Ph.D. Thesis Oral Defense

Stanford Artificial Intelligence Laboratory (SAIL)

Valentin I. Spitkovsky

Grammar Induction and Parsing with Dependency-and-Boundary Models

Problem: Unsupervised Parsing (and Grammar Induction)

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- **Input: Raw Text**

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NN	NNS	VBD	IN	NN	◇
Factory	**payrolls**	**fell**	**in**	**September**	**.**

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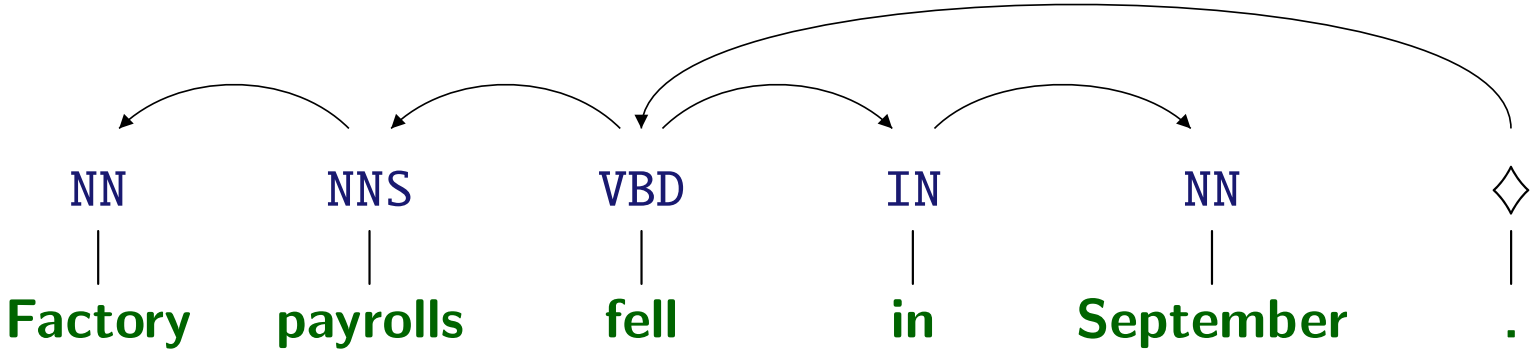
  ... By most measures, the nation's industrial sector is now growing very slowly — if at all. Factory payrolls fell in September. So did the Federal Reserve ...

- **Output: Syntactic Structures (and a Probabilistic Grammar)**



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- **Insert your favorite reason(s) why you'd like to parse anything in the first place...**
- **... adjust for any data without reference tree banks: — i.e., understudied languages or genres (e.g., legal).**
- **Potential applications:**
  - **machine translation**
    — word alignment, phrase extraction, reordering;
  - **web search**
    — retrieval, query refinement;
  - **question answering, speech recognition, etc.**

Evaluation: Directed Dependency Accuracy

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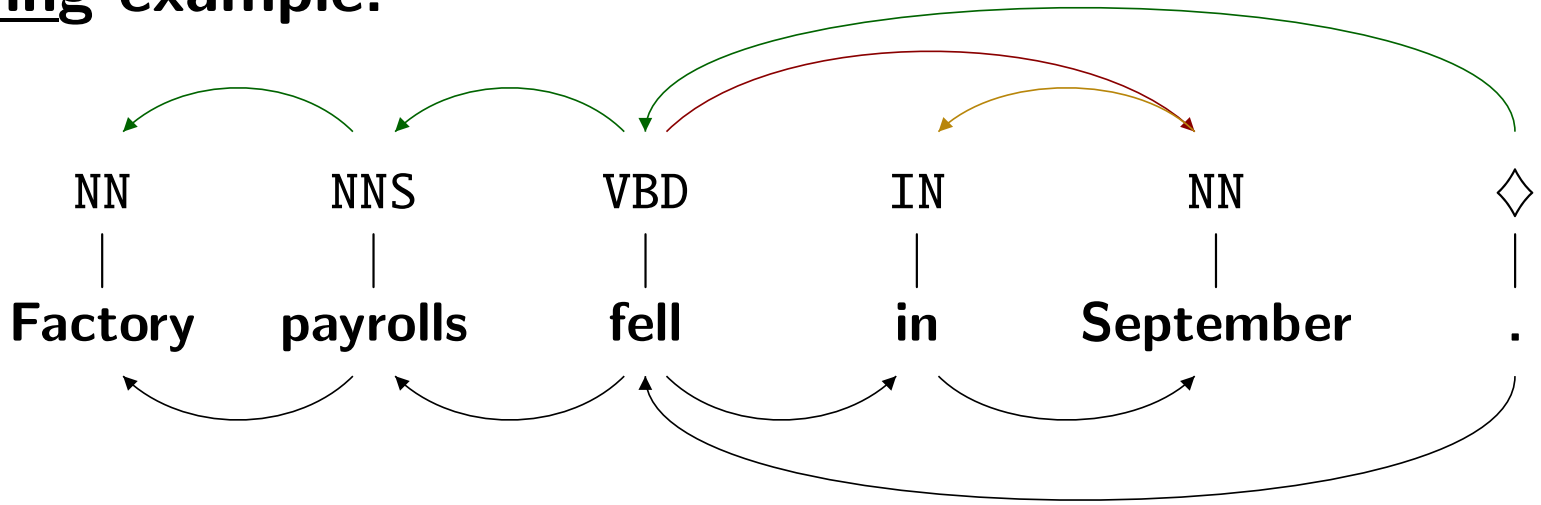
Scoring example:



Directed Score: $\frac{3}{5} = 60\%$ **(left/right-branching baselines:** $\frac{2}{5} = 40\%$**)**

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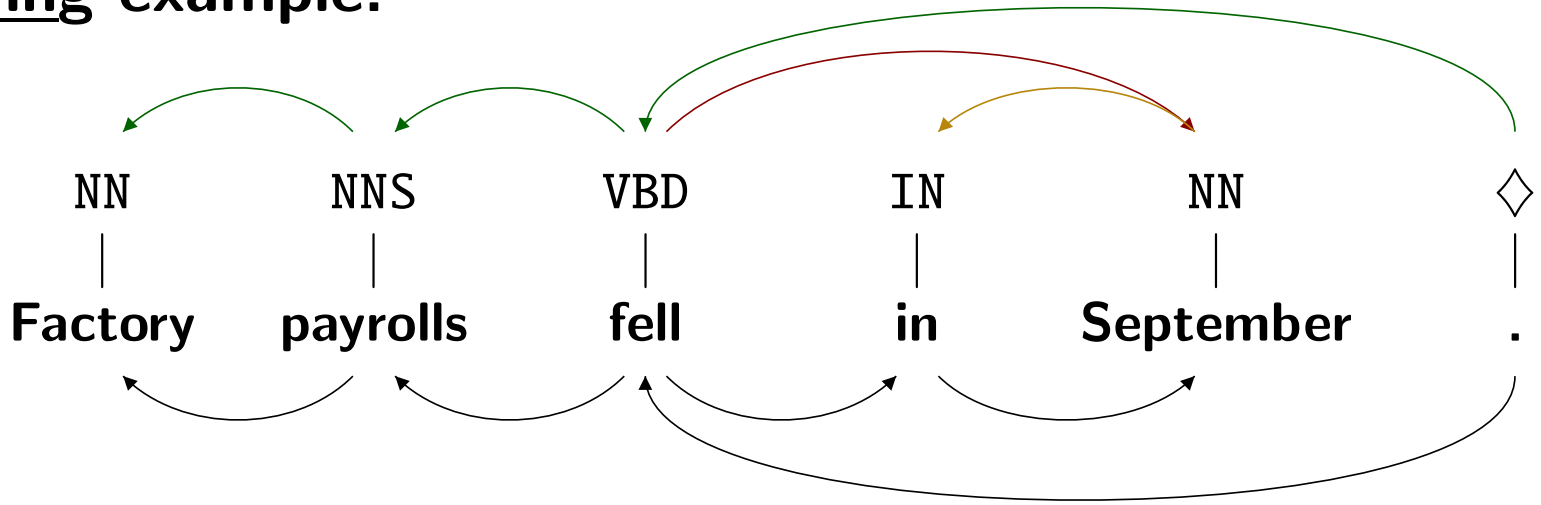

Directed Score: $\frac{3}{5} = 60\%$ **(left/right-branching baselines:** $\frac{2}{5} = 40\%$**);**

Undirected Score: $\frac{4}{5} = 80\%$ **(left/right-branching baselines:** $\frac{4}{5} = 80\%$**).**

Prior Art: A Brief History

- **1992 — word classes (Carroll and Charniak)**
- **1998 — greedy linkage via mutual information (Yuret)**
- **2001 — iterative re-estimation with EM (Paskin)**

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- 2004 — annealing techniques (Smith and Eisner)
- 2005 — contrastive estimation (Smith and Eisner)
- 2006 — structural biasing (Smith and Eisner)
- 2007 — common cover link representation (Seginer)
- 2008 — logistic normal priors (Cohen et al.)
- 2009 — lexicalization and smoothing (Headden et al.)
- 2009 — soft parameter tying (Cohen and Smith)

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h

e.g.: verb

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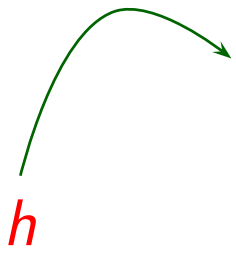

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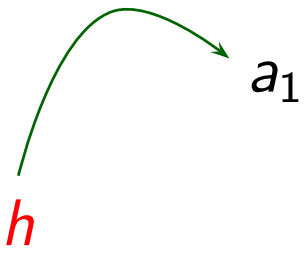

e.g.: verb noun

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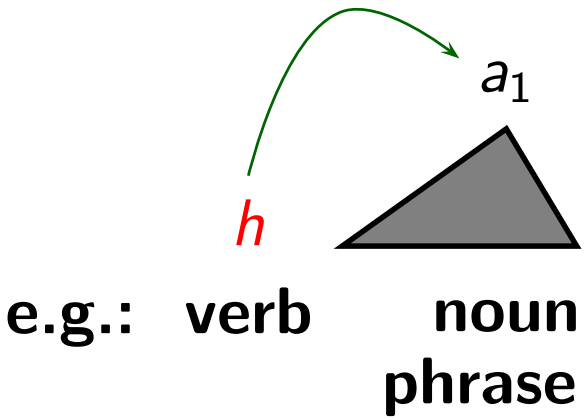

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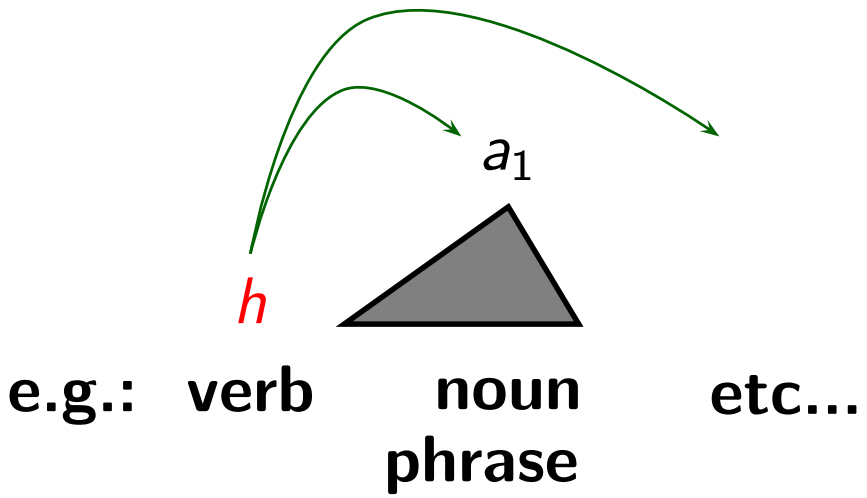

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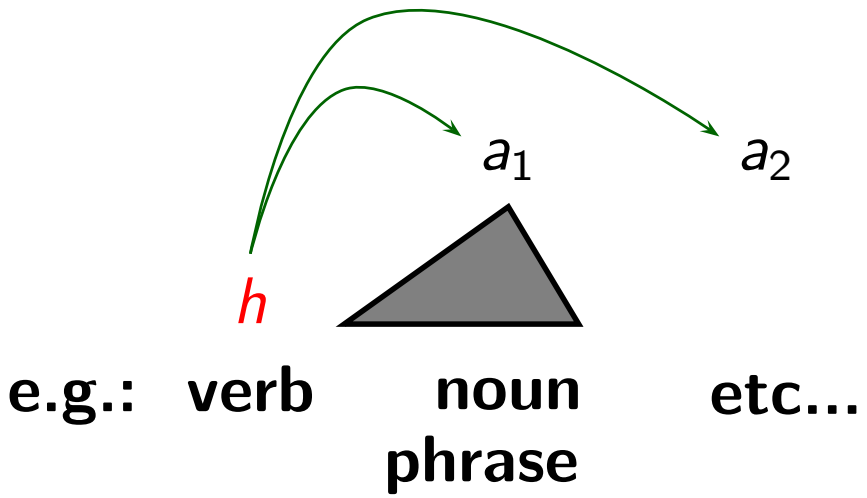

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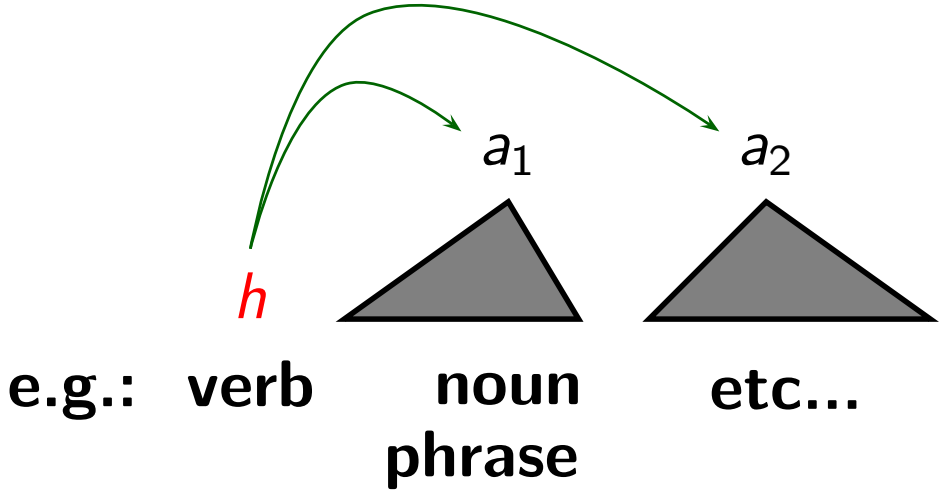

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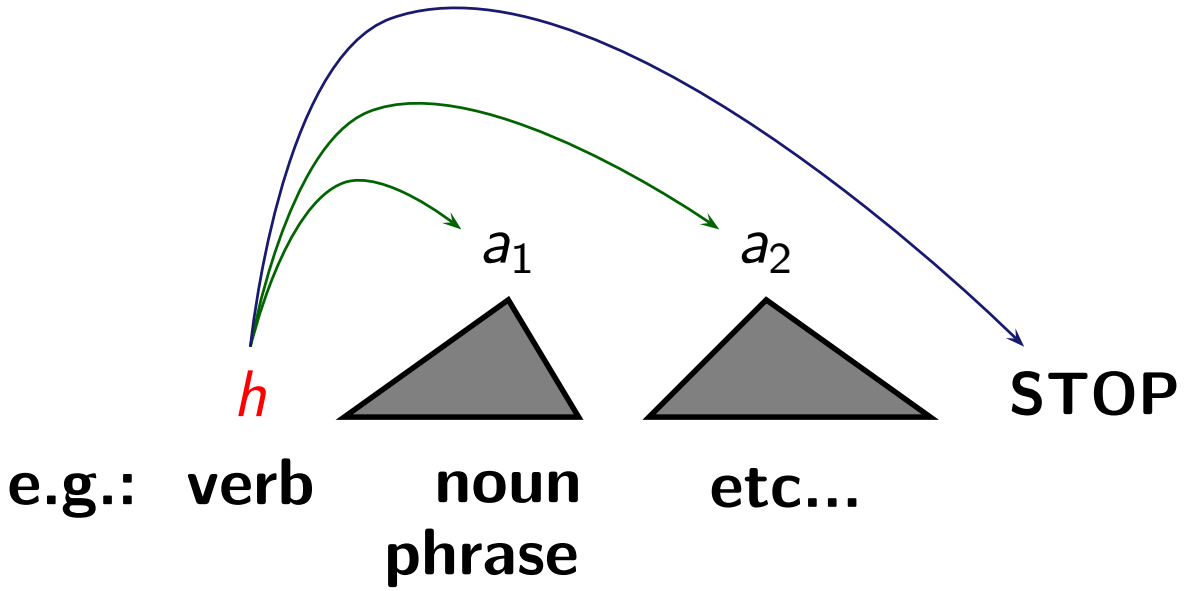

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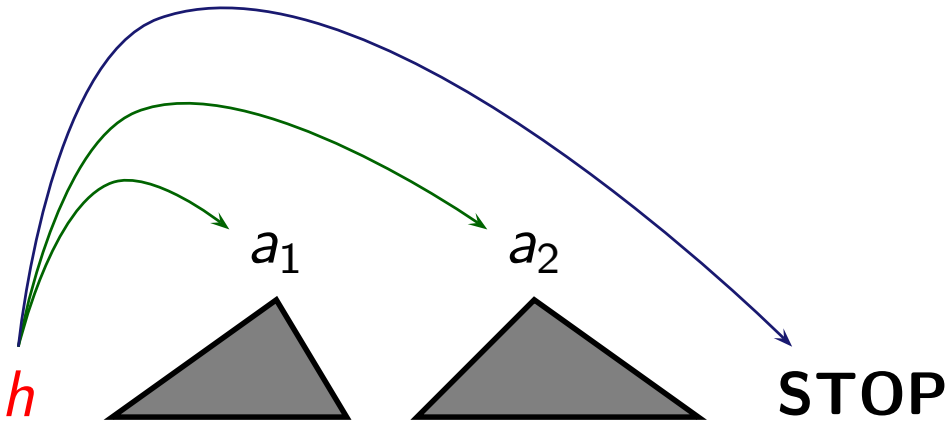

$$\mathbb{P}(t_h) = \prod_{dir \in \{\mathrm{L},\mathrm{R}\}} \left[\underline{\mathbb{P}_{\mathrm{STOP}}(c_h, dir, \overbrace{1_{n=0}}^{adj})} \prod_{i=1}^{n} \underline{\mathbb{P}(t_{a_i})}\, \mathbb{P}_{\mathrm{ATTACH}}(c_h, dir, c_{a_i}) \; \underline{(1 - \mathbb{P}_{\mathrm{STOP}}(c_h, dir, \overbrace{1_{i=1}}^{adj}))} \right]_{n=|args(h,dir)|}$$

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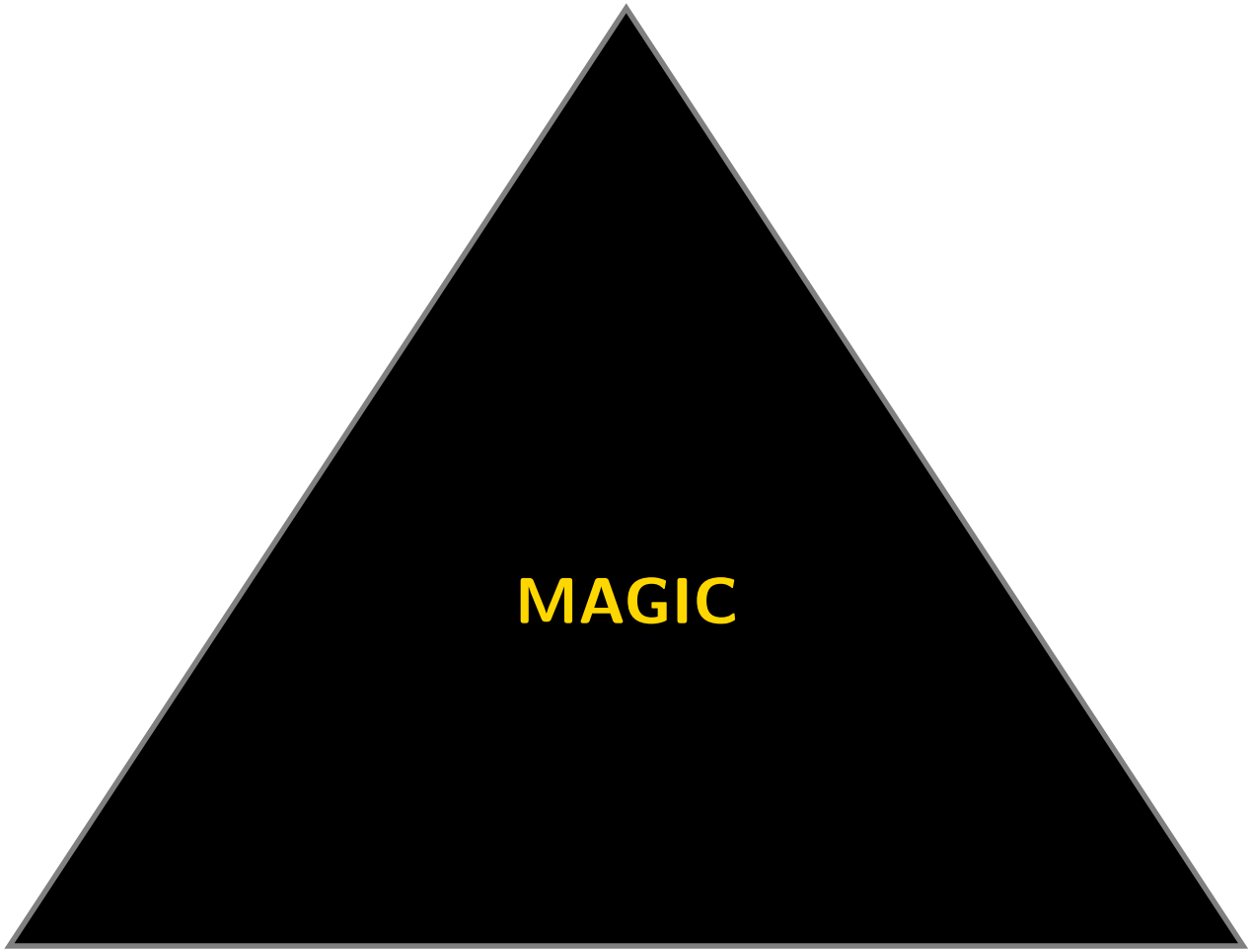

