

Incremental Semantic Interpretation of Dialogue Contributions

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Kolloquium Linguistik, Universität Bielefeld, 07.11.2012

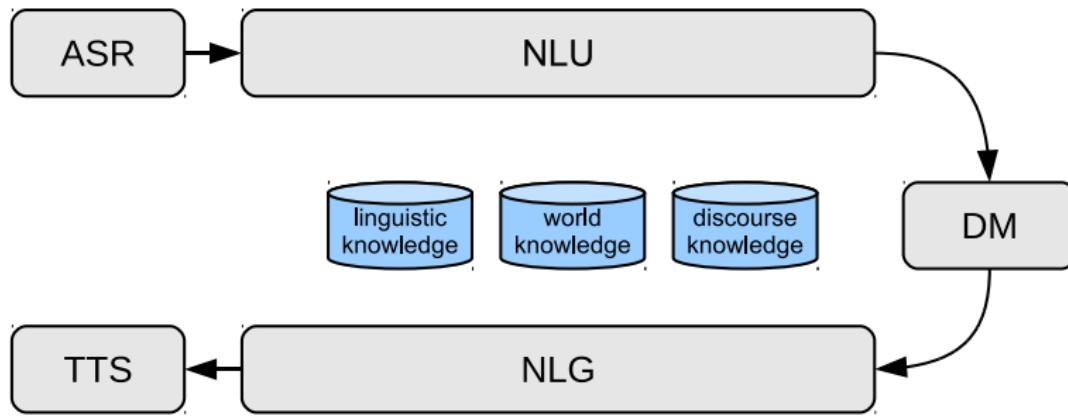
Outline

① Introduction

② Theory: Incremental Semantic Construction

③ Application: Incremental Reference Feedback

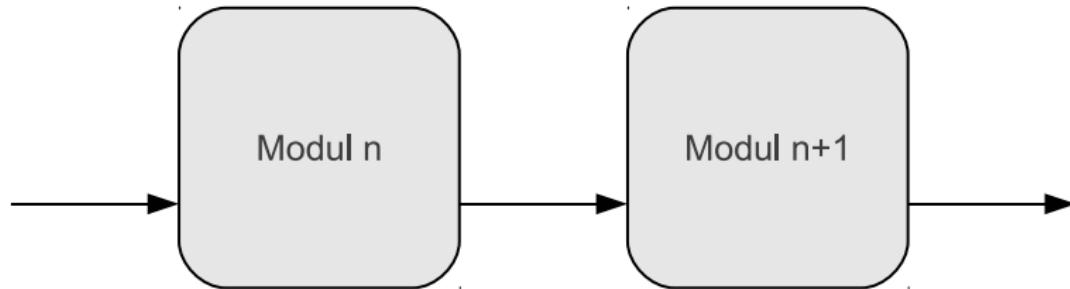
Introduction: Spoken Dialogue Systems



Introduction: Incremental Processing

Incrementality, Schlangen and Skantze [2009], citing Levelt [1989]

Each processing component is triggered into activity by a minimal amount of its characteristic input.

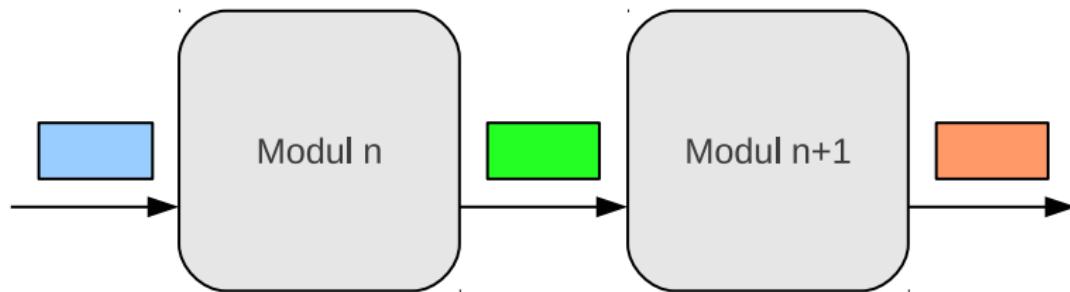


information flow between two modules

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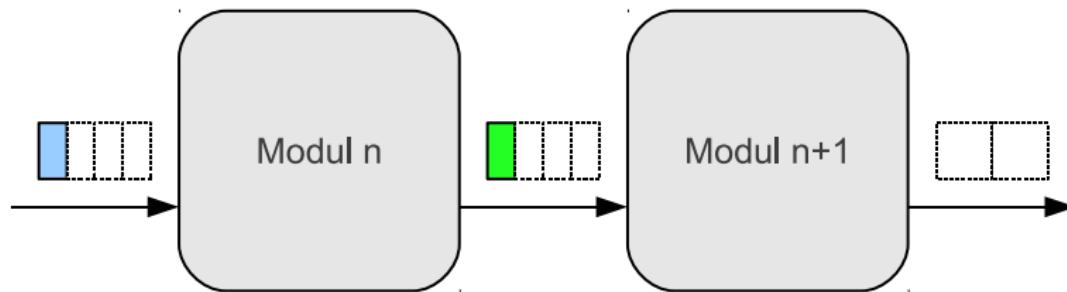


non-incremental information flow

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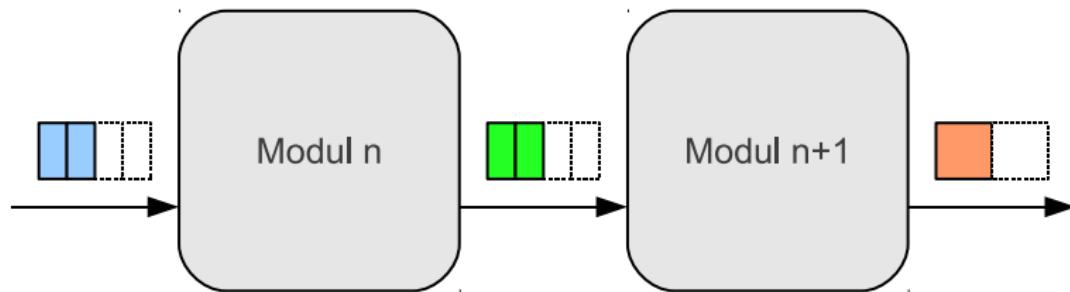


incremental information flow: *early propagation*

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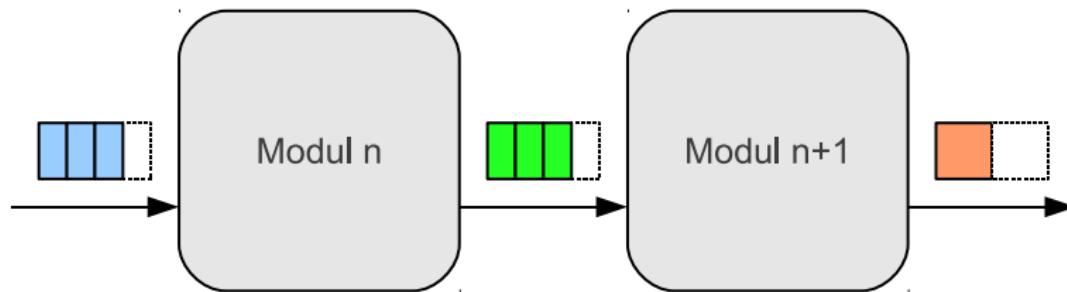


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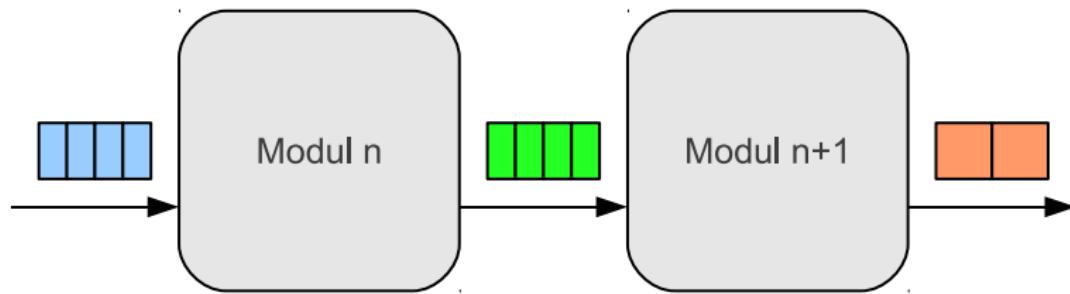


