Viterbi Training Improves Unsupervised Dependency Parsing

Valentin I. Spitkovsky

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Daniel Jurafsky (Stanford University)
and **Christopher D. Manning** (Stanford University)

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   — theoretical insights (mathematically sound)

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NN	NNS	VBD	IN	NN	♢
|	|	|	|	|	|
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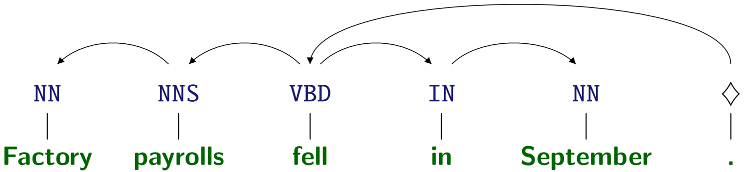
- **Output: Syntactic Structures (and a Probabilistic Grammar)**



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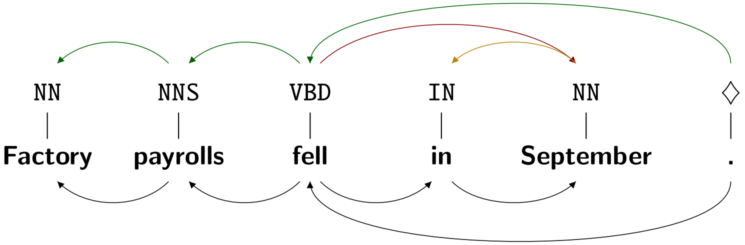

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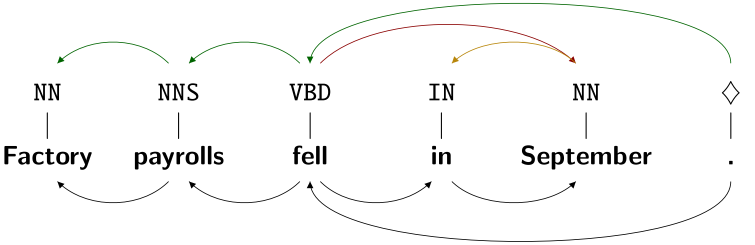

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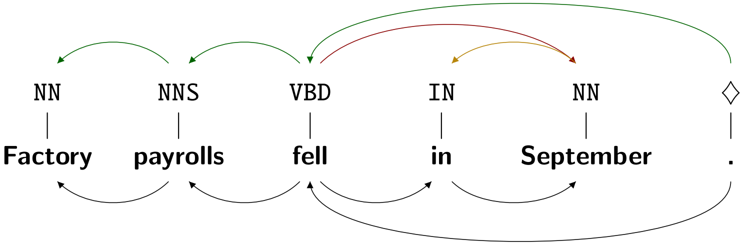

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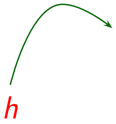

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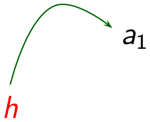

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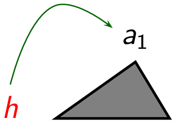

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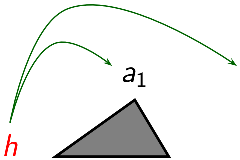

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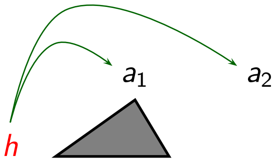

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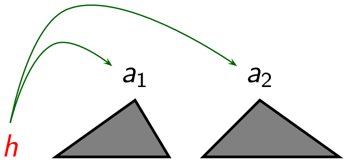

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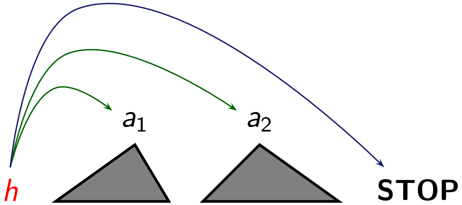

