Incremental Tree-Adjoining Grammars

Vera Demberg

Cluster of Excellence “Multimodal Computing and Interaction”
Universität des Saarlandes

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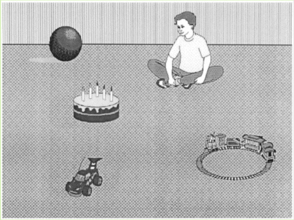
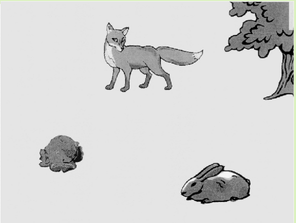
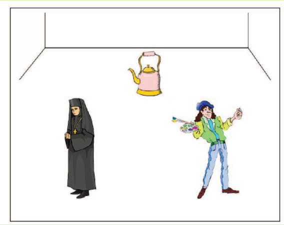
Reminder last week's materials

Evidence for incremental processing and even predictive processes

- Visual World and Eye-tracking
- Eye-tracking in Reading
- ERP / EEG







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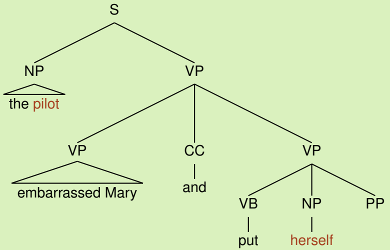
Either..or



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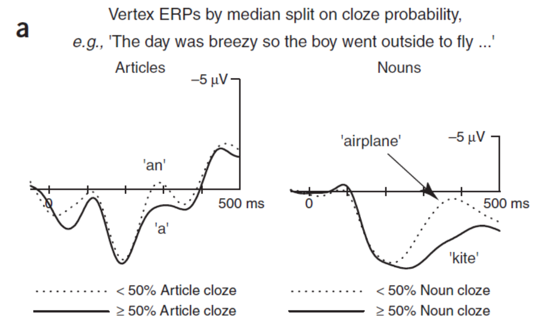

Reminder of last weeks experimental findings

Results and Conclusions:

- Processing is generally **incremental** (syntax and semantics)
- Evidence for syntactic connectedness at specific points in the sentence (c-command relation)
- People **anticipate arguments**
- They do **not anticipate adjuncts**

Question for next few sessions:
How can we model incremental processing?

Reminder of last weeks experimental findings

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How can we model incremental processing?

Psycholinguistic Modelling

What is a cognitive model of language processing?

$\boxed{\text{Input: words}} \Rightarrow \boxed{\text{Output: per word difficulty}}$

- **Processing Model** (parser)
- **Linking Theory** (relates the parsing process to processing difficulty), e.g.
  - quantifying the ease with which particular structures are constructed or accessed
  - quantify how long it takes to disambiguate between alternatives
  - information theoretic measure, e.g. surprisal / entropy

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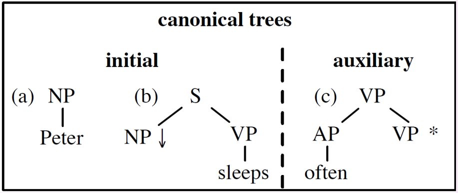
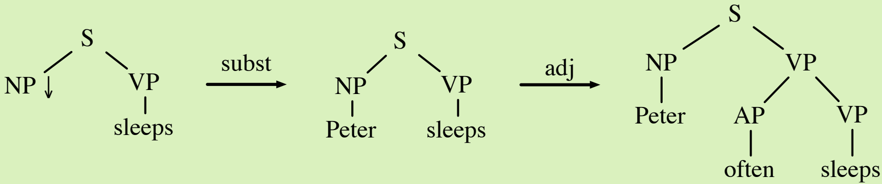
Lexicalized Tree-Adjoining Grammar

Lexicon



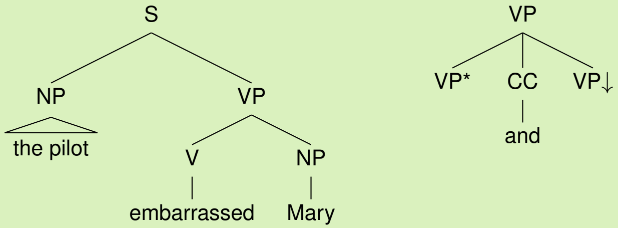
LTAG-Derivation for *Peter often sleeps.*



How suitable is TAG for explaining the experimental results we have seen?

TAG has been argued to be a suitable grammar formalism, consider:

Examples from experiments



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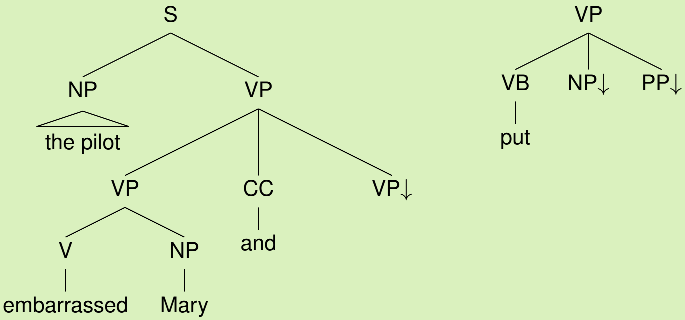