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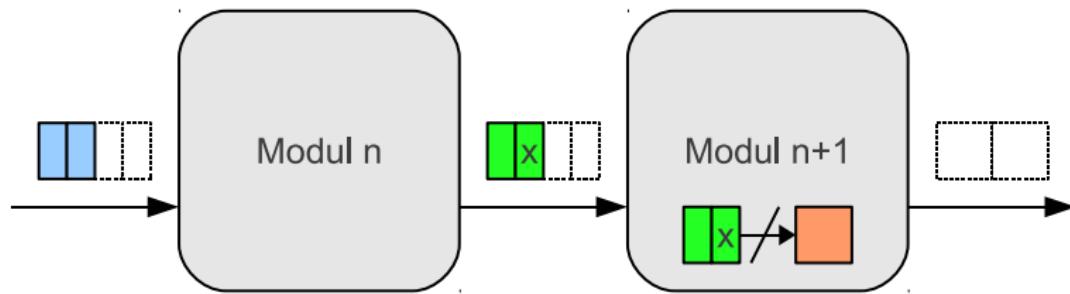


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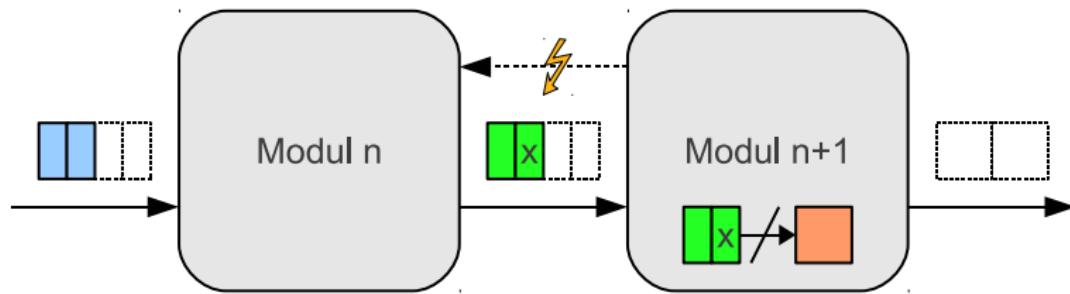


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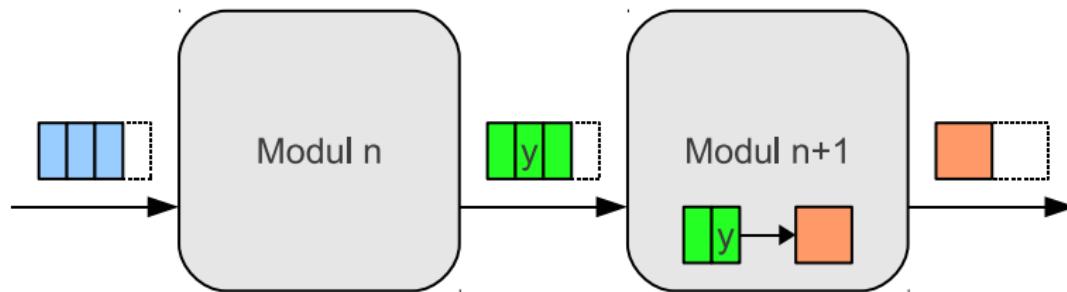


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Introduction: Motivating Incremental SDS

- ① psycho-linguistic plausibility Tanenhaus and Brown-Schmidt [2008]
 - reference resolution, early disambiguation etc

- ② descriptive adequacy

• SDS can handle complex situations involving multiple referents and complex discourse contexts

- ③ computational benefits

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 - speed (by early propagation): why wait with processing?
but communicative overhead
 - need only the most recent information on lexical choices
but often many choices
 - can be used for other purposes (e.g., planning)

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but risk of gardenpathing
 - efficiency (by interaction): reduce workload
but risk of increased workload with certain utterances

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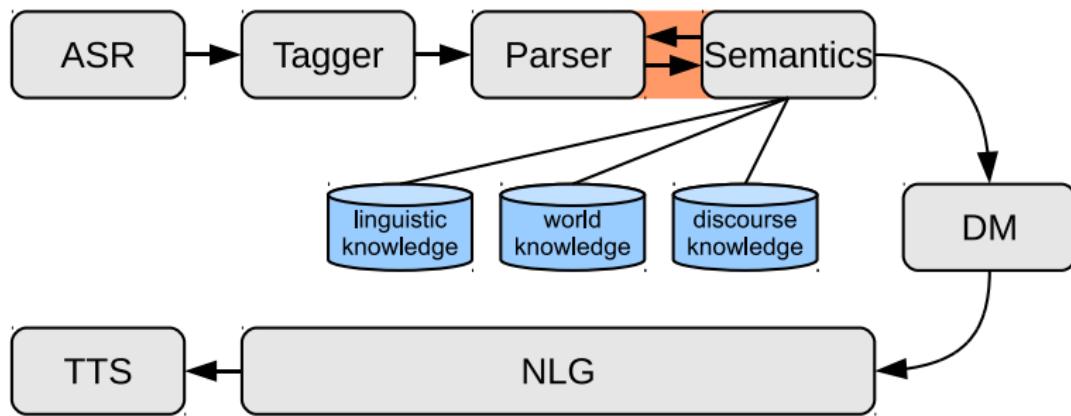
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Introduction: Aims of the Approach



Goal: Prune semantically implausible syntactic readings,
i.e. readings without referential success.

Related Work

- Purver et al. [2011] - incremental semantic construction within Dynamic Syntax, centered on grammaticality, rather monolithic
- Poesio and Traum [1997], Poesio and Rieser [2010] - incremental semantic construction with λ calculus for TAG, focus on discourse structure, no implementation yet?
- Lison [2008] - incremental semantic construction with CCG, incremental statistical parse selection, no interaction, word-versus phrase-incremental?
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Theory: Incremental Semantic Construction

Incrementality in Semantic Construction

- Goal: for an input find a semantic representation that is maximally informative and open to combination with further semantic increments
- three factors that influence a *syntax driven* incremental semantic construction
 - type of syntactic structure building
(top-down-parsing, bottom-up-parsing)
 - type of semantic structure
(feature incrementality)
 - type of reference mechanism
(incremental reference feedback)

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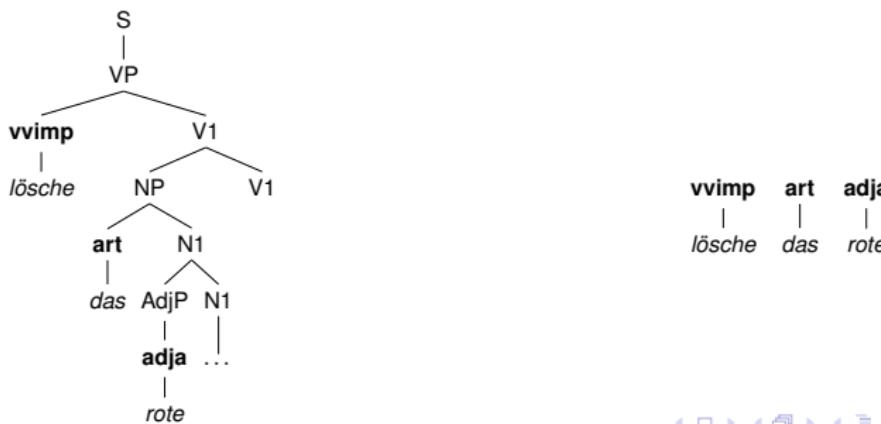
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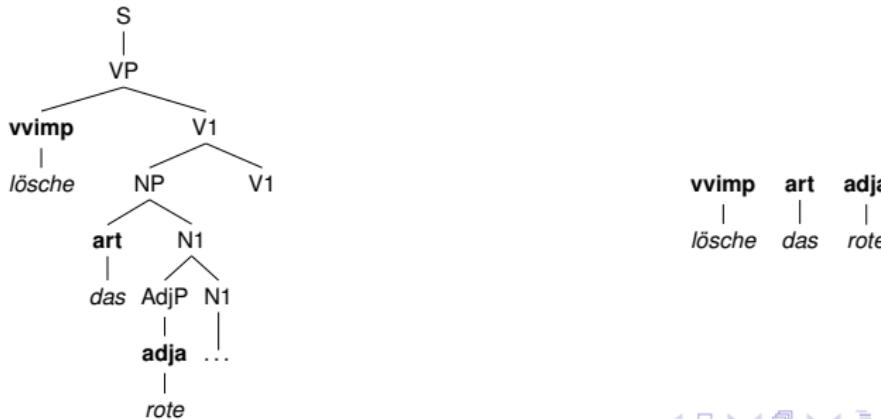
Incrementality in Semantic Construction

