Is there any logic in logical forms?

Ann Copestake

Computer Laboratory, University of Cambridge

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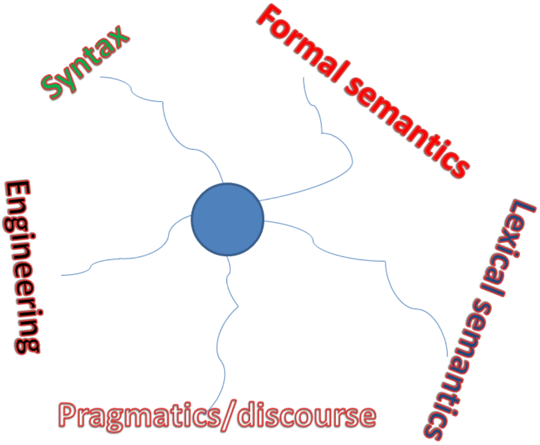
Compositional semantics for grammar engineering

- Criteria for semantics for broad-coverage grammars:
  - Meaning representation (logical form?) for every utterance.
  - Capture all and only information from syntax and morphology.
  - Underspecify when that information is absent.
  - No hidden syntactic assumptions.
- Other desiderata: logically-sound; cross-linguistically adequate; realization and parsing; incremental processing; shallow parsing; support applications (robust inference); statistical ranking; lexical semantics ...

Computational compositional semantics



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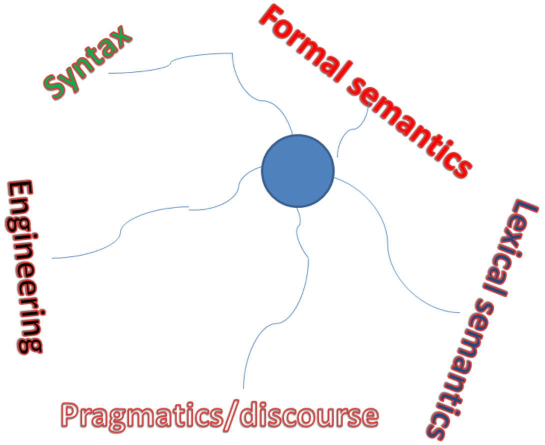

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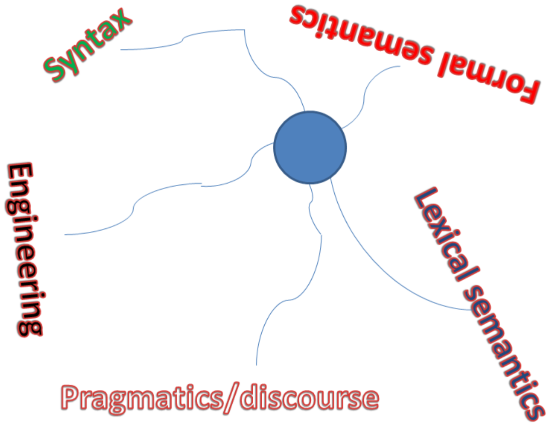

Outline

1. Semantics in DELPH-IN
   - Engineering
   - MRS and variants
2. Lexical semantics
   - Lexicalized compositionality
3. Shopping for philosophy?

Outline.

1 Semantics in DELPH-IN
- Engineering
- MRS and variants

2 Lexical semantics
- Lexicalized compositionality

3 Shopping for philosophy?

Broad-coverage processing and computational semantics

- Several high-to-medium-throughput broad-coverage grammars with semantic output: e.g., C&C/Boxer, XLE, DELPH-IN.
- Effective statistical techniques for syntactic parse ranking.
- DELPH-IN (`www.delph-in.net`)
  - in this talk: Minimal Recursion Semantics (MRS: Copestake et al, 2005); English Resource Grammar (Flickinger 2000); English Resource Semantics (ERS: e.g., Bender et al, 2015/in about two hours . . .)
  - tools (Oepen, Packard, Callmeier, Carroll, Copestake . . .)
  - Other resource grammars: Jacy (Japanese), GG (German), SRG (Spanish),
    also varying size grammars for Norwegian, Portuguese, Korean, Chinese . . .
  - Grammar Matrix: Bender et al (2002).

A real example

Very few of the Chinese construction companies consulted were even remotely interested in entering into such an arrangement with a local partner.

A real example

Very few of the Chinese construction companies consulted were even remotely interested in entering into such an arrangement with a local partner.

modified quantifier

A real example

Very few **of** the Chinese construction companies consulted were even remotely interested in entering into such an arrangement with a local partner.

partitive

A real example

Very few of the Chinese **construction companies** consulted were even remotely interested in entering into such an arrangement with a local partner.

compound nominal

A real example

Very few of the Chinese construction companies **consulted** were even remotely interested in entering into such an arrangement with a local partner.

reduced relative

A real example

Very few of the Chinese construction companies consulted were **even remotely** interested in entering into such an arrangement with a local partner.

modified modifier

A real example

Very few of the Chinese construction companies consulted were even remotely interested in entering into **such an** arrangement with a local partner.

