From Baby Steps to Leapfrog: How "Less is More" in Unsupervised Dependency Parsing

Valentin I. Spitkovsky

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and **Daniel Jurafsky** (Stanford University)

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  — **closest in NLP: cautious named entity classification** (Collins and Singer, 1999; Yarowsky, 1995)

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- **Leapfrog: a combination (best of both worlds)**
  — intended as an efficiency hack (but performs best)

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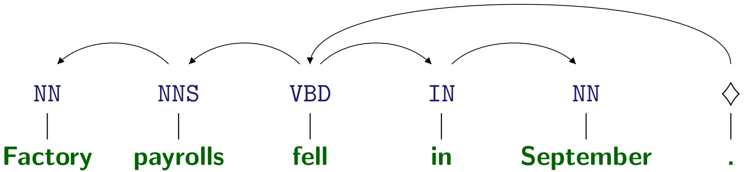
- **Output: Syntactic Structures (and a Probabilistic Grammar)**



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  - **question answering, speech recognition, etc.**

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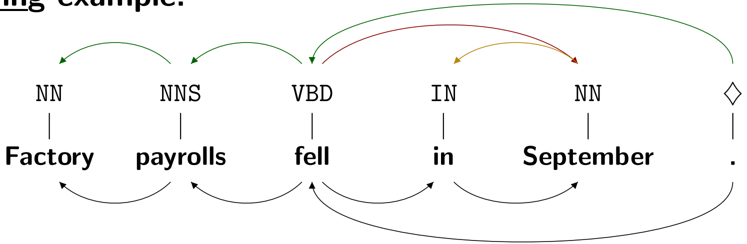
Scoring example:



Directed Score: $\frac{3}{5} = 60\%$ (**baseline**: $\frac{2}{5} = 40\%$);

Undirected Score: $\frac{4}{5} = 80\%$ (**baseline**: $\frac{4}{5} = 80\%$).

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- 2009 — soft parameter tying (Cohen and Smith)

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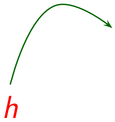

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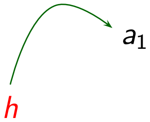

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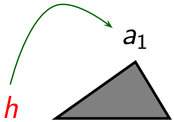

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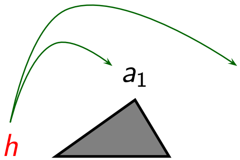

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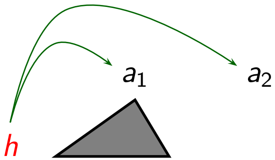

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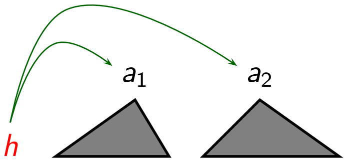

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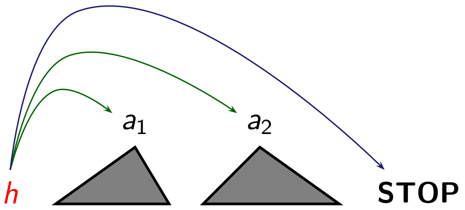

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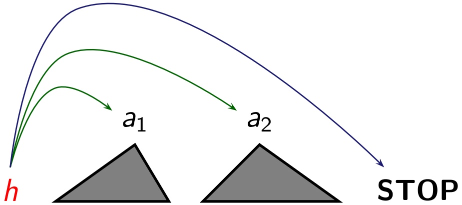

$$\mathbb{P}(t_h) = \prod_{dir \in \{\text{L},\text{R}\}} \left[\underline{\mathbb{P}_{\text{STOP}}(c_h, dir, \overbrace{1_{n=0}}^{adj})} \prod_{i=1}^{n} \underline{\mathbb{P}(t_{a_i})}\, \mathbb{P}_{\text{ATTACH}}(c_h, dir, c_{a_i}) \underline{(1 - \mathbb{P}_{\text{STOP}}(c_h, dir, \overbrace{1_{i=1}}^{adj}))}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

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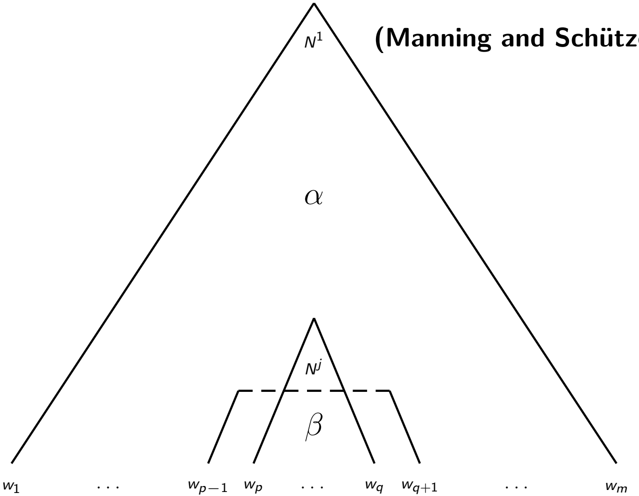

