ICDL Tutorial – WELCOME!

- 09:00-11:00: Primer on DFT
- 11:00-11:30: coffee break
- 11:30-13:30: Hands-on session 1 (CEDAR)
- 13:00-14:00: lunch
- 14:00-15:00: Case study 1: VWM
  - Hands-on session 2 (COSIVINA)
- 15:00-16:00: Case study 2: IOWA
  - Hands-on session 3 (simulating empirical data)
- 16:00-16:30: coffee break
- 16:30-18:00: Case study 3: WOLVES
  - Hands-on session 4 (simulating complex architectures / data)

University of East Anglia

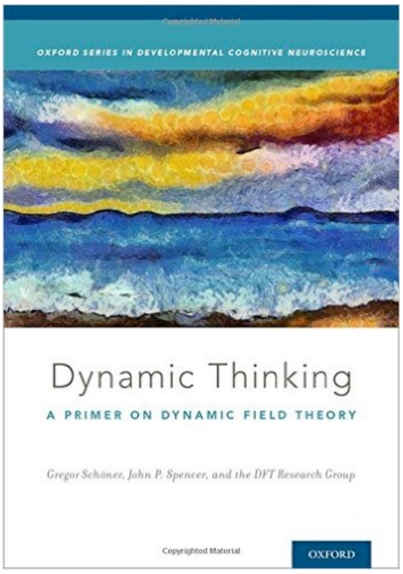
1

Primer on DFT

John P. Spencer
Professor
School of Psychology
University of East Anglia
Norwich, UK

University of East Anglia

2



www.dynamicfieldtheory.org

3

The Big Picture

- What is a theory?
- What is a model?
- What is the relation between the two?
- What function do theories/models serve?

4

Formal theories are essential

Creates challenges…

- Not everyone understands models
  - Summer schools and primer events!
- Which modeling approaches should be taught as part of graduate training?

University of East Anglia

5

DFT

- 29 years old (first conference proceedings paper published in 1993; the neural dynamics of saccadic eye movements)
- Over 100 papers since 2001
- Topics:
  - Working memory; spatial categorization; word learning; executive function; imitation; robotics; visual scene representation; habituation; behavioral organization; object recognition and representation; spatial memory; spatial language; saccadic eye movements; spatial attention; feature-based attention; visual working memory; dual-task performance; hierarchical word learning; motor planning; reaching; multi-object tracking; model-based fMRI
  - And the development of all this stuff…

University of East Anglia

6

Where does DFT fit in?

Many classes of models…

- Cognitive models (prototype models; Bayesian models)
- Process models (multivariate time series models; SUSTAIN)
- Hybrid and production models (ACT-R)
- Neural process models: do process in a neural way…

University of East Anglia

7

Classes of neural process models

- Biophysical models
- DFT
- Connectionism

Two key dimensions…

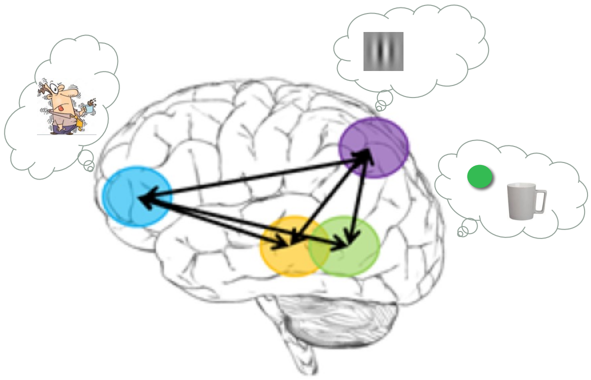
- How neural are they?
- How are they linked to behavior?

<u>DFT tries to find the Goldilock's zone</u>: just the right amount of neural to be grounded; just the right amount of behavior to be testable and integrative

University of East Anglia

8

DFT



DFT provide a framework for formalizing dynamic thinking…

- A Thought: a pattern of local decisions
- Thinking: movement from one pattern to another
- Behaving: connecting these patterns to sensorimotor systems
- Developing: shaping these patterns step-by-step through hours, days, weeks, and years of generalized experience

University of East Anglia

9

DFT: Neural reality

The reality of neural systems

- The neural system is densely interconnected; massively recurrent
  - Can go from any neuron in the brain to any other neuron in the brain in 5-8 steps.
  - The vast majority of cells are part of recurrent loops rather than feed-forward pathways
- The creates a stability problem: how do neural systems maintain a stable pattern of activation in the presence of massive interactivity

University of East Anglia

10

Dynamical Systems Theory

The solution: neural dynamics

- Dynamical systems theory gives us the concepts we need to understand how neural populations can form neural attractor states…stable patterns of activation

What kind of attractors?

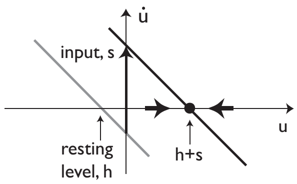
- Stable when at rest (no seizures)
- When system detects an input, it 'represents' that the input is present (turns 'on')
- We also want a system that can maintain a working memory of the input when it disappears

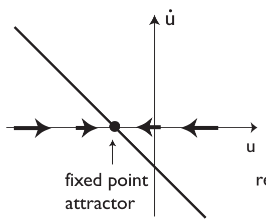
University of East Anglia

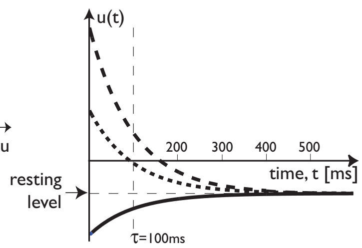
11

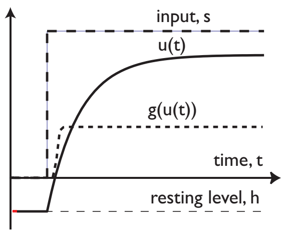
Linear dynamical systems

- Attractor (rate of change = 0)
- Exponential relaxation to fixed point
- Input shifts the location of the attractor in phase space
- [simulator]







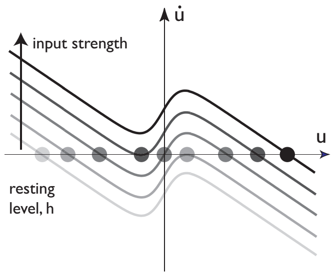


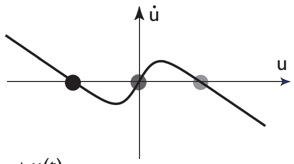
University of East Anglia

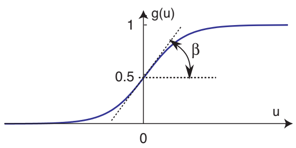
12

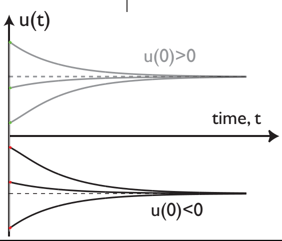
Non-linear dynamical systems

- Make neuronal activation non-linear
- System can be bi-stable (‘off’ and ‘on’ attractors)—current state determines where the system travels
- Input shifts the attractors [simulator]





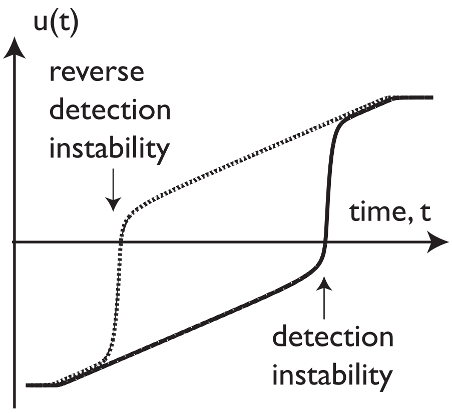




University of East Anglia

13

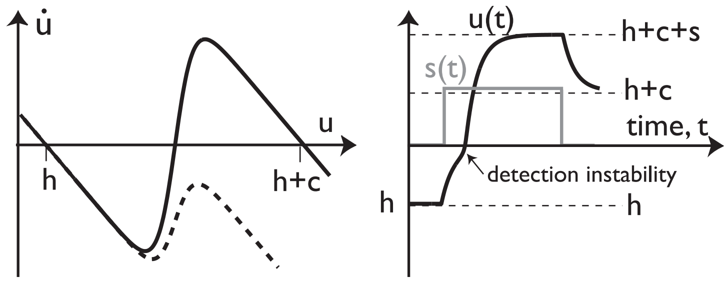
Non-linear systems show hysteresis



University of East Anglia

14

Strongly non-linear systems show self-sustaining activation

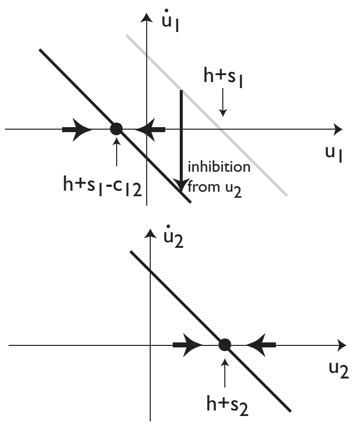


[simulator]

15

Dynamical coupling

- We can couple multiple dynamical nodes together to capture system interactions (excitatory, inhibitory)
- [simulator]



16

Summary: Neural Dynamics

- Fixed point attractor = special place in a stable system (negative slope) where rate of change is zero
- Bifurcation = a shift in the number or quality of attractor states (happens in non-linear systems)
- Instability = a shift from one attractor to another
  - Detection instability
  - Memory instability
- Hysteresis = point where the instability happens is not symmetric coming vs. going
- Self-sustaining state = system stays in the ‘on’ state even when input removed
- Dynamical coupling captures how a system of multiple neuronal units interact

University of East Anglia

17

Fields: Metric spaces

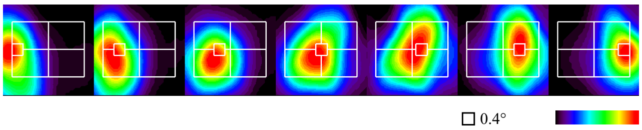
- A single dynamical node can ‘represent’ the presence/absence of input, but it can’t tell you what that input is (features) or where it is (space)
- For that, we need metric spaces…
  - Green hue value
  - 20 deg to the right of midline
  - The dog is similar to the cat

University of East Anglia

18

How do we represent metrics neurally?

