

Probabilistic Induction for an Incremental Semantic Grammar

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Robust Incremental SEMantic Resources for Dialogue



Dialogue is Incremental

We don't always speak in "complete" sentences

A: So what is that? Is that er . . . booklet or something?

B: It's a [[book]]

C: [[Book]]

B: Just . . . [[talking about al– you know alternative]]

D: [[On erm . . . renewable yeah]]

B: energy really I think

A: Yeah *[BNC D97 2038-2044]*

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- We're not dealing with individual grammatical *sentences*
- What does this tell us for grammar, parser, generator?
- Can we build (or learn) a suitable grammar?

Outline

- 1 Dialogue & Incrementality
 - Compound Contributions
 - Requirements for Grammar
- 2 Tools for Incrementality
 - Dynamic Syntax
 - Type Theory with Records
- 3 DS/TTR: The DYLAN Framework
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- Nearly 20% of BNC contributions continue another
- Over 70% continue something already apparently complete
- Pauses, role changes, continuations, self/other repair ...
- Incremental parsing & generation, highly coordinated

Incremental Processing

BNC KIND 160-164

A: So if you start at the centre [pause] and draw a line and mark off seventy two degrees,

B: Mm.

A: and then mark off another seventy two degrees and another seventy two degrees and another seventy two degrees and join the ends,

B: Yeah.

A: you'll end up with a regular pentagon.

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- NLG must be suspended and restarted in context
- NLU must be suspended and restarted in context

Parsing ↔ Generation

BNC KPY 1005-1008

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B: Chorlton?

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- Linguistic context must be available

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BNC H5H 110-111

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- Need representations which can be extended incrementally

Syntax, But Not As We Know It

Syntactic Dependencies

A: I'm afraid I burnt the kitchen ceiling

B: But have you

A: burned myself? Fortunately not.

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- Syntactic constituency not respected

Not Always Collaborative

Lerner (1991)

Daughter: Oh here dad, a good way to get those corners out
Dad: is to stick yer finger inside.
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- Not just plan recognition and extension

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- Psycholinguistic Models (Sturt, Crocker)
- Computational Models (Roark, Hale)
 - Efficient, predictive parsing models
 - Based on string-licensing syntactic grammars
- Categorical Grammar (Steedman, Clark, Milward)
 - Well-defined syntax/semantics interface
 - Incremental parsing by type-raising - requires look-ahead
 - (although see Hefny et al, 2001)

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- Psycholinguistic models (De Smedt, Kempen, Guhe)
 - Modular / parallel generator components
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- Self-Monitoring Models (Neumann, van Noord)
 - Interleaved parsing ↔ generation
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- Formal model (Poesio & Rieser)
 - Lexicalised TAG
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 - Lexicalised TAG
 - PTT for dialogue/utterance context
 - Detailed plan recognition
- String-licensing grammar
- NLU/NLG interface unclear
- Relies on collaborative plan recognition

Previous Approaches - Dialogue

- General abstract model (Schlangen & Skantze)
- Incremental NLU (Schlangen, Buss, Peldszus, Aist et al)
 - Faster NLU and reference resolution
- Incremental NLG (Skantze, Hjalmarsson)
 - Faster, more natural generation with repair

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- NLU/NLG reversibility?
- Linguistic structure, constraints?
- Linguistic context?

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- An incremental dialogue framework
 - *Jindigo* (Schlangen & Skantze, 2009)

Outline

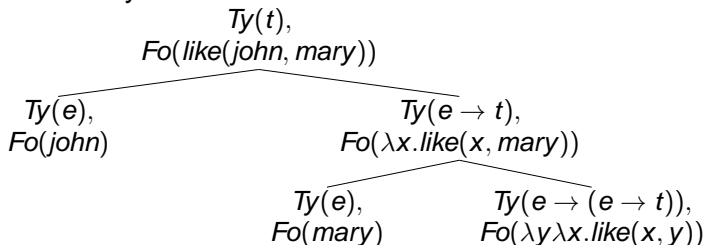
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Dynamic Syntax

- An inherently incremental grammatical framework
- Word-by-word incremental construction of semantic interpretation:
 - no autonomous level of syntax
 - “syntax” defined via constraints on incremental semantic structure-building
 - “grammar” is a set of procedures for incremental parsing
 - “trees” are semantic representations defined using LoFT (Blackburn & Meyer-Viol, 1994)
- Monotonic growth with underspecification-plus-enrichment
- Predictivity: requirements for later satisfaction

DS Trees as semantic representations

- End product of parsing is a semantic tree
 - Nodes decorated with $Ty()$ type and $Fo()$ formula labels
- “John likes Mary”:



- Daughter order does not reflect sentence order!
- Nodes interpretable as terms in the λ -calculus
- NPs map onto terms of type e using the ϵ -calculus.

Actions as tree-building procedures

- Incremental tree growth driven by *requirements* e.g. $?Ty(t)$
- Node under development marked by *pointer* \diamond
- Words induce sets of *lexical* actions: “*john*”

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IF      ?Ty(e)
THEN    put(Fo(john));      ?Ty(e)
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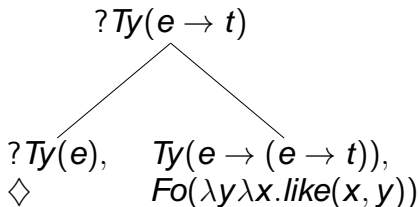
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```

IF      ?Ty( $e \rightarrow t$ )
THEN   make( $\langle \downarrow_1 \rangle$ ); go( $\langle \downarrow_1 \rangle$ );
          put( $Fo(\lambda y \lambda x. like(x, y))$ );
          put( $Ty(e \rightarrow (e \rightarrow t))$ )
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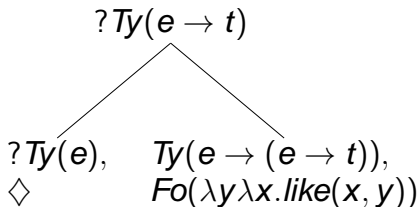


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- General *computational* actions are also available e.g. requirement fulfillment, beta-reduction

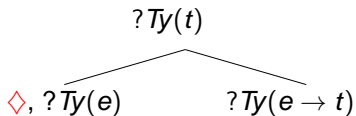
Unfolding then building up the tree

Processing *John fainted*

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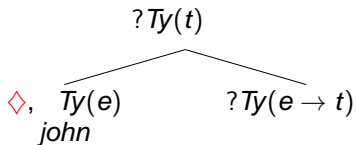
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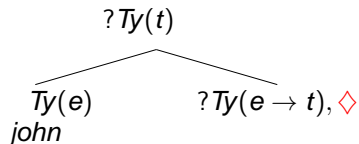
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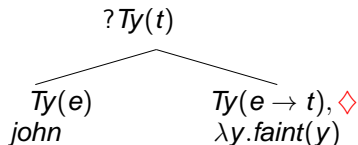
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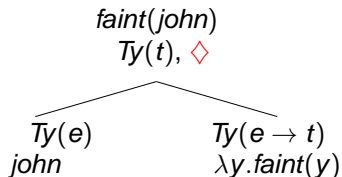
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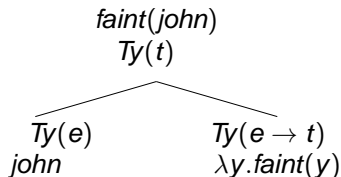
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\rightsquigarrow *faint(john)*

