Incremental Parsing with TAG

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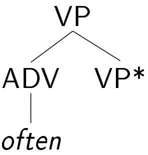
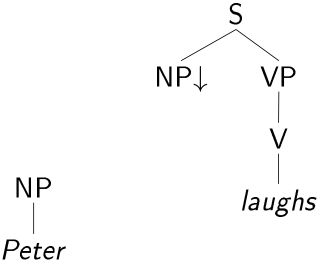
Tree Adjoining Grammar (TAG)

- tree-rewriting formalism
- a set of (elementary) trees with two operations

initial trees

auxiliary trees



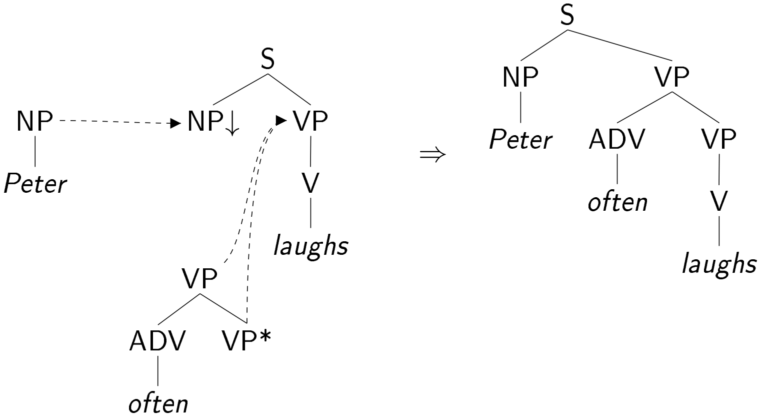


Tree Adjoining Grammar

Operations

Substitution Replacing a leaf with an initial tree

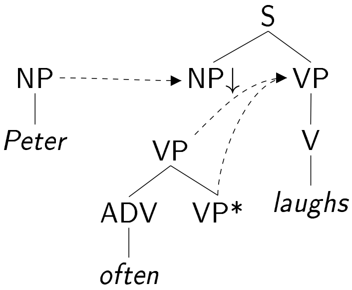
Adjunction Replacing an internal node with an auxiliary tree



Tree Adjoining Grammar

Some linguistic principles:

- Lexicalization: Each elementary tree has at least one non-empty lexical item, its anchor. (LTAG)
- Predicate argument co-occurence: Elementary trees of predicates contain slots for the arguments they subcategorize for.



Why is TAG interesting?

- **Mildly context-sensitive** formalism
  1. It generates (at least) all context-free languages.
  2. It captures a limited amount of cross-serial dependencies, e.g. the copy language $\{ww|w \in \{a,b\}^*\}$.
  3. It can be parsed in polynomial time. $(O(n^6))$
  4. It has constant growth property.

  $\Rightarrow$ appropriate to describe natural languages

- Important characteristics
  1. **Extended domain of locality** - elementary trees can be arbitrarily large.
  2. **Factoring of recursion** - adjunction operations allows to put recursive structures into separate elementary trees.

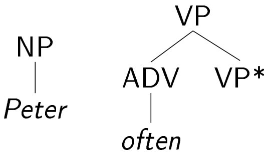
Why incremental parsing?

- Psycholinguistic evidence
  - Humans build up semantic representation before reaching the end of the sentence.
  - Interpretation is based on fast, left-to-write construction of syntactic relations.
- Boost in speed

Incremental TAG parsing

- [Sturt and Lombardo, 2005] argue that models of human parsing incorporate an operation similar to adjunction in TAG.
- Traditional LTAG does not allow full connectedness.

Peter often ...



Where is incrementality encoded?

