Turbo Parser Redux: From Dependencies to Constituents

André Martins

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Structured Prediction and NLP

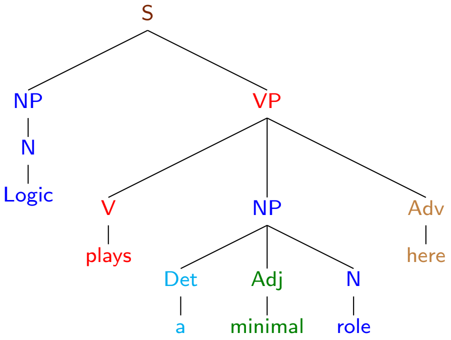
Structured prediction: a machine learning framework for predicting structured, constrained, and interdependent outputs

NLP deals with *structured* and *ambiguous* textual data:

- machine translation
- speech recognition
- syntactic parsing
- semantic parsing
- information extraction
- ...

Constituent/Phrase-Structure Parsing

```
S --> NP VP
NP --> Det Adj N
VP --> V NP Adv
Adj --> minimal
Adv --> here
Det --> a
N --> logic
N --> role
V --> plays
```

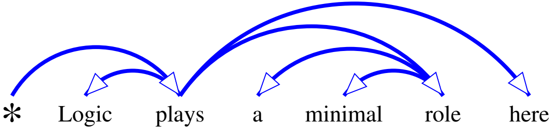


Example extracted from the Penn Treebank.

(Magerman, 1995; Charniak, 1996; Johnson, 1998; Collins, 1999; Klein and Manning, 2003)

Dependency Parsing

Map **sentences** to their **syntactic structure.**



- A lexicalized syntactic formalism
- Grammar functions represented as lexical relationships (dependencies)

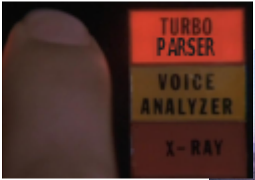
(Eisner, 1996; McDonald et al., 2005; Nivre et al., 2006; Koo et al., 2007)

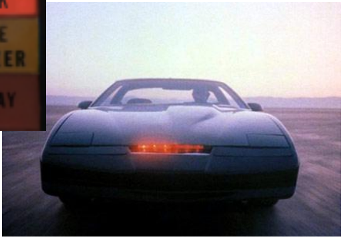
Outline

1. **Turbo Parsers**

2. **Parsing as Reduction**
   - Dependencies and Constituents
   - Head-Ordered Dependency Trees
   - Reduction-Based Constituent Parsers
   - Experiments
   - Conclusions

What is a Turbo Parser?





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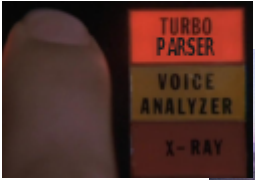
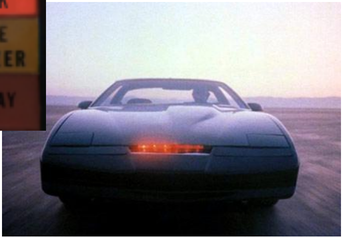




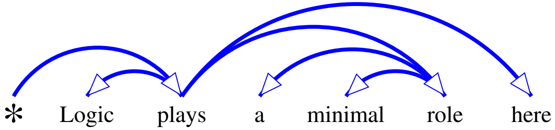
- **A parser that runs inference in factor graphs, ignoring global effects caused by loops (Martins et al., 2010)**
- name inspired from *turbo* decoders (Berrou et al., 1993)

Examples of Turbo Parsers

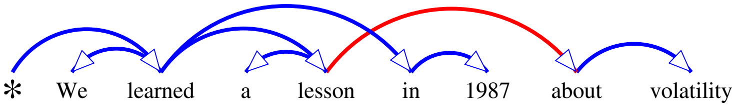
- Exponential-sized ILP formulation (Riedel and Clarke, 2006)
- Polynomial-sized ILP formulation with multi-commodity flows (Martins et al., 2009)
- Belief propagation decoder (Smith and Eisner, 2008; Martins et al., 2010)
- Dual decomposition decoder (Koo et al., 2010)
- AD^3 decoder (Martins et al., 2011, 2013)

An Important Distinction

- A projective tree:



- A non-projective tree:



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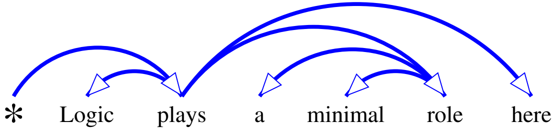

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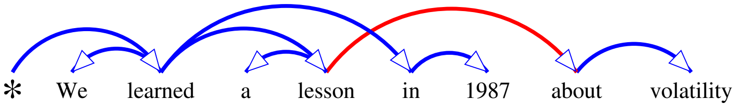
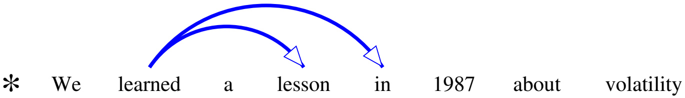


Non-projective trees are suitable for languages with flexible word order (Dutch, German, Czech,...).