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- usually only provided by top-down-parsers
- drawbacks: many hypotheses, problems with left-recursion
- Roark presents solutions for both problems:



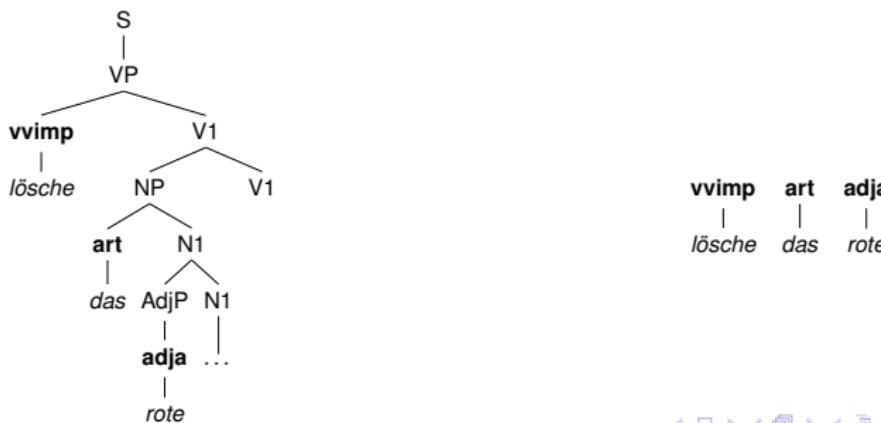
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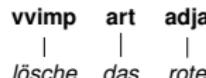
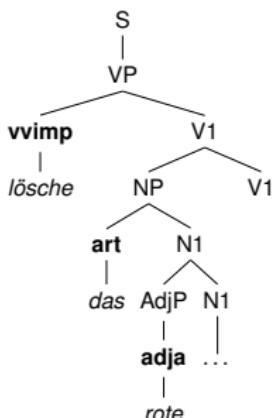
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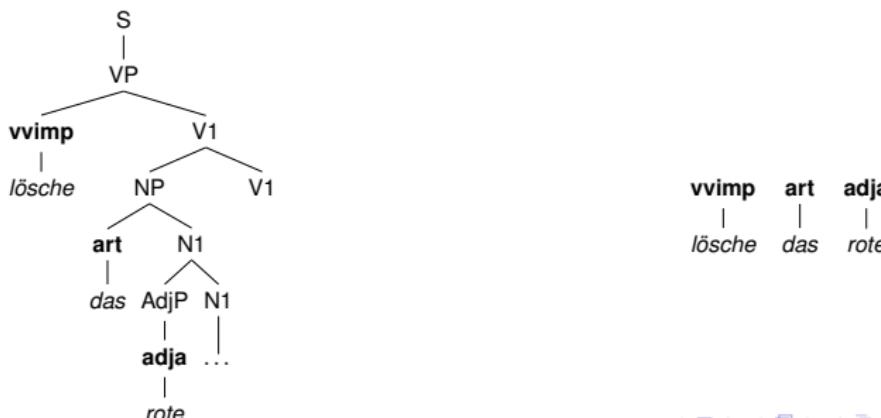
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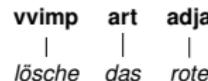
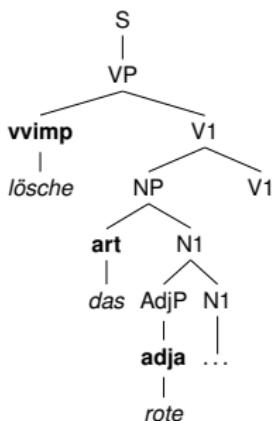
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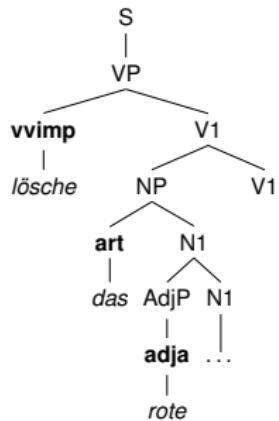


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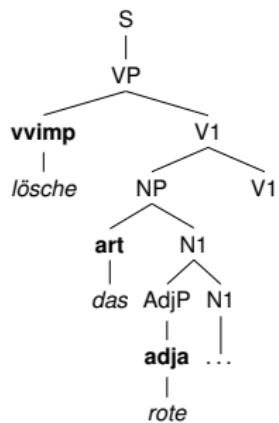
Tree-Interpretation: Bottom up?



Tree-interpretation bottom-up, inside-out:

- need to underspecify open nodes
- need to re-interpret the whole tree every time it expands

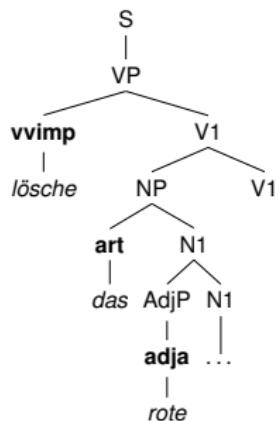
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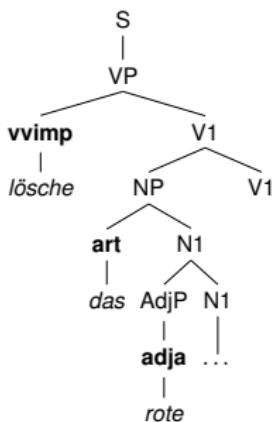


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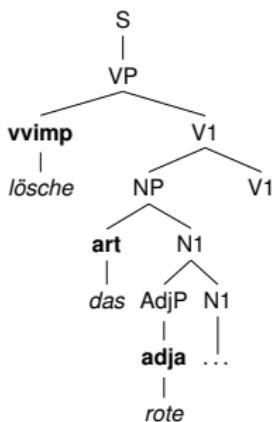


- linearise semantic combination in parallel to the top-down expansion of the tree
- every expansion of a non-terminal node adds a rule-specific construction semantic increment
(parser action: predict)
- every recognition of a terminal node adds a lexical semantic increment
(parser action: match)
- no need to underspecify open nodes
- no need to re-interpret the tree
- *monotonic growth, synchronised with parsing*