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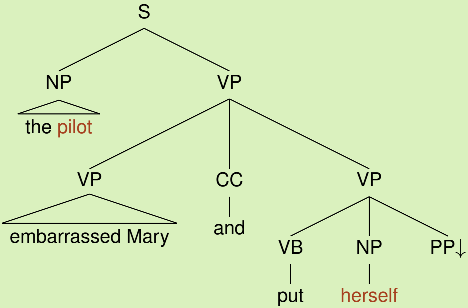

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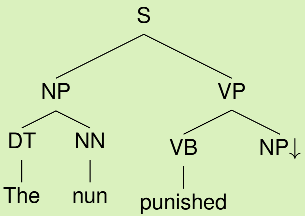

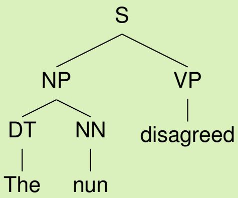

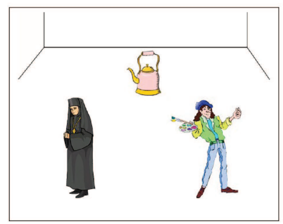

- TAG adjunction can model e.g. connectedness at *herself*.
- Subcategorization frames in elementary trees allow to account for simple prediction effects.

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LTAG and strict incrementality

But LTAG is not incremental and does not allow for general connectedness.

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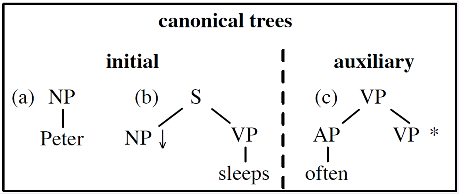

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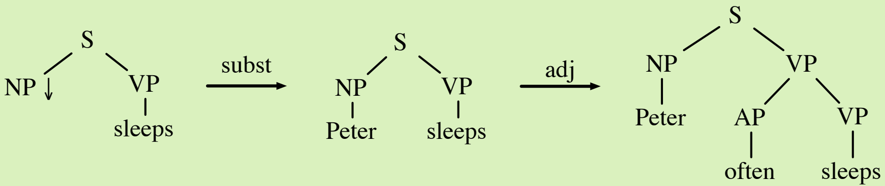


Suggestions for an incremental version of TAG.

When is LTAG not incremental?

- if we have two or more dependents but no head
- if we have a grand-parent and a child, but not parent

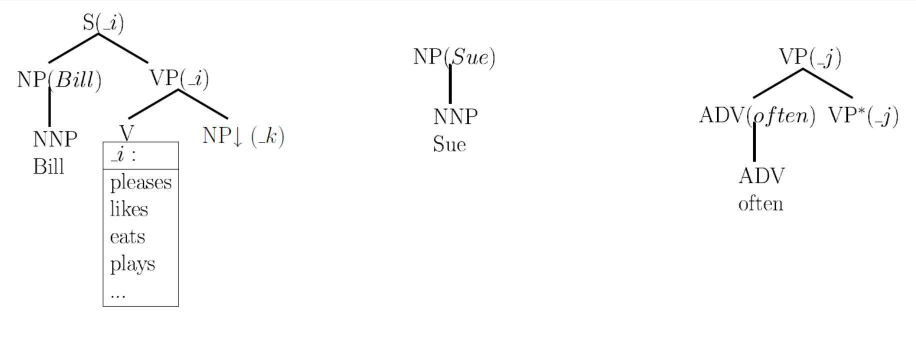
$\Rightarrow$ so need to insert missing structure

Versions of TAG that support full connectedness:

- Dynamic Version of TAG (DVTAG, Mazzei 2005)
- PsychoLinguistically motivated TAG (PLTAG, Demberg 2010)

The DVTAG Formalism (graphics taken from Mazzei 2005)

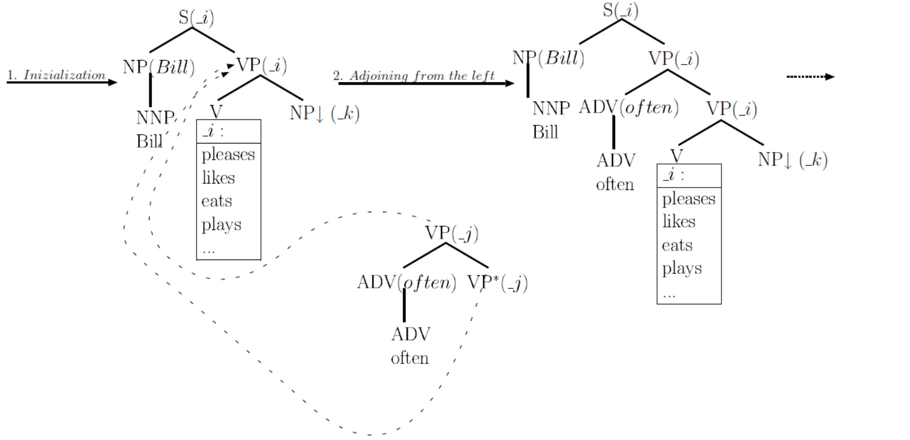
Lexicon



- Lexical items can be underspecified

The DVTAG Formalism (graphics taken from Mazzei 2005)