Components of a parser:

- a (competence) grammar
- a parsing strategy
- a memory organizing strategy
- an oracle

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Approaches

LTAG-spinal - "Incremental" parser

Incremental LTAG Parsing
L. Shen and A. K. Joshi (2005)

DVTAG - Strictly incremental parser

Dynamic TAG and lexical dependencies
A. Mazzei, V. Lombardo and P. Sturt (2007)

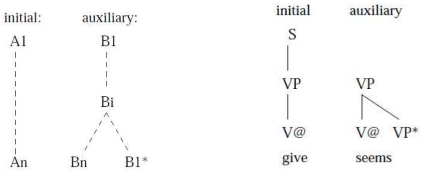
Outline

Outline

LTAG-spinal

Variant of LTAG

- initial tree only contains its *spine*
- auxiliary tree only contains its *spine* and a foot node directly linked to the spine



Definition: Spine

The *spine* of an elementary tree is the path from the root node to the anchor of the tree.

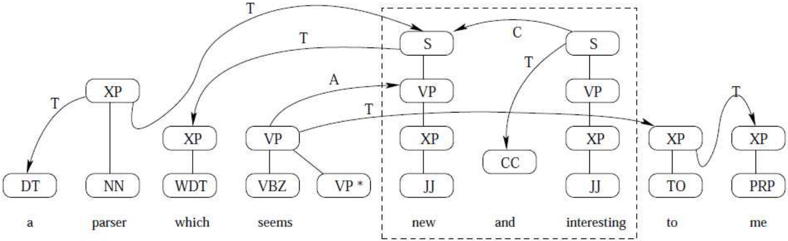
LTAG-spinal formalism

Operations

Adjunction (A) Same as in LTAG.

Attachment (T) Attachment of an initial tree α to a node n of another tree α': add the root of α to n as a new child.

Conjunction (C) Special operation to build coordination structures.



LTAG-spinal formalism

Relation to LTAG

- LTAG-spinal is more powerful than CFG. [Shen and Joshi, 2005a]
- LTAG-spinal with attachment constraints is weakly equivalent to traditional LTAG. [Shen et al., 2007]

LTAG-spinal formalism

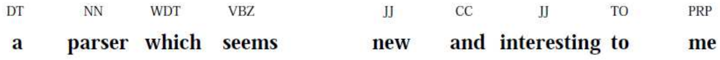
Relation to LTAG

- LTAG-spinal is more powerful than CFG. [Shen and Joshi, 2005a]
- LTAG-spinal with attachment constraints is weakly equivalent to traditional LTAG. [Shen et al., 2007]
- LTAG-spinal trees generalize over predicates with different subcategorization frames.

The Parsing Algorithm

- Four types of **parser operations**:
  - Attachment, adjunction, conjunction
  - Generation: generate a possible spine for a given word according to the context and the lexicon (Supertagging)
- Variant of the shift-reduce algorithm, using a **stack of disconnected treelets** to represent the left context
  - **Shift**: Read a word, generate a list of possible elementary trees for this word. For each elementary tree, push it into the stack.
  - **Reduce**: Pop the top two treelets from the stack, combine them by attachment, adjunction or conjunction and push the combined tree into the stack.
- Beam-search to prune the search space

Example



G: generate T: attach A: adjoin C: conjoin

Graph taken from `http://libinshen.net/Documents/ijc04_slides.ps`

Example

1 G								
$\boxed{\text{DT}}$	NN	WDT	VBZ	JJ	CC	JJ	TO	PRP
a	**parser**	**which**	**seems**	**new**	**and**	**interesting**	**to**	**me**

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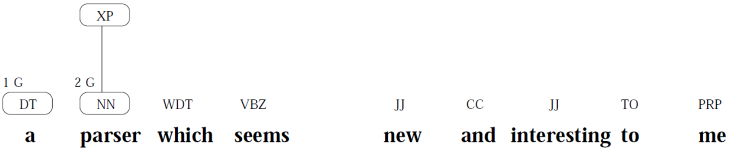
Example



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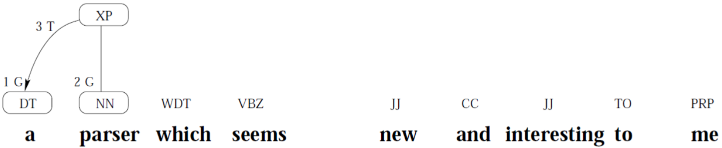