predeterminer

[LOGON (2014-08-09) – ERG (1214)]

h_4:part_of$\langle 0{:}8\rangle(x_5\{\text{PERS } \mathit{3}, \text{NUM } \mathit{pl}\}, x_6\{\text{PERS } \mathit{3}, \text{NUM } \mathit{pl}\})$,
h_7:udef_q$\langle 0{:}8\rangle(x_5, h_8, h_9)$,$h_4$:_very_x_deg$\langle 0{:}4\rangle(e_{10},e_{11}\{\text{SF } \mathit{prop}\})$,
h_4:little-few_a$\langle 5{:}8\rangle(e_{11}, x_5)$,$h_{12}$:_the_q$\langle 12{:}15\rangle(x_6, h_{14}, h_{13})$,
h_{15}:_chinese_a_1$\langle 16{:}23\rangle(e_{16},x_6)$,$h_{15}$:compound$\langle 24{:}46\rangle(e_{18},x_6, x_{17})$,
h_{19}:udef_q$\langle 24{:}36\rangle(x_{17}, h_{20}, h_{21})$,$h_{22}$:_construction_n_of$\langle 24{:}36\rangle(x_{17}, i_{23})$,
h_{15}:_company_n_of$\langle 37{:}46\rangle(x_6, i_{24})$,$h_{15}$:_consult_v_1$\langle 47{:}56\rangle(e_{25},i_{26}, x_6)$,
h_2:_even_x_deg$\langle 62{:}66\rangle(e_{28},e_{29})$,$h_2$:_remotely_x_deg$\langle 67{:}75\rangle(e_{29}, e_3)$,
h_2:_interested_a_in$\langle 76{:}86\rangle(e_3, x_5, x_{30}\{\text{PERS } \mathit{3}, \text{NUM } \mathit{sg}, \text{GEND } \mathit{n}\})$,
h_{31}:udef_q$\langle 90{:}145\rangle(x_{30}, h_{32}, h_{33})$,$h_{34}$:nominalization$\langle 90{:}145\rangle(x_{30}, h_{35})$,
h_{35}:_enter_v_1$\langle 90{:}98\rangle($
$e_{36}\{\text{SF } \mathit{prop}, \text{TENSE } \mathit{untensed}, \text{MOOD } \mathit{indicative}, \text{PROG } \mathit{+}, \text{PERF } \mathit{-}\}, i_{37})$,
h_{35}:_into_p$\langle 99{:}103\rangle(e_{38},e_{36}, x_{39}\{\text{PERS } \mathit{3}, \text{NUM } \mathit{sg}\})$,
h_{40}:_such+a_q$\langle 104{:}111\rangle(x_{39}, h_{42}, h_{41})$,
h_{43}:_arrangement_n_1$\langle 112{:}123\rangle(x_{39})$,
h_{35}:_with_p$\langle 124{:}128\rangle(e_{44},e_{36}, x_{45}\{\text{PERS } \mathit{3}, \text{NUM } \mathit{sg}, \text{IND } \mathit{+}\})$,
h_{46}:_a_q$\langle 129{:}130\rangle(x_{45}, h_{48}, h_{47})$,$h_{49}$:_local_a_1$\langle 131{:}136\rangle(e_{50},x_{45})$,
h_{49}:_partner_n_1$\langle 137{:}145\rangle(x_{45})$

$h_{48} =_q l_{49}, h_{42} =_q l_{43}, h_{32} =_q l_{34}, h_{20} =_q l_{22}, h_{14} =_q l_{15},$
$h_8 =_q l_4, h_1 =_q l_2$

ERG: some practicalities

- ERG: hand-written, domain-independent grammar.
- Maxent parse selection models based on manual choice of analyses (Redwoods Treebanks).
- ERG has about $80 \pm 10\%$ coverage on edited text (various strategies for remainder).
- Open Source.
- Downloadable corpora:
  - Manually selected/checked (Redwoods Treebank): DeepBank (PTB/WSJ data), WeScience etc
  - Automatically processed: Wikiwoods.
- Various output formats for syntax and semantics.
- Used on many projects since 1990s, including large-scale end-user applications.

Quantifier scope ambiguity

Some dog chased every cat

$\exists x[\text{big}'(x) \wedge \text{dog}'(x) \wedge \forall y[\text{cat}'(y) \implies \text{chase}'(x,y)]]$
$\forall y[\text{cat}'(y) \implies \exists x[\text{big}'(x) \wedge \text{dog}'(x) \wedge \text{chase}'(x,y)]]$

Using generalized quantifiers and event variables:

some(x, big(x) ∧ dog(x), every(y, cat(y), chase(e,x,y)))
$\exists x[\text{big}'(x) \wedge \text{dog}'(x) \wedge \forall y[\text{cat}'(y) \implies \text{chase}'(x,y)]]$

every(y, cat(y), some(x, big(x) ∧ dog(x), chase(e,x,y)))
$\forall y[\text{cat}'(y) \implies \exists x[\text{big}'(x) \wedge \text{dog}'(x) \wedge \text{chase}'(x,y)]]$

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$\forall y[\text{cat}'(y) \implies \exists x[\text{big}'(x) \wedge \text{dog}'(x) \wedge \text{chase}'(x, y)]]$

MRS underspecifies scope ambiguity

Some big dog chased every cat

l1:some(x,h1,h2), h1 qeq l2, l2:big(e',x), l2:dog(x),
l4:chase(e,x,y), l5:every(y,h3,h4), h3 qeq l6, l6:cat(y)

Elementary predications (EPs) and scope constraints (qeqs)

some(x, big(e',x) $\wedge$ dog(x), every(y, cat(y), chase(e,x,y)))
h1=l2, h3=l6, h2=l5, h4=l4

every(y, cat(y), some(x, big(e',x) $\wedge$ dog(x), chase(e,x,y)))
h1=l2, h3=l6, h2=l4, h4=l1