LTAG-Derivation for *Bill often pleases Sue.*



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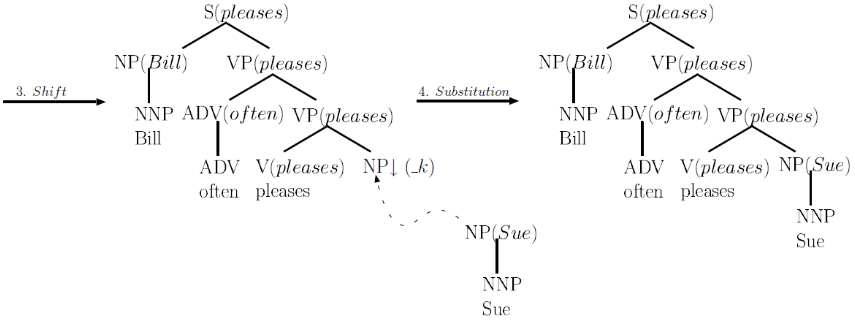
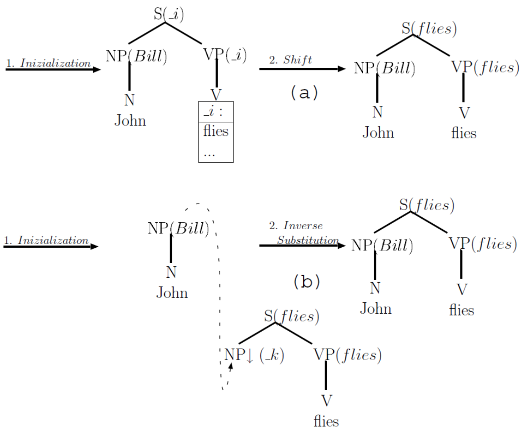


The DVTAG Formalism (graphics taken from Mazzei 2005)

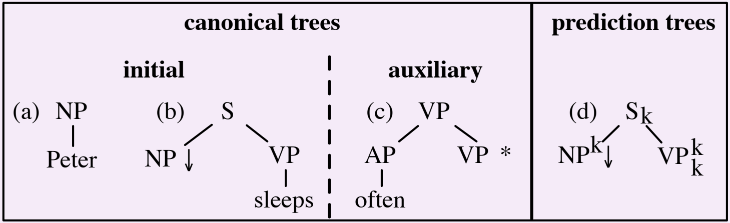
LTAG-Derivation for *Bill often pleases Sue.*

- DVTAG lexicon contains canonical trees plus additional trees which allow for connectedness
- Operations extended to *Inverse Substitution*, *Inverse Adjunction* and *Shift*
- Spurious ambiguity
- Ambiguity is in the lexicon
- DVTAG lexica are huge

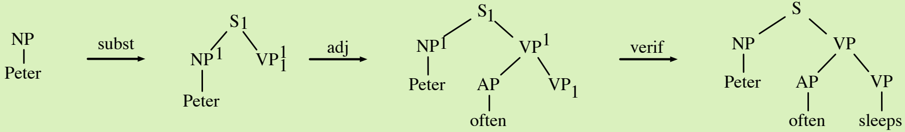


The PLTAG Formalism

Lexicon



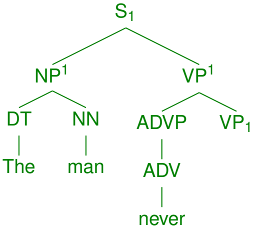
PLTAG-Derivation for *Peter often sleeps.*



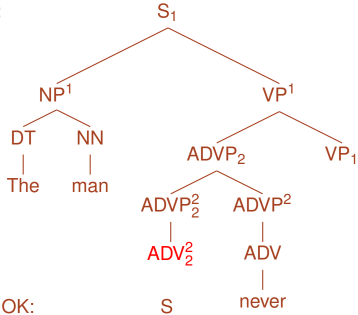
PLTAG – Valid Partial Derivations

Some examples of valid and invalid partial derivations.

OK:



not OK:



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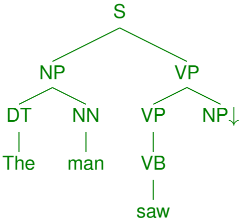

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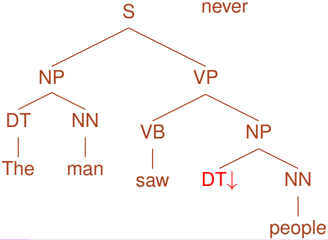
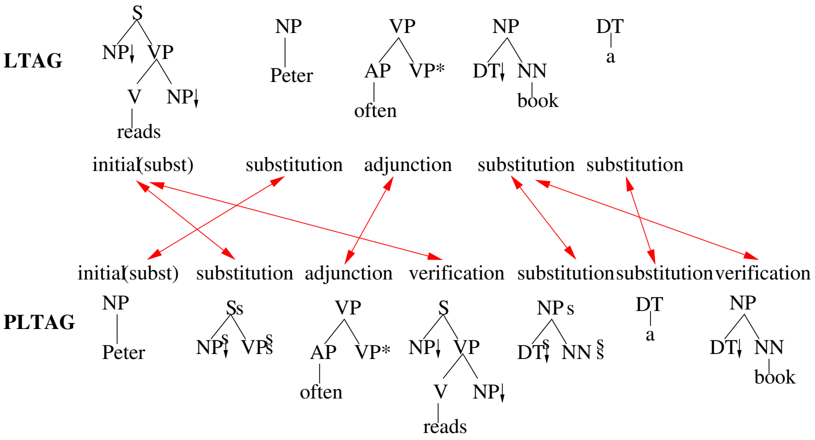


The relationship between LTAG and PLTAG

Every LTAG derivation can be translated into an equivalent PLTAG derivation.



PLTAG and LTAG are equally expressive.

