University of Waterloo

# How to build a brain

## Cognitive Modelling

Terry & Chris
Centre for Theoretical Neuroscience
University of Waterloo

CTN Waterloo

CNRG computational neuroscience research group
compneuro.uwaterloo.ca

# So far...

- We have learned how to implement
  - high-dimensional vector representations
  - linear transformations
  - nonlinear transformations
  - recurrent, dynamic networks

# Semantic pointer architecture

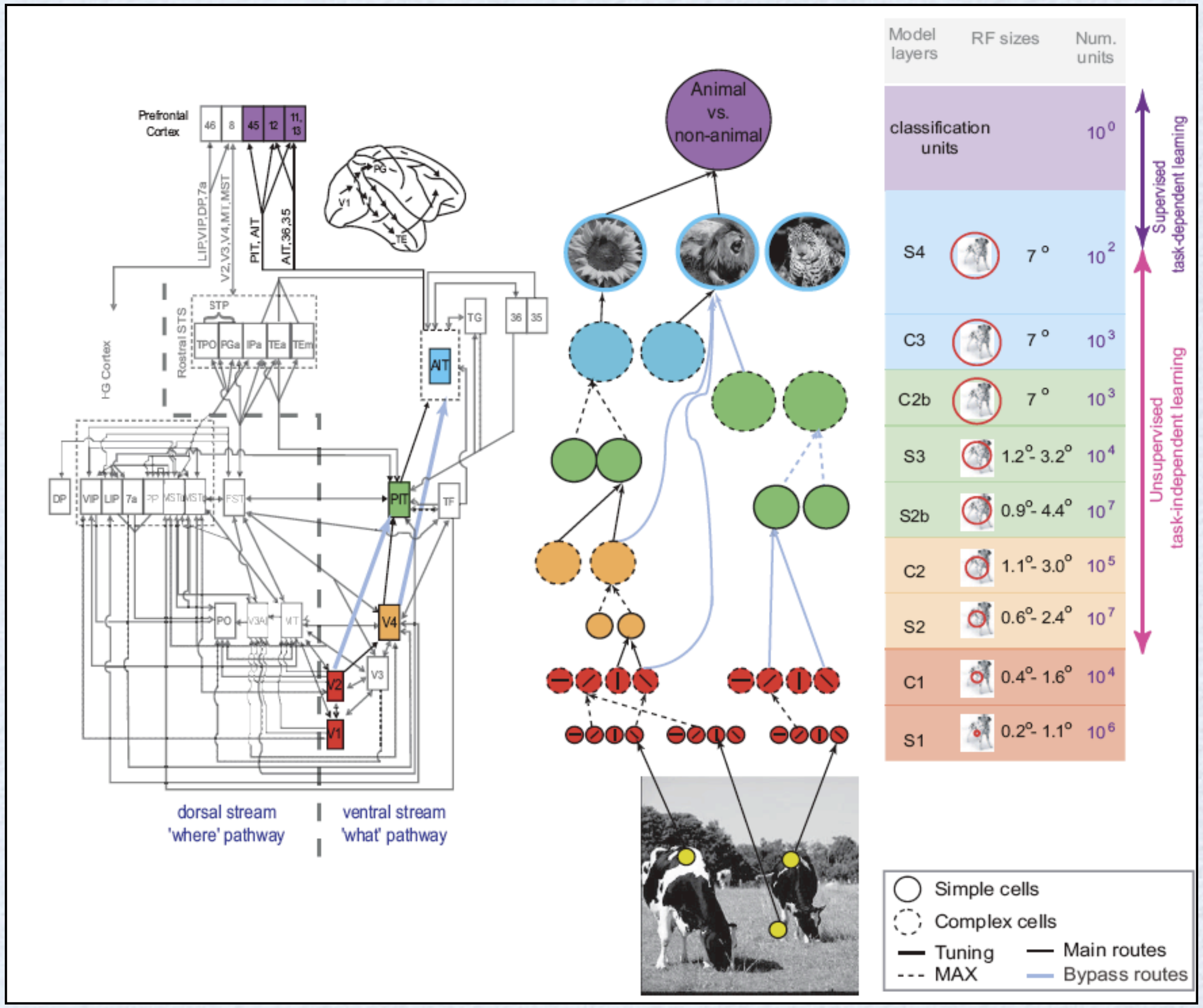
- The semantic pointer architecture uses these building blocks to construct cognitive models
- Three things to outline:
  - Semantics
  - Syntax
  - Control

