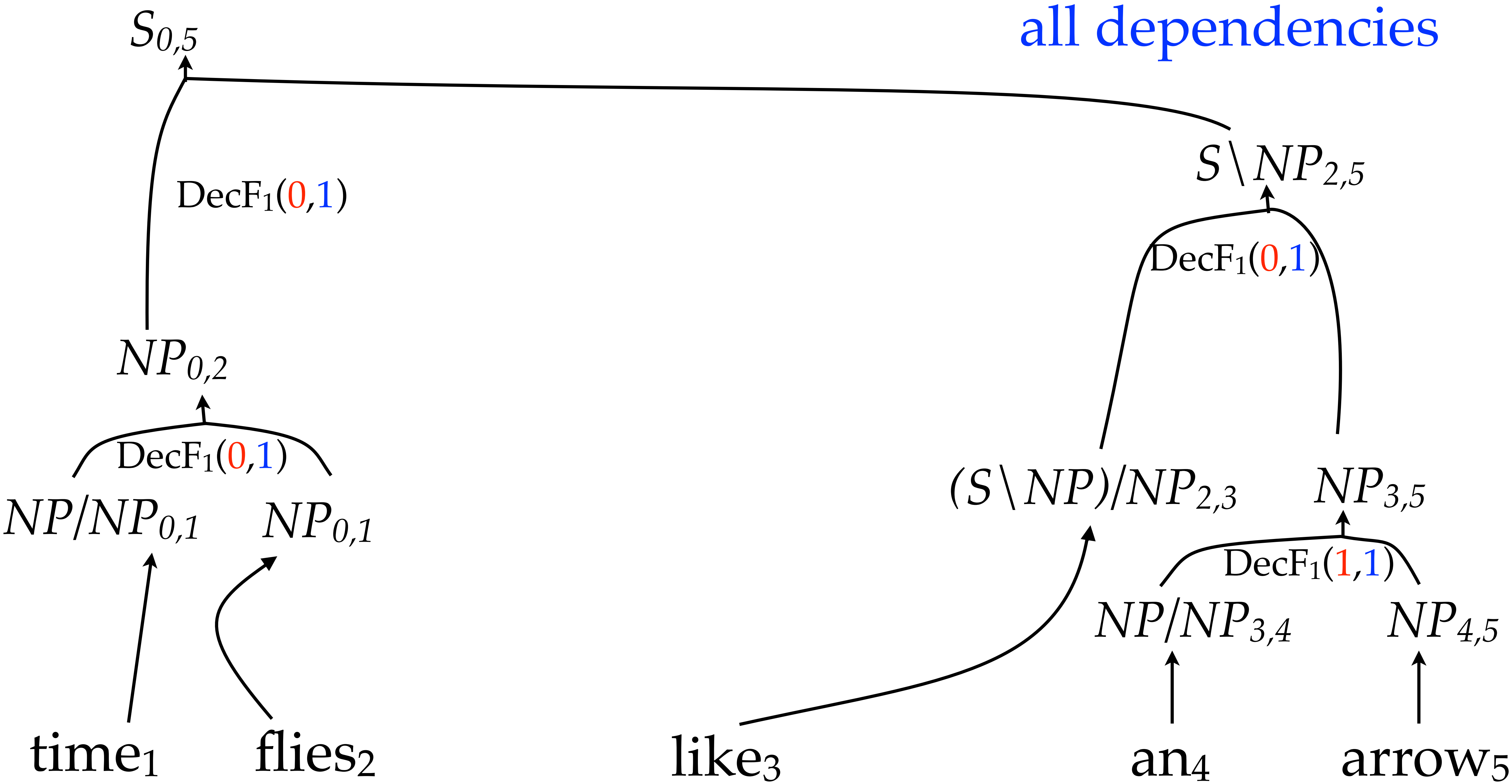

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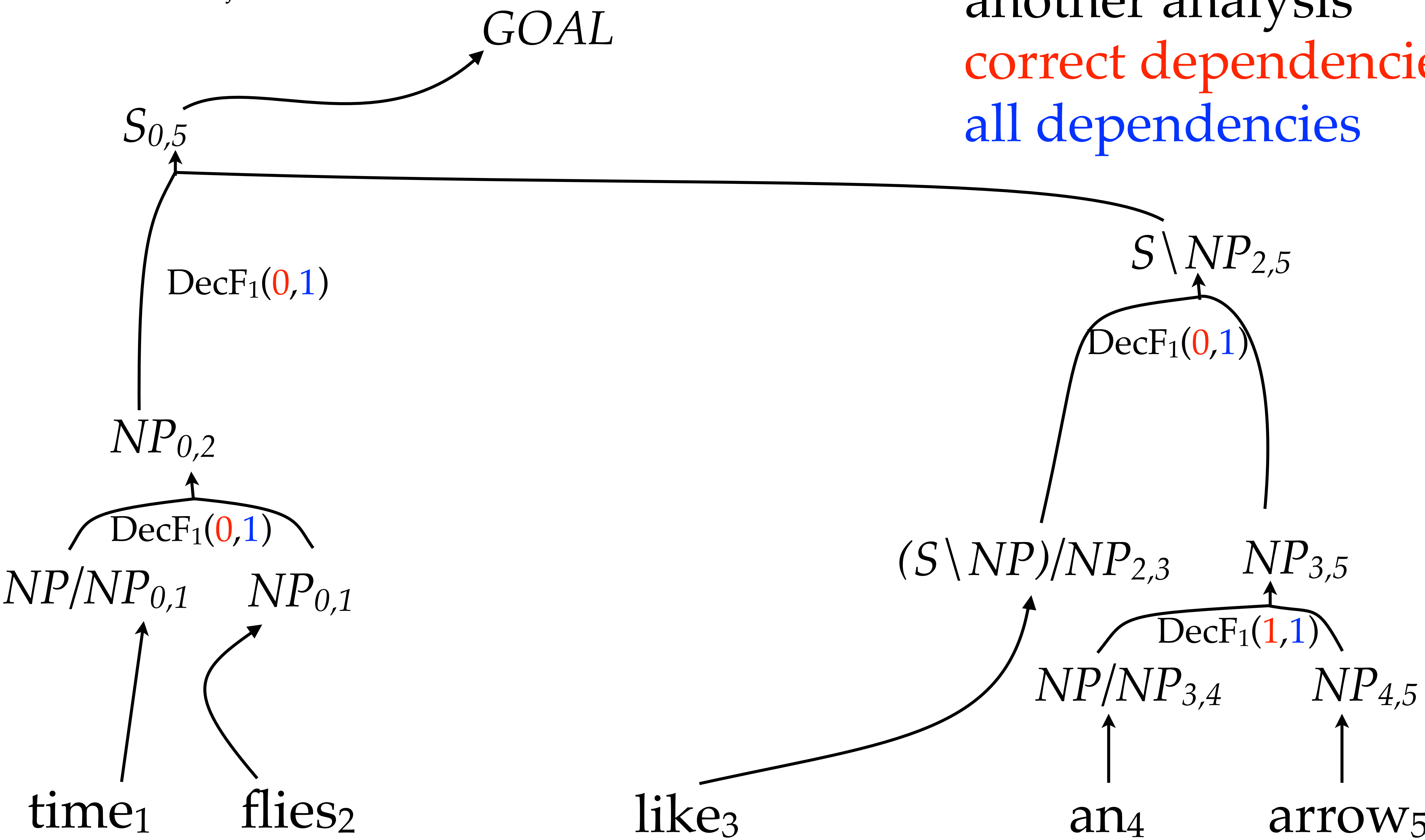

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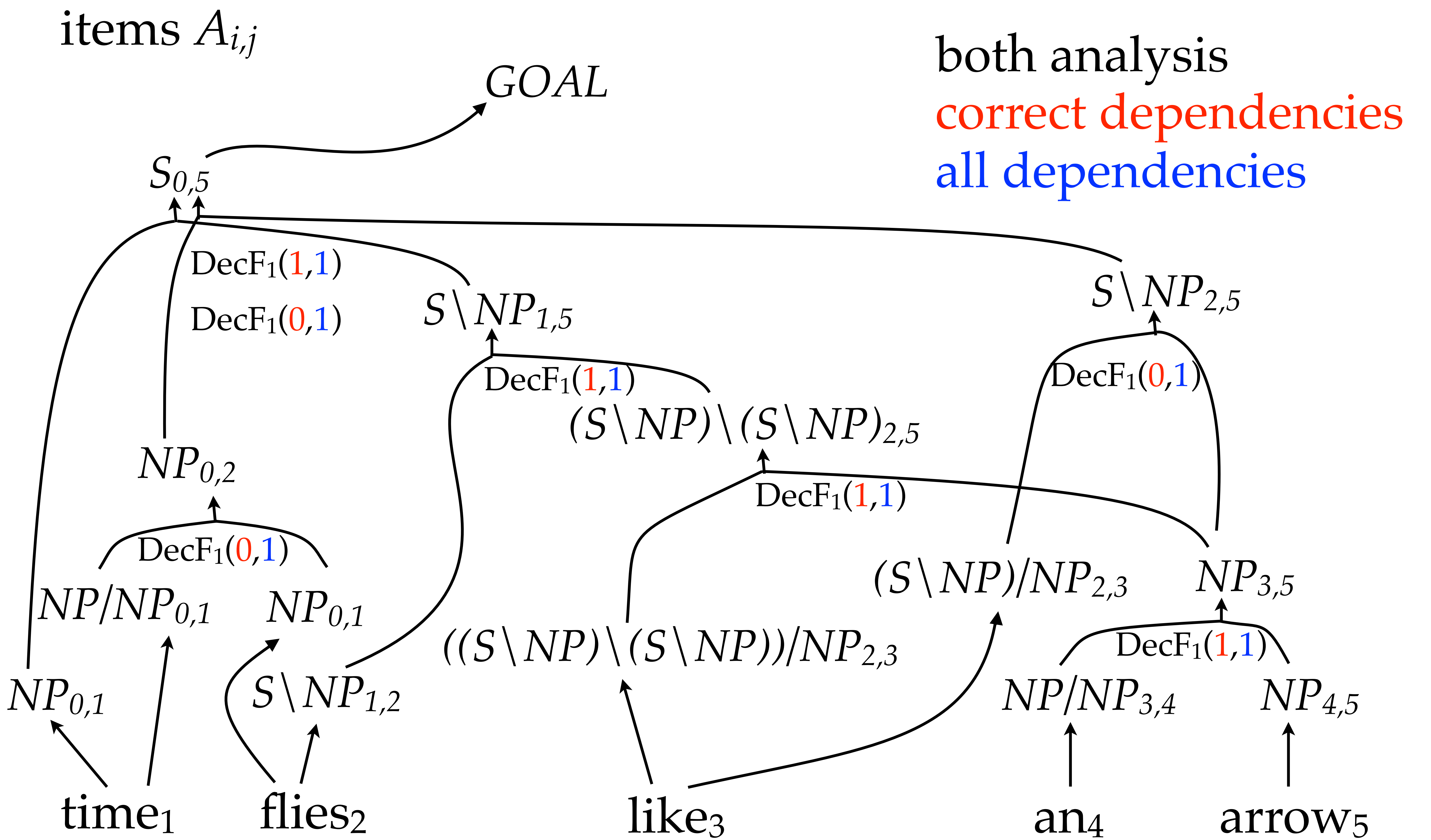
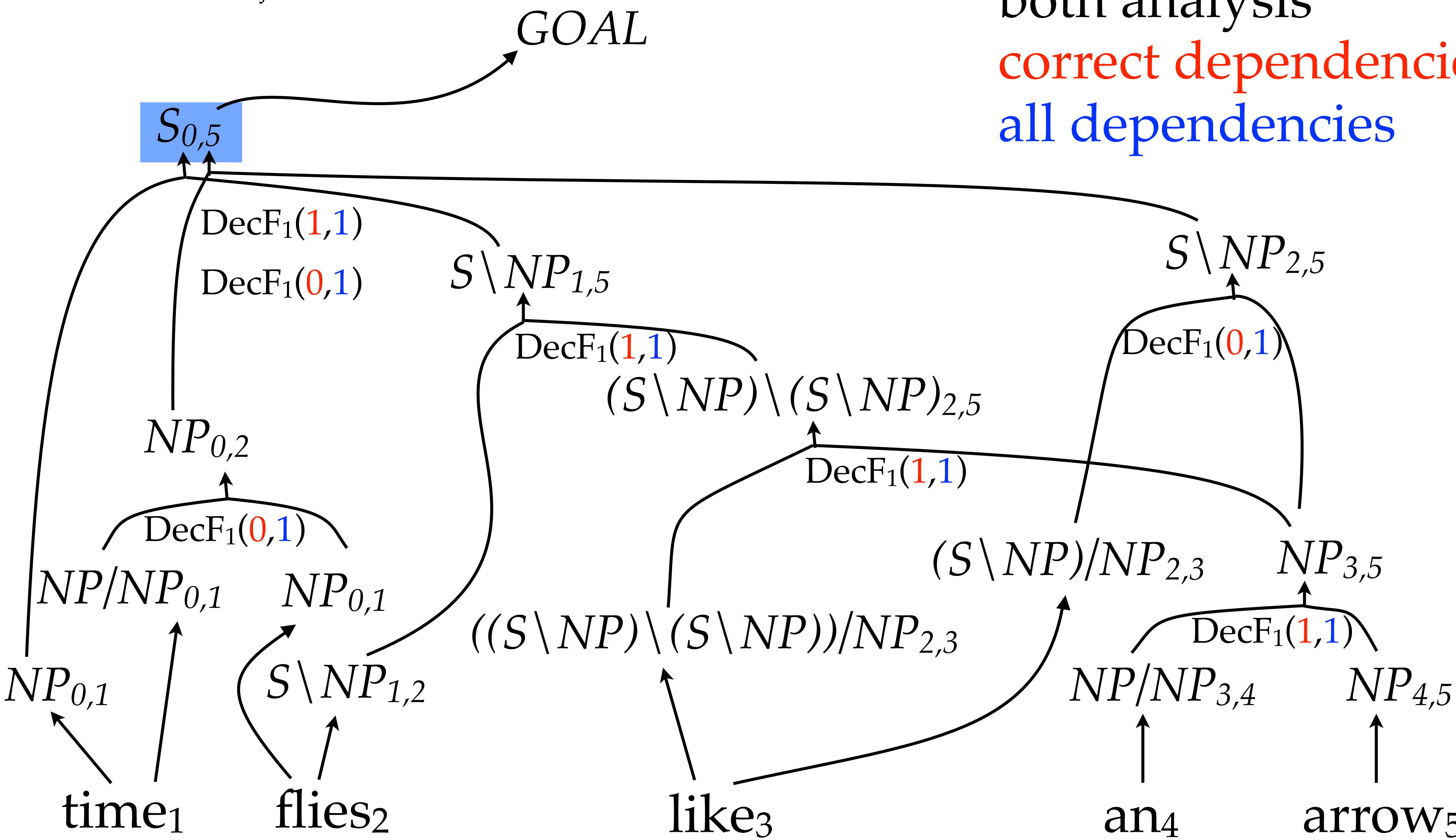


Approximate Losses with CKY

items $A_{i,j}$

both analysis
correct dependencies
all dependencies



Decomposability Revisited

F-measure

$|y \cap y'| = n$ correct dependencies returned

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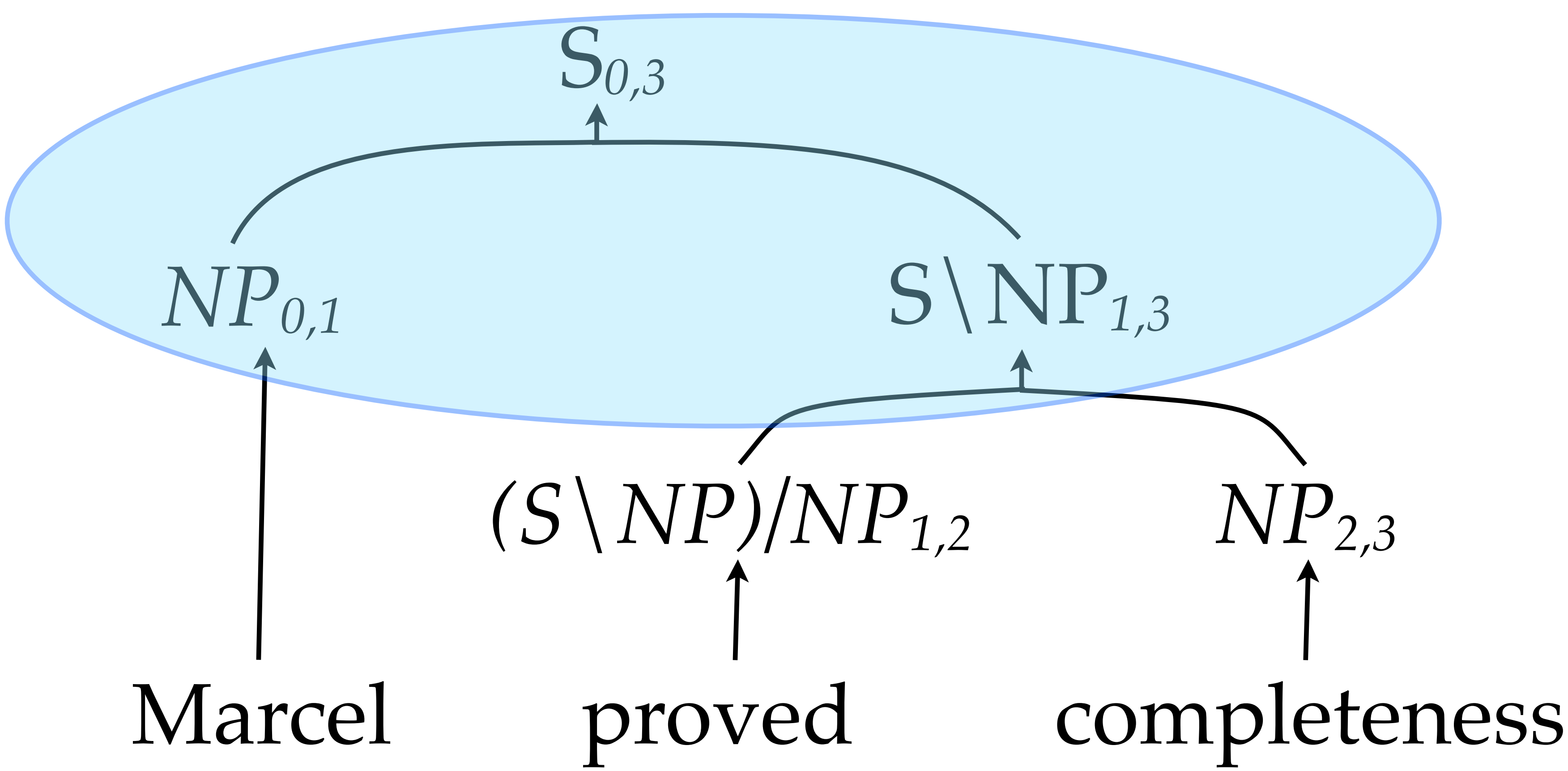
$$F_1(y, y') = \frac{2n}{d + |y|}$$



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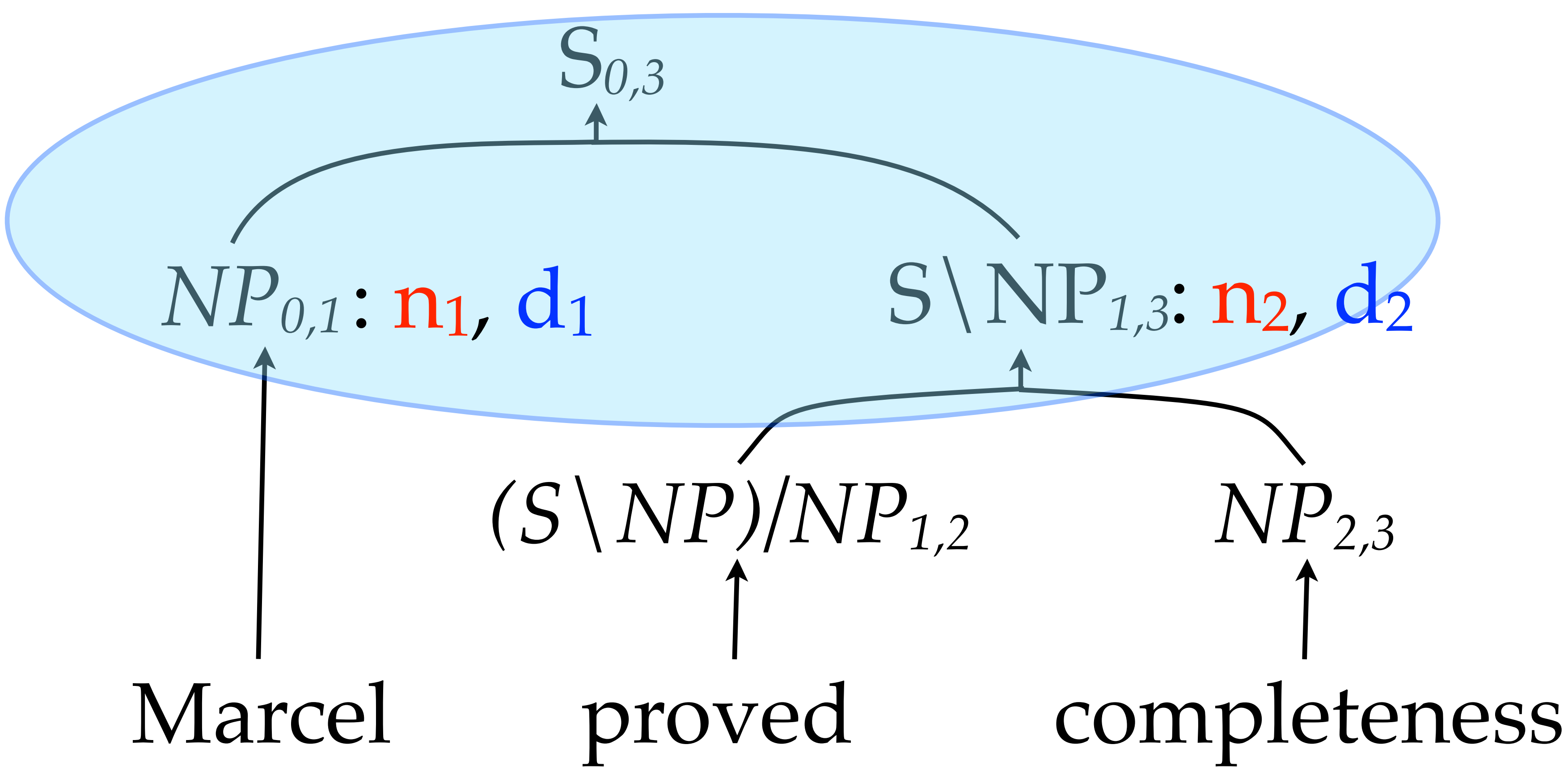

