

Constraint Language for LRS

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Semantic Underspecification in HPSG

- Historically, HPSG's answer to semantics has been to encode the apparatus of well-formedness constraints alongside grammar:
 - Cooper storage: QSTORE [Pollard & Sag, 1994]
 - Massively overgenerated
 - Many other theoretical objections [Pollard & Yoo, 1998]
 - FS representation amounted to algorithmic storage devices, augmented with “principles”
 - Situation semantics in place of semantic typing, e.g. $e \rightarrow t$.

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 - Cooper storage: QSTORE [Pollard & Sag, 1994]
 - Minimal Recursion Semantics: MRS [Egg, 1998; ERG]
 - First to separate underspecified semantic object (logical term) from syntactic tree
 - Does not commit to the “real semantics” – more of a front end
 - Also first to think of this in terms of semantic *descriptions* subject to a fixed, extra-grammatical resolution procedure (acyclicity, free variables, etc.)
 - No true semantic typing.

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 - Minimal Recursion Semantics: MRS [Egg, 1998; ERG]
 - Underspecified Hole Semantics: Ty2U [Richter & Sailer, 1999]
 - First to attempt a “real semantics”
 - But used FSs to explicitly represent dominance [Muskens, 1995]
 - Semantic typing (hooray!) – but encoded in feature logic
 - But assumed description level and existence of extra-grammatical resolution.

Semantic Underspecification in HPSG

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 - Constraint Language for Lambda Structures: CLLS [Egg & Erk, 2001]
 - Has a “real semantics,” but not your semantics
 - Traditional λ -calculus: beta-reduction instead of underspecification
 - No universal principles whatsoever – even so-called CLLS for HPSG [Egg & Erk, 2002] was just phrase-structure rules with FSs
 - No semantic typing, but somehow seemed to feel guilty about not having it.

Lexical Resource Semantics (LRS): why bother?

- All semantic idiosyncrasies are lexical, as a matter of design
- True semantic typing – no excuses
- In other respects, a different combination of choices on issues already under discussion:
 - (+CLLS, +Ty2U) real semantics
 - (+MRS, +Ty2U) descriptions, which can be underspecific; no beta-reduction; constraint-based
 - (+MRS) formerly tried using FSs, but not anymore
 - (-MRS) antecedents of constraints also have access to semantics; semantic description language itself is richer in other respects
- **But this particular combination presents both challenges and opportunities:**
 - Extra-grammatical resolution is a Good Thing: doesn't clutter up the grammar for linguists; computational linguists own the resolution procedure
 - Lots more potential there than just acyclicity – compatible with performing semantic inference:
 - E.g., $\forall x.[\text{horse}(x) \rightarrow \text{run}(x)], \text{horse}(\text{SEABISCUIT}) \vdash \text{run}(\text{SEABISCUIT})$
 - But even with just the basics, LRS's use of variables not even known to be PTIME
 - For the rest of this talk, "Resolution" = tractably eliminating superfluous underspecification
 - "Real semantics" means that underspecification is a matter of convenience

Assumptions

- We assume that semantic composition is built on a tripartite distinction among:
 - Internal content: nuclear contribution of semantic head
 - External content: contribution of semantic head's maximal syntactic projection
 - Semantic contribution: of pieces of Ty2 terms by component signs.
- LRS assumes more than this, and so the language I am describing (CLLRS) could encode a wider range of theories than LRS.

The CLLRS model

- **We augment the models that come with standard feature logic:**
 - $@sem: U \rightarrow \mathcal{P}(Ty2)$
 - $\{pivot\}: U \rightarrow \mathcal{P}(Ty2)$
 - $^{\wedge}root: U \rightarrow \mathcal{P}(Ty2)$
 - $/contributor: Ty2 \rightarrow \mathcal{P}(U)$
- **No extra expressive power here:**
 - Logical-form semantics: we model Ty2 terms, not what Ty2 models
 - This could still be encoded in typed feature logic (and it is definitely not worth doing so).

The CLLRS model

- **We augment the standard type system for feature logic with functional types and polymorphic variables, but only for semantic terms:**
 - `semtype [t,f]: t.`
 - `semtype [student,book]: (s->e->t).`
 - `semtype read: (s->e->e->t).`
 - `semtype [every,indefinite,exists]: (e->t->t->t).`
 - `semtype w: var(s).`
 - `semtype q: var(e->t->t->t).`
 - `semtype [a,e,x,y,z]: var(e).`
 - `semtype lambda: (var(A)->B->(A->B)).`
- **And, oh yeah, immediate/improper subterms.**