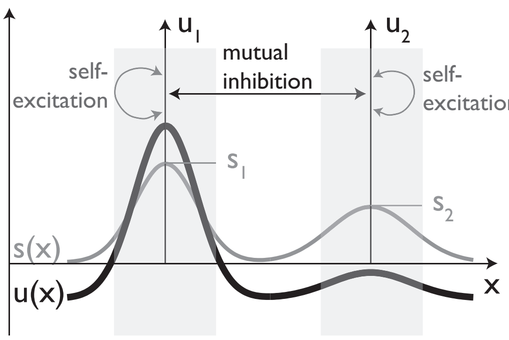
- Simplest example: topographic representation in visual cortex…



University of East Anglia

19

From nodes to fields



[simulator]

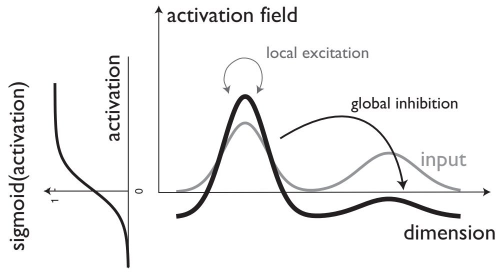
University of East Anglia

20

Dynamic fields

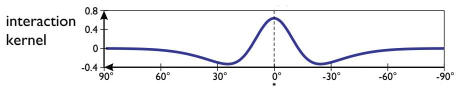
$$\tau\dot{u}(x,t) = -u(x,t) + h + s(x,t) + \int k(x-x')g\big(u(x',t)\big)dx' + q\xi(x,t)$$

$$g(u) = \frac{1}{1+\exp\left(-\beta u\right)}.$$



$$k(x-x') = \frac{c_{\mathrm{exc}}}{\sqrt{2\pi}\sigma_{\mathrm{exc}}}\exp\left[-\frac{(x-x')^2}{2\sigma_{\mathrm{exc}}^2}\right] - \frac{c_{\mathrm{inh}}}{\sqrt{2\pi}\sigma_{\mathrm{inh}}}\exp\left[-\frac{(x-x')^2}{2\sigma_{\mathrm{inh}}^2}\right] - c_{\mathrm{glob}}.$$

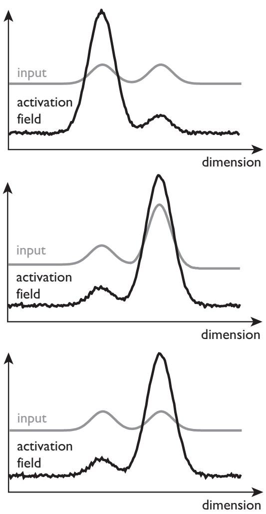
$$s(x,t) = \sum_i a_i \exp\left[-\frac{(x-p_i)^2}{2w_i^2}\right].$$



University of East Anglia

21

Different interactions = different behaviors



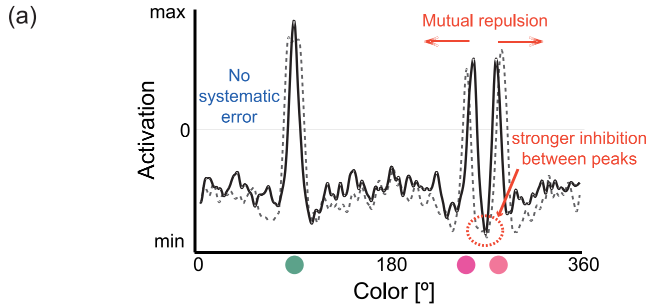
- Global inhibition → winner-take-all
- [simulator]

University of East Anglia

22

Different interactions = different behaviors

- Local-excitation / surround inhibition → multi-peak [simulator]



- Weak interactions = self-stabilized peaks
- Strong interactions = self-sustaining peaks

23

Summary: Dynamic Fields

- Neuronal dynamics distributed over a metric space = dynamic field
- Fields combine...
  - Sigmoidal non-linearity
  - Neural interaction function (convolution kernel)
  - inputs
- Different neural interactions yield different behaviors
  - Self-stabilized (input-driven 'encoding')
  - Self-sustaining (working memory 'consolidation')
  - Winner-take-all (decision-making)
  - Multi-peak (multi-item working memory)

24

Dynamic fields are not a neural analogy

- Evidence suggests that the brain actually work this way
- Neural population dynamics captured by DFT are observable in cortex (e.g., surround inhibition)

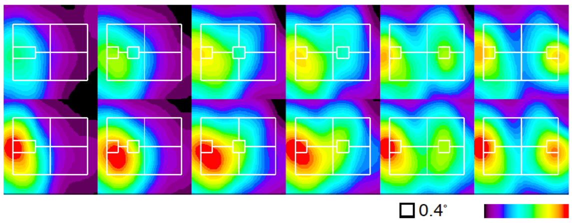


Figure 6. The measured two-dimensional DPAs (*top*) of composite stimuli (from *left* to *right*, 0.4–2.4° separation) were compared to the superpositions of the representations of their component elementary stimuli (*bottom*). The DPAs were based on spike activity of 178 cells averaged over the time interval from 30 to 80 msec after stimulus onset. Same conventions as in Figure 2*B*, the color scale was normalized to peak activation separately for each column. For small stimulus separation, note the remarkably reduced level of activation for the measured as compared to the superimposed responses. The bimodal distribution recorded for the largest stimulus separation comes close to match the superposition. However, inhibitory interaction can still be observed.

Jancke et al. (1999)

University of East Anglia

25

Neural dynamics over multiple timescales

- Thus far, we've covered local decisions (peaks) within neural populations
- In some cases, these decisions are short-lived → detect a stimulus and then relax back to resting state
- In other cases, these decisions can remain for up to 30 or more seconds → self-sustaining peaks (working memory)
- But what about neural dynamics that extend over the timescales of learning and development?

University of East Anglia

26

Memory traces

- Operates like a linear system at each field site (activation in field moves attractor to 1; absence of activation moves attractor to 0)
- Accumulate a trace as long as above-threshold activity
- Can have a convolution kernel that smears memory trace effects out over metric space
- Can also have a separate decay rate

$$\tau_{\mathrm{mem}}\dot{u}_{\mathrm{mem}}(x,t) = -u_{\mathrm{mem}}(x,t) + g(u(x,t)) \tag{2.4}$$

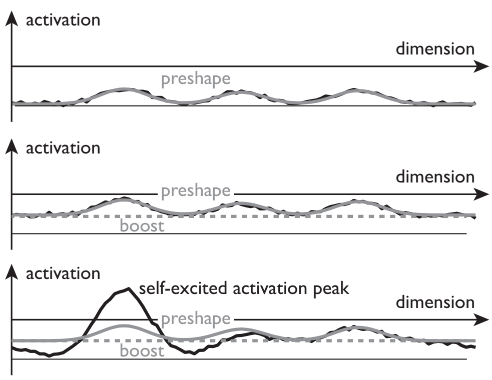
$$\tau\,\dot{u}(x.t) = -u(x,t) + h + s(x,t) + c_{\mathrm{mem}}u_{\mathrm{mem}}(x,t) + \int k(x-x')g\big(u(x',t)\big)dx' \tag{2.5}$$

University of East Anglia

27

Building peaks from memory traces

- Memory trace + h boost

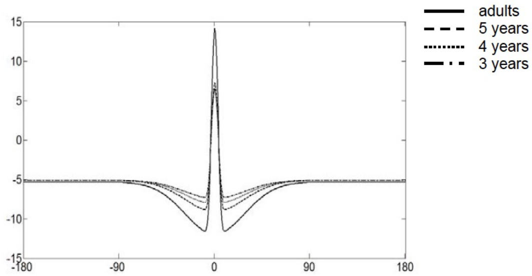


University of East Anglia

28

What about development?

- Spatial precision hypothesis: excitatory and inhibitory neural interactions become stronger over development (via a self-organizing or locally Hebbian process)
- This has multiple consequences…
  - Peaks build faster (faster RTs)
  - Peaks become narrower (enhance discrimination)
  - Peaks become stronger and more self-sustaining (more robust WM and higher capacity)



University of East Anglia

29

Summary: Learning & Development

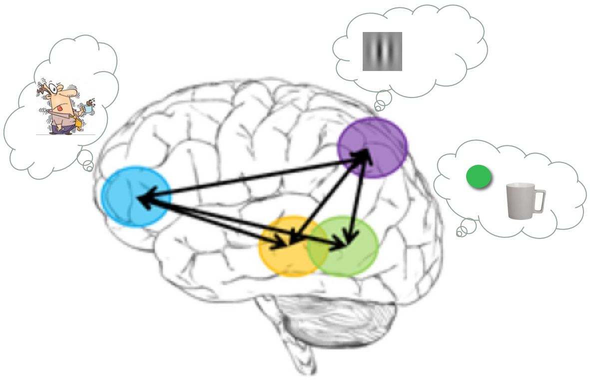
- Memory traces open up DFT to neural processes that extend over a *learning* timescale
- We can also capture *developmental* change by increasing the strength of excitatory and inhibitory neural interactions
- Recent work suggests a link between the accumulation of memory traces distributed over metric dimensions and developmental changes in neural interaction strength
  - Learning and development might be mechanistically related

University of East Anglia

30

Beyond single fields: Neural architectures

Dynamic thinking happens in a whole brain…



This requires coupling DFs into a larger architecture

University of East Anglia

31

New challenge: Integration

Once you start coupling fields together to create neural architectures, you confront new challenges…

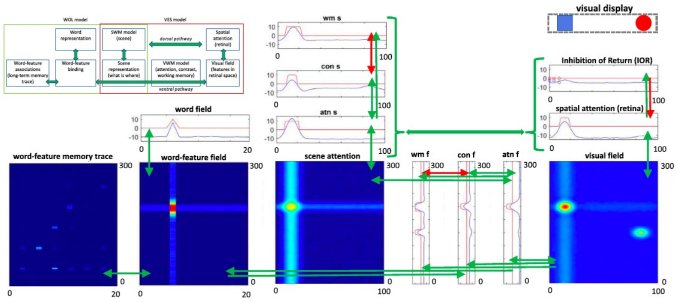
- Coupling: we usually reciprocally couple fields to reflect the recurrence in neural systems (vs. feed-forward)
  - Only above-threshold peaks contribute to inter-field interactions
  - Field activities are convolved with a kernel (like a connectivity matrix between two fields)
- Integration: how do you connect fields of different dimensionality?
  - Special binding dimensions like space or words
- Does the model scale up? Can you integrate smaller architectures into larger ones?

University of East Anglia

32

Word learning (WOLVES)

Figure 4
The Overall Architecture of WOLVES



Note. Scene WMs and memory traces are not shown for representational simplicity. Arrows represent uni/bidirectional (green: excitatory, red: inhibitory) connectivity in the model. See text for additional details. WOLVES = word-object learning via visual exploration in space. See the online article for the color version of this figure.