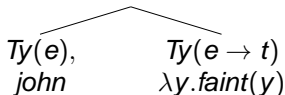


Generation

- Speakers go through the same tree-growth actions, except they also have a somewhat richer goal tree.
- Each word licensed must update partial tree towards the goal tree via *subsumption* constraint
- Generating *John fainted*

GOAL TREE

$Ty(t), \diamond$
faint(john)



TEST TREE

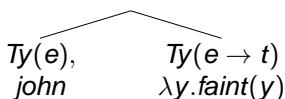
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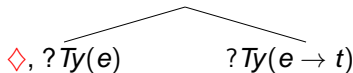
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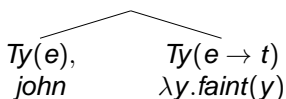


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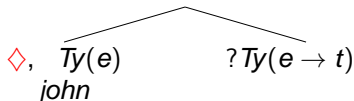
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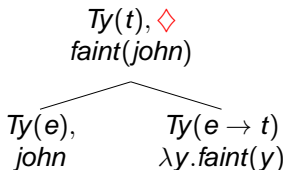


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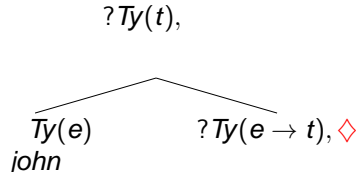
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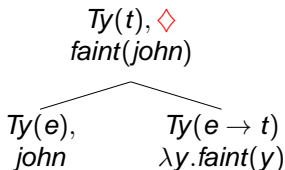


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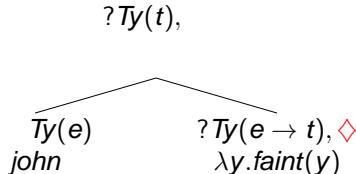
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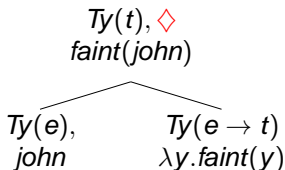


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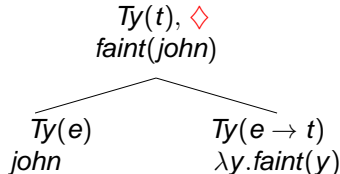
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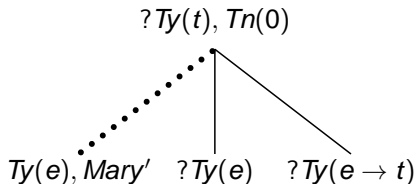
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Structural Underspecification

- “Unfixed” nodes - building underspecified tree relations



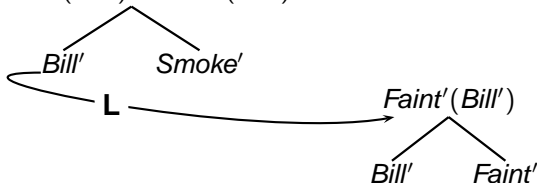
- Left-dislocation “Mary, John likes”

LINKed trees

- **Relative clauses:** pairs of LINKed trees evaluated as conjunction

e.g. Bill, **who fainted**, smokes.

$Smoke'(Bill') \wedge Faint'(Bill')$



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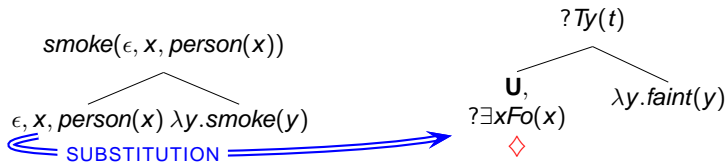
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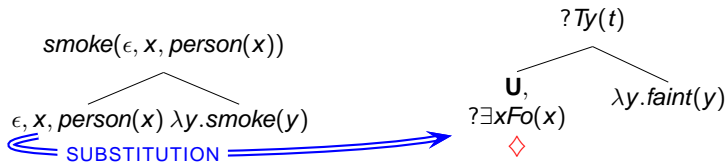


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- Context must include trees and action sequences

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Some specific shortcomings

- No principled way to incorporate context information
 - e.g. constraints over speaker/hearer identity
- Generation requires a goal *tree*
 - i.e. knowledge of how the LF is to be compiled
- FOL/ ϵ -calculus formulae hard to integrate with dialogue systems
 - usually DRT or frame-like constructs

Outline

- 1 Dialogue & Incrementality
 - Compound Contributions
 - Requirements for Grammar
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 - Dynamic Syntax
 - **Type Theory with Records**
- 3 DS/TTR: The DYLAN Framework
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Type Theory With Records

- (Cooper, 2005; Betarte & Tasistro, 1998), following Martin-Löf

- *Records* are sequences of label/value pairs:

$$\begin{bmatrix} l_1 = v_1 \\ l_2 = v_2 \\ l_3 = v_3 \end{bmatrix}$$

- *Record types* are sequences of label/type pairs:

$$\begin{bmatrix} l_1 : T_1 \\ l_2 : T_2 \\ l_3 : T_3 \end{bmatrix}$$

- Record types are true iff they are *inhabited/witnessed*
 - = there exists at least one record of that type
 - = successful type judgements for each label/value pair:

$$v_1 : T_1, v_2 : T_2, v_3 : T_3$$

Type Theory With Records

- Types can be *dependent* on earlier (higher-up) types:

$$\left[\begin{array}{l} l_1 : T_1 \\ l_2 : T_2(l_1) \\ l_3 : T_3(l_1, l_2) \end{array} \right]$$

- We can have *nested* records and record types:

$$\left[\begin{array}{l} l_1 : T_1 \\ l_2 : \left[\begin{array}{l} l'_1 : T'_1 \\ l'_2 : T'_2 \end{array} \right] \\ l_3 : T_3(l_1, l_2.l'_1, l_2.l'_2) \end{array} \right]$$

- We can have *functional* record types:

$$\lambda r : \left[\begin{array}{l} l_1 : T_1 \\ l_2 : T_2 \end{array} \right] \left(\left[\begin{array}{l} l_3 : T_3 \\ l_4 : T_4(r.l_1, r.l_2) \end{array} \right] \right)$$

Type Theory With Records

- Subtype-supertype relations:

$$[h_1 : T_1] \sqsubset [h_1 : T_2] \quad \text{if} \quad T_1 \sqsubset T_2$$

$$\left[\begin{array}{l} h_1 : T_1 \\ h_2 : T_2 \end{array} \right] \sqsubset [h_1 : T_1]$$

- All records are of type []
- Manifest (singleton) types:

$$[x : john] \sqsubset [x : e] \quad \text{if} \quad john \sqsubset e$$

$$[x_{=john} : e]$$

Type Theory With Records

- Used for sentential semantics, e.g. Cooper (2005)

- “A man left”: $\left[\begin{array}{l} x : man \\ p : leave(x) \end{array} \right]$

- for truth: x must be a man, p a proof that x left

- “Every man left”:
 $\lambda r : \left[x : man \right] \left(\left[p : leave(r.x) \right] \right)$

- Similarities to DRT representation:

x
man(x) leave(x)

- Used for dialogue modelling in the information-state-based tradition
 - (Cooper & Ginzburg, 2002; Ranta & Cooper, 2004; Fernandez, 2006; Ginzburg, 2012)

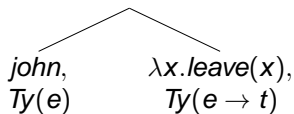
The best of both worlds?