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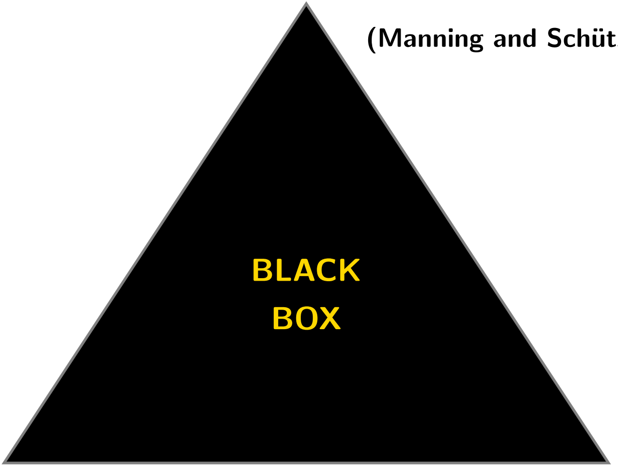

w_1 $\cdots$ w_{p-1} w_p $\cdots$ w_q w_{q+1} $\cdots$ w_m

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- **Evaluation: Section 23 of WSJ$^{\infty}$ (all sentences).**

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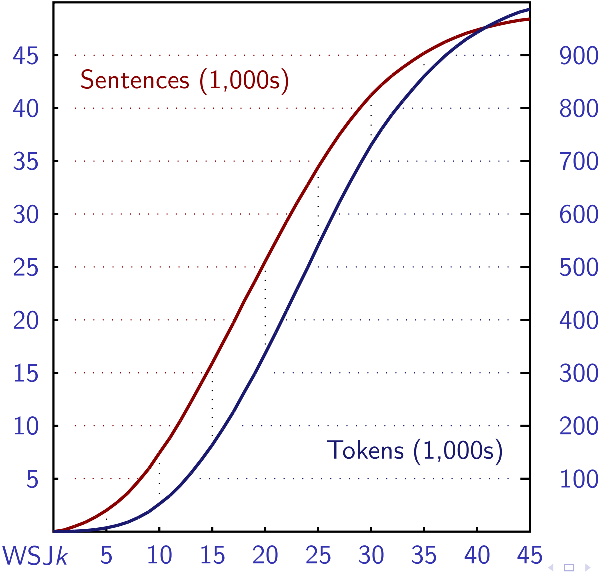

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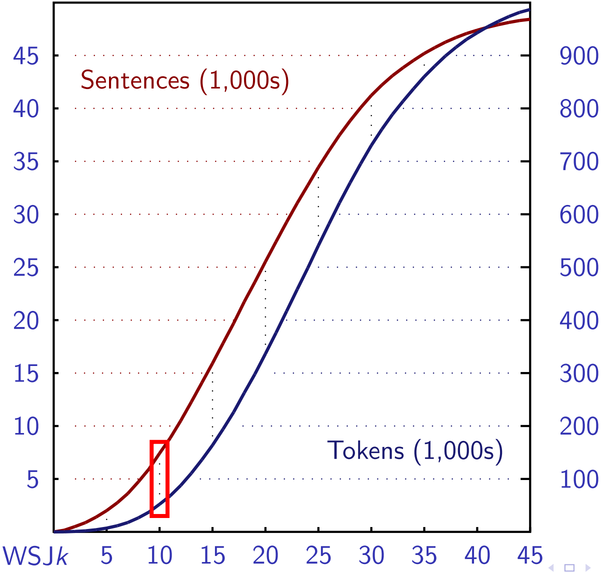

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- **we will explore (three) judicious uses of data and simple, scalable machine learning techniques**

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- **initialization matters!**

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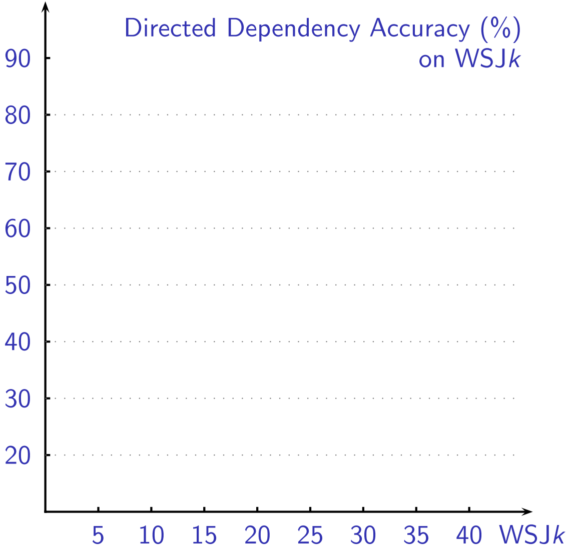

