The goals of computational semantics: DELPH-IN and deep learning

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Top-down vs. Bottom-up

Top-down vs. Bottom-up

overarching

incremental

Top-down vs. Bottom-up

overarching classical incremental neural

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"Bottom-up theories are intrinsically unfalsifable."

- Grounding
- Lexical meaning
- Sentence meaning



Goal: explain how language relates to the world

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Goal: generalise to new situations

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- → Alex Kuhnle, Huiyuan Xie

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- Goal: capture vagueness
 - More natural for deep learning

Lexical Similarity

democracy	water	happiness		
aubergine	flood	јоу		
computer	law	cat		
earthquake	lawyer	dog		

Lexical Similarity

Rank correlation on several lexical similarity datasets:

Model	SL noun	SL verb	SimVerb	MEN	WS sim	WS rel
Skip-gram	.40	.23	.21	.62	.69	.46
SVO Skip-g.	.44	.18	.23	.60	.61	.24
My work	.46	.25	.26	.52	.60	.16

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- Goal: model context dependence (specific usage vs. general meaning)

Dependency Minimal Recursion Semantics



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 $\forall x \exists y \exists z \text{ picture}(x) \Rightarrow [\text{story}(z) \land \text{tell}(y) \land \text{ARG1}(y, x) \land \text{ARG2}(y, z)]$

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- → Weiwei Sun, Michael Goodman

DELPH-IN and Deep Learning

Complementary strengths

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Complementary strengths

Combine them to reach our goals!