Comparison DVTAG and PLTAG

- Both strongly equivalent to LTAG
- Both introduce new operations
  (inversed subst & adj, shift / verification)
- Prediction explicitly marked in PLTAG
- Prediction granularities differ
- PLTAG lexicon (7k + 3k templates) smaller than
  DVTAG lexicon (6m templates);
  (both automatically generated from PTB)
- Both formalisms support multi-anchored trees
- Parsing algorithm and broad coverage parser for
  PLTAG only.

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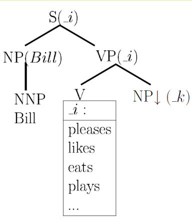

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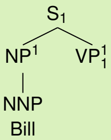

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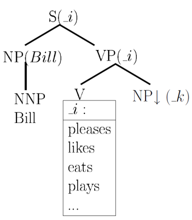

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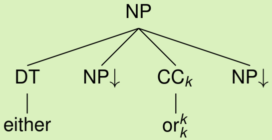

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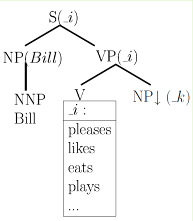

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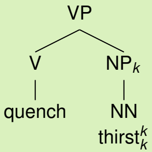

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Discussion: Incremental TAG formalisms

- What is tree adjoining grammar?
  - Where's the grammar?
  - What are the standard TAG operations?
- Why is TAG suitable for modelling experimental results?
  - the pilot embarrassed Mary and put herself in an awkward situation
  - either..or
  - prediction of arguments but not adjuncts
- In how far does TAG not support incremental processing?
- What are the mechanisms in DVTAG and PLTAG to allow for incremental derivations?

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Steps in Constructing the Parser

1. Conversion of the Penn Treebank into PLTAG format
2. Lexicon Induction
3. The Incremental Parsing Algorithm
4. The Probability Model
5. Parser Evaluation

Step 1: Treebank Conversion

Converted Penn Treebank into TAG format [Xia et al. 2000]

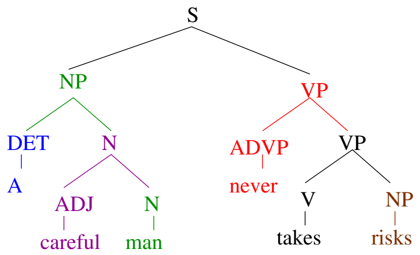
- **Head percolation table** for determining how to cut up the tree into elementary trees [Magerman, 1994]
- **PropBank** [Palmer et al., 2003] for discriminating arguments and modifiers
- **Noun phrase annotation** for the Penn Treebank [Vadas & Curran, 2007]
- Multi-anchored trees (e.g. either... or, pick... up)

The resulting structure is less flat, contains head information and argument / modifier distinction.

Step 2: Lexicon Induction

Creating the lexicon:

Sentence Tree:



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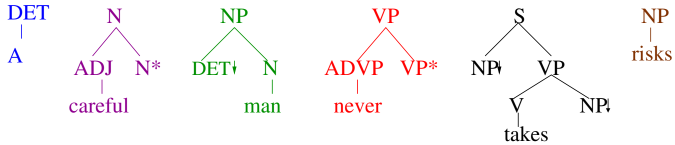

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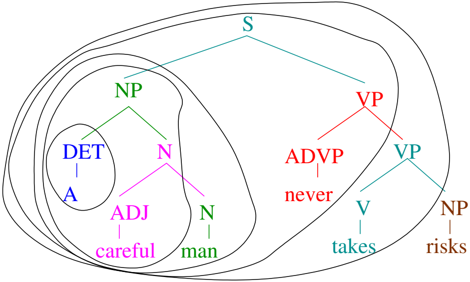
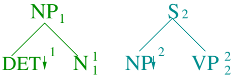


Prediction Lexicon Entries:



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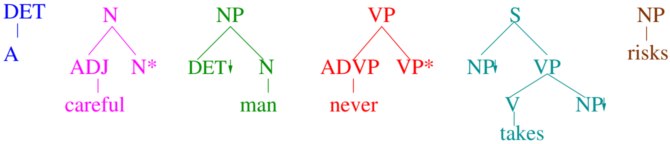
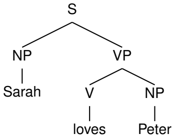


But how should we deal with the problem of indetermination?

- Prediction trees are not lexicalized.
- So a parser could use infinitely many of them at any time.
- Our approach: only allow combination of prediction trees which have been observed in training.
- Left recursion?!
- People are not able to deal with infinite left recursion either.



Sarah loves Peter

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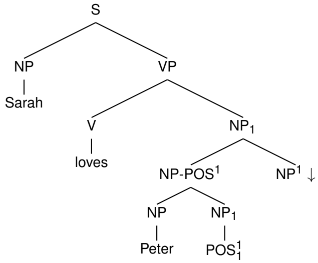

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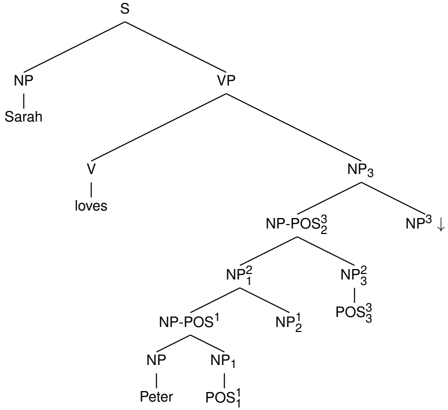