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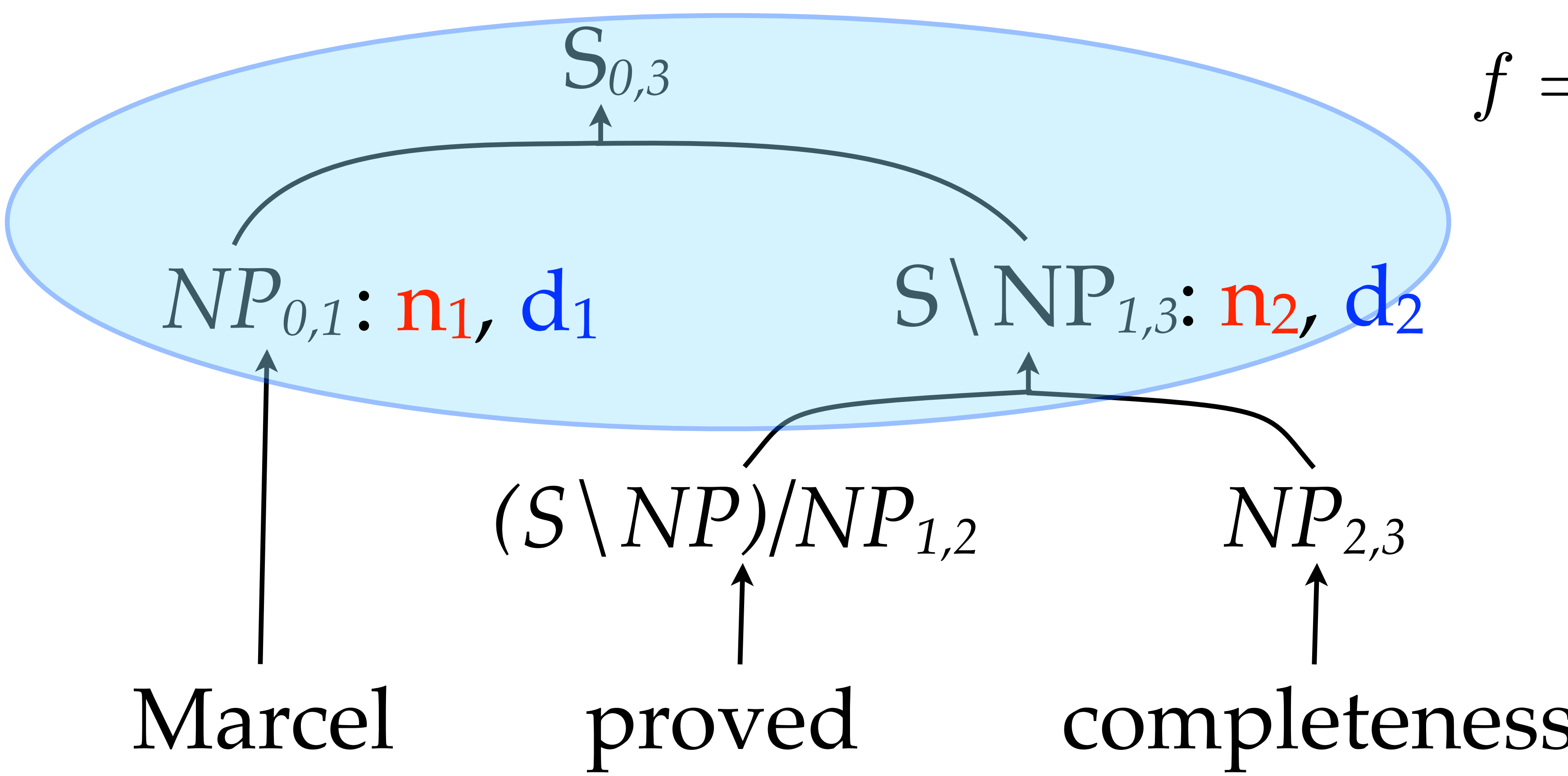
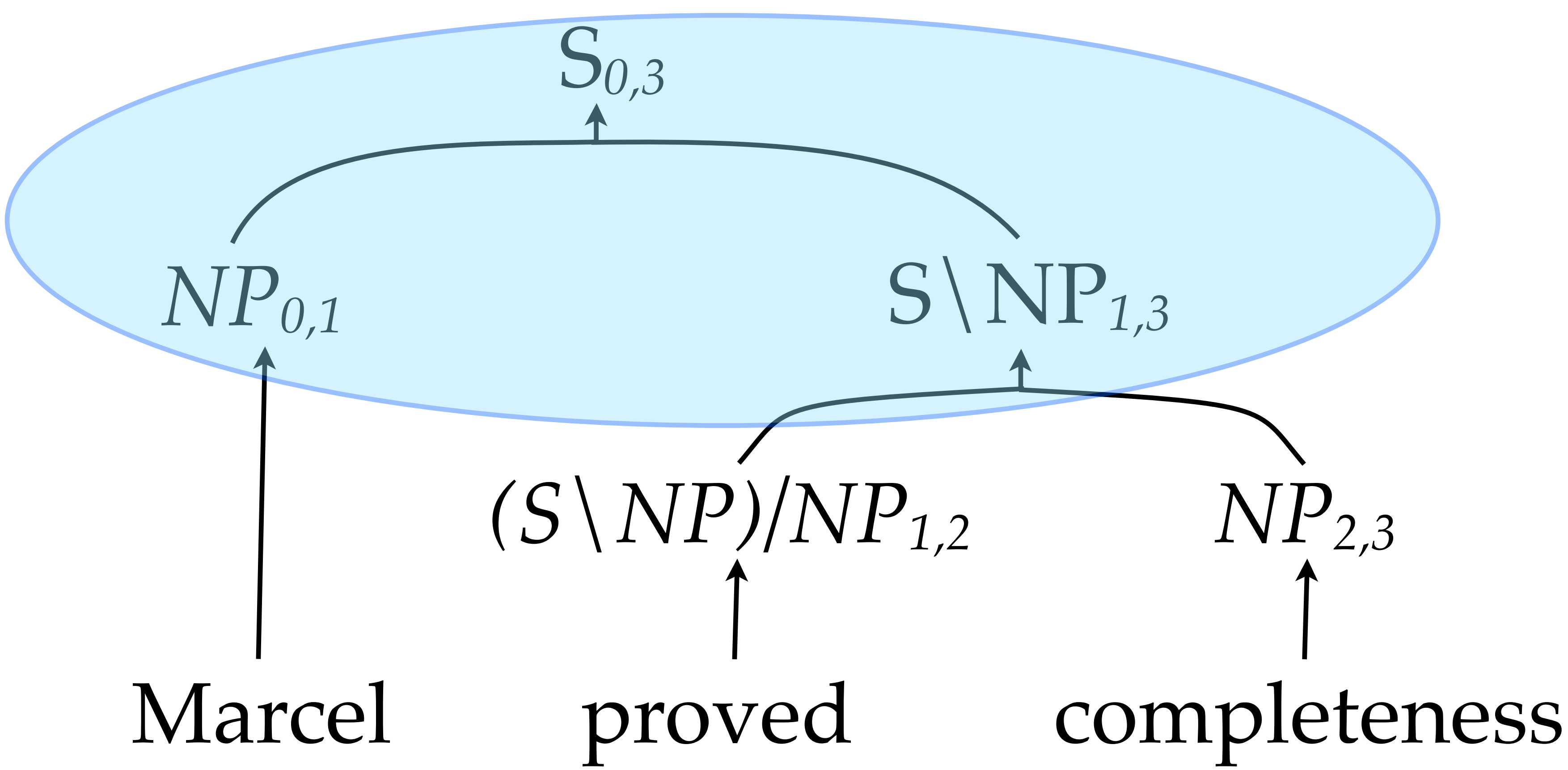


$$f = \frac{2n_1}{d_1 + |y|} \otimes \frac{2n_2}{d_2 + |y|}$$

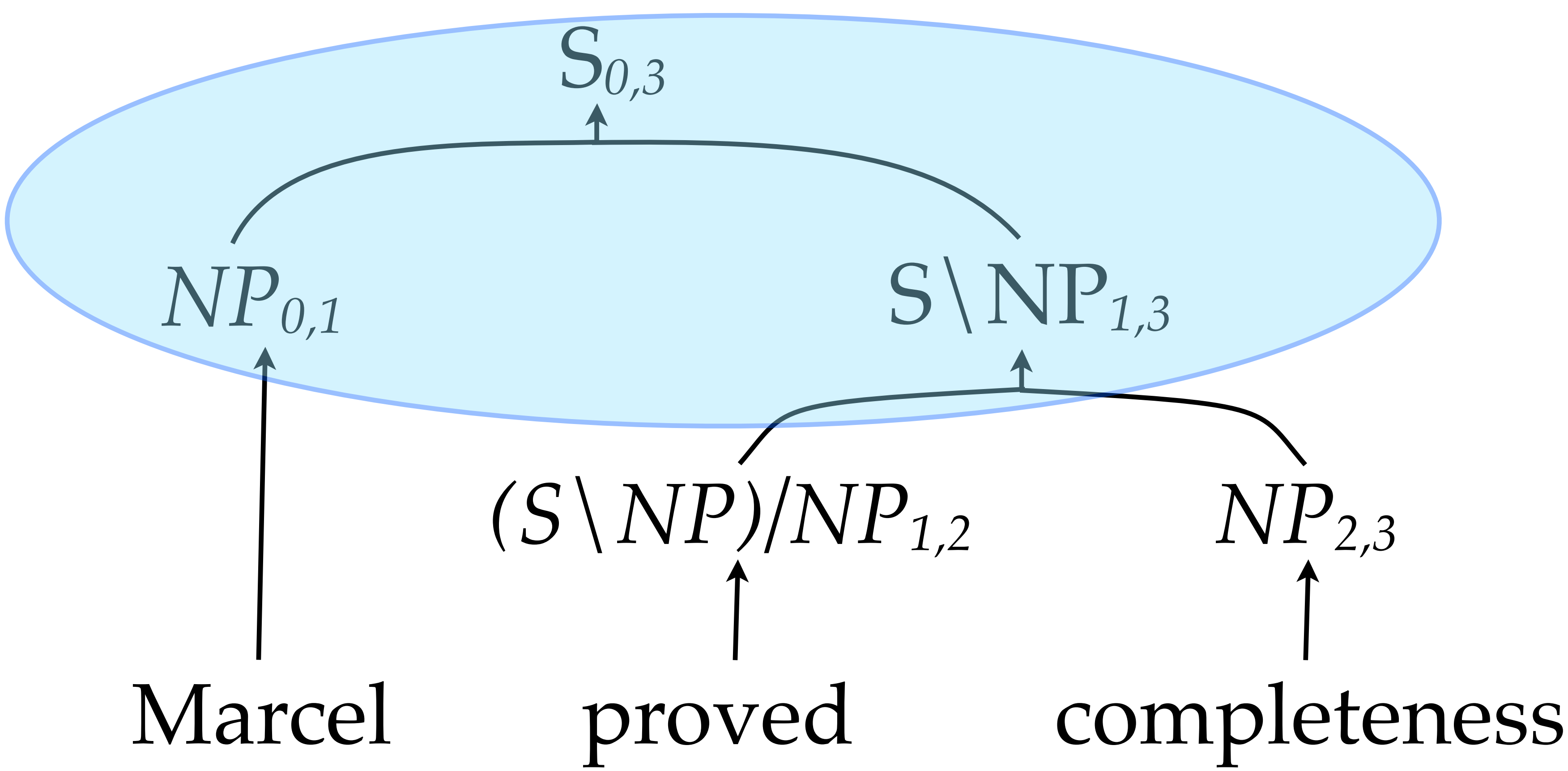
$$= \frac{2(n_1 + n_2)}{d_1 + d_2 + 2|y|}$$

Exact Loss Functions



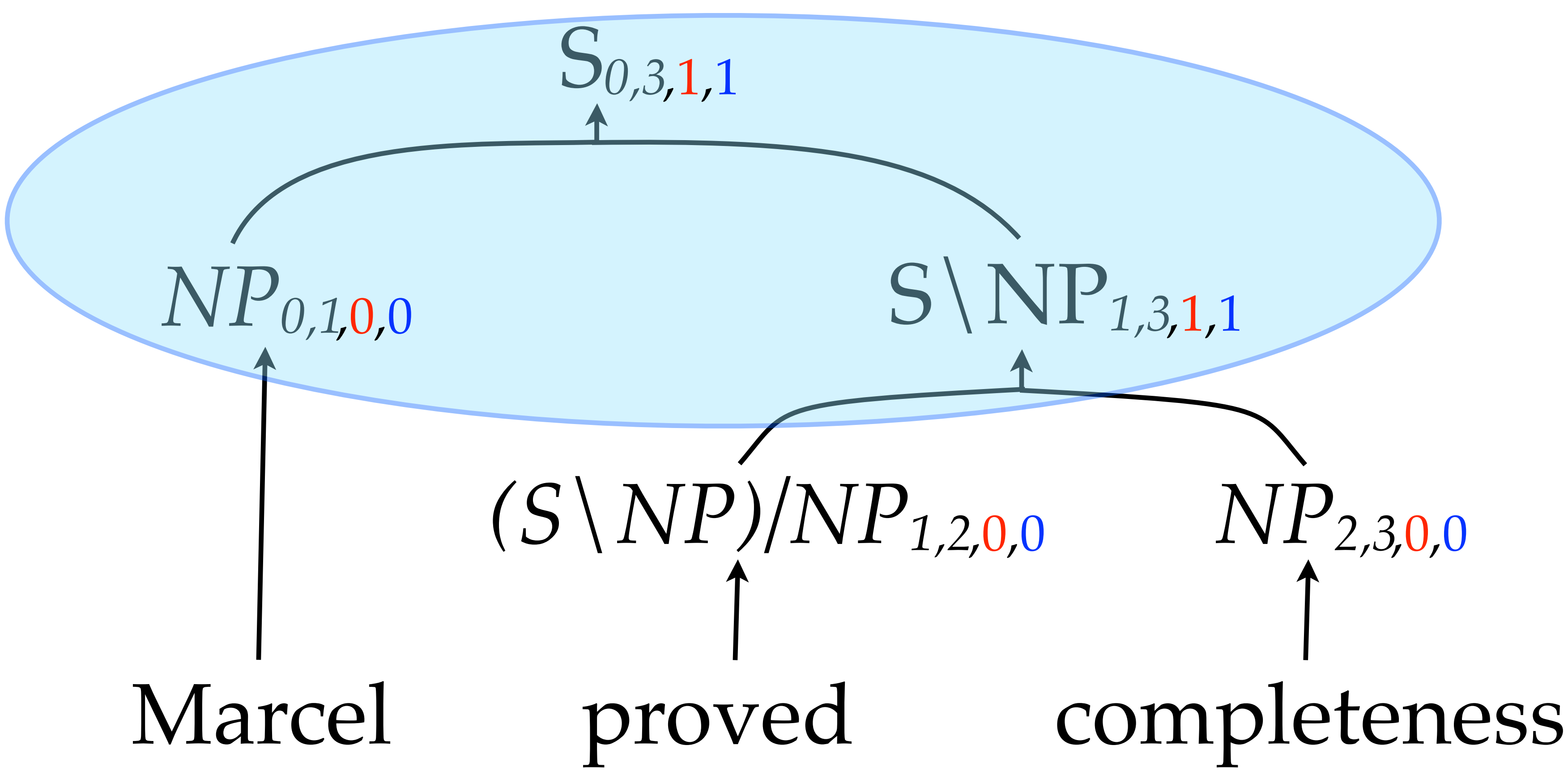
Exact Loss Functions

- Treat sentence-level F_1 as *non-local feature* dependent on n, d.



Exact Loss Functions

- Treat sentence-level F_1 as *non-local feature* dependent on n, d.
- Result: new dynamic program over items $A_{i,j,n,d}$



Exact Losses with State-Split CKY

items $A_{i,j,{\color{red}n},{\color{blue}d}}$

correct dependencies

all dependencies

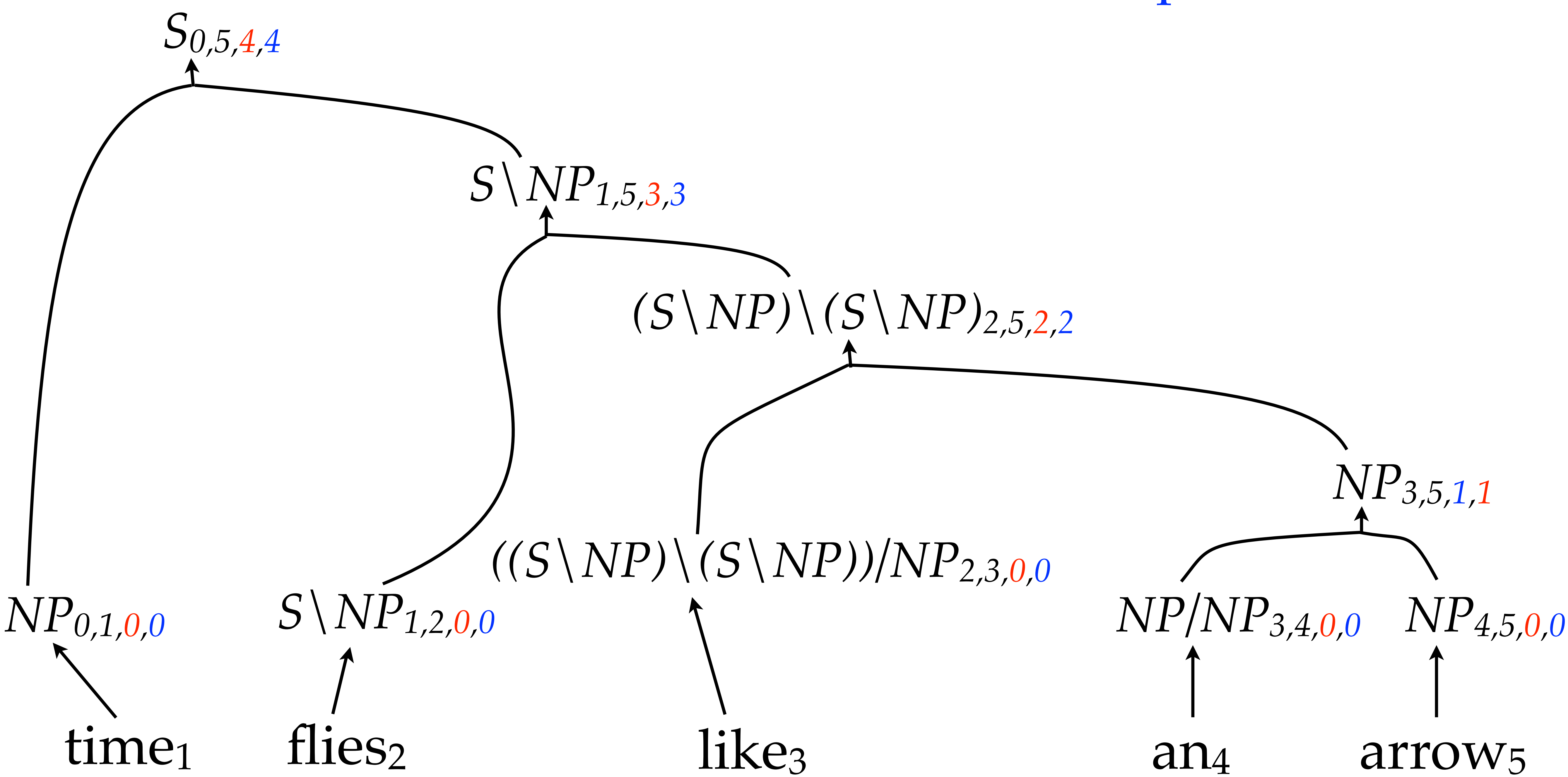
time$_1$ flies$_2$ like$_3$ an$_4$ arrow$_5$

