DFT models of grounded cognition

Daniel Sabinasz Computational Neuroscience: Neural Dynamics Winter semester 22/23

Motivation

- Towards neural dynamic models of the higher cognitive competences
- e.g.,
 - Language understanding
 - Reasoning
 - Logical reasoning
 - Analogical reasoning
 - Planning

. . .

- Cognition understood as the algorithmic processing of symbols
- Analogy with computers
 - Symbolic problem representation
 - Algorithm operating on these symbols

• Example: Reasoning

The Porsche is parked to the left of the Dodge The Ferrari is parked to the right of the Dodge

Therefore, the Dodge is parked to the left of the Ferrari

 $\exists x \exists y \exists z (Porsche(x) \land Porsche(x) \land Dodge(y) \land Ferrari(z) \\ LeftOf(x, y) \land RightOf(z, y)) \Rightarrow LeftOf(y, z)$

Example by Ragni & Knauff (2013)

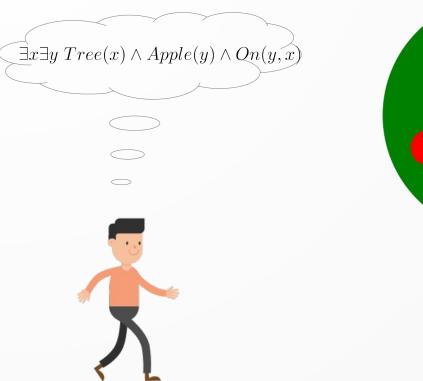
- Motivation
 - Computers are universal problem solvers (Turing, 1936)
 - Apparent flexibility of human cognition suggests similar mechanism

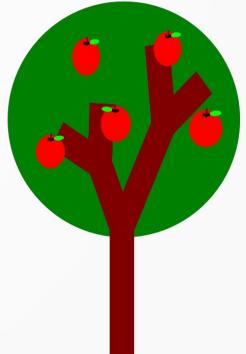
(Classical) Computational Cognitive Modeling:

Model cognitive processes as algorithms

- Still relevant today
- Many cognitive modelers believe that the neurons of the brain implement algorithms
- Even in the neural dynamics community, many build neural dynamic implementations of algorithms as models of cognitive processes

- Sensory-motor representations transduced into a completely new symbolic representational format
- That format is amodal
- Algorithms operate on these symbols
- The result is then transduced back to motor representations in order to act





Challenges (review: Barsalou, 1999)

- No empirical evidence for algorithmic processing of amodal symbols in the brain
- Strong evidence that the higher cognitive competences make use of perceptual-motor representations and processes

Challenges (review: Barsalou, 1999)

- Symbol grounding problem (Harnad, 1990)
 - The algorithmic manipulation of amodal symbols cannot account for why we have a sense of understanding what our reasoning is about

Challenges (review: Barsalou, 1999)

- Inconsistencies with neural principles of computation
 - central processor that performs the algorithm
 - random access memory

. . . .

Hypothesis

- Higher cognitive competences reuse and extend evolutionarily older perceptual-motor representations and processes, rather than being implemented by a fundamentally new kind of process
 - They are *grounded* in these representations and processes



 Higher cognitive competences make use of the same neural principles as more primitive sensorymotor processes

Hypothesis

- These neural principles are the principles of DFT
 - Detection
 - Selection
 - Working memory
 - Coordinate transforms
 - Binding through space
 - Search

Research program

- Demonstrate how the higher cognitive competences may emerge from the neural principles postulated in DFT
- ... possibly using the exact same neural populations as more primitive sensory-motor processes

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PERCEPTUAL GROUNDING OF LANGUAGE

PERCEPTUAL GROUNDING

- The process of associating natural language with denoted perceptual representations
- ... as a necessary step towards language understanding

the black swan that sits below a tree





FIRST STEP: SPATIAL LANGUAGE

- Perceptual grounding of language in general is an ambitious project
- Need to approach this in small steps
- First step: Grounding spatial language, i.e., language involving terms that stand for spatial relational concepts
- e.g., "the green object which is to the left of the red object"
- in front of, inside, on top of, ...
- Cognitive architecture for grounding simple spatial language (Lipinski et al., 2012)

SPATIAL COMPARISON

- Compare two objects w.r.t. their spatial relation
- "Where is the green object relative to the red object?" -> to the right