- TTR gives us a type-theoretic framework, applicable to dialogue phenomena
- DS gives us an incremental framework using type theory as an underlying mechanism
- Can we combine the two?

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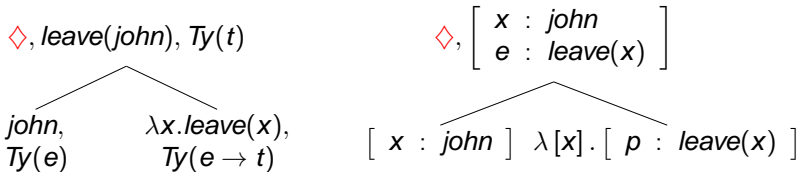
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◇, *leave(john)*, $Ty(t)$



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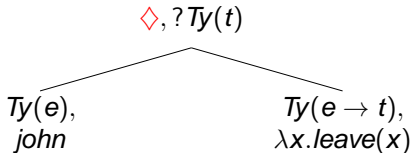


Combining DS with TTR

- Replace $Fo()$ epsilon-calculus labels with TTR record types

Combining DS with TTR

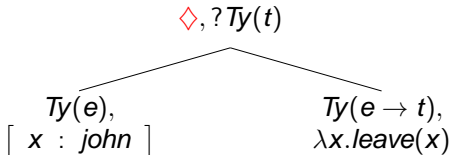
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IF $?Ty(e)$
THEN $put(Ty(e))$
 $put(Fo(john))$
ELSE abort