# SPA: Semantics

- Semantic pointers are: Compressed, content-based 'addresses' to information in association cortices
- 'Pointer' because they are used to recall 'deep' semantic information (content-based pointer)
- 'Semantic' because they themselves define a 'surface' semantic space

# SPA: Semantics

- E.g. The pointer would be the activity of the top level of a standard hierarchical visual model for object recognition
- This pointer can then support 'symbol' manipulation
- It can also be used to reactivate a full visual representation

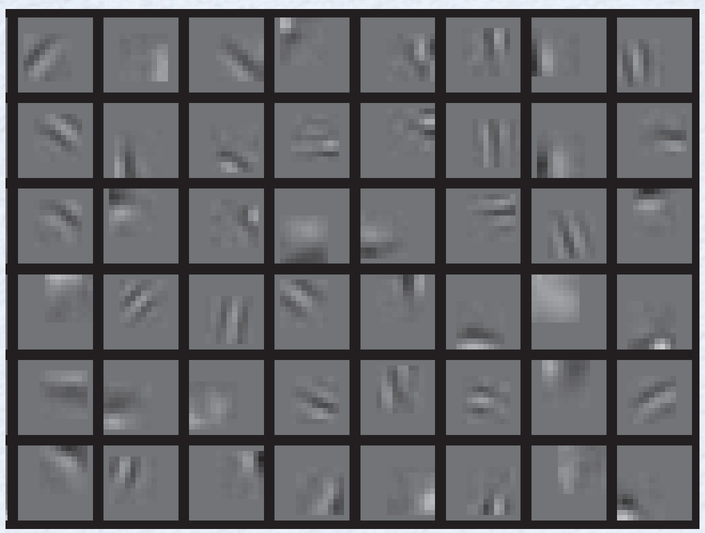



Serre et al., 2007 PNAS

# SPA: Surface/deep semantics

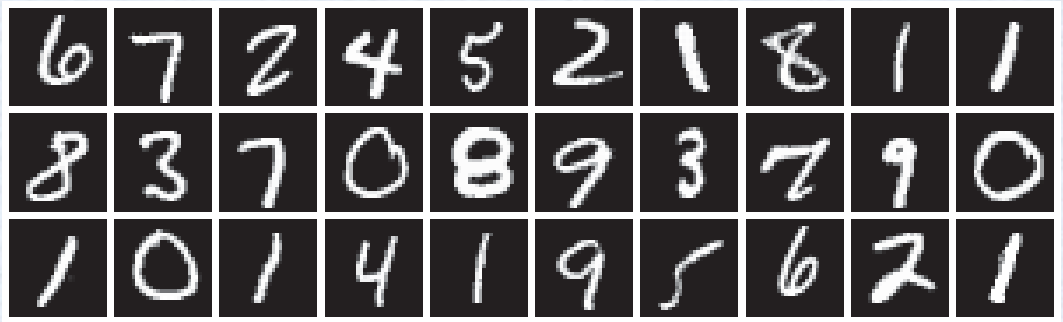
- Applied to numbers: a) neuron tuning; b) generic SPs; c) input; d) reconstruction; e) surface semantics

a)

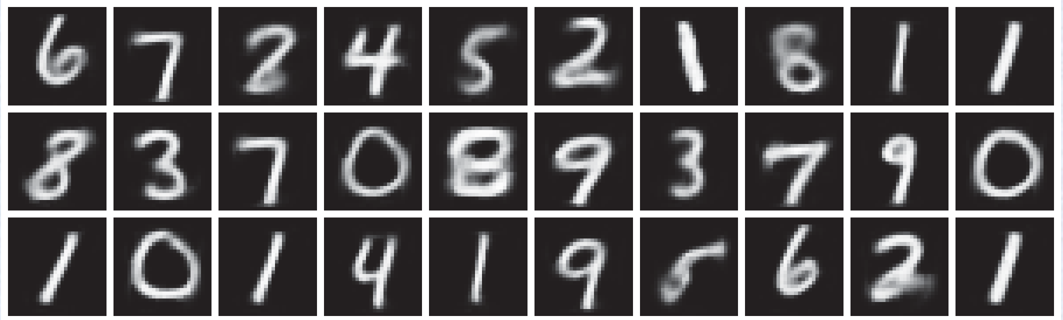


b)