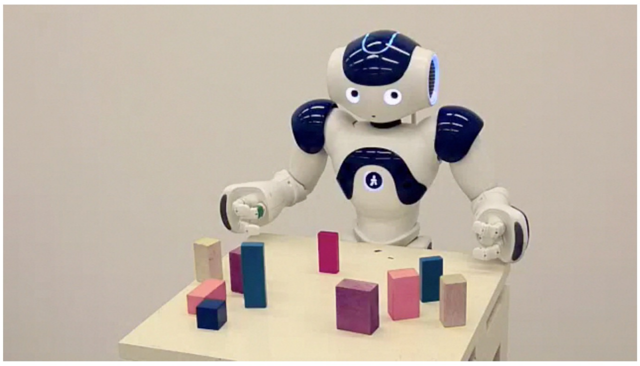
- Binding visual features through space
- Integrating words and object features

University of East Anglia

33

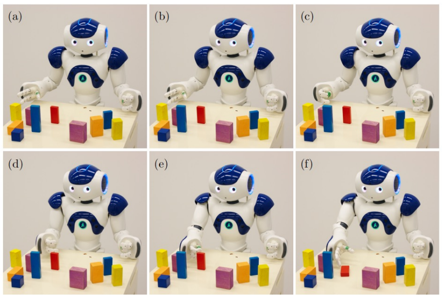
Beyond brains: Embodied agents

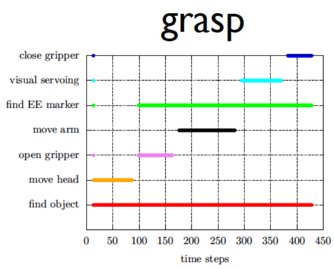
- DFT can be coupled to sensori-motor fields to guide autonomous decision-making and autonomous action

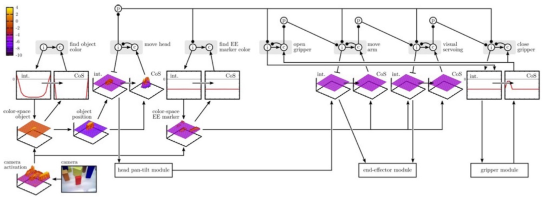


University of East Anglia

34







find object -> look at object -> open gripper -> move arm (coarse) -> move arm (visual servoing) -> close gripper ->…

University of East Anglia

35

DFT: Conclusions

DFT provides a theoretical approach to dynamic thinking…

- How neural systems form stable local decisions (peaks)
- How those decisions give rise to different types of cognitive processes (encoding, working memory, winner-take-all decision-making, multi-item WM)
- How real-time neural processes extend across the timescales of learning and development
- How these local processes can be combined into larger-scale cognitive systems that learn and develop
- And how whole-brain theories can be coupled to a body to enable autonomous, real-world behavior

University of East Anglia

36

DFT Conclusions

- What is a theory?
  - All the principles of DFT combined – those are the theoretical commitments
- What is a model?
  - A local instantiation of a DF model using the tools/concepts of DFT
- What is the relation between the two?
  - DFT blurs the boundaries between models and theories with its quest for an integrated theory of the brain in a body
- What function do theories/models serve?
  - To integrate findings, even findings from different domains
  - To make predictions at both behavioral and neural levels
  - To inspire new ideas and push the boundaries of what is possible

University of East Anglia

37

ICDL Tutorial

- 09:00-11:00: Primer on DFT
- 11:00-11:30: coffee break
- **11:30-13:30: Hands-on session 1 (CEDAR)**
- 13:00-14:00: lunch
- 14:00-15:00: Case study 1: VWM
  - Hands-on session 2 (COSIVINA)
- 15:00-16:00: Case study 2: IOWA
  - Hands-on session 3 (simulating empirical data)
- 16:00-16:30: coffee break
- 16:30-18:00: Case study 3: WOLVES
  - Hands-on session 4 (simulating complex architectures / data)

University of East Anglia

38

Introduction to CEDAR

Optimal for building DF models quickly, tuning them up, and designing complex architectures.

Also allows interface with robotics.

University of East Anglia

39

CEDAR Exercise

- You have built three types of fields – one for multi-peak 'encoding', one for working memory, and one for selection
- Now let's build an integrated architecture that encodes the stimuli, selects one of the items, and then consolidates that item in working memory.
- These are key steps involved in building a scene representation (which we will see later in WOLVES)

University of East Anglia

40

Introduction to COSIVINA

Optimal for situating DF models in specific tasks (e.g., for quantitatively fitting data).

We have both matlab and python versions.

University of East Anglia

41

Getting Started

See www.dynamicfieldtheory.org

- Download COSIVINA
  - https://github.com/cosivina/cosivina
- Download pyCOSIVINA
  - https://github.com/cosivina/cosivina_python
- Download jsonlab
  - https://github.com/fangq/jsonlab
- Download examples
  - https://github.com/cosivina/cosivina_dft_projects

University of East Anglia

42

Run example from primer lecture

- Navigate to the COSIVINA folder in matlab
- Type ‘setpath’
- In the ‘examples’ folder, open…

launcherTwoNeuronSimulator.m

- Hit ‘run’

University of East Anglia

43

ICDL Tutorial – WELCOME!

- 09:00-11:00: Primer on DFT
- 11:00-11:30: coffee break
- 11:30-13:30: Hands-on session 1 (CEDAR)
- 13:00-14:00: lunch
- **14:00-15:00: Case study 1: VWM**
  - Hands-on session 2 (COSIVINA)
- 15:00-16:00: Case study 2: IOWA
  - Hands-on session 3 (simulating empirical data)
- 16:00-16:30: coffee break
- 16:30-18:00: Case study 3: WOLVES
  - Hands-on session 4 (simulating complex architectures / data)

University of East Anglia

44

Case Study: VWM

A simple model that captures a lot of data and grounds our understanding of learning and development.

University of East Anglia

45

Working Memory and the Developing Brain

John P. Spencer
Professor
School of Psychology
University of East Anglia
Norwich, UK

University of East Anglia

46

Working Memory in a Dynamic World

Football as a case study…

- Dynamic balance between distraction and focus
- Hold one focus in mind – follow the ball – and then switch to new focus – throw-ins
- Working memory is key to holding these goals in mind

University of East Anglia

47

Overview

Fascinating finding about working memory (WM):

- Children go from holding just 1 item in WM during infancy to 3-4 items by 10 years

How does this happen?

- Lots of data showing brain changes using fMRI and fNIRS but *how* does this improvement happen?
- Computer models to the rescue…

Conclusion: DF models offer novel insights into *how development happens* suggesting new ways to help at-risk children.

University of East Anglia

48

What is working memory?

And how does it change over development?

University of East Anglia

49

Varieties of working memory

Working memory
- A memory system that holds information in an active state in the service of mental operations (e.g., mental rotation)
  - Contrasts with short-term memory (passive storage)
  - Contrasts with long-term memory

Verbal working memory
- Holds verbal information in mind (articulatory loop)

Visuo-spatial working memory
- Visuo-spatial sketchpad (spatial working memory)
- Visual working memory (colours, shapes, etc)

University of East Anglia

50

Visual Working Memory (VWM)

- VWM is a central cognitive system used – over 10,000 times each day -- to remember and compare items that cannot be simultaneously foveated and to detect changes in the world when they occur

University of East Anglia

51

Visual Working Memory

Case 1: Large feature difference makes it easy

Case 2: Need to remember subtle featural detail

WM is very limited: we can only hold about 3-5 items in WM

- https://www.youtube.com/watch?v=IGQmdoK_ZfY

University of East Anglia

52

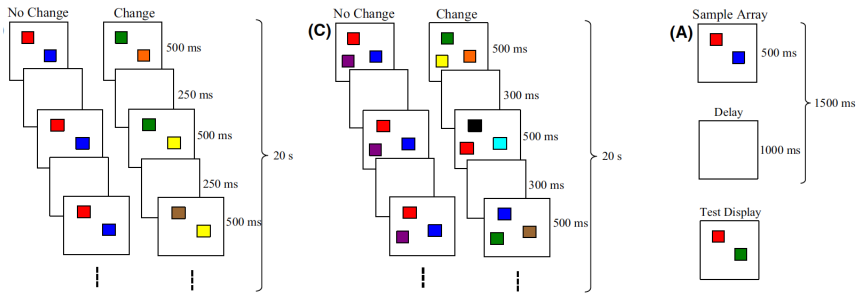
Visual Working Memory (VWM)

- VWM is a great target for early assessment & intervention
  - We can measure VWM early in development
  - Individual differences in infancy are predictive of school outcomes up to 11 years later
  - VWM is open to intervention (e.g., parenting interventions)

University of East Anglia

53

Measuring Changes in VWM over Development

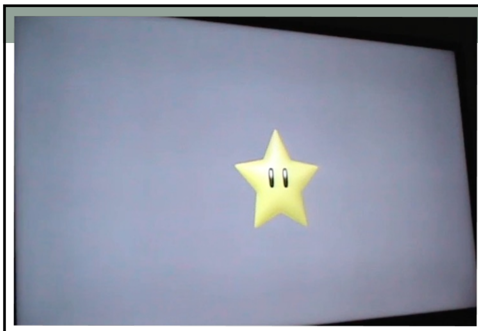


Infant / Child PL Task

Child / Adult CD Task

University of East Anglia

54

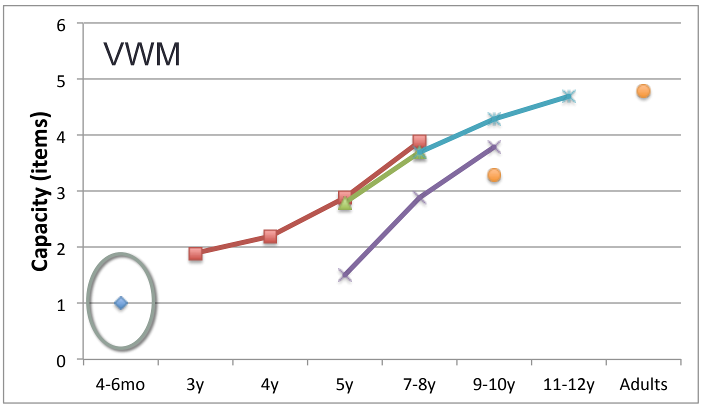


University of East Anglia

55

VWM over development

Dramatic changes in visual WM capacity from 1 item in infancy to 3-4 items by 9-10yrs



Simmering (2018). *Monographs of SRCD*. Rose et al. (2012). *Psychological Science*.

University of East Anglia

56

How does WM change?

