Punctuation: Making a Point in Unsupervised Dependency Parsing

Valentin I. Spitkovsky

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and **Hiyan Alshawi** (Google Inc.)

Example: Raw Word Stream

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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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- **formatting (missing structural cues):**

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- **raw word streams often difficult even for humans**
  — e.g., transcribed utterances (Kim and Woodland, 2002)

Example:

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 NNPS VBD IN DT JJ NN

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- less crude in inference
  — (reasonably) weak in final decoding

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- **strong constraint**

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word head , head word word ,

head word word word word word word word .

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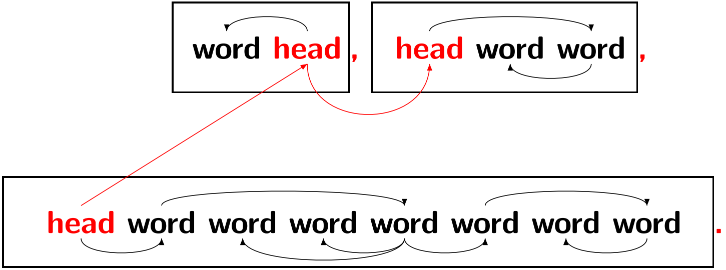

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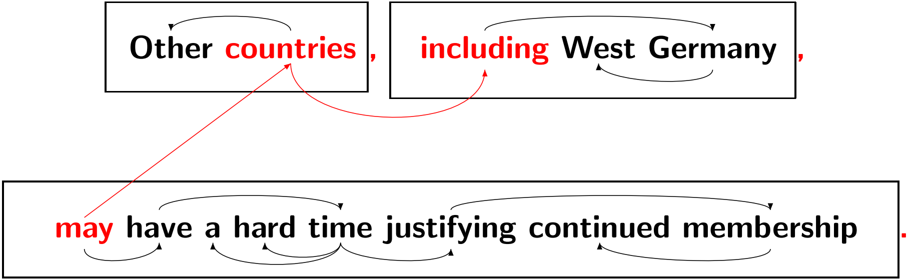

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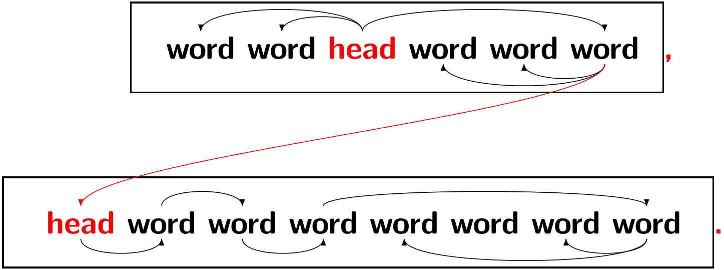

Intuition:

- **weak constraint: (head $\leftarrow$ external word) in inference**

IFI also has nonvoting preferred shares ,

which are quoted on the Milan stock exchange .

Linguistic Analysis:

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- **lowest dominating non-terminals:**

	%
S	32.5
NP	27.2
VP	13.3
PP	10.1
SBAR	6.7
ADVP	3.3
QP	2.5
SINV	2.0
ADJP	1.0
	98.5

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Maryland Club also distributes tea , which ...

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- **weak (in inference), e.g.,**

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— now 92.9% agreement with head-percolated trees

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Her recent report classifies the stock as a "hold."

Linguistic Analysis:

- **generalization:**
  — no path from the root may enter a fragment twice
  — 95.0% agreement with head-percolated trees

- **simple violations: "seamless" quotations and even lists**

Her recent report classifies the stock as a "hold."

The company said its directors, management and subsidiaries will remain long-term investors and ...

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"Capitalizing on Punctuation"

— more common (particularly in long sentences)
— more uniform (better coverage of constructs)

Problem: Unsupervised Learning of Parsing

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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 ...

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- **Input: Raw Text (Sentences, Tokens and POS-tags)**

  ... 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 ...

NN	NNS	VBD	IN	NN	♢
Factory	payrolls	fell	in	September	.