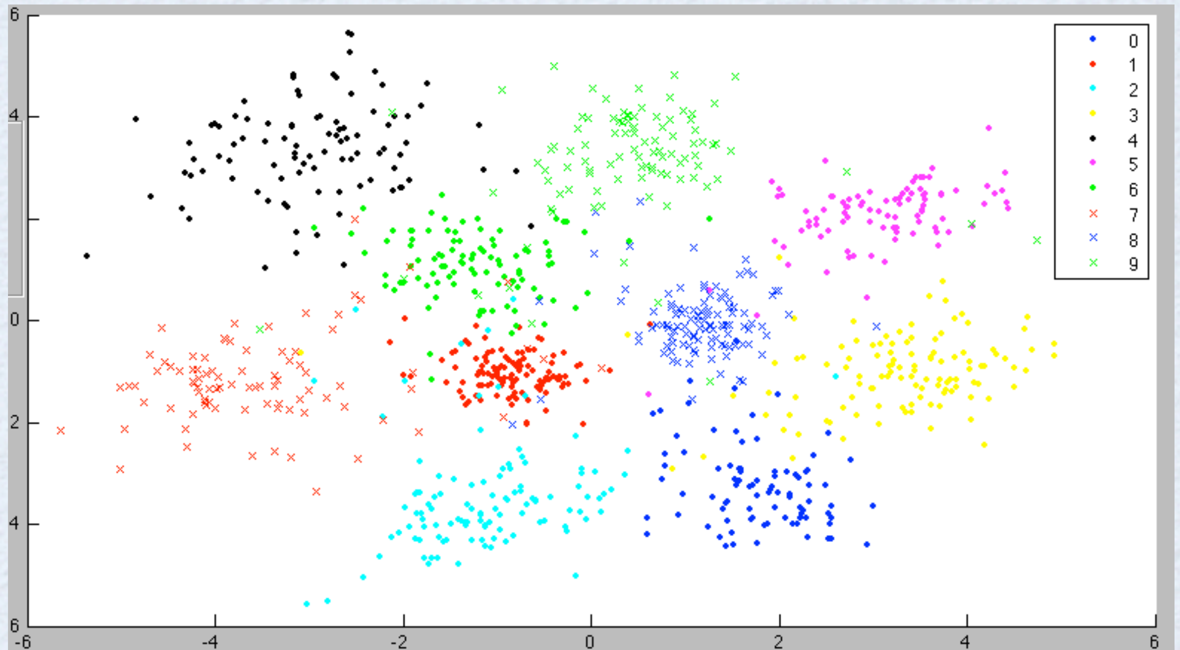
c)



d)



e)



# SPA: Surface/deep semantics

- Solomon & Barsalou (2004) showed that false pairings that were lexically associated take longer to process (e.g. dog-card 100ms quicker than banana-monkey)
- Kan et al. (2003) fMRI observed activation in perceptual systems only in the difficult cases
- Deep processing is not needed when a simple lexically-based strategy is sufficient to complete the task

# SPA: Syntax

- Vector Symbolic Architectures (VSAs)
- Smolensky's Tensor Products
- Kanerva's Spatter Codes
- Gayler's Multiply, Add, Permute (MAP) method
- Plate's Holographic Reduced Representations (HRRs)

# Structure representations

- All VSAs have some combination of 3 operations
  - Multiply (bind)
  - Add (compose)
  - Hide (protect from other vectors)
- Chosen VSA: HRRs
  - Constant vector length
  - Protect and bind happen in 1 step
  - Real valued

# Structured representations

- HRRs (Plate, 1991; circular convolution)
- Circular convolution (binding)

$$\mathbf{C} = \mathbf{A} \otimes \mathbf{B}$$
$$c_j = \sum_{k=0}^{n-1} a_k b_{j-k}$$