CLLRS constraint algebra

- literal/type consistency:
 $\text{literal}(N, \text{Lit1}, \text{Type1}) \setminus \text{literal}(N, \text{Lit2}, \text{Type2})$
 $\iff \text{Lit1}=\text{Lit2}, \text{Type1}=\text{Type2}.$
- pivot and root are functions:
 $\text{pivot}(X, N) \setminus \text{pivot}(X, M) \iff N=M.$
 $\text{root}(X, N) \setminus \text{root}(X, M) \iff N=M.$
- immediate subterm irreflexivity:
 $\text{ist}(N, N, _) \implies \text{fail}.$
- immediate subterm uniqueness:
 $\text{ist}(M1, N, A) \setminus \text{ist}(M2, N, A) \iff M1=M2.$
- subterm anti-symmetry:
 $\text{st}(M, N), \text{st}(N, M) \iff M=N.$
- Note the lack of arity consistency: applications are explicit parts of term trees.

This is what grammar gets you:

kim walks

File View Tools

Zoom: 100%

hd_subj:kim walks

hd_subj_ph
PHON
DTRS
HD_DTR
NON_HD_DTRS

SEMANTICS

= CLLRS =

\wedge ap (ap (lambda/ (8), b/ (8)) / (8), c) / (8)

A

ap (ap (exists2/ (8), a/ (8)) / (8), E) / (8)

kim/ (7) { ap (ap (ap (walk/ (8), b/ (8)) / (8), a/ (8)) / (8), kim/ (7)) / (8)

SUBJ_GAP

synsem

loc

cat

HEAD 10

MARKING

val

SPR 12

SUBJ <>

COMPS 5

CONT 13

CONTENT *mgsat(content)*

FA_STRUC *cont*

NON_LOC

SYNSEM

LOC

CAT

VAL

CONT

CONTENT

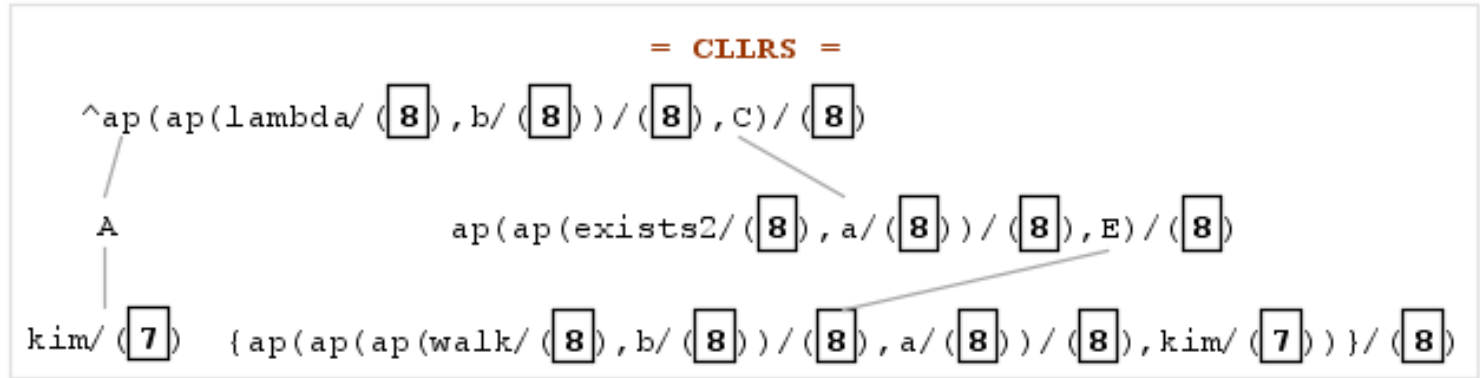
FA_STRUC

NON_LOC

lexicon:kim lexicon:walks

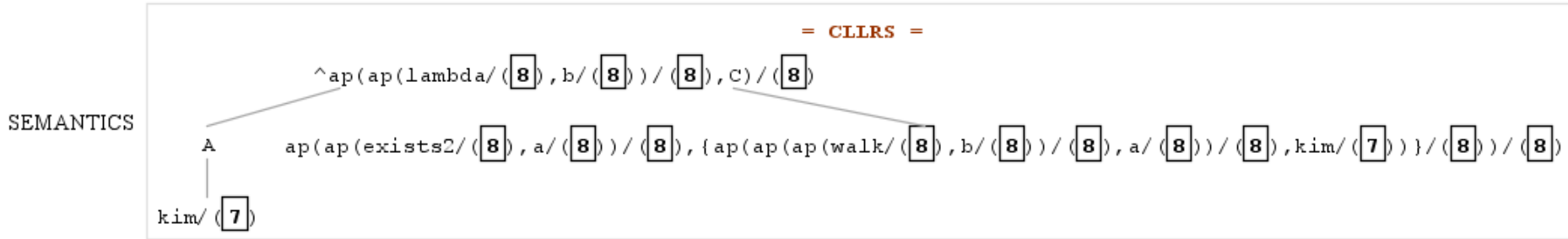
0) This is what we need to resolve:

SEMANTICS



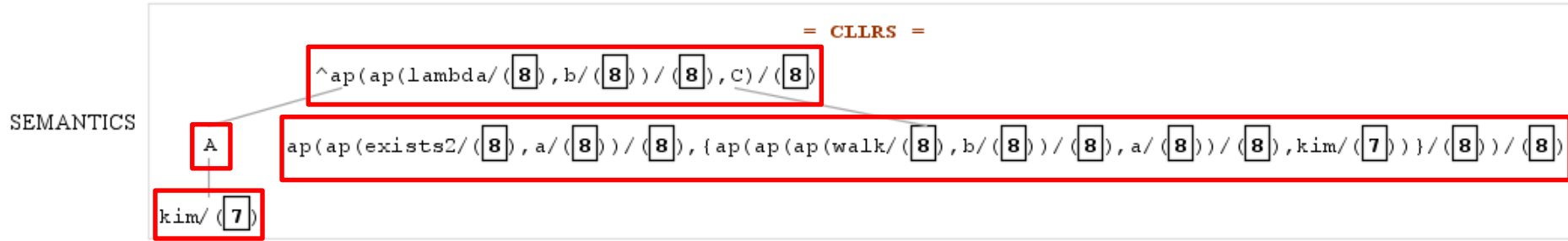
(Clearly, we also have a GUI problem)

1) Use the type system:



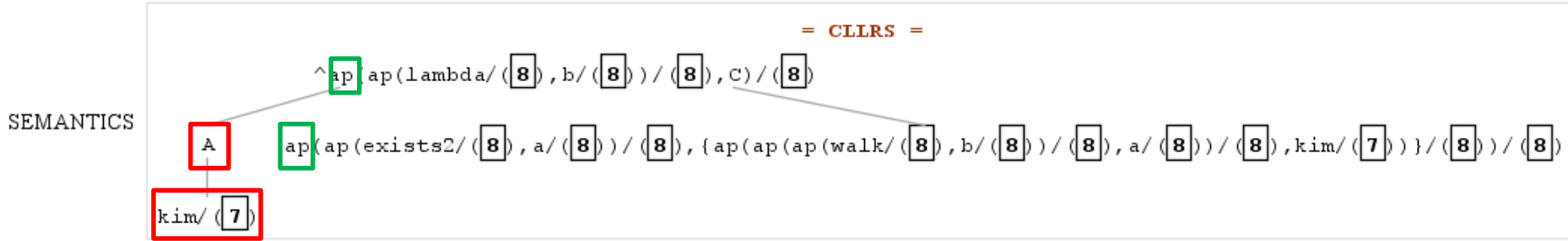
Out of 153 rejected candidate pairs for combination, 124 pairs (81%) were determined because of the type system; 26 (17%) because of cyclicity.

2) Identify “modules:”



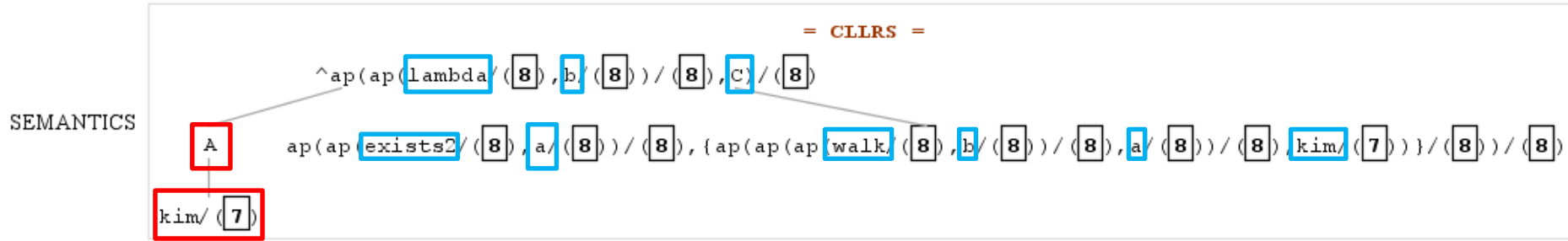
These are characterized by subgraphs connected by immediate subterm edges and no improper subterm edges.

3) Identify “tops” of modules:



Tops are the term itself and the RHS of any improper subterm edge.