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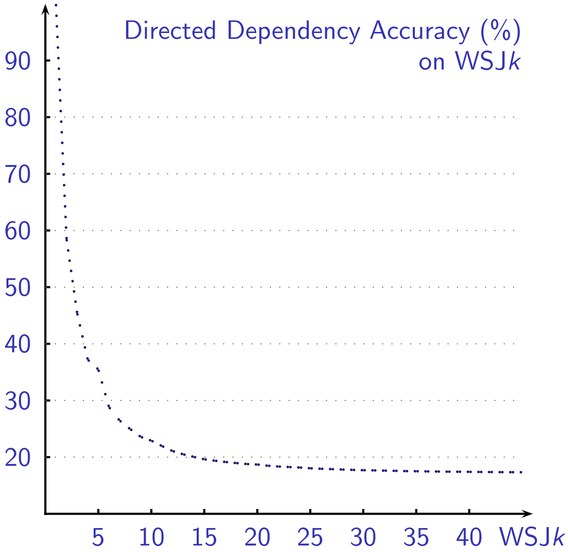

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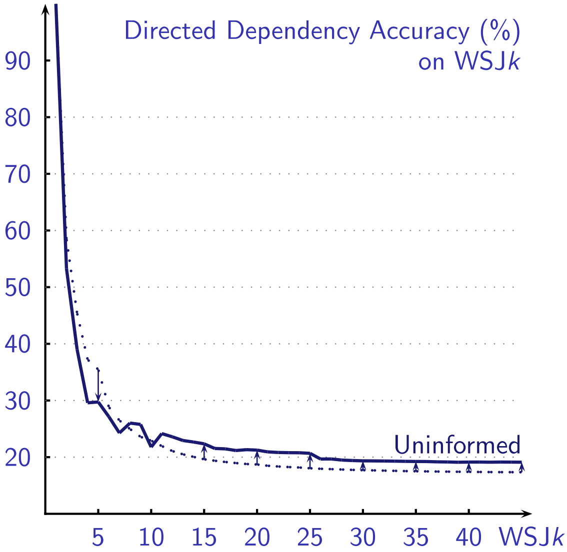

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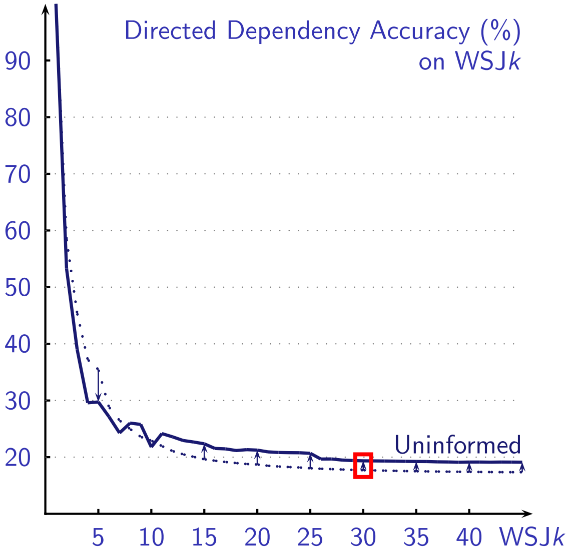

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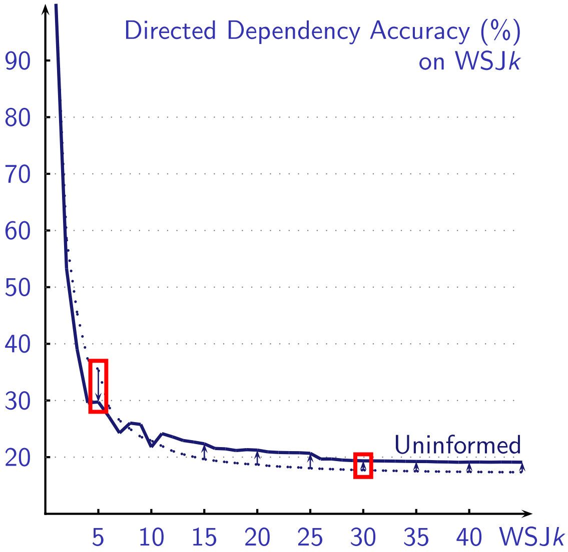