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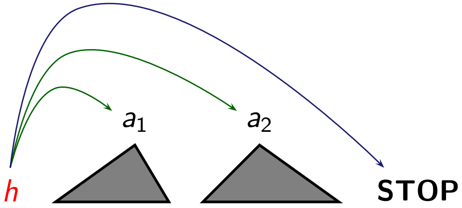

$$\mathbb{P}(t_h) = \prod_{dir \in \{\mathrm{L},\mathrm{R}\}} \left[\underline{\mathbb{P}_{\mathrm{STOP}}(c_h, dir, \overbrace{1_{n=0}}^{adj})} \prod_{i=1}^{n} \underline{\mathbb{P}(t_{a_i})}\, \mathbb{P}_{\mathrm{ATTACH}}(c_h, dir, c_{a_i}) \right.$$

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- **supervised objective would be convex (counting):**

$$\hat{\theta}_{\text{SUP}} = \arg\max_{\theta} \prod_{s} \mathbb{P}_{\theta}(t^*(s))$$

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

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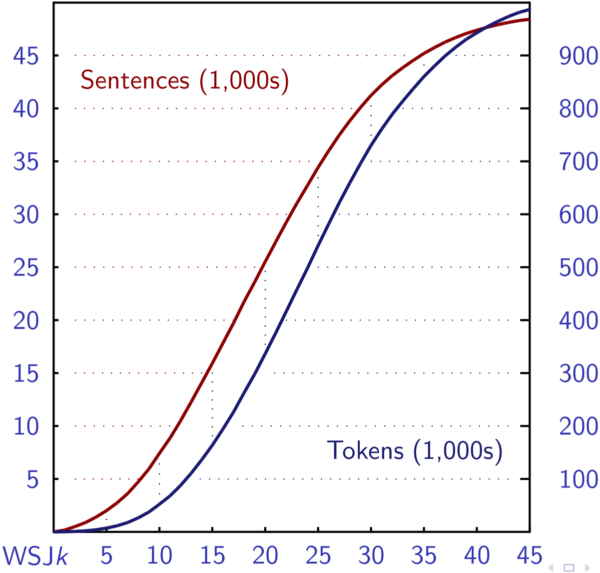

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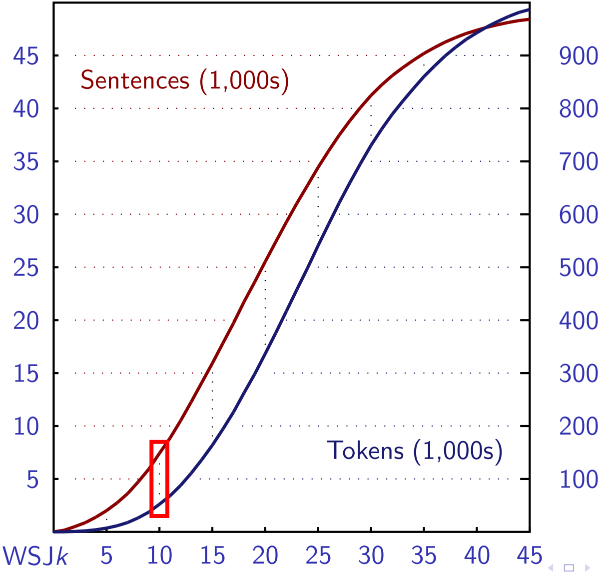
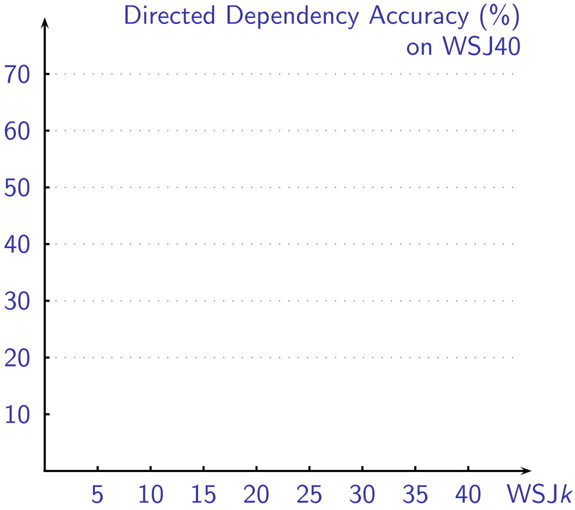