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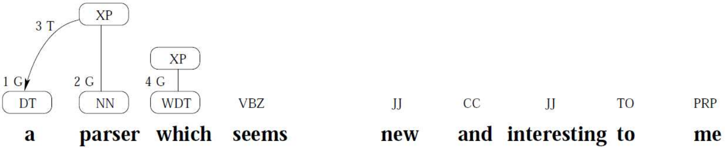

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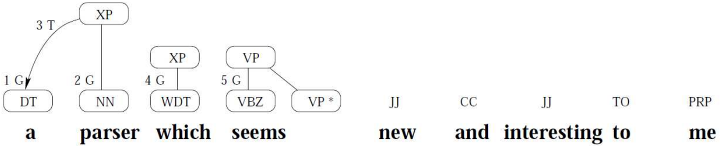

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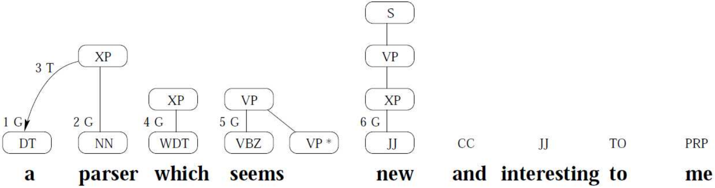

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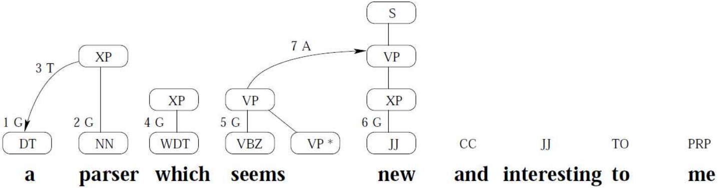

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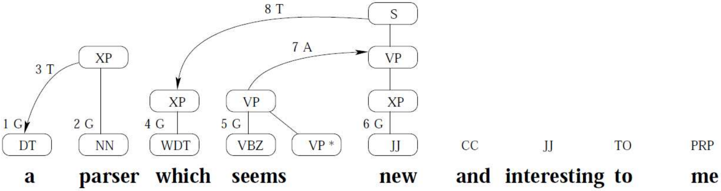

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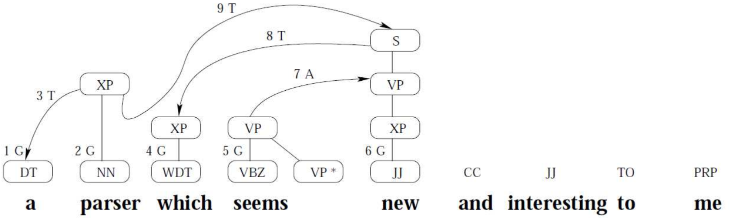

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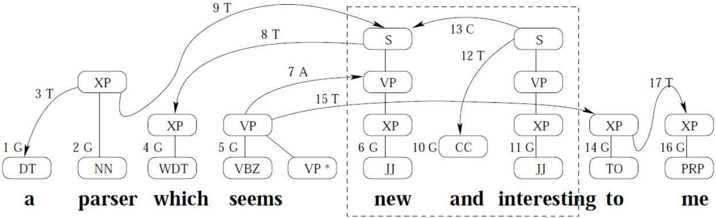

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Flex Model vs. Eager Model

Pseudo-ambiguity in the shift-reduce derivation:
A adjoins to B, B adjoins to C

- $((A \rightarrow B) \rightarrow C)$
- $(A \rightarrow (B \rightarrow C))$

Flex Model vs. Eager Model

Pseudo-ambiguity in the shift-reduce derivation:
A adjoins to B, B adjoins to C

- $((A \rightarrow B) \rightarrow C)$
- $(A \rightarrow (B \rightarrow C))$

Flex Model

- Both derivations are allowed.

Eager Model

- Only $((A \rightarrow B) \rightarrow C)$ is allowed.

Features and Learning

Features extracted from gold-standard parses have the following format:

(`operation`, `main_spine`, `child_spine`, `spine_node`, `context`)

- `spine_node`: node on the `main_spine` onto which the `child_spine` is attached/adjoined/conjoined
- `context`: dependent on the type of operation; includes amongst others the (0,2) window in the sentence

Weights for the features are learned using a perceptron-like algorithm as proposed in [Collins, 2002].