4 Lipinski et al. (2012)



SPATIAL COMPARISON: REQUIRED OPERATIONS

- find objects in the perceptual input
 - "Where is the green object relative to the red object?"

target

reference

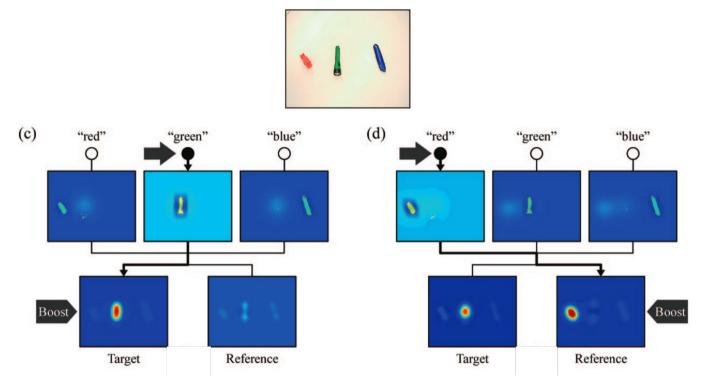
- perform coordinate transformation to get the position of the target object relative to the reference object
- compare that relative position to relational templates



⁵ Lipinski et al. (2012)



FINDING OBJECTS IN THE PERCEPTUAL INPUT

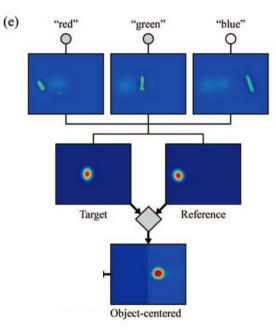


⁶ Lipinski et al. (2012)



COORDINATE TRANSFORMATION



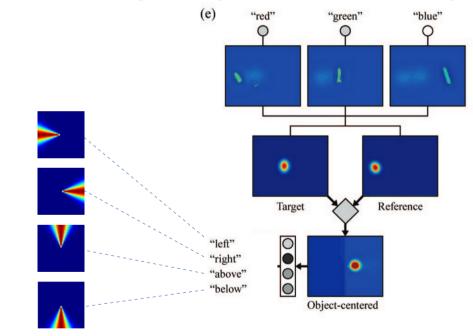


⁷ Lipinski et al. (2012)



COMPARING TO A SPATIAL TEMPLATE

"Where is the green object relative to the red object?"





⁸ Lipinski et al. (2012)



TARGET IDENTIFICATION

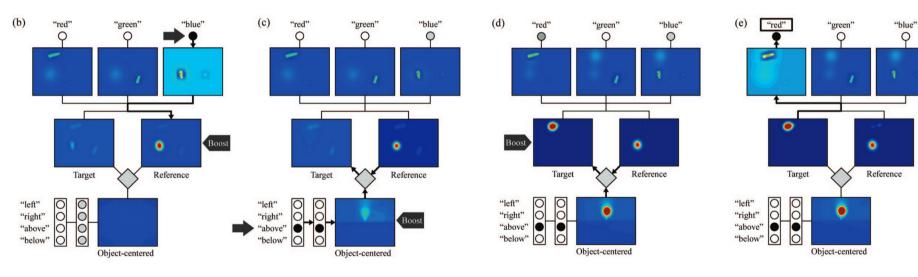
- Find an object which bears a given relation to a given reference object
- "Which object is above the blue object?"





TARGET IDENTIFICATION

"Which object is above the blue object?"

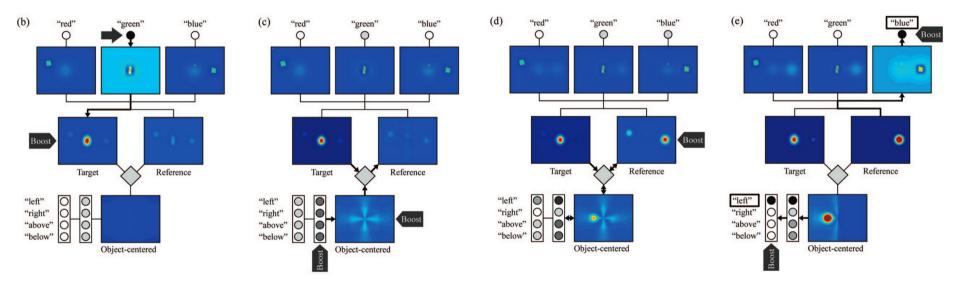


Boost



RELATION AND REFERENCE SELECTION

"Where is the green object?"