Classic EM: The Lay of the Land



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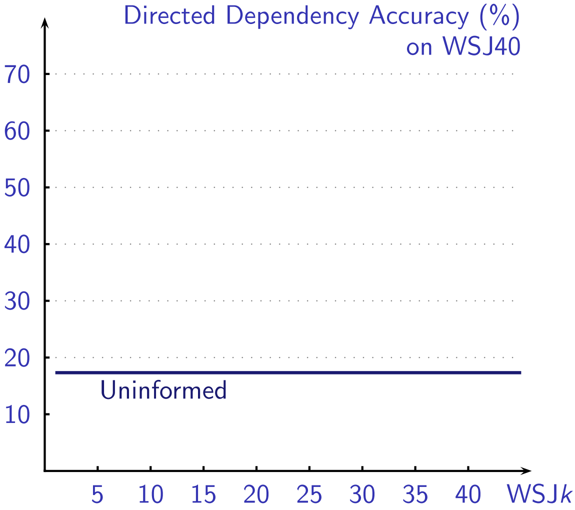

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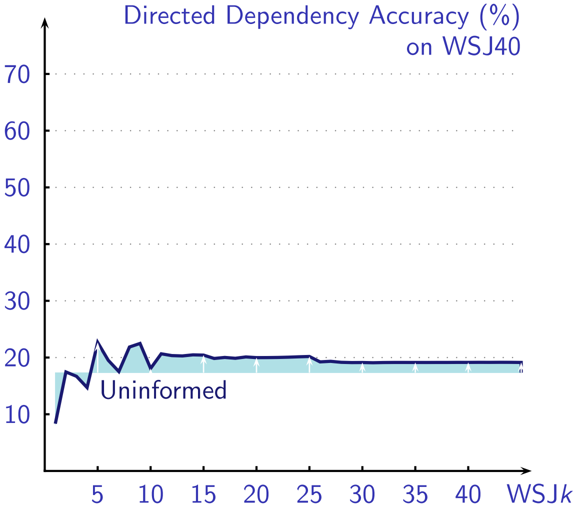

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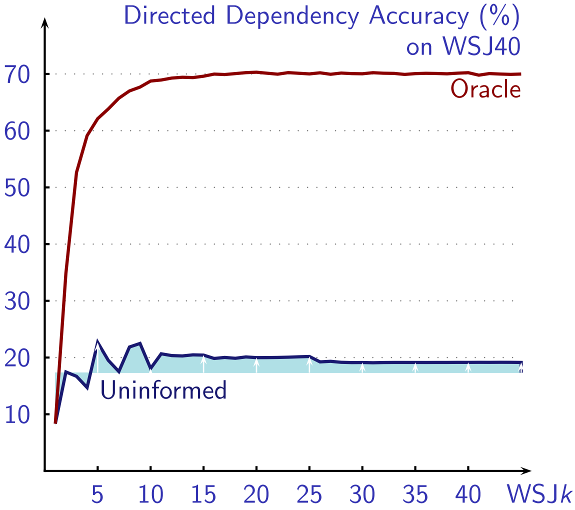

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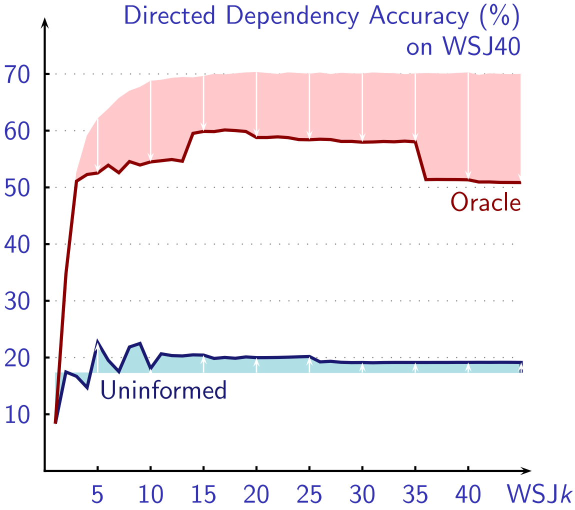