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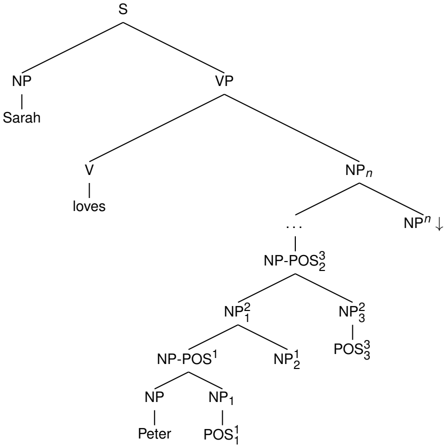
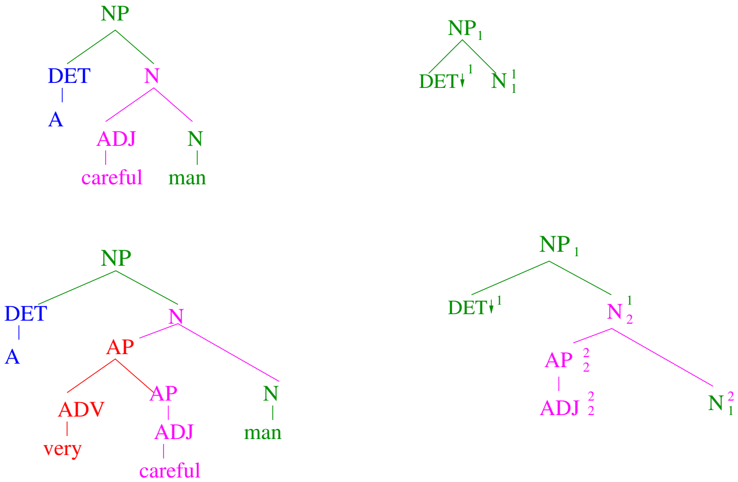


Sarah loves Peter's father's neighbor's ... books.

Step 2: Lexicon Induction

Pre-combined prediction trees:



Step 3: The Parsing Algorithm

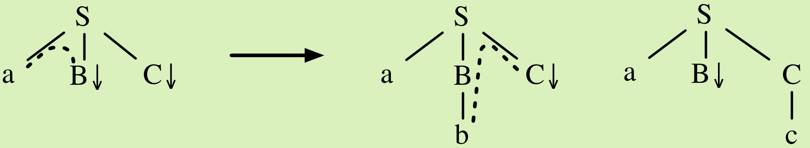
Requirements:

- Produce incremental and fully connected structures at every point in time
- Only produce valid PLTAG trees

Helpful Concept: **Fringes**

- tree can be described by its depth-first traversal
- only part of incremental tree is relevant at each step

Example: Substitution



(a) yes (b) no

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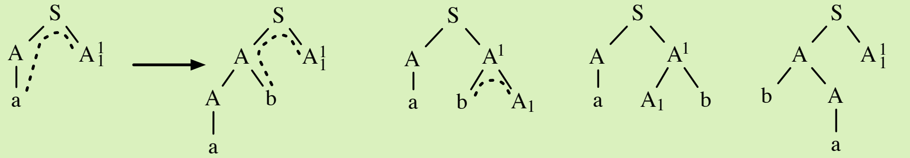
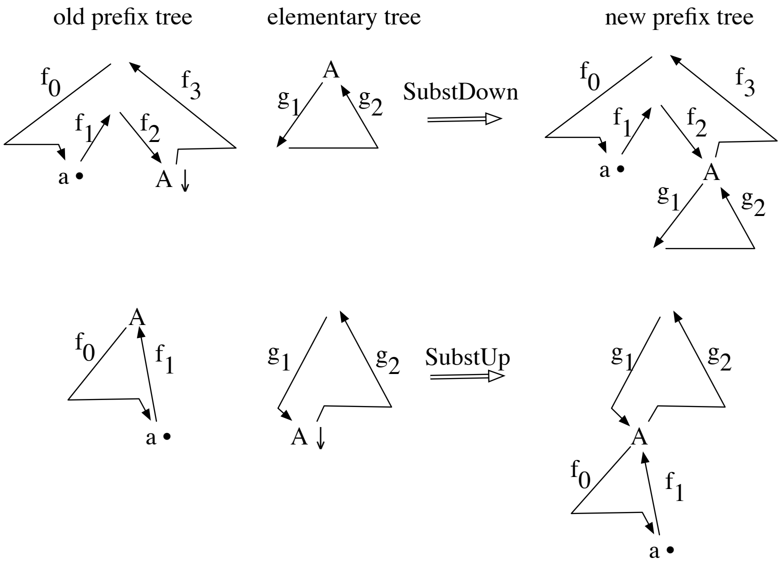
Example: Adjunction



(a) yes (b) yes (c) no (d) no

Parsing Rules



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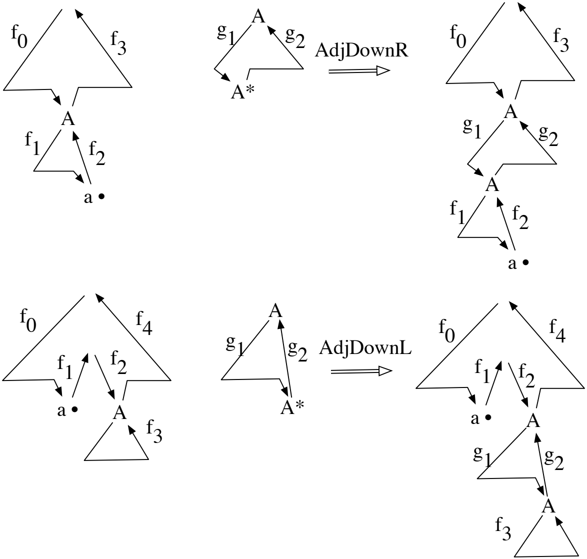