Evaluation

- LTAG-spinal treebank (see [Shen and Joshi, 2005b])
- Training, development and test data from WSJ
- Syntactic dependency for evaluation against PTB

model	beam	sen/sec	f-score %
Flex	10	0.37	89.3
Eager	10	0.79	88.7

With an extension (Combined Parses) and beam=100: 94.2%

What we have seen so far

Parser for LTAG-spinal

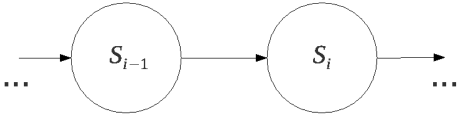
- Incremental?
  - Input is processed incrementally, but only partially
  - Structure is not fully connected (usage of a stack)
  - Look-ahead of 2 words
- Implemented: efficient statistical parsing
- Generative power of grammar is stronger than CFG
- Motivation?

Outline

Dynamics

Dynamic Grammar

- The syntactic analysis is viewed as a dynamic process
  $\Rightarrow$ A sequence of **transitions** between adjacent syntactic **states** S_{i-1} and S_i.
- A syntactic state contains all the syntactic information about the fragment already processed.



Dynamics and Incrementality

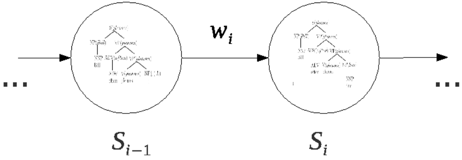
Incremental processing:

- Each input word w_i defines a transition from S_{i-1} (left-context) to S_i.
- States as partial syntactic structures

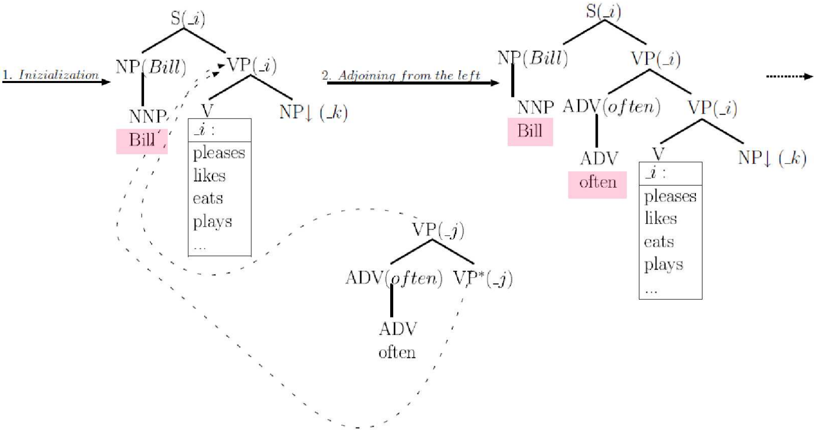
Strong connectivity:

- Impose that transitions do not produce disconnected trees

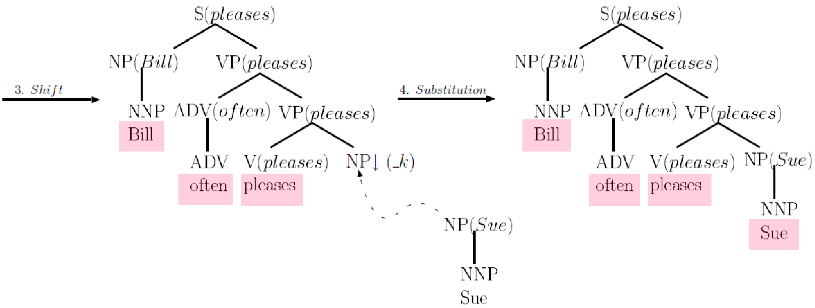
Parsing strategy is part of the grammar
$\Rightarrow$ Incrementality-in-compentence



Dynamics in TAG - Intuition (I)



Dynamics in TAG - Intuition (II)



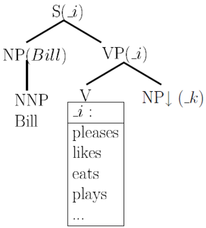
At step i, the elementary tree anchored in w_i is combined with the partial structure spanning the words $w_1 \ldots w_{i-1}$.