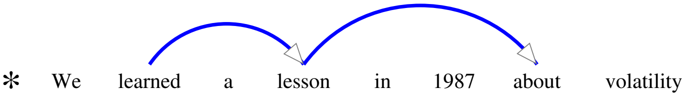
First-Order Scores for Arcs

* We learned a lesson in 1987 about volatility

Second-Order Scores for Consecutive Siblings



Second-Order Scores for Grandparents



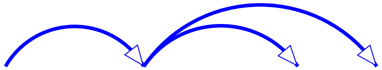
Scores for Arbitrary Siblings

* We learned a lesson in 1987 about volatility

Scores for Head Bigrams

* We learned a lesson in 1987 about volatility

Third-Order Scores for Grand-siblings



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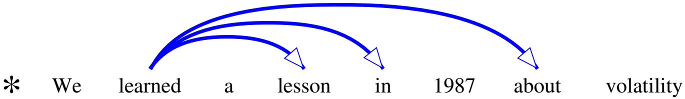
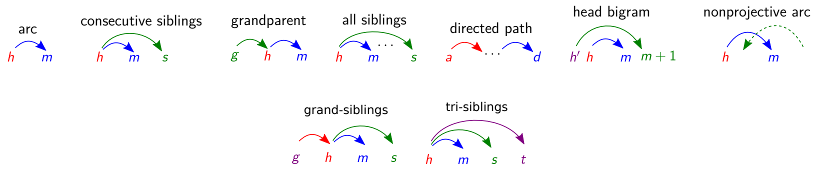
Third-Order Scores for Tri-siblings

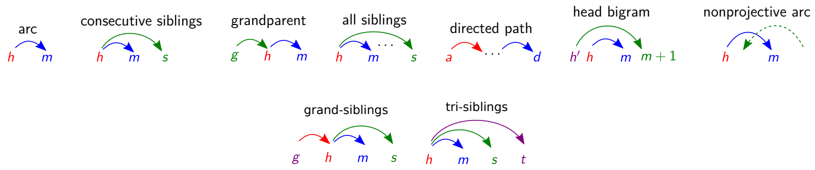


Decoding



- How to deal with all these parts?

Decoding



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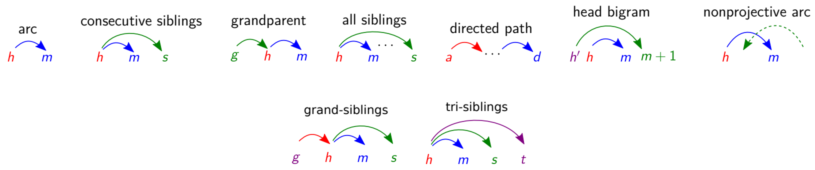
- Beyond arc-factored models, non-projective parsing is **NP-hard** (McDonald and Satta, 2007)—**need to embrace approximations!**

Decoding



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	parser	AF	CS	G	AS	DP	HB	NPA	GS	TS
McDonald et al. (2006)	projective + greedy	✓	✓							
Smith et al. (2008)	loopy BP	✓	✓	✓	✓					
Martins et al. (2010)	LP solver	✓		✓	✓			✓		
Koo et al. (2010)	dual decomp.	✓	✓							
Martins et al. (2011)	AD^3	✓	✓	✓	✓	✓	✓	✓		
Martins et al. (2013)	AD^3 & active set	✓	✓	✓	✓		✓		✓	✓

Factor Graph Representations

- For each input $x \in \mathcal{X}$: a **large** set of candidate outputs $\mathcal{Y}(x)$
- **Decoding problem:**

$$\widehat{y} = \arg \max_{y \in \mathcal{Y}(x)} F_{\mathbf{w}}(x, y)$$

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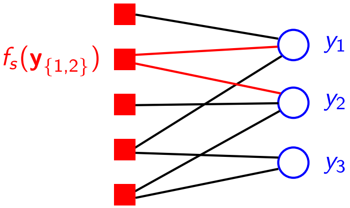
- **Key assumption:** $F_{\mathbf{w}}$ decomposes into (overlapping) *parts*

$$\boxed{F_{\mathbf{w}}(x, y) := \sum_{s} f_s(\mathbf{y}_s)}$$



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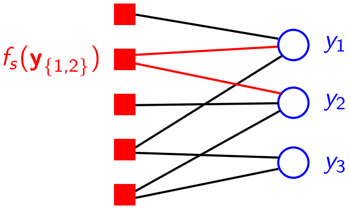
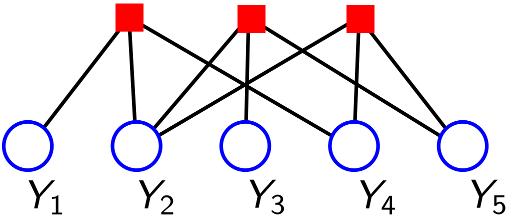


- **Examples:** HMMs, CRFs, PCFGs, general graphical models

Factors as Machines



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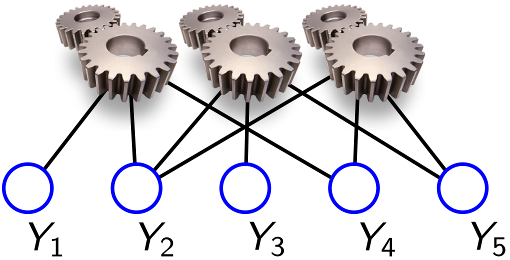

Alternating Directions Dual Decomposition (AD^3)

A general purpose algorithm, suitable for many scenarios in NLP and IR.