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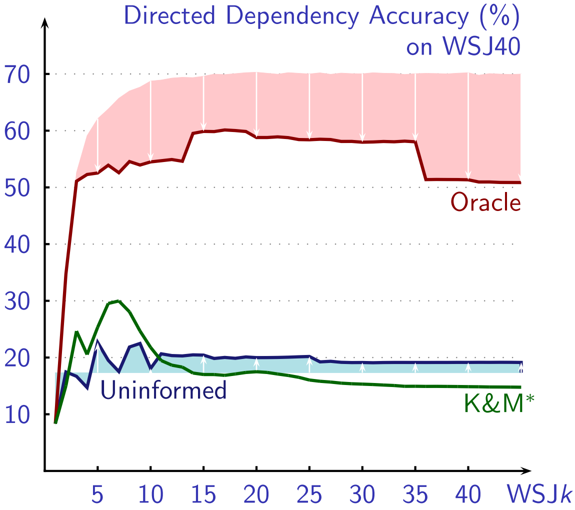

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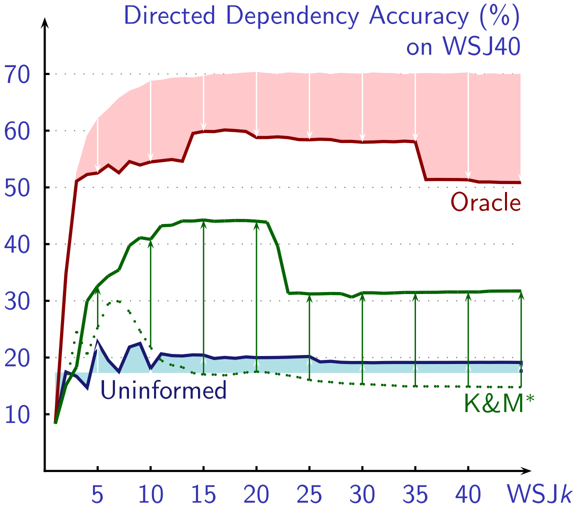

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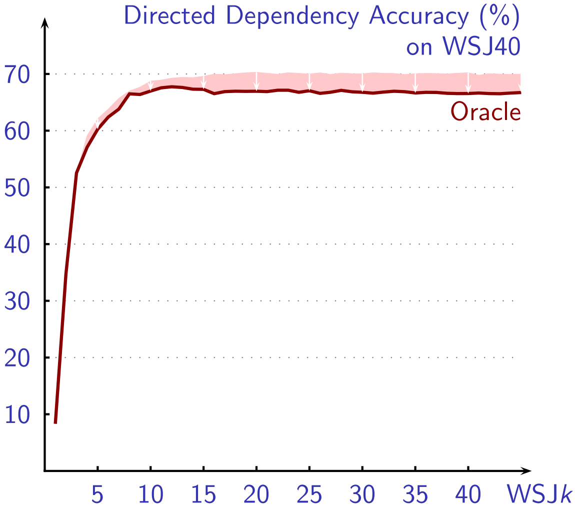