Exact Losses with State-Split CKY

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

correct dependencies

all dependencies

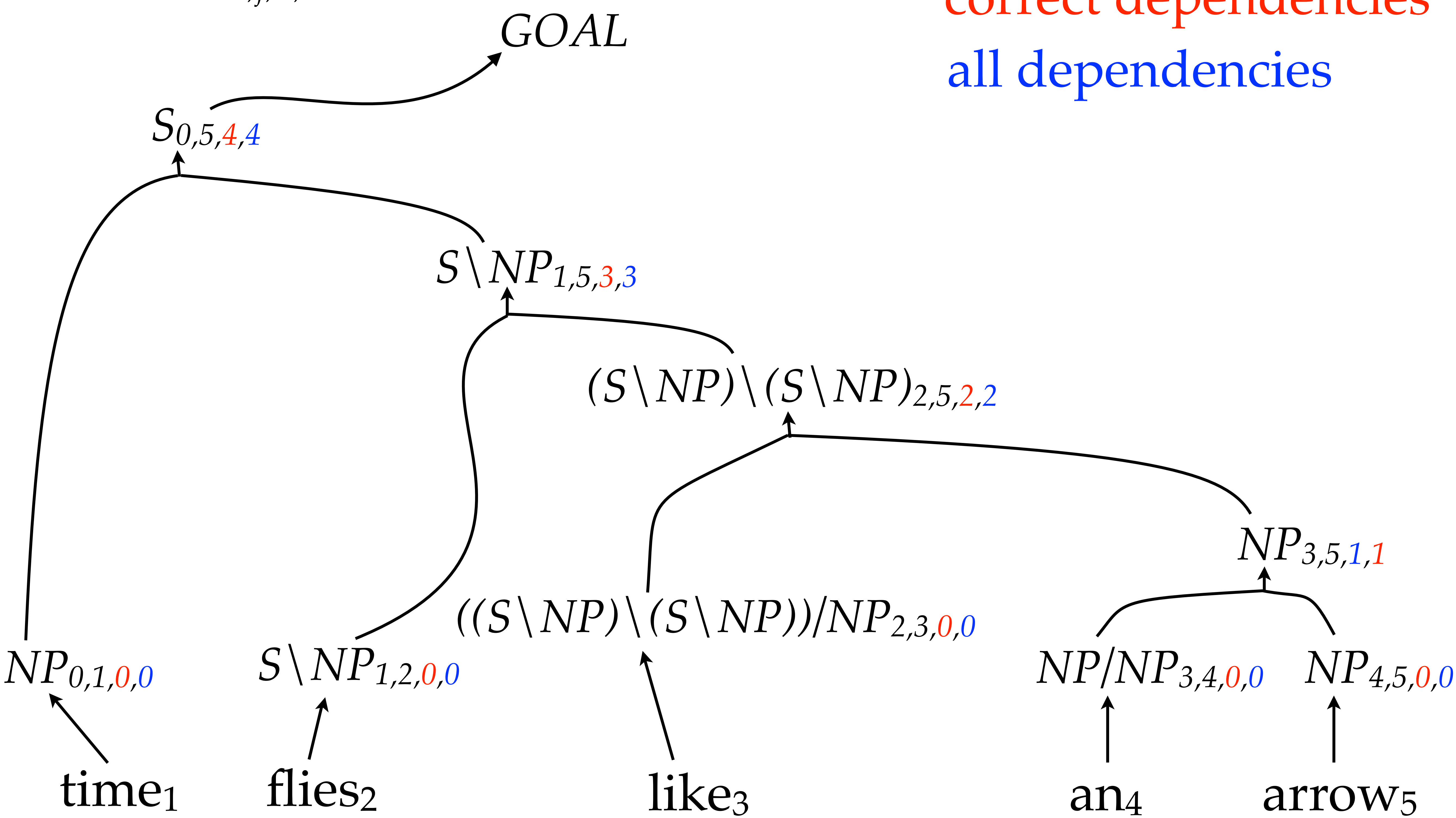


Exact Losses with State-Split CKY

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

correct dependencies

all dependencies



Exact Losses with State-Split CKY

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

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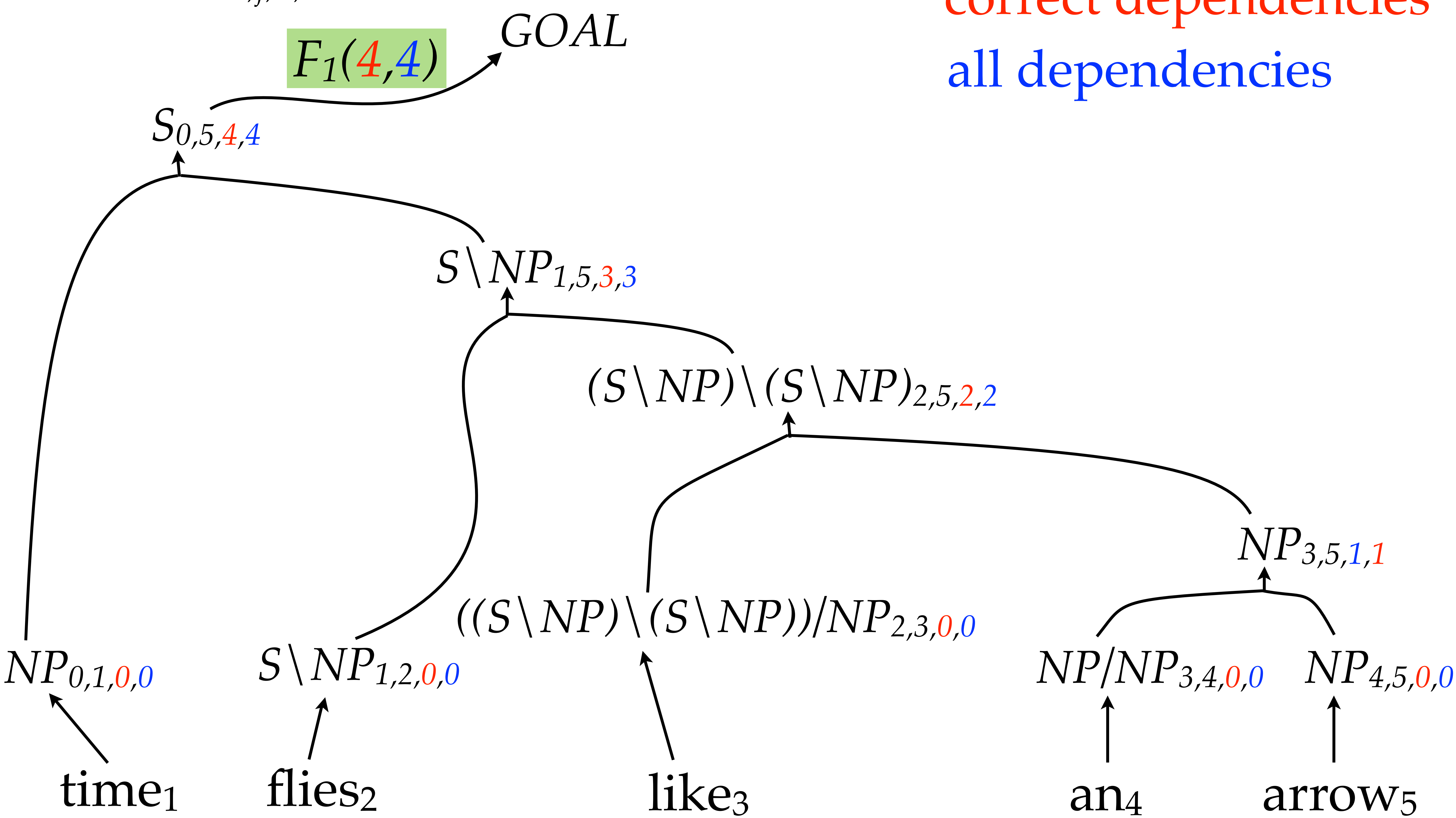
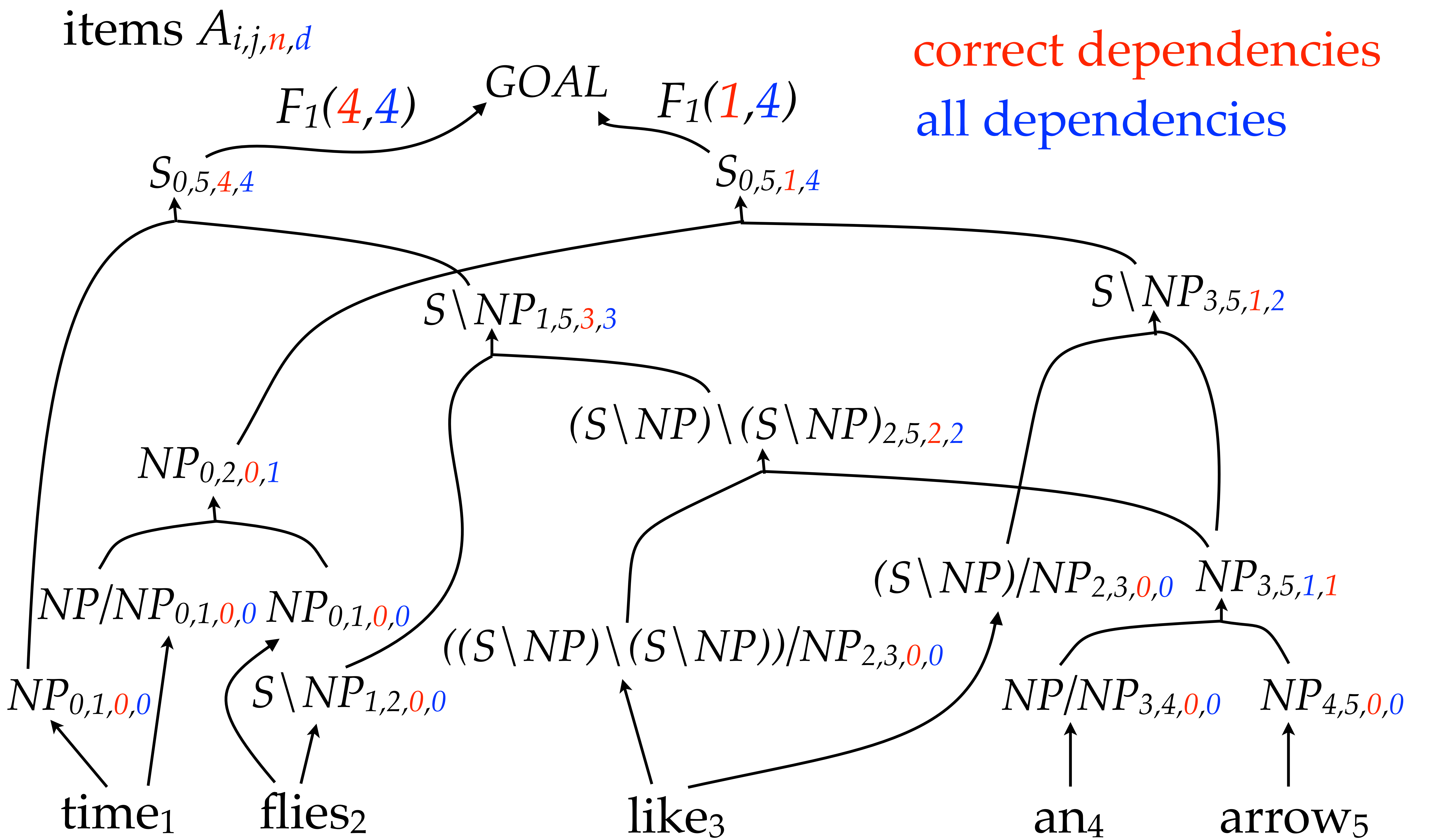


Exact Losses with State-Split CKY



Exact Losses with State-Split CKY

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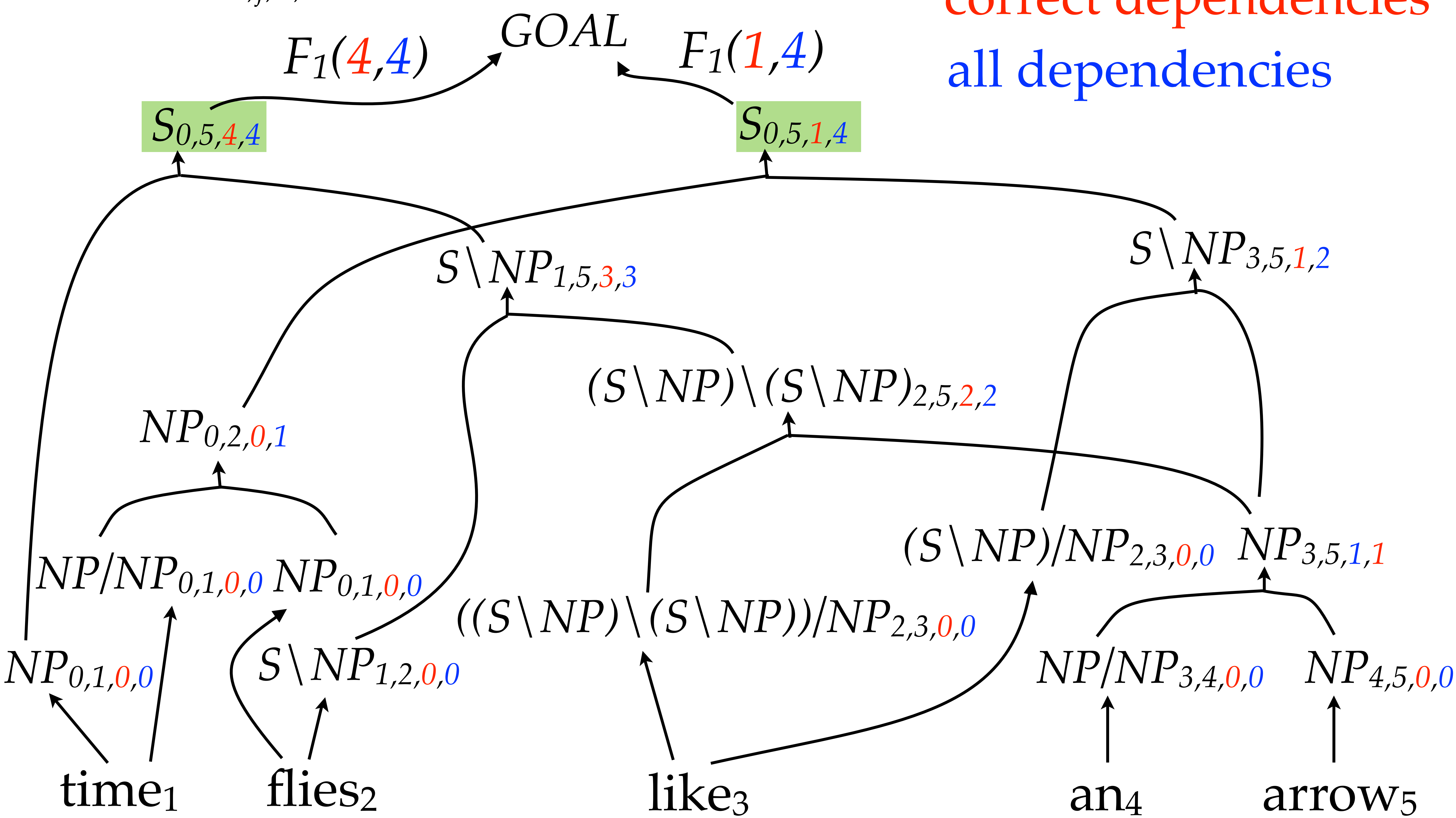
correct dependencies

all dependencies

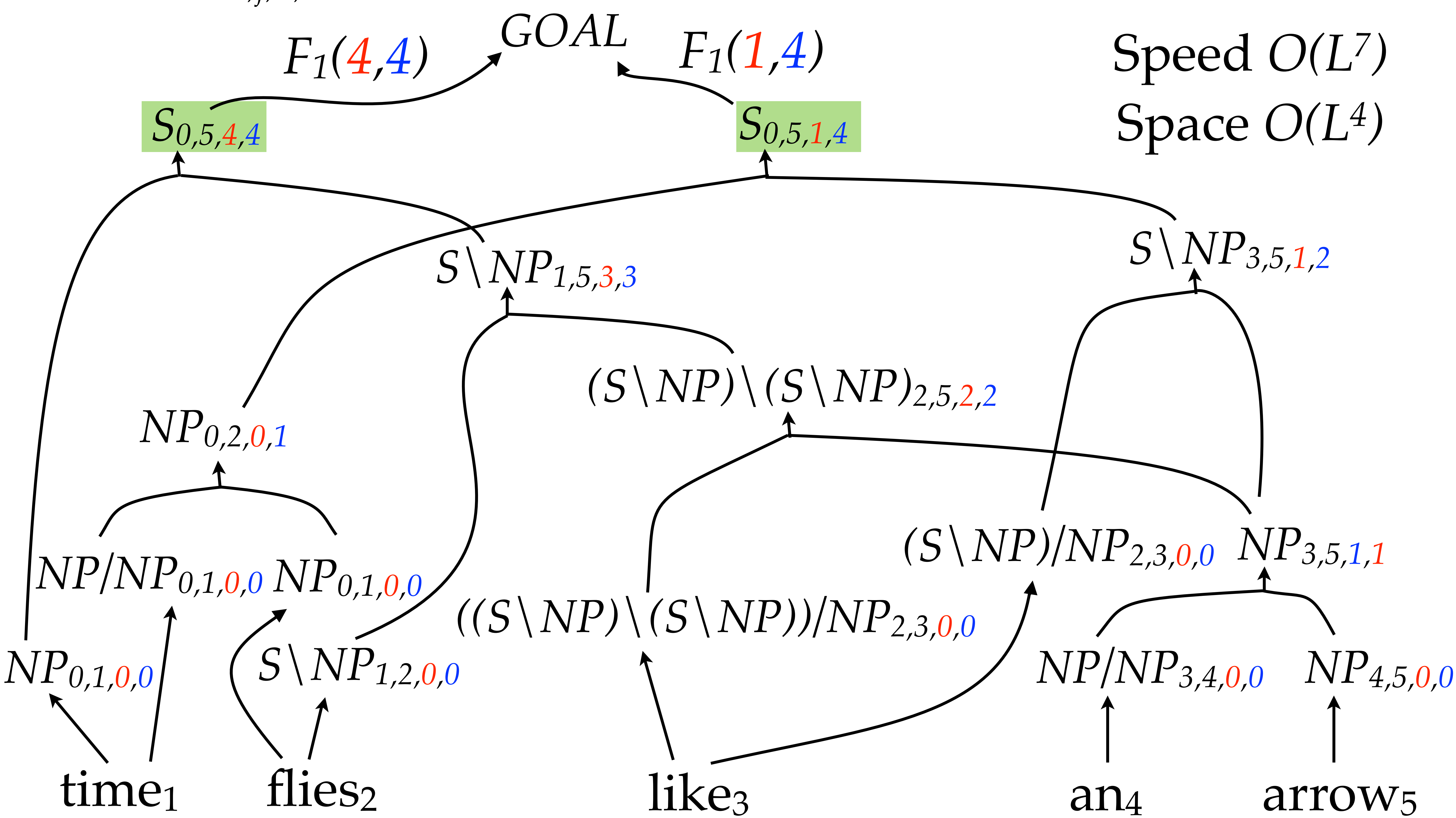


Exact Losses with State-Split CKY

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

Speed $O(L^7)$

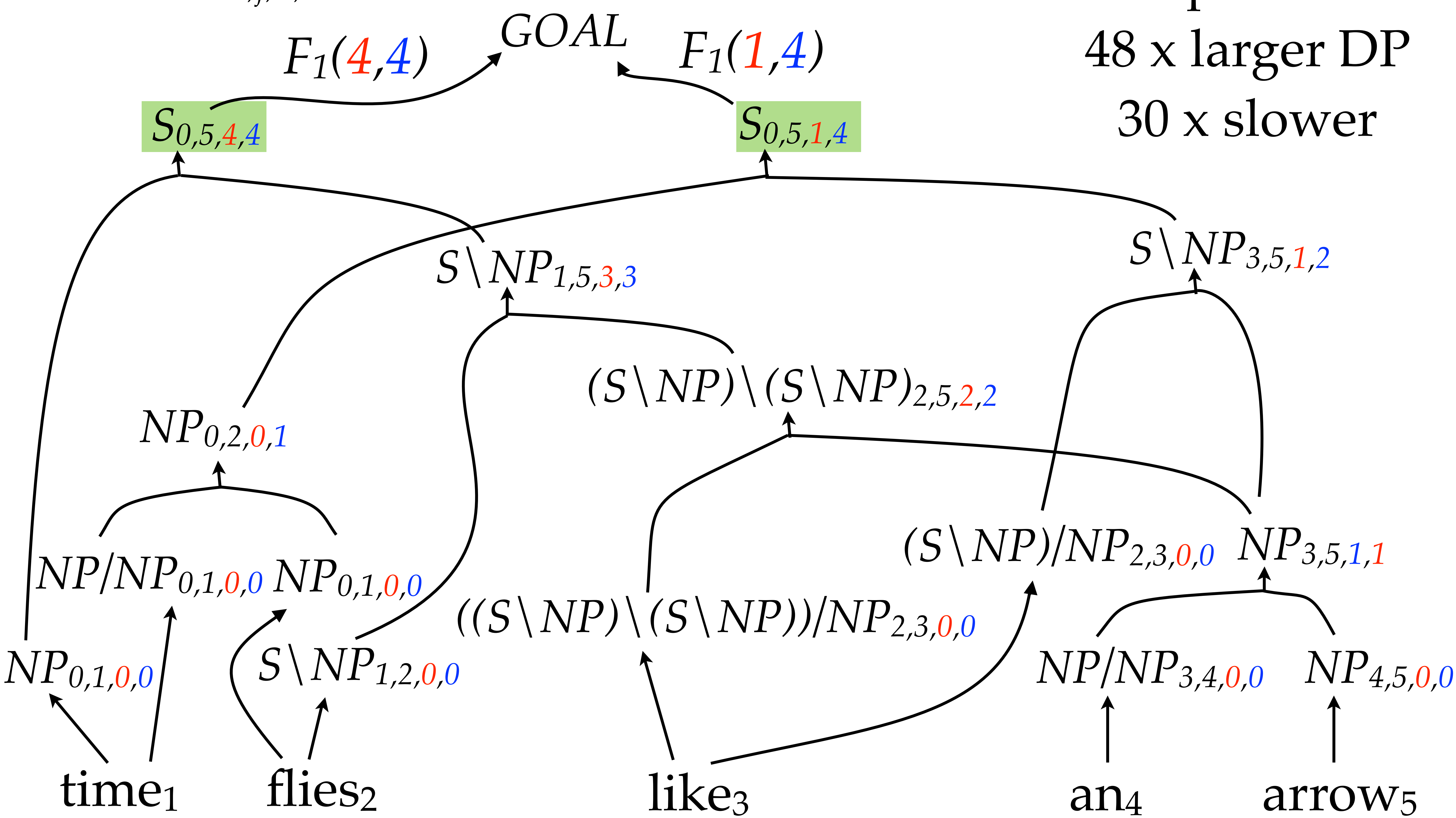
Space $O(L^4)$



Exact Losses with State-Split CKY

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

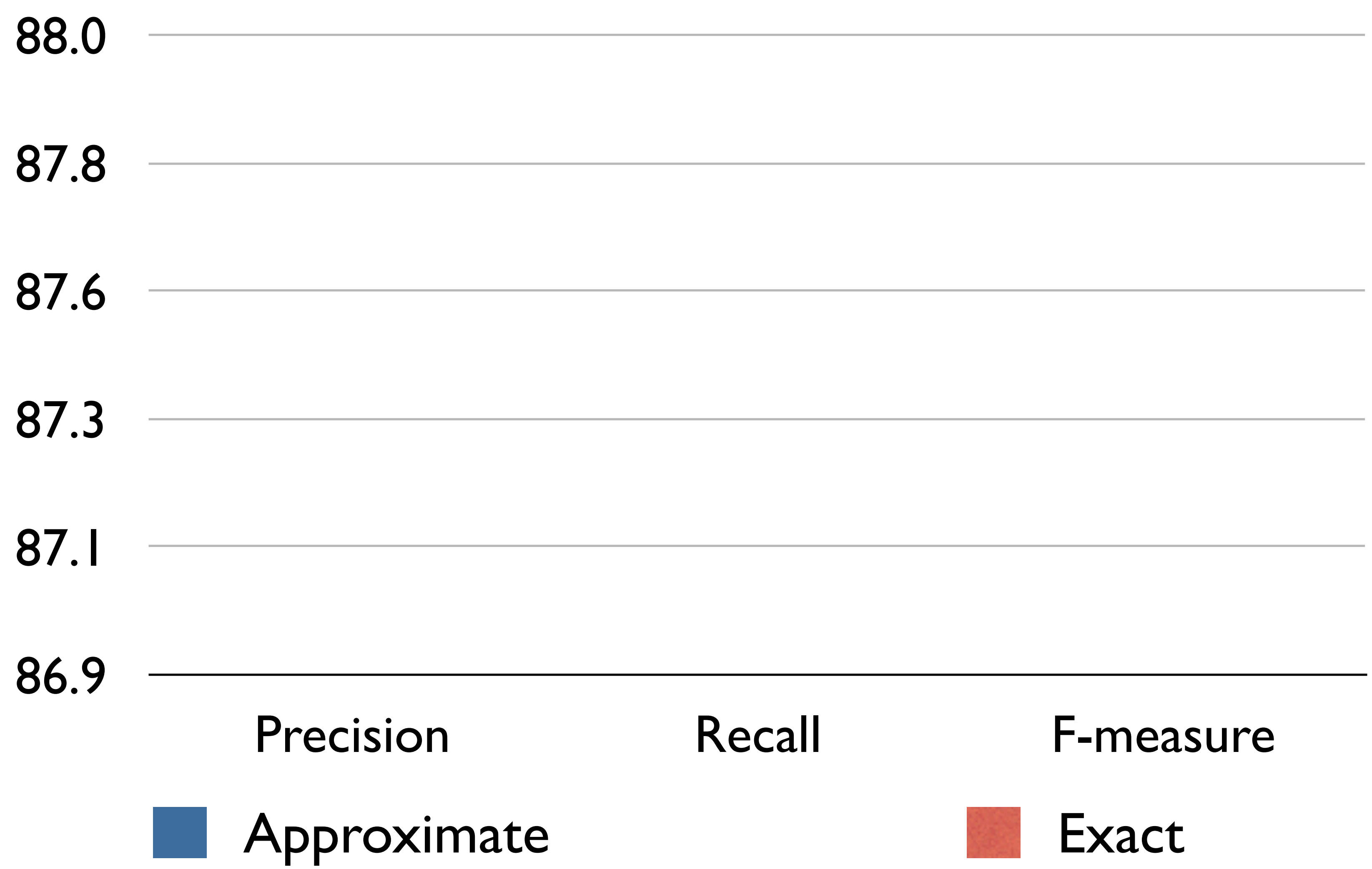
in practice
48 x larger DP
30 x slower



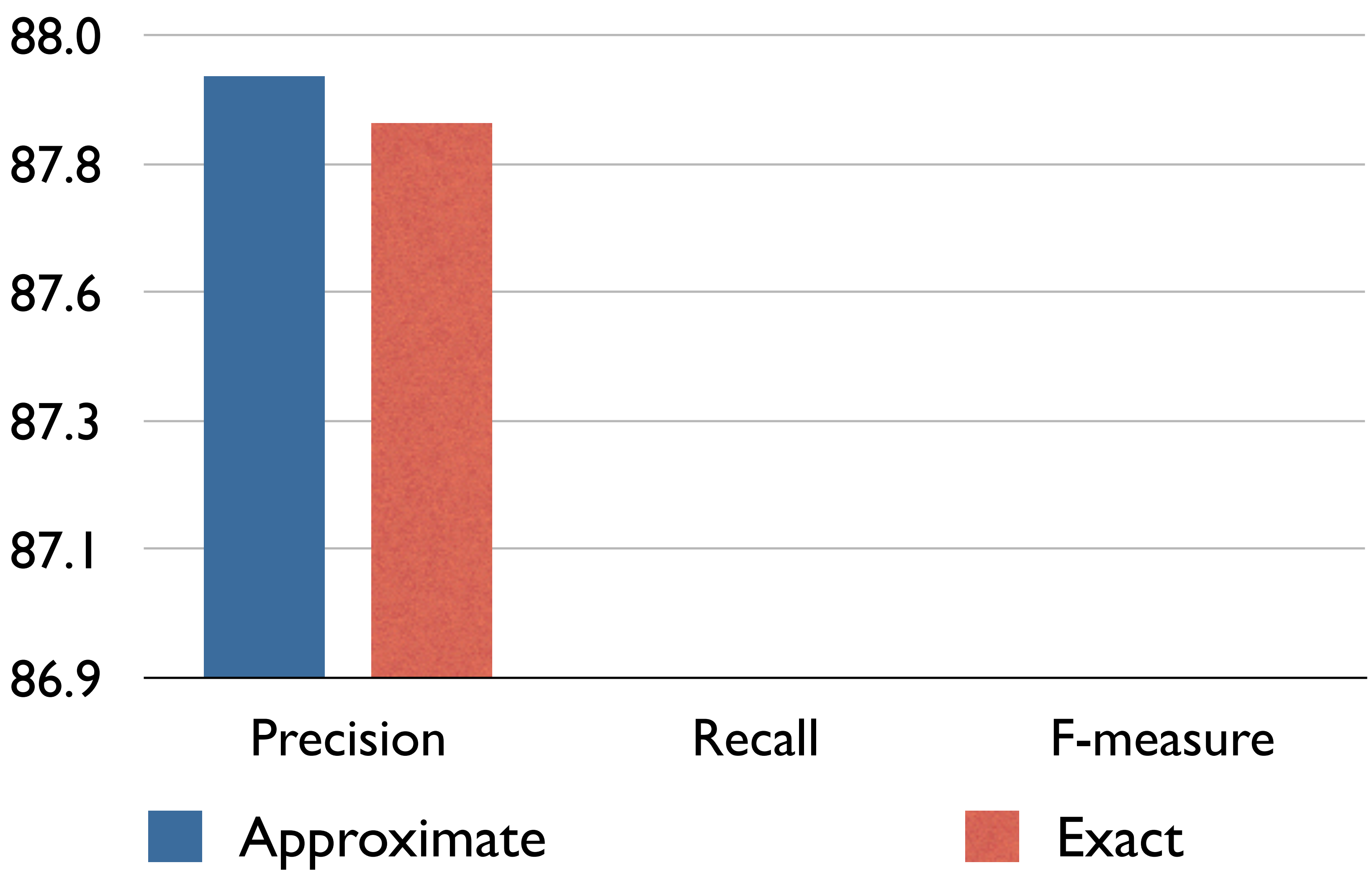
Experiments

- Standard parsing task:
  - C&C Parser and supertagger (Clark & Curran 2007).
  - CCGBank standard train/dev/test splits.
  - Piecewise optimisation (Sutton and McCallum 2005)