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- Problems with factor graph representations

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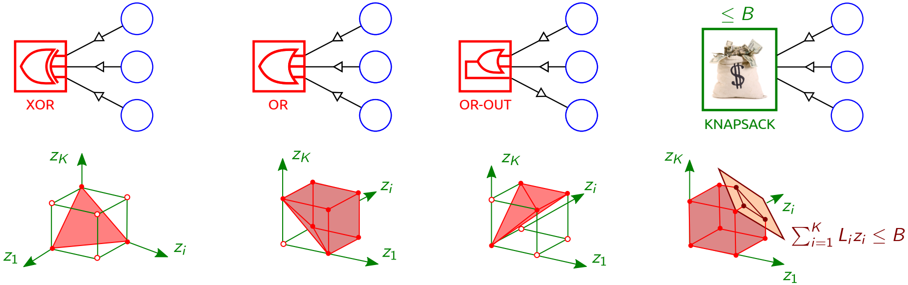
High level idea:

- Decompose a complex problem into local subproblems (factors), constrained to be globally consistent
- Iterate between solving the local subproblems and penalizing the global disagreements (via Lagrange multipliers)
- FOL/knapsack constraints: the local subproblems correspond to projections onto "hard constraint" polytopes

Projecting onto Hard Constraint Polytopes



- All projections can be computed in linear time (Martins et al., 2015)
- **Applications:** Markov logic networks (Richardson and Domingos, 2006), constrained conditional models (Roth and Yih, 2004), summarization (Almeida and Martins, 2013), ...

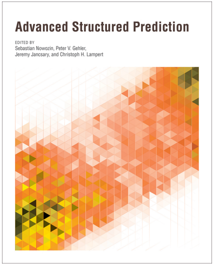
Some Problems in Which AD^3 Have Been Applied

- Dependency parsing (Martins et al., 2011, 2013)
- Frame semantics (Das et al., 2012)
- Broad-coverage semantic parsing (Martins and Almeida, 2014)
- Compressive summarization (Almeida and Martins, 2013)
- Coreference resolution (Almeida et al., 2014)

Could be a great fit to many other applications!!

Literature Pointers

- André F. T. Martins.
  "AD^3: A Fast Decoder for Structured Prediction."
  Book chapter of *Advanced Structured Prediction*, Sebastian Nowozin, Peter V. Gehler, Jeremy Jancsary, and Christoph H. Lampert (Editors), MIT Press, 2014.



- A. Martins, M. Figueiredo, P. Aguiar, N. Smith, E. Xing.
  "AD3: Alternating Directions Dual Decomposition for MAP Inference in Graphical Models."
  JMLR 2015.

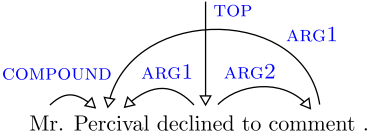
More details: EMNLP 2014 tutorial on "LP Decoders for NLP."

Parsing Accuracies/Runtimes

SOTA accuracies for the largest non-projective datasets (CoNLL-2006 and CoNLL-2008):

Extension: Broad-Coverage Semantic Parsing

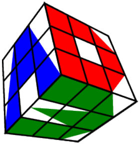
Same idea applied to **semantic role labeling**.



Best results in the SemEval 2014 shared task:

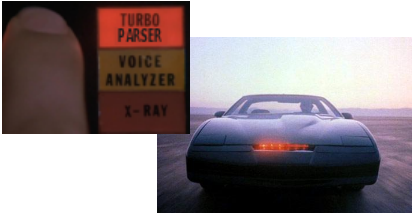
- André F. T. Martins and Mariana S. C. Almeida.
  "Priberam: A Turbo Semantic Parser with Second Order Features."
  SemEval 2014.

Try It Yourself: AD^3 Toolkit



- Freely available at: *http://www.ark.cs.cmu.edu/AD3*
- Implemented in C++, includes a Python wrapper (thanks to Andy Mueller)
- Many built-in factors: logic, knapsack, dense, and some structured factors
- You can implement your own factor (only need to write a local MAP decoder!)
- Toy examples included (parsing, coreference, Potts models)

Try It Yourself: TurboParser



- Freely available at: *http://www.ark.cs.cmu.edu/TurboParser*
- Implemented in C++, includes a Python wrapper
- Not just parsing, but a full NLP pipeline now!
- Includes multilingual POS tagging, dependency parsing, semantic role labeling, entity recognition, coreference resolution (all trainable on any dataset).