Combining DS with TTR

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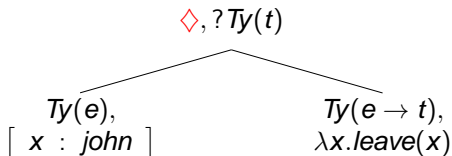


```

IF      ?Ty(e)
THEN   put(Ty(e))
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```


Combining DS with TTR

- Replace $Fo()$ epsilon-calculus labels with TTR record types
- Interpret $Ty()$ simple type labels as referring to *final* TTR field type

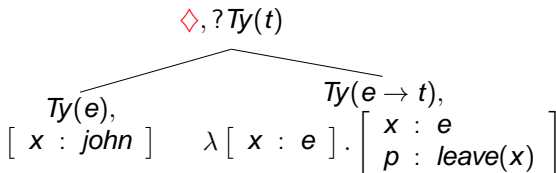


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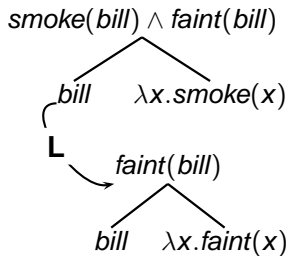
- Replace $Fo()$ epsilon-calculus labels with TTR record types
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- Function application as before for DS `elimination` process

$$\begin{array}{c}
 \diamond, Ty(t), \left[\begin{array}{l} x : john \\ p : leave(x) \end{array} \right] \\
 \swarrow \quad \searrow \\
 \begin{array}{c} Ty(e), \\ \left[x : john \right] \end{array} \quad \lambda \left[x : e \right] \cdot \begin{array}{c} Ty(e \rightarrow t), \\ \left[\begin{array}{l} x : e \\ p : leave(x) \end{array} \right] \end{array}
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Adding in LINK relations

- For LINKed trees, we need conjunction

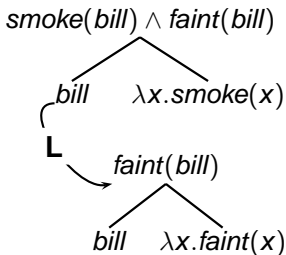
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Adding in LINK relations

- For LINKed trees, we need conjunction
- Use *extension*: \oplus where $r_1 \oplus r_2$ adds r_2 to the end of r_1
 - (for distinct labels; identical fields collapse (Cooper, 1998))

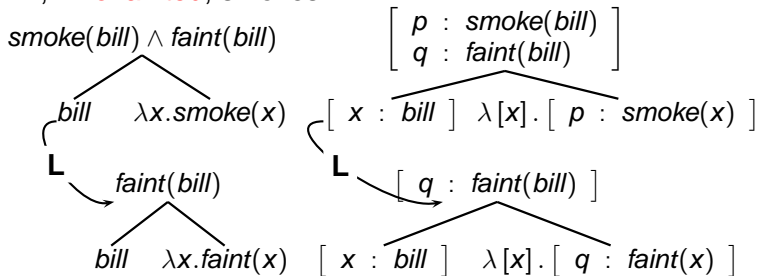
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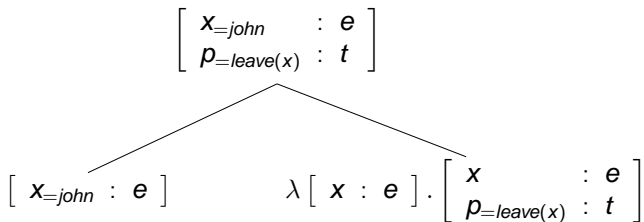
DS/TTR

- Recent work integrating DS with TTR (Purver et al, 2011)

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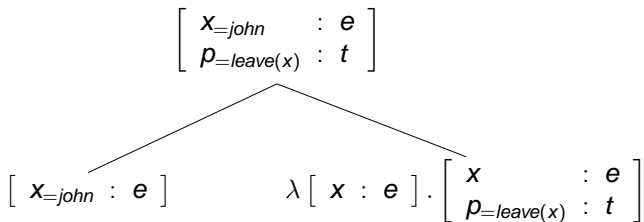
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DS/TTR

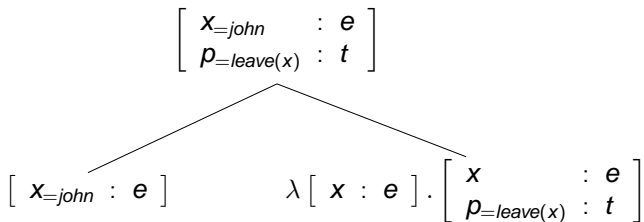
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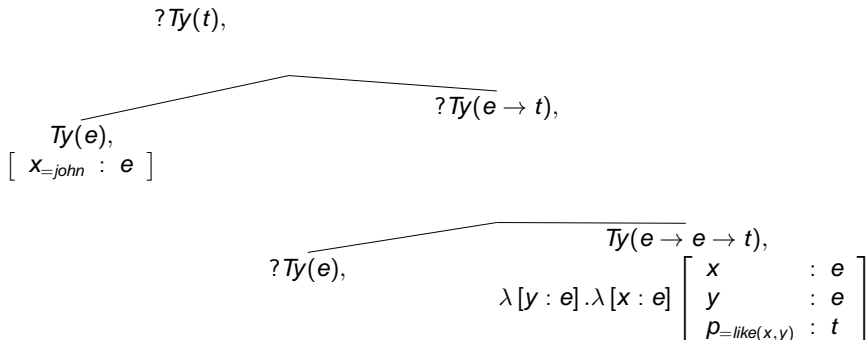
- TTR *record types* now provide the semantic content of each node of the DS trees
- LINKed trees for relative clauses and adjuncts are easily incorporated by extending (intersecting) *record types*
- Recently, a Davidsonian event-based semantics for tense has been incorporated (Cann, 2010, see next slide)

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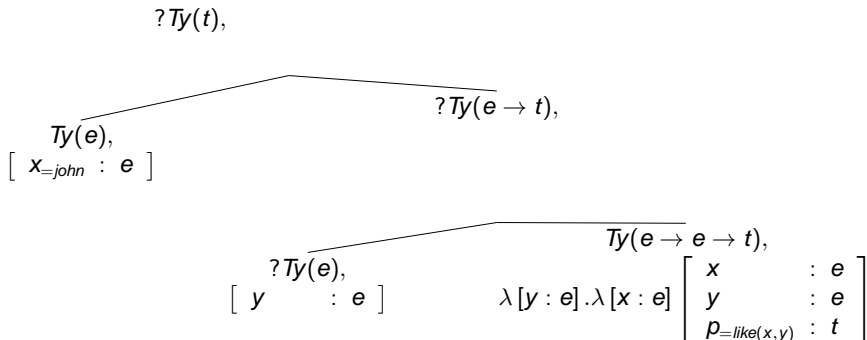
Root Node Type Deduction

- Inference of maximal semantic content (Hough, 2011)



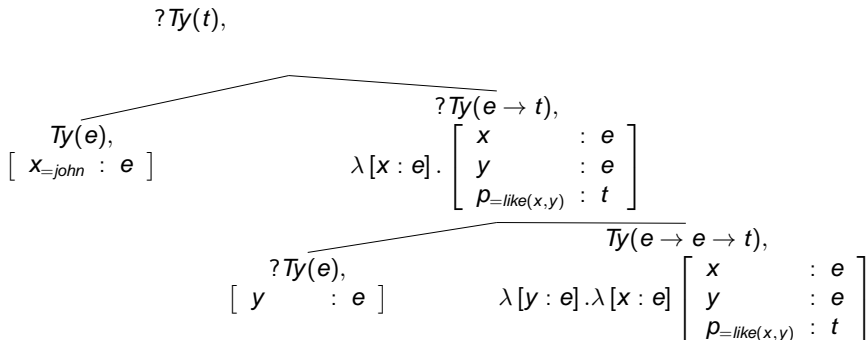
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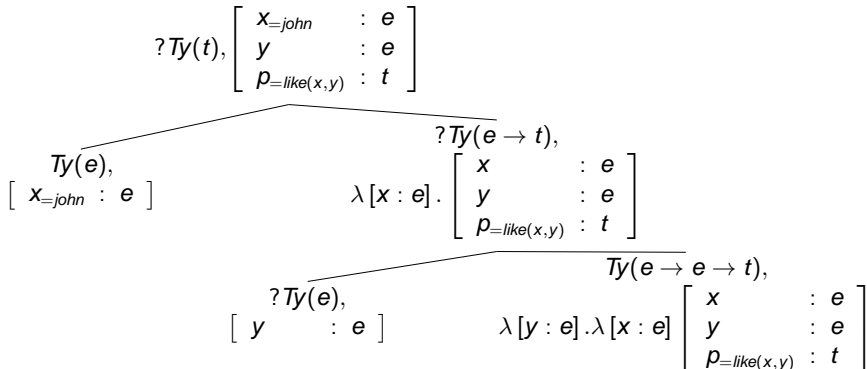
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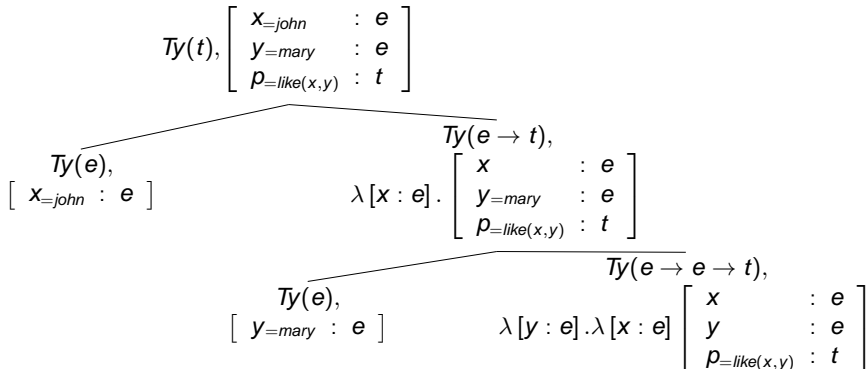
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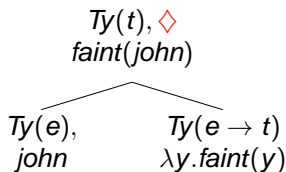
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Generation from Goal Concepts

- We can now generate from a goal *concept* (not *tree*)

GOAL TREE



TEST TREE

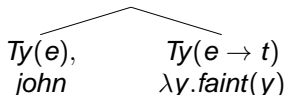
$?Ty(t), \diamond$

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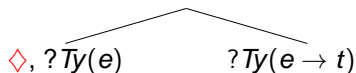
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$Ty(t), \diamond$
 $faint(john)$



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GOAL TREE

$Ty(t), \diamond$
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$Ty(e),$
john

$Ty(e \rightarrow t)$
 $\lambda y.faint(y)$

$\diamond,$

$Ty(e)$
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TEST TREE

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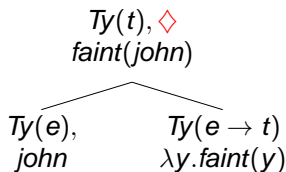
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Gen: "John"

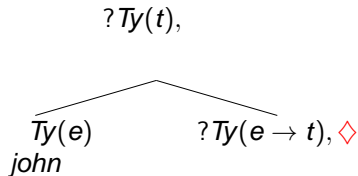
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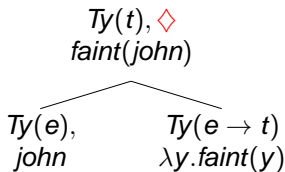


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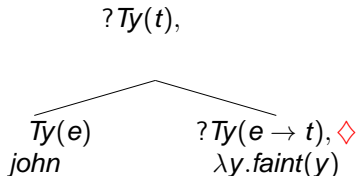
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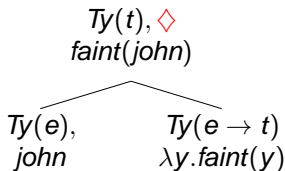


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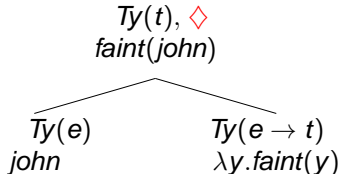
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GOAL CONCEPT

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? $Ty(t)$, \diamond

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Incremental Semantic Construction with DS-TTR

- Davidsonian semantics, LINKed trees: incremental interpretation

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$$\left[\begin{array}{ll} \mathit{event}_{=e1} & : e_s \\ \mathit{RefTime} & : e_s \\ \mathit{p1}_{=today(\mathit{RefTime})} & : t \\ \mathit{p2}_{=\mathit{RefTime} \circ \mathit{event}} & : t \end{array} \right]$$

A: Today

Incremental Semantic Construction with DS-TTR

- Davidsonian semantics, LINKed trees: incremental interpretation

$event_{=e1}$:	e_s
$RefTime$:	e_s
$\rho1_{=today(RefTime)}$:	t
$\rho2_{=RefTime \circ event}$:	t
$x_{=robin}$:	e
$\rho_{=arrive(event,x)}$:	t

A: Today.. Robin arrives

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$x1$:	e
$p3_{=from(event,x1)}$:	t

A: Today.. Robin arrives
B: From?

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$x_{=robin}$:	e
$p_{=arrive(event,x)}$:	t
$x1_{=Sweden}$:	e
$p3_{=from(event,x1)}$:	t

A: Today.. Robin arrives

B: From?

A: Sweden

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$p_{=arrive(event, x)}$:	t
$x1_{=Sweden}$:	e
$p3_{=from(event, x1)}$:	t
$x2_{=Elisabeth}$:	e
$p4_{=with(event, x2)}$:	t

A: Today.. Robin arrives

B: From?

A: Sweden

B: With Elisabeth?

Incremental Semantic Construction with DS-TTR

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$x_{=robin}$:	e
$p_{=arrive(event, x)}$:	t
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$x2_{=}$:	e
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A: Today.. Robin arrives

B: From?

A: Sweden

B: With Elisabeth?

- Online, collaborative, incremental construction of meaning as needed for dialogue.

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A	:	$participantA$
B	:	$participantB$
u	:	$utt-event$
s_u	:	e
p_s	:	$spkr(u, s_u)$
a_u	:	e
p_a	:	$addr(u, a_a)$

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B	:	$participantB$	
u	:	$utt-event$	$[u : utt(s_u, a_u)]$
$s_u(= A)$:	e	
p_s	:	$spkr(u, s_u)$	$[u : utt(A, B)]$
$a_u(= B)$:	e	
p_a	:	$addr(u, a_a)$	

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$$\diamond, Ty(e), \left[\begin{array}{l} u_0 : \text{utt}(s_0, a_0) \\ x : \text{john} \end{array} \right]$$

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Adding utterance context

- Add minimal utterance context information (see Poesio & Traum/Rieser)
 - Utterance event (for each word)
 - Speaker and addressee for that event

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- Content can refer to context, but not vice versa
- Assume this information available when parsing a word

Using utterance context

- Can use this to provide identity for indexicals

- “I”:
IF $?Ty(e), [\text{ctxt} : [u : \text{utt}(s_u, a_u)]]$,
THEN $\text{put}(Ty(e),$
 $\text{put}([\text{ctxt} : [u : \text{utt}(s_u, a_u)]])$
 $\text{cont} : [s_u : e])$

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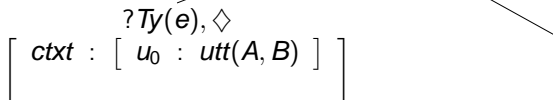
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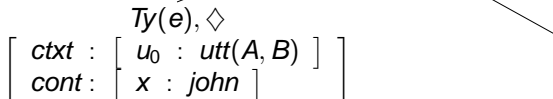
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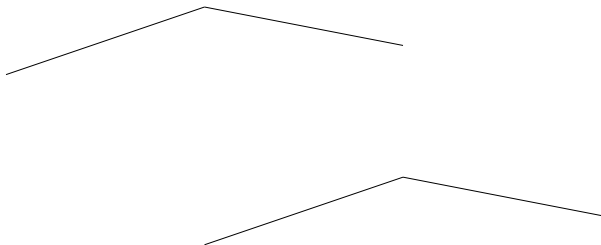
```
IF      ?Ty(e), [ ctxt : [ u : utt(su, au) ] ],
THEN   put(Ty(e)),
       put( [ ctxt : [ u : utt(su, au) ] ] )
         [ cont : [ su : e ] ] )
```

- “myself”:

```
IF      ?Ty(e), [ ctxt : [ u : utt(su, au) ] ] ],
       ↑0↑1*↓0 [ cont : [ x(= su) : e ] ] ]
THEN   put(Ty(e)),
       put( [ ctxt : [ u : utt(su, au) ] ] )
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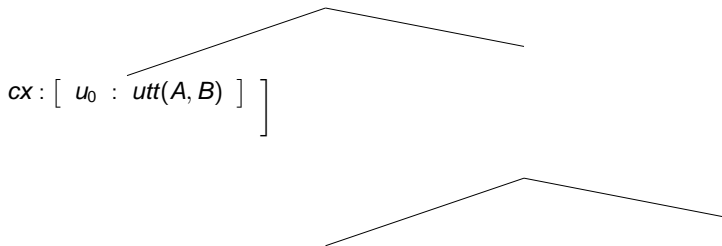

Split utterances with indexicals

- A: I like ... B: yourself.



Split utterances with indexicals

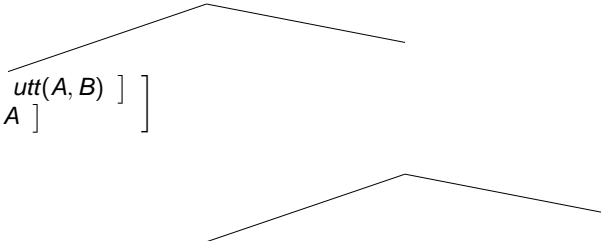
- A: I like ... B: yourself.



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$$cx : \left[\begin{array}{l} u_0 : utt(A, B) \\ x : A \end{array} \right]$$



Split utterances with indexicals

- A: I like ... B: yourself.

$$\begin{array}{l} cx : [u_0 : utt(A, B)] \\ ct : [x : A] \end{array}$$

$$cx : [u_1 : utt(A, B)]$$

Split utterances with indexicals

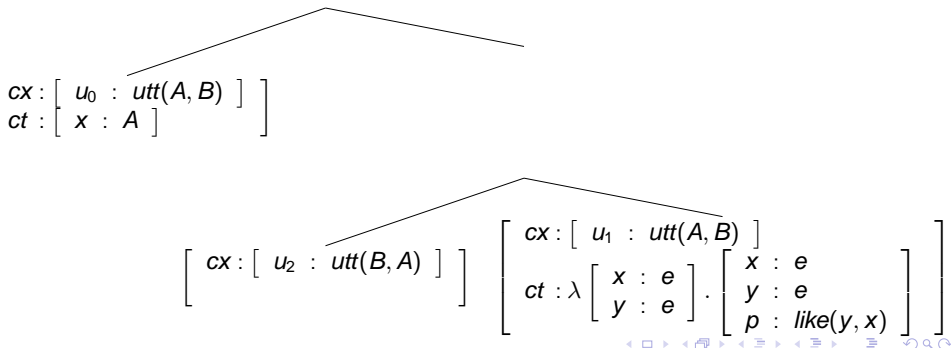
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$$\begin{array}{l}
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 ct : [x : A]
 \end{array}
]$$