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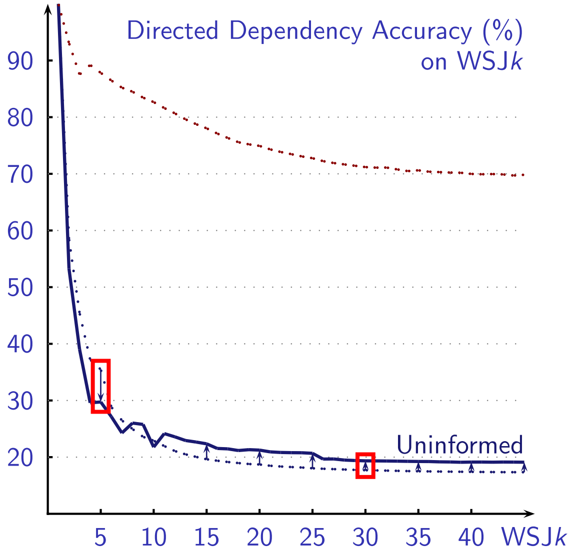

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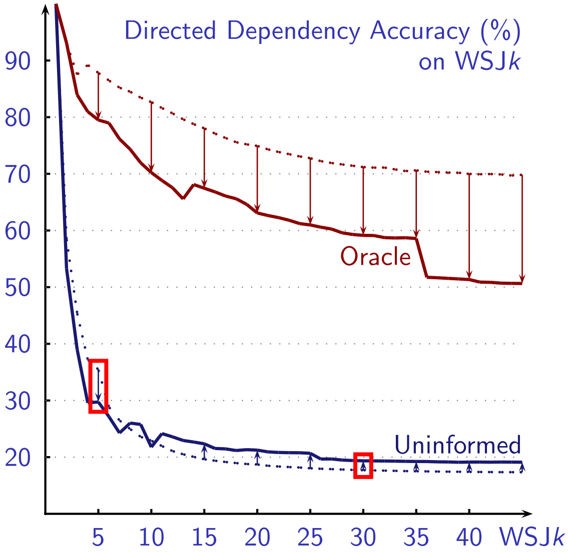

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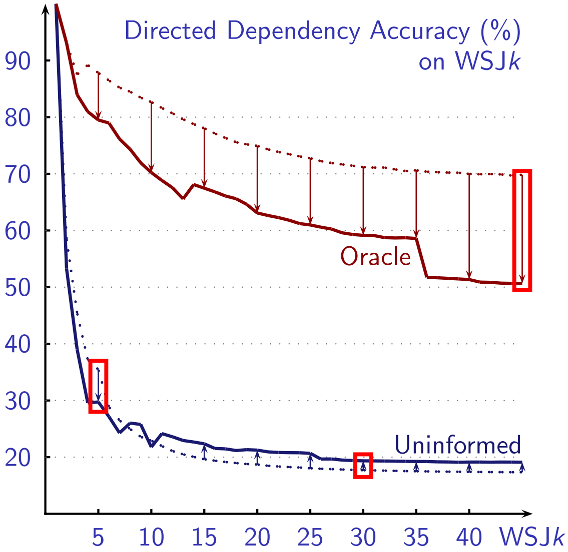

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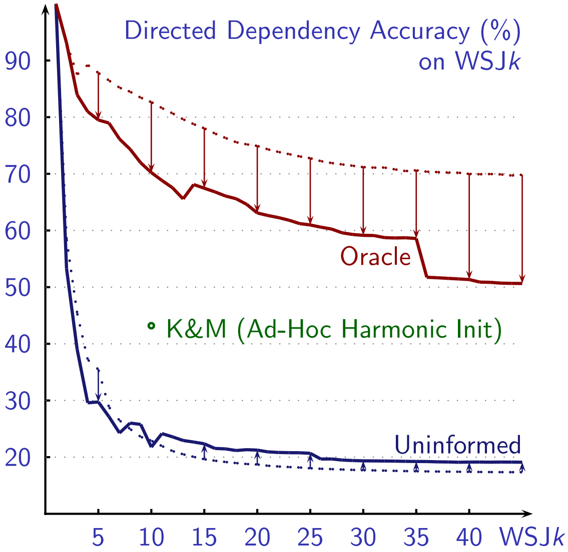

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- **... this *really is* grammar induction!**

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- **WSJ1** — **Atone** **(verbs!)**

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  It is.
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- $\boxed{\textbf{WSJ3}}$ — **Become a Lobbyist** (**determiners!**)
  But many have.
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successive approximations!