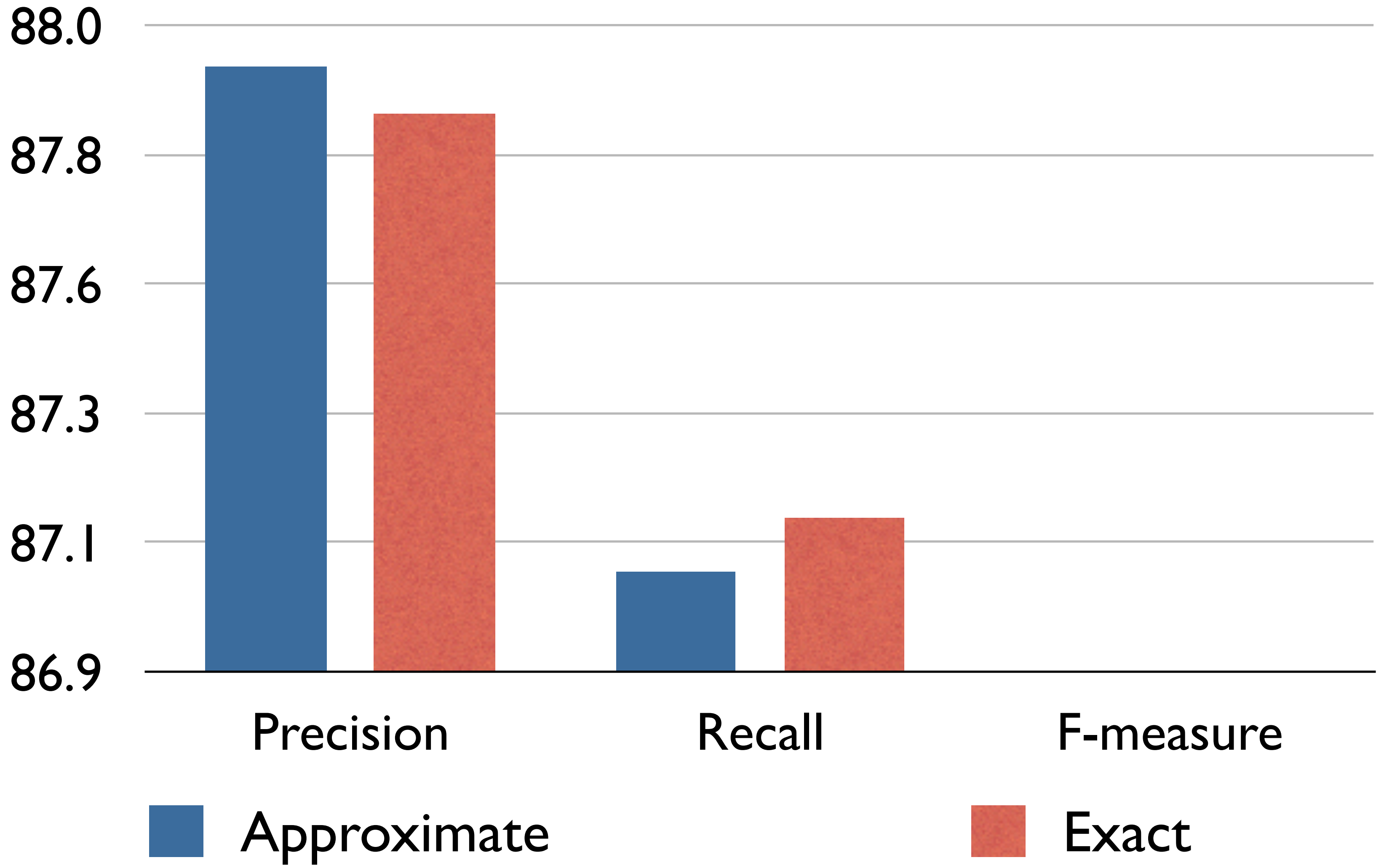
Exact versus Approximate



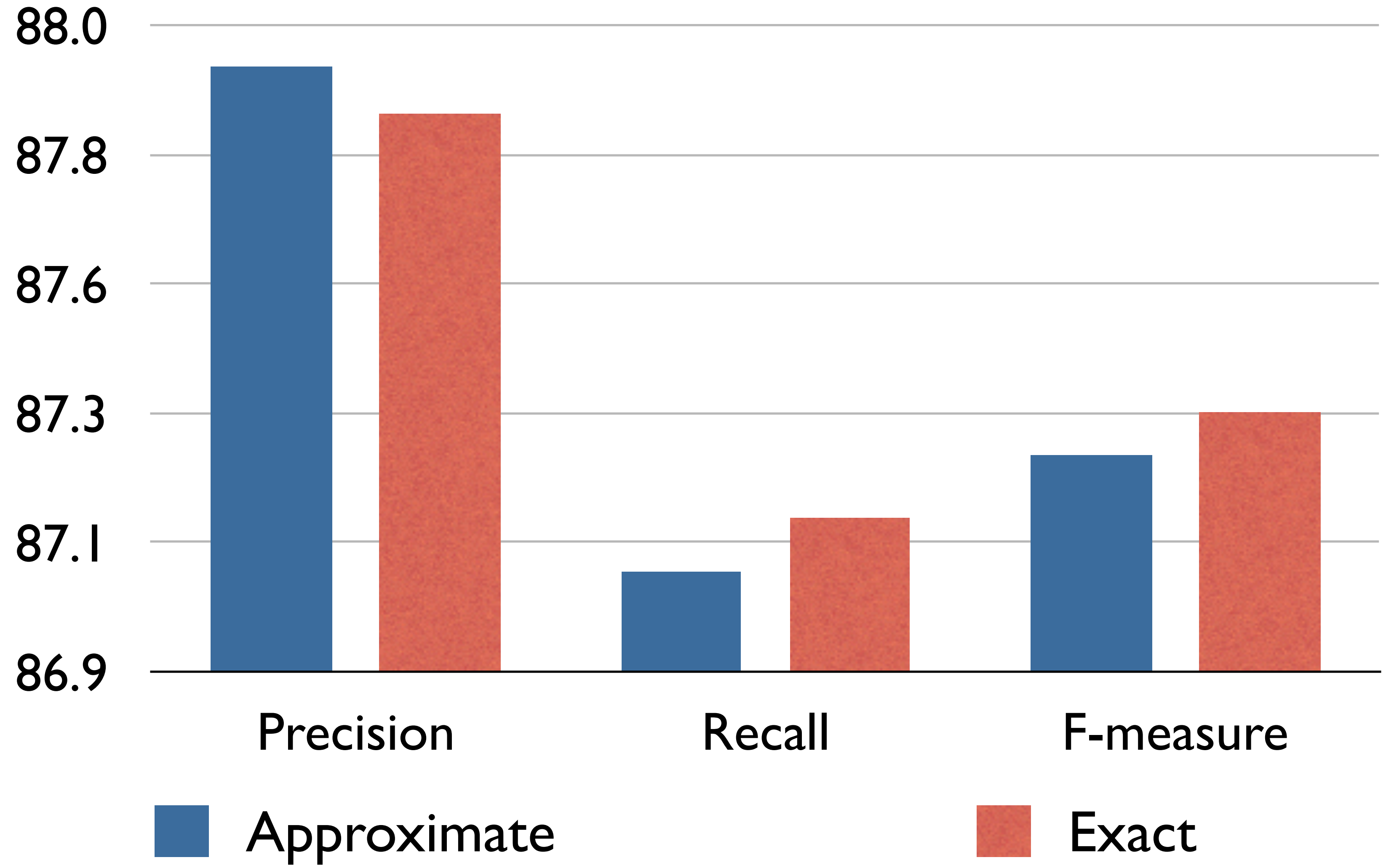
Exact versus Approximate



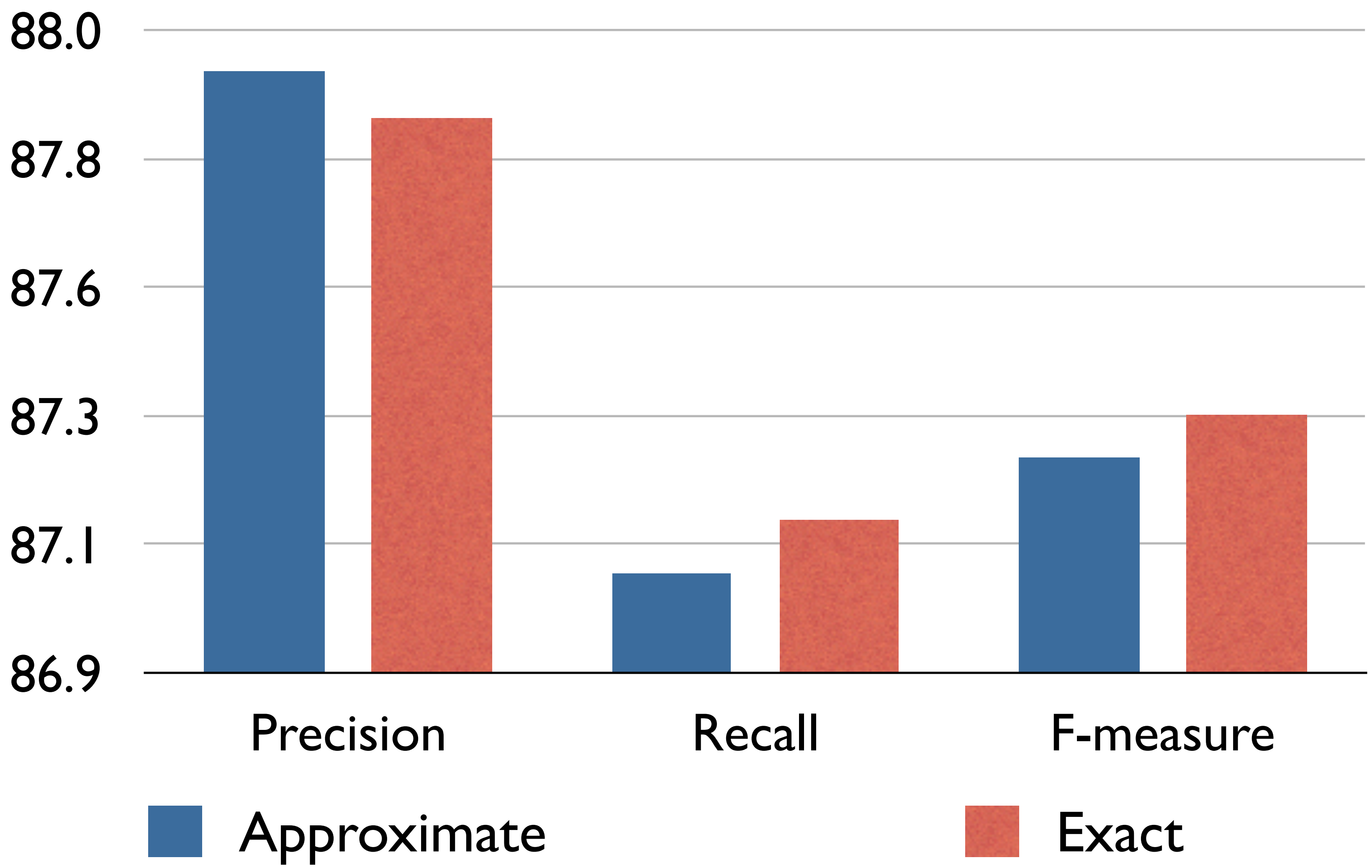
Exact versus Approximate



Exact versus Approximate



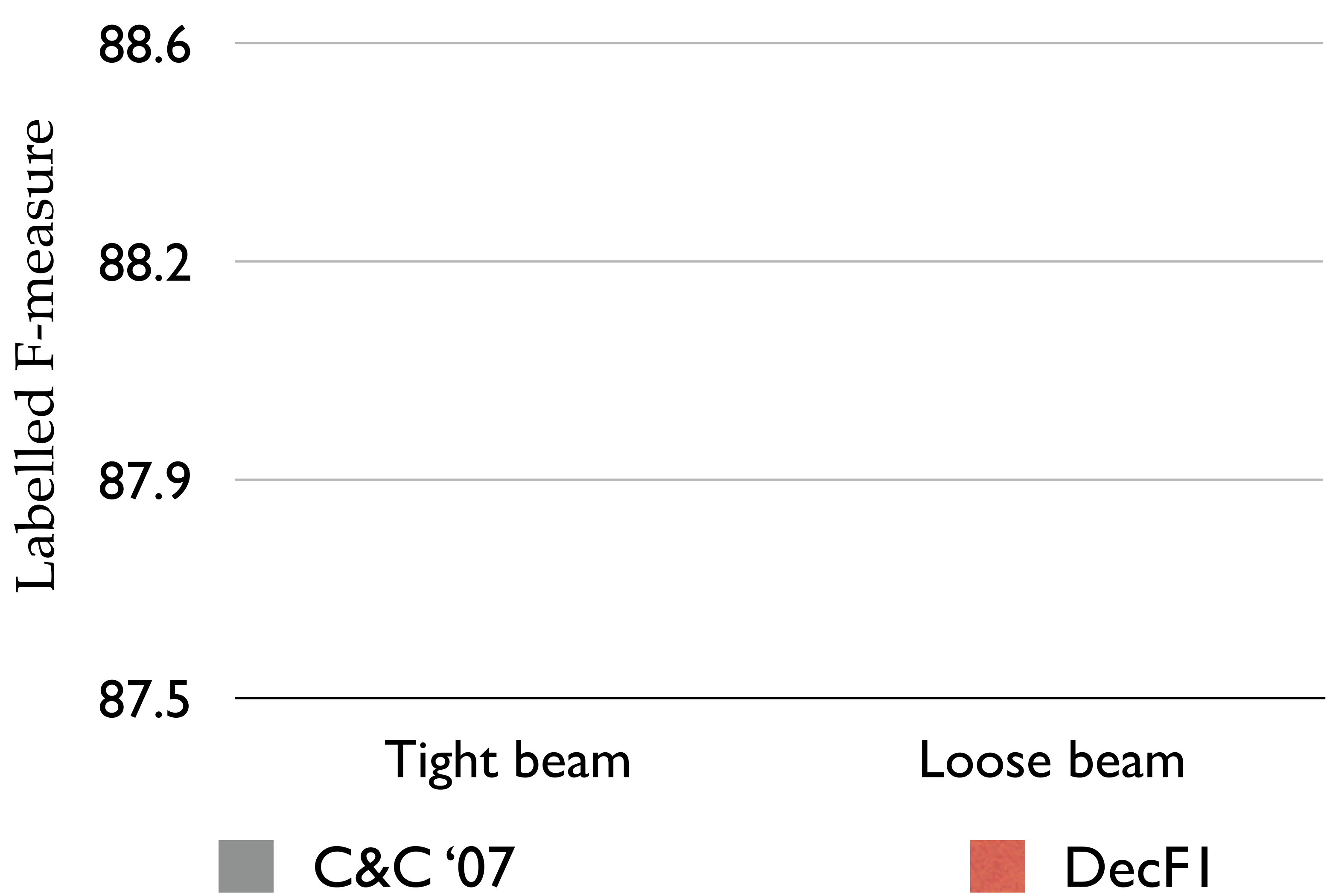
Exact versus Approximate



Approximate loss functions work, and much faster!

Softmax-Margin beats CLL

Test set results



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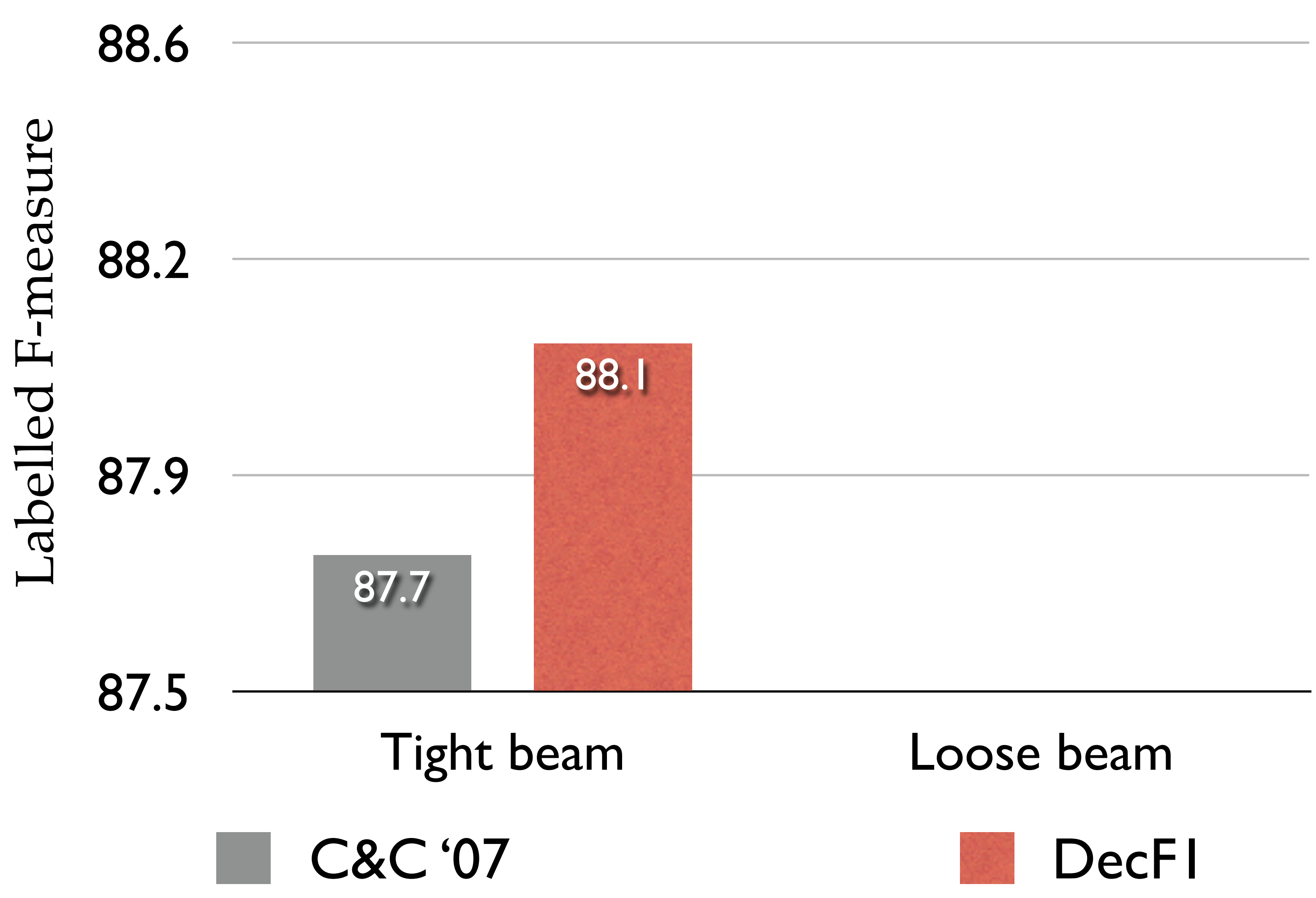