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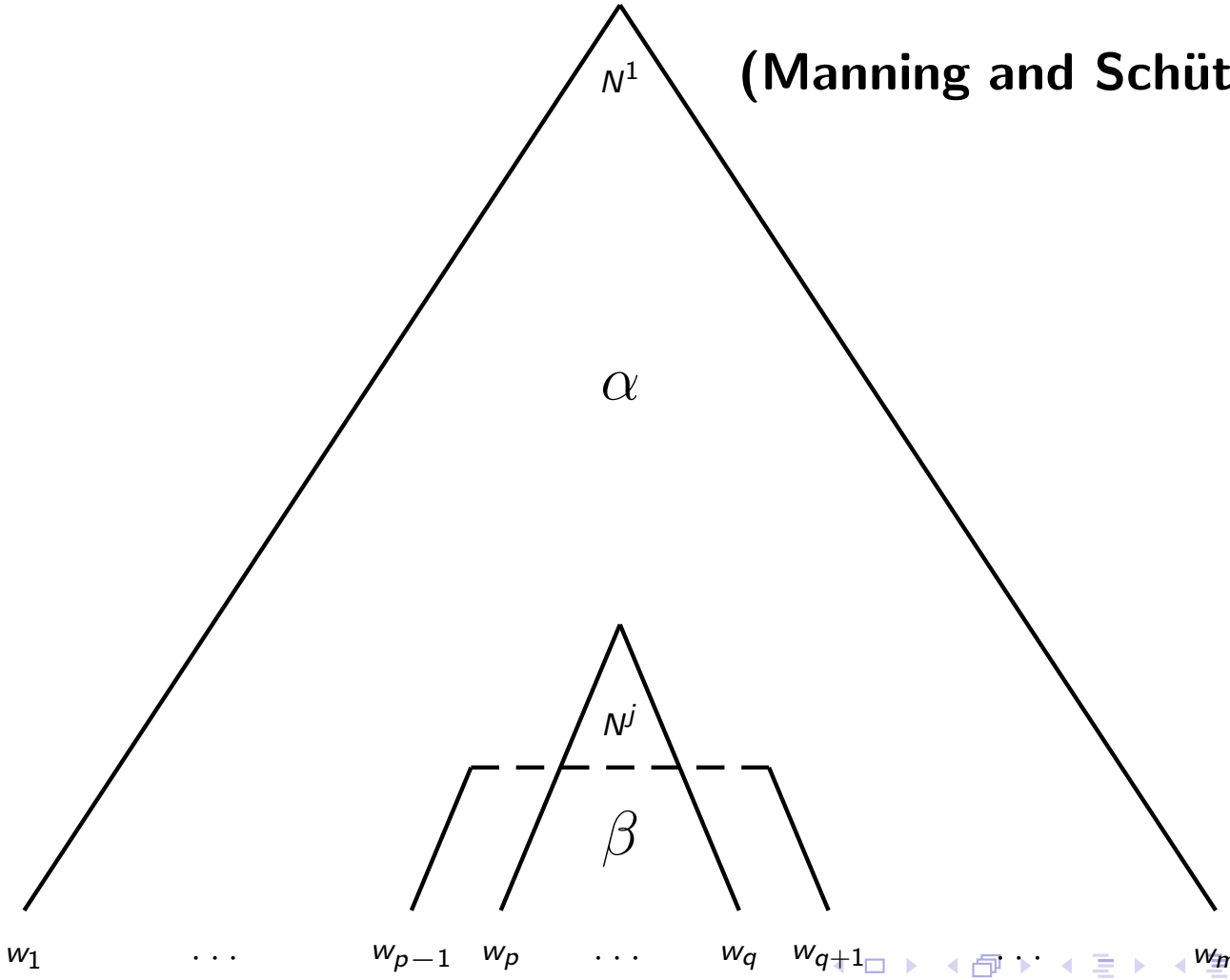
- **parameter fitting via expectation-maximization (EM)**
  - **by means of inside-outside re-estimation (Baker, 1979)**



(Manning and Schütze, 1999)

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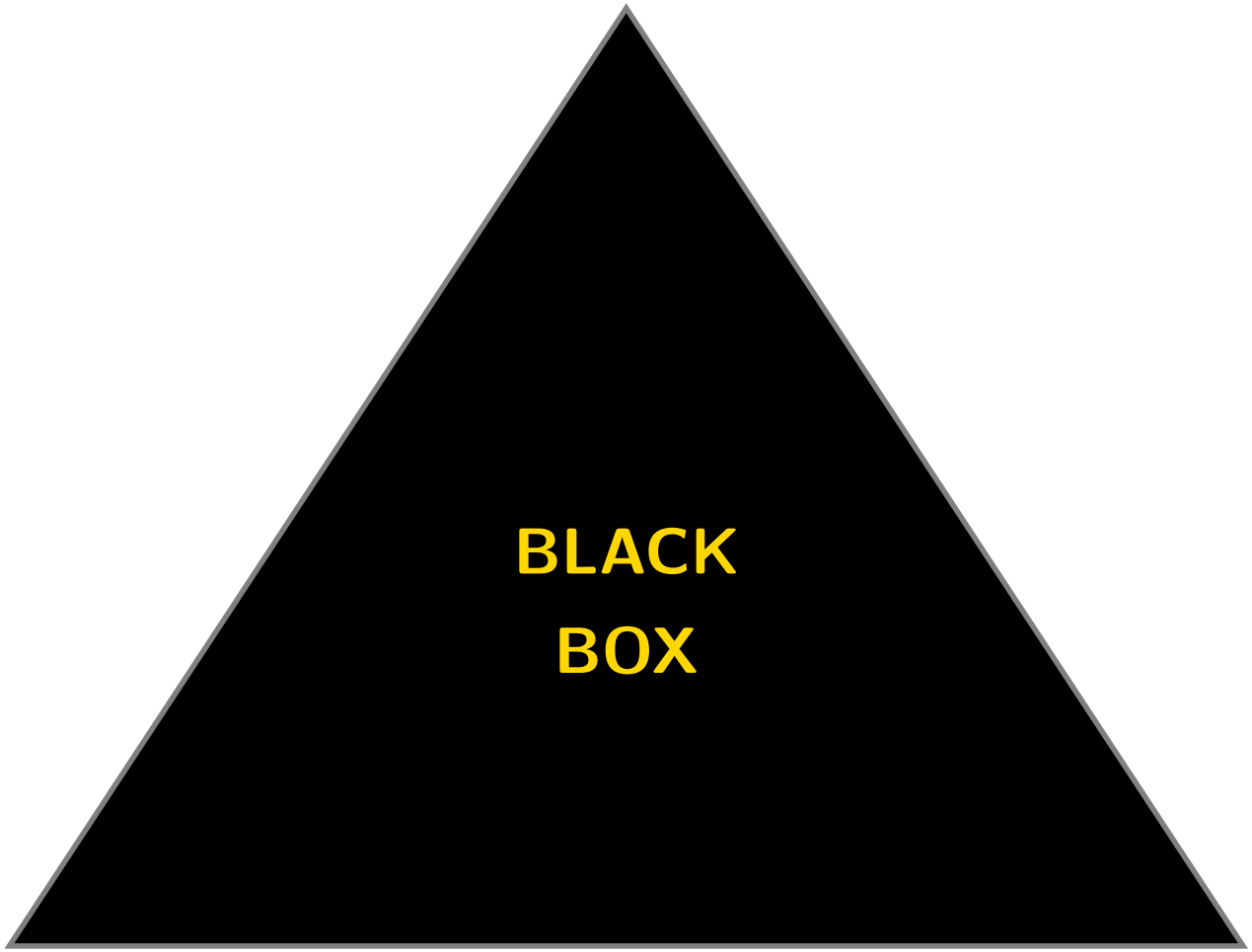
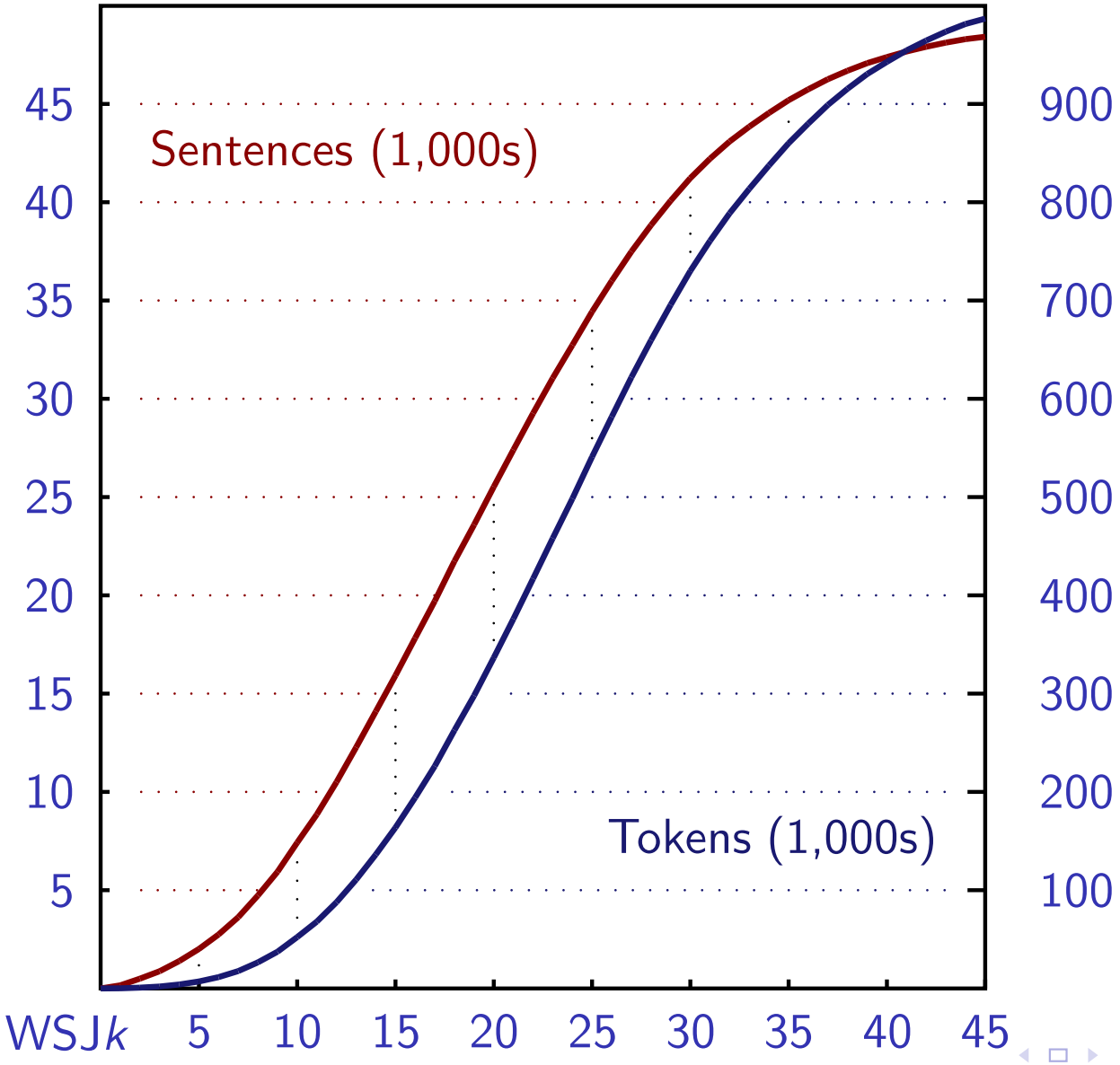
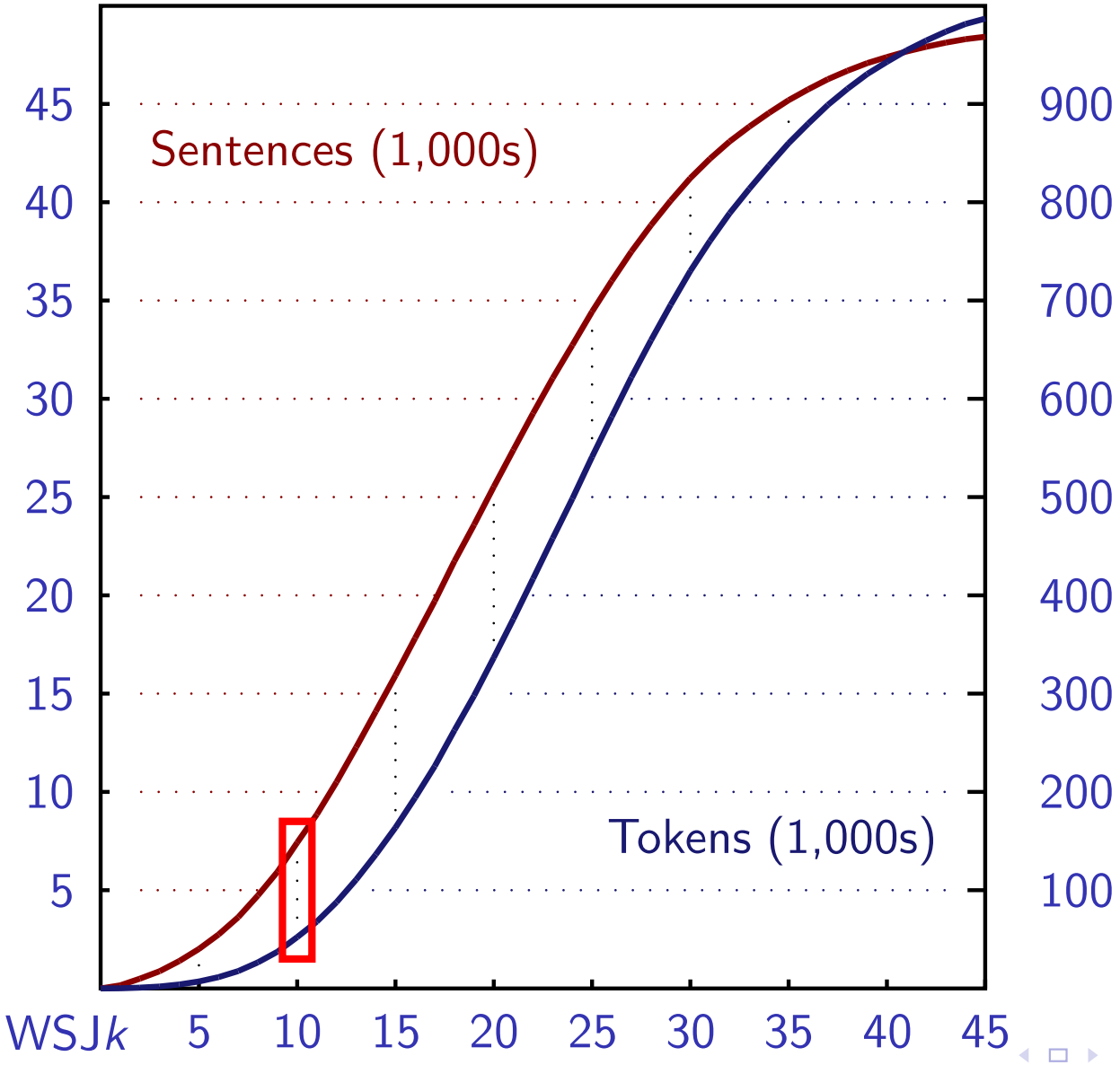


Prior Art: The Standard Corpus — WSJ



Prior Art: The Standard Corpus — WSJ10



Outline

- **Introduction to the Grammar Induction Problem**
  - **The Inputs and Outputs** (text $\rightarrow$ dependency parses)
  - **A Probabilistic Model** (DMV)
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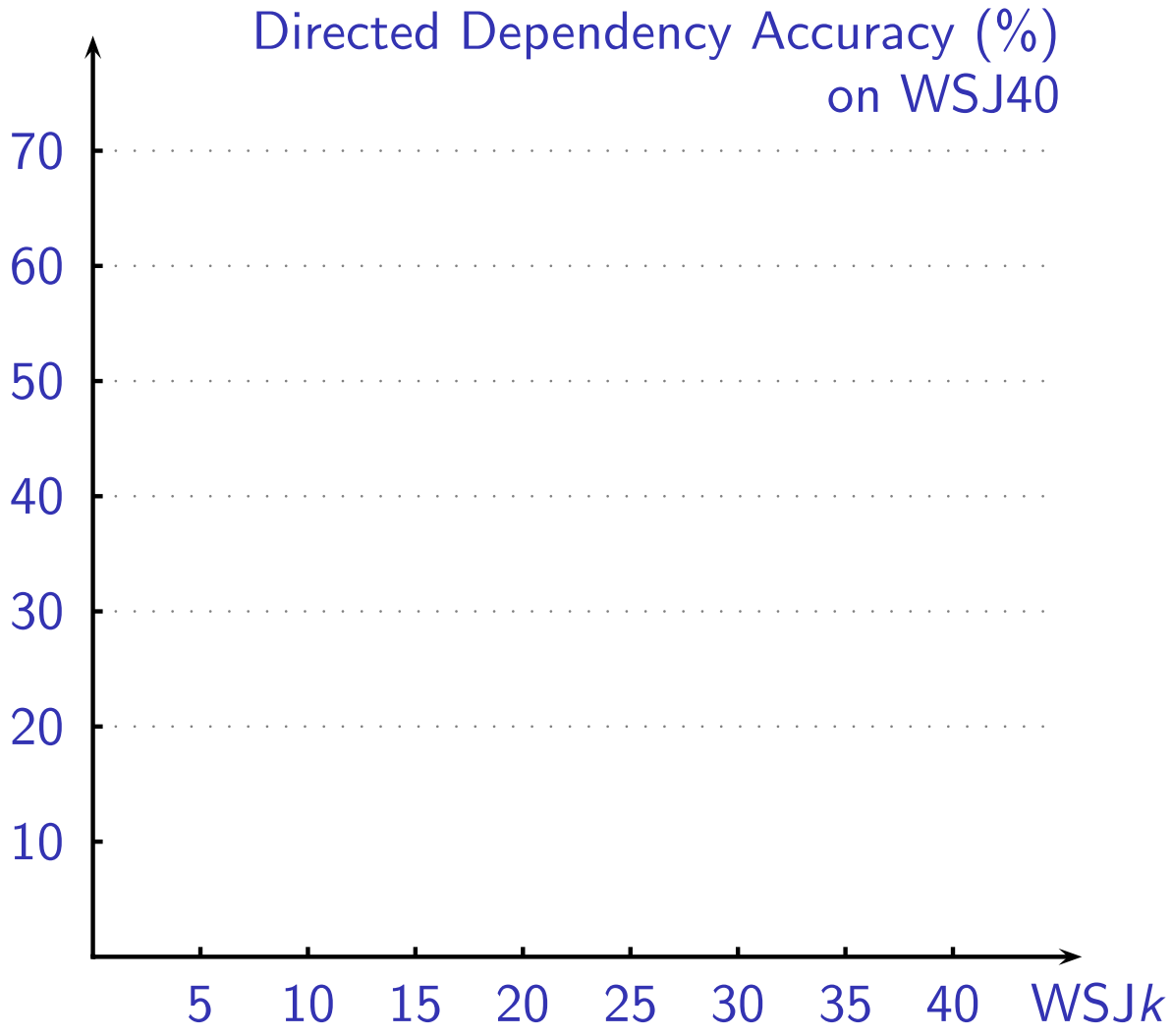
Optimization

Viterbi Training

Baby Steps

Lateen EM

Issue I: Why so little data?