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every(y, cat(y), some(x, big(e',x) ∧ dog(x), chase(e,x,y)))
h1=l2, h3=l6, h2=l4, h4=l1

MRS underspecifies scope ambiguity

Some big dog chased every cat

l1:some(x,h1,**h2**), h1 qeq l2, l2:big(e',x), l2:dog(x),
l4:chase(e,x,y), **l5**:every(y,h3,h4), h3 qeq l6, l6:cat(y)

Elementary predications (EPs) and scope constraints (qeqs)

some(x, big(e',x) $\wedge$ dog(x), every(y, cat(y), chase(e,x,y)))
h1=l2, h3=l6, **h2=l5**, h4=l4

every(y, cat(y), some(x, big(e',x) $\wedge$ dog(x), chase(e,x,y)))
h1=l2, h3=l6, h2=l4, h4=l1

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Some big dog chased every cat

l1:some(x,h1,h2), h1 qeq l2, l2:big(e',x), l2:dog(x),
l4:chase(e,x,y), l5:every(y,h3,**h4**), h3 qeq l6, l6:cat(y)

Elementary predications (EPs) and scope constraints (qeqs)

some(x, big(e',x) $\wedge$ dog(x), every(y, cat(y), chase(e,x,y)))
h1=l2, h3=l6, h2=l5, **h4=l4**

every(y, cat(y), some(x, big(e',x) $\wedge$ dog(x), chase(e,x,y)))
h1=l2, h3=l6, h2=l4, h4=l1

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l4:chase(e,x,y), l5:every(y,h3,**h4**), h3 qeq l6, l6:cat(y)

Elementary predications (EPs) and scope constraints (qeqs)

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every(y, cat(y), some(x, big(e',x) $\wedge$ dog(x), chase(e,x,y)))
h1=l2, h3=l6, h2=l4, **h4=l1**

MRS vs (deep) syntax

MRS more abstract, less language-dependent:
e.g., Bender (2008) on Wambaya.

1. Construction semantics: e.g., relative clauses:
every cat who slept snored
l5:every(y,h3,h4), h3 qeq l6, l6:cat(y), l6:sleep(e,y), l7:snore(e1,y)
2. Construction semantics: additional predications:
tree house
l1:house(x), l3:**udef_q**(y,h2,h3), h2 qeq l2, l2:tree(y), l2:**cmpd**(e,x,y)
house in a tree
l1:house(x), l3:a(y,h2,h3), h2 qeq l2, l2:tree(y), l2:in(e,x,y)
3. Words with no direct semantic contribution:
relative clause *who*, infinitival *to*, expletive *it* etc
4. Multiword expressions: verb-particle, idioms etc.

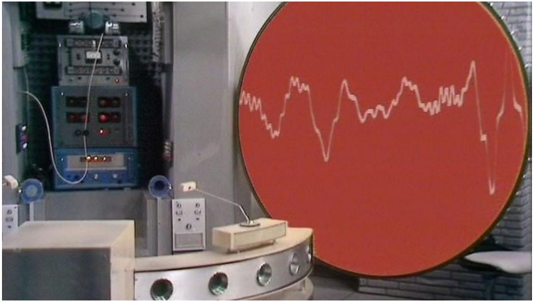
MRS vs predicate calculus

Copestake et al (2005) formally describe MRS as a meta-language for predicate calculus object language.
But, as used in ERS:

- NOT a fragment: produce some sort of MRS for everything including: generics, liar sentences, *circular square*, greetings . . .
- contradictions, speakers with different word uses . . .
- interpretation of 'logical' vocabulary isn't determined: *or* (exclusive or not?), *all* (domain of quantification, really universal?) and so on.
- **linguistic entities**: unique variable for each noun, verb, adjective, adverb and preposition.

None of this is new, but rarely explicit . . .

Dr Who, The Green Death, episode 5 (1973)



BOSS (Bimorphic Organisational Systems Supervisor),
a megalomaniac supercomputer.

The Doctor asks BOSS:

> *If I were to tell you that the next thing I say would be true, but the last thing I said was a lie, would you believe me?*

Linguistic entities

- Assume separate step of equating linguistic entities with world entities to get reference.
- It is possible to 'ground' entities in microworlds or limited domains (e.g., NLIDs, playing Civilization etc).
- But broad coverage?

  the Chinese construction companies consulted

- Note: lexical chains require lexical information:

  Der Bus ist das Zuhause der Band.
  Es ist sehr gemütlich.

  OR

  Er fährt nicht sehr schnell.

The ‘logical’ fragment of ERS

- Cannot produce model-theoretic interpretation for all ERS.
- But: reasonable semantics for a (substantial) fragment.
- Methodology:
  - Think of MRS as annotation, not replacement.
  - Use intuitions about truth conditions to develop ERS for the ‘logical’ fragment.
  - Assume similar structures outside fragment.
  - Note: there are some structures which don’t simply follow from syntax: e.g., generalized quantifiers, ‘small clauses’.
- But: lexical semantics?
- Even without model-theoretic semantics, we want compositionality (motivation from learnability, substitution).