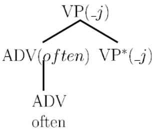
$\Rightarrow$ Updated left-context spanning the words $w_1 \ldots w_i$

DVTAG

Dynamic Version of TAG

Elementary trees similar to LTAG trees, BUT



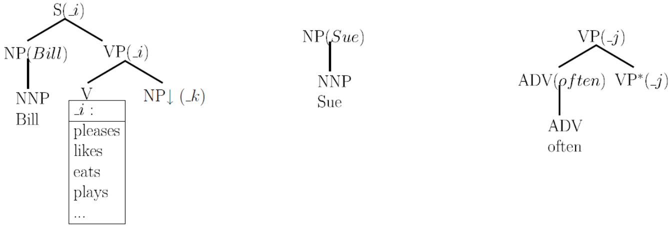


DVTAG

Dynamic Version of TAG

Elementary trees similar to LTAG trees, BUT

- Lexical items (but not the left-anchor) can be **underspecified**. The preterminal category is paired with a finite list of values. $\Rightarrow$ **predicted nodes** to fulfill full connectivity

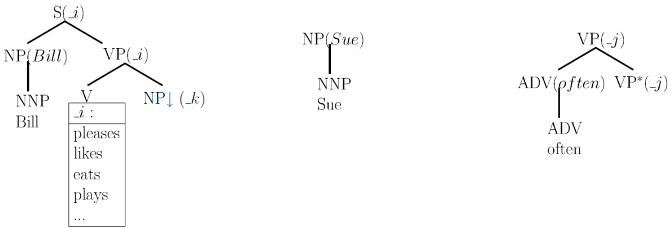


DVTAG

Dynamic Version of TAG

Elementary trees similar to LTAG trees, BUT

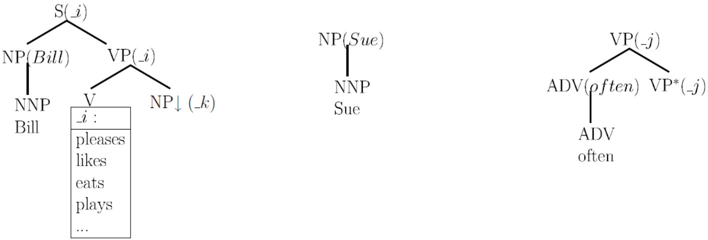
- Lexical items (but not the left-anchor) can be **underspecified**. The preterminal category is paired with a finite list of values. $\Rightarrow$ **predicted nodes** to fulfill full connectivity
- Distinction between left/right auxiliary trees



DVTAG

Head feature

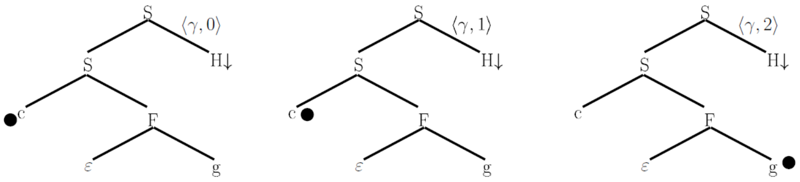
- Feature that indicates the lexical head of each node in the elementary tree
- Needed to compute a *dependency tree*



Some DVTAG terminology

Dotted tree

A pair $\langle \gamma, i \rangle$ where γ is a tree and i is an integer such that $i \in 0 \ldots |YIELD(\gamma)|$.
Moreover, all the symbols on the yield that are on the left of the dot are terminal symbols.