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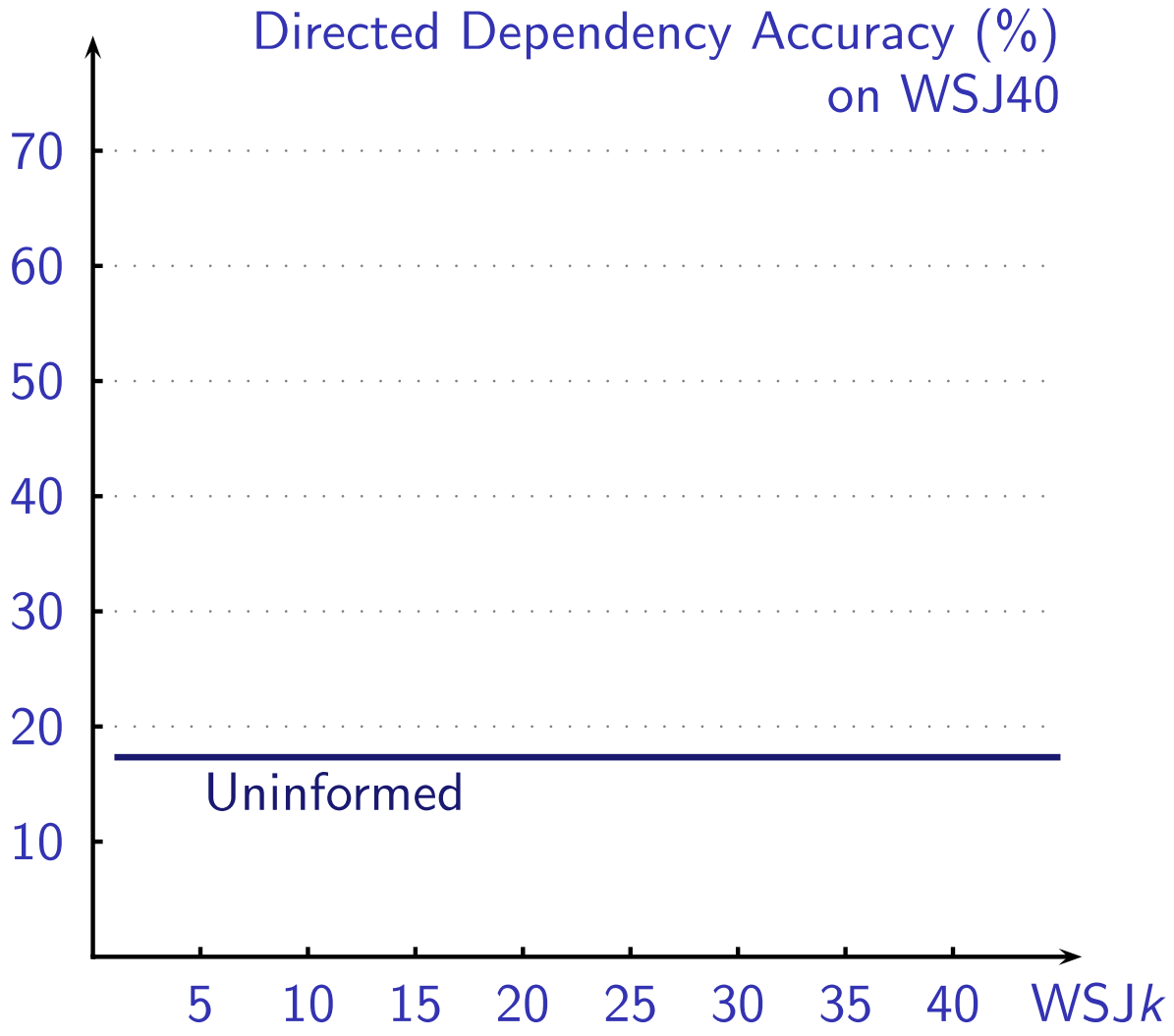

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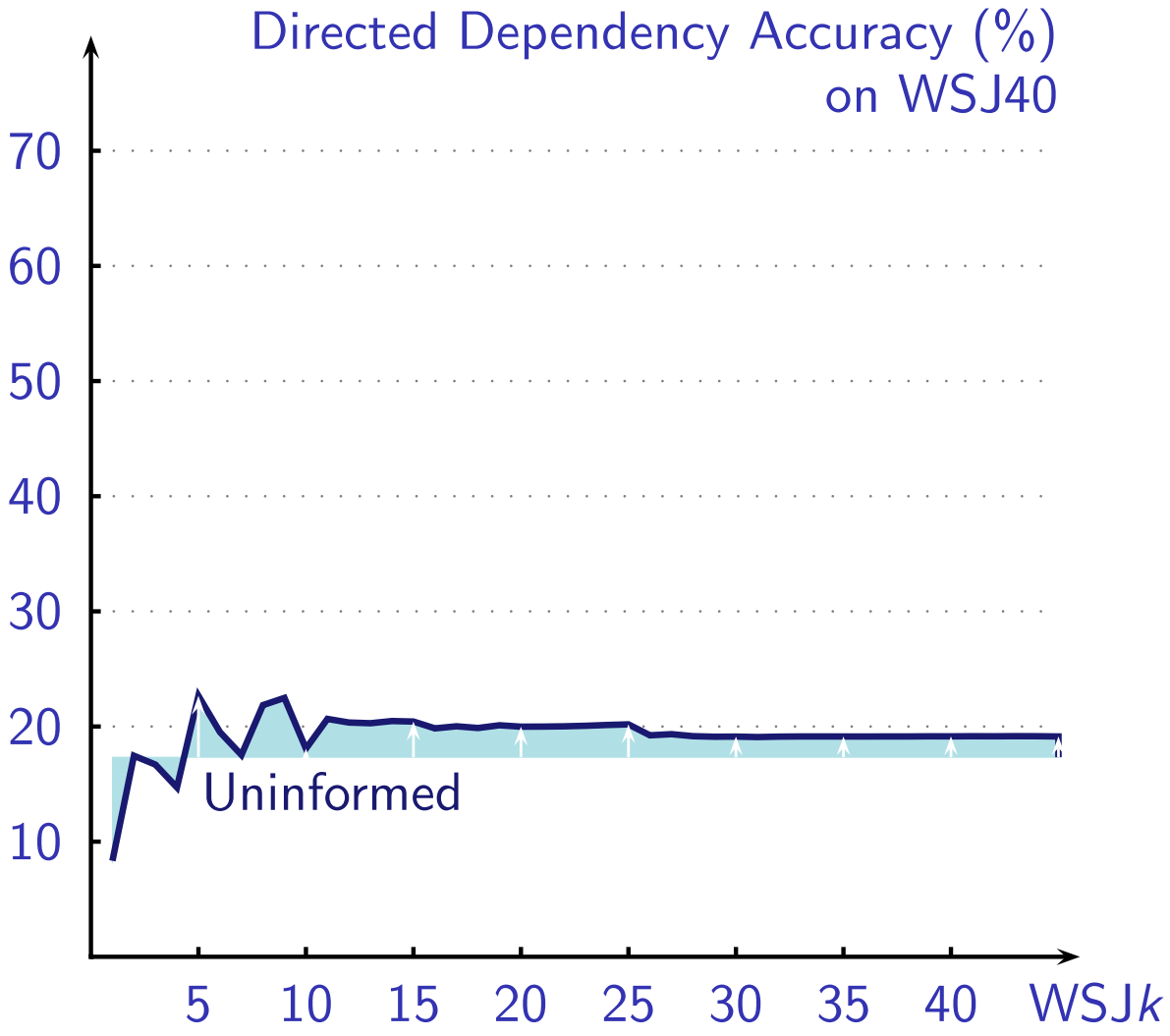

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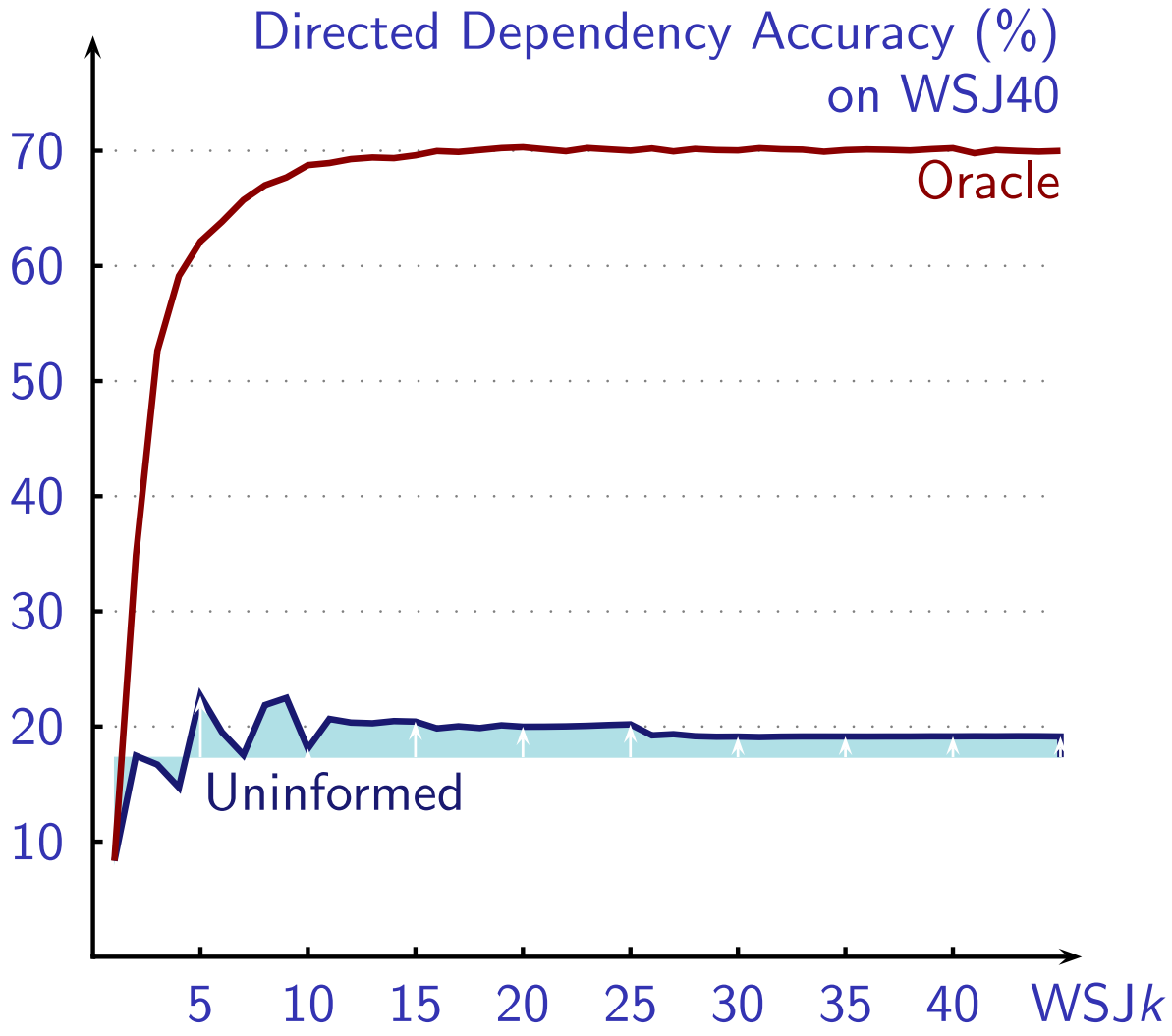

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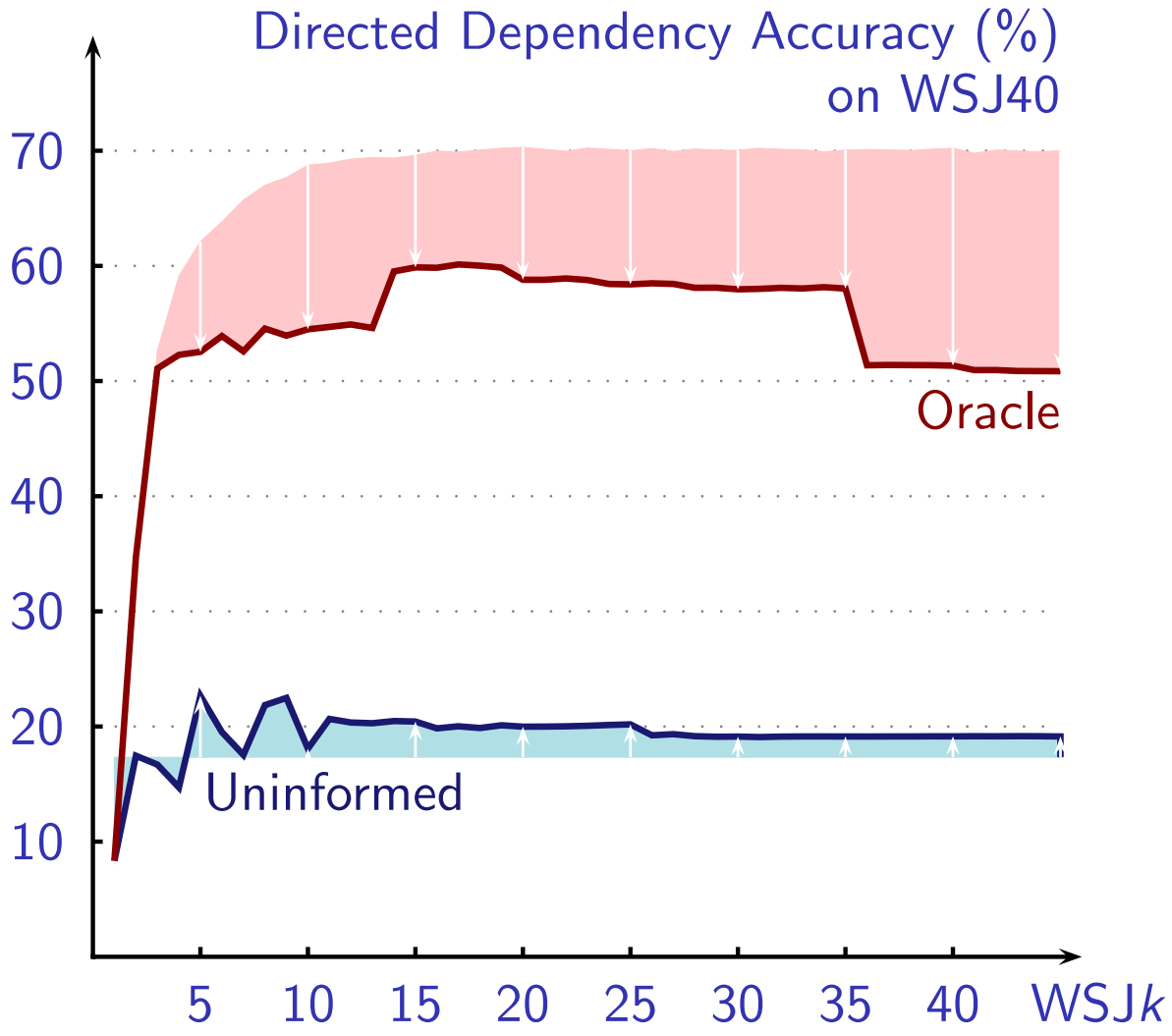

Issue II: Non-convex objectives...

- **maximizing the probability of data (sentence strings):**

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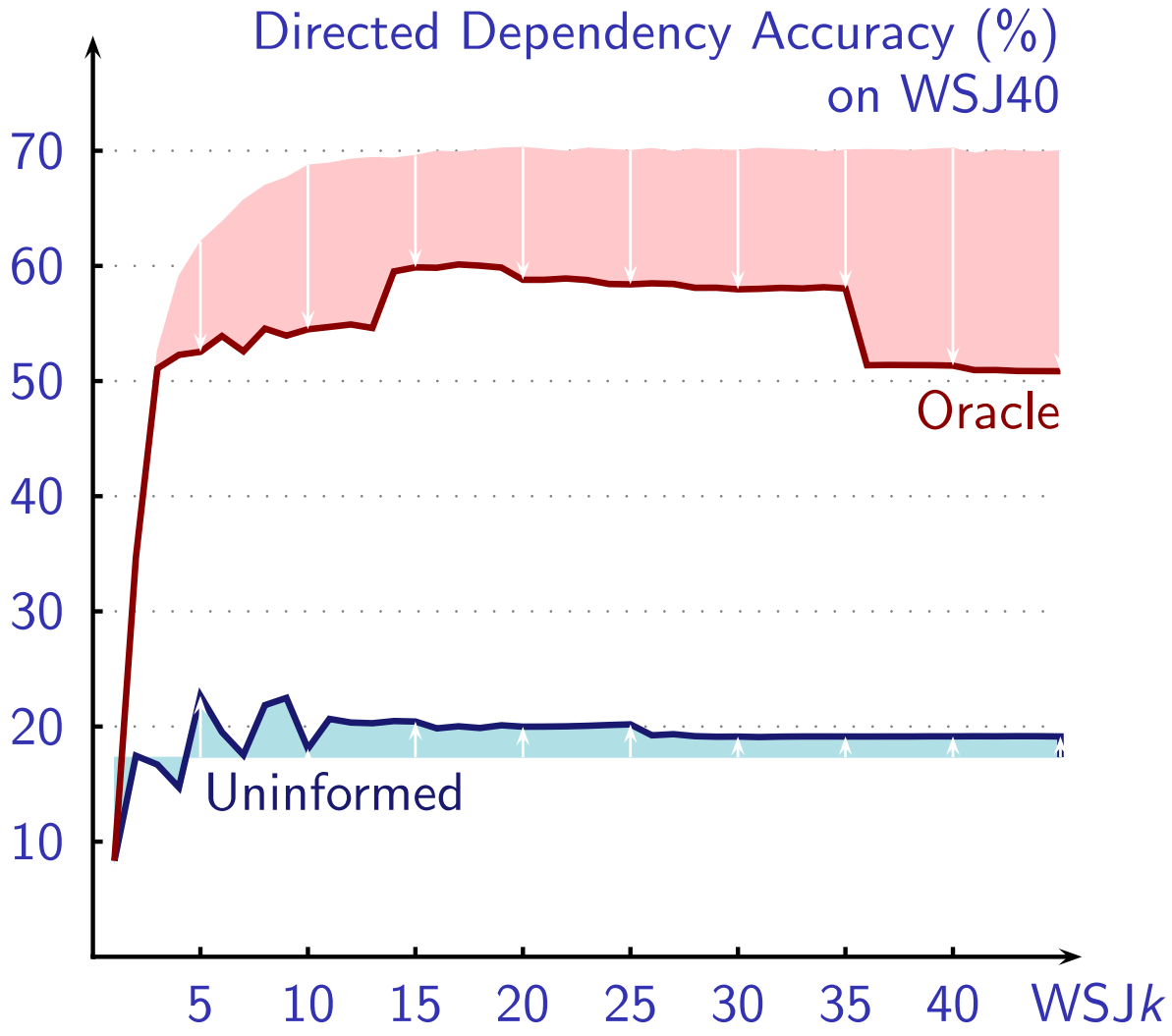
- **could optimize likeliest parse trees (also non-convex):**

$$\hat{\theta}_{\text{VIT}} = \arg\max_{\theta} \sum_{s} \max_{t \in T(s)} \log \mathbb{P}_{\theta}(t)$$

Classic EM: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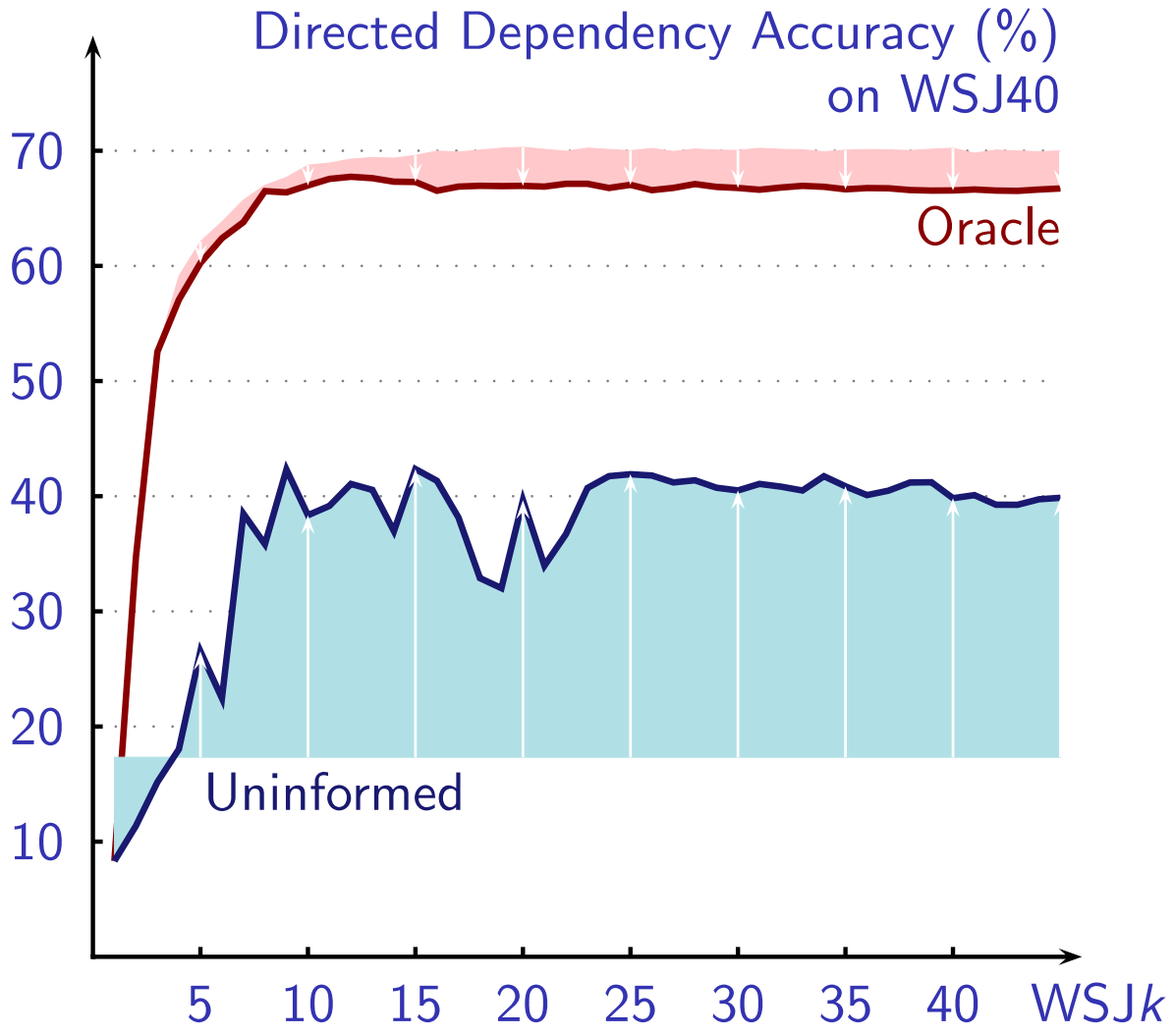
Viterbi EM: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- **Classic EM: "focus across the board"**
  - **hard to see the trees for the forest...**

    ... but known to work with shorter inputs!