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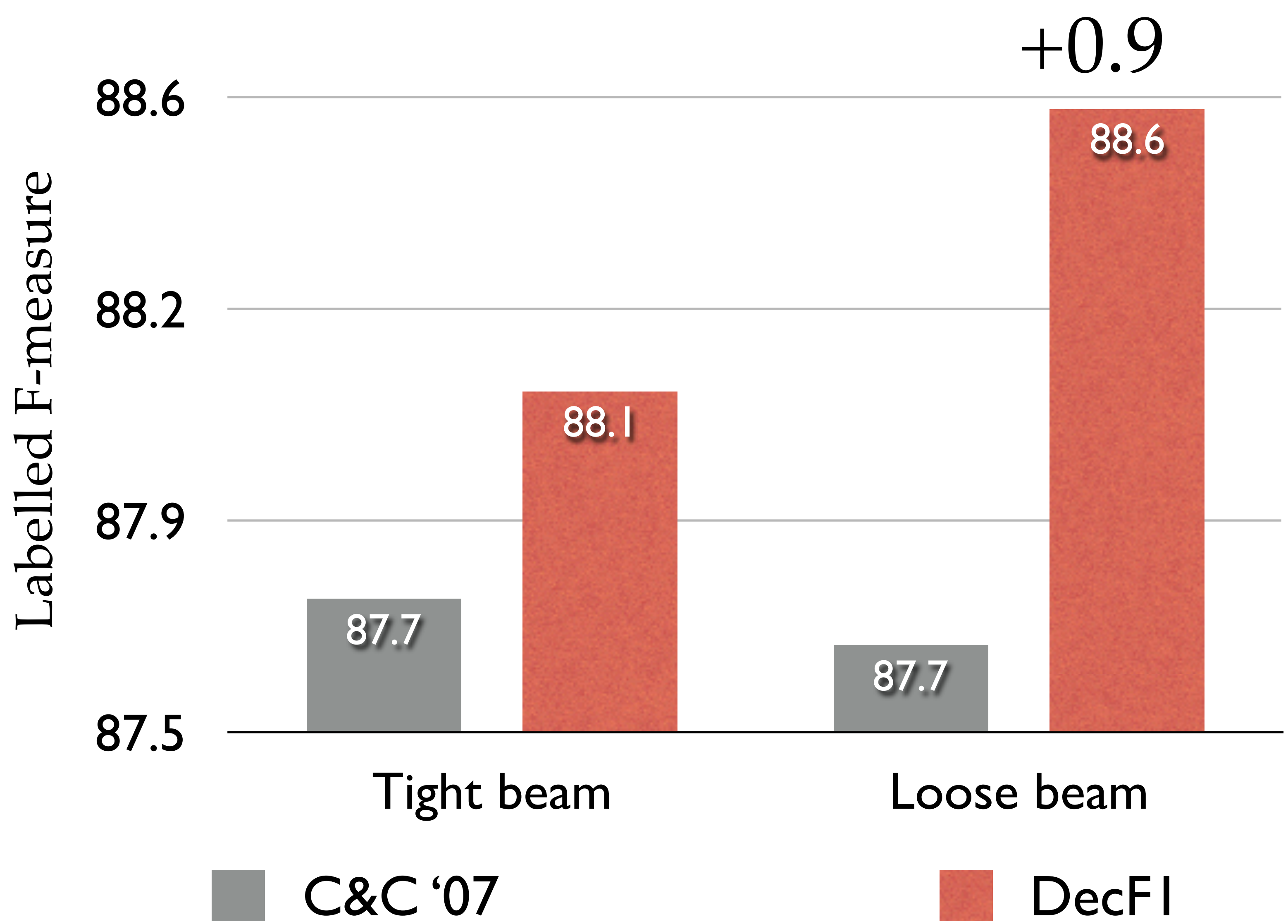
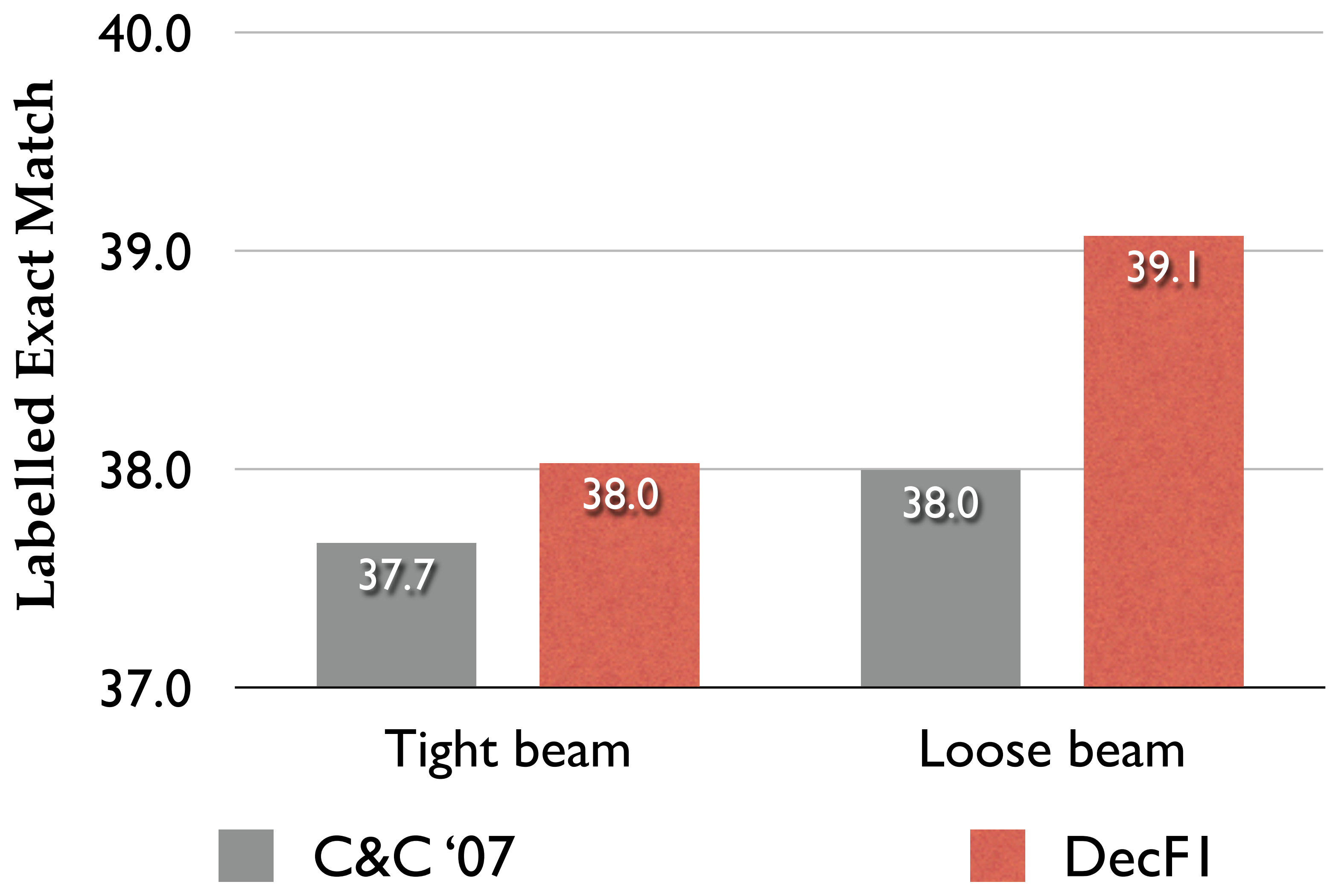


Softmax-Margin beats CLL

Does task-specific optimisation degrade accuracy on other metrics?

Softmax-Margin beats CLL

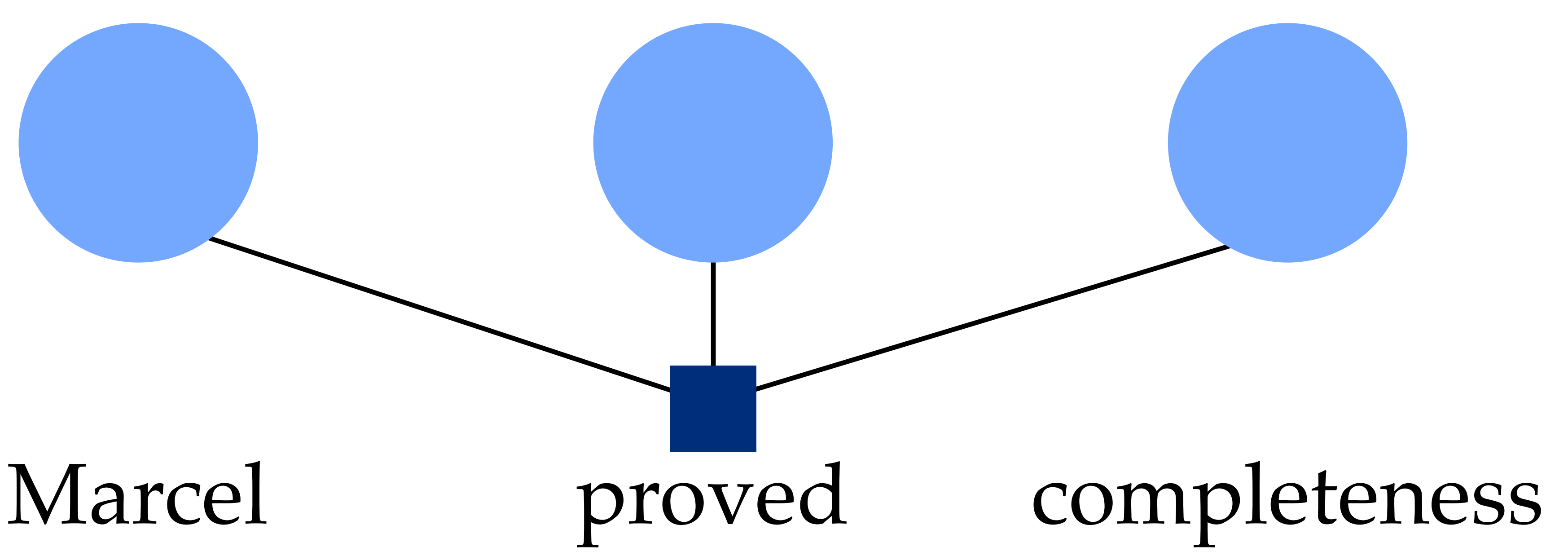
Does task-specific optimisation degrade accuracy on other metrics?



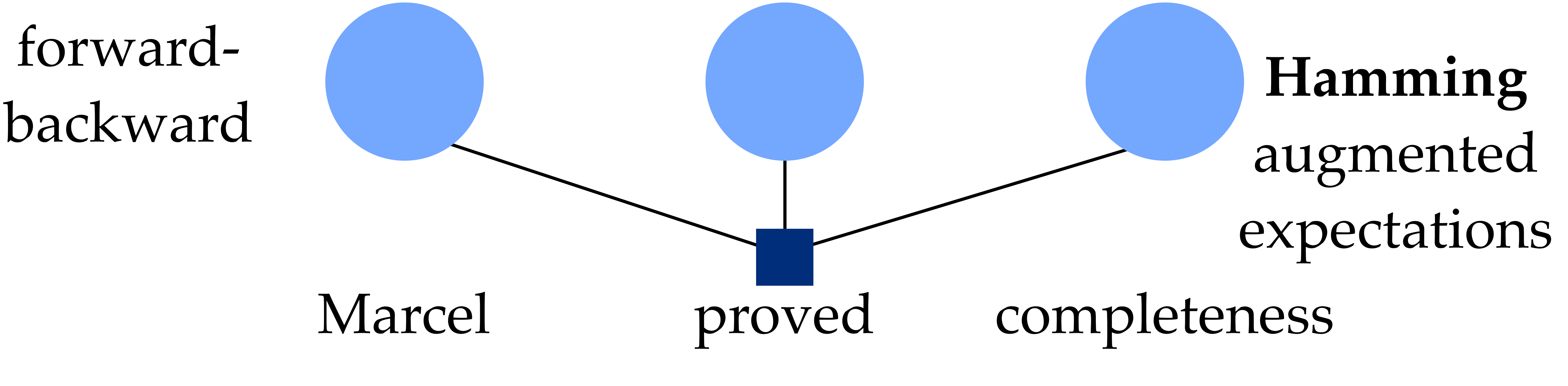
Integrated Model + SMM

Marcel proved completeness

Integrated Model + SMM



Integrated Model + SMM



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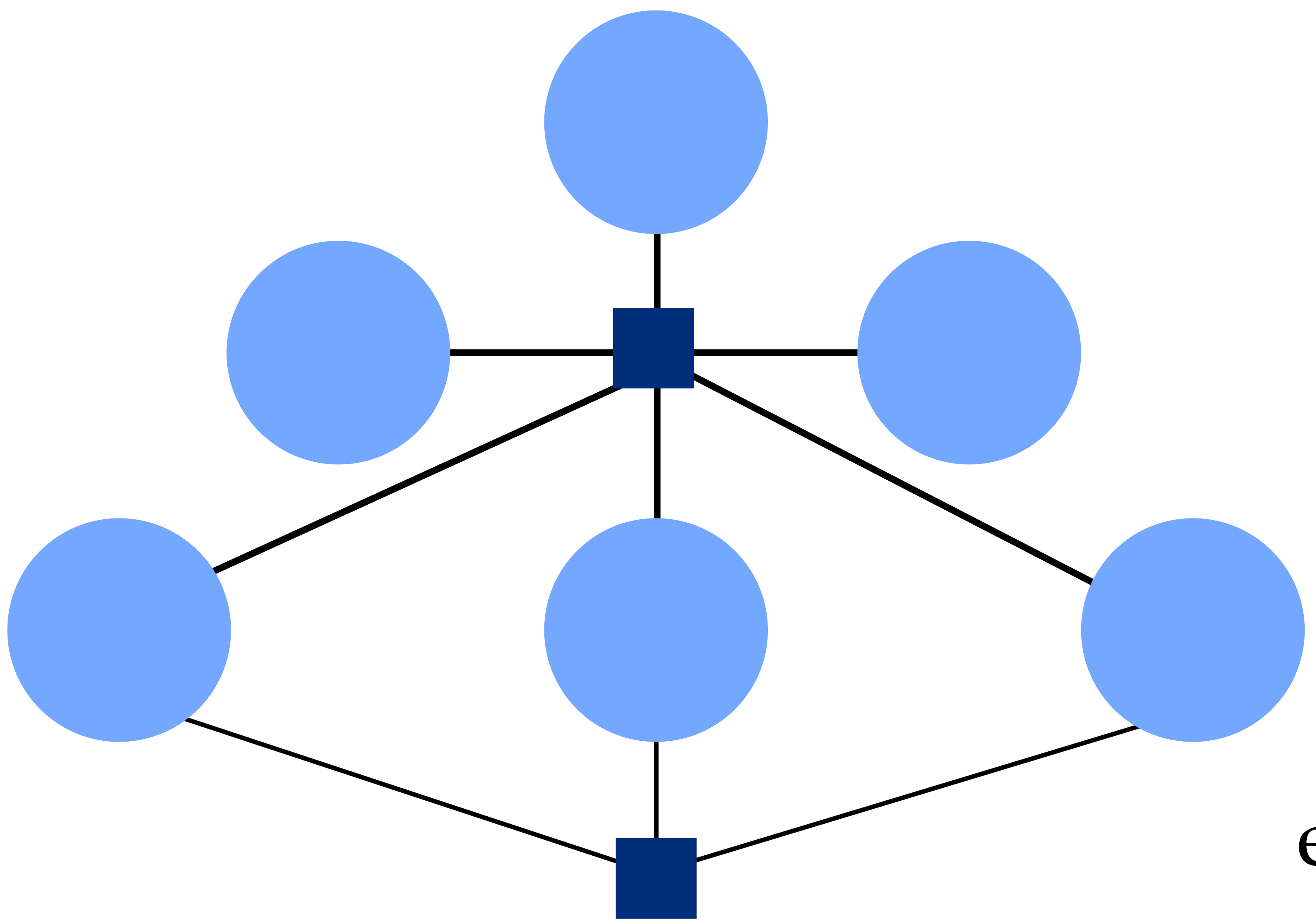

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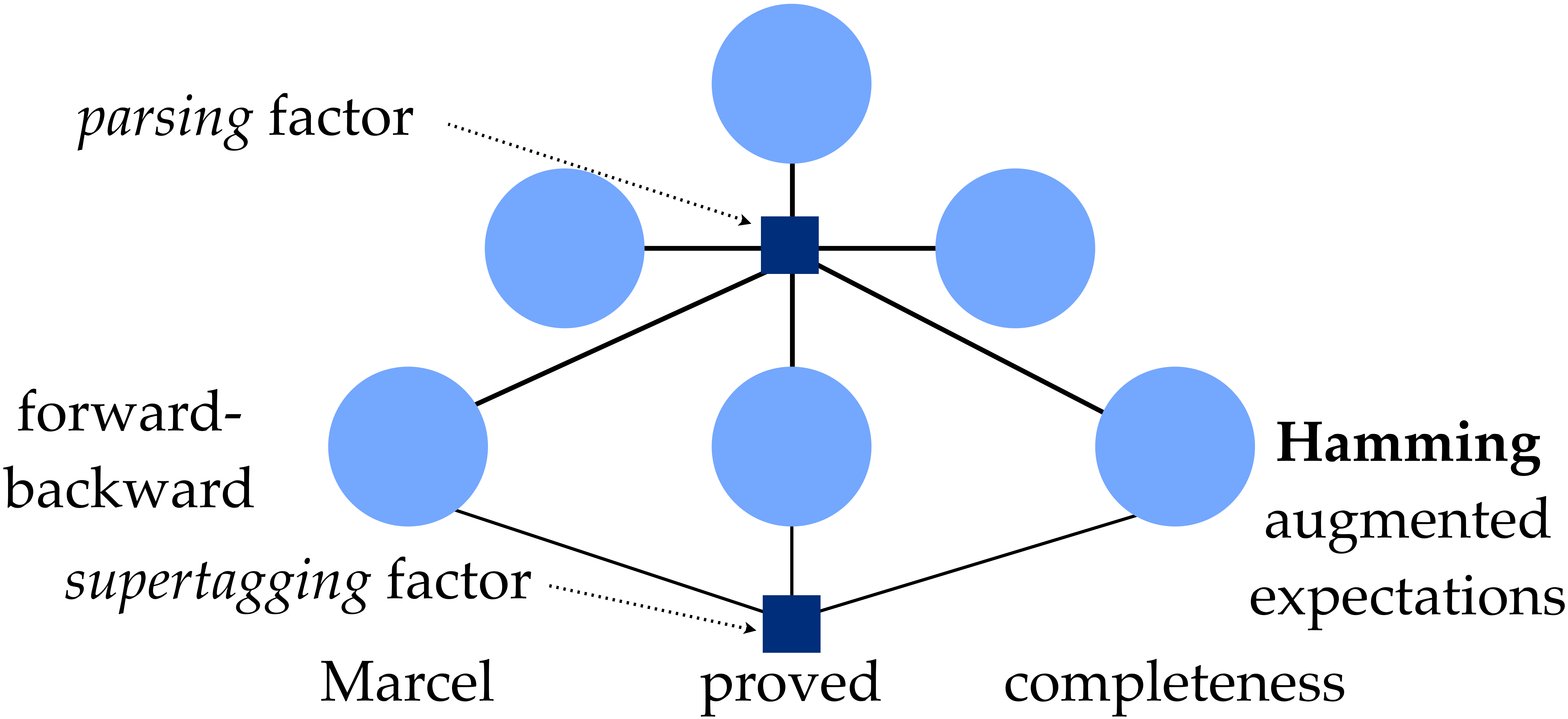