GROUNDING

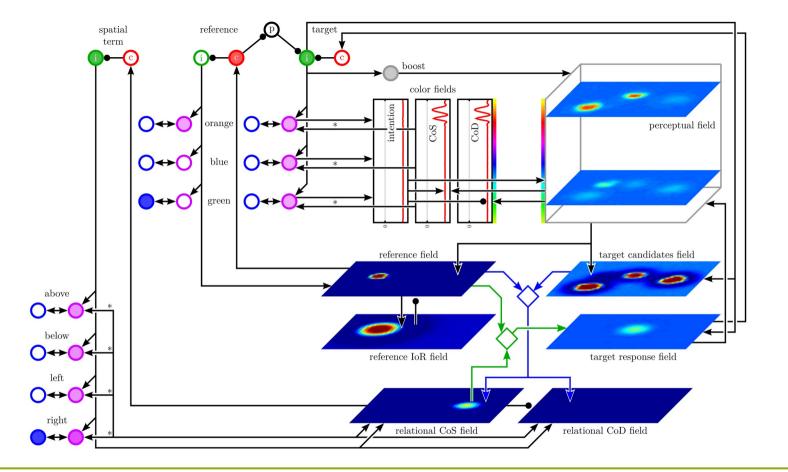
- Grounding a phrase which describes an object: finding the described object in the visual input
- e.g., "the red object to the left of the green object"
- Requires hypothesis testing



Another desideratum: Autonomy

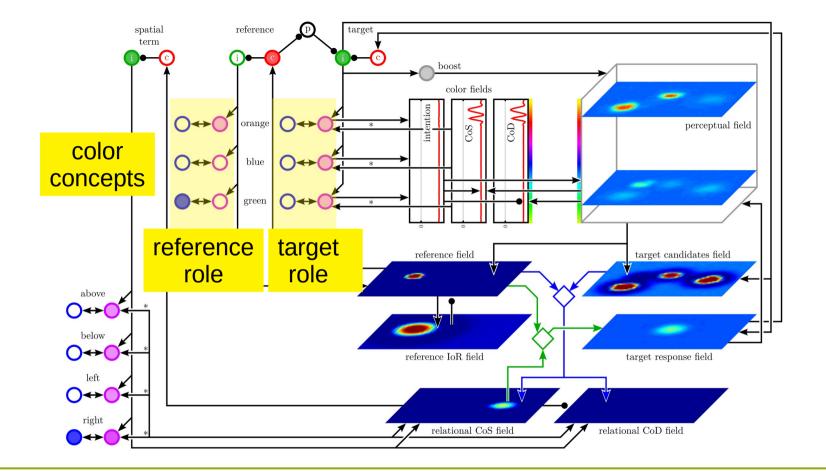






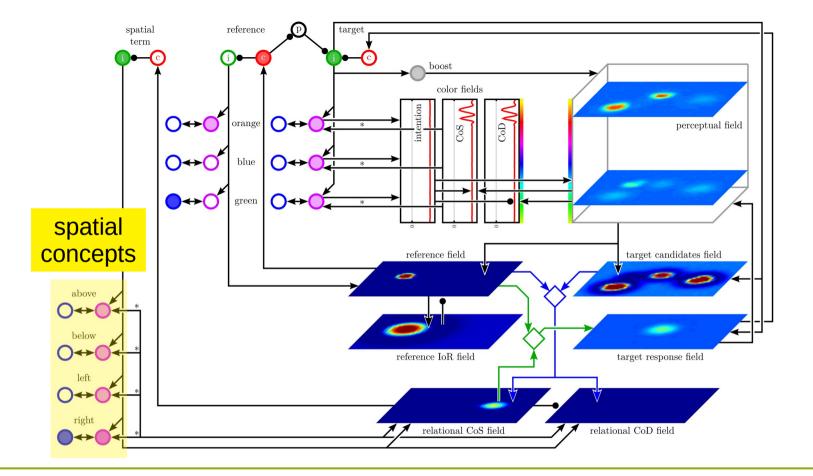
¹³ Richter et al. (2014)





