Profiting from Mark-Up:
Hyper-Text Annotations for Guided Parsing

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  — linguistic structure underdetermined by raw text

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```
(((List (the fares (for ((flight) (number 891)))))) .)
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Phileas Fogg

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- solution: mark-up!

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  — instead of rushing to discard it, try polishing!

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- minor yet recurring theme: less is more

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  [CoNLL] (Spitkovsky et al., 2010)

  — methodology: experimental design (hundreds of runs)
  [ACL] (Spitkovsky et al., 2010)

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  4. **WSJ — just over $1M$ tokens** (Marcus et al., 1993)
  5. **Brown — under $400K$ tokens** (Francis and Kucera, 1979)

Syntax of Mark-Up: POS Sequences <a, b, i, u>

	%
NNP NNP	16.1
NNP	8.3
NNP NNP NNP	5.4
NN	5.4
JJ NN	2.6
DT NNP NNP	1.8
NNS	1.8
JJ	1.5
VBD	1.3
DT NNP NNP NNP	1.2
JJ NNS	1.1
NNP NN	1.0
NN NN	1.0
VBN	0.8
NNP NNP NNP NNP	0.8
	50.0

Syntax of Mark-Up: Dominating Non-Terminals

	%
NP	74.5
VP	12.9
S	6.8
PP	1.6
ADJP	0.9
FRAG	0.8
ADVP	0.5
SBAR	0.5
PRN	0.2
NX	0.2
	99.0

Syntax of Mark-Up: Common Constituents

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$$\mathrm{S} \rightarrow \mathtt{N}\underline{\mathtt{P\ V}}\mathtt{P}$$

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$$\mathrm{S} \rightarrow \mathtt{N}\underline{\mathtt{P\ V}}\mathtt{P} \rightarrow \mathtt{DT}\ \underline{\mathtt{NNP\ NNP\ VBZ\ NP\ PP}}\ \mathtt{S}$$

Syntax of Mark-Up: Constituent Productions

	%
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
NP → DT JJ NN	1.1
NP → NNS	1.0
NP → JJ NN	0.8
NP → NP NP	0.8
	35.3

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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
NP → DT JJ NN	1.1
NP → NNS	1.0
NP → JJ NN	0.8
NP → NP NP	0.8
	35.3

Syntax of Mark-Up: Constituent Productions

	%
NP → NNP NNP	9.6
NP → NNP	4.6
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NP → NNP NNP NNP	2.4
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Syntax of Mark-Up: Common Dependencies

..., but [$_{\text{S}}$ [$_{\text{NP}}$ the <a>*Toronto Star*]**[$_{\text{VP}}$ reports [$_{\text{NP}}$ this]**
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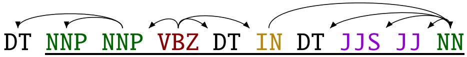

DT NNP NNP VBZ DT IN DT JJS JJ NN

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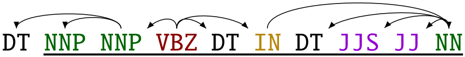

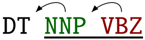

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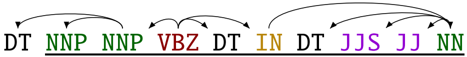

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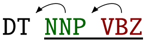
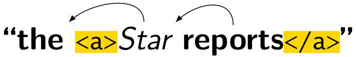


DT NNP VBZ

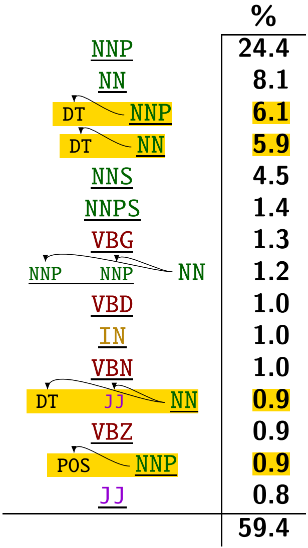


“the <a>*Star* reports</a>”

Syntax of Mark-Up: Head-Outward Spawns

	%
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
DT JJ NN	0.9
VBZ	0.9
POS NNP	0.9
JJ	0.8
	59.4

Syntax of Mark-Up: Head-Outward Spawns



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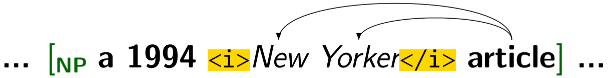
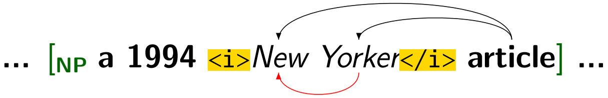
Syntax of Mark-Up: Exception



… [$_{\text{NP}}$ **a 1994** <i>*New Yorker*</i> **article**] **…**

Syntax of Mark-Up: Exception



… [$_{\text{NP}}$ a 1994 <i>*New Yorker*</i> article] …

- **consequence of bare NPs**
  — … and "head percolation" rules

Syntax of Mark-Up: Summary

- **not just single words** **(lots of long noun phrases)**

Syntax of Mark-Up: Summary

- not just single words (lots of long noun phrases)
- some verbs, adjectives, etc. (i.e., not just nouns)

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- 11% of all sentences in the blog are annotated

- 9% have multi-token bracketings

Proposed Constraints: Constituents?