Fringe of $\langle \gamma, i \rangle$
Set of nodes that are accessible for operations

DVTAG Operations

Combination of a left-context $\langle \Lambda, i \rangle$ with an (unanalysed) elementary tree $\langle \gamma, 0 \rangle$

- 2 substitution operations
- 4 adjoining operations
- a shift operation

"Normal" operations

- Substitution $Sub^{\rightarrow}$
- Adjoining from the left $\nabla_L^{\rightarrow}$
- Adjoining from the right $\nabla_R^{\rightarrow}$
- Shift Shi

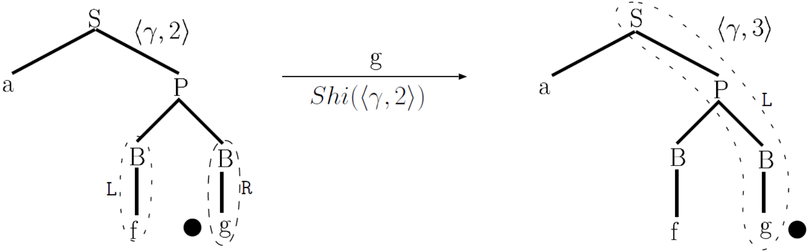
Inverse operations

- Inv. substitution $Sub^{\leftarrow}$
- Inv. adj. from the left $\nabla_L^{\leftarrow}$
- Inv. adj. from the right $\nabla_R^{\leftarrow}$

DVTAG Operations

Shift

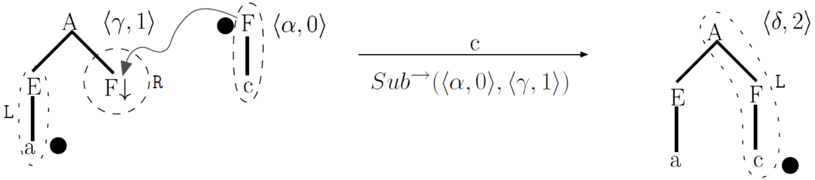
$Shi(\langle\gamma, i\rangle)$ takes as input a single dotted tree $\langle\gamma, i\rangle$ and returns the dotted tree $\langle\gamma, i+1\rangle$. It can be applied only if a terminal symbol belongs to the fringe of $\langle\gamma, i\rangle$.



DVTAG Operations

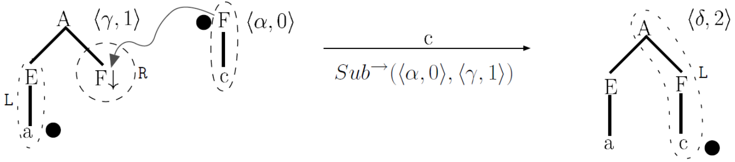
Substitution

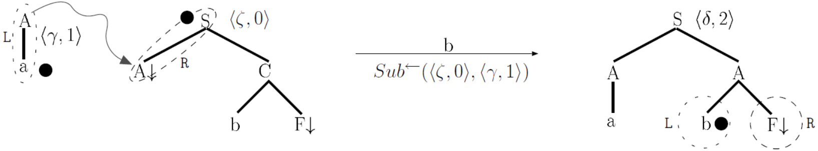
$Sub^{\rightarrow}(\langle\alpha,0\rangle,\langle\gamma,i\rangle)$:
If there is a substitution node N in the fringe of $\langle\gamma,i\rangle$ such that $label(N)=label(root(\alpha))$, the operation returns a new dotted tree $\langle\delta,i+1\rangle$ such that δ is obtained by grafting α into N.