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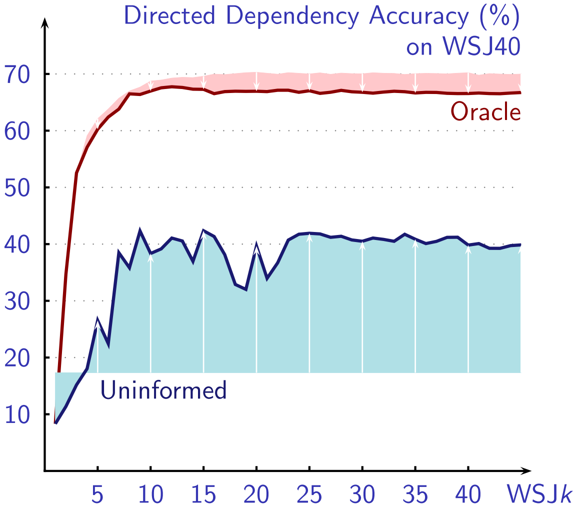

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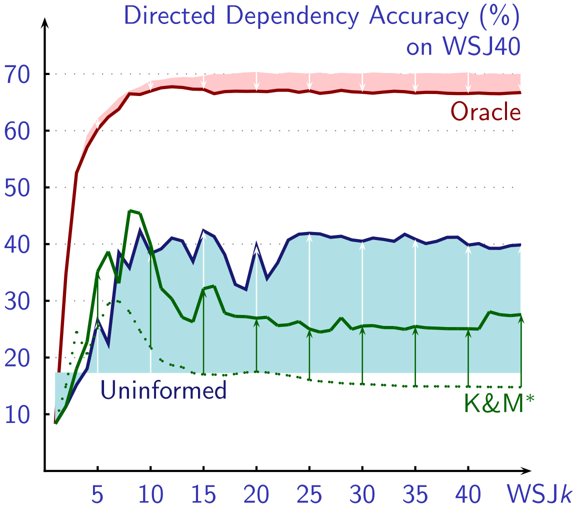

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THE PARTY'S OVER

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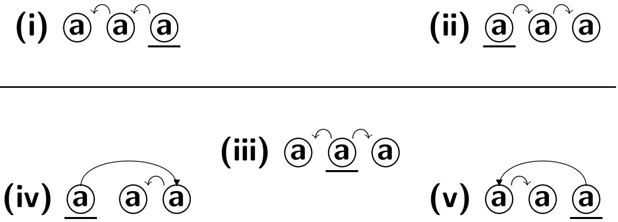

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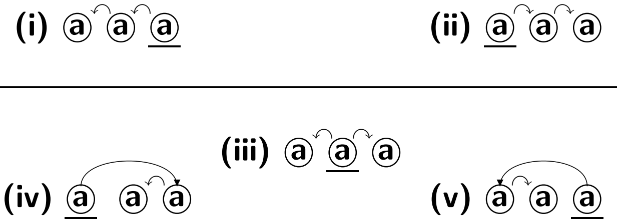

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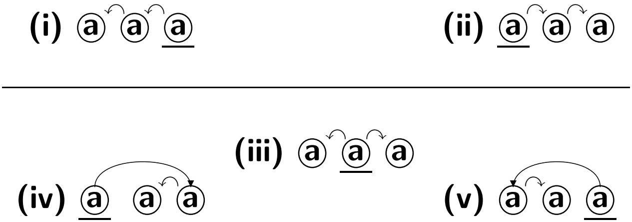

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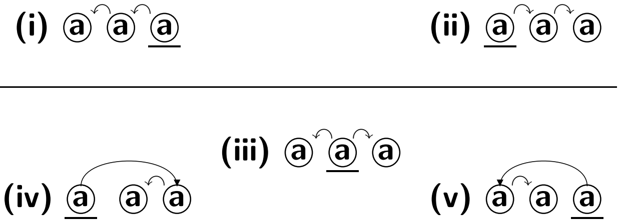

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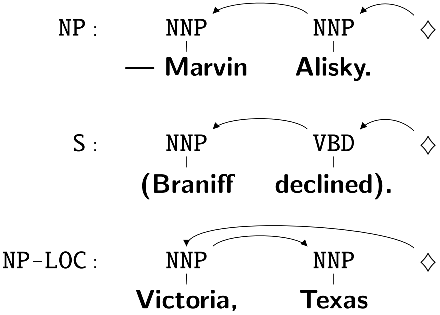

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Thanks!

Questions?