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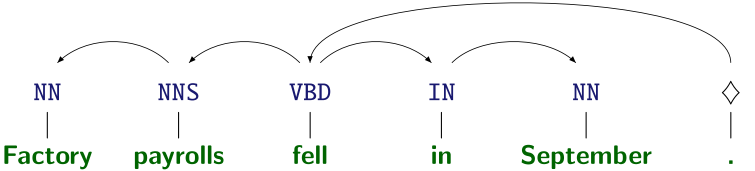
  ... By most measures, the nation's industrial sector is now growing very slowly — if at all. Factory payrolls fell in September. So did the Federal Reserve ...

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



Scoring: Directed Dependency Accuracy

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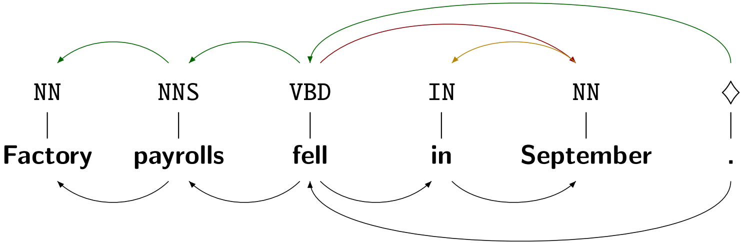

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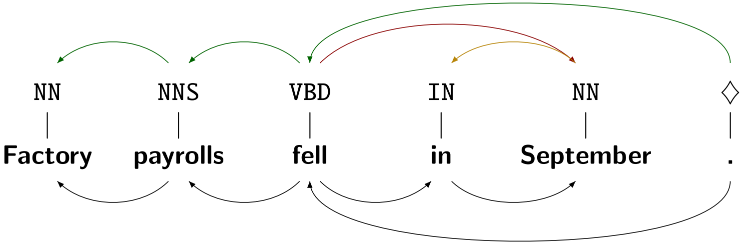

Directed score: $\frac{3}{5} = 60\%$

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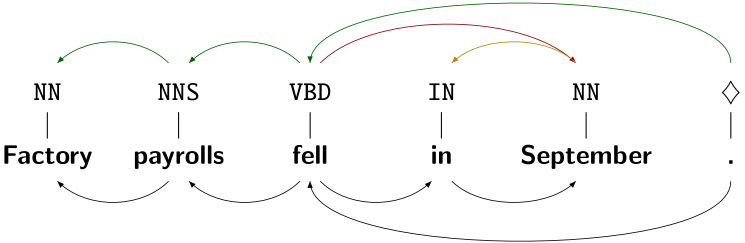

Directed score: $\frac{3}{5} = 60\%$ **(right/left-branching baselines:** $\frac{2}{5} = 40\%$**).**

DMV: Dependency Model with Valence

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- **a head-outward model, with word classes and valence/adjacency** **(Klein and Manning, 2004)**

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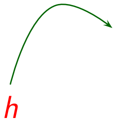

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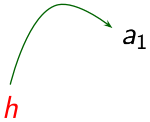

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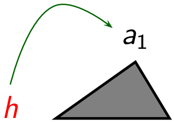

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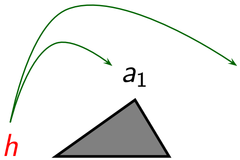

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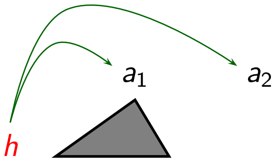

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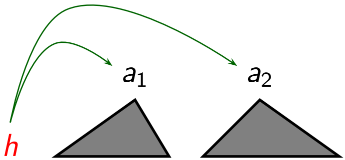

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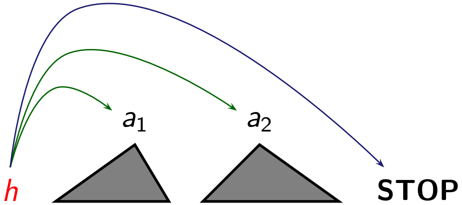