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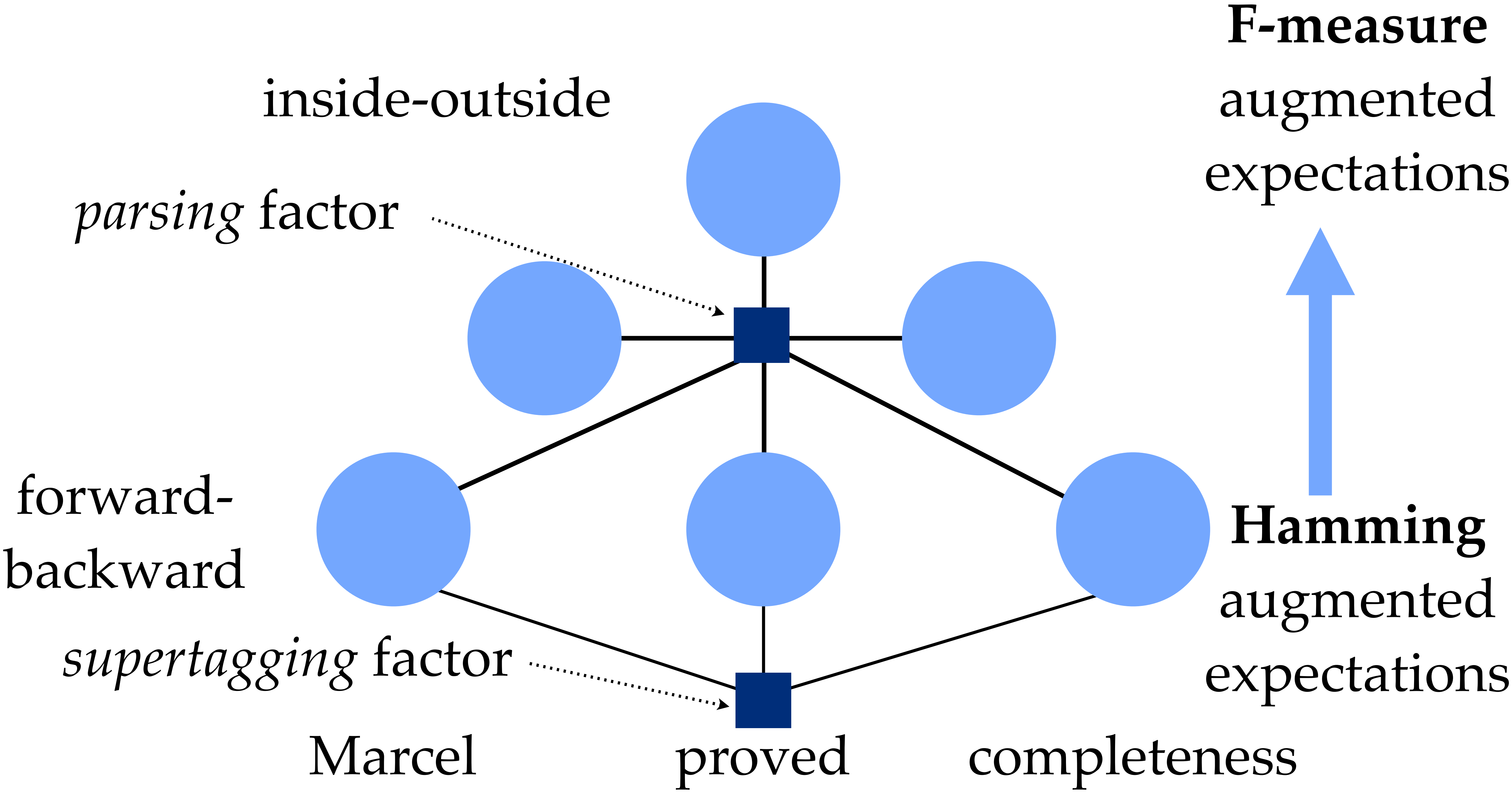
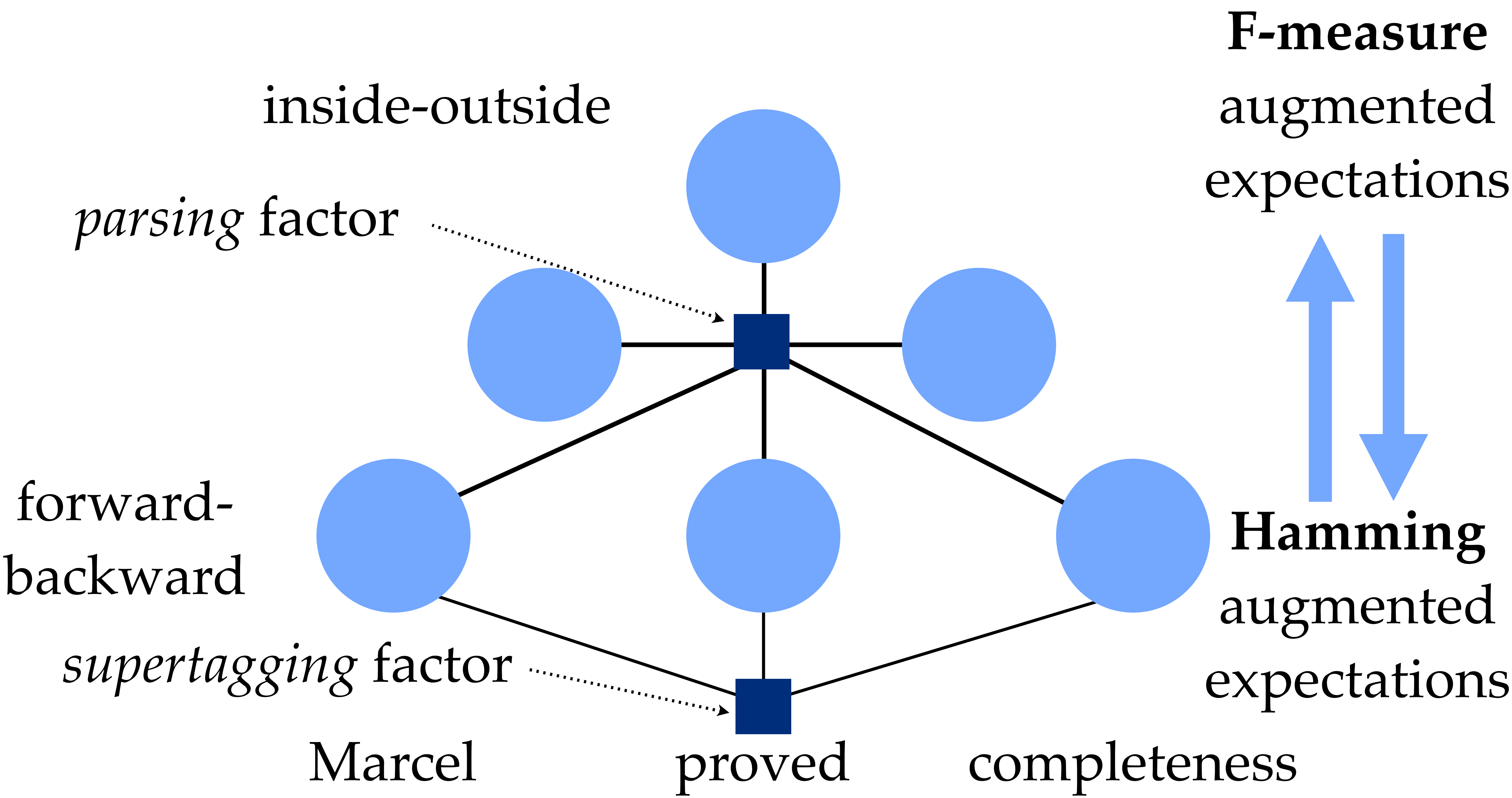
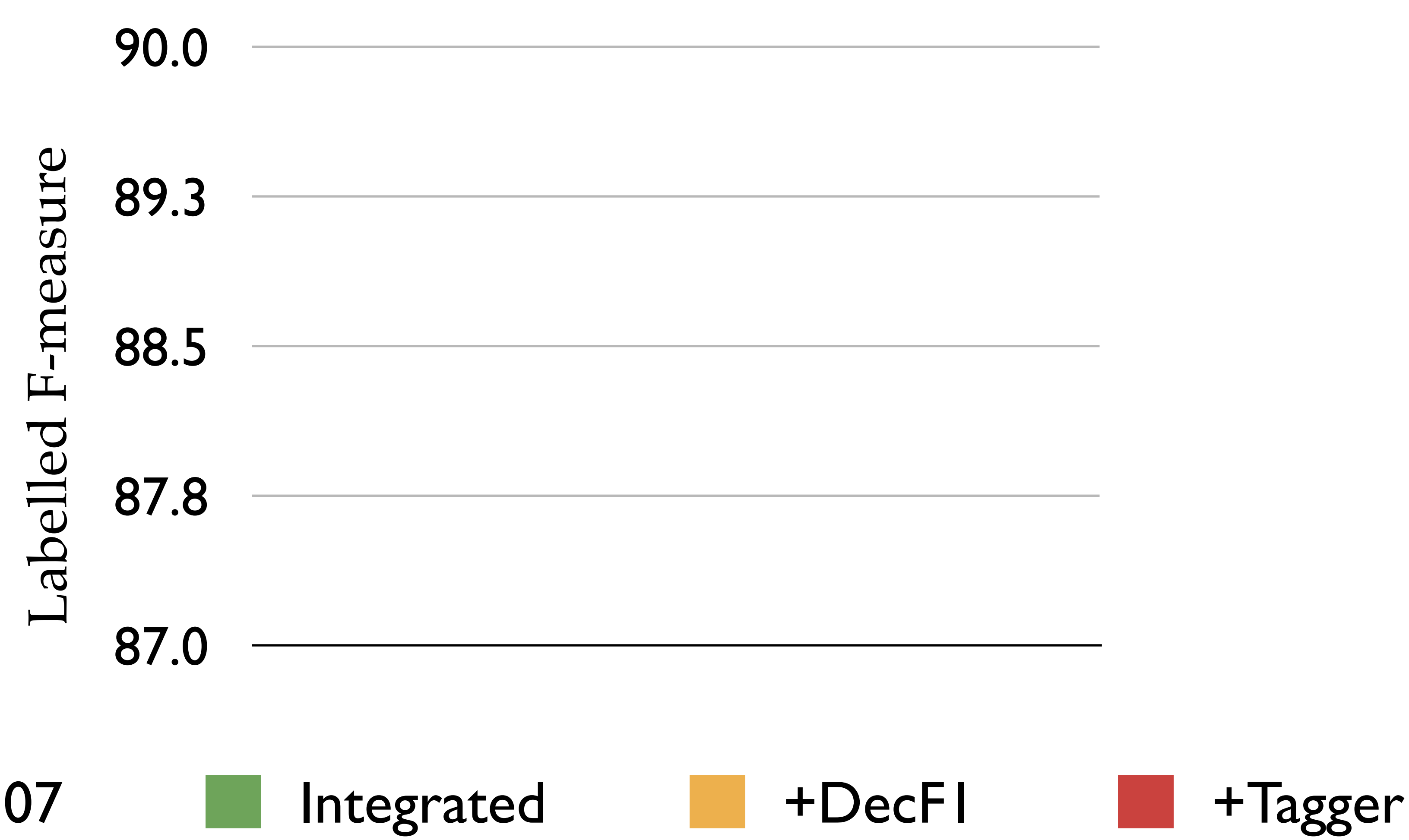


Integrated Model + SMM



Results: Integrated Model

- F-measure loss for parsing sub-model (+DecF_1).
- Hamming loss for supertagging sub-model (+Tagger).
- Belief propagation for inference.



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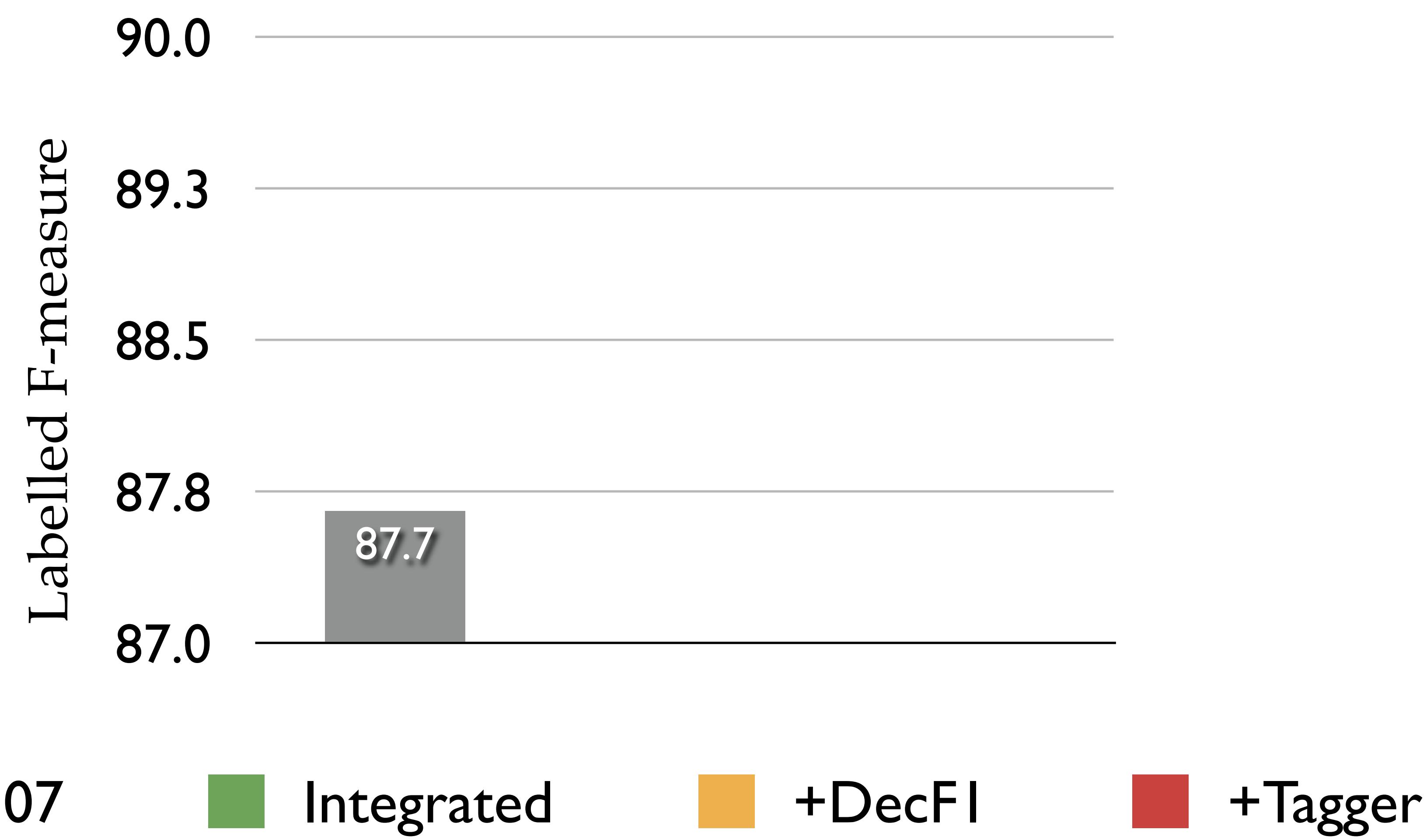

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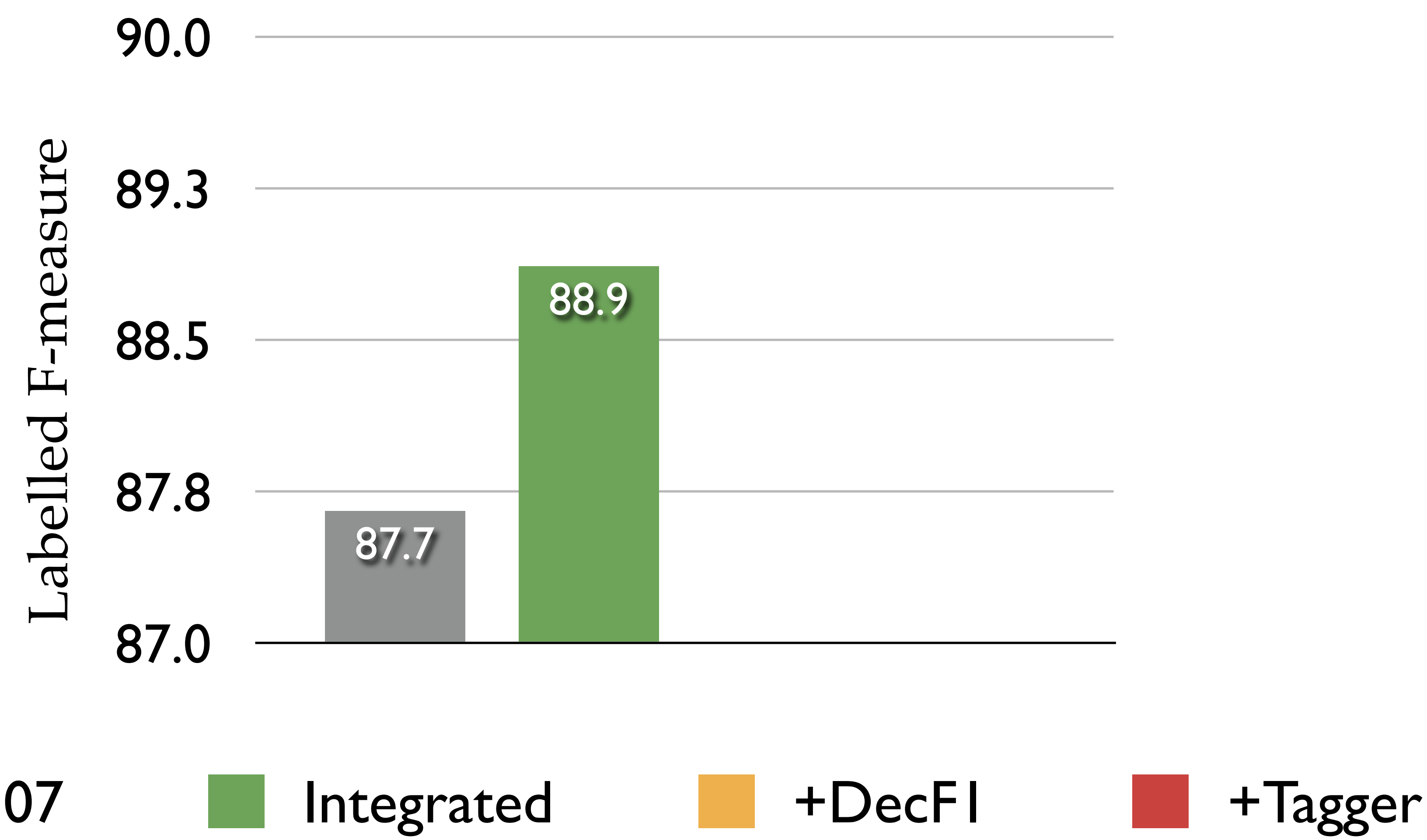

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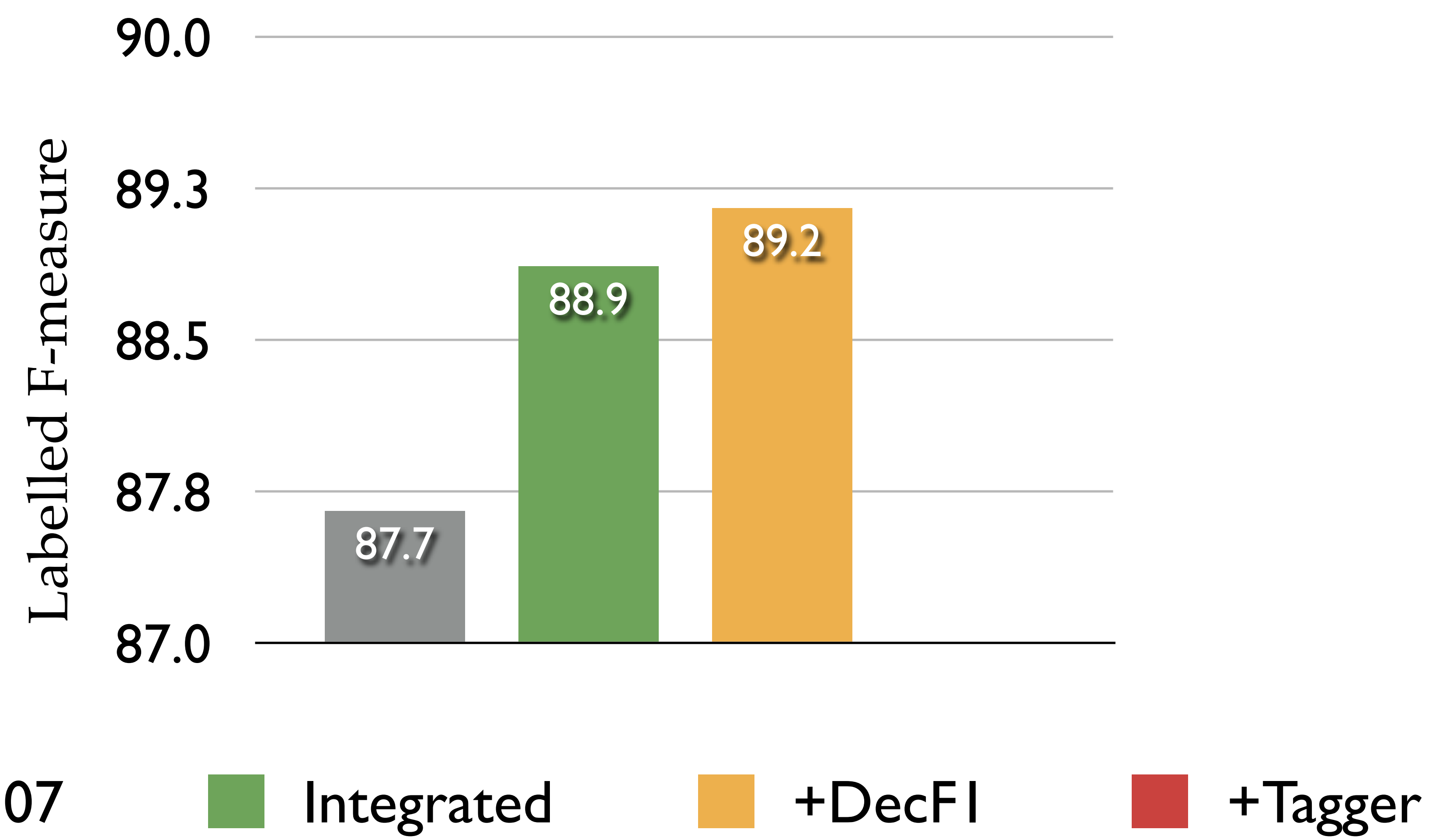

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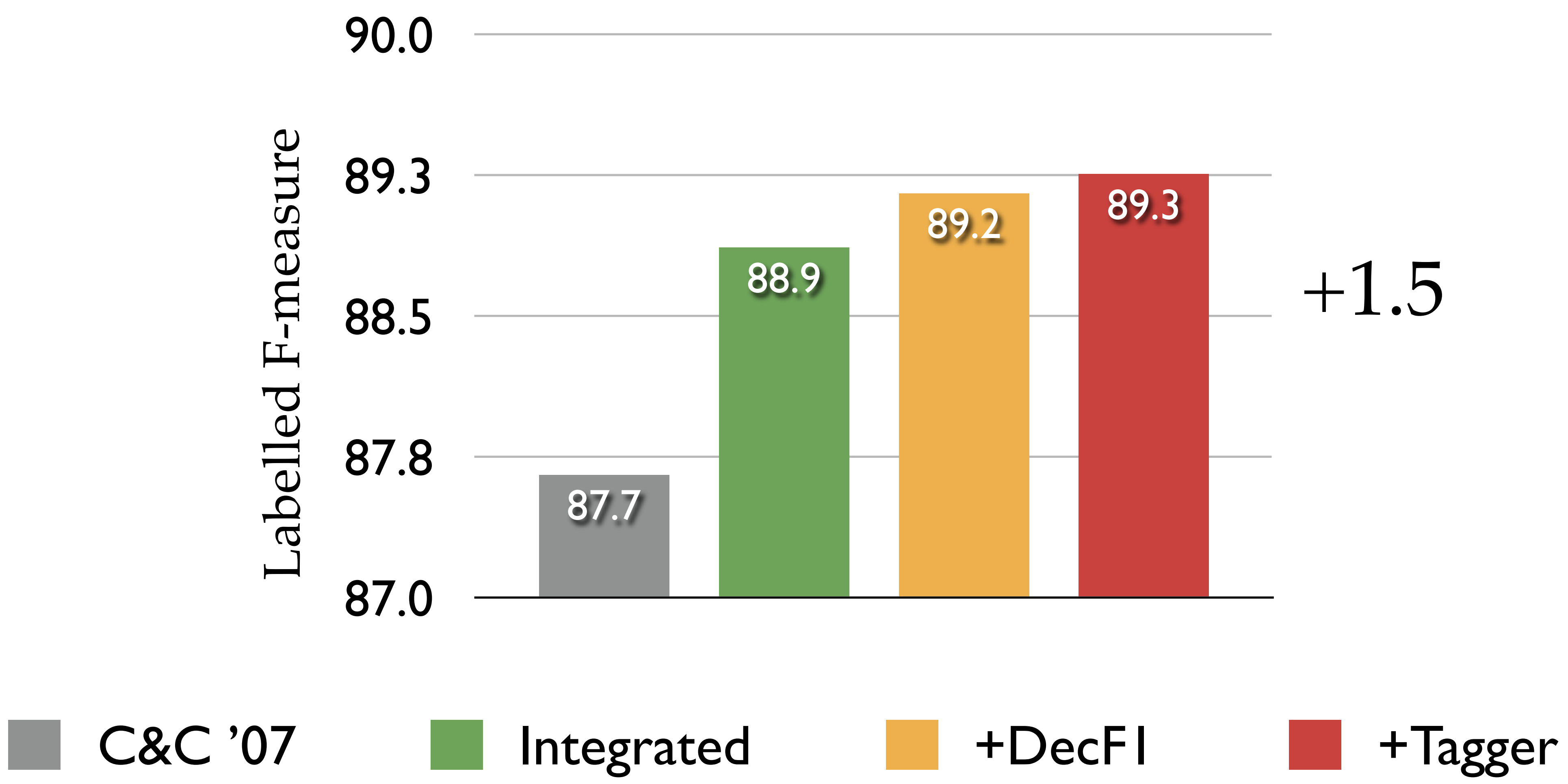

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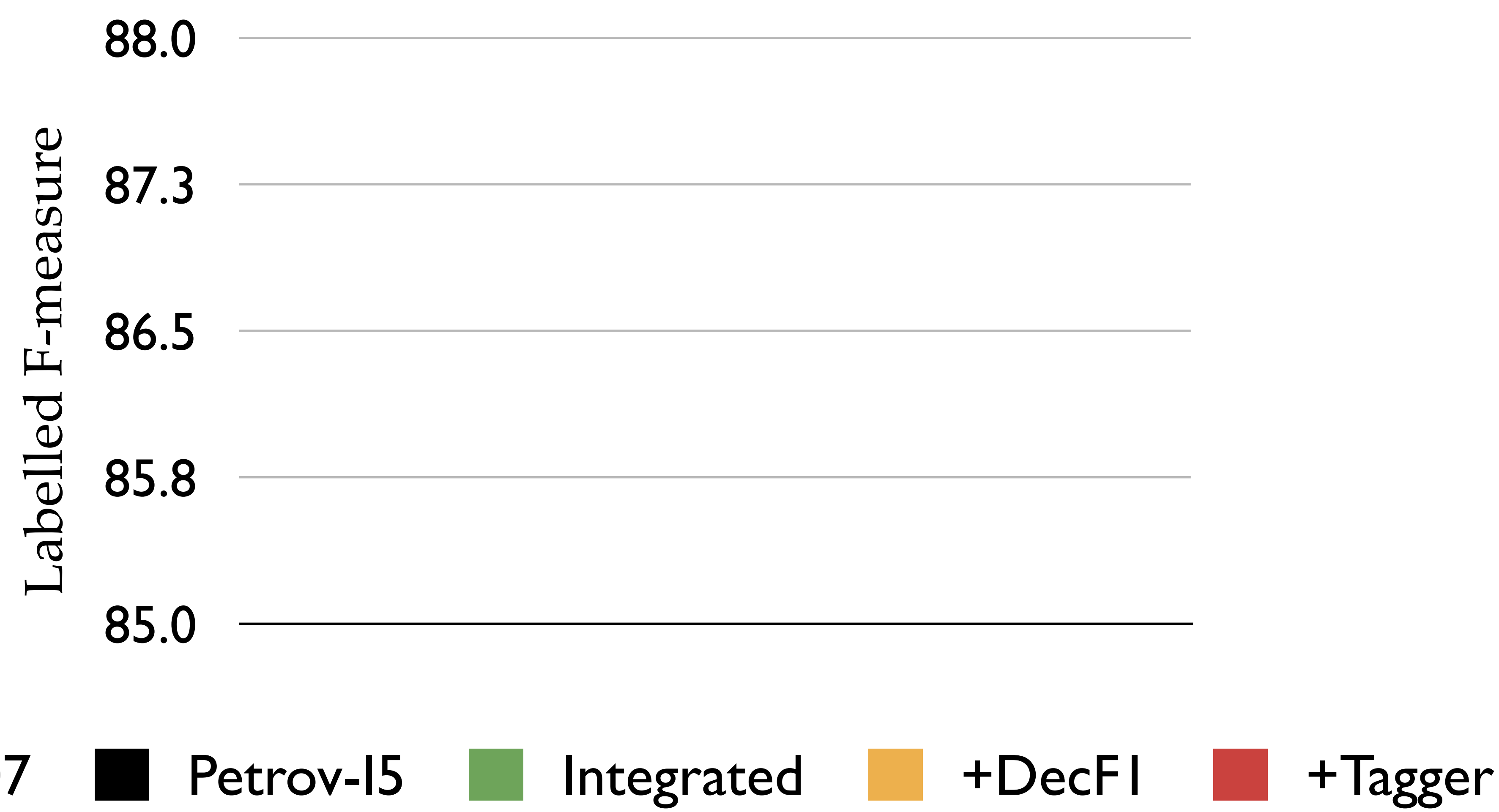