Outline

1. Turbo Parsers

2. **Parsing as Reduction**
   - Dependencies and Constituents
   - Head-Ordered Dependency Trees
   - Reduction-Based Constituent Parsers
   - Experiments
   - Conclusions

In a Nutshell (Fernández-González and Martins, 2015, ACL)

- Constituent parsers are slow (heavy grammar constant)
- Dependency parsers are faster, but their output is less informative
- How to get the best of both worlds?

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Our proposal: a reduction of constituent parsing to dependency parsing

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Our proposal: a reduction of constituent parsing to dependency parsing

- Rooted in a novel formalism: **head-ordered dependency trees**
- Works for **any out-of-the-box dependency parser**
- Competitive for English and morphologically rich languages
- Results above the state of the art for **discontinuous parsing**

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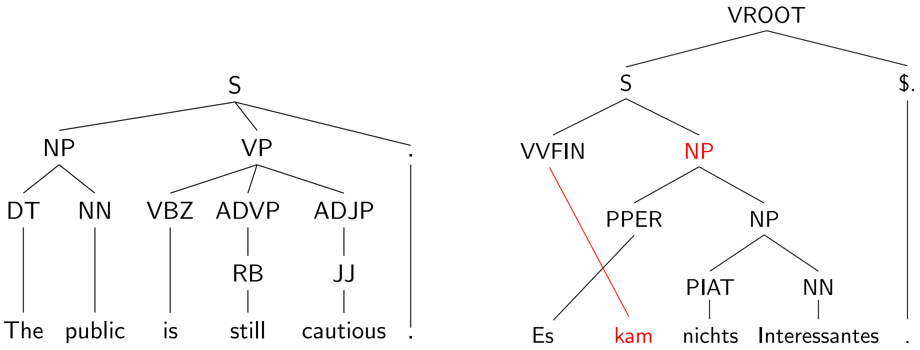
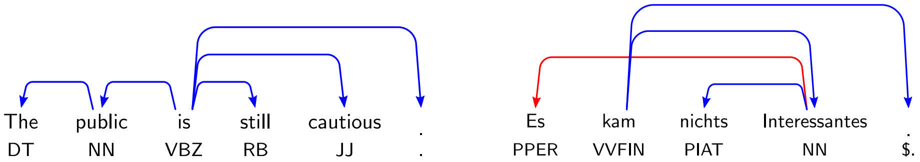
Continuous and Discontinuous C-Trees



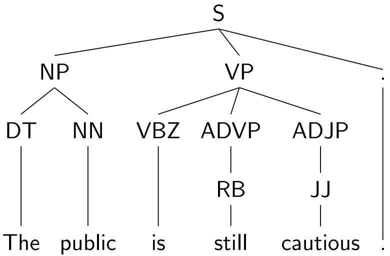
- CFG generate **continuous** trees, LCFRS generate **discontinuous** trees (Vijay-Shanker et al., 1987)
- ... but existing discontinuous parsers are too slow and inaccurate!

Projective and Non-Projective D-Trees



- Continuous and discontinuous c-trees “project” respectively to **projective** and **non-projective** d-trees (Gaifman, 1965)
- Non-projectiveness is suitable for languages with flexible word order (Dutch, German, Czech, etc.)

Projecting C-Trees onto D-Trees...



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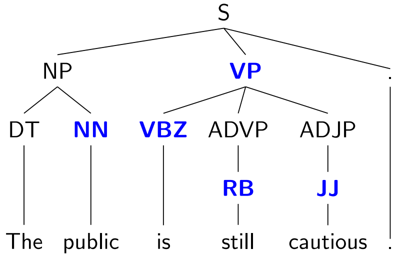

1. apply set of head rules:

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NP	$\rightarrow$	DT NN
VP	$\rightarrow$	VBZ ADVP ADJP
		...

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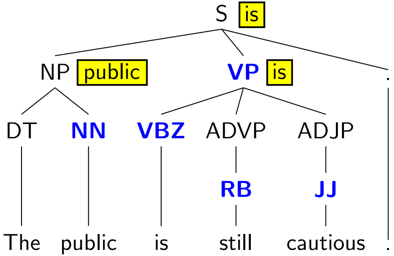

1. apply set of head rules:

   S → NP **VP** .
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   VP → **VBZ** ADVP ADJP
   ...

2. lexicalize

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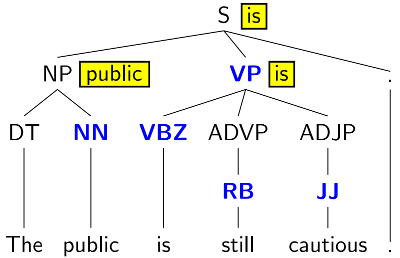

1. apply set of head rules:

S	$\rightarrow$	NP VP .
NP	$\rightarrow$	DT NN
VP	$\rightarrow$	VBZ ADVP ADJP
		...