Elms and beeches

http://www.geograph.org.uk/photo/1512369

Elms and beeches

http://www.geograph.org.uk/photo/2297984 http://www.geograph.org.uk/photo/1512369

RMRS: Split off most of EP's arguments: relate to predicate via anchor

MRS:
l1:some(x,h1,h2), h1 qeq l2,
l2:dog(x),
l3:chase(e,x,y),
l4:every(y,h3,h4), h3 qeq l65,
l5:cat(y)

RMRS:
l1:a1:some, BV(a1,x), RSTR(a1,h1), BODY(a1,h2), h1 qeq l2,
l2:a2:dog(x),
l3:a3:chase(e), ARG1(a3,x), ARG2(a3,y),
l4:a4:every, BV(a4,y), RSTR(a4,h3), BODY(a4,h4), h3 qeq l5,
l5:a5:cat(y)

Allows omission or underspecification of arguments.

RMRS: Split off most of EP's arguments: relate to predicate via anchor

MRS:
l1:some(x,h1,h2), h1 qeq l2,
l2:dog(x),
l3:chase(e,x,y),
l4:every(y,h3,h4), h3 qeq l65,
l5:cat(y)

RMRS:
l1:**a1**:some, BV(**a1**,x), RSTR(**a1**,h1), BODY(**a1**,h2), h1 qeq l2,
l2:**a2**:dog(x),
l3:**a3**:chase(e), ARG1(**a3**,x), ARG2(**a3**,y),
l4:**a4**:every, BV(**a4**,y), RSTR(**a4**,h3), BODY(**a4**,h4), h3 qeq l5,
l5:**a5**:cat(y)

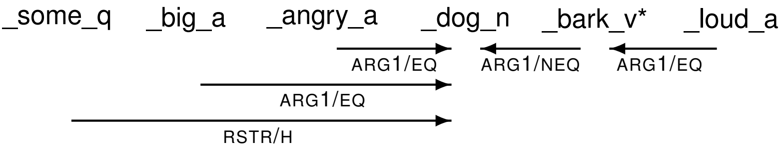
Allows omission or underspecification of arguments.

DMRS

Some big angry dog barks loudly

some(x4, big(x4) $\wedge$ angry(x4) $\wedge$ dog(x4), bark(e2,x4) $\wedge$ loud(e2))

l1:a1:_some_q, BV(a1,x4), RSTR(a1,h5), BODY(a1,h6),
l2:a2:_big_a(e8), ARG1(a2,x4),
l2:a3:_angry_a(e9), ARG1(a3,x4),
l2:a4:_dog_n(x4), l4:a5:_bark_v(e2), ARG1(a5,x4),
l4:a6:_loud_a(e10), ARG1(a6,e2), h5 $=_q$ l2



Dependency MRS (DMRS)

- predicates with simple inventory of links, no variables;
- all information is retained so inter-convertible with MRS (without external information source);
- structure is minimal (no redundancy);
- applicable to different grammars, robust to changes in grammars;
- much easier to work with for most applications.
- However: Simplified DMRS . . .

No attempt at direct logical interpretation for DMRS: but this is perhaps less misleading than MRS variables.

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Compositional semantics and distributional semantics

- Standard approach in formal semantics is meaning postulates but:
  - formalization? (e.g., non-monotonicity)
  - don't capture many aspects of lexical semantics
  - Fregean assumptions of shared intensions, shared word senses are implausible.
- distributional semantics and compositional semantics:
  - composing distributions
  - supporting inference
  - Here: the formal link: based on ideas from 'Lexicalised compositionality' (with Aurélie Herbelot); note also Katrin Erk (2013, 2015) and others.

Linking distributional semantics and Montague Grammar

- Take a microworld and a corresponding model (in MG sense).
- Use MG fragment to generate all sentences which are true in that world (restricting logical connectives to $\wedge$).
- Produce MRS representations for those sentences.
- Generate distributions from MRS analyses (**ideal distributions**).
- Ideal distributions give hyponymy etc, and also link to models (via MRS linguistic entities).

MG sentences

Microworld S_1: A jiggling black sphere (a) and a rotating white cube (b)

Possible utterances (restrict lexemes to *a*, *sphere*, *cube*, *object*, *rotate*, *jiggle*, *black*, *white*):

a sphere jiggles
a black sphere jiggles
a cube rotates
a white cube rotates
an object jiggles
a black object jiggles
an object rotates
a white object rotates

and *a black black sphere jiggles* etc

LC context sets

Logical forms in simplified MRS:
a sphere jiggles: $a(x1), \text{sphere}^\circ(x1), \text{jiggle}^\circ(e1, x1)$
a black sphere jiggles:
$a(x2), \text{black}^\circ(x2), \text{sphere}^\circ(x2), \text{jiggle}^\circ(e2, x2)$

Context set for *sphere* (paired with S_1):

$$\text{sphere}^\circ = \{ \quad < [x1][a(x1), \text{jiggle}^\circ(e1, x1)], S_1 >, \\ < [x2][a(x2), \text{black}^\circ(x2), \text{jiggle}^\circ(e2, x2)], S_1 > \}$$

Context set: pair of **distributional argument tuple** and **distributional LF.**