Fowler & Penn (2010)

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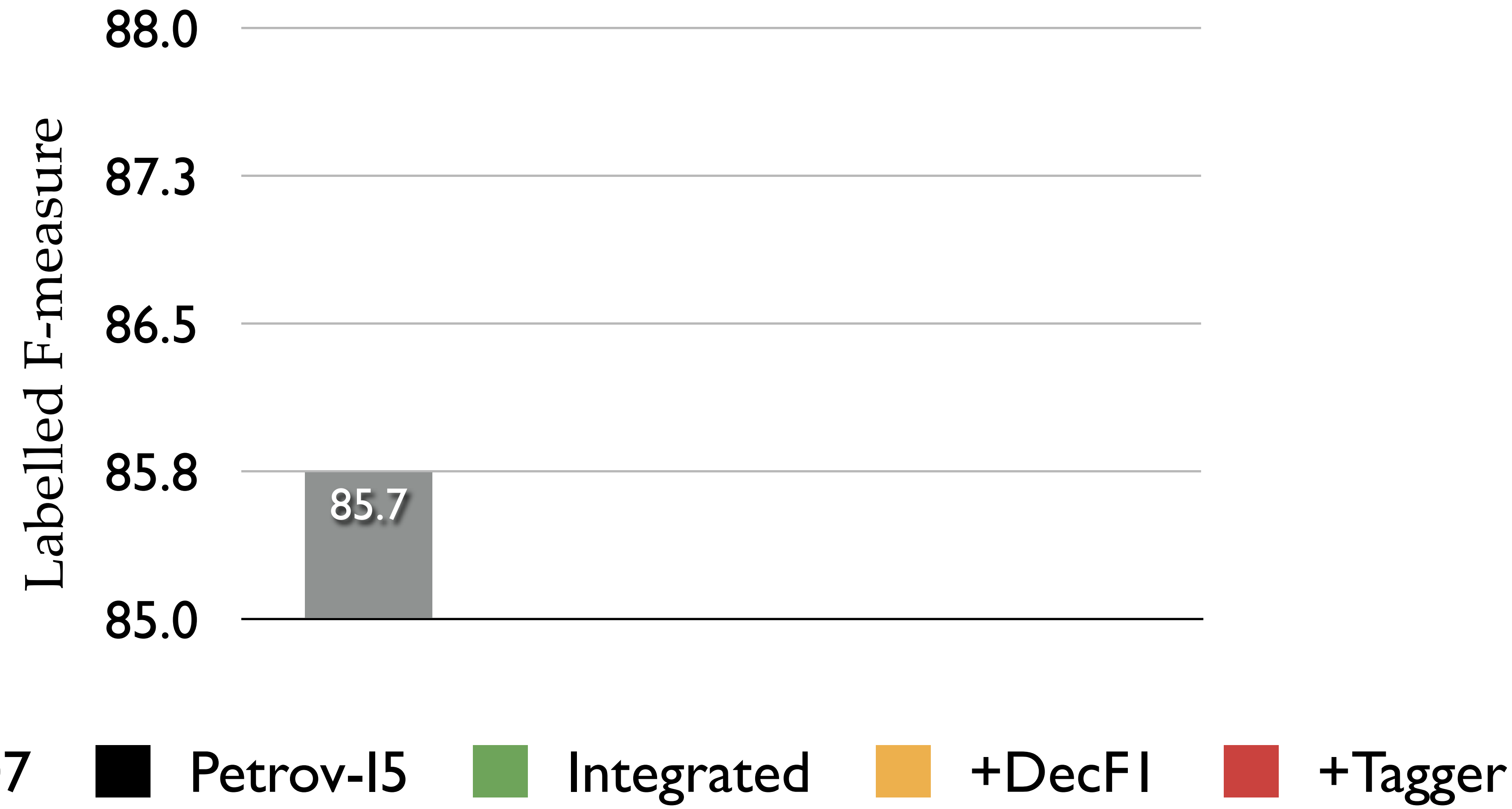

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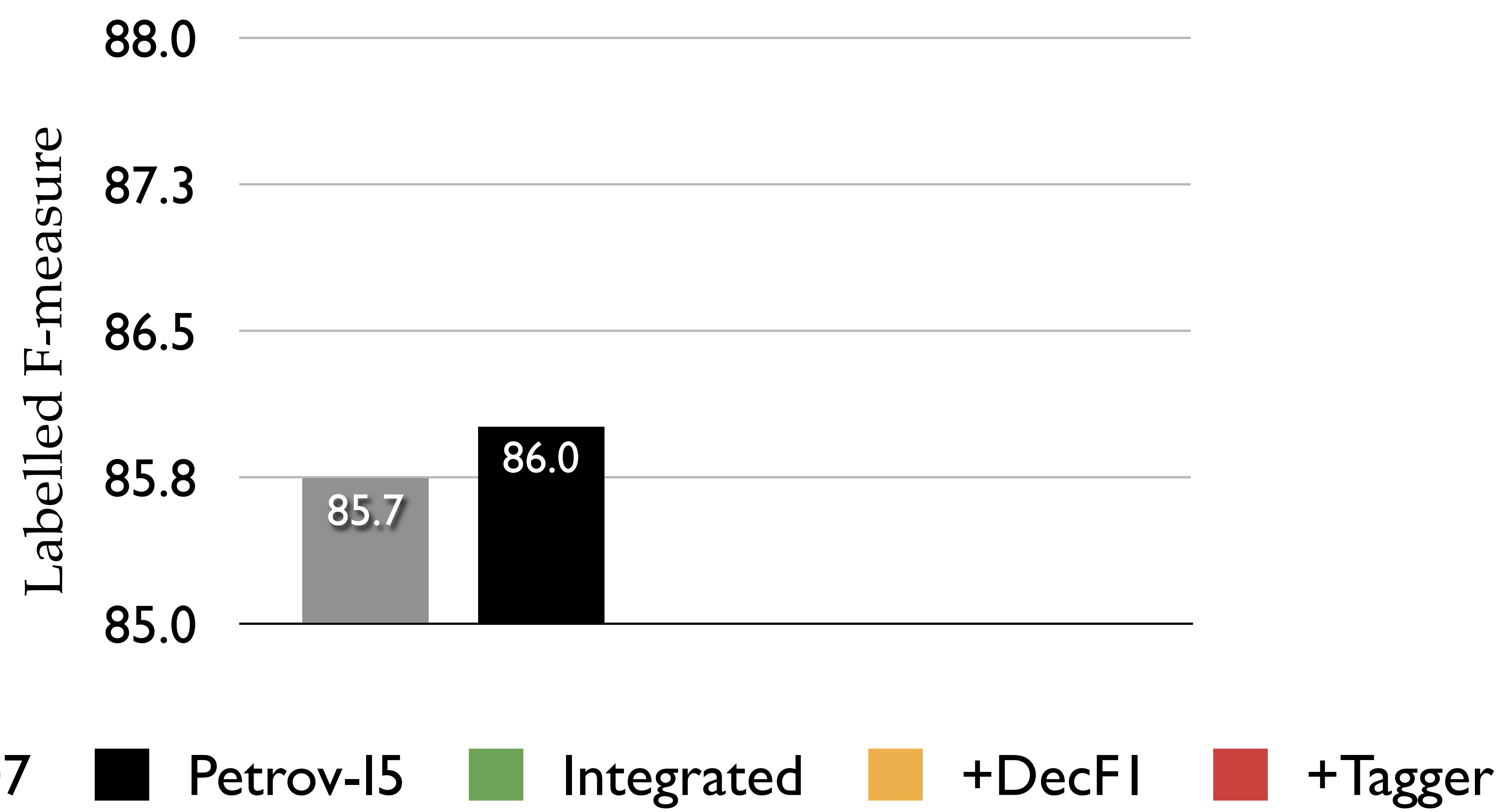

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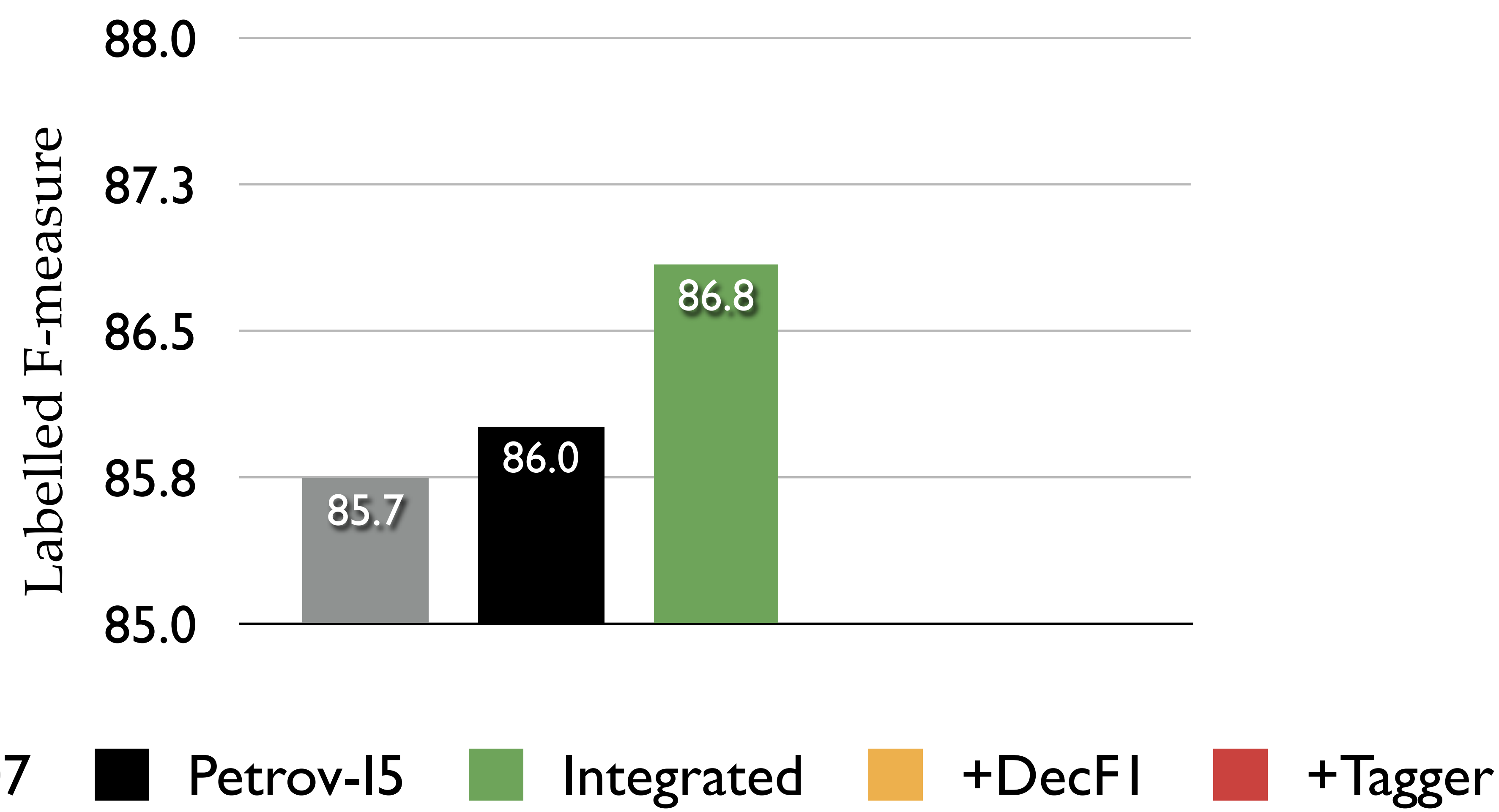

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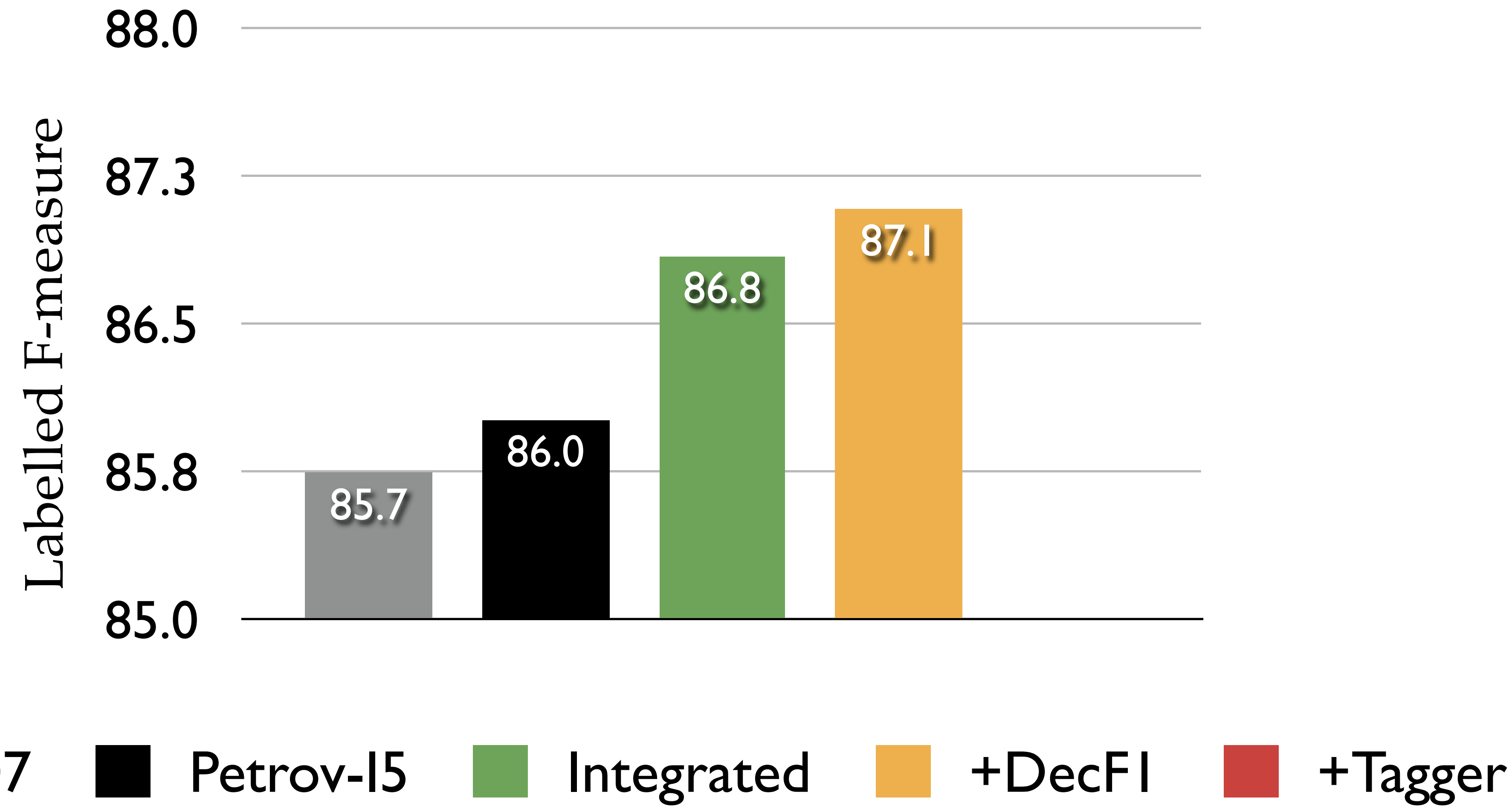

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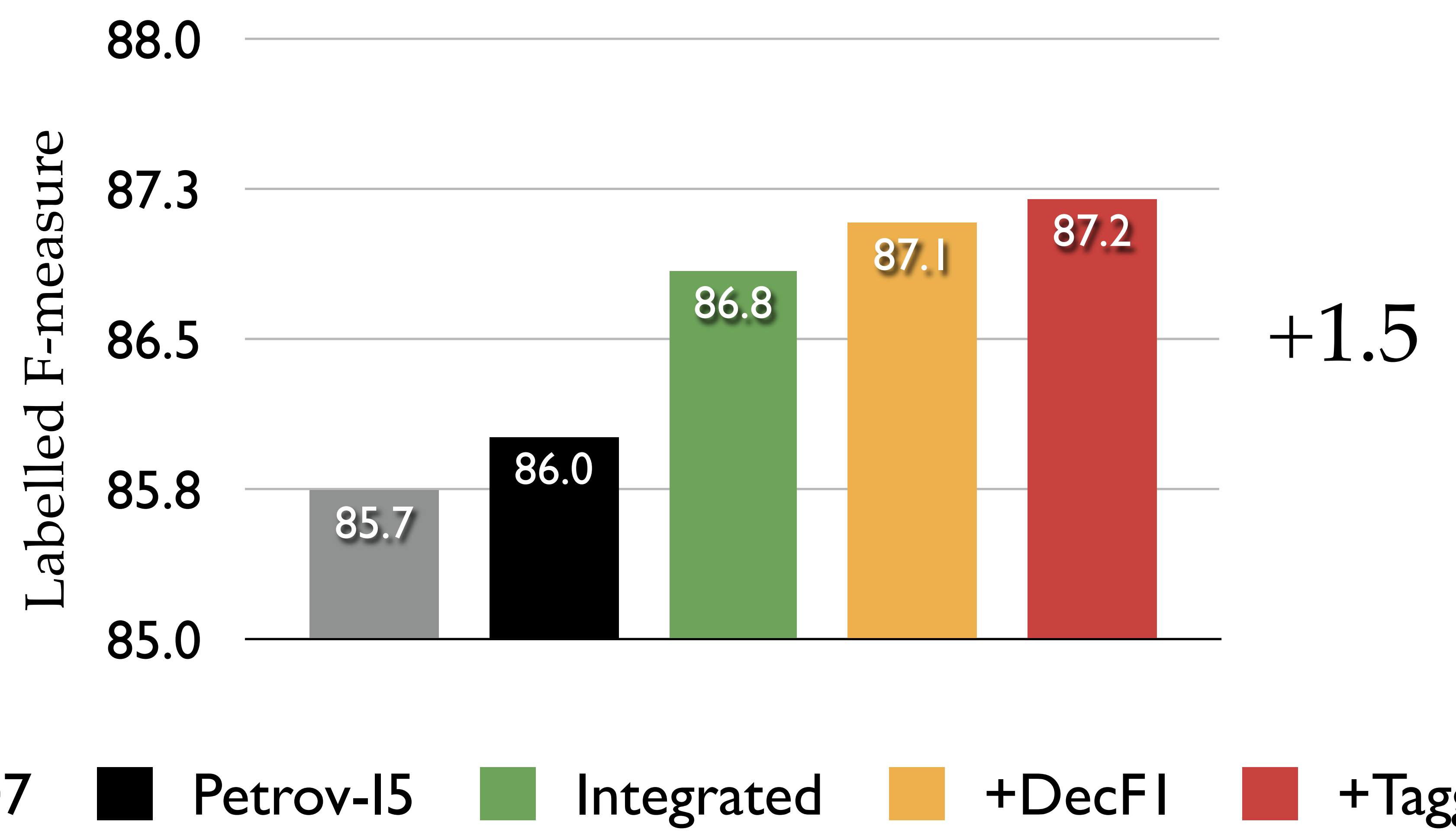
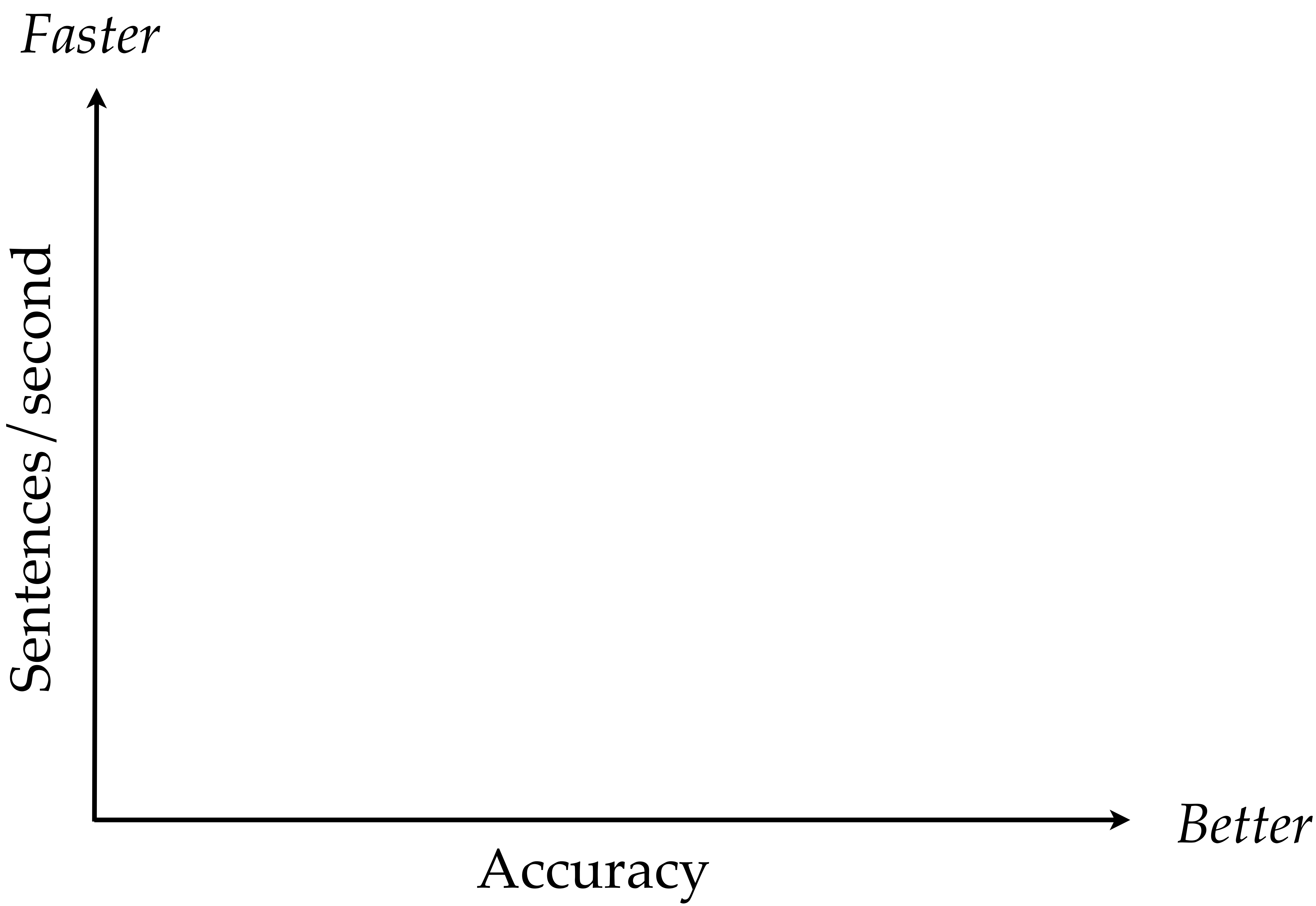