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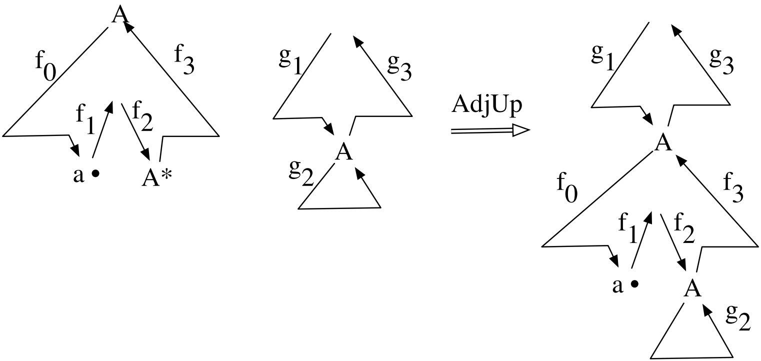
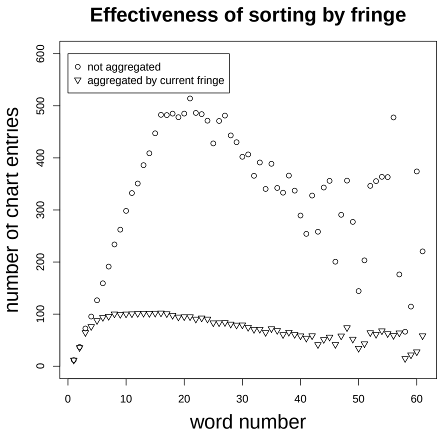


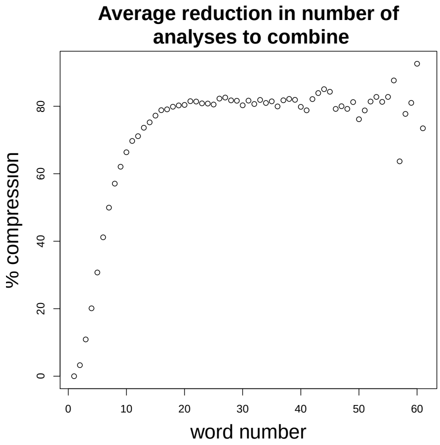
Step 3: The Parsing Algorithm (contd)

Efficiency – or how to get the parser to run for sentences with length > 3

- Trying out all prediction trees at each word is intractable.
  $>$ 1000 prediction trees vs. average ambiguity of canonical trees $\approx$ 50
- Introduce Supertagging for **prediction trees**.
  Parser only tries 20 most promising prediction trees.
- Beam Search
- Use of a chart (trees bundled by identical current fringes)

Effectiveness of Chart Parsing





(Statistics shown with beam search in use - without beam search, a much larger effect can be expected.)

Step 4: Probability Model

Generative model (enables us to easily estimate surprisal)

Substitution: $\sum_{\varepsilon} P(\varepsilon|\eta_\beta) = 1$

Adjunction: $\sum_{\varepsilon} P(\varepsilon|\eta_\beta) + P(NONE|\eta_\beta) = 1$

Verification: $\sum_{\varepsilon} P(\varepsilon|\pi_\beta) = 1$

$$
\begin{aligned}
P(\varepsilon|\eta_\beta) &= P(\tau_\varepsilon|\eta_\beta) \times P(\lambda_\varepsilon|\tau_\varepsilon, \lambda_\eta) \\
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P(\eta_\beta) &= P(\tau_\eta, \lambda_\eta, c_\eta, n_\eta, b_\eta, a_f, tm)
\end{aligned}
$$

based on [Chiang, 2000]

Explanation

Probabilities are normalized with respect to other elementary trees ε that can attach at node η in prefix tree β with the same operation.

elementary trees	ε	prefix tree	β	prediction trees	π
tree structures	τ	integration point node	η	a tree's head leaf	λ

Step 4: Probability Model

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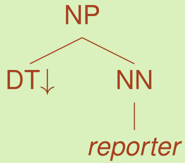
\end{aligned}
$$

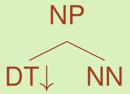
based on [Chiang, 2000]

Explanation

elementary tree ε:



is estimated as template τ_ε:



and lexeme λ_ε: *reporter*

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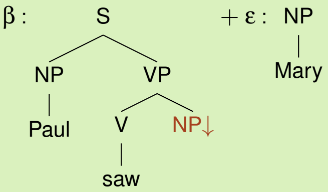

integration node η_β

elementary trees	ε	prefix tree	β	prediction trees	π
tree structures	τ	integration point node	η	a tree's head leaf	λ