Ideal distribution for S_1

$$\begin{array}{lll}
\text{sphere}^\circ = & \{ & <[x1][a(x1), \text{jiggle}^\circ(e1, x1)], S_1>, \\
 & & <[x2][a(x2), \text{black}^\circ(x2), \text{jiggle}^\circ(e2, x2)], S_1>\} \\
\text{cube}^\circ = & \{ & <[x3][a(x3), \text{rotate}^\circ(e3, x3)], S_1>, \\
 & & <[x4][a(x4), \text{white}^\circ(x4), \text{rotate}^\circ(e4, x4)], S_1>\} \\
\text{object}^\circ = & \{ & <[x5][a(x5), \text{jiggle}^\circ(e5, x5)], S_1>, \\
 & & <[x6][a(x6), \text{black}^\circ(x6), \text{jiggle}^\circ(e6, x6)], S_1>, \\
 & & <[x7][a(x7), \text{rotate}^\circ(e7, x7)], S_1>, \\
 & & <[x8][a(x8), \text{white}^\circ(x8), \text{rotate}^\circ(e8, x8)], S_1>\} \\
\text{jiggle}^\circ = & \{ & <[e1, x1][a(x1), \text{sphere}^\circ(x1)], S_1>, \\
 & & <[e2, x2][a(x2), \text{black}^\circ(x2), \text{sphere}^\circ(x2)], S_1>, \\
 & & <[e5, x5][a(x5), \text{object}^\circ(x5)], S_1>, \\
 & & <[e6, x6][a(x6), \text{black}^\circ(x6), \text{object}^\circ(x6)], S_1>\}
\end{array}$$

Ideal distribution for S_1, continued

$$\begin{aligned}
\text{rotate}^\circ = \quad \{ \quad & < [e3, x3][a(x3), \text{cube}^\circ(x3)], S_1 >, \\
& < [e4, x4][a(x4), \text{white}^\circ(x4), \text{cube}^\circ(x4)], S_1 >, \\
& < [e7, x7][a(x7), \text{object}^\circ(x7)], S_1 >, \\
& < [e8, x8][a(x8), \text{white}^\circ(x8), \text{object}^\circ(x8)], S_1 >\} \\
\text{black}^\circ = \quad \{ \quad & < [x2][a(x2), \text{sphere}^\circ(x2), \text{jiggle}^\circ(e2, x2)], S_1 >, \\
& < [x5][a(x5), \text{object}^\circ(x5), \text{jiggle}^\circ(e5, x5)], S_1 >\} \\
\text{white}^\circ = \quad \{ \quad & < [x4][a(x4), \text{cube}^\circ(x4), \text{rotate}^\circ(e4, x4)], S_1 >, \\
& < [x8][a(x8), \text{object}^\circ(x8), \text{rotate}^\circ(e8, x8)], S_1 >\}
\end{aligned}$$

Context sets as vectors

	jiggle$^\circ$(e,x)	rotate$^\circ$(e,x)	sphere$^\circ$(x)	cube$^\circ$(x)	object$^\circ$(x)
sphere$^\circ$	1	0	0	0	0
cube$^\circ$	0	1	0	0	0
object$^\circ$	1	1	0	0	0
black$^\circ$	1	0	1	0	1
white$^\circ$	0	1	0	1	1

- Hyponomy etc: direct from distribution.
- One way of generalizing over the context sets.
- RMRS semantic representation allows more possibilities for fine-grained decomposition.

Relationship to standard notion of extension

For a predicate P, the distributional arguments of P$^\circ$ correspond to P$'$, assuming real world equalities.

$$\begin{aligned}\text{sphere}^\circ = \ \{ \ & < [x1][a(x1), \text{jiggle}^\circ(e1, x1)], S_1 >,\\ & < [x2][a(x2), \text{black}^\circ(x2), \text{jiggle}^\circ(e2, x2)], S_1 > \}\end{aligned}$$

distributional arguments $x1, x2 =_{rw} a$ (where $=_{rw}$ stands for real world equality):

$$\begin{aligned}\text{object}^\circ = \ \{ \ & < [x5][a(x5), \text{jiggle}^\circ(e5, x5)], S_1 >,\\ & < [x6][a(x6), \text{black}^\circ(x6), \text{jiggle}^\circ(e6, x6)], S_1 >,\\ & < [x7][a(x7), \text{rotate}^\circ(e7, x7)], S_1 >,\\ & < [x8][a(x8), \text{white}^\circ(x8), \text{rotate}^\circ(e8, x8)], S_1 > \}\end{aligned}$$

distributional arguments $x5, x6 =_{rw} a$, $x7, x8 =_{rw} b$

Ideal distribution properties

- Requires some notion of entity in distribution which is mappable into MG entities.
- Lexical similarity, hyponymy, (denotational) synonymy in terms of context sets.
- Word ‘senses’ as subspaces of context sets.
- Given context sets, learner can associate lexemes with real world entities on plausible assumptions about perceptual similarity.
- Ideal distribution is unrealistic, but we hypothesize it can be approximated (partially) from actual distributions.

Distributional semantics and modality

- Multiple microworlds (possible worlds): cubes and spheres rotating and jiggling. Add *spherical* and *cubical*.
- Distribution for each world (as before), vectors summed, normalized by number of distributions for that word.

	jiggle$^\circ$(e,x)	rotate$^\circ$(e,x)	spherical$^\circ$(x)	cubical$^\circ$(x)
sphere$^\circ$	0.5	0.5	1	0
cube$^\circ$	0.5	0.5	0	1
object$^\circ$	0.5	0.5	0.5	0.5

- *object* has possible properties which include everything possible for *sphere*, *cube* etc but very few necessary properties.

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object$^\circ$	0.5	0.5	0.5	0.5

- *object* has possible properties which include everything possible for *sphere*, *cube* etc but very few necessary properties.

Actual distributions

- People don't say everything . . .
- What they say isn't a random sample of an ideal distribution.
- e.g., basic level categories vs words like *object* or *thing*. Although: "We need to make more things; we need to design more things; we need to sell more things."
- Actual distributions can be augmented to get closer to ideal distributions: e.g., via generics such as *cubes are objects*.
- Herbelot (2015) shows how to construct distributions with individuals.