Fowler & Penn (2010)

Results: Efficiency vs. Accuracy



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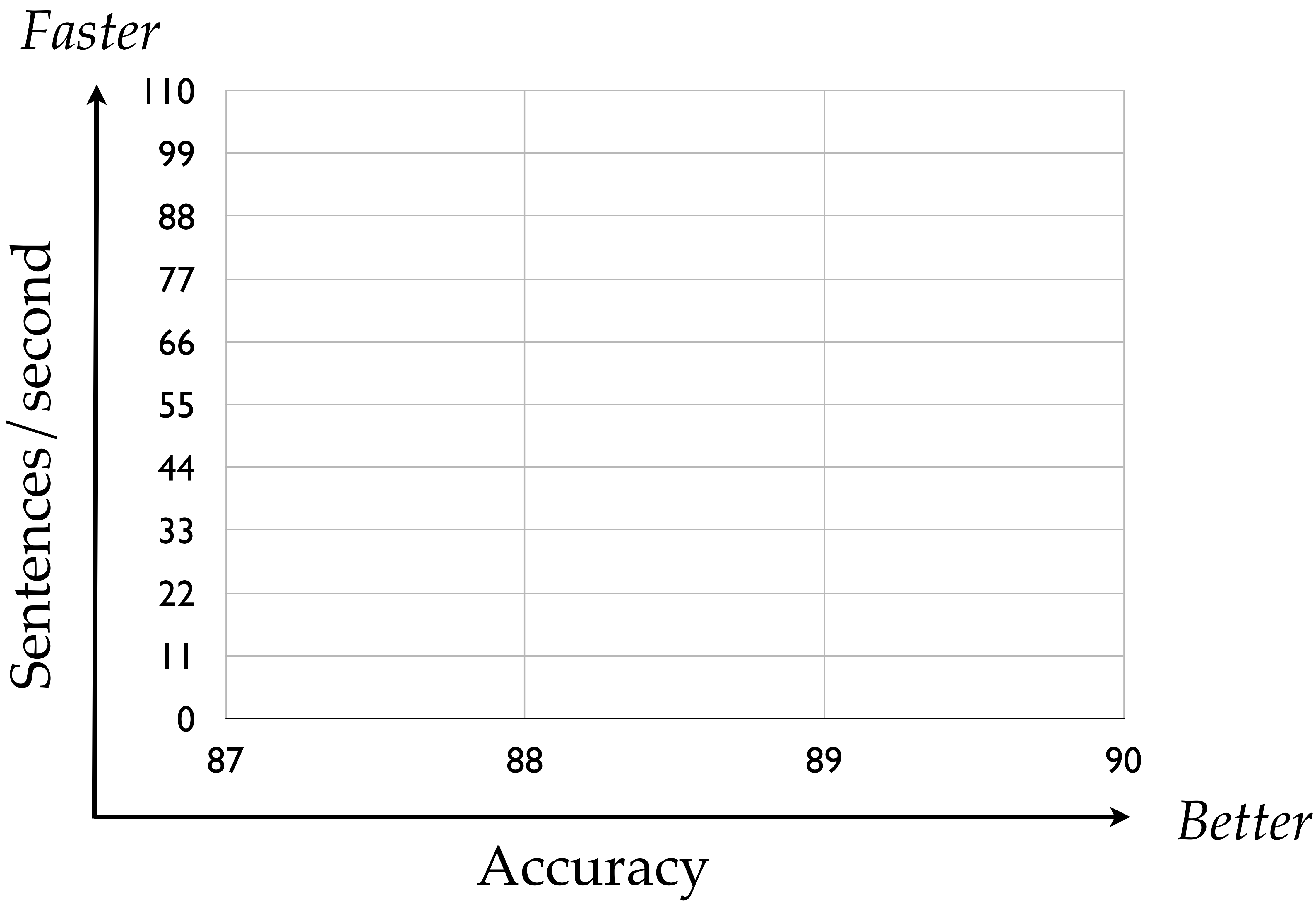

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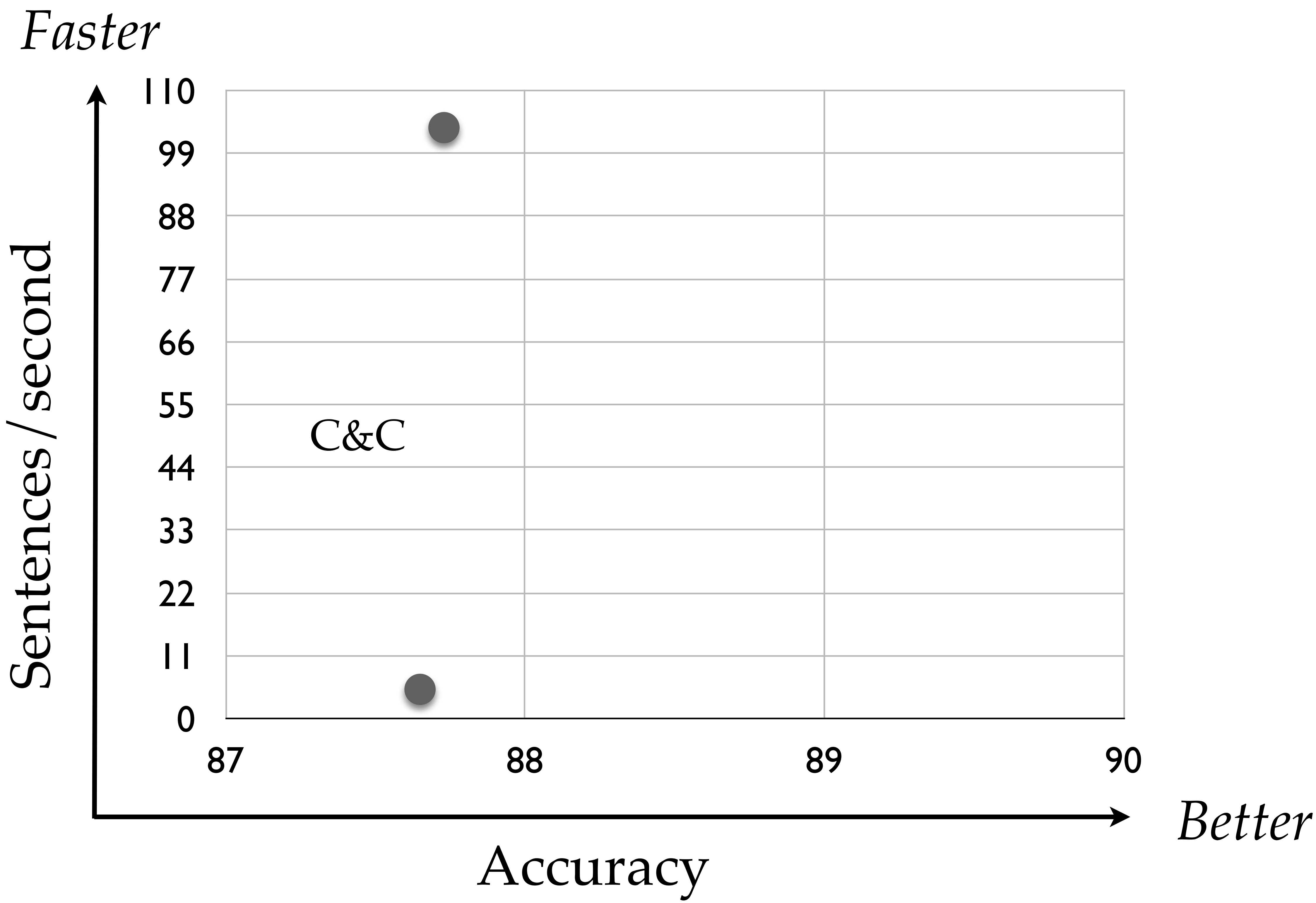

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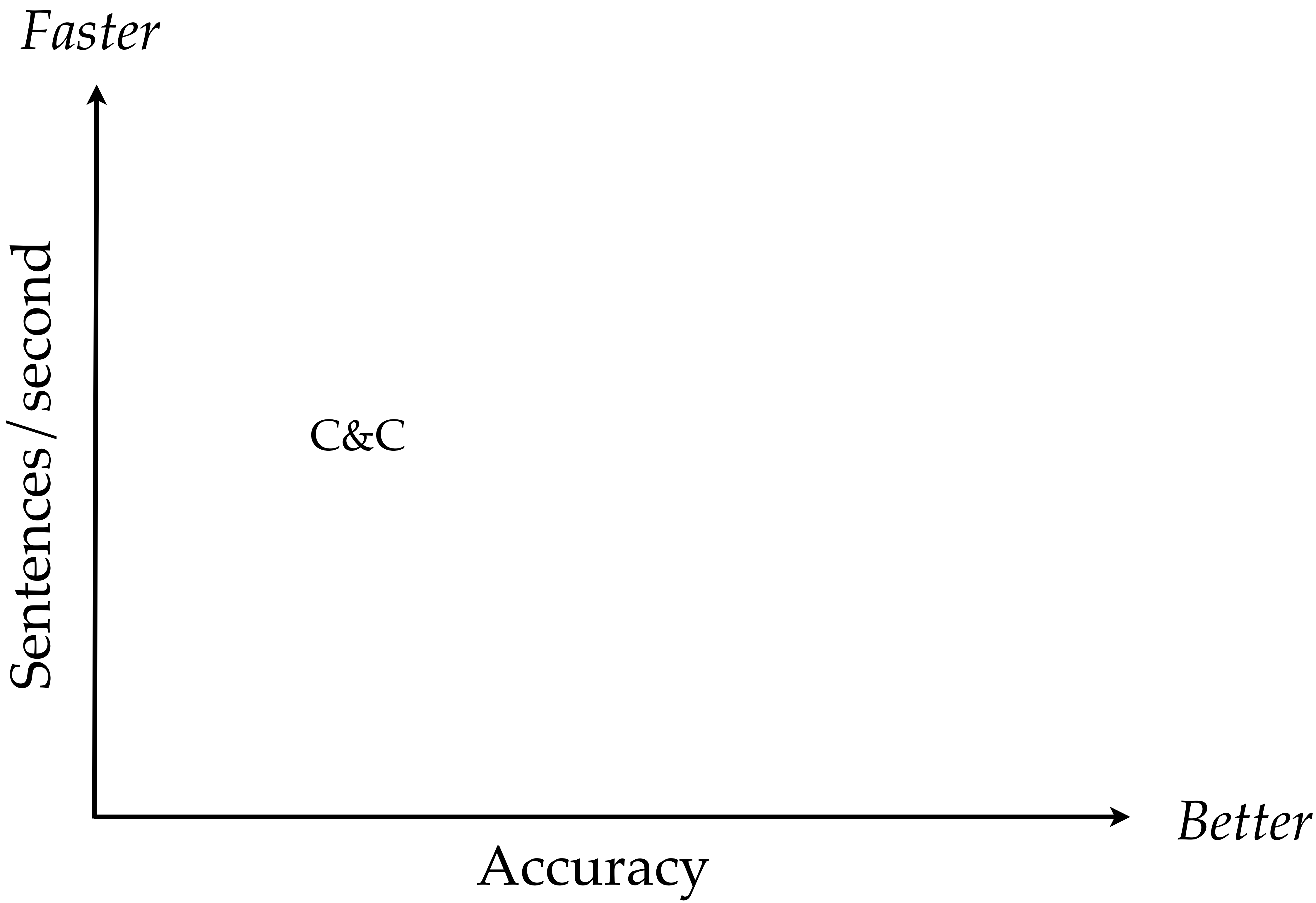

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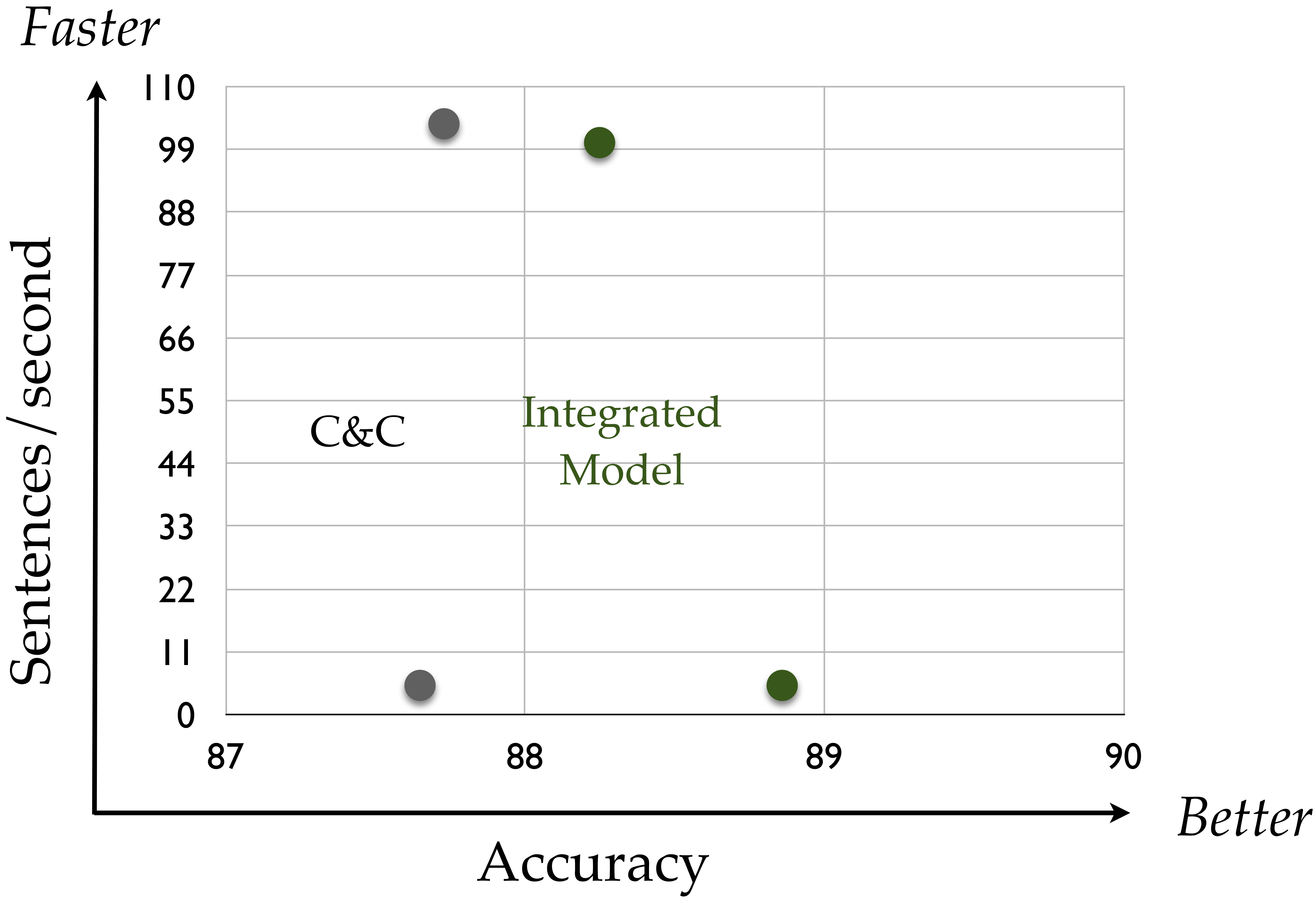

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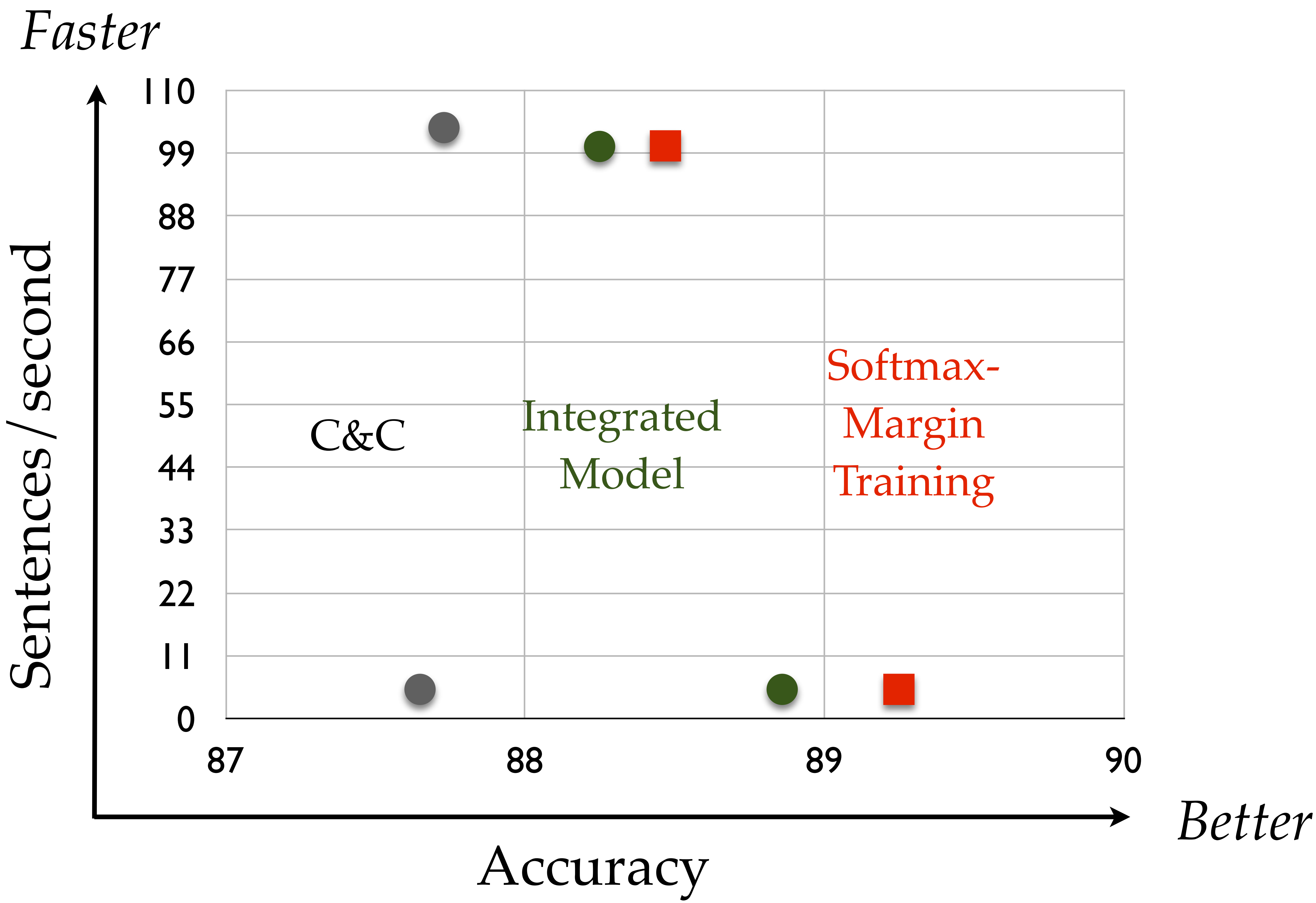


Summary

- Softmax-Margin training is easy and improves our model.
- Approximate loss functions are fast, accurate and easy to use.
- Best ever CCG parsing results (87.7 $\rightarrow$ 89.3).

Future Directions

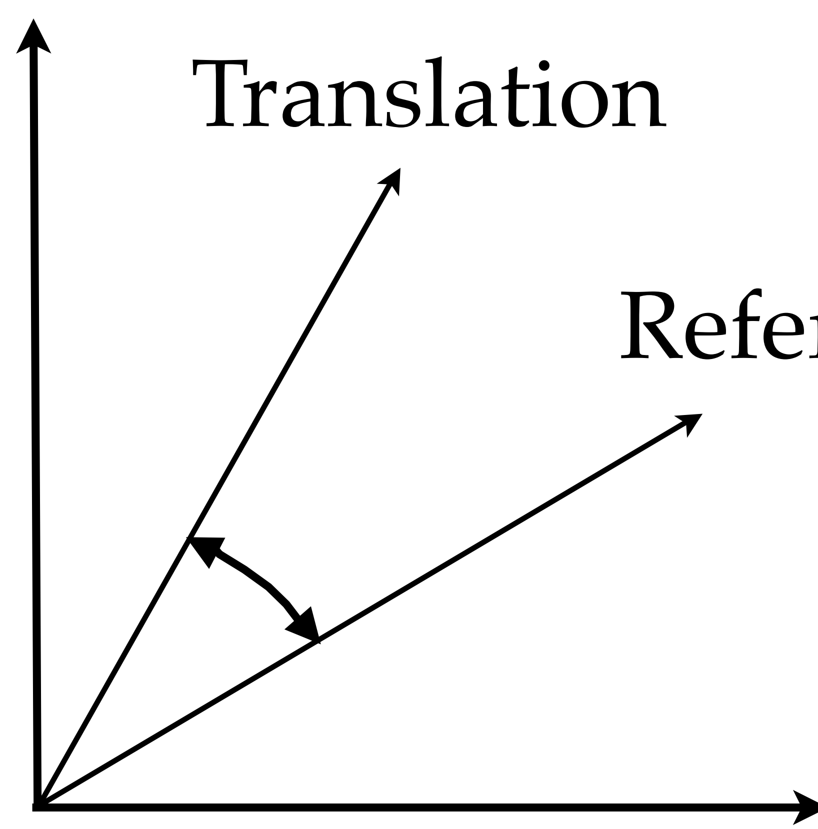
- What can we do with the presented methods?
  - BP for other complex problems e.g. SMT
  - Semantics for SMT.
  - Simultaneous parsing of multiple sentences.

BP for other NLP pipelines

- Pipelines necessary for practical NLP systems
- More accurate integrated models often too complex
- This talk: Approximate inference can make these models practical
- Use it for other pipelines e.g. POS, NER tagging & Parsing
- Hard: BP for syntactic MT, another weighted intersection problem between LM & TM

Semantics for SMT

- Compositional & distributional meaning representation to compute vectors of sentence-meaning (Greffenstette & Sadrzadeh, 2011; Clark, to appear)
- Syntax (e.g. CCG) drives compositional process
- Directions: Model optimisation, evaluation, LM



Parsing beyond sentence-level

- Many NLP tasks (e.g. IE) rely on uniform analysis of constituents
- Skip-Chain CRFs successful to predict consistent NER tags across sentences (Sutton & McCallum, 2004)
- Parse multiple sentences at once and enforce uniformity of parses

1. The securities and exchange commission issued ...

NP/N $\quad$ N

NP

2. ... responded to the statement of the securities and exchange commission

NP $\quad$ $conj$ $\quad$ NP

$NP\backslash NP$

NP

Related Publications

- A Comparison of Loopy Belief Propagation and Dual Decomposition for Integrated CCG Supertagging and Parsing. with Adam Lopez. In *Proc. of ACL*, June 2011.
- Efficient CCG Parsing: A* versus Adaptive Supertagging. with Adam Lopez. In *Proc. of ACL*, June 2011.
- Training a Log-Linear Parser with Softmax-Margin. with Adam Lopez. In *Proc. of EMNLP*, July 2011.
- A Systematic Comparison of Translation Model Search Spaces. with Adam Lopez, Hieu Hoang, Philipp Koehn. In *Proc. of WMT*, March 2009.

Thank you