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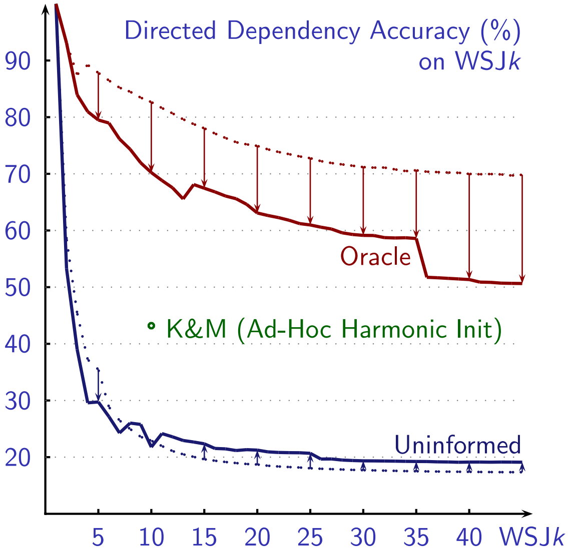

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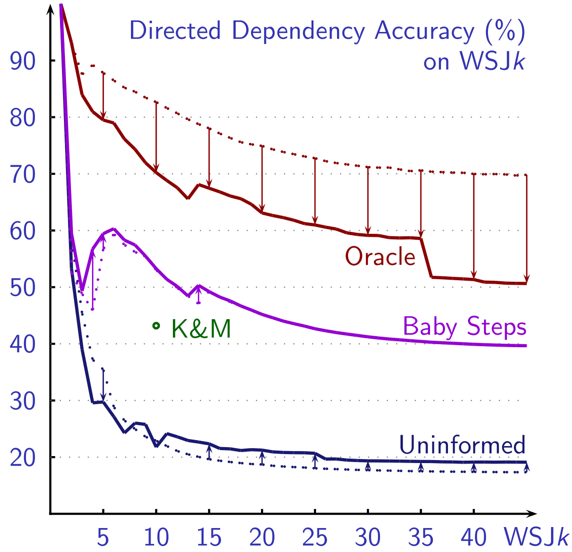

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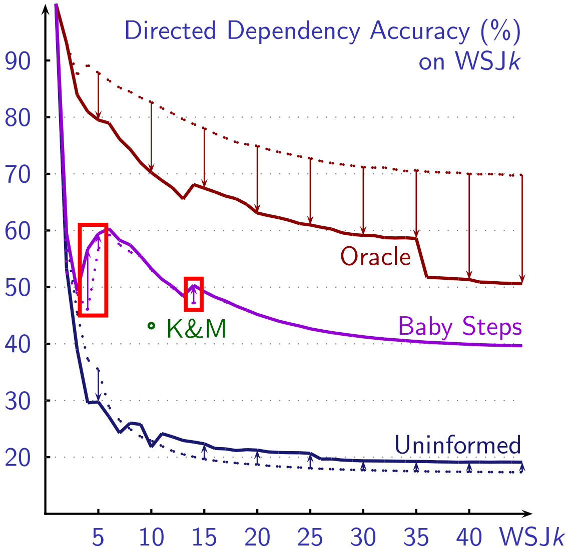

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- **about a year behind state-of-the-art (on long sentences)**

Idea II: Less is More

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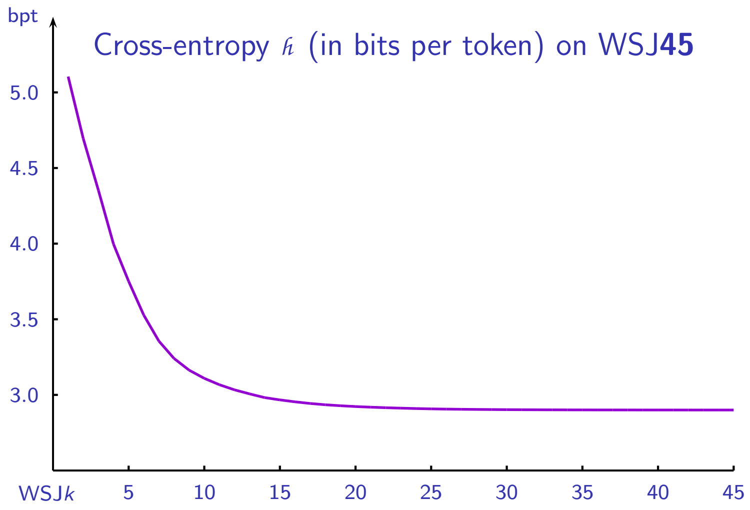
- **perhaps train where *Baby Steps* flatlines!**