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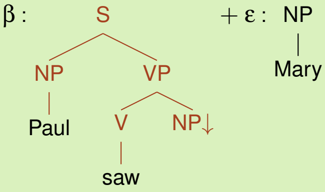

integration tree template τ_η

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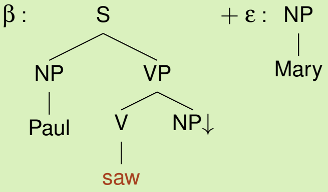

integration tree lexeme λ_η

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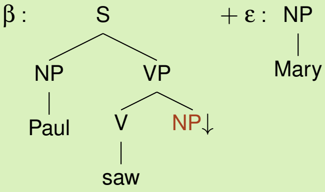

integration node category c_η

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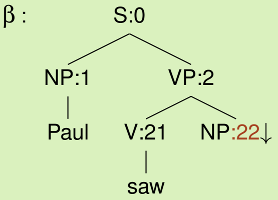

integration node position n_η

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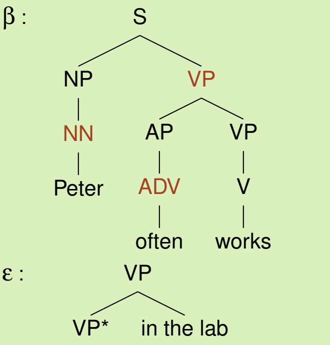

attachment context b_η & level a_f

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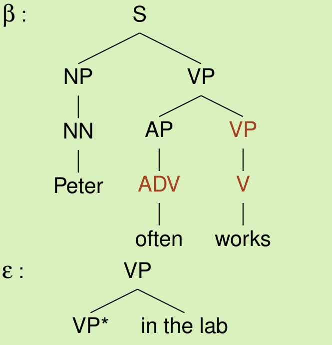

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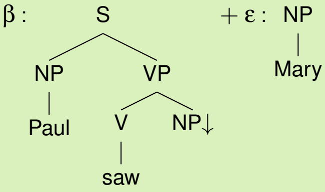

a trace mark *tm* which marks whether there is a trace at the beginning or end of the fringe

elementary trees	ε	prefix tree	β	prediction trees	π
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Parser Evaluation

Parser Performance:

Model	Prec	Recall	F-score	Cov
PLTAG parser	79.43	79.39	79.41	98.09
Pred tree oracle	81.15	81.13	81.14	96.18
No gold POS	77.57	77.24	77.41	98.09

Comparison to other TAG parsers:

Model	incr	con	pred	impl	F
Mazzei et al. (2007)	+	+	+	−	n/a
This work (gold POS)	+	+	+	+	79.4
Kato et al. (2004)	+	+	−	+	79.7
Shen and Joshi (2005)	(+)	−	−	+	(87.4)
Chiang (2000)	−	−	−	+	86.7

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Shen and Joshi (2005)	(+)	–	–	+	(87.4)
Chiang (2000)	–	–	–	+	86.7

Discussion on Incremental TAG parsing

- What difficulty arises in parsing from the prediction trees not being lexicalized?
- What's the problem with left recursion?
- Which measures were taken to make parsing tractable?
- In how far is incremental parsing more difficult / error-prone than non-incremental parsing?

The Linking Theory

Before I get to the linking theory, I will briefly introduce two theories of processing difficulty, that our processing theory is inspired by:

- Surprisal
- Dependency Locality Theory

Surprisal [Hale 2001, 2003; Levy, 2008]

"Forward-looking measure"

Key idea: Processing difficulty at $w_i \propto$ amount of Surprisal at perceiving w_i

How to calculate surprisal:

- Calculate prefix probabilities:

$$pp_{w_n} = -log \sum_{T \in Trees} p(T|w_1 \dots w_n)$$

- Surprisal s of word w_n: $s_{w_n} = pp_{w_n} - pp_{w_{n-1}}$
- [Hale 2001; Roark 2001, 2009; Levy 2008]

Explains **Prediction Effects** (either..or processing) and **Anti-locality effects**.

Surprisal [Hale 2001, 2003; Levy, 2008]

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Explains **Prediction Effects** (either..or processing) and **Anti-locality effects**.

DLT – Integration Cost

"Backward looking measure"

Key idea: predicts difficulty based on

- heads and their dependents: integration cost occurs at heads of phrases
- discourse referents: number of DR between head and its dependent

SRC

+2

	The	reporter	who	*t*	attacked	the	senator	admitted	the	error.
DR:	0	1	0		1	0	1	1	0	1
IC:	0	1	0		1	0	1	3	0	1

ORC

+2 +2

	The	reporter	who	the	senator	attacked	*t*	admitted	the	error.
DR:	0	1	0	0	1	1		1	0	1
IC:	0	1	0	0	1	3		3	0	1

Explains locality effects: SRC/ORC asymmetry, center embedding

Comparison of DLT and Surprisal

Comparison

Surprisal:	"forward-looking"	difficulty caused by violated expectations
DLT:	"backward-looking"	difficulty caused by long-distance integrations

Effects	Surprisal	DLT
Either-or Prediction	+	–
English Relative Clause	–	+
German Relative Clause	+	–
Facilitating Ambiguity	+	–
Storage Cost Effects	–	+
Center Embedding	NA	+

Conclusions:

- The two theories explain different parts of the data – can they be combined in a unified theory?

[Demberg & Keller, 2009, Cognition]

Step 5: The Linking Theory

Translates the PLTAG parser states into processing difficulty:

- Big changes in the probability distribution cause processing difficulty.
- Each of these predicted trees π has a time-stamp t.
- At verification time, the tree's nodes' decay d is calculated based on the time stamp (recently-accessed structures are easier to integrate).