2. lexicalize
3. drop constituent nodes

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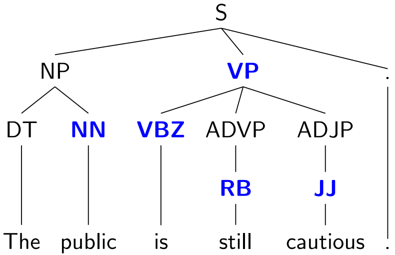
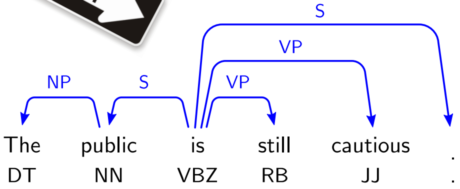
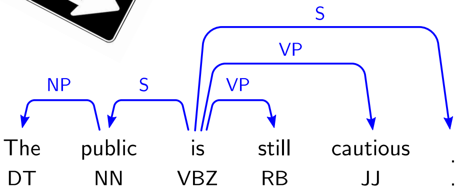




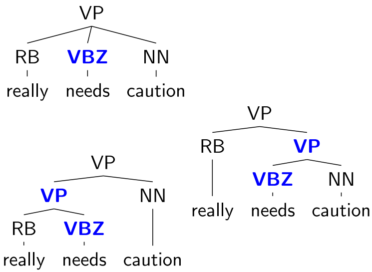
... And Back?

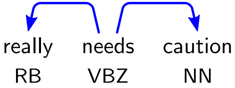


… And Back?

really	needs	caution
RB	VBZ	NN

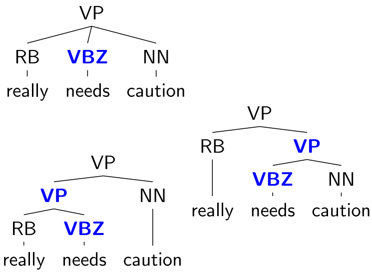
… And Back?

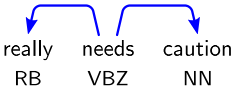




left-branch? right-branch? flat?

… And Back?





left-branch? right-branch? flat?

This paper: formal equivalence results to "invert" this projection.

Related Work

- Store structural information in the dependency labels (Hall and Nivre, 2008)
- Manual transformation rules toward multi-representational treebanks (Xia and Palmer, 2001; De Marneffe et al., 2006; Xia et al., 2008)
- Apply second-stage constituent parser (Kong et al., 2015)
- Joint dependency and constituent parsing (Carreras et al., 2008; Rush et al., 2010)

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Key idea: endow d-trees with additional structure, by making each head attach its modifiers in a particular order

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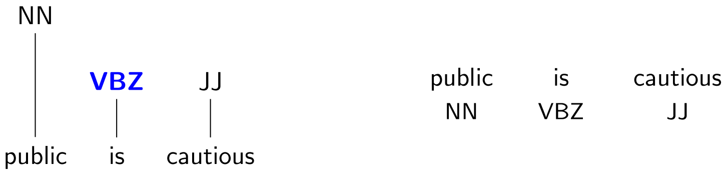

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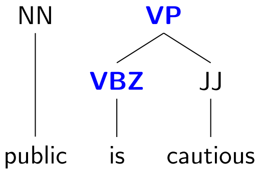

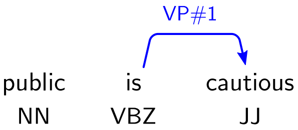

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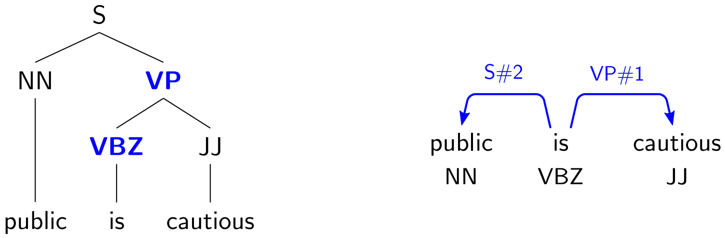
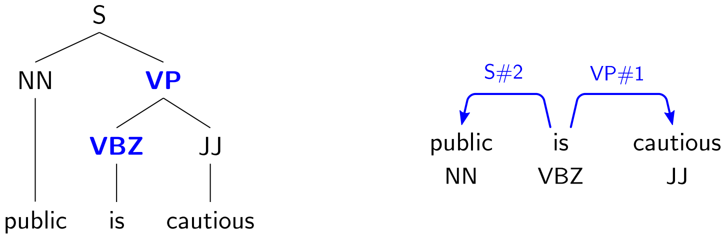


Strictly Ordered D-Trees

Key idea: endow d-trees with additional structure, by making each head attach its modifiers in a particular order



Proposition

Binary c-trees = strictly ordered d-trees

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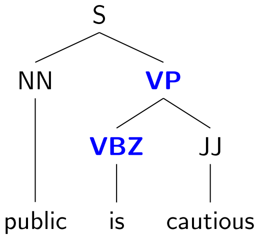
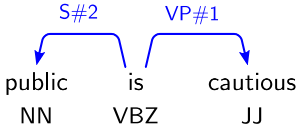




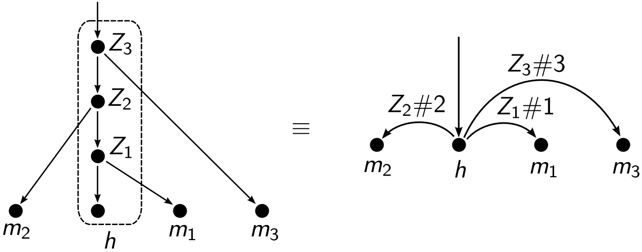
Proposition

Binary c-trees = strictly ordered d-trees

- Same number of symbols (dependency alphabet = phrasal alphabet)