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- **... but we'll polish them anyway!**

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Proposed Constraints: Dependencies!

- a more stylistically-forgiving framework
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- then slowly relax it
- every example demonstrating a softer constraint doubles as a counter-example against all previous

Proposed Constraints: Strict

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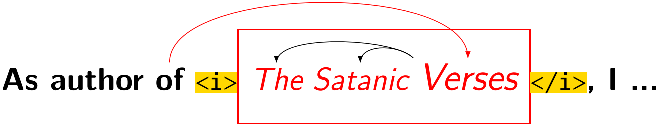

As author of `<i>` *The Satanic Verses* `</i>`**, I ...**

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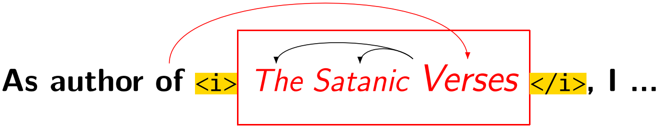

As author of `<i>` *The Satanic Verses* `</i>`, I ...

— just 35.6% agreement with head-percolated trees

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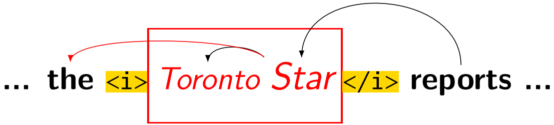

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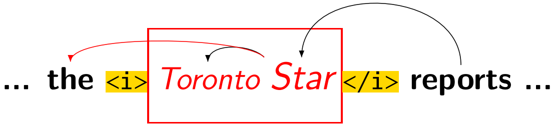

... the <i> *Toronto Star* </i> reports ...

— already 87.5% agreement with head-percolated trees

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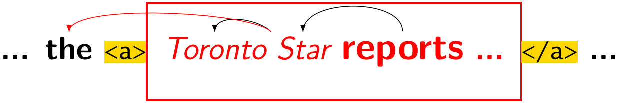

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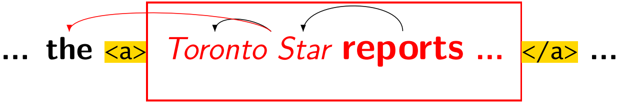

... the <a> *Toronto Star* **reports ...** </a> **...**

— now 95.1% agreement with head-percolated trees

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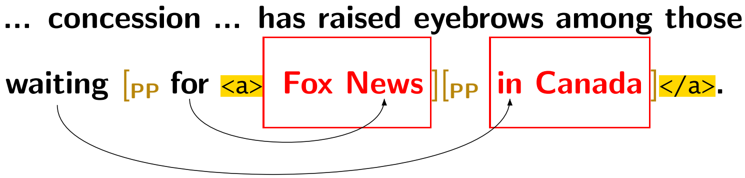

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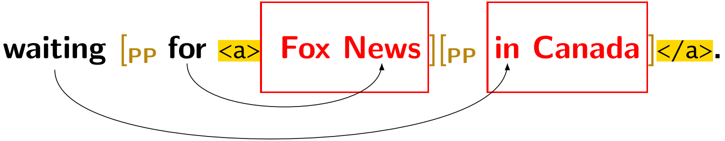

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— finally, 98.9% agreement with head-percolated trees

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- **first two can easily guide Viterbi training!**

Experimental Results: Dependency Accuracy (%)

Incarnation	**WSJ10**	**WSJ$^\infty$**	
(Cohen and Smith, 2009)			**Brown100**
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(Headden et al., 2009)			
BLOG			

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(Cohen and Smith, 2009)	62.0	42.2	
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- perhaps bigger gains if lexicalized?

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	POS Sequence	**WEB** *Count*
	Sample web sentence, chosen uniformly at random.	
1	DT NNS VBN	**82,858,487**
	All rights reserved.	
2	NNP NNP NNP	**65,889,181**
	Yuasa et al.	
3	NN IN TO VB RB	**31,007,783**
	Sign in to YouTube now!	
4	NN IN IN PRP$ JJ NN	**31,007,471**
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- **ambiguous noun phrases: "click here" and "print post"**

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http://nlp.stanford.edu:8080/parser/

(NP (ADJP (NP (JJ Libyan) (NN ruler))
(JJ Mu))
(“ ‘) (NN ammar) (NNS al-Qaddafi))

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  ... and so forth!

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- **are there broader NLP implications?**

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- **a complete analysis of every annotated sentence**

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http://cs.stanford.edu/~valentin/

Thanks!

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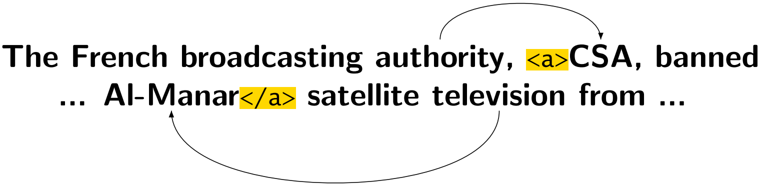
Proposed Constraints: Exception

- **remaining 1.1% mostly due to parser errors...**
- **a (very rare) true negative disagreement:**



The French broadcasting authority, <a>CSA, banned
... Al-Manar</a> satellite television from ...