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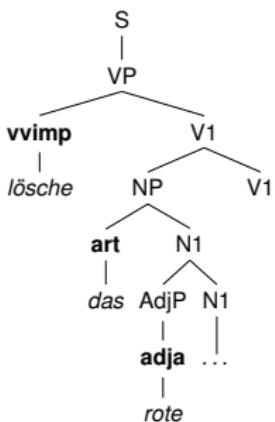
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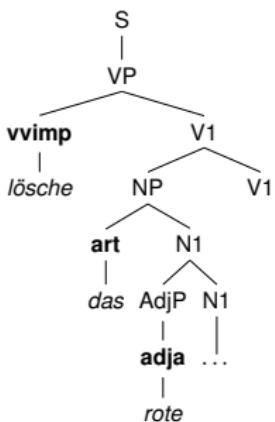
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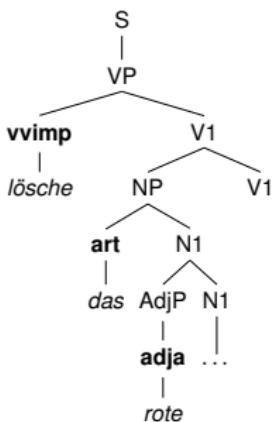
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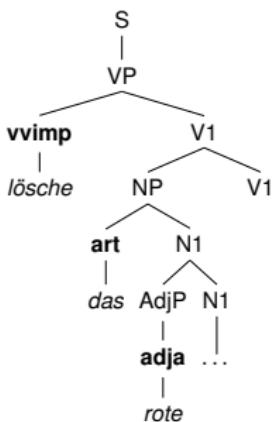
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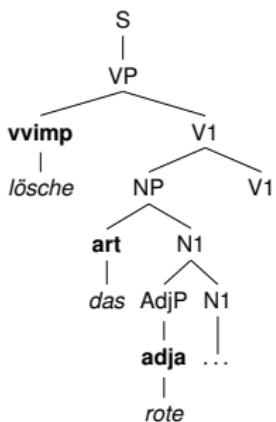
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- representation language: first order predicate logic with generalized quantifiers, sortal variables
- scope underspecification: break up into elementary predication with labels and holes, standard conjunction, add scope constraints
- underspecification of predicate argument structure: break up further into elementary predication with anchors, characteristic variable and argument-relations

Every dog chases a cat.

$\text{every}(x, \text{dog}(x), \exists(y, \text{cat}(y), \text{chase}(x,y)))$
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$$\langle h_0, \\ \{ \ell_1: \text{every}(x, h_1, h_2), \\ \ell_2: \text{dog}(x), \\ \ell_3: \text{chase}(e, x, y), \\ \ell_4: \text{some}(y, h_3, h_4), \\ \ell_5: \text{cat}(y) \}, \\ \{ h_1 =_q \ell_2, h_3 =_q \ell_5 \} \rangle$$

RMRS introduction

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 $\ell_3:a_3:\text{chase}(e_1), \text{ARG}_1(a_3, x_1), \text{ARG}_2(a_3, x_2),$ 
 $\ell_4:a_4:\text{some}(), \text{BV}(a_4, x_2), \text{RSTR}(a_4, h_3), \text{BODY}(a_4, h_4),$ 
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RMRS forward composition

- classic RMRS Copestake [2007] uses a *set of named slot* to represent the open positions, the syntax-semantic interface picks the right slot to fill
- only one slot of each sort open
- however, left recursive rules in incremental processing may require to have multiple slots of the same sort open
- therefore we reinterpret the slots as a stack of unnamed slots, where only the top element can be filled

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$[\ell_3:a_3:e_1] \{ [\ell_5:a_5:x_2] np - arg \}$
 $\ell_1:a_1:\text{every}(), \text{BV}(a_1, x_1), \text{RSTR}(a_1, h_1), \text{BODY}(a_1, h_2), h_1 =_q \ell_2,$
 $\ell_2:a_2:\text{dog}(x_1),$
 $\ell_3:a_3:\text{chase}(e_1), \text{ARG}_1(a_3, x_1), \text{ARG}_2(a_3, x_2),$
 $\ell_4:a_4:\text{some}(), \text{BV}(a_4, x_2), \text{RSTR}(a_4, h_3), \text{BODY}(a_4, h_4), h_3 =_q \ell_5$

$[\ell_6:a_6:e_6] \{ \} \ell_6:a_6:\text{cat}(x_6)$

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 $\ell_3:a_3:\text{chase}(e_1), \text{ARG}_1(a_3, x_1), \text{ARG}_2(a_3, x_2),$
 $\ell_4:a_4:\text{some}(), \text{BV}(a_4, x_2), \text{RSTR}(a_4, h_3), \text{BODY}(a_4, h_4), h_3 =_q \ell_5$
 $\ell_6:a_6:\text{cat}(x_6), \ell_6 = \ell_5, a_6 = a_5, x_6 = x_2$

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 $\ell_1:a_1:\text{every}(), \text{BV}(a_1, x_1), \text{RSTR}(a_1, h_1), \text{BODY}(a_1, h_2), h_1 =_q \ell_2,$
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 $\ell_4:a_4:\text{some}(), \text{BV}(a_4, x_2), \text{RSTR}(a_4, h_3), \text{BODY}(a_4, h_4), h_3 =_q \ell_5$
 $\ell_5:a_5:\text{cat}(x_2)$

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RMRS forward composition

RMRS structure under construction with a stack of slots

An RMRS structure under construction is a 6-tuple $\langle GT, H, S, R, C, E \rangle$,

- with GT the global top hole h_0 ,
- with H the hook $[\ell:a:i]$, consisting of the local top label ℓ , the anchor a and the index i ,
- with S the stack of slots of the form $[\ell_n:a_n:i_n]$,
- with R the bag of EPs and argument relations,
- with C the bag of constraints and
- with E the set of variable equalities.

RMRS forward composition

Forward slot filling combination

Given two RMRSSs, one being the functor

$rmrs_f = \langle GT_f, H_f, S_f, R_f, C_f, E_f \rangle$ with the top slot

$\text{top}(S_f) = [\ell_f:a_f:i_f]$ and one being the argument

$rmrs_a = \langle GT_a, H_a, S_a, R_a, C_a, E_a \rangle$ with its hook $H_a = [\ell_a:a_a:i_a]$, the slot filling combination $rmrs_f \triangleleft rmrs_a$ yields an RMRS

$rmrs = \langle GT, H, S, R, C, E \rangle$, s.t.

- $GT = GT_f = GT_a$
- $H = H_f$
- $S = \text{merge-stacks}(S_a, \text{pop}(S_f))$
- $R = R_f \cup R_a$
- $C = C_f \cup C_a$
- $E = E_f \cup E_a \cup \{\ell_f = \ell_a, a_f = a_a, i_f = i_a\}$

Basic slotfilling combinators

$$\begin{aligned} [-] &= [\ell:a:u] \{ \} . \\ [\circ] &= [\ell:a:u] \{ [\ell:a:u] \} . \\ [=] &= [\ell:a:u] \{ [\ell:a:u][\ell:a:u] \} . \\ [+] &= [\ell:a:u] \{ [\ell_1:a_1:u][\ell:a:u] \} . \\ [+_{\ell}] &= [\ell:a:u] \{ [\ell:a:u][\ell_1:a_1:u] \} . \\ [+ \ell] &= [\ell:a:u] \{ [\ell:a_1:u][\ell:a:u] \} . \end{aligned}$$

A worked example: a toy grammar

S	\rightarrow	S kon S	[Conj]	NP0	\rightarrow	PP NP0	[+]
S	\rightarrow	VP	[Arg1] \triangleleft [adr]	NP0	\rightarrow	NP	[o]
VP	\rightarrow	vvimp V1	[=]	NP	\rightarrow	pper	[o]
V1	\rightarrow	NP0 V1	[Arg2]	NP	\rightarrow	art N2	[Q]
V1	\rightarrow	V1 AdvP	[+]	N2	\rightarrow	N1	[o]
V1	\rightarrow	V1 PP	[+]	N2	\rightarrow	N1 NP	[+]
V1	\rightarrow	ϵ	[−]	N1	\rightarrow	AdjP N1	[+ ℓ]
PP	\rightarrow	appr NP	[PP]	N1	\rightarrow	N1 PP	[+]
AdvP	\rightarrow	adv	[Adv]	N1	\rightarrow	N1 AdvP	[+]
AdjP	\rightarrow	adja	[Adj]	N1	\rightarrow	nn	[o]