- Circular correlation (unbinding)

$$\mathbf{B} \approx \mathbf{A} \oplus \mathbf{C}$$
$$b_j = \sum_{k=0}^{n-1} a_k c_{j+k}$$

$$\mathbf{A} \oplus \mathbf{C} \approx \mathbf{A}' \otimes \mathbf{C}$$

# Circular convolution

- Circular convolution in the frequency space is piece-wise multiplication:

$$FFT(\mathbf{A} \otimes \mathbf{B}) = FFT(\mathbf{A}).FFT(\mathbf{B})$$

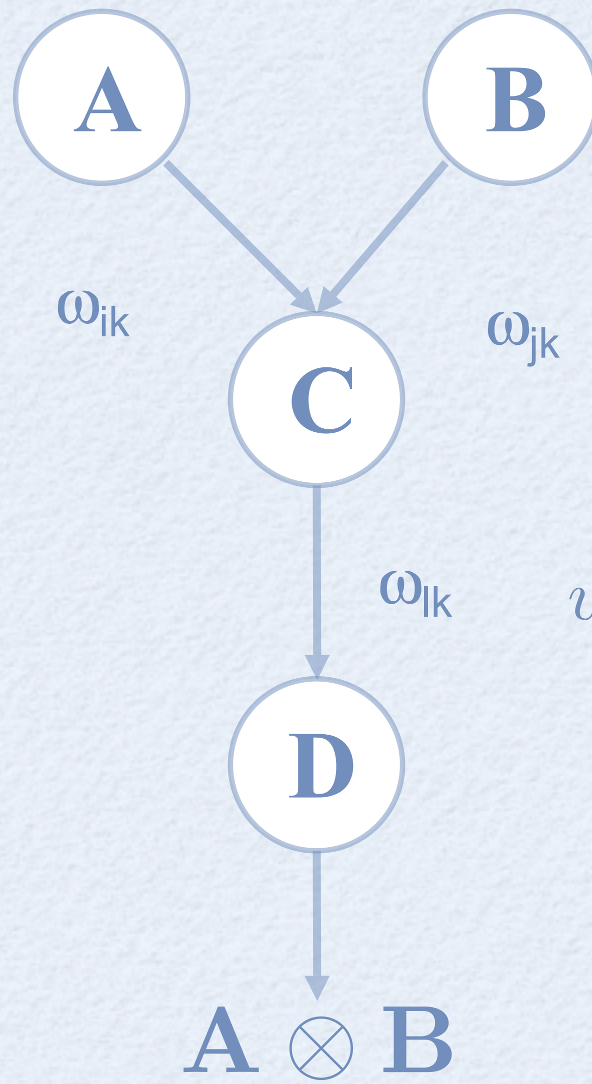