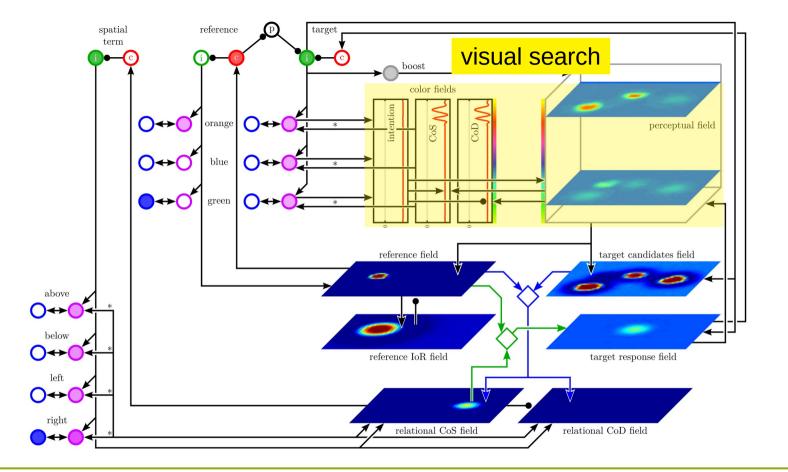
¹⁴ Richter et al. (2014)





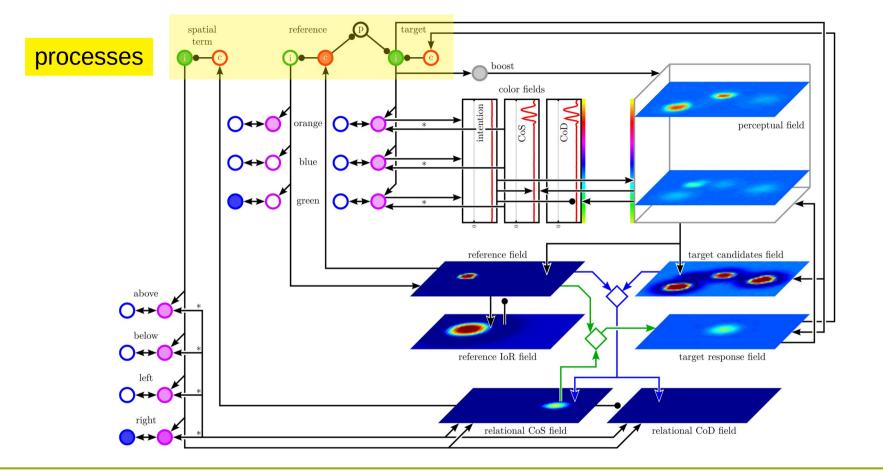
¹⁵ Richter et al. (2014)





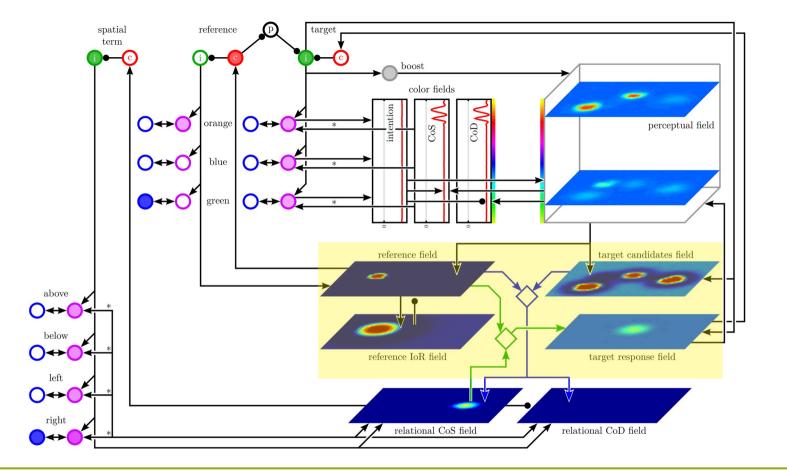
¹⁶ Richter et al. (2014)