DVTAG Operations

Substitution and inverse Substitution

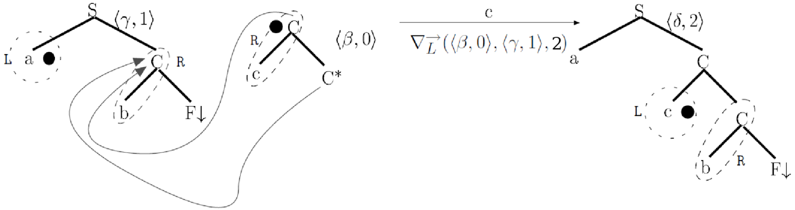




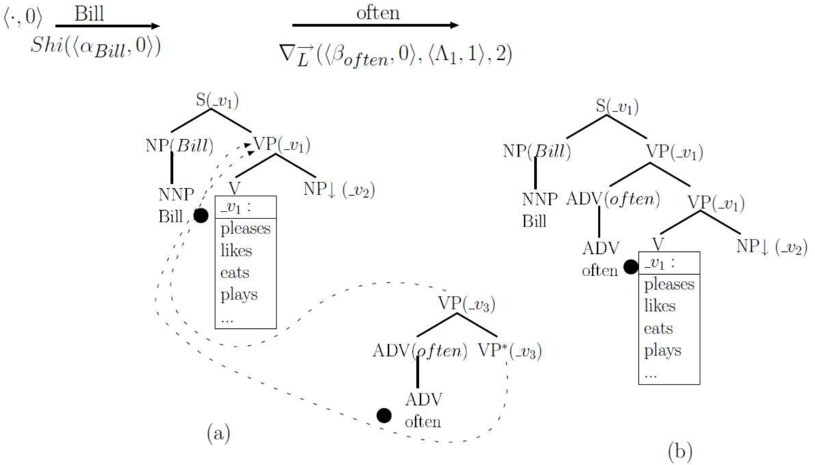
DVTAG Operations

Adjoining from the left

$\nabla_L^{\rightarrow}(\langle\beta,0\rangle,\langle\gamma,i\rangle,add)$ where β is a left auxiliary tree:
If there is a non-terminal node N at position add in the fringe of $\langle\gamma,i\rangle$ such that $label(N) = label(root(\beta))$, the operation returns a new dotted tree $\langle\delta,i+1\rangle$ such that δ is obtained by grafting β into N.



Example derivation



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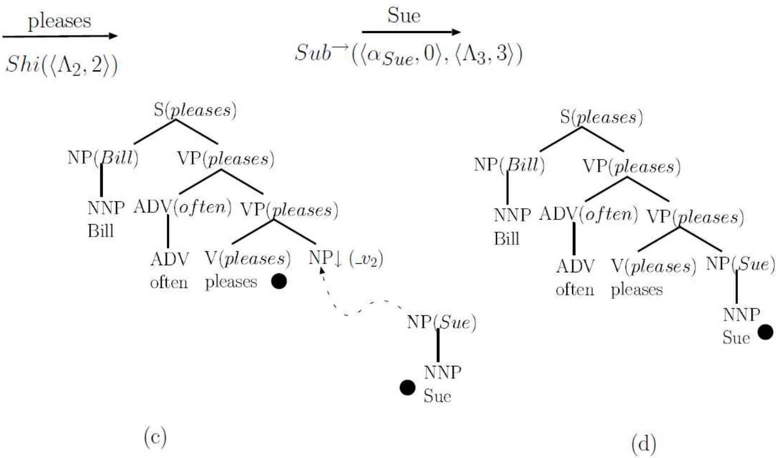

A wide-coverage DVTAG

Ways to build a grammar:

1. Manually write it (XTAG, FTAG)
2. Automatically extract it from treebanks

Anticipated problem: Size of grammar because of predicted nodes

Grammar seizes in comparison

	# of tree templates
XTAG	1,200
DVTAG from XTAG	6,000,000

Grammar seizes in comparison

	# of tree templates
XTAG	1,200
DVTAG from XTAG	6,000,000
DVTAG from PTB	12,000

Grammar seizes in comparison

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DVTAG from PTB	12,000
LTAG-spinal	1,200

Numbers are taken from [Mazzei, 2005] and [Shen et al., 2007], and rounded.

Outline

Conclusion

LTAG-spinal

- Parsing strategy specifies the "incremental" nature.
- In fact, not very incremental (stack, look-ahead)
- Efficient, implemented parser available

DVTAG

- The (competence) grammar determines the parsing strategy
- Natively fulfills a strict version of incrementality
- Resembles left-corner strategy ($\Rightarrow$ center embeddings)
- Grammars grow very large in size

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Discussion

- Why would we want incrementality in competence?
- For NLP applications the "incremental" parser might be enough.
- Can psycholinguistic findings/memory profiles be explained with these grammers?