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- **incremental step: smooth WSJk; re-init WSJ$(k+1)$**

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  Darkness fell.

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- **WSJ3** — **Become a Lobbyist**
  But many have. (**determiners!**)
  They didn't.

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- **shaping** **(Skinner, 1938)**

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- **starting small** (Elman, 1993)
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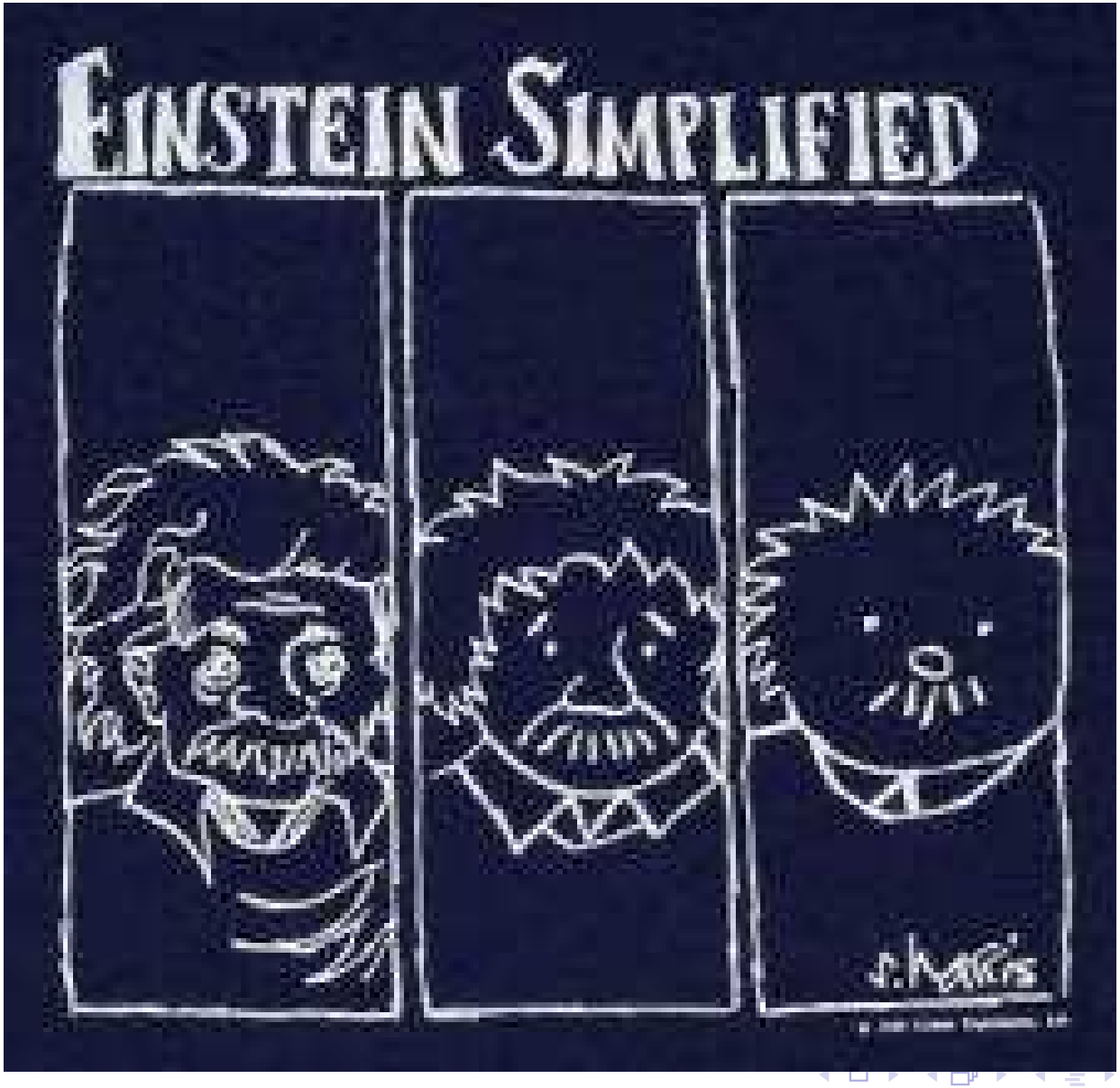
successive approximations!

Aside I: Speaking of successive approximations...



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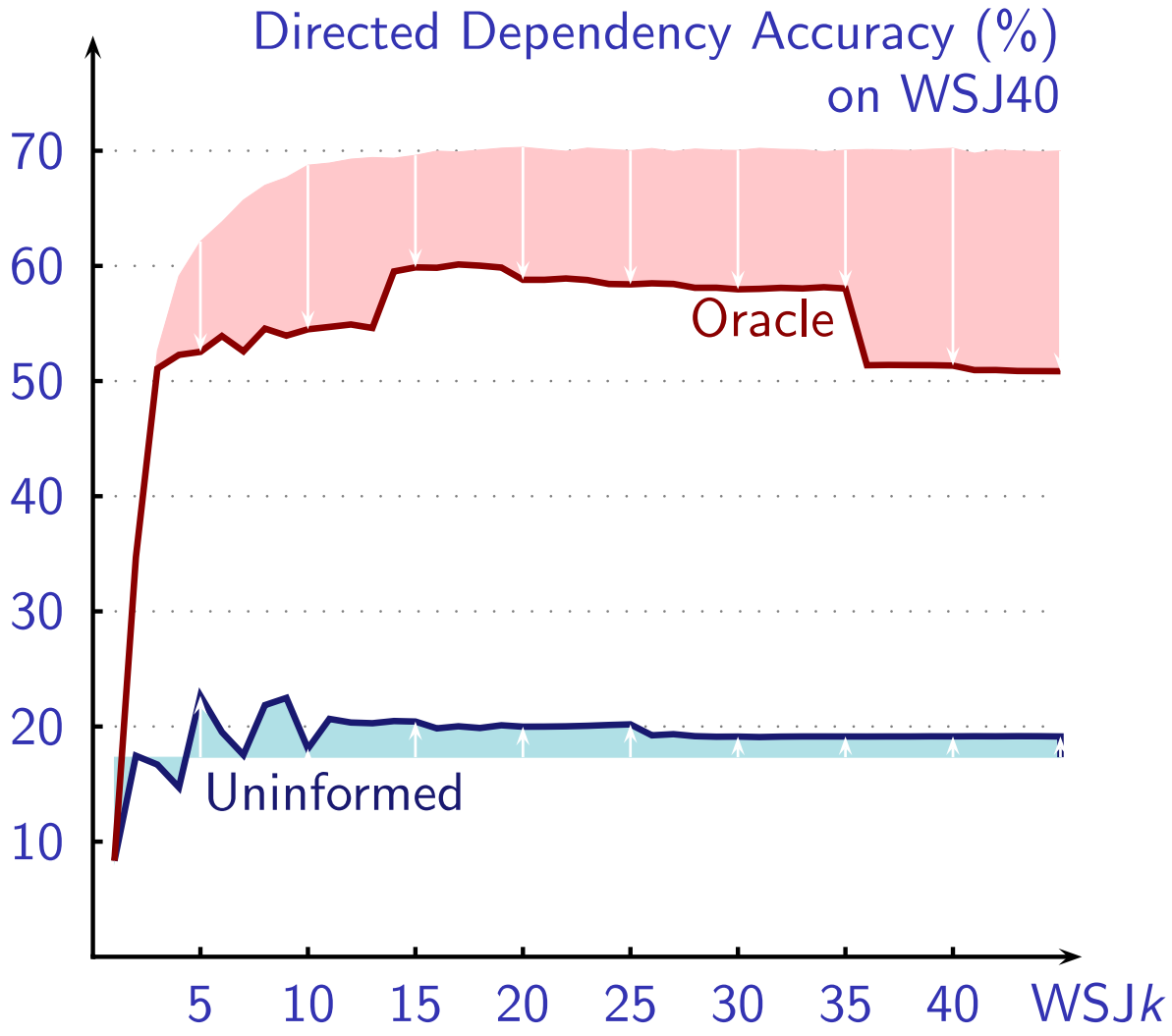

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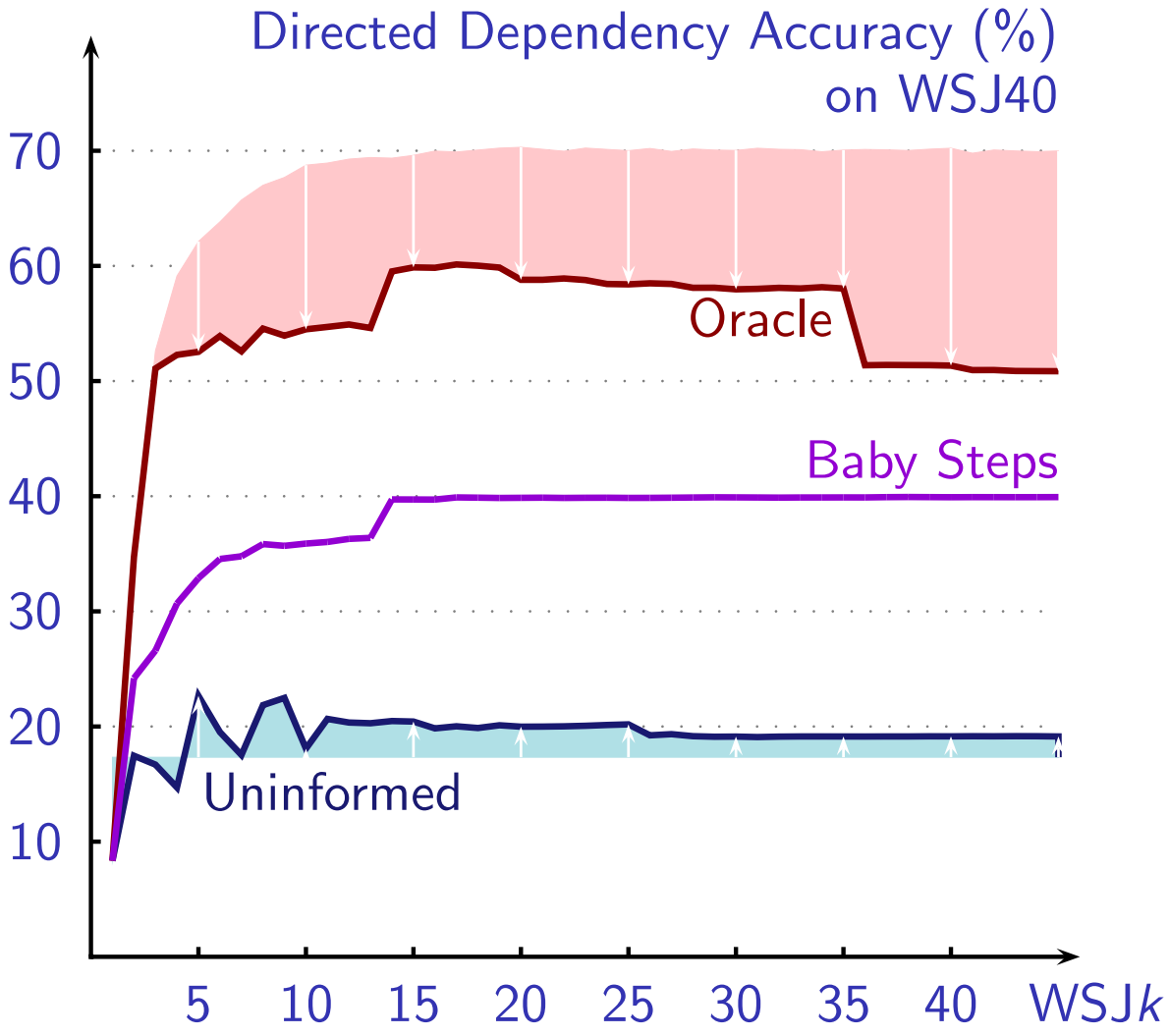

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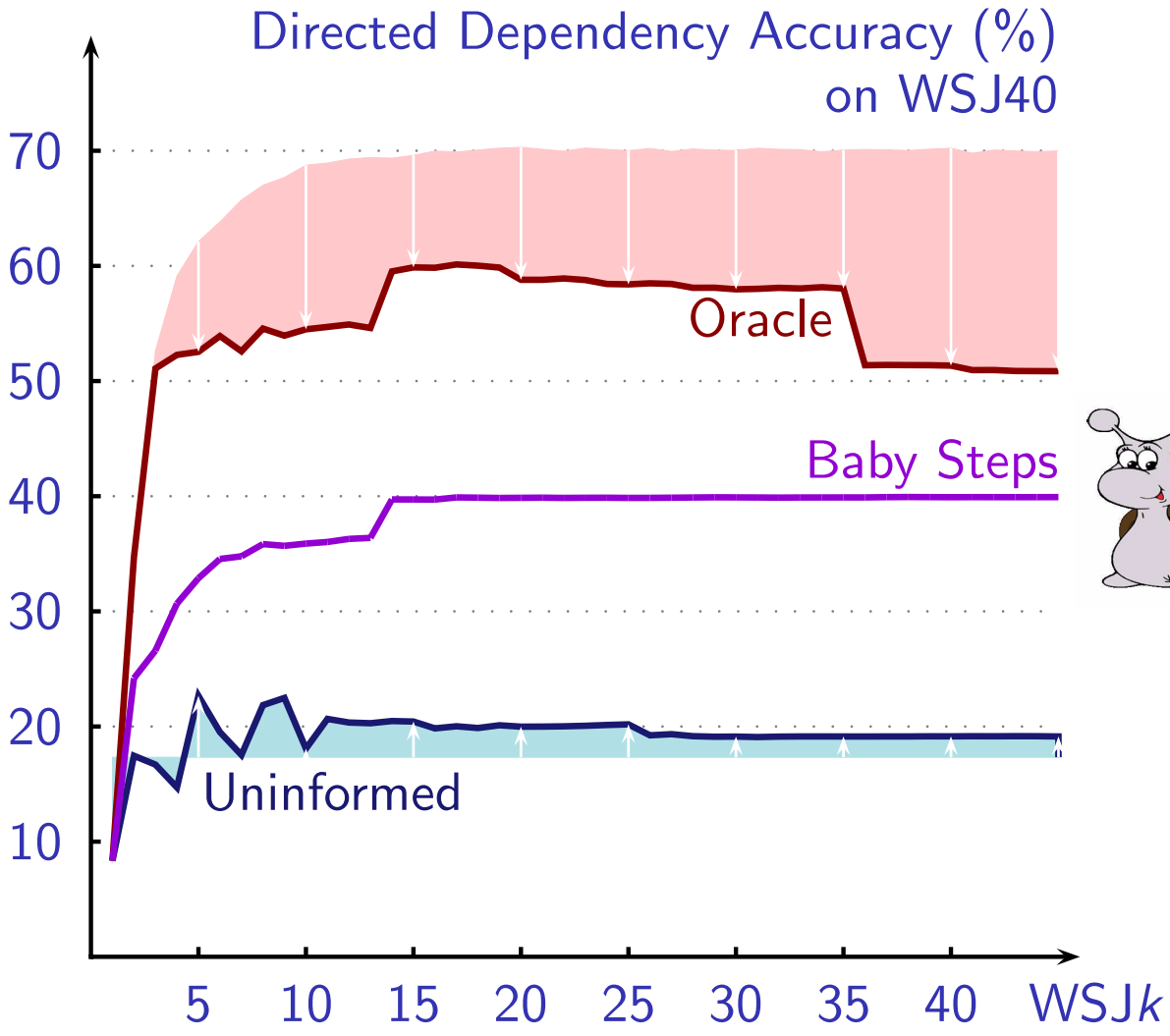

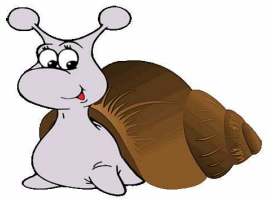

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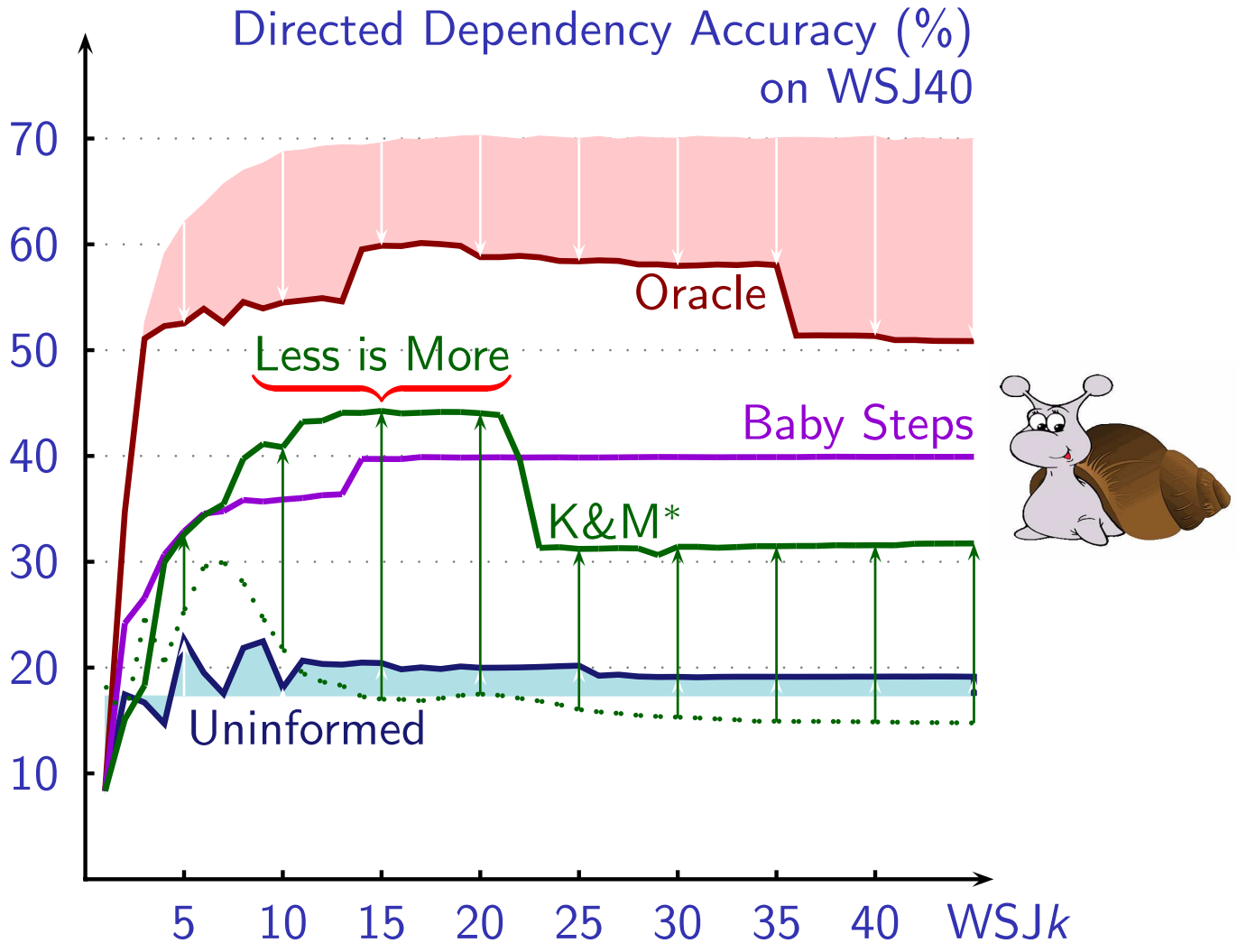