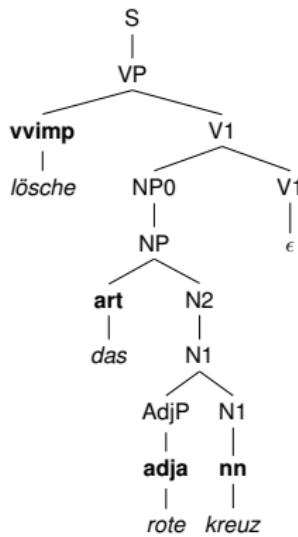
A worked example: semantic macros

[Arg1]	=	$[\ell:a:u]$	$\{ [\ell_1:a_1:x_1][\ell:a:u] \} \text{ARG}_1(a, x_1)$
[Arg2]	=	$[\ell:a:u]$	$\{ [\ell_1:a_1:x_1][\ell:a:u] \} \text{ARG}_2(a, x_1)$
[Arg3]	=	$[\ell:a:u]$	$\{ [\ell_1:a_1:x_1][\ell:a:u] \} \text{ARG}_3(a, x_1)$
[adr]	=	$[\ell:a:x]$	$\{ \} \ell:a:\text{addressee}(x)$
[Q]	=	$[\ell:a:x]$	$\{ [\ell:a:e_1][\ell_2:a_2:x] \} \text{BV}(a, x),$ $\text{RSTR}(a, h_1), \text{BODY}(a, h_2), h_1 =_q \ell_2$
[PP]	=	$[\ell:a:u]$	$\{ [\ell_1:a_1:e_1][\ell_2:a_2:x_2] \} \text{ARG}_1(a_1, u),$ $\text{ARG}_2(a_1, x_2)$
[Adj]	=	$[\ell:a:x]$	$\{ [\ell:a_1:e_1] \} \text{ARG}_1(a_1, x)$
[Adv]	=	$[\ell:a:u]$	$\{ [\ell_1:a_1:e_1] \} \text{ARG}_1(a_1, u)$
[Conj]	=	$[\ell:a:u]$	$\{ [\ell_1:a_1:u_1][\ell:a:u][\ell_3:a_3:u_3] \}$ $\text{LEFT}_i(a, u_1), \text{LEFT}_\ell(a, h_1),$ $\text{RIGHT}_i(a, u_3), \text{RIGHT}_\ell(a, h_3),$ $h_1 =_q \ell_1, h_3 =_q \ell_3$

A worked example: generic lexical entries

adja:	$[\ell:a:e]$	{ }	$\ell:a:_\text{lemma}(e)$
adv:	$[\ell:a:e]$	{ }	$\ell:a:_\text{lemma}(e)$
appr:	$[\ell:a:e]$	{ }	$\ell:a:_\text{lemma}(e)$
art:	$[\ell:a:u]$	{ }	$\ell:a:_\text{lemma}()$
kon:	$[\ell:a:u]$	{ }	$\ell:a:_\text{lemma}(u)$
nn:	$[\ell:a:x]$	{ }	$\ell:a:_\text{lemma}(x)$
pper	$[\ell:a:x]$	{ }	$\ell:a:\text{pper}(x)$
vvimp:	$[\ell:a:e]$	{ }	$\ell:a:_\text{lemma}(e)$

A worked example: derivation



$[\circ]$
 □ [Arg1] □ [adr] □ [=] □ [[löschen]]
 □ [Arg2] □ [\circ] □ [Q] □ [[das]]
 □ [\circ] □ [+ ℓ] □ [Adj] □ [[rote]]
 □ [\circ] □ [[kreuz]]
 □ [-]

$[\ell_0:a_0:e_0] \{ \}$
 $\ell_0:a_0:_\text{löschen}(e_0), \text{ARG}_1(a_0, x_2), \text{ARG}_2(a_0, x_4),$
 $\ell_2:a_2:\text{addressee}(x_2),$
 $\ell_4:a_4:_\text{def_q}(), \text{BV}(a_4, x_4), \text{RSTR}(a_4, h_1), \text{BODY}(a_4, h_2), h_1 =_q \ell_7,$
 $\ell_7:a_7:_\text{rot}(e_{10}), \text{ARG}_1(a_{10}, x_4),$
 $\ell_7:a_7:_\text{kreuz}(x_4)$

A worked example: derivation

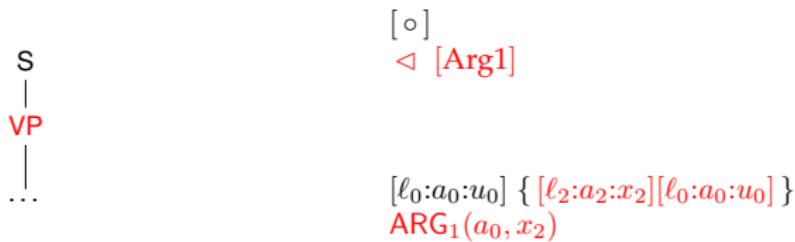
[\circ]

S

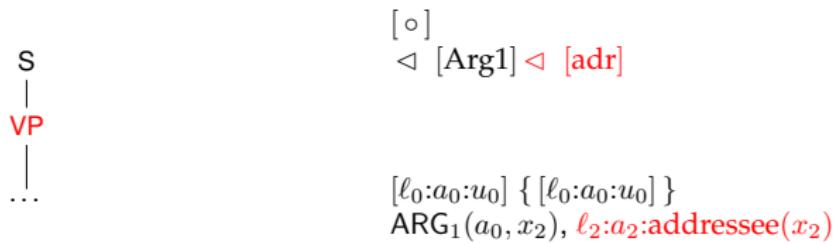
...

$[\ell_0:a_0:u_0] \{ [\ell_0:a_0:u_0] \} .$

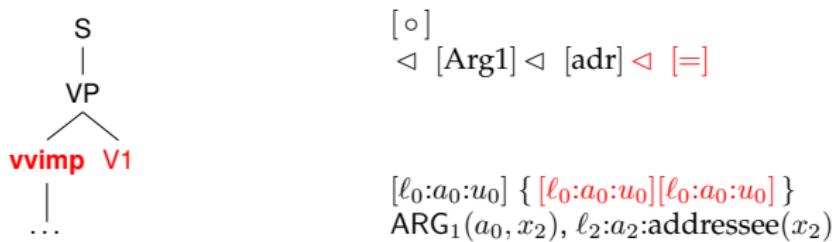
A worked example: derivation



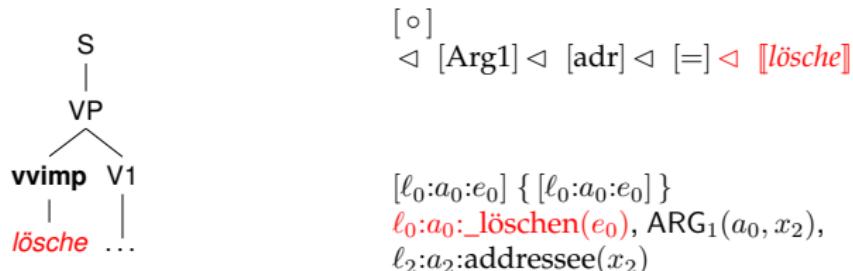
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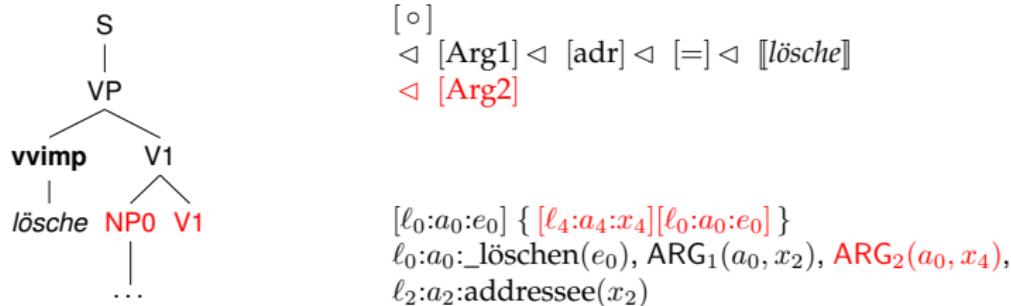
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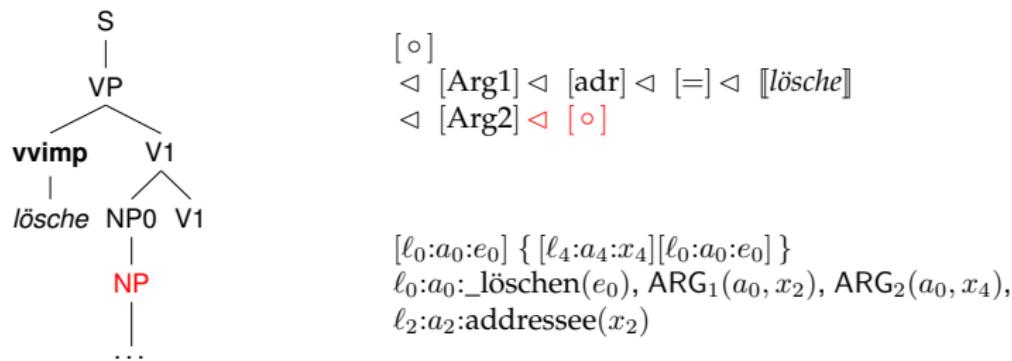
A worked example: derivation