Estimation of Processing Difficulty D_{w_i}

$$D_{w_i} = \overbrace{-\log \sum_{\beta_{w_1 \dots w_i}} P(\beta_{w_1 \dots w_i}) + \log \sum_{\beta_{w_1 \dots w_{i-1}}} P(\beta_{w_1 \dots w_{i-1}})}^{\text{Surprisal}}$$
$$\underbrace{-\log \sum_{\pi} P(\pi)^{(1-d^{t_\pi})}}_{\text{Verification Cost}}$$

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Psycholinguistic Evaluation

Linking Theory translates the PLTAG parsing process into processing difficulty estimates:

- Based on parallel, probabilistic parsing with a generative model.
- Big changes in the probability distribution cause processing difficulty (surprisal).
- Long-distance dependencies as evident from verification of nodes which were predicted a long time ago, cause processing difficulty.

Evaluation of Processing Theory based on PLTAG

- Broad-Coverage Evaluation on Dundee Corpus
- Psycholinguistic Case Studies

The Dundee Corpus

Dundee eye-tracking corpus [Kennedy et al. 2003]

- ca. 51.000 words of British newspaper articles (from The Independent)
- 10 subjects

Broad-Coverage Evaluation on Dundee Corpus

	Prediction Theory	
Predictor	Coef	Sig
Intercept	230.31	***
WordLength	3.93	***
WordFrequency	-8.92	***
PrevWordFreq	-4.53	***
PrevWordFixated	-30.96	***
LaunchDistance	-0.88	***
LandingPosition	70.34	***
WordNoInSentence	-0.14	***
BigramProb	-3.06	***
PredictTheory	0.38	**
WordLength:Freq	-1.44	***
WordLength:Posit	23.06	***

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

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Broad-Coverage Evaluation on Dundee Corpus

	Prediction Theory		Structural Surprisal		Lexical Surprisal	
Predictor	Coef	Sig	Coef	Sig	Coef	Sig
Intercept	230.31	***	230.44	***	230.43	***
WordLength	3.93	***	3.99	***	3.97	***
WordFrequency	-8.92	***	-8.88	***	-8.89	***
PrevWordFreq	-4.53	***	-4.50	***	-4.53	***
PrevWordFixated	-30.96	***	-30.95	***	-30.94	***
LaunchDistance	-0.88	***	-0.88	***	-0.88	***
LandingPosition	70.34	***	70.38	***	70.37	***
WordNoInSentence	-0.14	***	-0.14	***	-0.14	***
BigramProb	-3.06	***	-2.99	***	-3.03	***
PredictTheory	0.38	**				
StructSurprisal			0.21			
LexicalSurprisal					-0.02	
WordLength:Freq	-1.44	***	-1.38	***	-1.39	***
WordLength:Posit	23.06	***	22.98	***	23.00	***

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

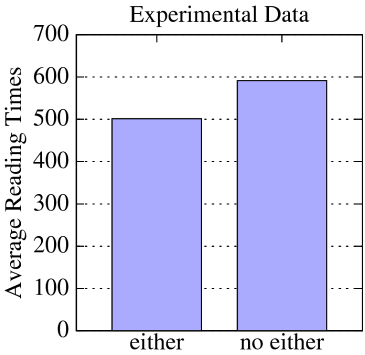
Either..or processing

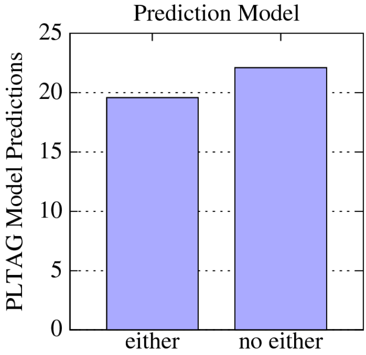
Evaluation on 48 sentences from experiment by [Staub and Clifton, 2006].

Example sentences:

Peter read either a book ***or an essay*** *in the school magazine.*

Peter read a book ***or an essay*** *in the school magazine.*





Summary PLTAG Syntax Modelling

PLTAG syntax:

- Models incrementality and prediction at syntax level
- Successfully replicates patterns observed in naturalistic data
- as well as psycholinguistic experiments

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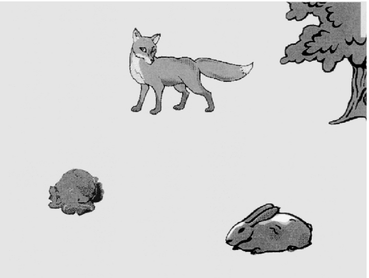
Limitations of syntax-only PLTAG model

But with syntax only, can't explain

- anticipatory eye movements in *Den Hasen frisst gleich der Fuchs.*



- Most garden path sentences, e.g. *The horse raced past the barn fell.*

Example: Semantic plausibilty affects syntax

The doctor sent for the patient arrived.
The flowers sent for the patient arrived.

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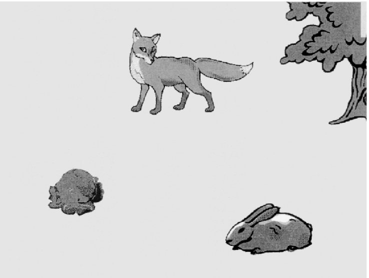

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Example: Semantic plausibilty affects syntax

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Incremental Semantics

Desired properties of semantics for PLTAG:

- simultaneous construction of syntax and semantics
- reflect the incrementality of the syntax
- direct syntax-semantics interface
- semantics that are useful in combination with some form of compositional distributional semantics, so we can calculate e.g. semantic surprisal