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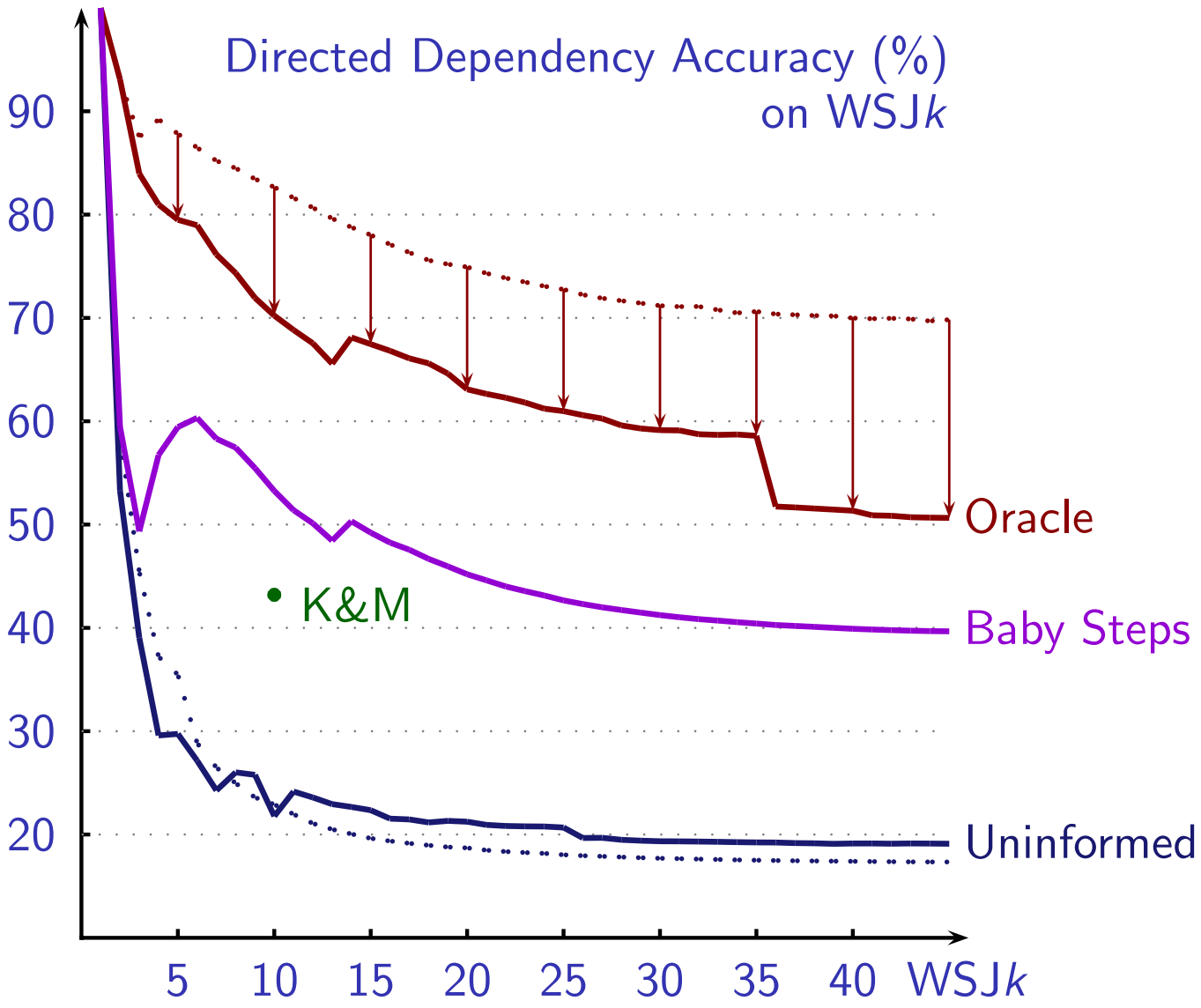

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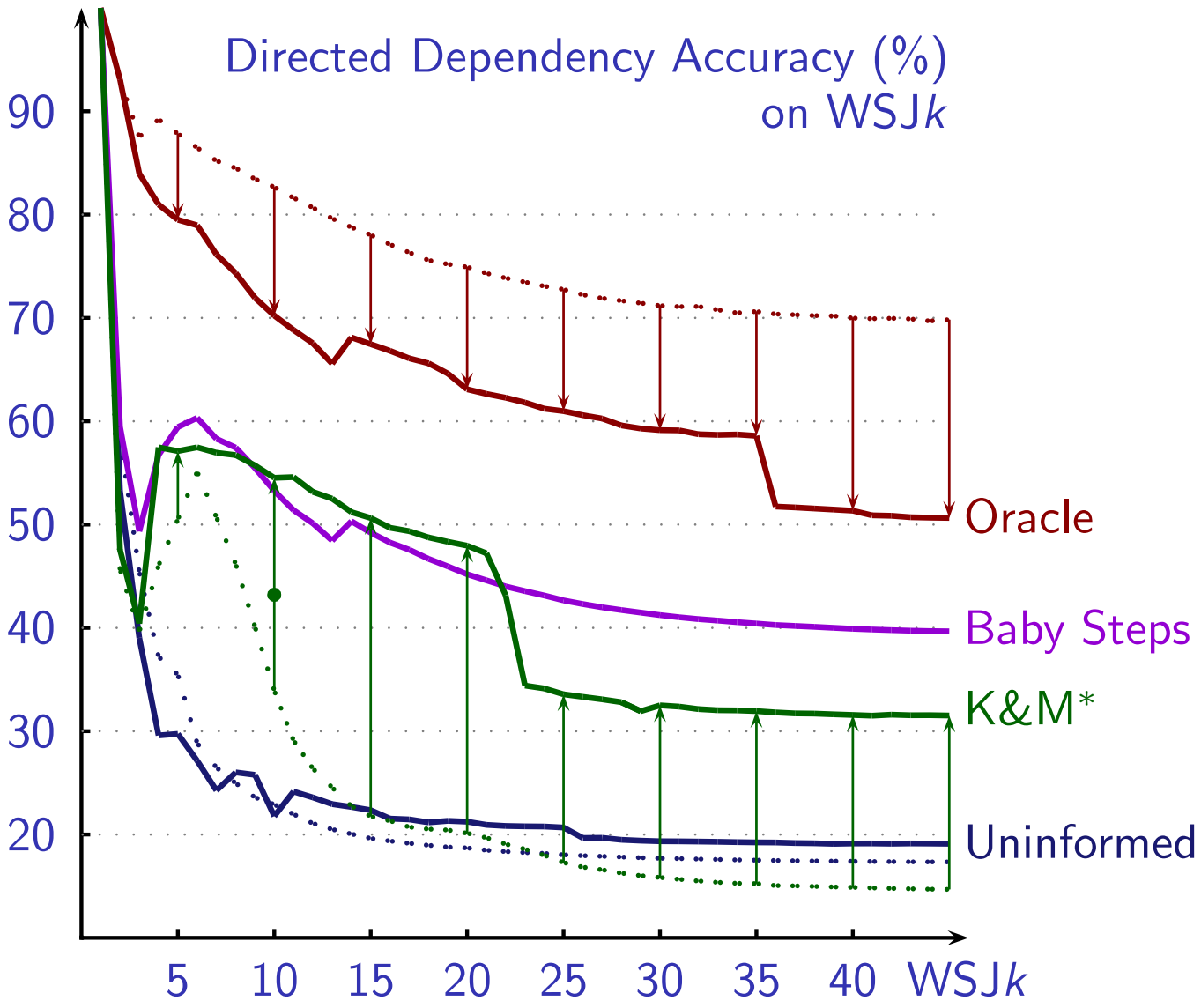

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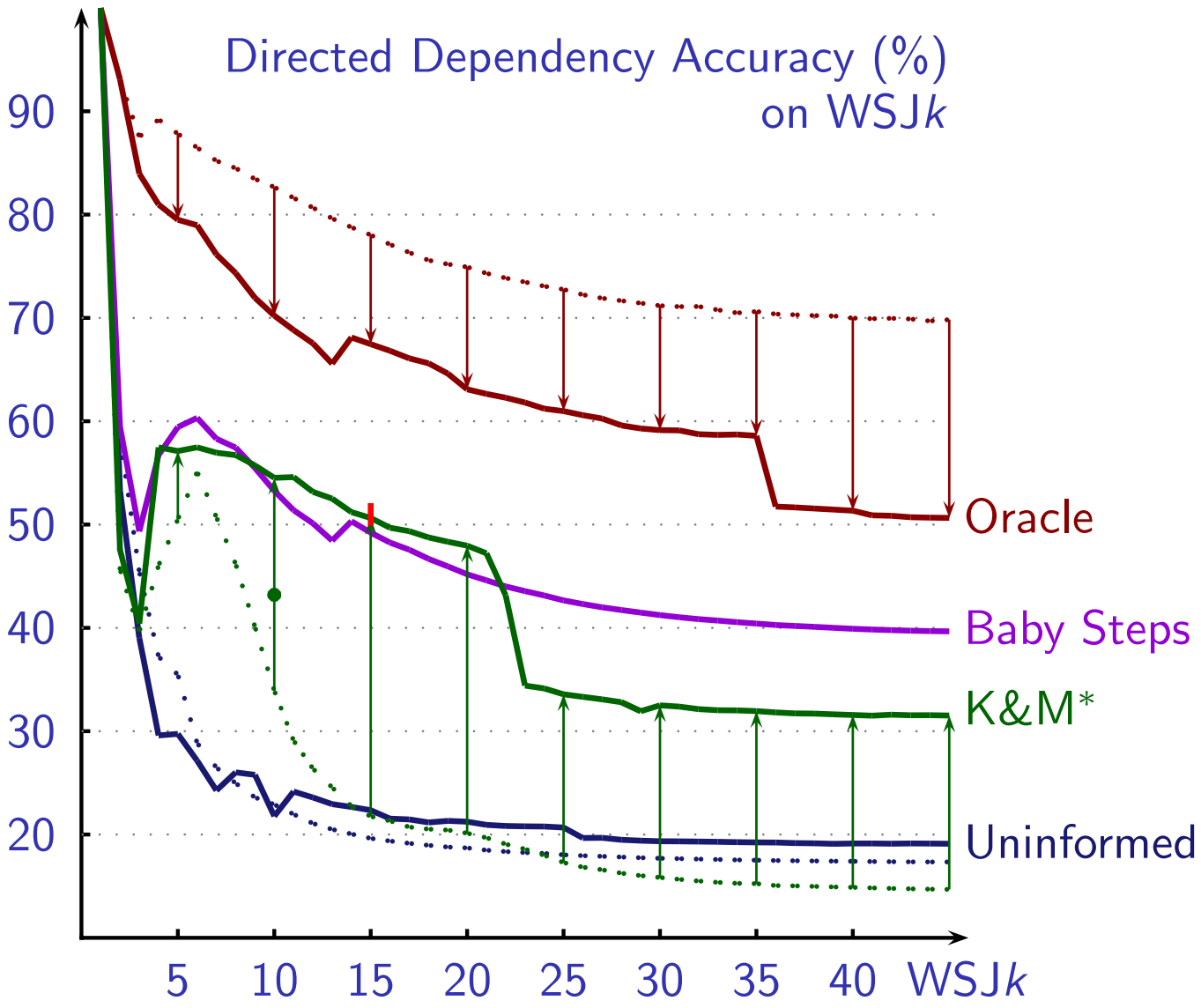

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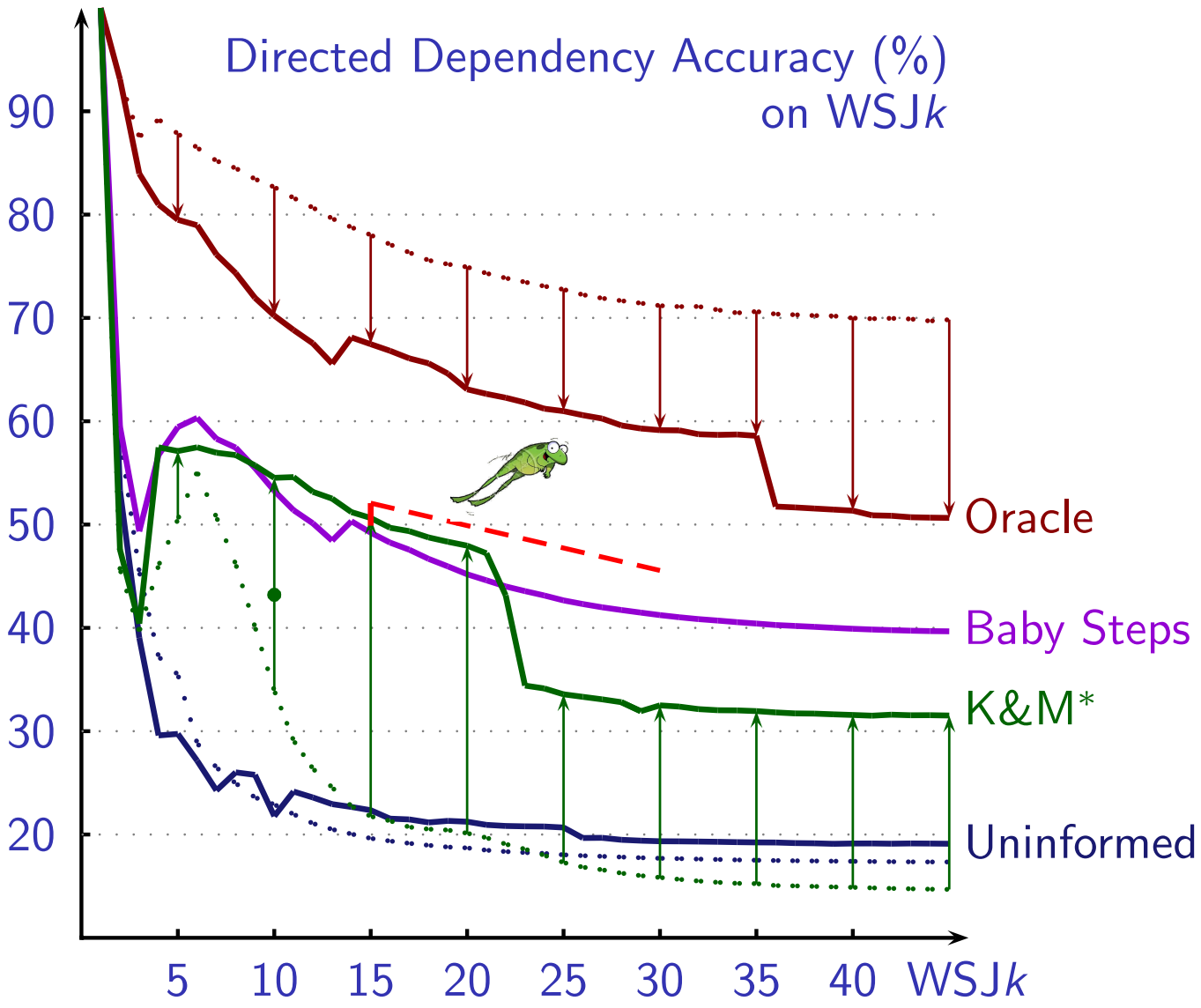

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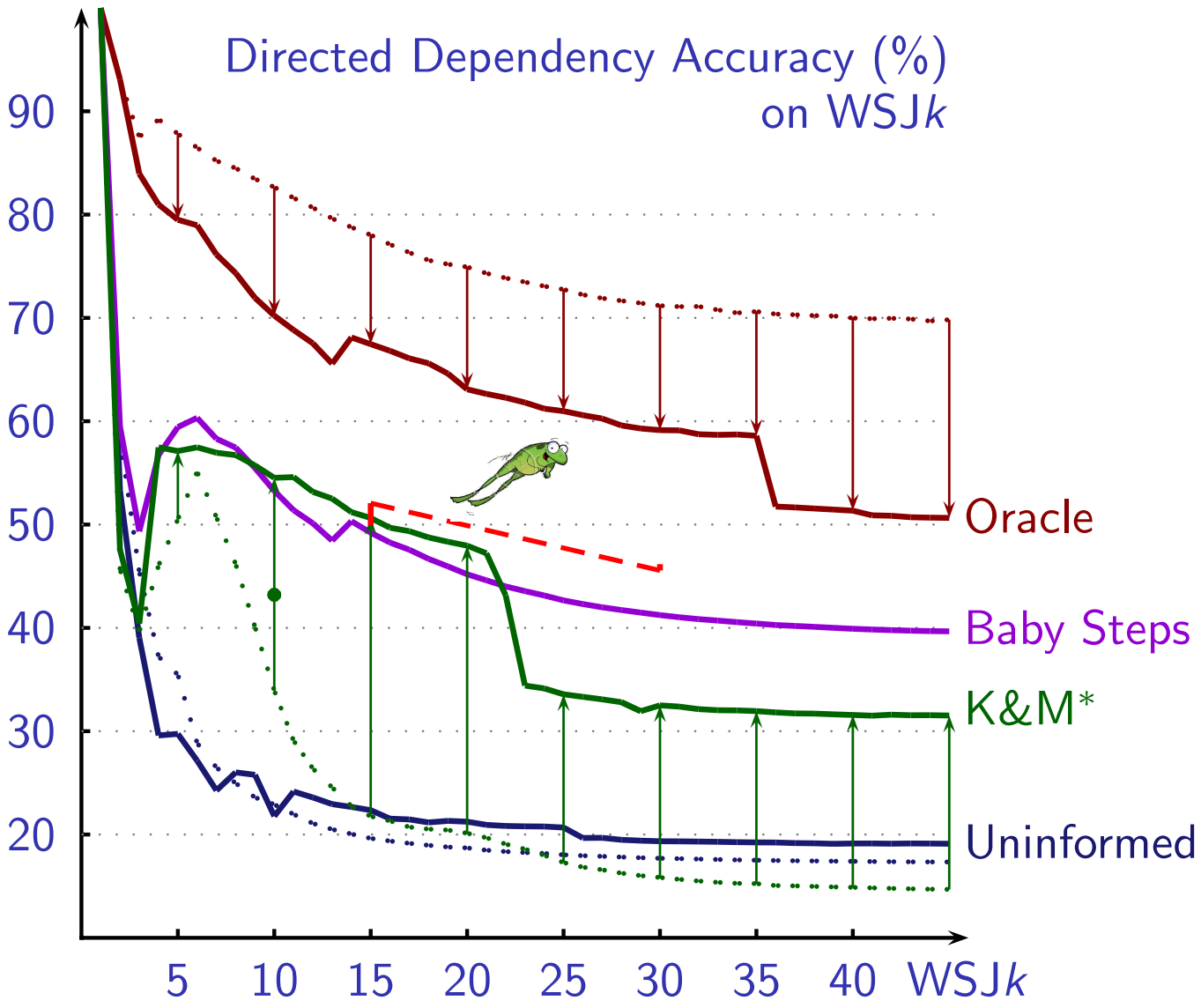