- Must use complex numbers, where

$$a * b = (a_1 + a_2 i) * (b_1 + b_2 i)$$

# Neural implementation

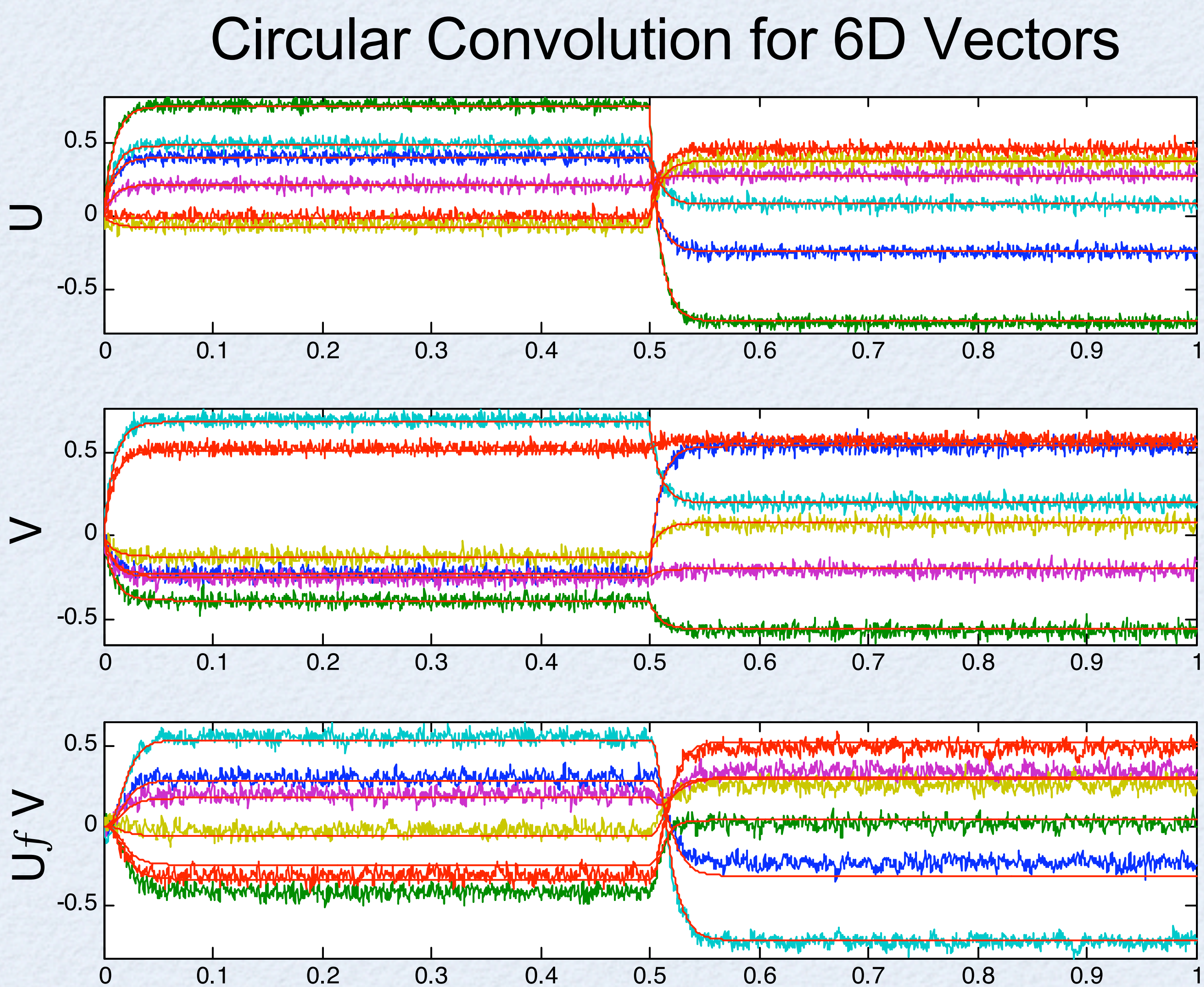
- Note first $\mathbf{A} \otimes \mathbf{B} = \mathbf{W}_{IFFT}(\mathbf{W}_{FFT}\mathbf{A}.\mathbf{W}_{FFT}\mathbf{B})$

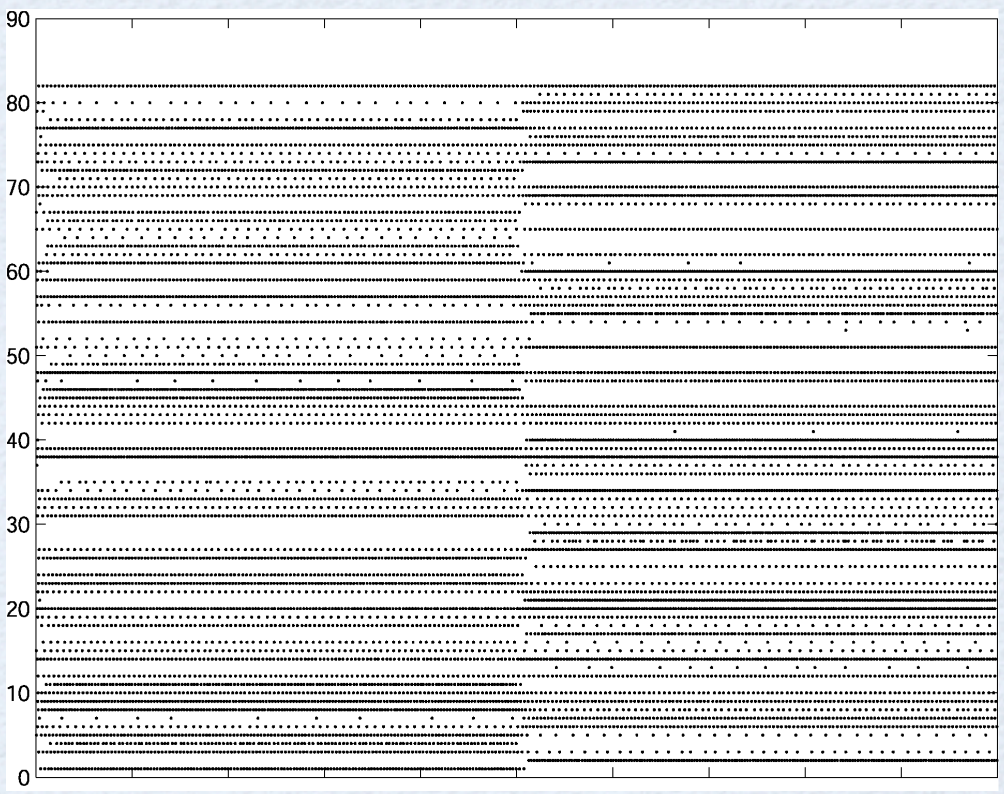
$$w_{ik} = \alpha_k \tilde{\phi}_{k_1 \ldots k_N} \mathbf{W}_{FFT} \phi_i^{\mathbf{A}}$$