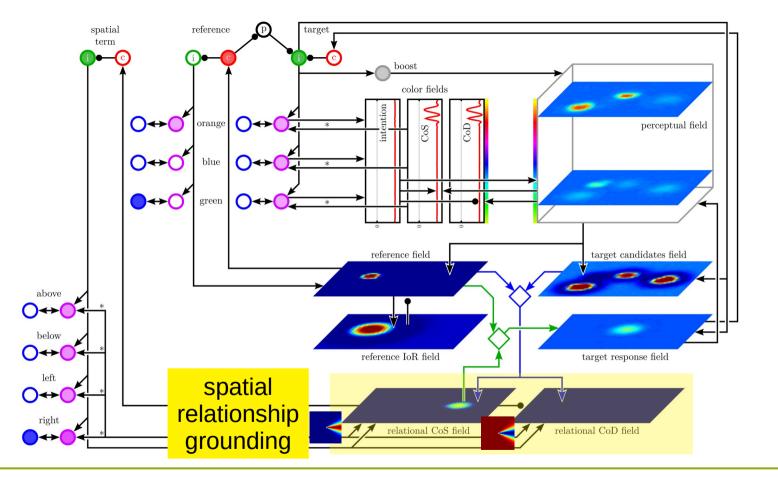
¹⁷ Richter et al. (2014)





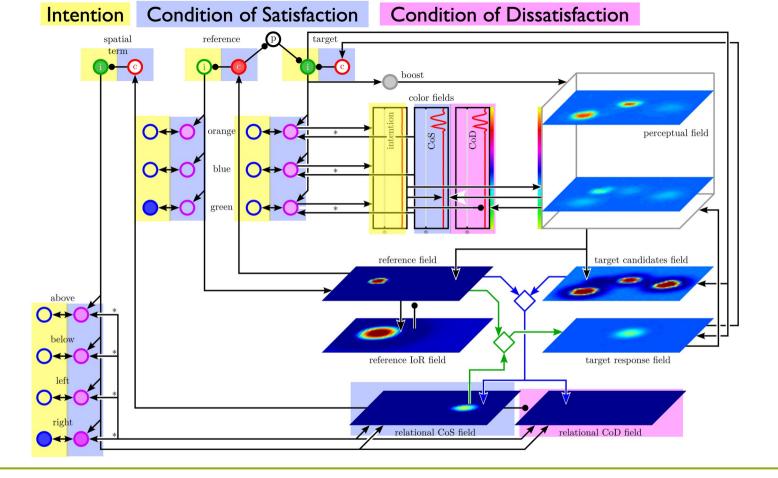
¹⁸ Richter et al. (2014)





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²⁰ Richter et al. (2014)



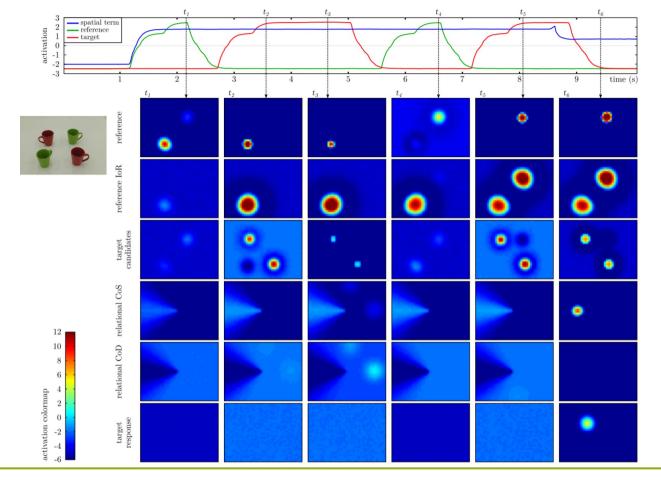
EXAMPLE



"The red object to the left of the green object"



²¹ Richter et al. (2014)



²² Richter et al. (2014)



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Driving home the point

- Presented a neural dynamic architecture that can ground simple spatial language composed of two color terms and a spatial relation term
- ... using neural principles formalized in DFT
- ... and building on perceptual-motor representations and processes
 - Neural fields... with their instabilities
 - Coordinate transformations
 - Visual search
 - Concepts
- This is a necessary step towards language grounding architectures more generally and, consequently, language understanding architectures

Next week

- Extensions to the architecture that can ground verbs and grammatically complex sentences
- ... towards compositionality

- Deductive reasoning via mental model formation
- Analogical reasoning