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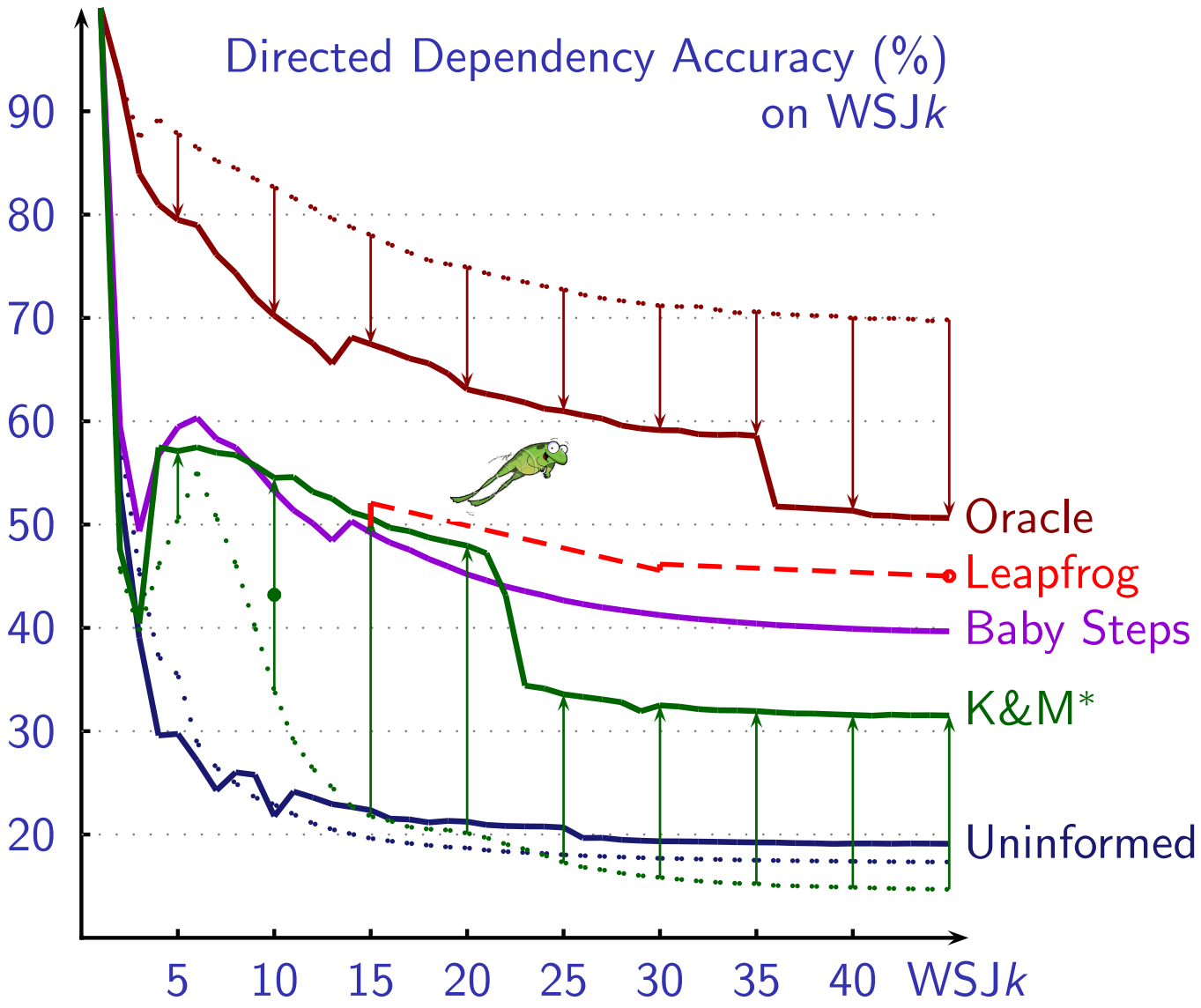
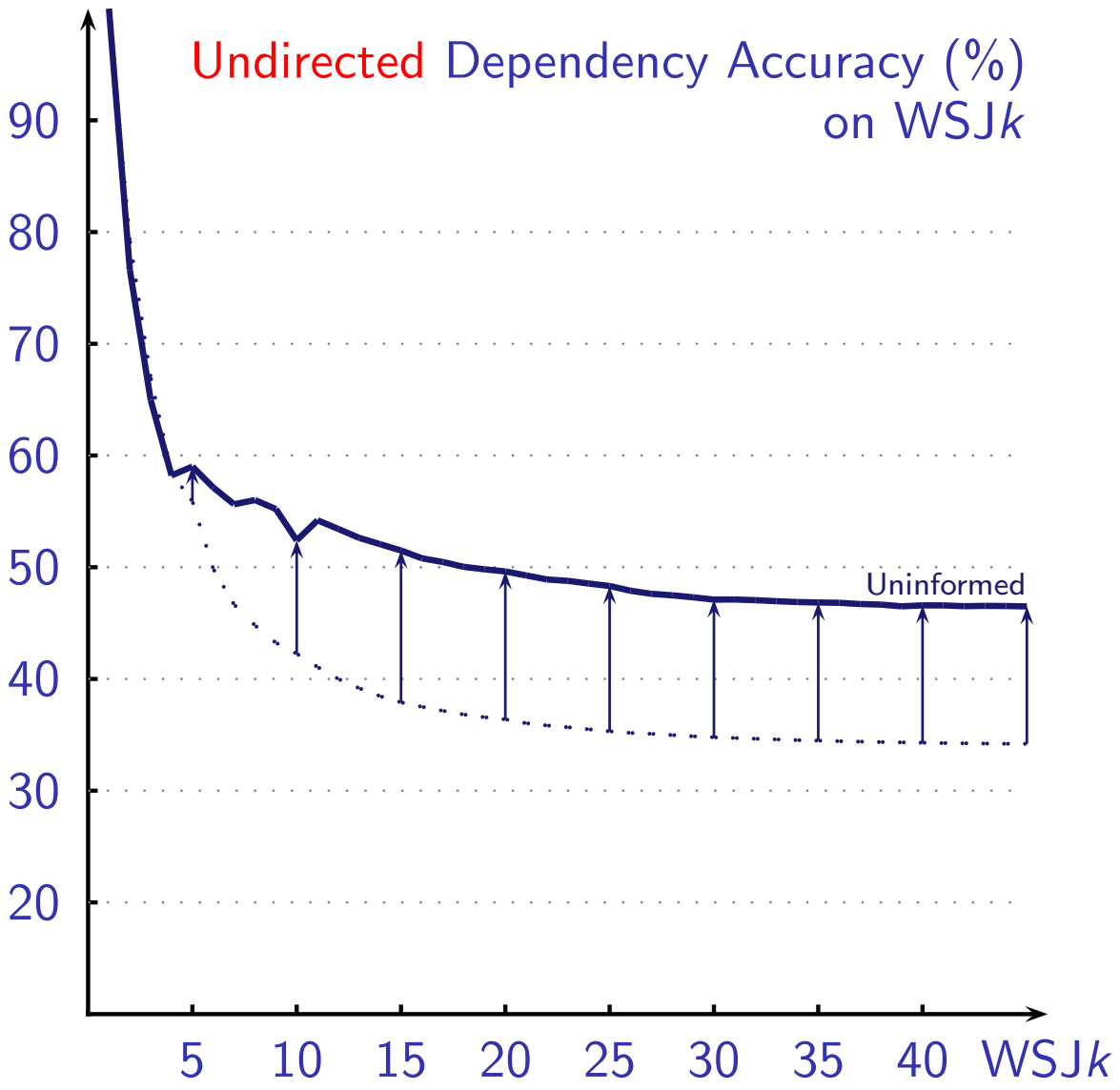


Aside II: Also, to be fair...



Lateen EM: Intuition

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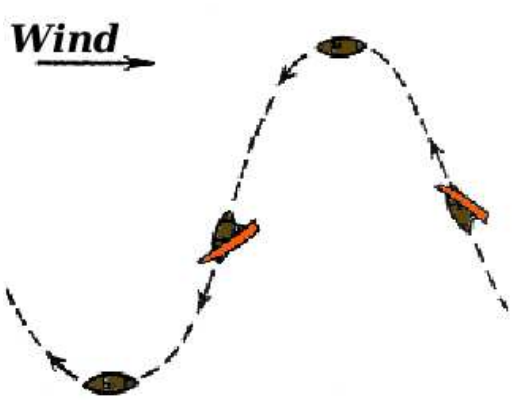

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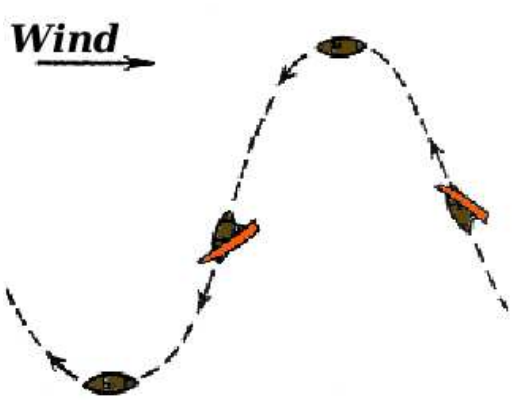

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Lateen strategies de-emphasize fixed points, e.g., by tacking around local attractors, in a zig-zag fashion.

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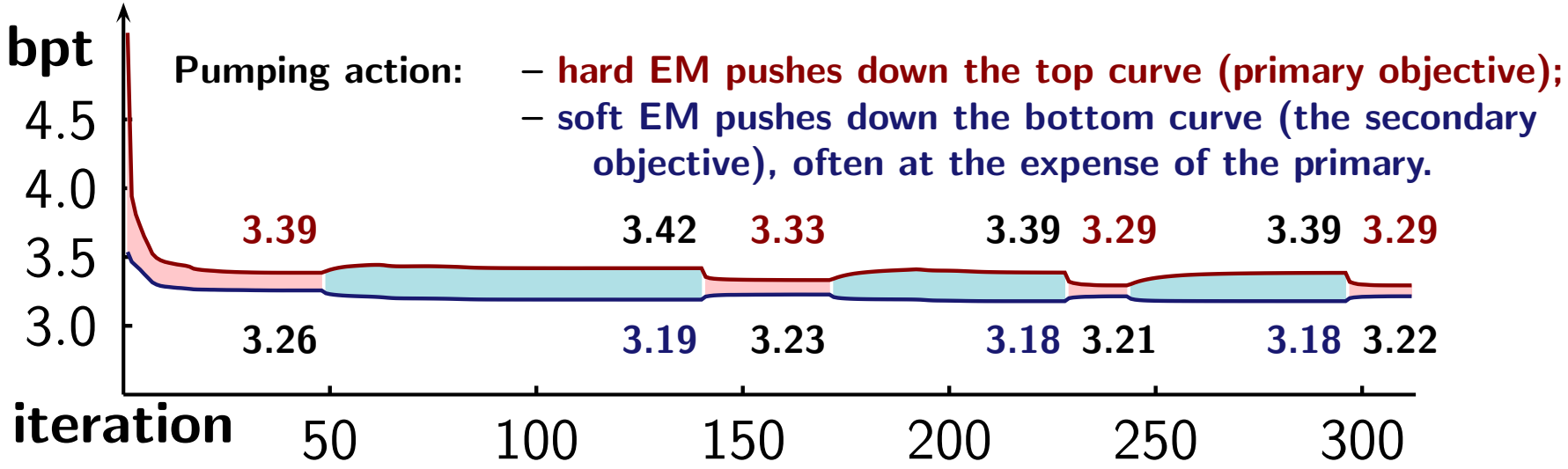
E.g., Italian grammar induction improves from 41.8% to 56.2% after three lateen alternations:



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- **30% faster, on average, than either standard EM.**

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Constraints

Web Markup

Punctuation

Capitalization

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- partial bracketings (Pereira and Schabes, 1992)

- synchronous grammars (Alshawi and Douglas, 2000)
- linear-time parsing, skewness of trees, etc. (Seginer, 2007)
- sparse posterior regularization (Ganchev et al., 2009)

Syntax of Markup: Common Constituents

..., but [$_S$ [$_{NP}$ the <a> *Toronto Star*][$_{VP}$ reports [$_{NP}$ this] [$_{PP}$ in the softest possible way],[$_S$ stating ...]]]

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NP → NNP NNP	9.6
NP → NNP	4.6
NP → NP PP	3.4
NP → NNP NNP NNP	2.4
NP → DT NNP NNP	2.1
NP → NN	1.8
NP → DT NNP NNP NNP	1.7
NP → DT NN	1.7
NP → DT NNP NNP	1.6
S → NP VP	1.4
NP → DT NNP NNP NNP	1.2
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"the <a>*Star* reports"

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NNP	24.4
NN	8.1
DT NNP	6.1
DT NN	5.9
NNS	4.5
NNPS	1.4
VBG	1.3
NNP NNP NN	1.2
VBD	1.0
IN	1.0
VBN	1.0
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- raw word streams often difficult even for humans
  — e.g., transcribed utterances (Kim and Woodland, 2002)

Example: Raw Word Stream

ALTHOUGH IT PROBABLY HAS REDUCED THE LEVEL OF EXPENDITURES FOR SOME PURCHASERS UTILIZATION MANAGEMENT LIKE MOST OTHER COST CONTAINMENT STRATEGIES DOESN'T APPEAR TO HAVE ALTERED THE LONG-TERM RATE OF INCREASE IN HEALTH-CARE COSTS THE INSTITUTE OF MEDICINE AN AFFILIATE OF THE NATIONAL ACADEMY OF SCIENCES CONCLUDED AFTER A TWO-YEAR STUDY

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- **strong constraint**

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word head	,	head word word	,

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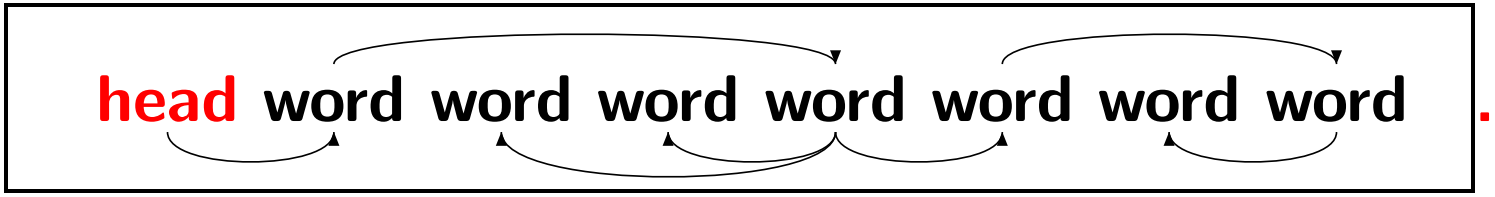

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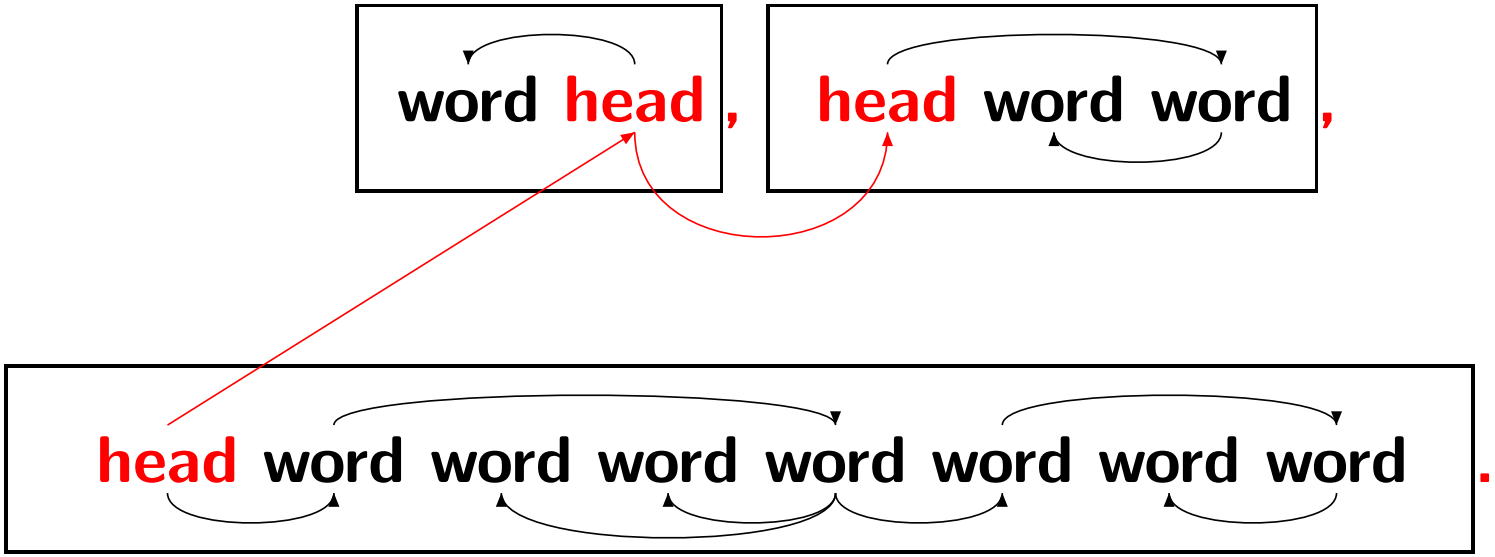

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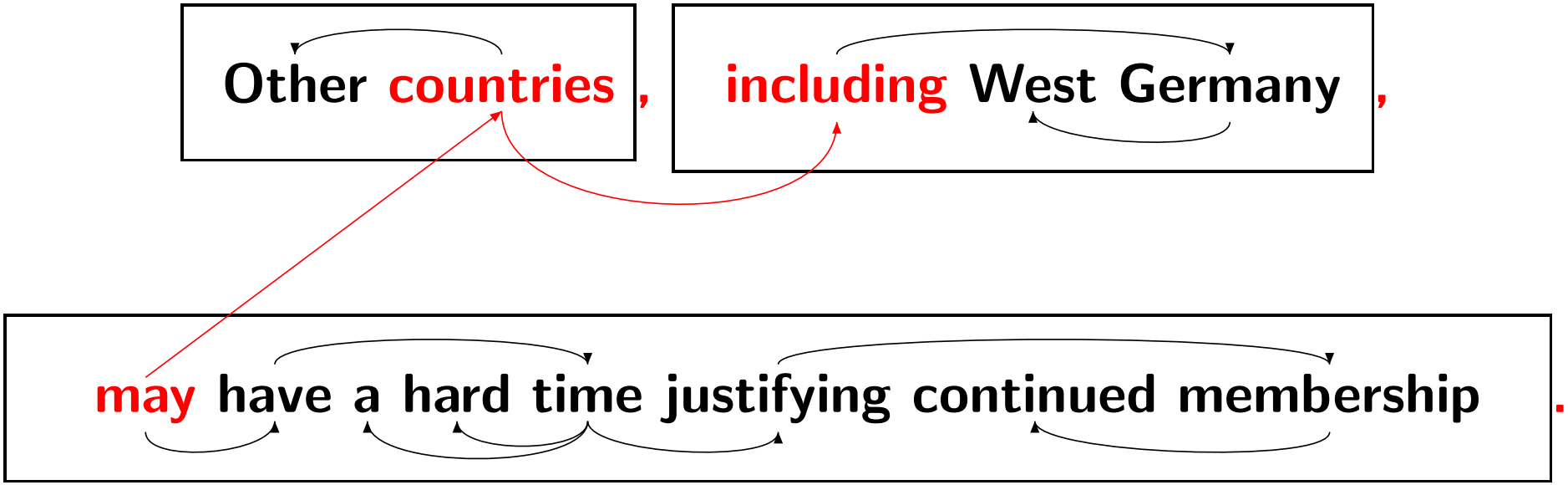

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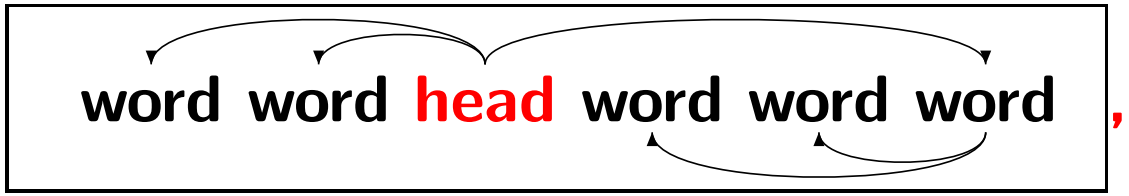

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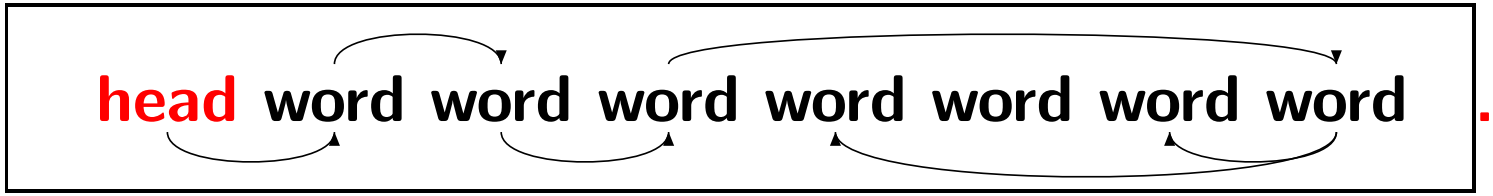