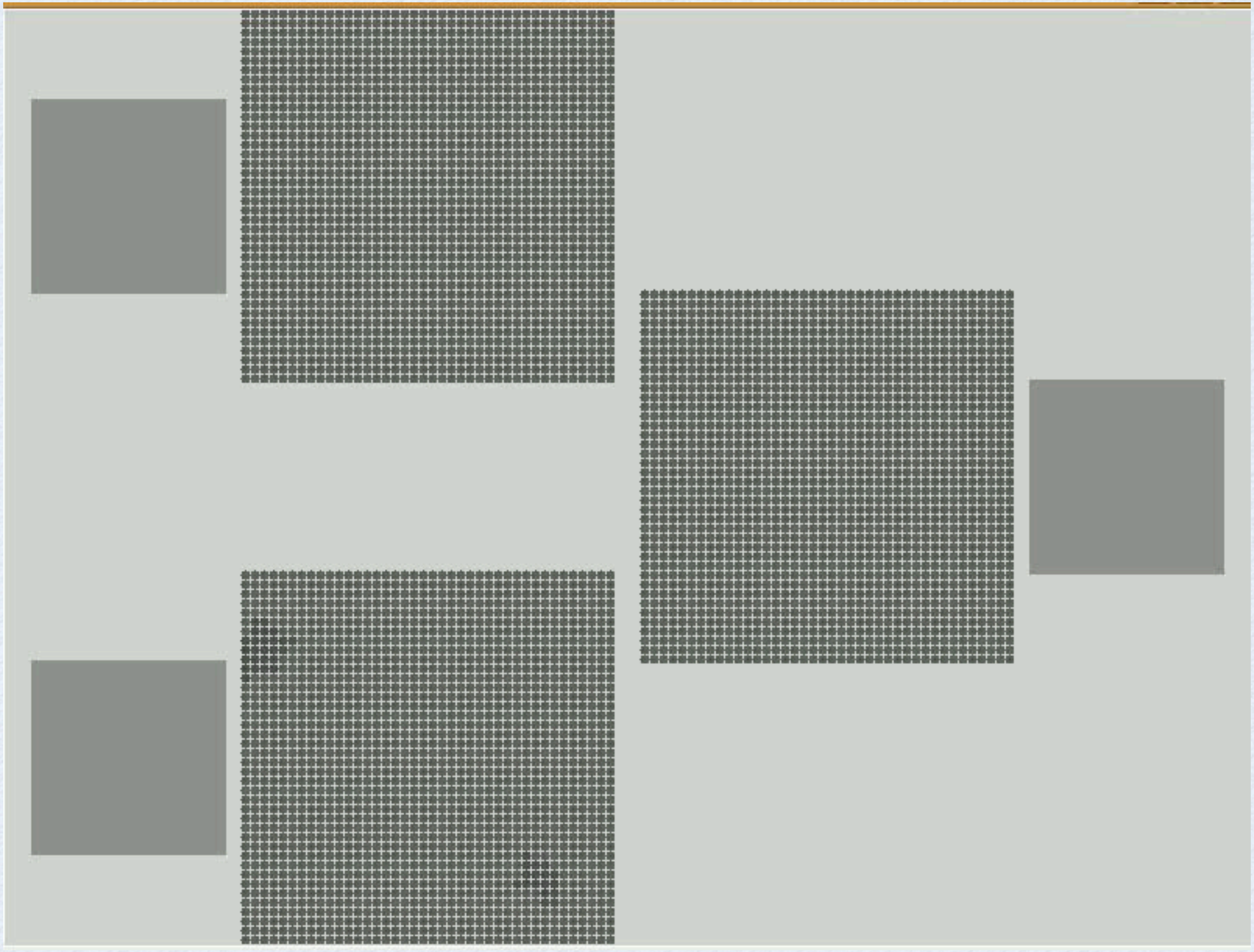

$$w_{lk} = \alpha_l \tilde{\phi}_l \mathbf{W}_{IFFT} \phi_k^{\mathbf{A}.\mathbf{B}}$$