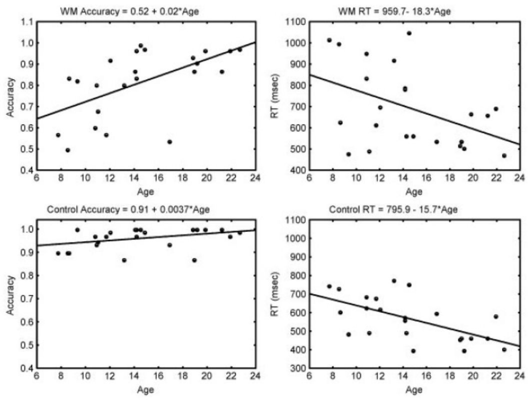
Looking to the brain for insights…

University of East Anglia

57

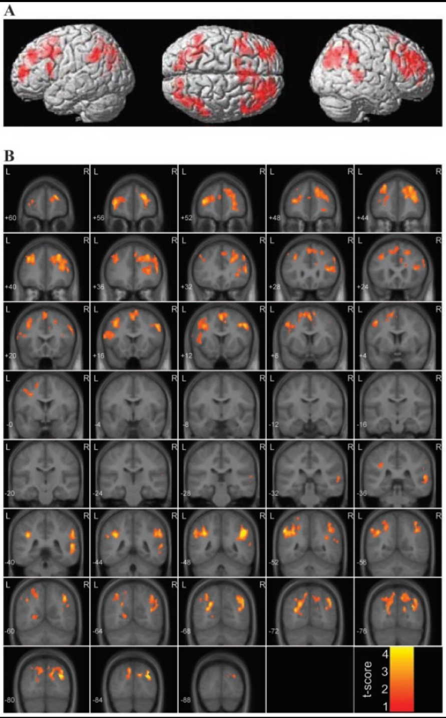
Kwon et al. 2002

- VSWM task using fMRI (detect spatial repetition 2-back in 3x3 grid; control task = detect item in center)
- Improvement in accuracy and latency



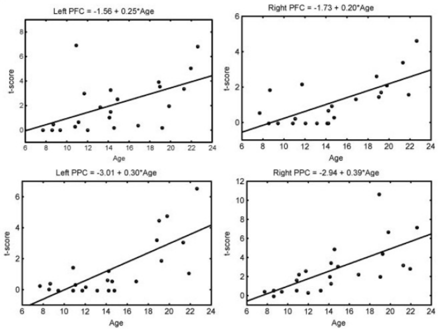
University of East Anglia

58



Kwon et al. 2002

- Increases in brain activity associated with improvements in performance with age as the strongest predictor



59

How does WM change?

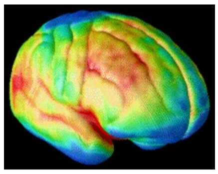
These data highlight which brain networks change, but they don't really explain how this change occurs.

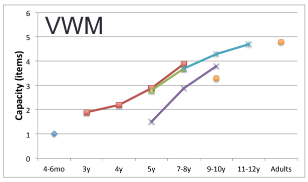
University of East Anglia

60

How Does WM Change?

- WM skills emerge as the brain matures

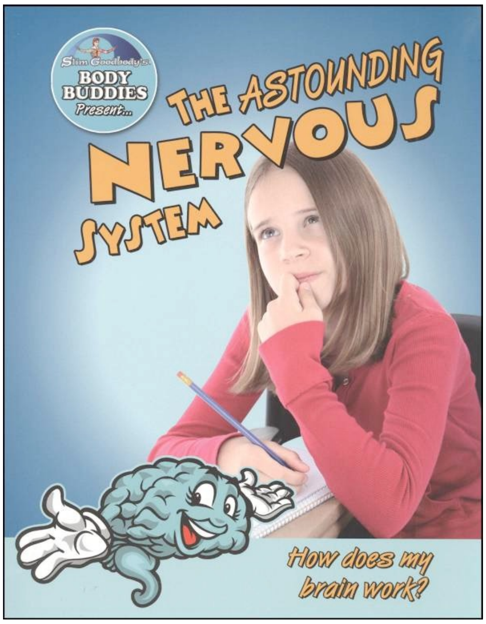




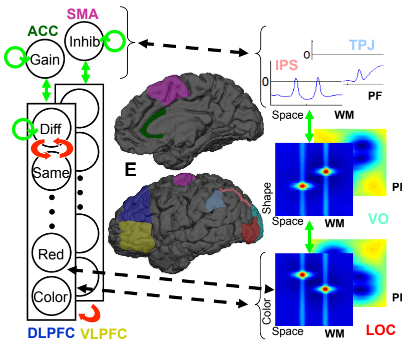
Not very satisfying…
- Just shifts the question to a different level: what explains brain maturation?
- Not terribly useful for intervention: how do we intervene in brain maturation?

University of East Anglia

61



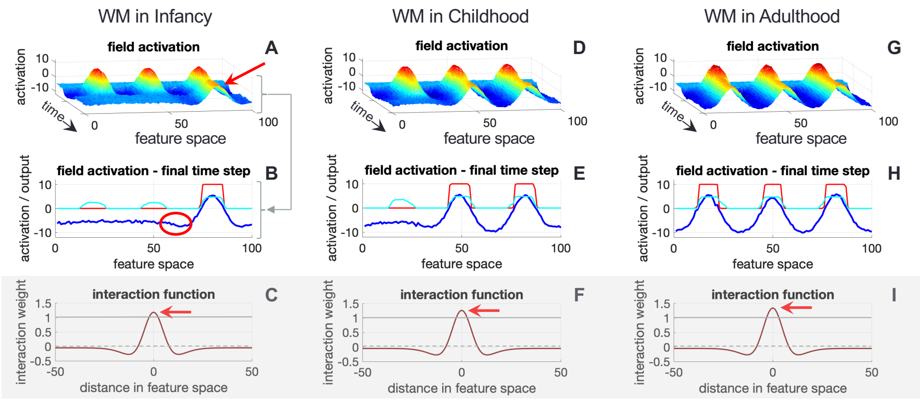
Computer models of how the brain works…
- Dynamic Field Theory



University of East Anglia

62

Spencer (2020)

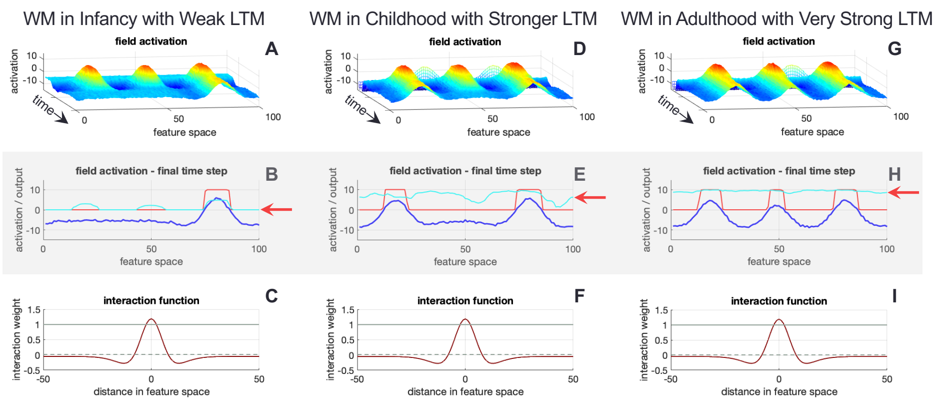


- Stronger local excitation leads to more robust WM
- More robust WM peaks increases capacity
- *WM capacity increases as excitation increases*

University of East Anglia

63

Spencer (2020)



- Memory traces accumulate locally to support WM
- As experience accumulates, WM abilities generalize
- *The brain develops itself via generalized experience*

University of East Anglia

64

VWM: Conclusions

- Brain data reveal which brain areas change over development
- Regarding *how* change occurs, brain models provide a mechanism: increase in neural excitation as experience generalizes across, for instance, features (colors)

University of East Anglia

65

VWM: Conclusions

How might this work guide interventions?

- Tells us how VWM operates – experience matters…
  - encourage caregivers to help provide the ‘right’ experiences for each child
- Gives us tools to assess changes in VWM as children develop
  - could provide targets for intervention work – is each child changing as predicted month-to-month as we intervene?

University of East Anglia

66

Hands-on: VWM

Introduction to coding in COSIVINA: how do you build a DF model that can be embedded in a task?

67

ICDL Tutorial – WELCOME!

- 09:00-11:00: Primer on DFT
- 11:00-11:30: coffee break
- 11:30-13:30: Hands-on session 1 (CEDAR)
- 13:00-14:00: lunch
- 14:00-15:00: Case study 1: VWM
  - Hands-on session 2 (COSIVINA)
- **15:00-16:00: Case study 2: IOWA**
  - Hands-on session 3 (simulating empirical data)
- 16:00-16:30: coffee break
- 16:30-18:00: Case study 3: WOLVES
  - Hands-on session 4 (simulating complex architectures / data)

69

Case Study: IOWA

Another simple model that captures a lot of data. Useful for highlighting the iterative nature of building a model, including fitting data and testing novel predictions.

University of East Anglia

70

University of East Anglia

71

Testing Predictions of a Neural Process Model of Visual Attention in Infancy Across Competitive and Non-Competitive Contexts

John P. Spencer — Professor, School of Psychology, University of East Anglia, Norwich, UK

Shannon Ross-Sheehy — University of Tennessee

Bret Eschman — Florida International University

University of East Anglia

1

The development of spatial attention

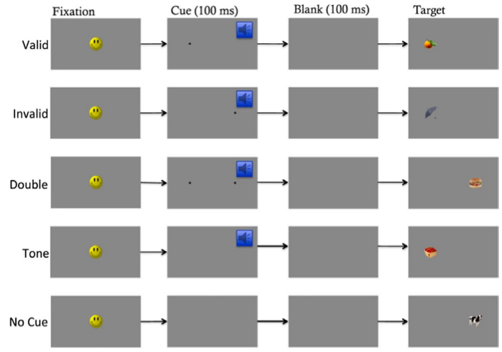
- Spatial information plays a key role in the early development of attention by providing an ecologically grounded continuous dimension along which infants and children can relate objects in the environment
- Attention and spatial processing systems develop gradually in early development as indexing of spatial locations and shifts of attention – both overt and covert – are integrated
- Evidence of changes in this integration comes from spatial orienting tasks which have become a benchmark for the study of early attention development

University of East Anglia

2

The IOWA task

- One spatial orienting tasks that has been particularly useful – the Infant Orienting With Attention (IOWA) task – examines how different types of spatial events influence covert orienting
- The tasks probes how a precue influences a later attentional shift
  - *Valid* precue
  - *Invalid* precue
  - *Double* precue
  - *Tone only*
  - *No cue*

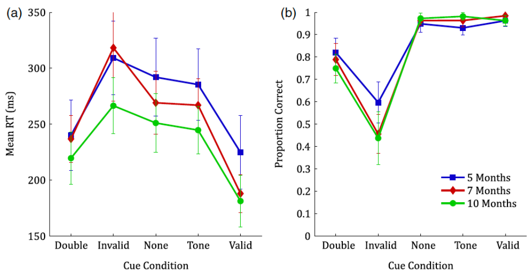


University of East Anglia

3

Ross-Sheehy, Schneegans, Spencer (2015)

- Results showed faster RTs for the 10mo infants, slower for the 5mo infants, and intermediate for the 7mo
- Cues had the greatest impact on 7 and 10mo infants, with faster RTs in valid conditions and slowest RTs in the invalid condition
- There was a speed-accuracy trade-off with older infants showing more erroneous shifts of attention in the double and invalid conditions



University of East Anglia

4

What changes in the brain underlie these shifts?