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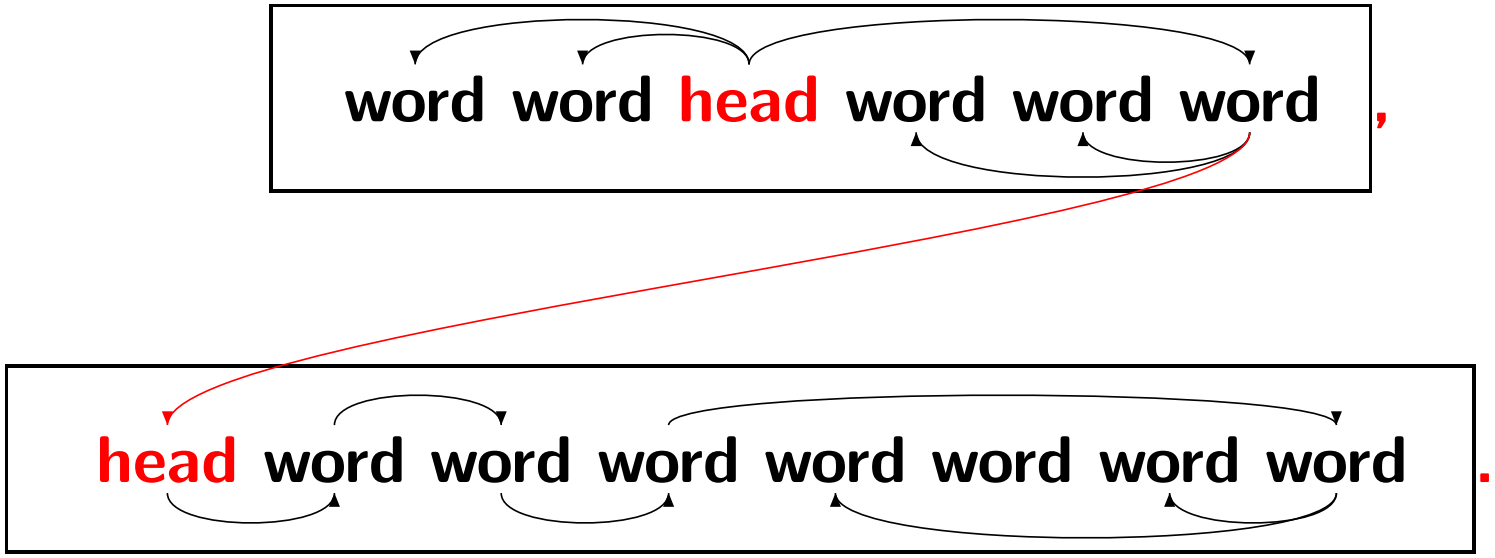

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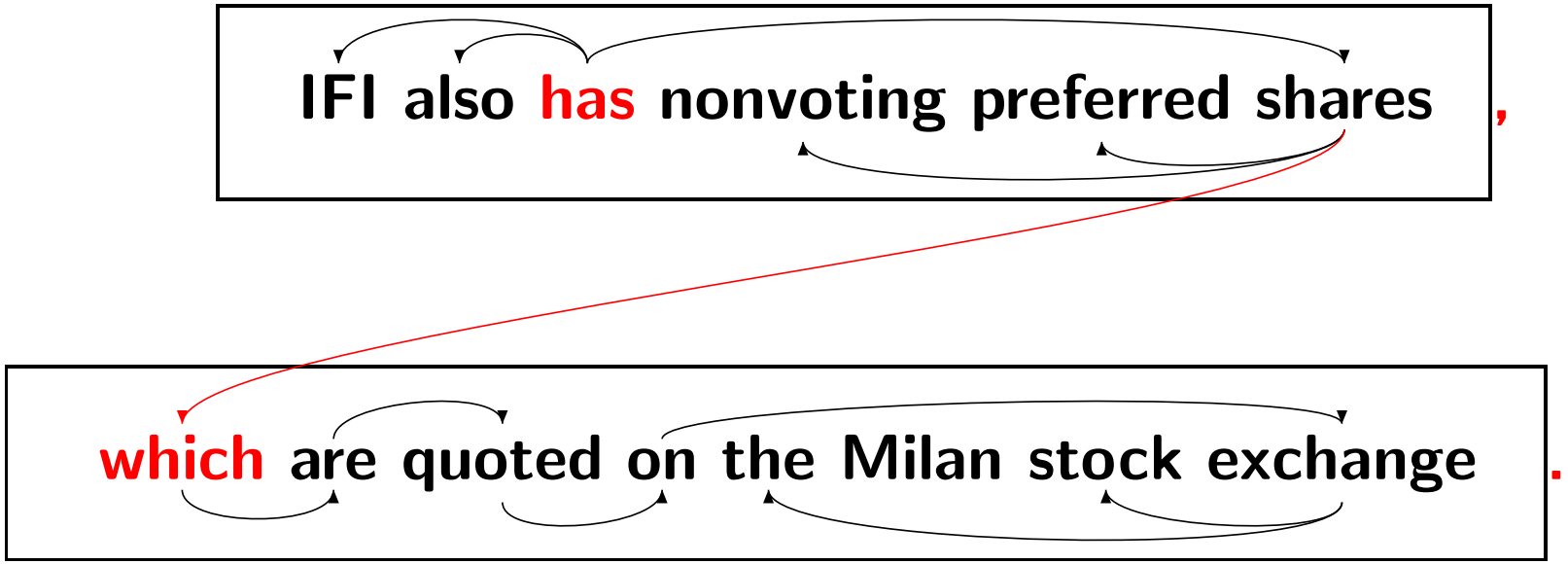

Linguistic Analysis:

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- **49.4% of inter-punctuation fragments are constituents**
- **many fragments derive precisely themselves:**

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WDT	1.6
MD	1.1
VBN	1.1
IN VBD	1.0
JJ	0.7
	52.8

Training:

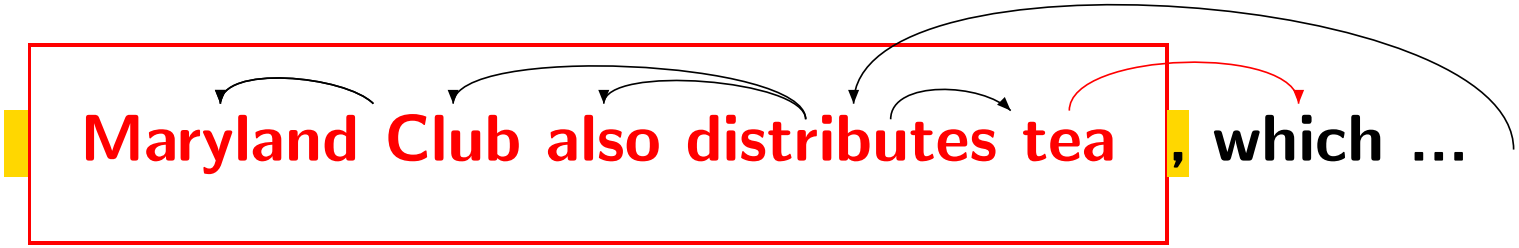
- **strong constraint, e.g.,**

... arrests followed a "*Snake Day*" at Utrecht ...

— already 74.0% agreement with head-percolated trees.

Inference:

- **weak constraint, e.g.,**



— now 92.9% agreement with head-percolated trees!

Modeling

Context-Sensitive Unsupervsed Tags
Dependency-and-Boundary Models
Reduced Models of Grammar

Example: Actually, state-of-the-art uses gold tags!

IN PRP RB VBZ VBN DT NN IN NNS IN DT
NNS NN NN IN RBS JJ NN NN NNS VBZ RB
VB TO VB VBN DT JJ NN IN NN IN JJ NNS
DT NNP IN NNP DT NN IN DT NNP NNP IN
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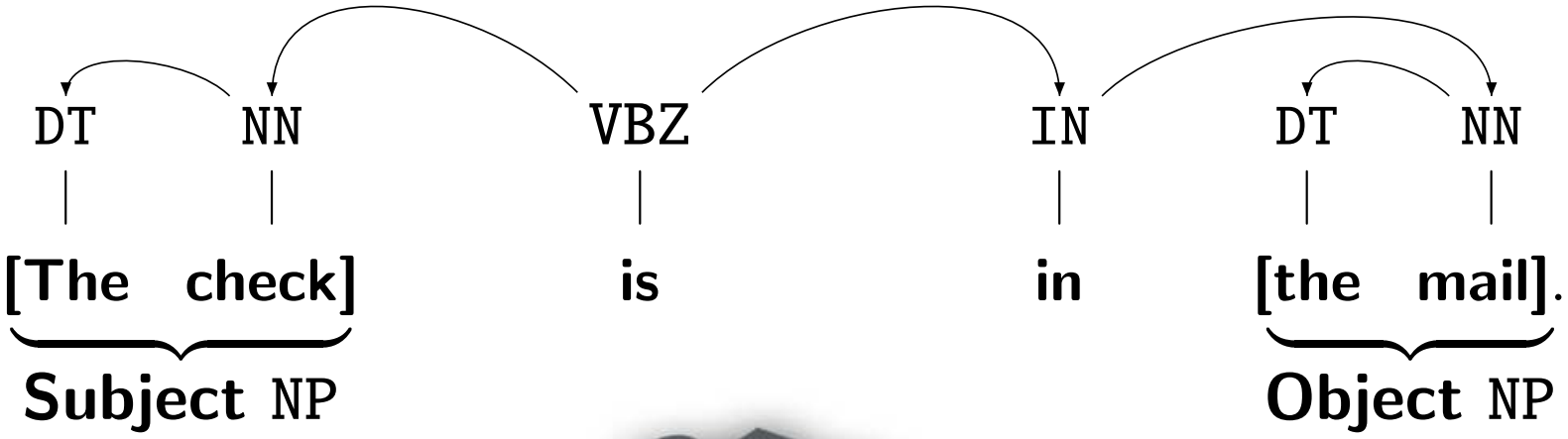

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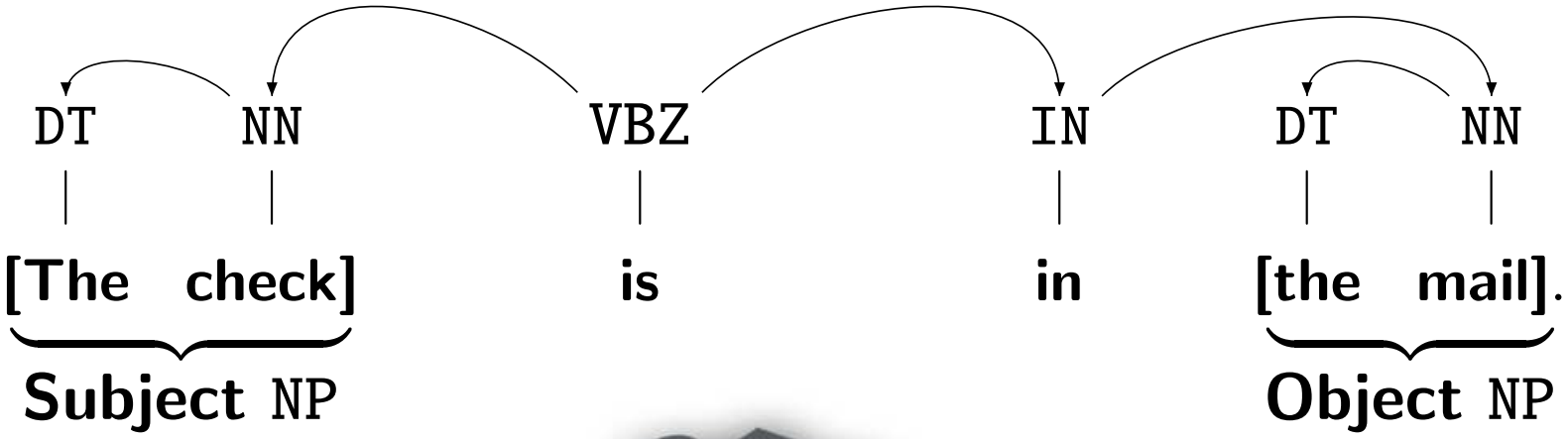

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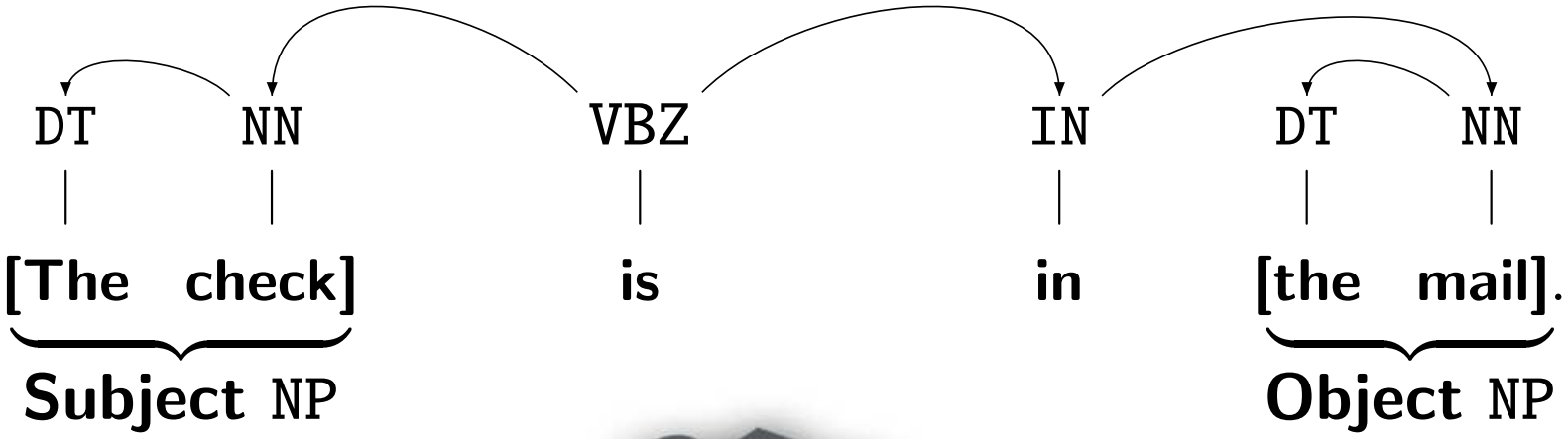

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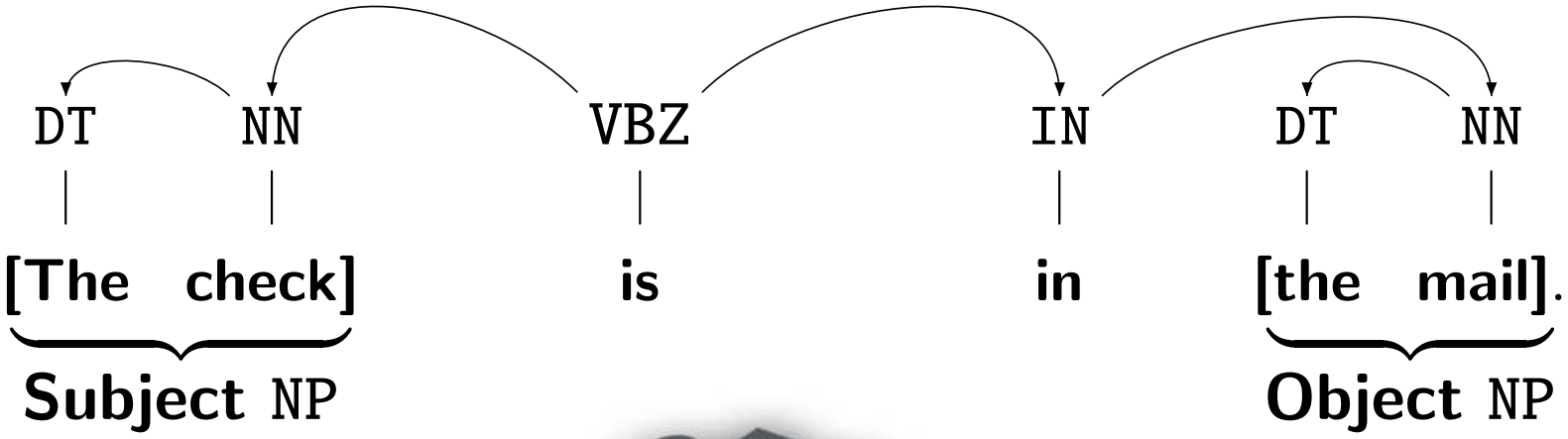

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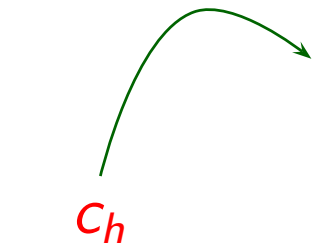

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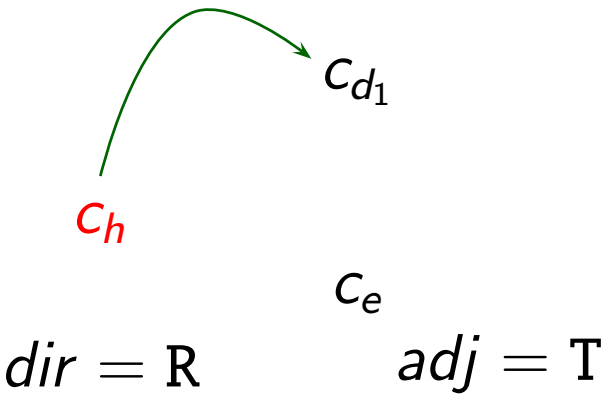

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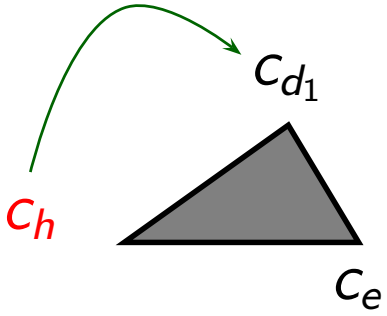

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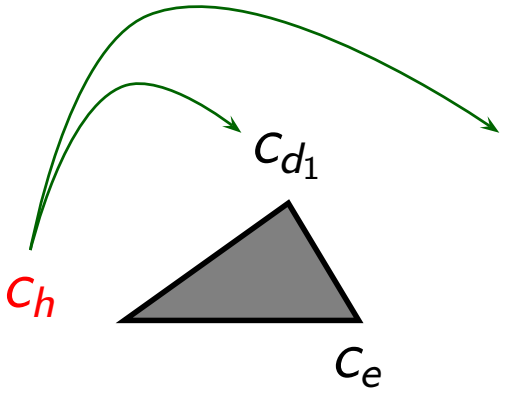

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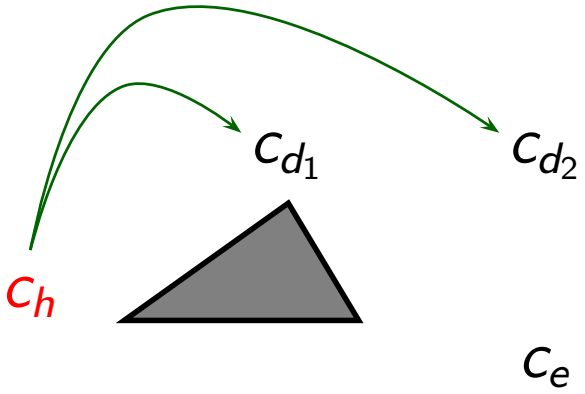

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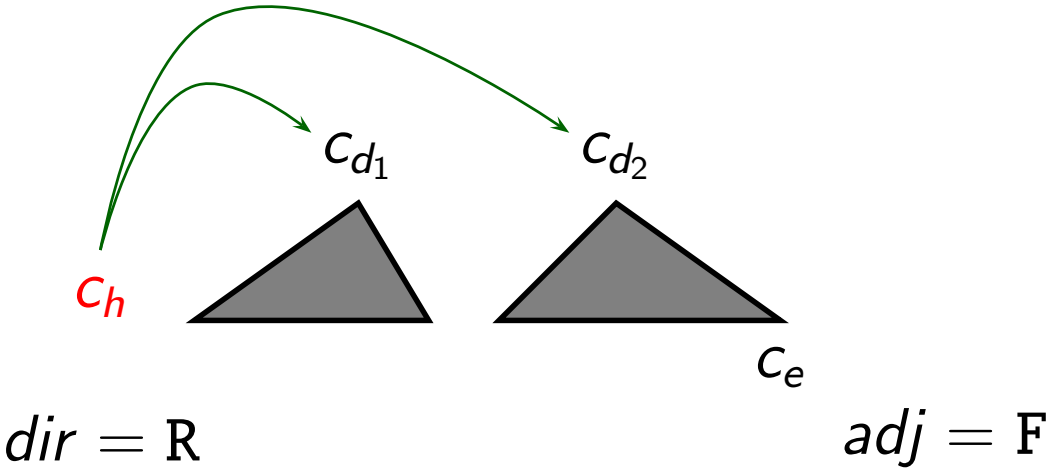