# Circular convolution results



# Circular convolution



# Clean-up memory*

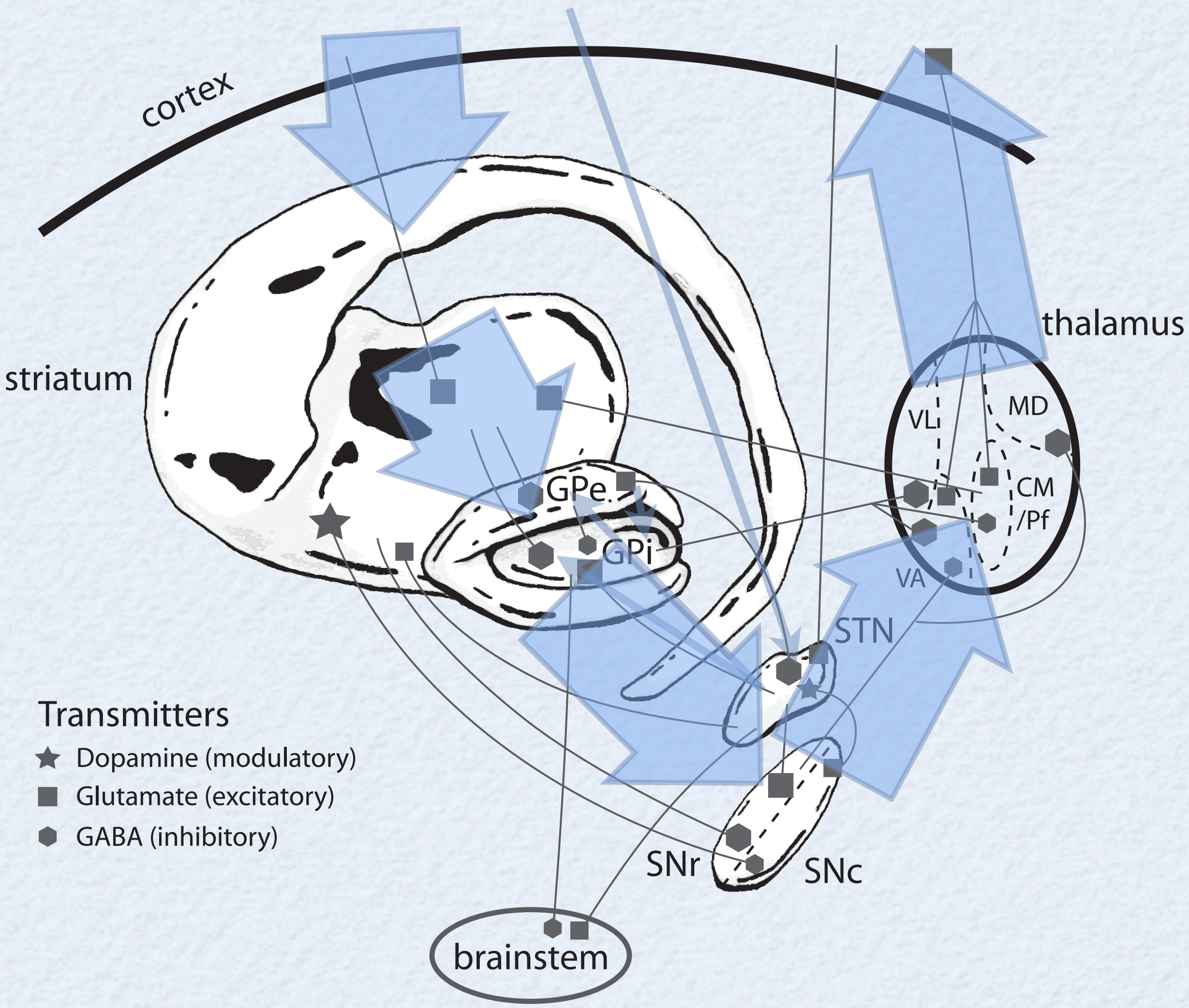
- To perform simple lexical processing, we need to ensure the result is a valid semantic pointer
- Because our chosen VSA is ‘reduced’, the output is typically not identical to a valid ‘answer,’ so we need to ‘clean up’ the results
- Elsewhere we have presented a fast spiking network solution to this (Stewart et al., 2010)
- Nengo includes an idealization of this to help build models