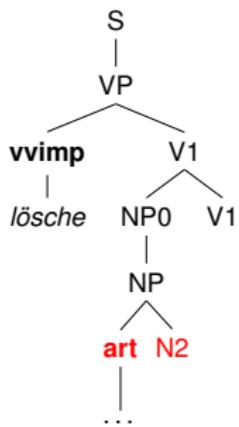
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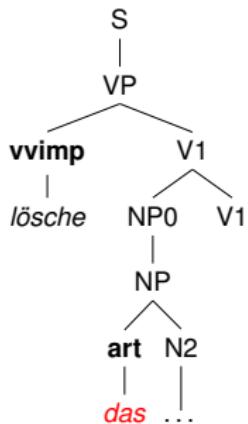
A worked example: derivation



[\circ]
 \lhd [Arg1] \lhd [adr] \lhd [=] \lhd [[lösche]]
 \lhd [Arg2] \lhd [\circ] \lhd [Q]

$[\ell_0:a_0:e_0] \{ [\ell_4:a_4:e_6][\ell_7:a_7:x_4][\ell_0:a_0:e_0] \}$
 $\ell_0:a_0:_löschen(e_0), \text{ARG}_1(a_0, x_2), \text{ARG}_2(a_0, x_4),$
 $\ell_2:a_2:\text{addressee}(x_2),$
 $\text{BV}(a_4, x_4), \text{RSTR}(a_4, h_1), \text{BODY}(a_4, h_2), h_1 =_q \ell_7$

A worked example: derivation

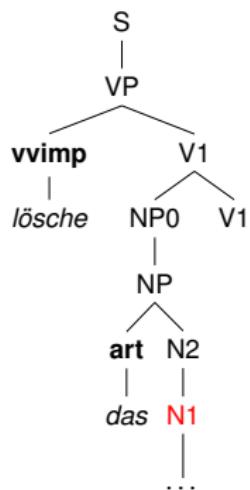


[◯]

◀ [Arg1] ◀ [adr] ◀ [=] ◀ [[lösche]]
◀ [Arg2] ◀ [◯] ◀ [Q] ◀ [[das]]

[$\ell_0:a_0:e_0$] { [$\ell_7:a_7:x_4$][$\ell_0:a_0:e_0$] } $\ell_0:a_0:_\text{löschen}(e_0), \text{ARG}_1(a_0, x_2), \text{ARG}_2(a_0, x_4),$ $\ell_2:a_2:\text{addressee}(x_2),$ $\ell_4:a_4:\text{def_q}(), \text{BV}(a_4, x_4), \text{RSTR}(a_4, h_1), \text{BODY}(a_4, h_2), h_1 =_q \ell_7$

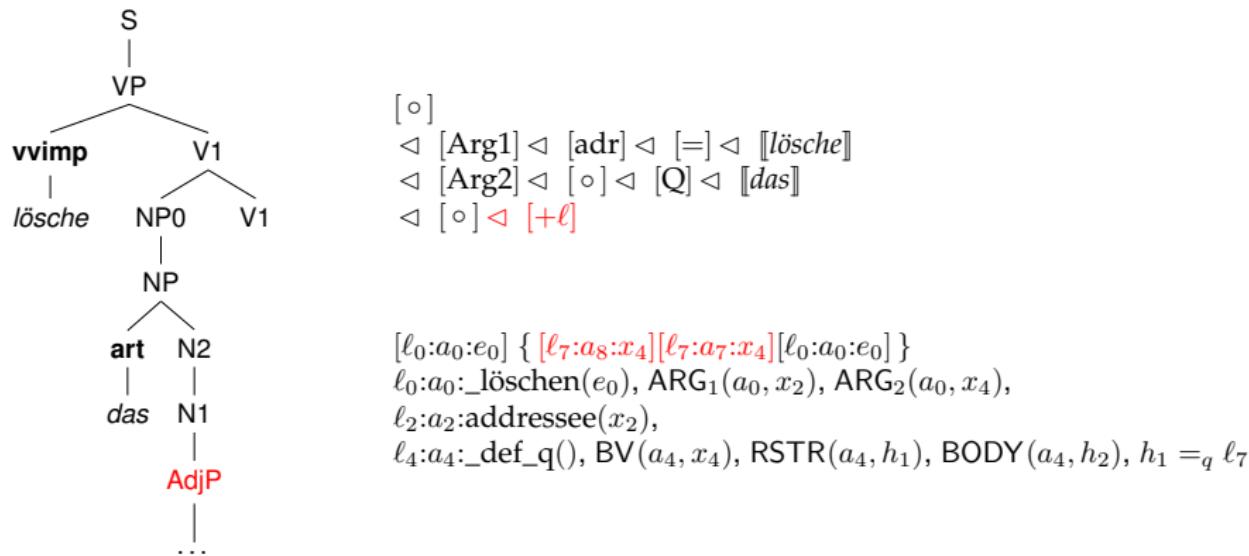
A worked example: derivation



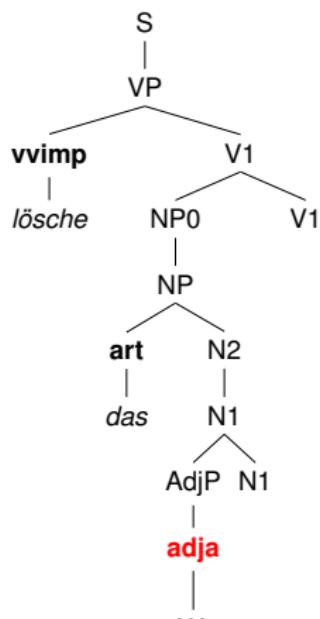
\circ
 $\lhd [Arg1] \lhd [adr] \lhd [=] \lhd [\text{[lösche]}]$
 $\lhd [Arg2] \lhd \circ \lhd [Q] \lhd [\text{[das]}]$
 $\lhd \circ$

$[\ell_0:a_0:e_0] \{ [\ell_7:a_7:x_4][\ell_0:a_0:e_0] \}$
 $\ell_0:a_0:_\text{löschen}(e_0), \text{ARG}_1(a_0, x_2), \text{ARG}_2(a_0, x_4),$
 $\ell_2:a_2:\text{addressee}(x_2),$
 $\ell_4:a_4:_\text{def_q}(), \text{BV}(a_4, x_4), \text{RSTR}(a_4, h_1), \text{BODY}(a_4, h_2), h_1 =_q \ell_7$

A worked example: derivation



A worked example: derivation

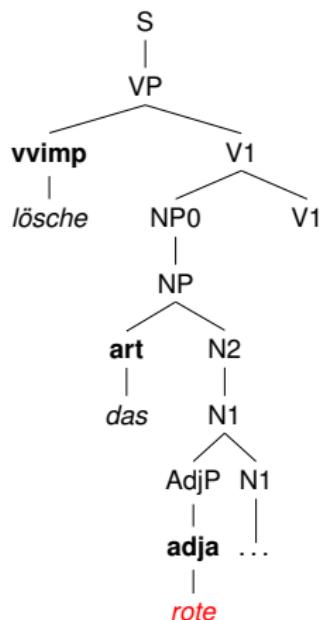


[]