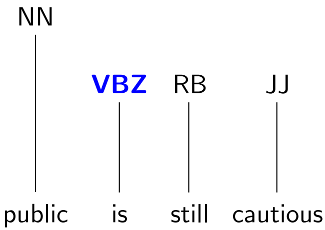
The Spinal View

- The order is given by the attachment position in the **spine** (Carreras et al., 2008)



Weakly Ordered D-Trees

Same, but allow **simultaneous** events (as long as the d-label is consistent)



public	is	still	cautious
NN	VBZ	RB	JJ

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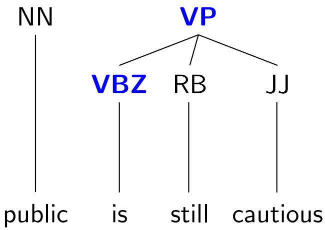

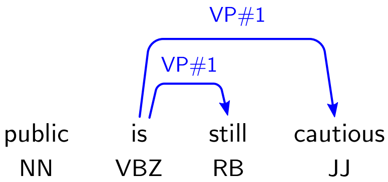

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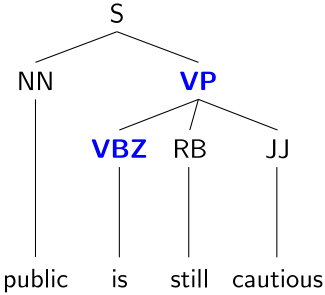

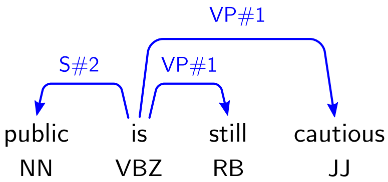

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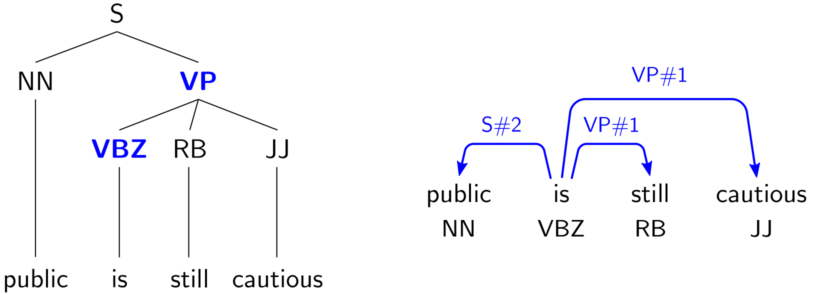

- Can every c-tree be represented like this?

Weakly Ordered D-Trees

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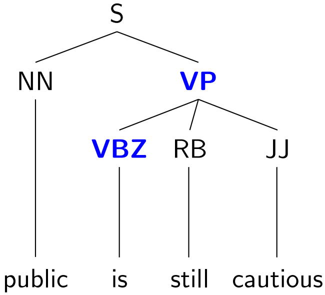

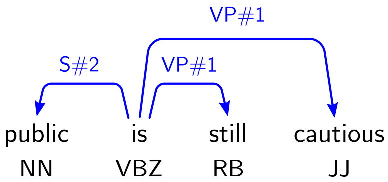

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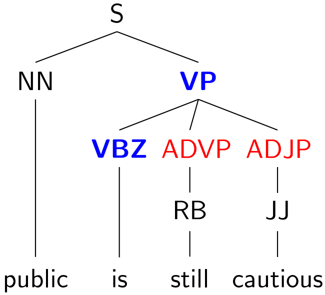

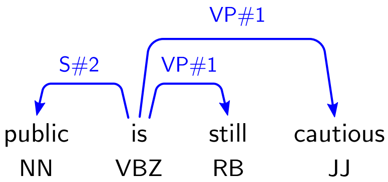

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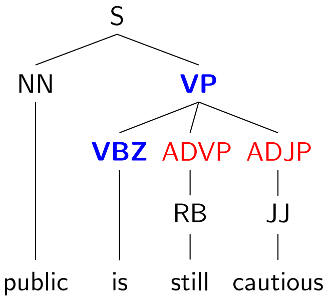

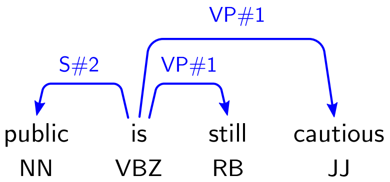

- Can every c-tree be represented like this? **No: unaries are lost.**

Proposition

Unaryless c-trees = weakly ordered d-trees

What About Projective Trees?

A head-ordered d-tree has the **nesting property** if, on each side of every head, closer modifiers are attached first.