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 ct : \lambda \left[\begin{array}{l} x : e \\ y : e \end{array} \right] . \left[\begin{array}{l} x : e \\ y : e \\ p : like(y, x) \end{array} \right]
 \end{array}
]$$

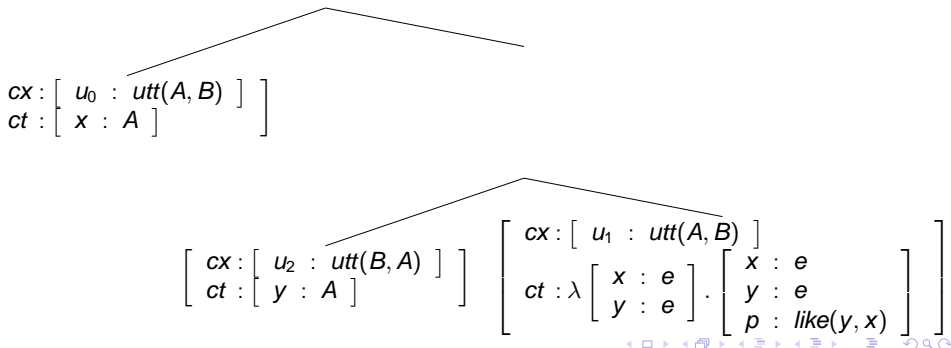
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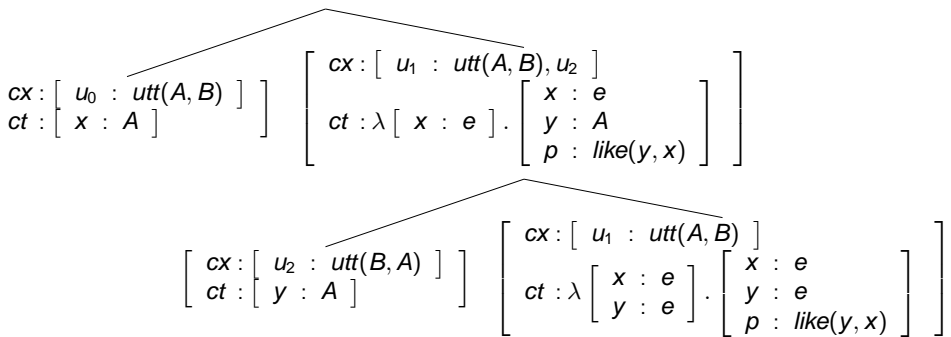
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Split utterances with indexicals

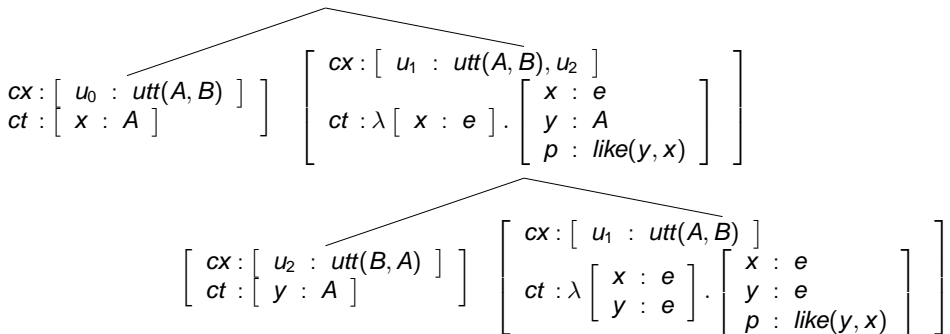
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Split utterances with indexicals

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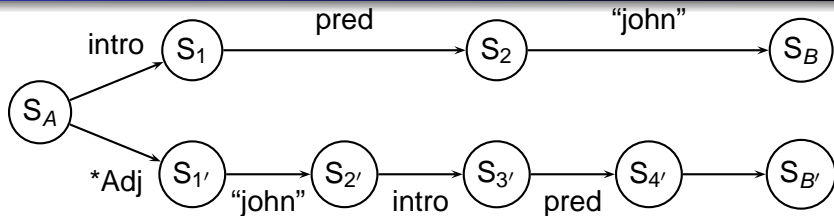
$$Ty(t), \left[\begin{array}{l} \text{ctxt} : \left[\begin{array}{l} u_0 : \text{utt}(A, B), u_1, u_2 \end{array} \right] \\ \text{cont} : \left[\begin{array}{l} x : A \\ y : A \\ p : \text{like}(x, y) \end{array} \right] \end{array} \right]$$



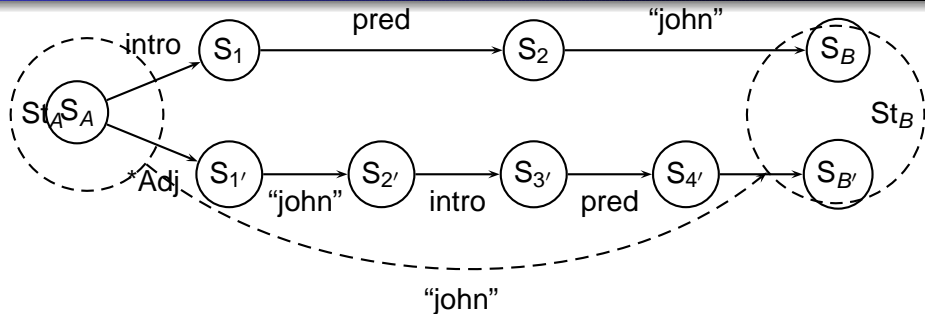
Parsing in Dynamic Syntax

- Parsing starts from some partial tree, proceeds in a time linear manner, reading the words in one by one, applying the corresponding lexical actions, optionally interspersing computational actions.
- This process is modelled on a Directed Acyclic Graph (DAG) (Purver et al. 2011, Sato, 2010) where:
 - Nodes = Trees
 - Edges = actions (lexical or computational)
 - Different Paths represent different parsing strategies.

DS Parse DAG

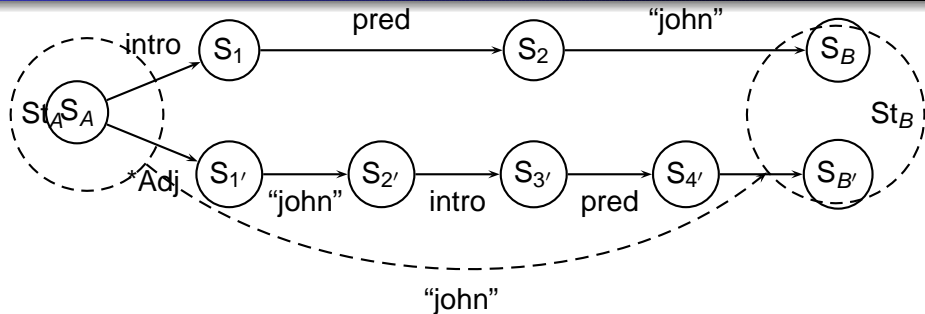


DS Parse DAG



- Integrate with word graph (and ASR "lattice")
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 - Edges = word transitions

DS Parse DAG



- Integrate with word graph (and ASR "lattice")
 - Nodes = tree sets
 - Edges = word transitions
- Graph *is* context model: words, trees, action sequences
 - Incremental *representation*

How are we doing now?