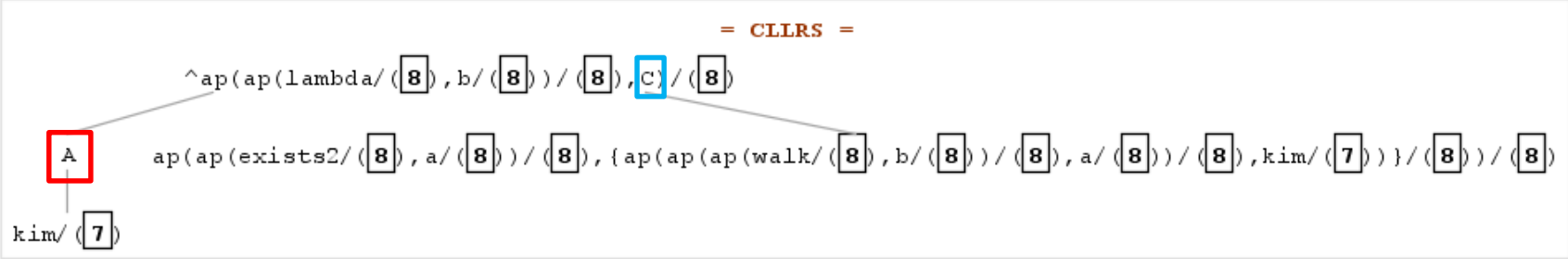
4) Identify “bottoms” of modules:



Bottoms are located by propagating downward from every top.

5) Non-determinately pick a top and bottom:

SEMANTICS



5) ...and speculatively combine them:

SEMANTICS

= CLLRS =

$$\hat{\text{ap}}(\text{ap}(\text{lambda}/\langle 8 \rangle, \text{b}/\langle 8 \rangle) / \langle 8 \rangle, \text{B}) / \langle 8 \rangle$$
$$\text{ap}(\text{ap}(\text{exists2}/\langle 8 \rangle, \text{a}/\langle 8 \rangle) / \langle 8 \rangle, \{ \text{ap}(\text{ap}(\text{ap}(\text{walk}/\langle 8 \rangle, \text{b}/\langle 8 \rangle) / \langle 8 \rangle, \text{a}/\langle 8 \rangle) / \langle 8 \rangle, \text{kim}/\langle 7 \rangle) \} / \langle 8 \rangle) / \langle 8 \rangle$$

5) Keep doing this step:

SEMANTICS








- CLLRS -

$\wedge \text{ap}(\text{ap}(\text{lambda} / \langle 8 \rangle, \text{b} / \langle 8 \rangle) / \langle 8 \rangle, \text{ap}(\text{ap}(\text{exists2} / \langle 8 \rangle, \text{a} / \langle 8 \rangle) / \langle 8 \rangle, \{\text{ap}(\text{ap}(\text{ap}(\text{walk} / \langle 8 \rangle, \text{b} / \langle 8 \rangle) / \langle 8 \rangle, \text{a} / \langle 8 \rangle) / \langle 8 \rangle, \text{kim} / \langle 7 \rangle\}) / \langle 8 \rangle) / \langle 8 \rangle) / \langle 8 \rangle$

Intuition behind this strategy

- There are fewer modules than there are subterms
- With top-bottom combinations, the number of modules strictly decreases
- Improper subterm edges are never added by inference – these are primitive constraints added directly by grammarians, and so the grammarian has control
- In the background, we are still doing type-driven subterm combination, but only when the result is determinate
- There is a possibility of generating many answers through speculation, but we can count them before displaying them, and they can be undone
- There are nevertheless very simple grammars for which known determinate-only solving does not yield a completely resolved semantic term – unacceptable
- In the meantime, documenting which sorts of speculation prove to be fruitful (and determinate) is an important source of information for:
 - finding new determinate constraint-solving strategies, and
 - statistical inference that can guess what will work best (shortest path to resolution).

What should we do now?

- + New chat
- Efficient Constraint Res  
-  Clear conversations
-  Dark mode
-  OpenAI Discord
-  Updates & FAQ
-  Log out






How do I make constraint resolution tractable in Lexical Resource Semantics?




What should we do now? ChatGPT knows...


+ New chat


Efficient Constraint Res  

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Constraint resolution in Lexical Resource Semantics can be made tractable by using a combination of techniques, such as:



1. Representing constraints in a logical form that allows for efficient reasoning, such as first-order logic or description logic.
2. Using algorithms for constraint satisfaction and optimization, such as backtracking or branch-and-bound.
3. Utilizing efficient data structures, such as decision diagrams or constraint networks, to represent and manipulate the constraints.
4. Applying heuristics and approximations to simplify the constraint satisfaction problem, such as using constraint relaxation or partial solutions.
5. Using machine learning to learn constraint patterns and make better decisions on constrains based on the learned patterns.

It's important to note that the best approach will depend on the specific application and the nature of the constraints.

 Regenerate response