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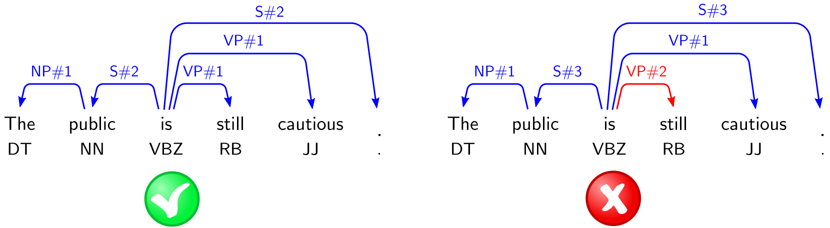

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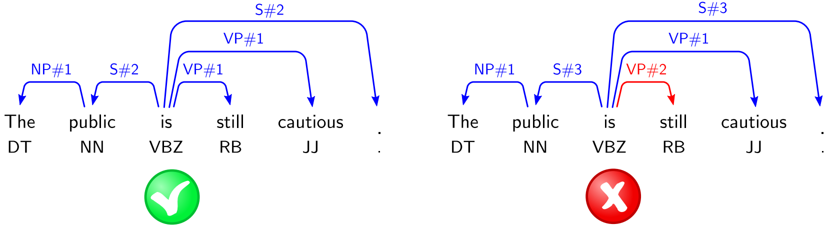
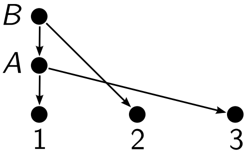


Proposition

Unaryless continuous c-trees = nested-weakly ordered projective d-trees

The Spinal View for Discontinuities

- Projective, but not nested:



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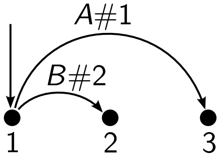
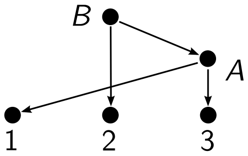


- Nested, but not projective:



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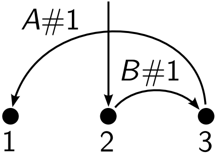

Outline

Reduction-Based Constituent Parsers

1. Convert c-treebank to head-ordered d-treebank. ✓
2. Encode head-orders in the d-labels, yielding a d-treebank.
3. Train a d-parser on the d-treebank.
4. Run the d-parser on new sentences. ✓
5. Convert the predicted d-trees into unaryless c-trees. ✓
6. Recover unary nodes.

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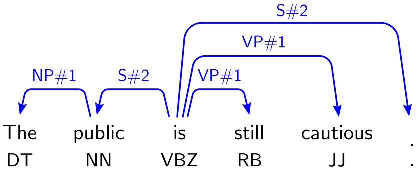
Label Encoding Strategies

direct encoding



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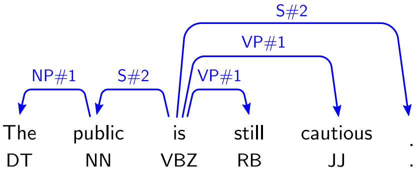
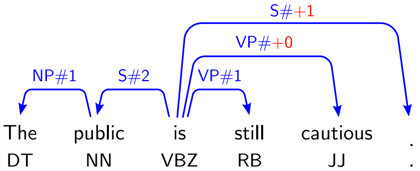


delta encoding



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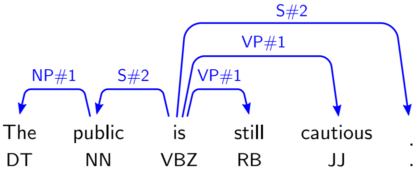

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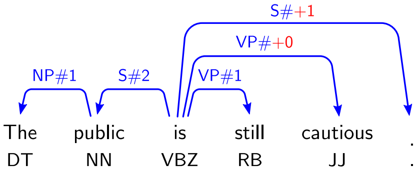
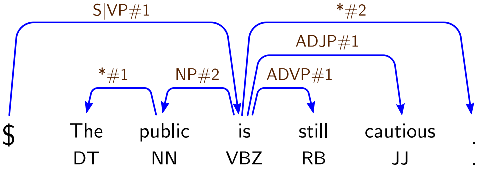


H&N encoding (Hall and Nivre, 2008)



Impact of Label Encoding

- Evaluated on the English PTB §22 (Marcus et al., 1993).

	# labels	dep (LAS)	const (F_1)
H&N encoding	731	87.86	89.39
Direct encoding	75	91.99	90.89
Delta encoding	**69**	**92.00**	**90.94**

- H&N encoding overgenerates labels, leading to a loss in accuracy
- Delta encoding performs consistently better than direct encoding on other datasets (see paper)

Reduction-Based Constituent Parsers

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Choice of Dependency Parser

- Evaluated on the English PTB §22 (Marcus et al., 1993).