Ideal distributions and philosophical approaches

- Alternative sources of ideal distributions, depending on underlying theoretical approaches.
- However, the ideal distributions end up being the same, if the same sentences are true/valid in a microworld.
- Copestake and Herbelot (2012) consider a speaker-dependent ideal distribution.
- Note the use of MRS as a way of splitting up sentences: i.e., decompositionality, not as a model itself.

Outline.

1 Semantics in DELPH-IN
- Engineering
- MRS and variants

2 Lexical semantics
- Lexicalized compositionality

3 Shopping for philosophy?

Alternative philosophical accounts?

- Fregean tradition has problems if we assume we want a meaning representation for every utterance.
- Also has problems as a psycholinguistically plausible account (e.g., generics learned earlier than quantifiers).
- CL can use explicit models for interfaces to databases etc, but no obvious counterpart in broad-coverage systems.
- Rare to see full MG (intensional contexts etc), and only done for smallish fragments.
- Meaning as use (late Wittgenstein): explicit in some early Computational Linguistics (Masterman/CLRU).
- But late Wittgenstein much more about what we can't do than what we can . . .

One alternative: Brandom's version of Inferentialism

- Brandom (1994, 2000): non-Platonist, non-representationalist philosophical approach.
- cf 'meaning as use' but prioritizes 'giving and asking for reasons'.
- 'good inference' as prior to truth (cf early Frege).
- Logical inferences are a subset of material inferences.

  Pittsburgh is to the west of Philadelphia
  Philadelphia is to the east of Pittsburgh

- Top-down: propositions decomposable but not built from atomic meanings (cf Frege's Context Principle).
- Emphasis on pragmatics.

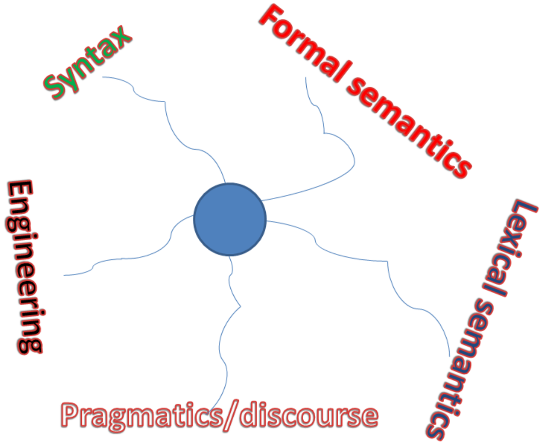
Inferentialism for computational linguists?

- Methodology of using human judgements (RTE etc) fits better with Brandom's 'commitment' to propositions than model-theoretic account: no theoretical problem with differing judgements.
- Not much in Brandom about differences in lexical semantics between speakers, but not obviously inconsistent.
- Lexical semantics: material inferences without further justification (e.g., 'east' and 'west').
- Explicitly logical vocabulary has important role: no need for us to abandon the stuff that works.
- MRS is a representation but use for decomposition/substitution consistent with inferentialism.

Shopping for philosophy?

- Not at all helpful for immediate grammar engineering!
- Philosophers and linguists taking us seriously (or not) ...
- Less contingent explanations for why we DON'T do things: e.g., intensional contexts.
- The point isn't whether or not Brandom (or others) are right, but what it leads us to investigate.
  e.g., use of language in more varied social contexts.
- Computational linguistics as empirical investigation of approaches to language semantics.

Computational compositional semantics



Some conclusions

- Computational compositional semantics is not bad/baby Montague Grammar: it has a coherent rationale.
- ‘logical’ fragment of ERS has interpretation analogous to MG fragment: it also guides ERS outside that fragment.
- MRS compositionality principle can be justified in terms of substitution, learnability or good engineering as well as formal semantics.
- Idealization of distributional semantics compatible with model theory.
- Inferentialism arguably better fit than MG for most CL practice.
- Maybe a computational approach is a way of making the philosophical debates more grounded?

Is there any logic in logical forms?

Is there any logic in logical forms?

some, sometimes . . .

STOP!

MRS composition: she chases some dog

dog [l4,x] l4:dog(x)
some [l8,x1] {[l9,x1]$_n$} l3:some(x1, h1, h2), h1 qeq l9
some dog $op_n(\text{Det}, \text{N})$
[l8,x] l3:some(x,h1,h2), l4:dog(x), h1 qeq l4

chases [l2,e] {[l2,x2]$_{subj}$, [l2,x3]$_{obj}$}, l2:chase(e,x2,x3)
chases some dog $op_{obj}(\text{V}, \text{NP})$
[l2,e] {[l2,x12]$_{subj}$}, l2:chase(e,x2,x), l3:some(x,h1,h2),
l4:dog(x), h1 qeq l4

she [l0,y] l0:pron(y)
she chases some dog $op_{subj}(\text{VP}, \text{NP})$
[l2,e] l2:pron(y), l2:chase(e,y,x), l3:some(x,h1,h2), l4:dog(x),
h1 qeq l4