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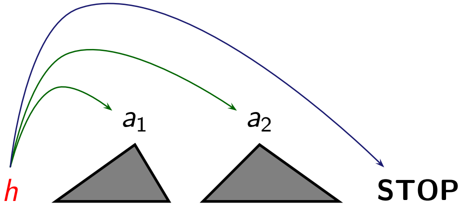

$$\mathbb{P}(t_h) = \prod_{dir \in \{\mathrm{L},\mathrm{R}\}} \left[\underline{\mathbb{P}_{\mathrm{STOP}}(c_h, dir, \overbrace{1_{n=0}}^{adj})} \prod_{i=1}^{n} \underline{\mathbb{P}(t_{a_i})}\, \mathbb{P}_{\mathrm{ATTACH}}(c_h, dir, c_{a_i}) \underline{(1 - \mathbb{P}_{\mathrm{STOP}}(c_h, dir, \overbrace{1_{i=1}}^{adj}))}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

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- **fast, simple and easily admits constraints**

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- **partial bracketings** **(Pereira and Schabes, 1992)**

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- **partial bracketings** (Pereira and Schabes, 1992)
  - synchronous grammars (Alshawi and Douglas, 2000)
  - linear-time parsing (Seginer, 2007)
  - skewness of trees (Seginer, 2007)
  - Zipfian distribution of words (Seginer, 2007)
  - sparse posterior regularization (Ganchev et al., 2009)
  - web markup-induced constraints (Spitkovsky et al., 2010)
  - semantic cues (Naseem and Barzilay, 2011)

Experimental Results: Unlexicalized

- **directed dependency accuracies for baselines, inference, training and an oracle:**

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(Section 23, all sentences)

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- **directed dependency accuracies compared to previous state-of-the-art**

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`http://nlp.stanford.edu/software/`
`stanford-postagger-2008-09-28.tar.gz:`
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(Come see our poster at EMNLP!)

Experimental Results: Multi-Lingual

- **further evaluation against CoNLL 2006/7 data sets — results generalize across languages:**

Arabic	**2006**		
	'7		
Basque	**'7**		
Bulgarian	**'6**		
Catalan	**'7**		
Czech	**'6**		
	'7		
Danish	**'6**		
Dutch	**'6**		
English	**'7**		
German	**'6**		
Greek	**'7**		
Hungarian	**'7**		
Italian	**'7**		
Japanese	**'6**		
Portuguese	**'6**		
Slovenian	**'6**		
Spanish	**'6**		
Swedish	**'6**		
Turkish	**'6**		
	'7		
Average:			

Experimental Results: Multi-Lingual

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		Inference Only	
Arabic	2006	+0.1	
	'7	+0.9	
Basque	'7	+0.8	
Bulgarian	'6	+1.1	
Catalan	'7	+0.8	
Czech	'6	+0.9	
	'7	+1.0	
Danish	'6	+0.9	
Dutch	'6	+1.0	
English	'7	+1.3	
German	'6	+0.8	
Greek	'7	+0.5	
Hungarian	'7	+0.4	
Italian	'7	+0.1	
Japanese	'6	+0.0	
Portuguese	'6	+0.7	
Slovenian	'6	+2.0	
Spanish	'6	+0.8	
Swedish	'6	+0.5	
Turkish	'6	+0.1	
	'7	+0.2	
Average:		+0.7	

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		Inference Only	Training & Inference
Arabic	2006	+0.1	+1.1
	'7	+0.9	+2.6
Basque	'7	+0.8	+0.6
Bulgarian	'6	+1.1	+1.6
Catalan	'7	+0.8	+0.9
Czech	'6	+0.9	+3.0
	'7	+1.0	+2.7
Danish	'6	+0.9	+0.2
Dutch	'6	+1.0	+3.0
English	'7	+1.3	+2.8
German	'6	+0.8	+1.6
Greek	'7	+0.5	+0.7
Hungarian	'7	+0.4	+1.4
Italian	'7	+0.1	-0.8
Japanese	'6	+0.0	+0.1
Portuguese	'6	+0.7	+0.8
Slovenian	'6	+2.0	+2.8
Spanish	'6	+0.8	+0.8
Swedish	'6	+0.5	+0.8
Turkish	'6	+0.1	+1.0
	'7	+0.2	+0.1
Average:		**+0.7**	**+1.3**

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  — "as words" breaks *n*-grams (Kahn et al., 2005)

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Summary:

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  — even better than markup...
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Summary:

- **punctuation helps dependency grammar induction — even better than markup...**
- **a popular approach: powerful models — priors prevent overfitting**
- **an alternative: overly simple models — constraints prevent *under*fitting**

Thanks!

Punctuation. It works...

Any questions?