Dependency Parser	**Dep (LAS)**	**Const (F_1)**	**# toks/s.**
MaltParser	88.95	86.87	5,392
MSTParser	89.86	87.93	363
ZPar	91.28	89.50	1,022
TurboParser-Basic	90.23	87.63	2,585
TurboParser-Standard	91.58	90.41	1,658
TurboParser-Full	91.70	90.53	959
TurboParser-Full + Labeler	**92.00**	**90.94**	912

- Best results: separate stages for d-parser and d-labeler
- The d-labeler is a simple sequence model for each head (see paper)

Reduction-Based Constituent Parsers

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Recovery of Unary Nodes

- We run independent classifiers at each c-node
- Each class is either `NULL` (no unary node pre-appended) or a concatenation of labels (*e.g.*, `S->ADJP` for a node `JJ`)
- To speed-up: only observed classes are considered (9.9 classes per node in PTB §22)
- A tiny fraction of the time is spent on this post-processing ($<$2%), with F_1-score of 99.43% in PTB §22

Outline

Experiments: English PTB

- Results on the English PTB §23 (Marcus et al., 1993).

Parser	LR	LP	F1	#Toks/s.
Klein and Manning (2003)	85.3	86.5	85.9	143
Hall et al. (2014)	88.4	88.8	88.6	12
Socher et al. (2013)	*89.1*	*89.7*	*89.4*	*70*
Charniak (2000)	89.5	89.9	89.5	–
Stanford Shift-Reduce (2014)	89.1	89.1	89.1	655
Petrov and Klein (2007)	90.0	90.3	90.1	169
This work	89.9	90.4	90.2	957
Zhu et al. (2013)	90.3	90.6	90.4	1,290
Carreras et al. (2008)	90.7	91.4	91.1	–
Zhu et al. (2013)	*91.1*	*91.5*	*91.3*	–
Charniak and Johnson (2005)	*91.2*	*91.8*	*91.5*	*84*

Grayed parsers are ensemble/reranking/semi-supervised systems.

Experiments: Morphologically Rich Languages

- Results on SPMRL14 shared task datasets (Seddah et al., 2014).

Parser	Bas	Fre	Ger	Heb	Hun	Kor	Pol	Swe	Avg.
Berkeley	70.50	**80.38**	78.30	86.96	81.62	71.42	79.23	79.19	78.45
Berkeley Tagged	74.74	79.76	78.28	85.42	85.22	78.56	86.75	80.64	81.17
Crabbé and Seddah (2014)	85.35	79.68	77.15	86.19	87.51	79.35	**91.60**	82.72	83.69
Hall et al. (2014)	83.39	79.70	78.43	87.18	**88.25**	**80.18**	90.66	82.00	83.72
This work	**85.90**	78.75	**78.66**	**88.97**	88.16	79.28	91.20	**82.80**	**84.22**
Björkelund et al. (2014)	*88.24*	*82.53*	*81.66*	*89.80*	*91.72*	*83.81*	*90.50*	*85.50*	*86.72*

Experiments: Discontinuous Parsing

- Results on the discontinuous TIGER treebank (Brants et al., 2002).

	TIGER-SPMRL, $L \leq 70$	F_1	EX
gold tags	Versley (2014b)	76.46	41.05
	This work	**80.98**	**43.44**
pred. tags	Versley (2014b)	73.90	37.00
	This work	**77.72**	**38.75**

	TIGER-H&N, $L \leq 40$	F_1	EX
gold tags	Hall and Nivre (2008)	79.93	37.78
	Versley (2014a)	74.23	37.32
	This work	**85.53**	**51.21**
pred. tags	Hall and Nivre (2008)	75.33	32.63
	van Cranenburgh and Bod (2013)	78.8–	40.8–
	This work	**82.57**	**45.93**

Experiments: Discontinuous Parsing

- Results on the discontinuous NEGRA treebank (Skut et al., 1997).

	NEGRA, $L \leq 40$	**F_1**	**EX**
gold tags	van Cranenburgh (2012)	72.33	33.16
	van Cranenburgh and Bod (2013)	76.8–	40.5–
	This work	**81.08**	**48.04**
pred. tags	van Cranenburgh and Bod (2013)	74.8–	38.7–
	This work	**77.93**	**44.83**

- We parse all sentences (regardless of length) in 27.1 seconds in a single core (618 toks/sec)
- Orders of magnitude faster than van Cranenburgh and Bod (2013)
- Similar speed as the easy-first system of Versley (2014a), but much higher accuracy

Outline

1. Turbo Parsers

2. **Parsing as Reduction**
   - Dependencies and Constituents
   - Head-Ordered Dependency Trees
   - Reduction-Based Constituent Parsers
   - Experiments
   - Conclusions

Conclusions

- We proposed a **reduction technique** that allows to implement a constituent parser when only a dependency parser is available.
- The technique is very **simple** and **flexible**: applicable to any dependency parser, regardless of its nature or kind.
- If the dependency parser is non-projective, we can predict **discontinuous constituent trees**.
- We showed empirically that the reduction leads to highly-competitive constituent parsers for English and 8 morphologically rich languages.
- We surpassed the state of the art in discontinuous parsing of German by a wide margin.

We're Hiring!

Excited about MT, crowdsourcing and Lisbon? $\Rightarrow$ jobs@unbabel.com.

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Acknowledgments

- Spanish Ministry of Economy and Competitiveness and FEDER (project TIN2010-18552-C03-01)
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- Priberam: QREN/POR Lisboa (Portugal), EU/FEDER programme, Intelligo project, contract 2012/24803.

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