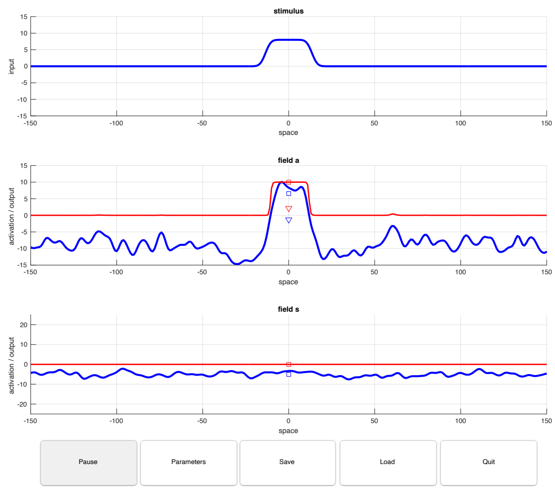
- Neural process models can be a useful tool here, shedding light on which types of neural changes underlie such empirical results
- Neural models implement known neurophysiological constraints, including how different functional neural populations interact to yield looks to the target under different conditions
- Critically, connections within and between model components can be manipulated to understand how particular behavioral patterns emerge
- Such models can also inform developmental hypotheses about how the neural system changes over time

University of East Anglia

5

Dynamic field model of spatial attention

- Visual input layer
- Spatial attention field
  - Local excitation / surround inhibition
  - Global inhibition (selects only one peak)
- Fixation node (boosts act near fovea)
- Gaze change node (boosts act in periphery)
- Saccade motor field
  - Peak generates eye movement
- Reset node (inhibits input during saccade)

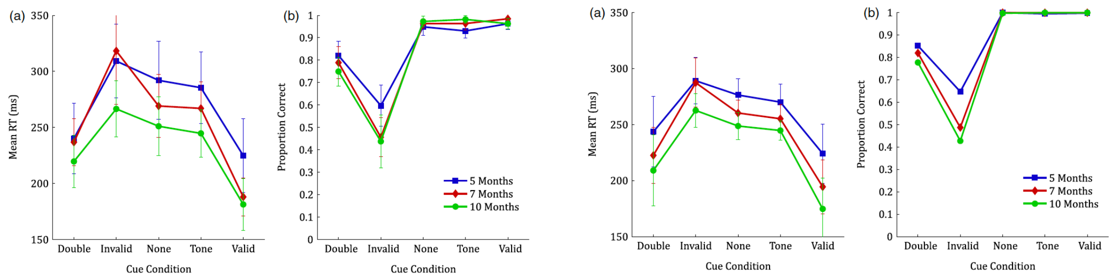


University of East Anglia

6

DF model of the IOWA task

- Simulator…
- https://github.com/cosivina/cosivina_dft_projects



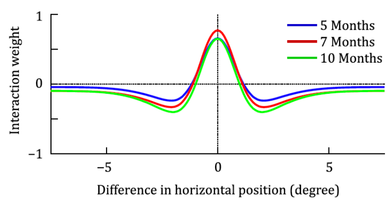
- RMSE = 12.8ms for RT data and 0.04 for accuracy data

University of East Anglia

7

How did we capture development?

- **Spatial precision hypothesis:** strength of excitation and inhibition increases in early development (Schutte et al., 2003; Simmering et al., 2008; Schutte & Spencer, 2009; Perone et al., 2011; Perone & Spencer 2013a,b, 2014)
  - Experience-dependent effect, e.g., exposure to spatial input patterns from retina which structure spatial maps in cortex may strengthen lateral connectivity within those maps
  - Myelination of cortical populations which enhances neural efficiency
- Developmental changes
  - Increase local excitation, surround inhibition, global inhibition in the attention field
  - Increase local excitation, global inhibition in the saccade field
  - Increase connectivity from attention to saccade field, from saccade field to reset node, and from reset node to attention and saccade fields
  - Decrease noise strength in attention and saccade fields

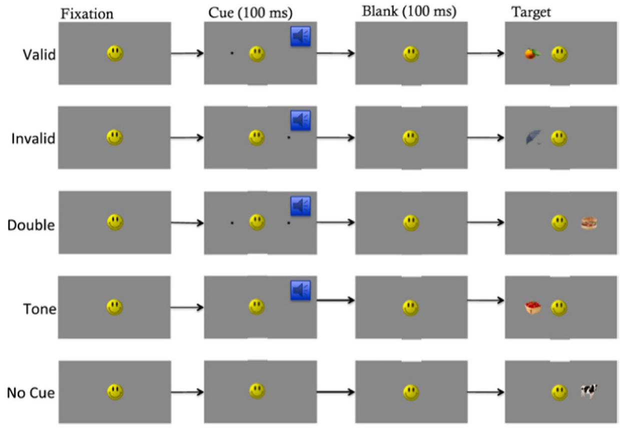


University of East Anglia

8

Novel predictions of DF model – Competition

- Simulated the model in competitive or 'overlap' conditions



University of East Anglia

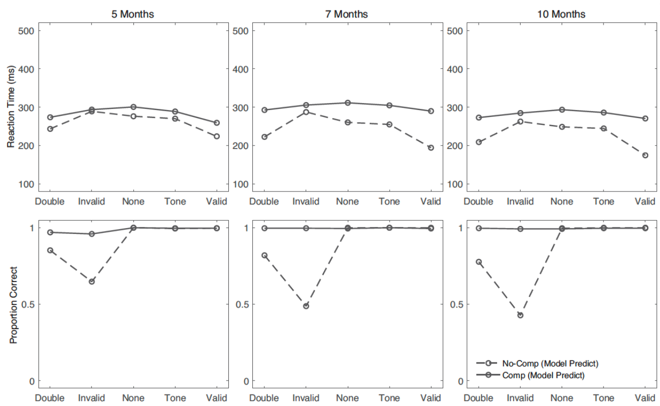
9

Novel predictions of DF model – Competition

- Simulated the model in competitive or 'overlap' conditions

5 novel predictions

1. Slower RTs in comp
2. Slowing greater for 7 and 10mo
3. Longest RTs in none cond with a flattening of RTs across cond
4. Few errors in invalid and double
5. Accuracy should increase with age relative to non-comp



University of East Anglia

10

Spencer, Ross-Sheehy, Eschman (2022)

- Tested these predictions with 31 5mo, 27 7mo, and 26 10mo in a within-subjects design
- Infants completed both non-competitive and competitive conditions with all cue types (valid, invalid, double, tone, none)
- Each block contained one of every trial type (2 x 5) in random order
- Infants completed up to 80 trials over the 10min experiment

University of East Anglia

11

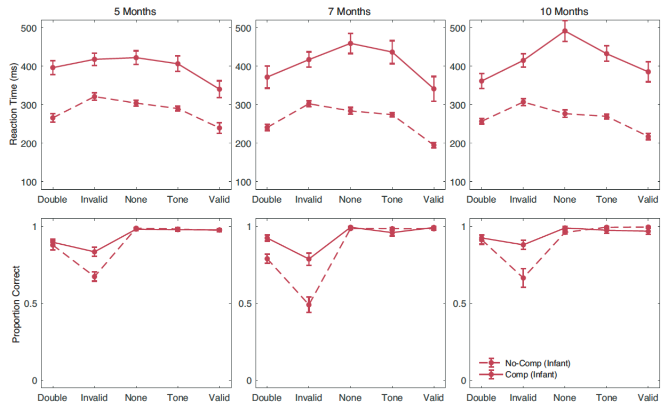
Results

5 novel predictions

1. Slower RTs in comp ✓
2. Slowing greater for 7 and 10mo ✓
3. Longest RTs in none cond ✓

with a flattening of RTs across cond X

4. Few errors in invalid and double ✓
5. Accuracy should increase with age relative to non-comp ✓



University of East Anglia

12

Can we improve the model fit?

- Although the DF model accurately predicted 5 novel effects, the fit of the model to the new data was relatively poor.
- Can we 'repair' the fit with modest parameter tuning?
- More critically, can we 'repair' the fit while holding the developmental changes constant? This would provide a strong test of the spatial precision hypothesis.

University of East Anglia

13

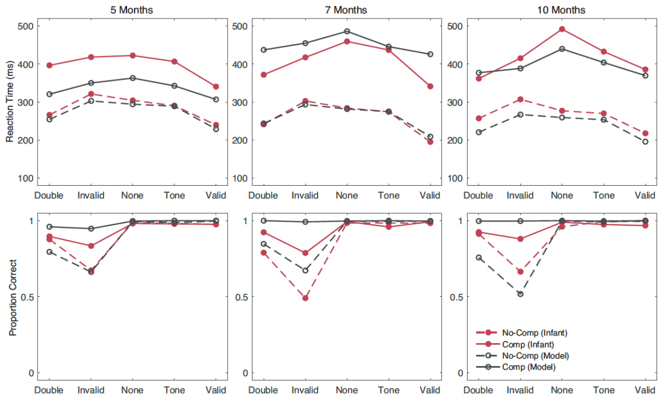
Model modifications

- In previous model, the fixation node was not used; this is critical here as fixation input varies by condition. Added that in and tuned parameters.
- With addition of fixation node, we now had to re-tune the gaze change node so these were in balance.
- Now the model showed better switching between the fixation state and shifts of attention, but the model often had two peaks simultaneously – a fixation peak and a target peak. Increased global inhibition in the attention field to fix this, keeping the developmental modulation the same.
- To boost errors, we increased the cue input strength and the noise strength, again keeping the developmental modulation the same

University of East Anglia

14

New simulation results



			Overall
2015 Model			
	Reaction time	No competition	26.7
		Competition	121.7
	Proportion correct	No competition	0.05
		Competition	0.07
2021 Model			
	Reaction time	No competition	15.9
		Competition	48.3
	Proportion correct	No competition	0.07
		Competition	0.07

- Overall RMSE = 37ms for RTs and 0.07 for accuracy

University of East Anglia

15

Conclusions and next steps

- DF model made 5 novel predictions which were generally supported with a new set of empirical data with infants
- The model achieved a good quantitative fit to the new data set while maintaining the integrity of the developmental hypothesis
- This provides strong support for this particular account of the development of spatial attention in infancy
- We are currently testing a new set of novel predictions using this model by removing the tone cue.
- We are also developing methods to optimize model parameters using tensorflow instead of doing this work ‘by hand’. This will enable us to more rigorously test the SPH and should improve the quantitative fit of the model.