- Incrementality ✓
 - Processing language word by word
- Incremental interpretation
 - Maximal semantic content calculated at each step
- Incremental representation
 - Contribution of each word/unit to representations built
- Incremental context
 - Context added to and read from incrementally
- Reversibility ✓
 - Representations common between parsing and generation
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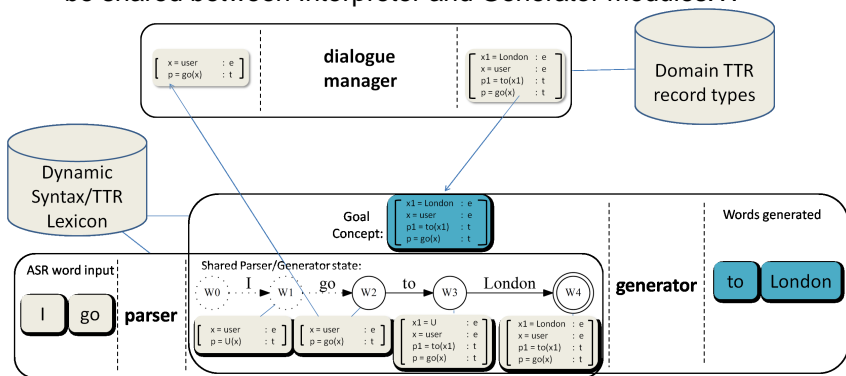
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So ...

- This seems like a suitable framework
- Can we actually do anything with it ... ?

Jindigo Module interaction: sharing parse state lattices

- Parse state DAG is common to generation and parsing, so can be shared between Interpreter and Generator modules. . .



But ...

- What about the coverage?

Outline

- 1 Dialogue & Incrementality
 - Compound Contributions
 - Requirements for Grammar
- 2 Tools for Incrementality
 - Dynamic Syntax
 - Type Theory with Records
- 3 DS/TTR: The DYLAN Framework
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 - Context and Parse Graphs
- 4 Learning Incremental Grammar
 - **Problem and Background**
 - Learning Lexical Entries

Problem: learning incremental semantic grammars

- DS is idiosyncratic: no independent level of syntactic processing, and word-by-word incremental
- Increasing coverage manually is unrealistic . . .
- We need to learn from data!

Problem: learning incremental semantic grammars

- DS is idiosyncratic: no independent level of syntactic processing, and word-by-word incremental
- Increasing coverage manually is unrealistic . . .
- We need to learn from data!
- Current induction methods developed for grammars that:
 - define syntactic structures over words
 - are not incremental, i.e. cannot deal with partial utterances/sentences
- Therefore hard or impossible to adapt directly

Previous work on induction

- Supervised: e.g. learning PCFGs from parsed corpora (e.g. Charniak, 1996)
 - successful for PSGs, but cognitively implausible
 - no data available for us
- Unsupervised: learning from raw, unannotated corpora
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- Unsupervised: learning from raw, unannotated corpora
 - less successful: computationally intractable in the worst case (Gold, 1967)
 - not clear how to apply to semantic problem
- Lightly supervised (latent variable supervised)
 - e.g. learn from sentences paired with Logical Form (LF)
- Plausible?
 - Shared focus of attention with others
 - 'Helpful' interaction e.g. corrective feedback (Saxton, 2010)

Semantically supervised learning

- Successfully applied to Combinatorial Categorical Grammar (Steedman, 2000), as it tightly couples compositional semantics with syntax (Zettlemoyer & Collins, 2007; Kwiatkowski et al. 2010; Kwiatkowski et al. 2011).
- Our problem of inducing DS lexical actions is in the same spirit ...
- ... except that CCG is not word-by-word incremental.
- Existing corpora annotated e.g. GeoQuery, PropBank, CHILDES
- Approach: hypothesize lexical entries which can be extended to yield the known LF

The problem

- Input:**
- the set of computational actions in Dynamic Syntax, G .
 - a set of training examples of the form $\langle S_i, T_i \rangle$, where S_i is a sentence of the language and T_i is the complete semantic tree representing the compositional structure of the meaning of S_i
 - (we will call T_i the *target tree*)

- Output:**
- a grammar consisting of the possible lexical actions for each word w
 - probability distributions θ_w over possible lexical actions specifying $p(a|w, T)$ in the context of a partial tree T

Simplifying Assumptions

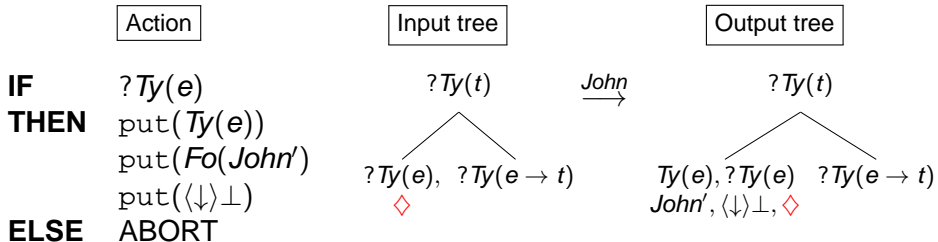
- Assume tree operations (i.e. lambda calculus) known
- Assume T_i is a *tree*, not a flat logical form
 - not a syntactic phrase-structure tree
 - correspondence of words *arrive* to LF elements $\lambda x. arrive'(x)$ unknown
- Assume lexical action probabilities conditioned only on pointed node type, and apply to only one type
 - θ_w specifies $p(a|w, T) \rightarrow p(a|w)$
 - (i.e. assume IF ? $Ty(X)$); learn THEN clause as sequence of atomic actions *go, make, put*)

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Lexical Actions

- Our task is to learn lexical actions:

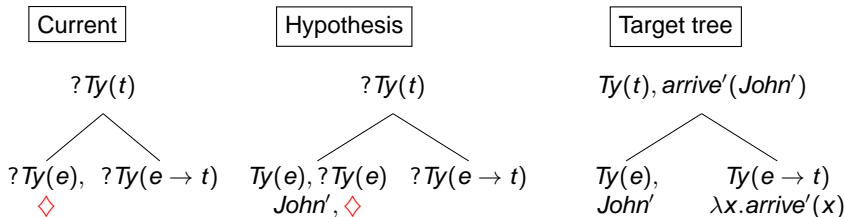


Method: incremental hypothesis construction

- DS is strictly monotonic:
 - Hypothesising lexical actions = an incremental search through the space of all monotonic extensions of the current tree T_{cur} that subsume the target tree T_t .
- Basic constraints on the structure of DS lexical actions makes the search space tractable.
- Hypothesis construction is integrated with parsing over a parse state DAG as above.
- Splitting and generalisation into possible lexical action subsequences.
- Probability estimation to keep most probable hypotheses.