Idea II: Less is More ... the Learning Curve



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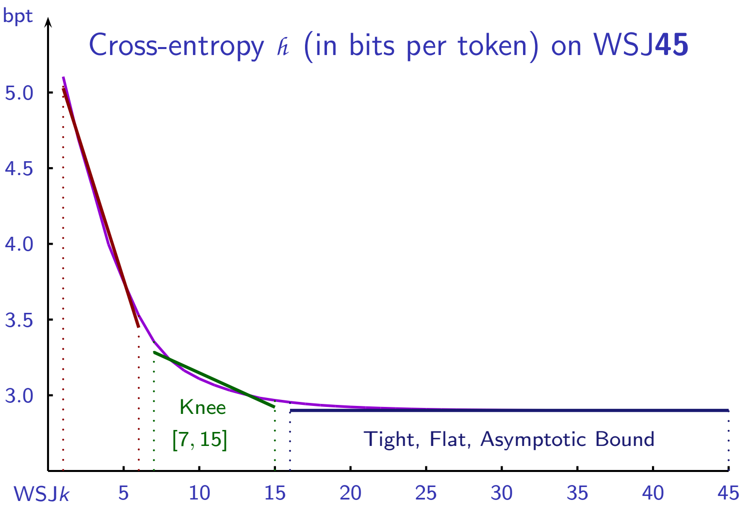

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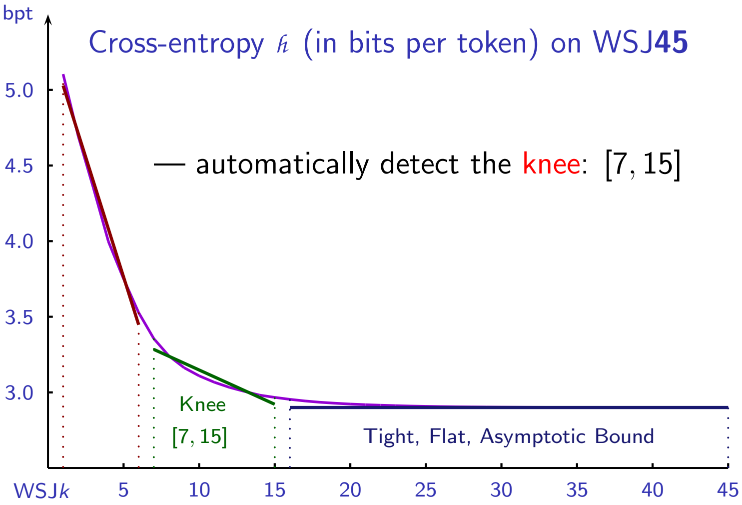

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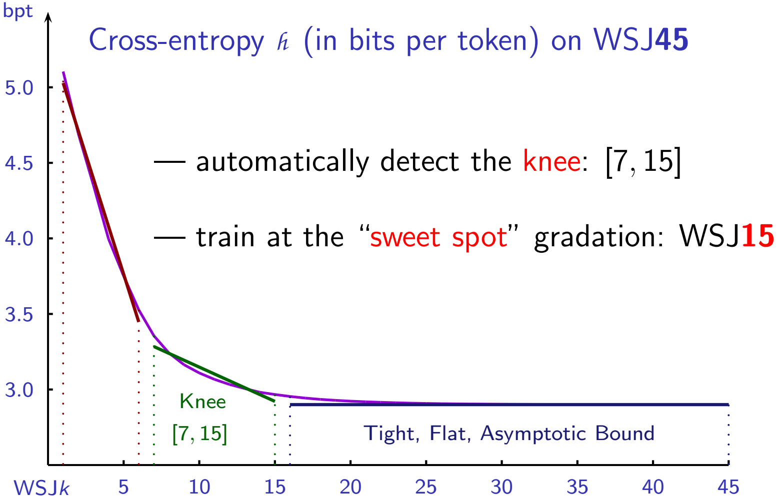

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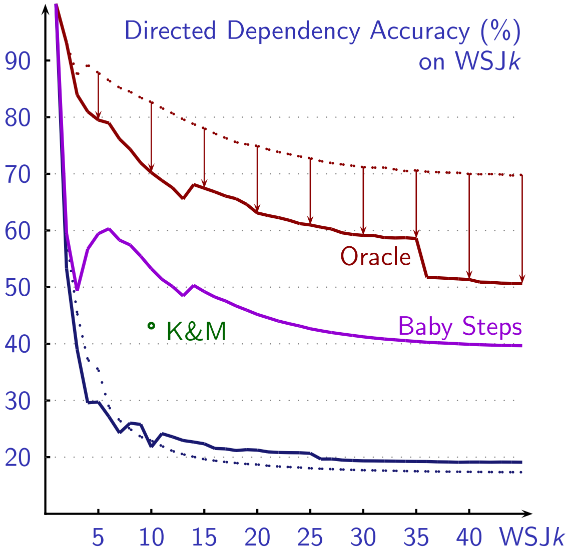