University of East Anglia

16

Conclusions and next steps

- More generally, we note that most accounts of competition effects in the literature emphasize developmental improvements in a ‘disengaging’ mechanism via inputs from frontal eye fields and DLPFC (e.g., Fan et al., 2005; Johnson & De Haan, 2015; Johnson et al., 1991).
- Our model shows, however, that developmental changes in competition effects can instead arise from more general changes in excitation / inhibition
- One possibility linking these views is that the dynamics captured by the gaze change node reflects these frontal inputs.
- We recently proposed a method to map neural activity in DF models to fMRI and fNIRS measures (Buss & Spencer, 2021); such methods could be used to directly link the DF model to neural measures of the infant brain.

University of East Anglia

17

Thanks to our fabulous team!

- <u>Funded by</u>: NIH R01HD083287 awarded to JPS

University of East Anglia

18

Hands-on: IOWA

Goal: To highlight how COSIVINA can be used to quantitatively simulate empirical data.

University of East Anglia

72

The future of DF simulation work

- We're working on a way to use tensorflow to optimize parameters of DF models
- Currently using our IOWA model as a test case
- This builds on pyCOSIVINA and new software called 'Dynamic Field Flow'
  - https://dynamicfieldtheory.org/software/
  - https://github.com/danielsabinasz/DynamicFieldFlow

University of East Anglia

74

ICDL Tutorial – WELCOME!

- 09:00-11:00: Primer on DFT
- 11:00-11:30: coffee break
- 11:30-13:30: Hands-on session 1 (CEDAR)
- 13:00-14:00: lunch
- 14:00-15:00: Case study 1: VWM
  - Hands-on session 2 (COSIVINA)
- 15:00-16:00: Case study 2: IOWA
  - Hands-on session 3 (simulating empirical data)
- 16:00-16:30: coffee break
- **16:30-18:00: Case study 3: WOLVES**
  - Hands-on session 4 (simulating complex architectures / data)

University of East Anglia

75

Case Study: WOLVES

A more complex neural architecture that simulates a lot of data quite well. Highlights what is possible by 'scaling up' from simpler DF models.

University of East Anglia

76

Word-Object Learning via Visual Exploration in Space (WOLVES): A Neural Process Model of Cross-Situational Word Learning

Larissa K. Samuelson

with…
Ajaz A. Bhat
John P. Spencer

University of East Anglia
SCHOOL OF PSYCHOLOGY
DEVELOPMENTAL DYNAMICS LABORATORY

1

Words are the building blocks of language

How do people learn the meanings of words when there are an infinite number of possible referents?

- One possibility: Track word-object co-occurrences (cross-situational statistical learning)

"Try some of the *banana*"

2

Words are the building blocks of language

How do people learn the meanings of words when there are an infinite number of possible referents?

- One possibility: Track word-object co-occurrences (cross-situational statistical learning)
- But what is the nature of this type of statistical learning?

Two classes of theories

- Hypothesis testing accounts
- Associative learning

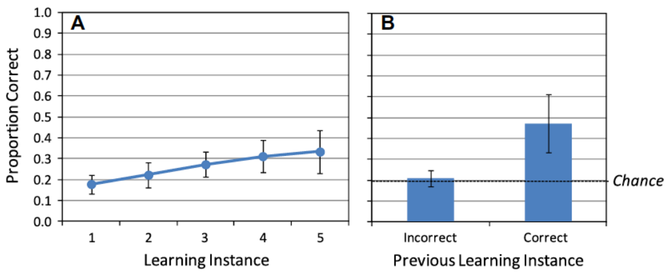
3

Hypothesis Testing

- Encounter a novel word
- Make a single hypothesis about the word-object mapping
- If later evidence shows that this hypothesis is wrong, form a new one and proceed to verification…

4

Hypothesis Testing



Trueswell et al. (2013). *Cognitive Psychology.*

5

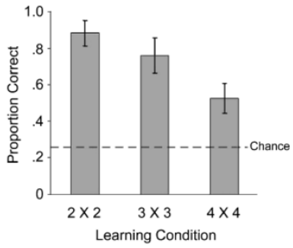
Associative Learning

- When encounter a novel word, form multiple associations between word and available objects
- Over time, refine these associations based on available co-occurrences
- Strongest association wins (as correct word usage should always drive you to one strong association)

6

Associative Learning

- 2 words x 2 pictures on each training trial; 3 x 3; 4 x 4
- Taught same 18 words
- 6 repetitions of each target word-ref pairing – so same exposure in each condition but different erroneous mappings (5.09 incorrect mappings in 2x2, 8.78 in 3x3, 12.22 in 4x4)
- 4 AFC test with one word on each test trial (foils from 18)



Yu & Smith (2007). *Psychological Science.*

7

Limitations of existing theories

- Both types of theories have been used to explain the same data; Yu and Smith (2012) used this to call for implementation-level theories
- Current theories are not comprehensive (tend to explain only a subset of data from specific tasks)
- Current theories fail to take time seriously despite evidence that how processes unfold in real time, over learning, and over development matter…

Yu & Smith (2012). *Psychological Review.*

8

Cross-Situational Word Learning

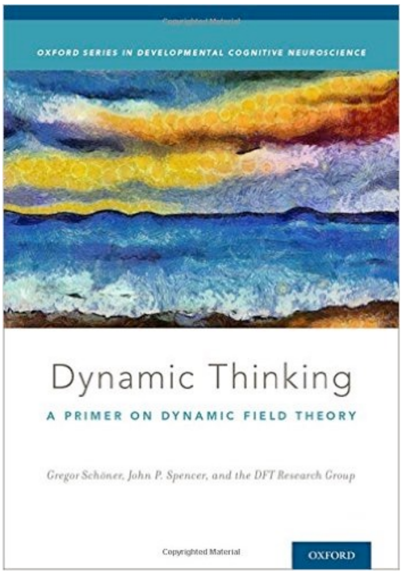
- 12-14 month old children can learn 4 words (Smith & Yu, 2008, Yu & Smith, 2011). Older kids and adults can learn up to 9-16 words.
  - What is changing over development?
- Individual differences: 'strong' vs 'weak' learners.
- Moment-by-moment variation in looking matters – strong learners have fewer, longer fixations.

9

Today's talk focuses on a new theory of CSWL

- WOLVES
  - Overview of model & demonstrate that it is a good model.
- Timescale of the task
  - Simulations that highlight role of attention and learning processes.
- Timescale of development
  - Present the first developmental account of CSWL highlighting the role of memory processes.
- Model evaluation
  - Is the theory comprehensive?
  - How does it fare relative to competitor models?

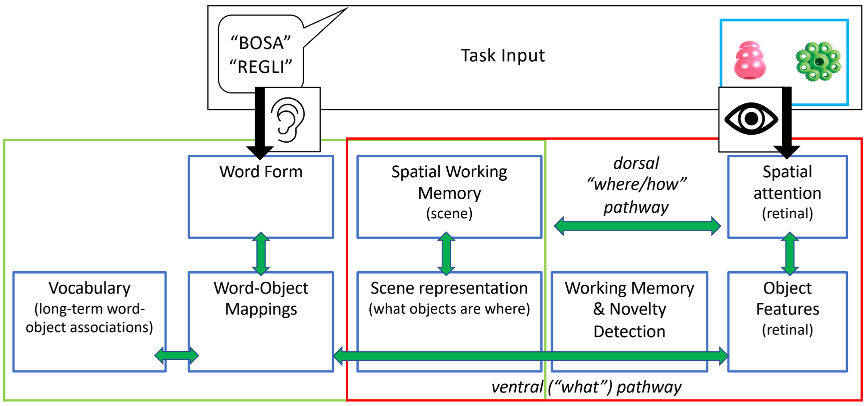
10



www.dynamicfieldtheory.org

11

WOLVES



Word-Object Learning

Samuelson, Smith, Perry & Spencer (2011); Samuelson, Jenkins & Spencer (2013)

Visual Exploration in Space

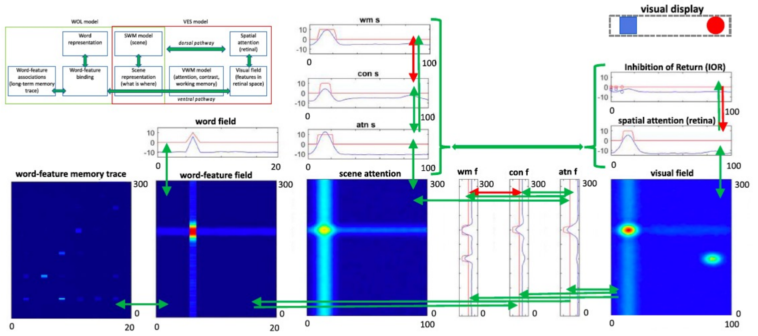
Johnson, Spencer & Schöner (2009); Perone & Spencer (2013b)

Bhat, Spencer, Samuelson (2021). *Psychological Review.*

12

WOLVES

Figure 4
The Overall Architecture of WOLVES



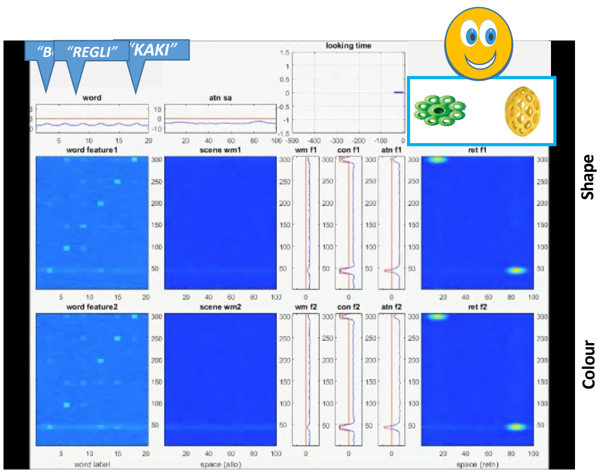
Note. Scene WMs and memory traces are not shown for representational simplicity. Arrows represent uni/bidirectional (green: excitatory, red: inhibitory) connectivity in the model. See text for additional details. WOLVES = word-object learning via visual exploration in space. See the online article for the color version of this figure.