\triangleleft [Arg1] \triangleleft [adr] \triangleleft [=] \triangleleft [[lösche]]
 \triangleleft [Arg2] \triangleleft [] \triangleleft [Q] \triangleleft [[das]]
 \triangleleft [] \triangleleft [+ℓ] \triangleleft [Adj]

$\ell_0:a_0:e_0 \{ [\ell_7:a_{10}:e_{10}][\ell_7:a_7:x_4][\ell_0:a_0:e_0] \}$
 $\ell_0:a_0:_löschen(e_0)$, ARG₁(a_0, x_2), ARG₂(a_0, x_4),
 $\ell_2:a_2:\text{addressee}(x_2)$,
 $\ell_4:a_4:\text{def_q}()$, BV(a_4, x_4), RSTR(a_4, h_1), BODY(a_4, h_2), $h_1 =_q \ell_7$,
ARG₁(a_{10}, x_4)

A worked example: derivation



[]

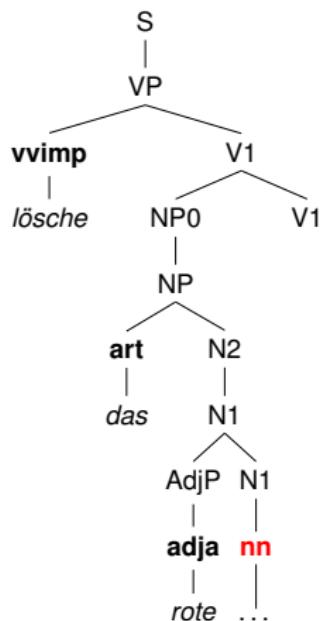
\triangleleft [Arg1] \triangleleft [adr] \triangleleft [=] \triangleleft [[lösche]]
 \triangleleft [Arg2] \triangleleft [] \triangleleft [Q] \triangleleft [[das]]
 \triangleleft [] \triangleleft [+ℓ] \triangleleft [Adj] \triangleleft [rote]

$[\ell_0:a_0:e_0] \{ [\ell_7:a_7:x_4][\ell_0:a_0:e_0] \}$

$\ell_0:a_0:_löschen(e_0)$, ARG₁(a_0, x_2), ARG₂(a_0, x_4),
 $\ell_2:a_2:\text{addressee}(x_2)$,

$\ell_4:a_4:\text{def_q}()$, BV(a_4, x_4), RSTR(a_4, h_1), BODY(a_4, h_2), $h_1 =_q \ell_7$,
 $\ell_7:a_{10}:\text{rot}(e_{10})$, ARG₁(a_{10}, x_4)

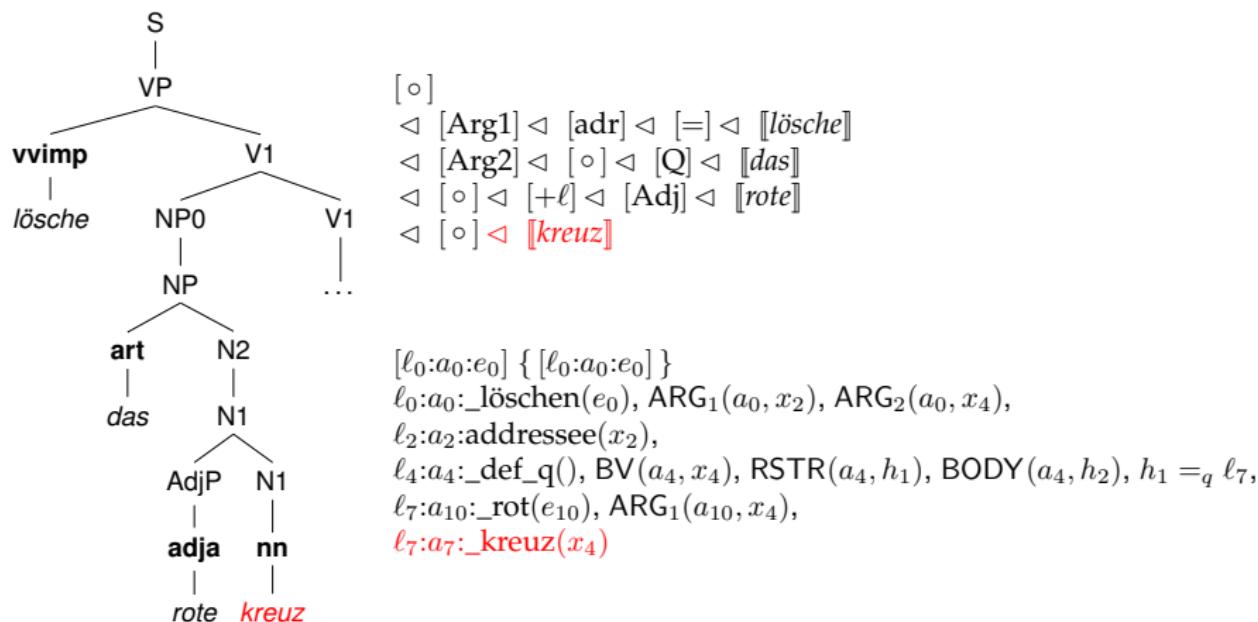
A worked example: derivation



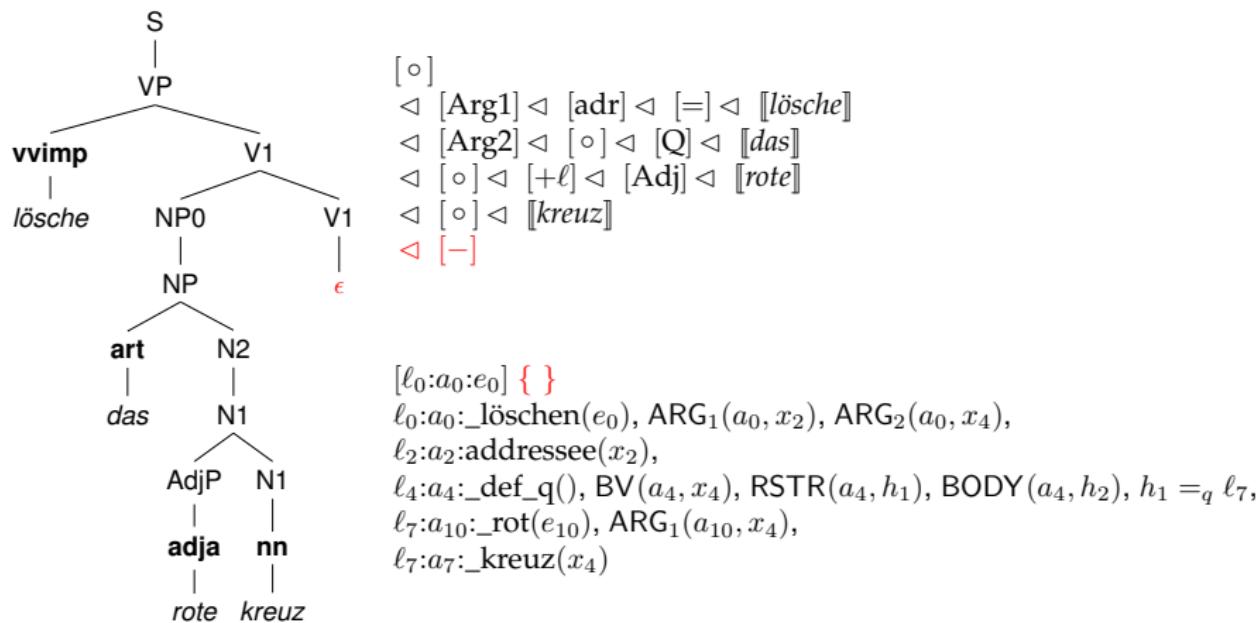
[o]
 □ [Arg1] □ [adr] □ [=] □ [[lösche]]
 □ [Arg2] □ [o] □ [Q] □ [das]
 □ [o] □ [+ℓ] □ [Adj] □ [rote]
 □ [o]