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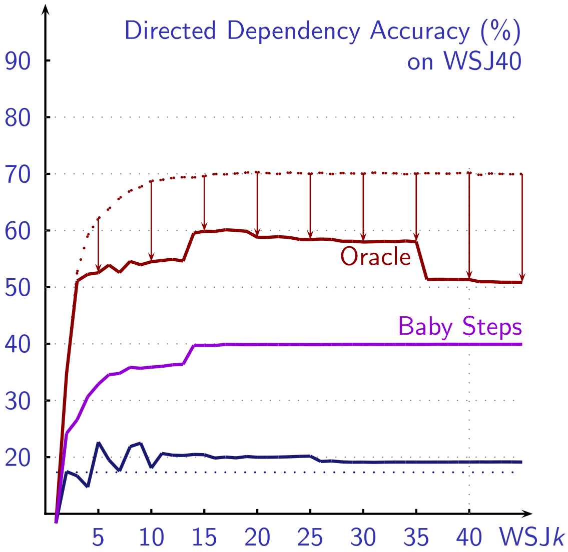

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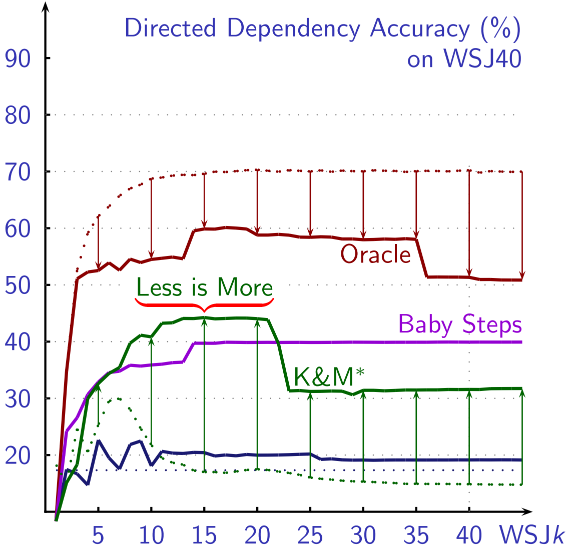

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- **ignores a decent complementary initialization strategy**

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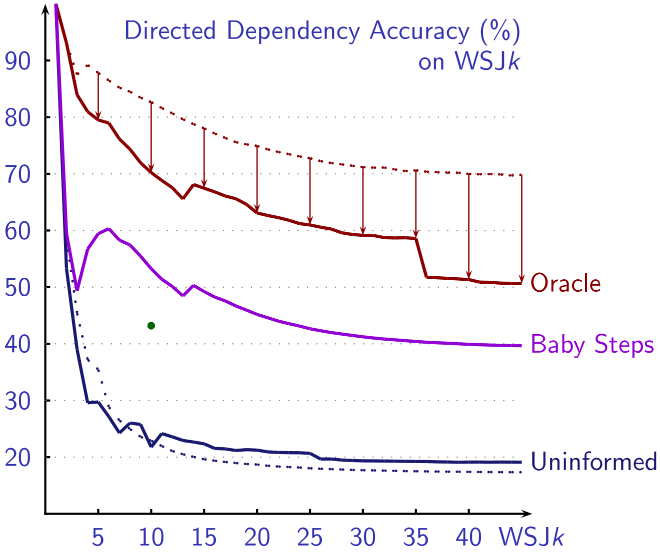

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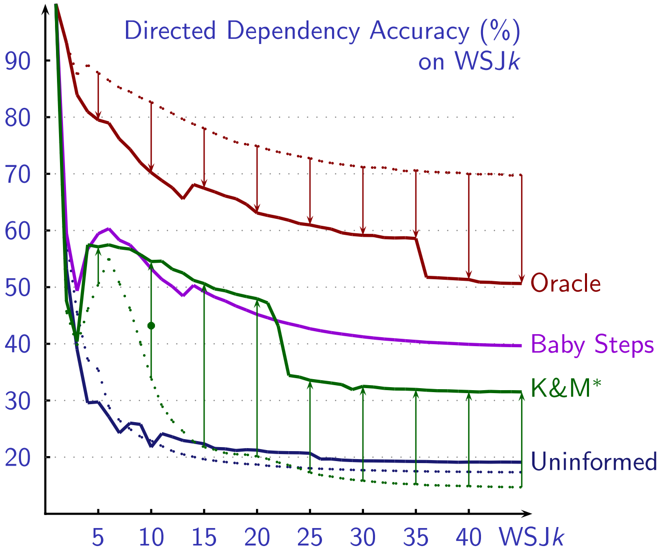