MRS composition: she chases some dog

dog **[l4,x]** l4:dog(x) hook

some [l8,x1] {[l9,x1]$_n$} l3:some(x1, h1, h2), h1 qeq l9

some dog $op_n(\text{Det}, \text{N})$

[l8,x] l3:some(x,h1,h2), l4:dog(x), h1 qeq l4

chases [l2,e] {[l2,x2]$_{subj}$, [l2,x3]$_{obj}$}, l2:chase(e,x2,x3)

chases some dog $op_{obj}(\text{V}, \text{NP})$

[l2,e] {[l2,x12]$_{subj}$}, l2:chase(e,x2,x), l3:some(x,h1,h2), l4:dog(x), h1 qeq l4

she [l0,y] l0:pron(y)

she chases some dog $op_{subj}(\text{VP}, \text{NP})$

[l2,e] l2:pron(y), l2:chase(e,y,x), l3:some(x,h1,h2), l4:dog(x), h1 qeq l4

MRS composition: she chases some dog

dog [l4,x] l4:dog(x)
some [l8,x1] {**[l9,x1]**$_{\mathbf{n}}$} l3:some(x1, h1, h2), h1 qeq l9 slot
some dog $op_{\mathrm{n}}(\mathrm{Det}, \mathrm{N})$
[l8,x] l3:some(x,h1,h2), l4:dog(x), h1 qeq l4

chases [l2,e] {[l2,x2]$_{\mathrm{subj}}$, [l2,x3]$_{\mathrm{obj}}$}, l2:chase(e,x2,x3)
chases some dog $op_{\mathrm{obj}}(\mathrm{V}, \mathrm{NP})$
[l2,e] {[l2,x12]$_{\mathrm{subj}}$}, l2:chase(e,x2,x), l3:some(x,h1,h2),
l4:dog(x), h1 qeq l4

she [l0,y] l0:pron(y)
she chases some dog $op_{\mathrm{subj}}(\mathrm{VP}, \mathrm{NP})$
[l2,e] l2:pron(y), l2:chase(e,y,x), l3:some(x,h1,h2), l4:dog(x),
h1 qeq l4

MRS composition: she chases some dog

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some [l8,x1] $\{$[l9,x1]$_n\}$ l3:some(x1, h1, h2), h1 qeq l9
some dog $op_n(\mathrm{Det}, \mathrm{N})$ hook fills slot, x1=x, l9=l4
[l8,x] l3:some(x,h1,h2), l4:dog(x), h1 qeq l4

chases [l2,e] $\{$[l2,x2]$_{subj}$, [l2,x3]$_{obj}\}$, l2:chase(e,x2,x3)
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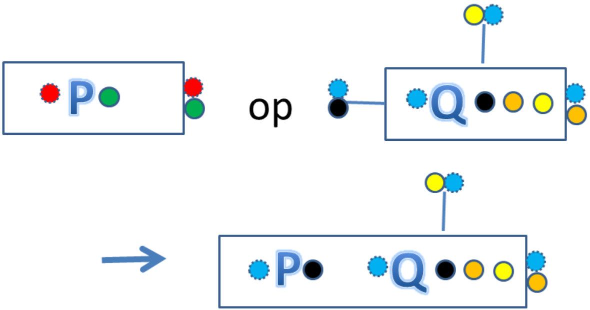
[l2,e] l2:pron(y), l2:chase(e,y,x), l3:some(x,h1,h2), l4:dog(x),
h1 qeq l4

Composition, schematically



Accumulate predications, combine hook variables with argument slot, variables not in hook or slot are inaccessible.

Semantics via incremental annotation (RMRS)

Most cats noisily chased a large dog

most_DAT cat_NN2 noisily_RR chase_VVD a_AT1 large_JJ dog_NN1

l1:a1:most_q
l2:a2:cat_n(x2)
l3:a3:noisy(e3)
l4:a4:chase(e4)
l5:a5:a(x5)
l6:a6:large(e6)
l7:a7:dog(x7)

Semantics via incremental annotation (RMRS)

Most cats noisily chased a large dog

most_DAT cat_NN2 noisily_RR chase_VVD a_AT1 large_JJ dog_NN1

l1:a1:most_q	a1:BV(x2)
l2:a2:cat_n(x2)	
l3:a3:noisy(e3)	
l4:a4:chase(e4)	
l5:a5:a(x5)	x5=x7
l6:a6:large(e6)	a6:ARG1(x7) l6=l7
l7:a7:dog(x7)	