Hypothesis construction

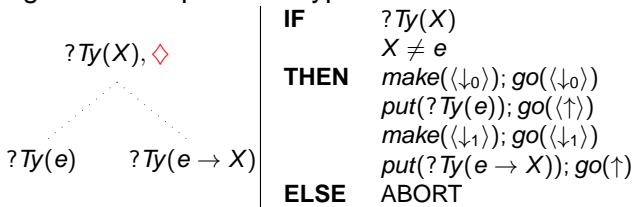
- Hypothesise extensions which subsume the target tree:



- This is just one of many possible hypotheses ...

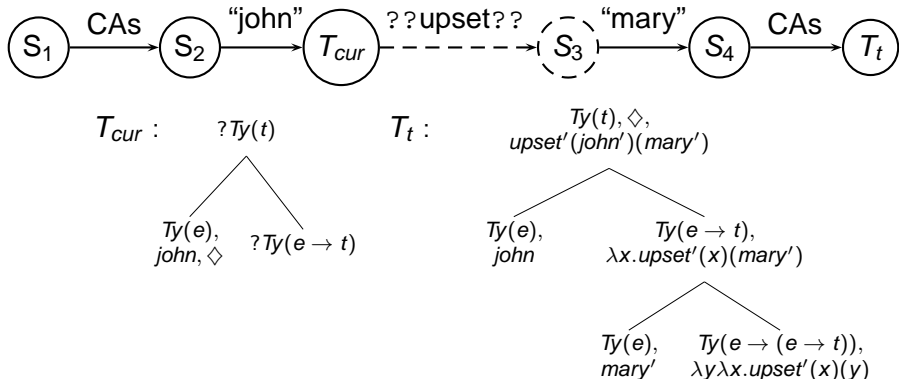
Constraining hypotheses

- Constraints imposed by tree logic, lambda calculus, type constraints
- Mother nodes compatible with daughter types, formulae
- No formula decoration without type decoration
- Finite type set
- Words add semantic formulae at one node only
- Package these as possible hypothesis macros:



Constraining hypotheses

- Constrain hypotheses within DAG paths:



- Hypotheses themselves form a (finite, bounded) DAG

Splitting lexical hypotheses

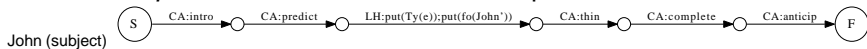
- Split DAG edges into possible word sequences
 - hypothesise possible set of split points
 - constraints: one semantic decoration subsequence per word, kept to the right
- DAG edges combine lexical and computational actions
- Lexical entries should be *general*
 - apply in all desired (tree) contexts
 - consign variation in start/end point to computational actions
- Lexical entries should be *efficient*
 - constrain possible context to those observed
 - i.e. lexicalising computational actions where possible

Generalisation through sequence intersection

- The output from each training example is a mapping from words to hypothesis *Candidate Sequences* extracted from the DAG.
- We refine and generalise over Candidate Sequences by *Sequence Intersection* modulo computational actions

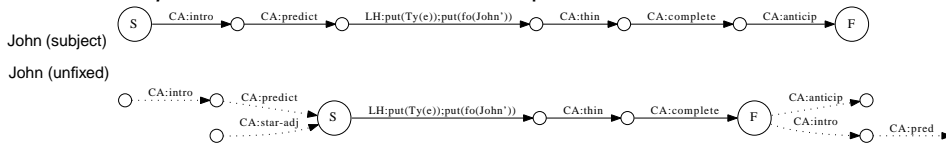
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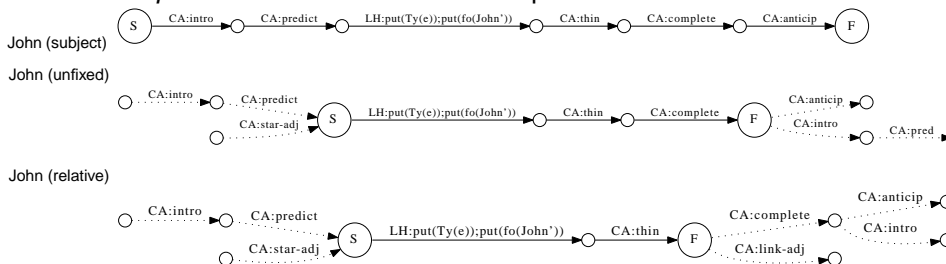
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- Lexical Ambiguity is postulated when the candidate sequences cannot be intersected in this manner.

Parameter Estimation

- Incremental version of Expectation-Maximisation
- Estimate $p(h|w)$ by summing over sequences HT_j containing it:

$$\theta''_w(h) = p(h|w) = \frac{1}{Z} \sum_{HT_j \in HT^h} p(HT_j | S) = \frac{1}{Z} \sum_{HT_j \in HT^h} \prod_{i=1}^n \theta'_{w_i}(h_i^j)$$

- Update probability distributions at each step:

$$\theta_w^N(h) = \frac{N-1}{N} \theta_w^{N-1}(h) + \frac{1}{N} \theta''_w(h)$$

- Reserve probability mass for unseen h in same way

Evaluation: Artificial corpus

- Need a corpus annotated with target trees
- Easiest way: generate one using a known grammar, and try to learn it back (see e.g. Pulman & Cussens, 2001)
- Use PoS type and token distributions from CHILDES
- 200 sentence set: 90% as training, 10% for test:

	Parsing Coverage	Same Formula
Top one	26%	77%
Top two	77%	79%
Top three	100%	80%

Evaluation: ambiguity & anaphora

- 10% of word types ambiguous between 2 or 3 senses
 - 57% learned both senses in top 3 hypotheses
 - but only one with both in top 2
- Relative pronouns: allow “copy-from-context” computational action
 - learned for only relative pronouns
 - learned syntactic/semantic constraints identical to manual grammars:

<i>who</i>	IF	? $Ty(e)$ $\langle \uparrow_* \uparrow_L \rangle Fo(X)$
	THEN	$put(Ty(e))$ $put(Fo(X))$ $put(\langle \downarrow \perp \rangle)$
	ELSE	ABORT

Scaling Up

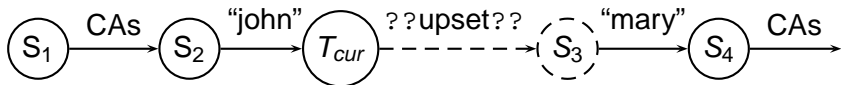
- Scaling this up will provide a probabilistic parser
- Can we do this without target *trees*?
 - incremental TTR compilation allows same method
 - can convert existing corpora (e.g. CHILDES) to TTR
 - but search space increases . . .

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 - but estimation problem increases ...
- Is this a reinforcement learning problem?



Thank you

Many people to thank: Arash Eshghi, Julian Hough, Ruth Kempson, Eleni Gregoromichelaki, Yo Sato, Wilfried Meyer-Viol, Graham White, Chris Howes, Pat Healey among others.