$\ell_0:a_0:e_0 \{ [\ell_7:a_7:x_4][\ell_0:a_0:e_0] \}$
 $\ell_0:a_0:_löschen(e_0), \text{ARG}_1(a_0, x_2), \text{ARG}_2(a_0, x_4),$
 $\ell_2:a_2:\text{addressee}(x_2),$
 $\ell_4:a_4:_\text{def_q}(), \text{BV}(a_4, x_4), \text{RSTR}(a_4, h_1), \text{BODY}(a_4, h_2), h_1 =_q \ell_7,$
 $\ell_7:a_{10}:_\text{rot}(e_{10}), \text{ARG}_1(a_{10}, x_4)$

A worked example: derivation



A worked example: derivation



Further work

Grammar transformation can increase the parsing performance:

① left-factored grammars

- delay rule identification for rules with equal first childs
- transform semantic rules accordingly (in theory yes, automatically no)
- no further refinements to the semantic construction needed

② left-corner transformed grammars

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Left-corner transformed grammars are a specific type of grammar transformation that aim to improve the efficiency of parser generation. The name comes from the fact that they transform a grammar into a form where every non-terminal symbol appears as the first symbol in at least one production rule. This transformation is particularly useful for incremental semantic construction because it allows the parser to quickly identify which semantic rules apply to a given input prefix. The resulting grammar is often called a "left-corner grammar" or "left-corner transformed grammar".

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- delay attachment decisions
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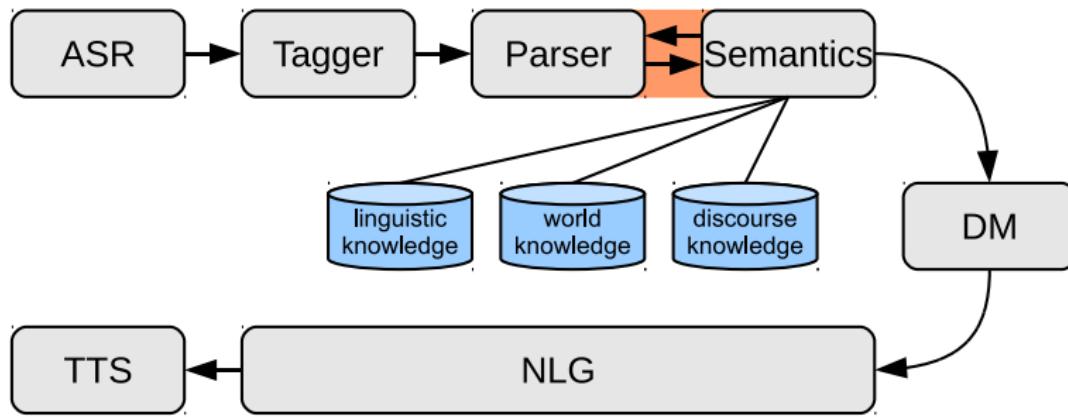
Recapitulation

- incrementality: early propagation
- incrementality: interaction / feedback
- top-down left-to-right tree interpretation
- monotonous, incremental construction

Application: Incremental Reference Feedback

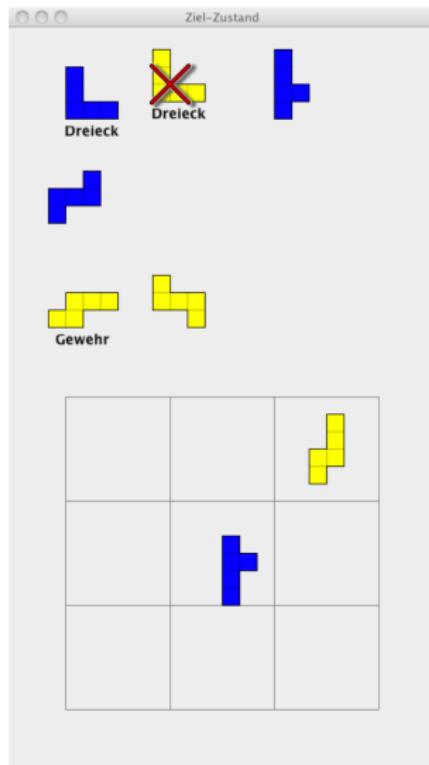
Joint work with Timo Baumann, Okko Buß, and David Schlangen

Idea



Incremental top-down parser, RMRS construction and reference resolution have been implemented in the InproTK Schlangen et al. [2010] for the Pentamino domain Fernández and Schlangen [2007].

Setting: Domain



Pentamino puzzle domain:

- Task oriented dialogue, instructor gives commands to a constructor in order to realise a desired state of the world
- Selecting, moving, deleting, rotating and mirroring of the puzzle pieces

Setting: Domain

A corpus collected in a WOz experiment:

- 20 participants, 284 games
- about 3000 utterances (each with dumped world state) of which...
- about 1600 have semantic annotation from the wizards next action, of which...
- about 1000 are free of pronouns.
- small command language, yet free and spontaneous speech

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Beispiele

in der ersten reihe das rote teil löschen
äh und jetzt nimm das kreuz .. das grüne in der linken spalte
und leg es nach ganz unten
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und im uhrzeigersinn drehen

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Setting: Modules

① ASR

- leave-one-out language model training
- run transcript versus offline recognition

② Tagger

③ Grammar

④ Parser

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③ Grammar

• simple grammar with handwritten rules for word ordering and part-of-speech constraints

④ Parser

• simple parser based on the grammar and tagger

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- small handmade core-grammar, weights set by hand, 35 rules

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- incremental n-best beam-search without conditioning functions
- no backtracking
- no beam pruning

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- derives variable assignments for all nominal predicate structures
- calculates the set of common objects

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Baseline / Variants

Compare the gold semantic annotation with the resolving world object according to...

① Just Syntax (JS)

- single-best derivation of only syntax

② External Filtering (EF)

...the system can access external knowledge bases to filter the possible worlds

③ Syntax Pragmatic Interaction (SPI)

...the system can interact with the user to resolve ambiguities

④ Combined Interaction and Filtering (CIF)

Baseline / Variants

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Results: Accuracy

	JS	EF	SPI	CIF
transcript	-1	563	518	364
	0	197	198	267
	1	264	308	392
	str.acc.	25.7%	30.0%	38.2%
	rel.acc.	44.9%	49.3%	64.2%
	incr.scr	-1567.66	-1248.26	-535.862
	avg.incr.scr	-1.52	-1.22	-0.52
recognition	-1	362	348	254
	0	122	121	173
	1	143	158	196
	str.acc.	22.6%	25.0%	31.0%
	rel.acc.	41.2%	44.1%	58.3%
	incr.scr	-1905.76	-1729.77	-1105.43
	avg.incr.scr	-1.86	-1.69	-1.01

Results: Efficiency

	readings	expansions	degrades	pruned deriv.	survived deriv.
no interaction	2186	247052	0	0	69510
interaction	1934	210137	140626	7310	60654
	88%	85%			87%

(for the transcript only, with robust parser operations activated)

Discussion

- grammar does not cover all that is wanted
- yet, there'll always be strange constructions in spontaneous speech
- semantic gold featured a discourse-history oracle: 30% of the corpus utterances had a semantic annotation without including a proper NP ("und nochmal drehen bitte"). -30% strict -10% relaxed max accuracy
- first experiments, only hand-set parameters

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Recapitulation

- incrementality: early propagation
- incrementality: interaction / feedback
- top-down left-to-right tree interpretation
- monotonous, incremental construction
- feedback improves NLUs accuracy and efficiency

Future Work

- write better grammar, train grammar
- probabilistic reference resolution
- optimise parameters
- automatic semantic rule acquisition
- VP advising
- experiment in a larger domain, more complex language

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Thank You!

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