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l2:a2:cat_n(x2)	
l3:a3:noisy(e3)	l3=l4 e3=e4
l4:a4:chase(e4)	a4:ARG1(x2) a4:ARG2(x5)
l5:a5:a(x5)	x5=x7
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```
l1:a1:most_q        a1:BV(x2)  a1:RSTR(h1)  h1 qeq l2
l2:a2:cat_n(x2)
l3:a3:noisy(e3)     l3=l4  e3=e4
l4:a4:chase(e4)     a4:ARG1(x2)  a4:ARG2(x5)
l5:a5:a(x5)         x5=x7  a5:RSTR(h5)  h5 qeq l6
l6:a6:large(e6)     a6:ARG1(x7)  l6=l7
l7:a7:dog(x7)
```

Semantics via incremental annotation (RMRS)

Most cats noisily chased a large dog

most_DAT cat_NN2 noisily_RR chase_VVD a_AT1 large_JJ dog_NN1

l1:a1:most_q	a1:BV(x2) a1:RSTR(h1) h1 qeq l2	a1:BODY(l5)
l2:a2:cat_n(x2)		
l3:a3:noisy(e3)	l3=l4 e3=e4	
l4:a4:chase(e4)	a4:ARG1(x2) a4:ARG2(x5)	
l5:a5:a(x5)	x5=x7 a5:RSTR(h5) h5 qeq l6	a1:BODY(l3)
l6:a6:large(e6)	a6:ARG1(x7) l6=l7	
l7:a7:dog(x7)		

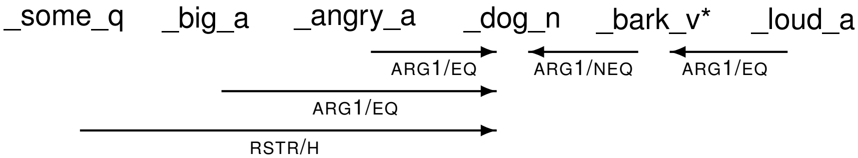
Semantics via incremental annotation (RMRS)

Most cats noisily chased a large dog

most_DAT cat_NN2 noisily_RR chase_VVD a_AT1 large_JJ dog_NN1

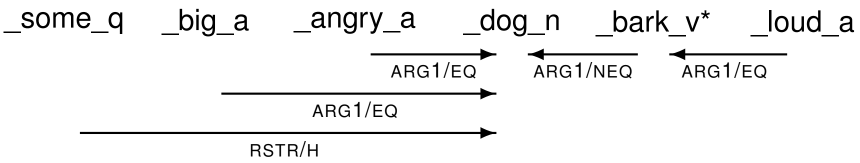
l1:a1:most_q	a1:BV(x2) a1:RSTR(h1) h1 qeq l2	a1:BODY(l3)
l2:a2:cat_n(x2)		
l3:a3:noisy(e3)	l3=l4 e3=e4	
l4:a4:chase(e4)	a4:ARG1(x2) a4:ARG2(x5)	
l5:a5:a(x5)	x5=x7 a5:RSTR(h5) h5 qeq l6	a1:BODY(l1)
l6:a6:large(e6)	a6:ARG1(x7) l6=l7	
l7:a7:dog(x7)		

DMRS



l1:a1:_some_q, BV(a1,x4), RSTR(a1,h5), BODY(a1,h6),
h5 qeq l2,
l2:a2:_big_a(e8), ARG1(a2,x4),
l2:a3:_angry_a(e9), ARG1(a3,x4),
l2:a4:_dog_n(x4),
l4:a5:_bark_v(e2), ARG1(a5,x4),
l4:a6:_loud_a(e10), ARG1(a6,e2)

DMRS



l1:a1:_some_q, BV(a1,x4), RSTR(a1,h5), BODY(a1,h6),
h5 qeq l2,
l2:a2:_big_a(e8), ARG1(a2,x4),
l2:a3:_angry_a(e9), ARG1(a3,x4),
l2:a4:_dog_n(x4),
l4:a5:_bark_v(e2), ARG1(a5,x4),
l4:a6:_loud_a(e10), ARG1(a6,e2)

Characteristic variables

l1:a1:_some_q, BV(a1,x4), RSTR(a1,h5), BODY(a1,h6),
h5 qeq l2,
l2:a2:_big_a(e8), ARG1(a2,x4),
l2:a3:_angry_a(e9), ARG1(a3,x4),
l2:a4:_dog_n(x4),
l4:a5:_bark_v(e2), ARG1(a5,x4),
l4:a6:_loud_a(e10), ARG1(a6,e2)

_some_q(x4,_big_a(e8,x4) ∧ _angry_a(e9, x4) ∧_dog_n(x4),
_bark_v(e2,x4) ∧_loud_a(e10,e2))

RMRS: EPs may have a distinguished argument.
Characteristic variable property: the distinguished argument of an RMRS EP (arg0) is unique to it.
Introduced into DELPH-IN grammars for grammar-internal reasons.

Characteristic variables

l1:a1:_some_q, BV(a1,x4), RSTR(a1,h5), BODY(a1,h6),
h5 qeq l2,
l2:a2:_big_a(e8), ARG1(a2,x4),
l2:a3:_angry_a(e9), ARG1(a3,x4),
l2:a4:_dog_n(x4),
l4:a5:_bark_v(e2), ARG1(a5,x4),
l4:a6:_loud_a(e10), ARG1(a6,e2)

_some_q(x4,_big_a(e8,x4) $\wedge$ _angry_a(e9, x4) $\wedge$_dog_n(x4),
_bark_v(e2,x4) $\wedge$_loud_a(e10,e2))

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Characteristic variables

l1:a1:_some_q, BV(a1,x4), RSTR(a1,h5), BODY(a1,h6),
h5 qeq l2,
l2:a2:_big_a(**e8**), ARG1(a2,x4),
l2:a3:_angry_a(**e9**), ARG1(a3,x4),
l2:a4:_dog_n(**x4**),
l4:a5:_bark_v(**e2**), ARG1(a5,x4),
l4:a6:_loud_a(**e10**), ARG1(a6,e2)

_some_q(x4,_big_a(**e8**,x4) ∧ _angry_a(**e9**, x4) ∧_dog_n(**x4**),
_bark_v(**e2**,x4) ∧_loud_a(**e10**,e2))

RMRS: EPs may have a distinguished argument.
Characteristic variable property: the distinguished argument of an RMRS EP (arg0) is unique to it.
Introduced into DELPH-IN grammars for grammar-internal reasons.

Back to DMRS

- looks more like syntax
- no variables: nodes instead of ‘linguistic entities’
- perhaps more room for fudging/flexibility:
  - ERS for *former president*: $\text{former}'(e, x), \text{president}'(x, y)$
  - DMRS could be read as less committed?