Full model includes ventral pathways for colour *and* shape as well as memory traces for all field except visual field, attention fields and IOR

13

WOLVES in action

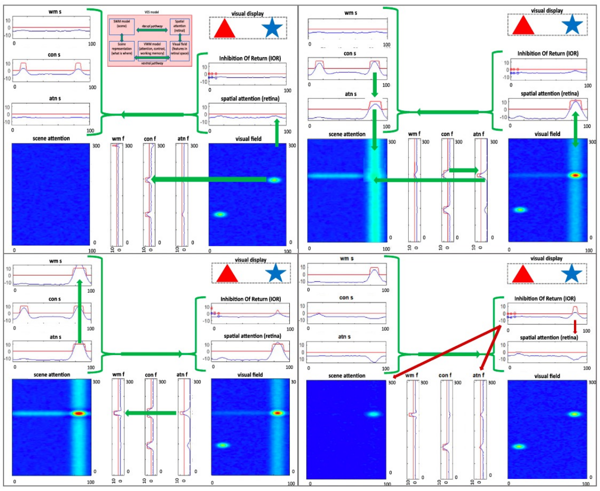
- VES cycles of novelty detection, consolidation in working memory, and release from fixation.
- WOL cycles of associative learning that is non-linear as memory traces evolve
- TDA cycles of top-down memory driven attention



14

VES Cycle

Figure 3
Visual Exploration in Space Model in Four Stages of an Autonomous Looking Cycle

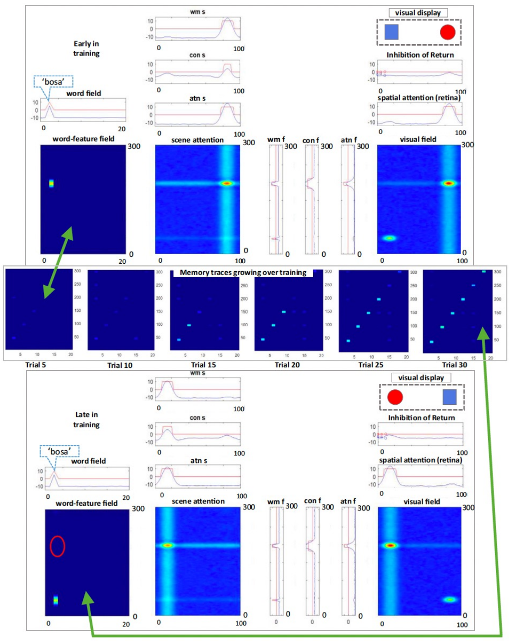


Note. The top-left panel shows the model detecting novel objects in the scene. The top-right panel shows the model attending to one object. The bottom-left panel shows the model having consolidated the object in working memory. The bottom-right panel shows model releasing attention to begin a new looking cycle. VES = visual exploration in space. See the online article for the color version of this figure.

15

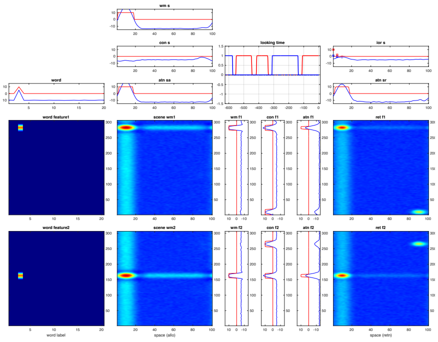
WOL Cycle

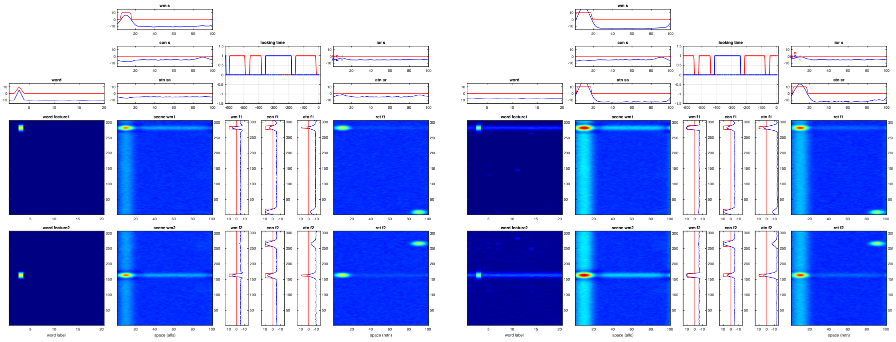
Figure 5
Processing in WOLVES During Smith and Yu's (2008) Cross-Situational Word Learning Task



16

TDA Cycle





17

Does WOLVES capture – and explain – empirical data?

Will compare WOLVES to Kachergis et al. (2012) as relevant: an AL model that distributes attention between known and novel associations; has memory decay to capture association frequency; one shot computation on each trial.

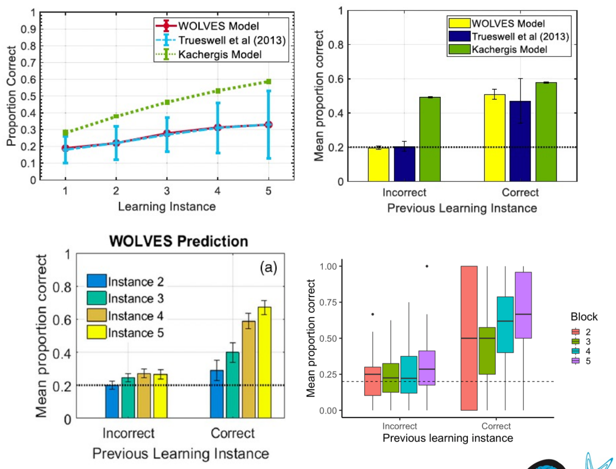
18

WOLVES explains HT data

WOLVES captures HT data. Why?

- Timing of task means WOLVES typically makes one look on a trial (so only forms one association)
- What if we extend the time?

Figure 13
Data from Trueswell et al. and the WOLVES and Kachergis Models



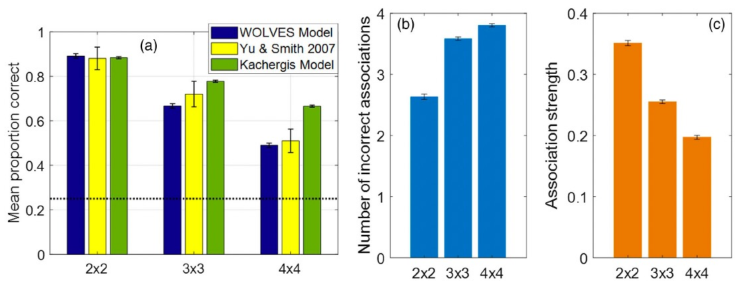
Bhat, Spencer, Samuelson (2021). *Psychological Review.*

19

WOLVES also explains associative learning data

- With more things to look at, WOLVES forms more incorrect associations with weaker association strengths

Figure 16
Data from Yu and Smith (2007) and the WOLVES and Kachergis Models



Bhat, Spencer, Samuelson (2021). *Psychological Review.*

20

Does WOLVES capture – and explain – empirical data?

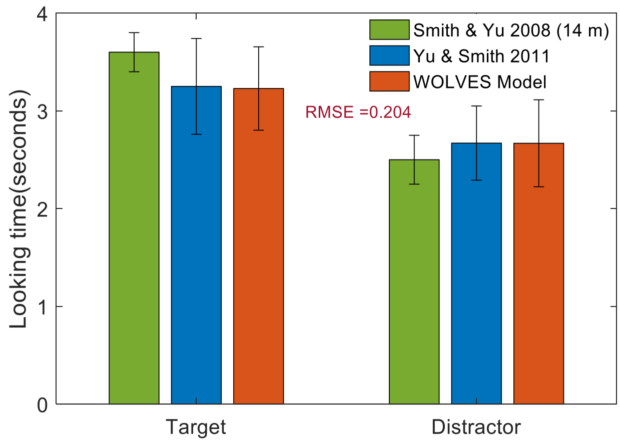
Yes and successfully generates novel predictions.

21

What about CSWL in early development?

22

Smith & Yu (2008) , Yu & Smith (2011)



Bhat, Spencer, Samuelson (2021). *Psychological Review.*

23

Smith & Yu (2008) , Yu & Smith (2011)

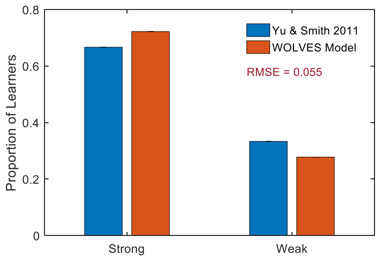
Measure	S & Y (2008)	Y & S (2011)		WOLVES	RMSE	MAPE
Test Trials						
Mean looking per 8s trial	6.10	5.92		6.26	.26	4.22
Pref. looking ratio	.60	.54		.54	.04	6.10
Mean words learned (of 6)	4.0	3.5		4.0	.35	7.14
Prop. Strong/weak learners	NA	.67		.74	.07	10.45
Mean looking to target per trial	3.6	3.25		3.36	.19	5.03
Mean looking to distractor per trial	2.5	2.67		2.89	.32	11.92
Training Trials		S	W			
Mean looking per 4s trial	3.04	2.96	3.07	3.01	.02	.71
Mean fixations per trial	NA	2.75	3.82	2.89	.22	6.98
Mean fixation duration	NA	1.69	1.21	1.31	.22	14.38

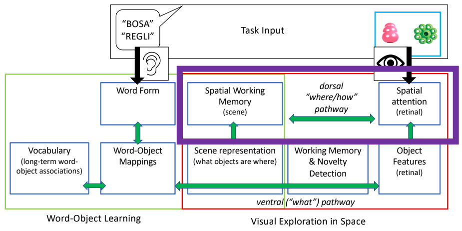
RMSE = Root Mean Squared Error, MAPE = Mean Absolute Percentage Error

Bhat, Spencer, Samuelson (2021). *Psychological Review.*

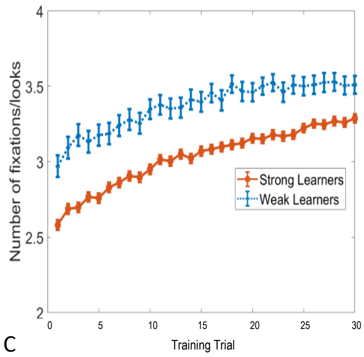
24

The Role of Spatial Attention



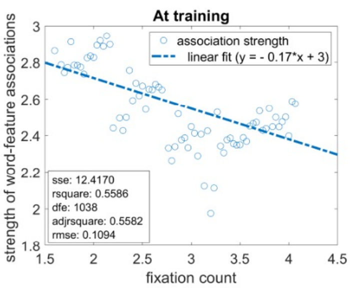


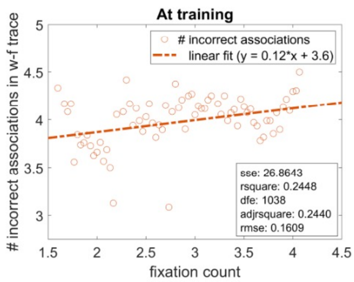
- Spatial attention parameter
  - atn_sa → atn_c
- Sort by strong/weak learners.
- Strong learners have fewer, longer fixations.



25

The Role of Spatial Attention





- As fixations go up, association strength goes down.
- As fixations go up, incorrect associations go up.