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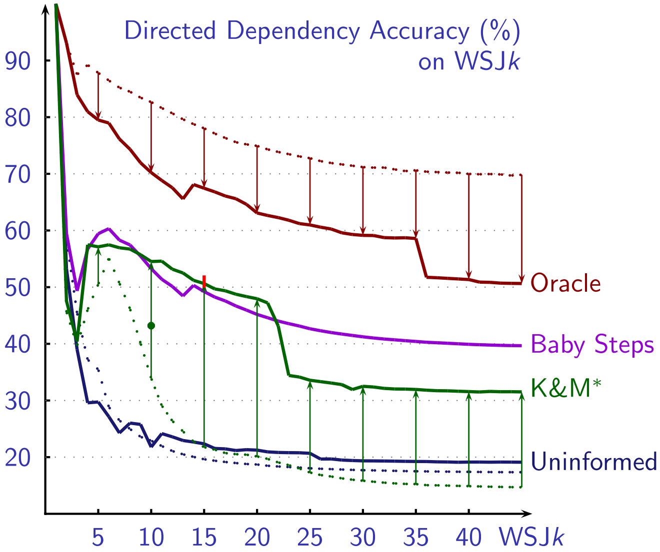

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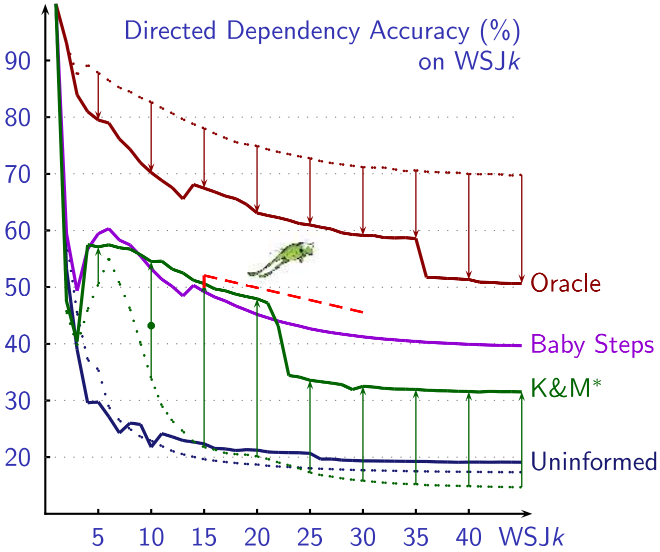

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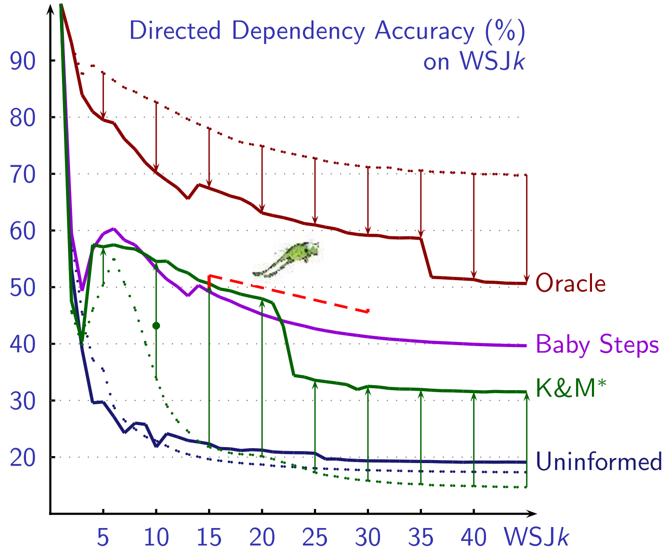

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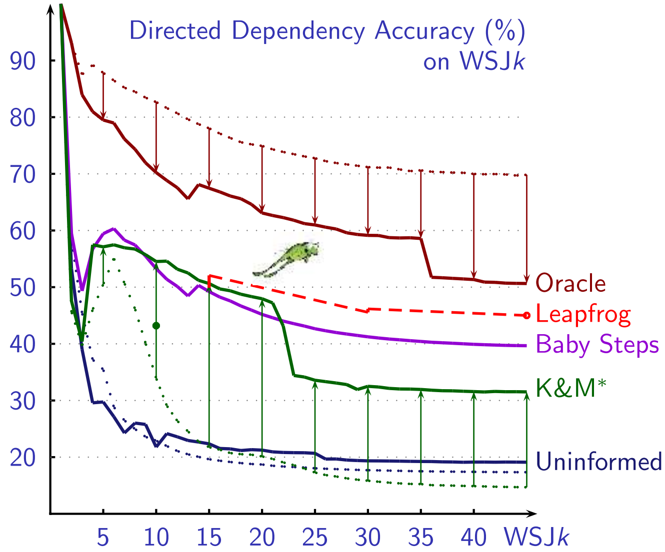

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- mirrors supervised boosting (Freund and Schapire, 1997)

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- ... more to come!

Thanks!

Questions?