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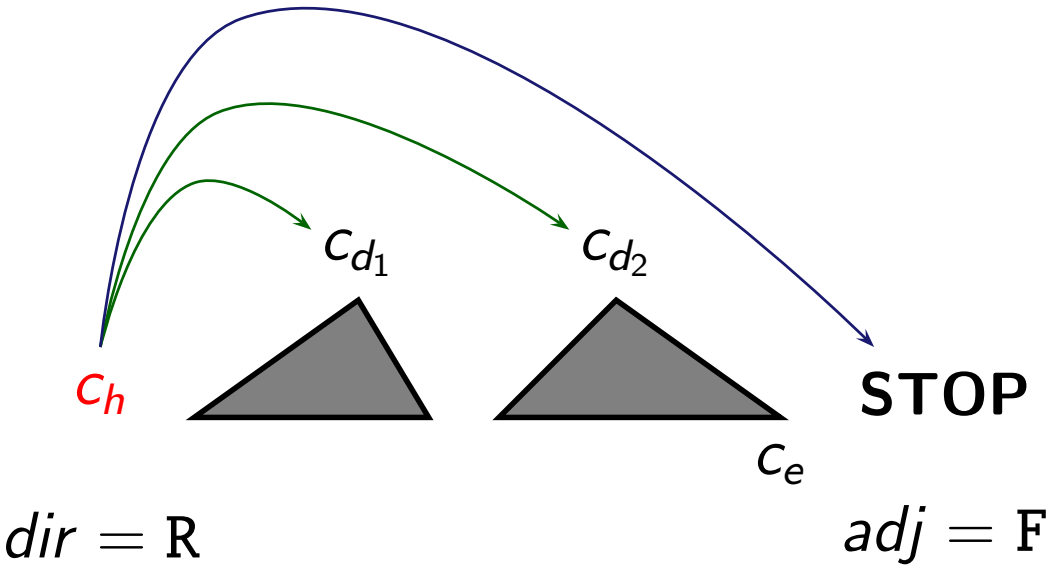

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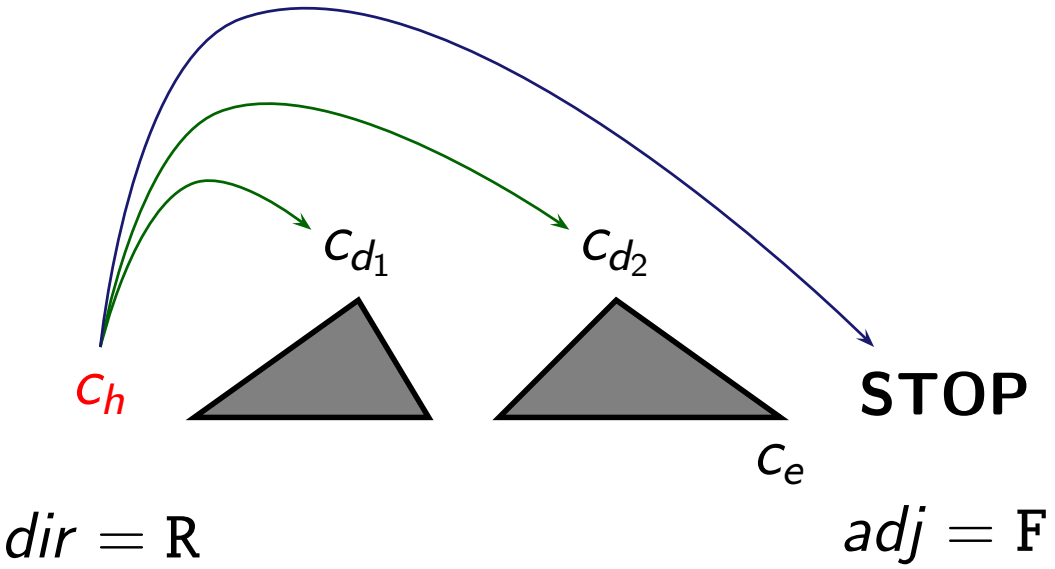

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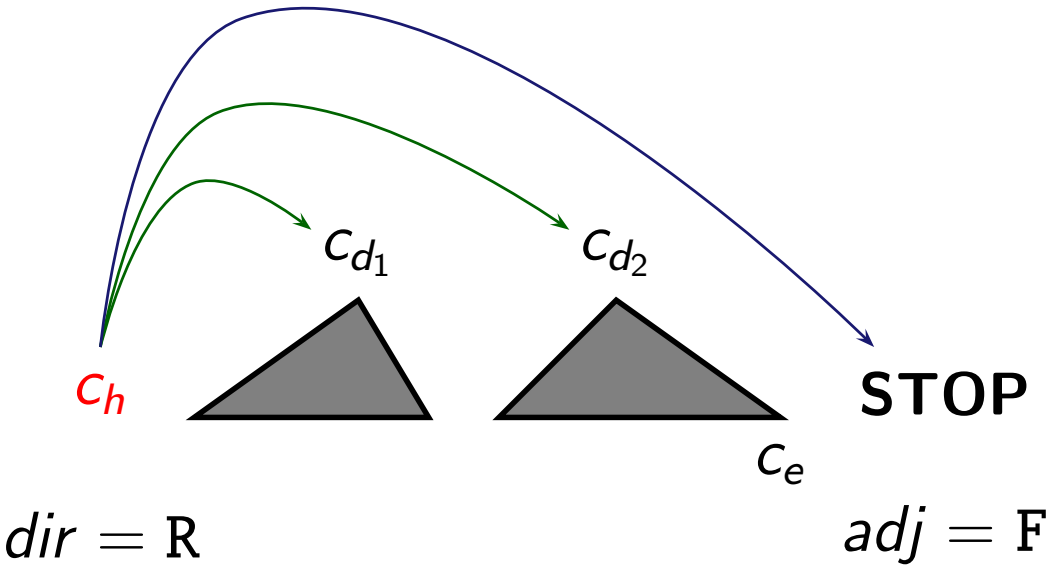

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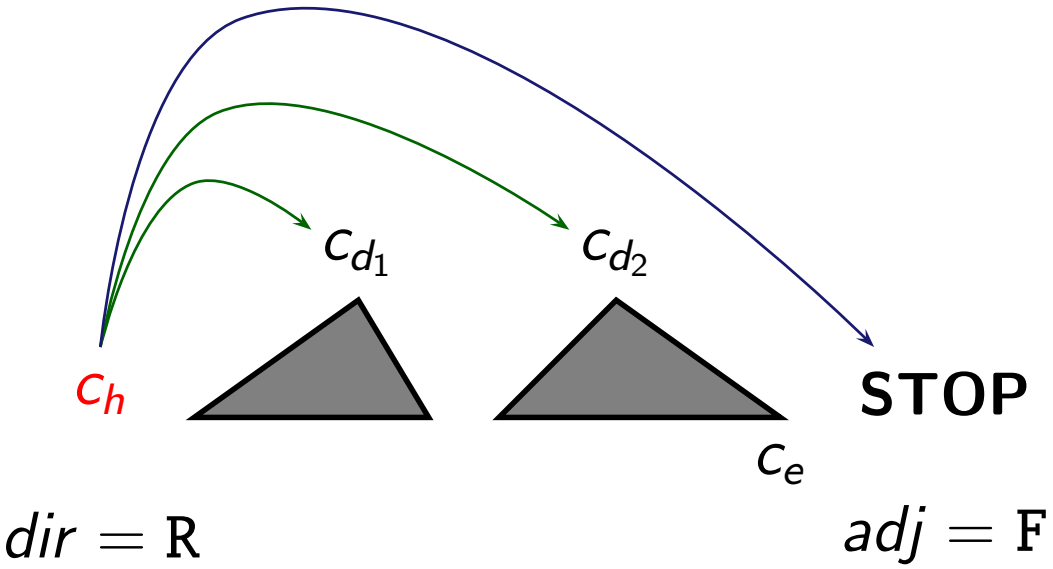

$$\mathbb{P}_{\text{ROOT}}(c_h \mid comp)\ \mathbb{P}_{\text{ATTACH}}(c_d \mid c_h, dir, cross)\ \mathbb{P}_{\text{STOP}}(\mid dir, adj, c_e, comp)$$

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  - **... and wouldn't it be nice if we could just split things up!**

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	4	**NP**	**DT**	**NNP**
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Example (cont'd)

DBM-2

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partial parse forests

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Integrated System

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(from Leapfrog)

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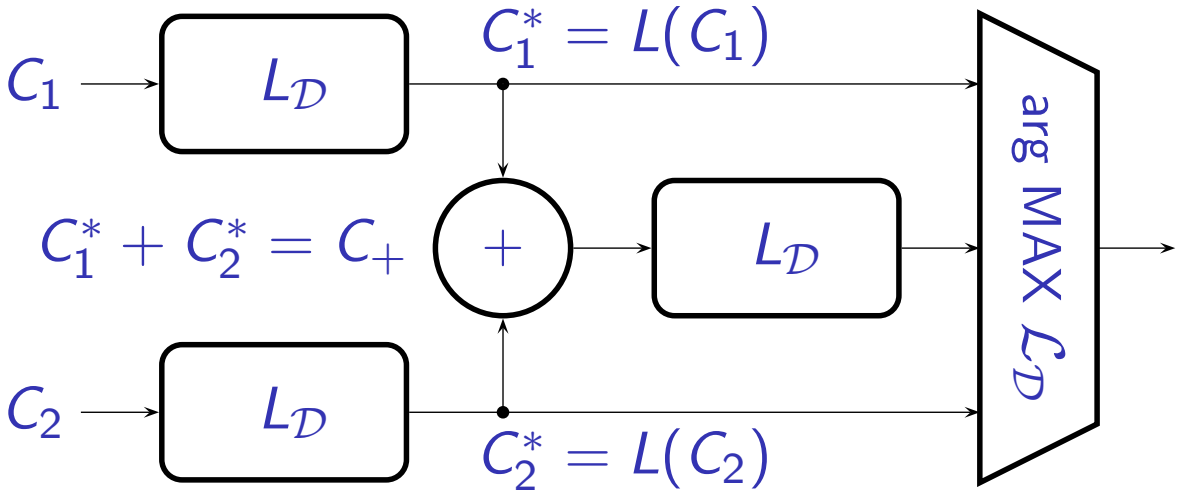

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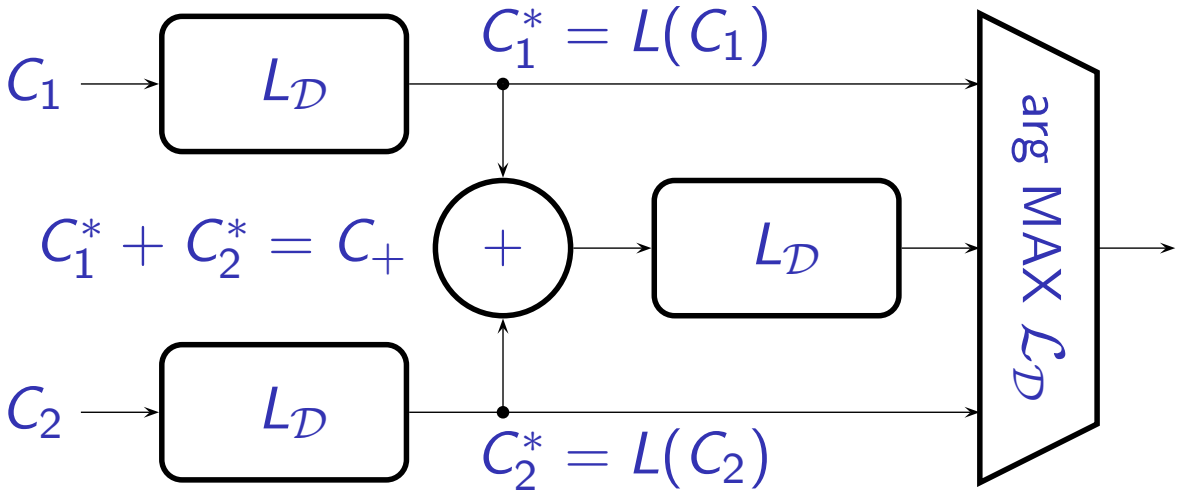

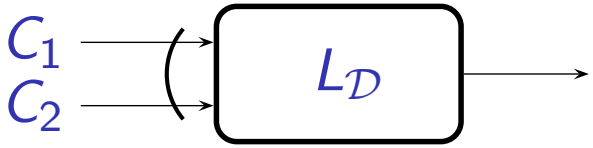

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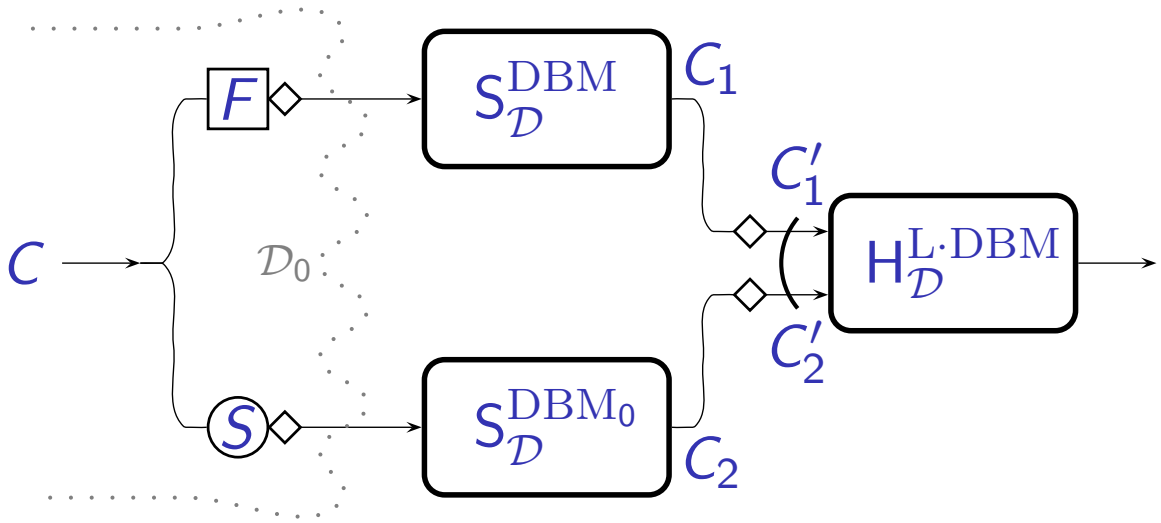

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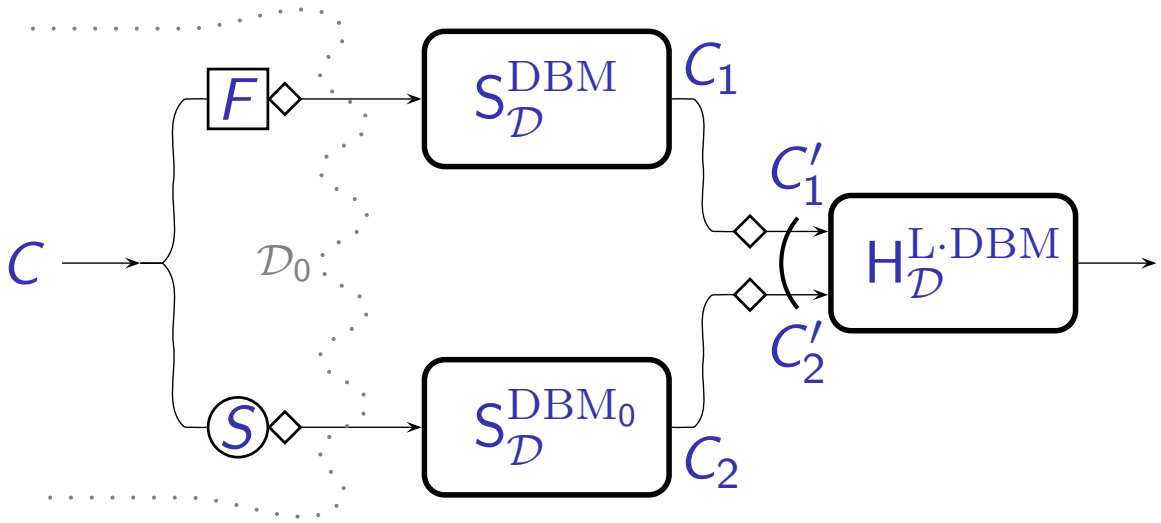

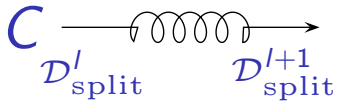

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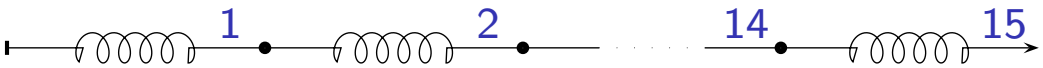

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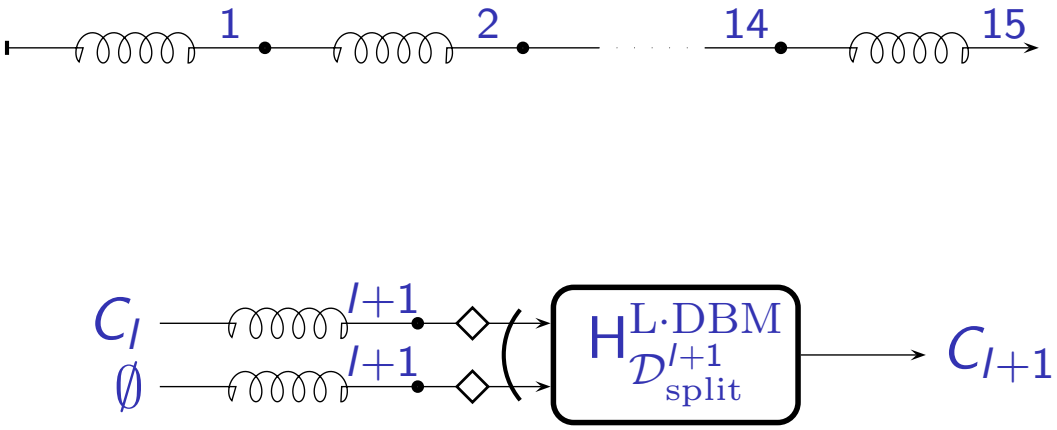

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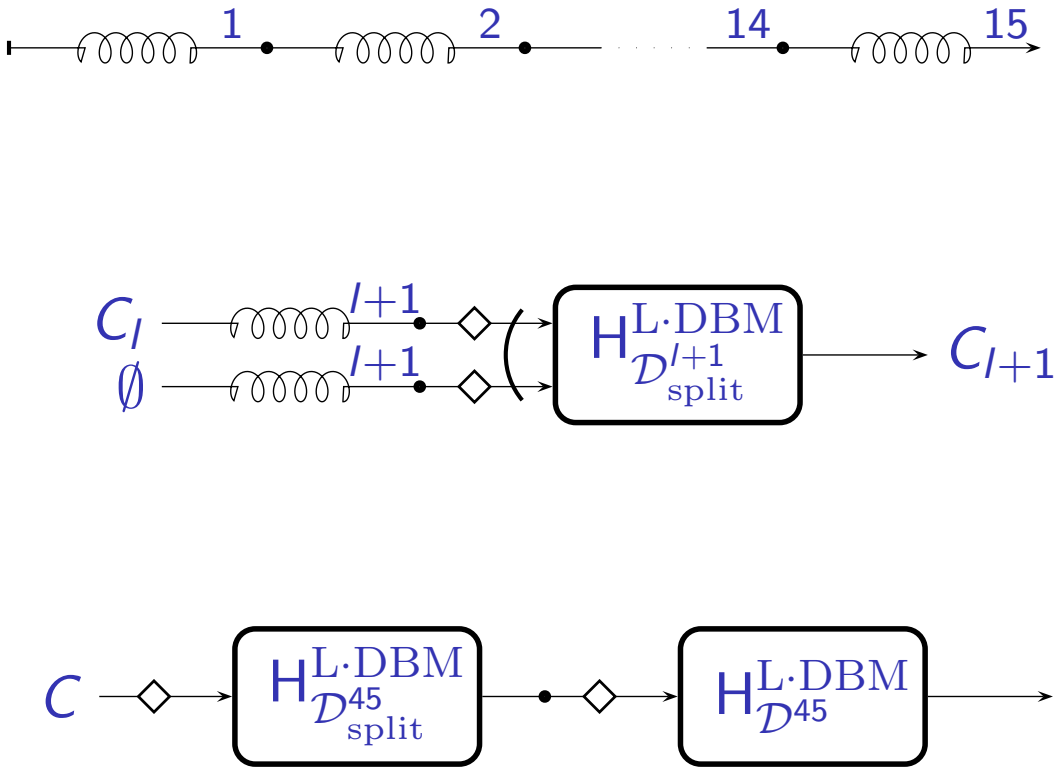

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During the same time, *supervised (constituency)* **parsing advanced from 91.8F_1 (Petrov, 2010) to 92.4F_1 (Shindo et al., 2012).**

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System: Results ... on 23 CoNLL sets

- **Also state-of-the-art for multi-lingual evaluation, across 19 languages from disparate families:**

English	+	**Arabic**	**Greek**
		Basque	**Hungarian**
		Bulgarian	**Italian**
		Catalan	**Japanese**
		Chinese	**Portuguese**
		Czech	**Slovenian**
		Danish	**Spanish**
		Dutch	**Swedish**
		German	**Turkish**

Thanks!

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Dramatization: http://www.youtube.com/embed/ncFCdCjBqcE?start=4&end=66.5

"... the real challenge is to make simple things look beautiful."

— Glenn Corteza, Tanguero Argentino

Thanks again!

Questions?