Bhat, Spencer, Samuelson (2021). *Psychological Review.*

26

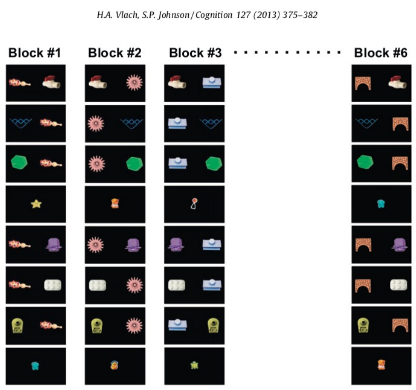
We created the difference between strong and weak learners via manipulation of a particular parameter.

This mechanistically relates variations in spatial attention to learning outcomes and highlights the contribution of real-time looking dynamics to CSWL.

27

Timescale of Development

- Vlach & Johnson (2013), Vlach & DeBrock (2017, 2019)

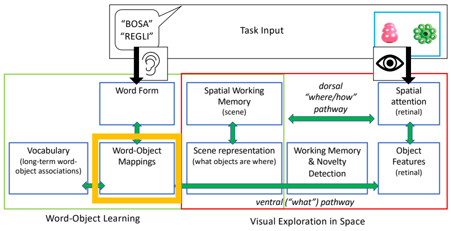


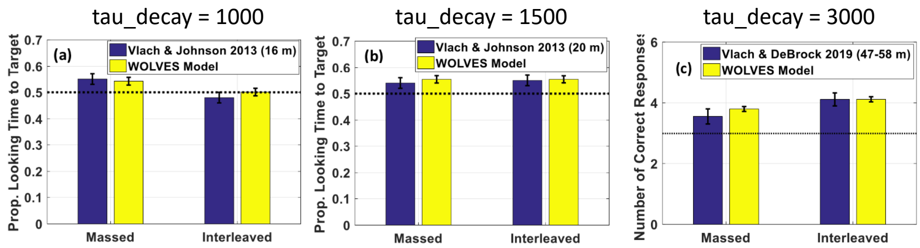
- 16 mo learn words from massed but not interleaved presentation.
- 20 mo learn equally with massed or interleaved.
- Older children learn better with interleaved presentation.

28

Timescale of Development

- Memory: Tau_Decay defines how fast a memory trace deteriorates.

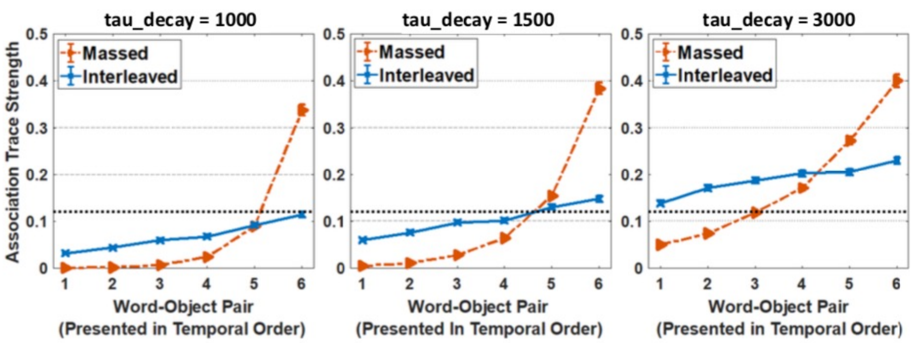




- Unified developmental account of CSWL

29

Timescale of Development



Bhat, Spencer, Samuelson (2021). *Psychological Review.*

30

We captured 60 datapoints from 12 months to 5 years with a change to just one parameter.

WOLVES is a powerful *developmental* model

This is because it has rich real-time and learning dynamics.

31

Is WOLVES a comprehensive theory?

Compared WOLVES to 2 competitor models:

- Kachergis et al. (2012)
- Stevens et al. (2017) – Pursuit: an HT model that uses an AL mechanism to weigh different hypotheses. Only adds a word to the lexicon if the conditional probability of hypothesis exceeds a threshold.

32

Model Validation; coverage & comparison

- 5 CSWL studies with adults
  - Trueswell et al. (2013), Yu & Smith (2007), Yu, Zhong & Fricker (2012), Yurovsky et al. (2012), Kachergis et al. (2012)
- 7 CSWL studies with infants, toddlers & children
  - Smith & Yu (2008), Yu & Smith (2011), Smith & Yu (2013), Vlach & Johnson (2013), Vlach & DeBrock (2019), Vlach & DeBrock (2017), Suanda etal. (2014)

Measure	Data Points	WOLVES		Kachergis et al.+		Pursuit*	
		RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
Grand Mean Specific tasks	69	.05	13.51	.08	19.95	.20	42.13
Standard Deviations	69	.04	15.79	.07	21.99	.13	25.52
Grand Mean 3 Gen Exp	15	.03	4.05	.21	47.42	.13	23.91
Grand Mean	132	.10	15.80	unable to capture			
Overall AIC	69	-239.67		-295.78		-193.32	

+Kachergigs et al. (2012, 2013, 2017); *Stevens et al. (2017)

Bhat, Spencer, Samuelson (2021). *Psychological Review.*

33

Is WOLVES a comprehensive theory?

Yes.

Also raises interesting questions about metrics for model comparison. AIC lowest for Kachergis model, but WOLVES clearly outperforms this competitor model.

Suggests that the penalty for 'free' parameters too steep and/or that other metrics – like model generalisation – are more useful.

34

Conclusions

- WOLVES
  - Formal neural-process account of CSLW based on autonomous real-time visual exploration and non-linear associative learning.
  - Captures a large range of data and beats other models in direct comparison.
- Timescale of the task
  - Mechanistically related the strength of spatial attention to learning outcomes.
- Timescale of development
  - Presented the first developmental account of CSWL based on changes in memory strength.
- Future Directions
  - Currently exploring how we can use the model to make predictions, understand relations between tasks, and understand individual differences.

35

Thank you

Members of Developmental Dynamics Lab, University of East Anglia

Funding: NICHD RO1HD045713 to L.K. Samuelson

36

37

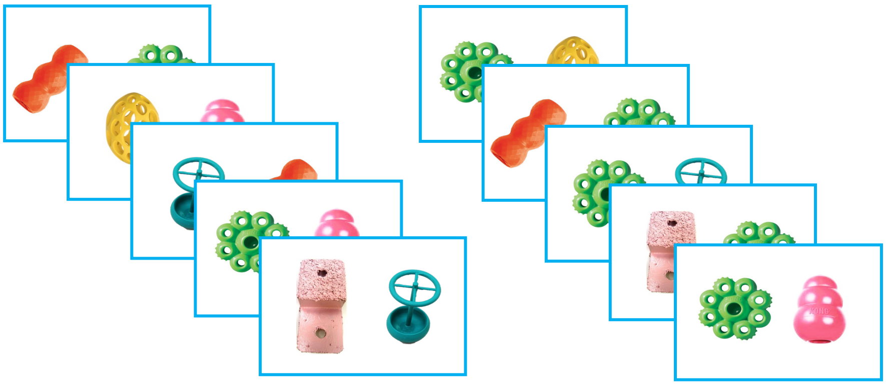
We've highlighted the real timescale.
What about the timescale of learning in the task and the timescale of development?

38

Timescale of the task

Smith & Yu (2008)

Smith & Yu (2013): Novelty Trap

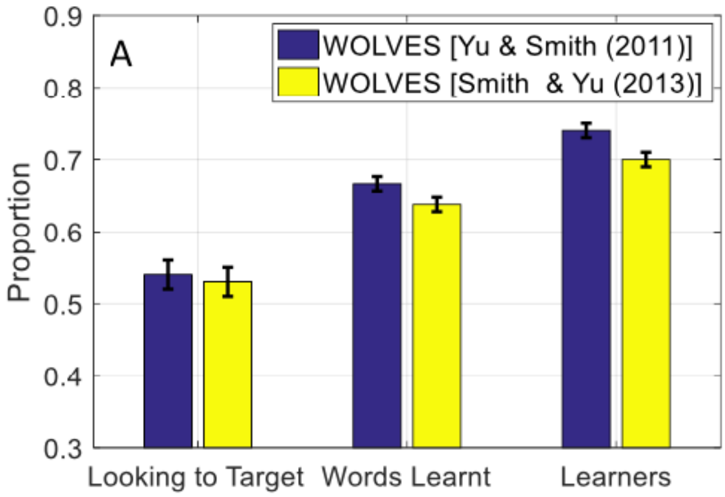


No overall difference in looks to target v. distractor at test

Fewer "learners"

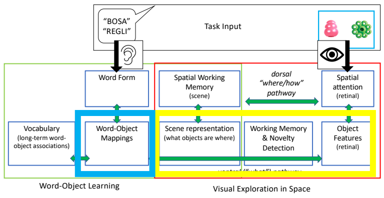
39

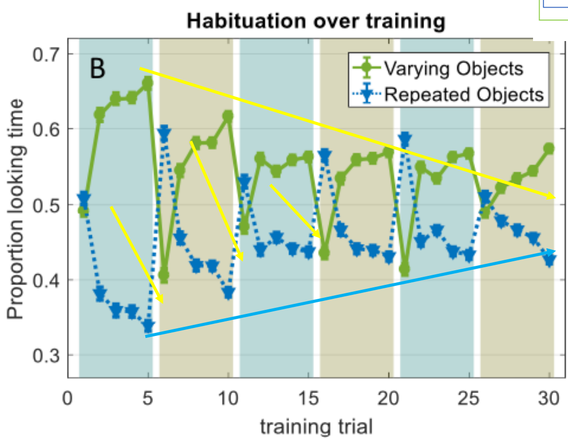
Timescale of the task



40

Timescale of the task





- Novelty detection & consolidation in working memory
- Top-down attention driven by growing associations

41

Two types of learning on timescale of the task:

- learning / habituating to visual features
- learning word + object mappings

42

77

Hands-on: WOLVES

Goal: to show how we handle the complexity of using a large architecture to simulate data from many different tasks.

78

WOLVES – Code Organisation

- Wolves core
  - Sim, GUI, Controls
  - Different Sim file for one task (bigger field)
  - XSIT_Manual_run.m → BAM file
- Experiments code
  - One for each study (lots of code duplication in each file – easy to copy, paste, edit)
- Analysis code
  - One for each study (since people measure different things)
- Support code
  - Misc tools (e.g., for computing root mean squared errors)

University of East Anglia

79

WOLVES – How to run

- Show basics

University of East Anglia

80

WOLVES – Running on an HPC

- We run 300 iterations per condition
- Simulated 132 data points over 12 experiments – that's a lot of simulation time
- On an HPC, we can distribute simulations over cores; conceptually, each simulation is a subject. So with 96 cores, we can run a full batch in about the same amount of time as 3 single runs.
- How? Job script on HPC with matlab; just need to copy over COSIVINA and jsonlab.

University of East Anglia

81

WOLVES – bells and whistles

- Example using reload option for recent project

University of East Anglia

82

The End?

You've earned beer/wine/cider/gin.
Stay in touch via dynamicfieldtheory.org!

University of East Anglia

83