# SPA: Control

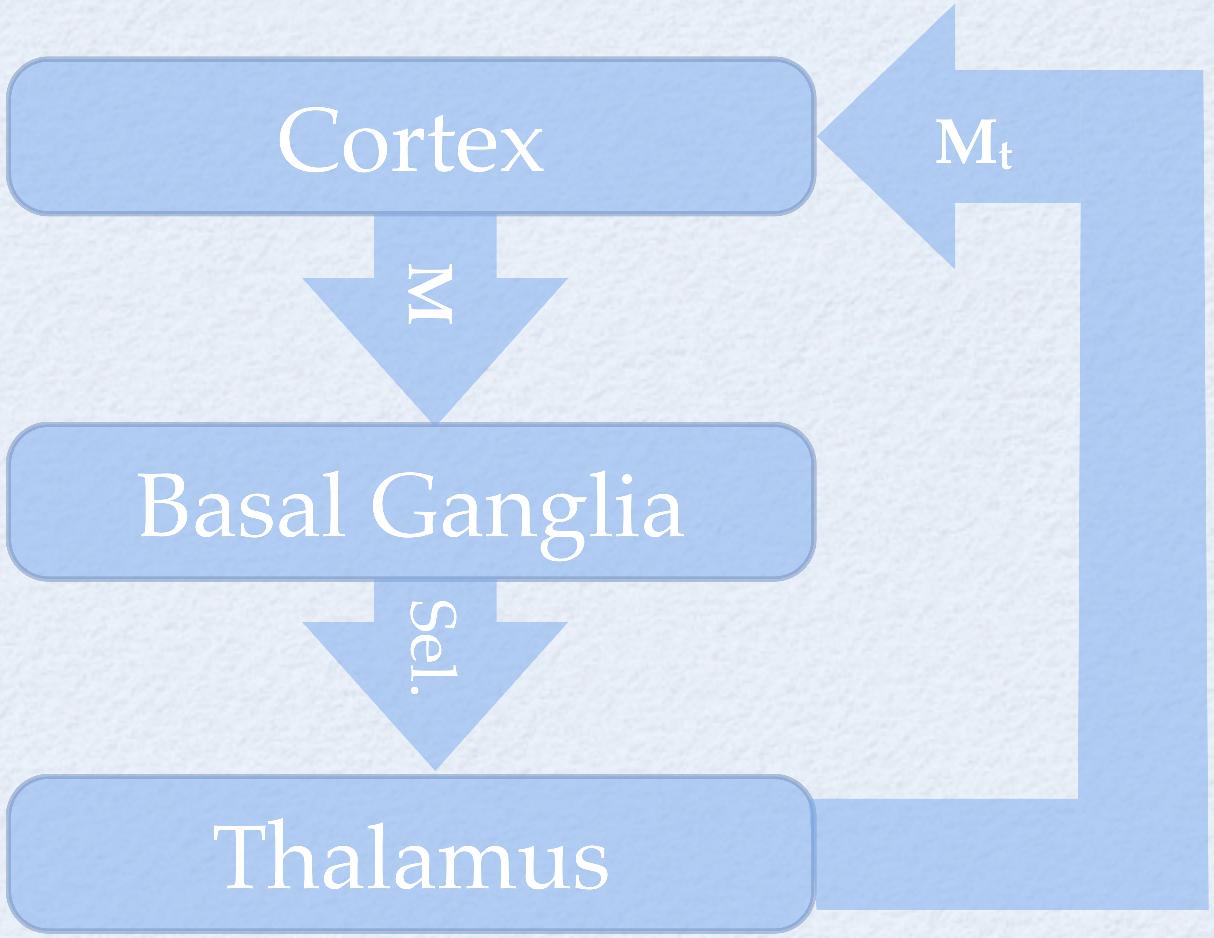
- Two main control issues in the brain:
  - Choosing the next best thing to do (action selection)
  - Applying the action to control the flow of information (routing)

# SPA: Action selection

- The basal ganglia has been implicated in action selection



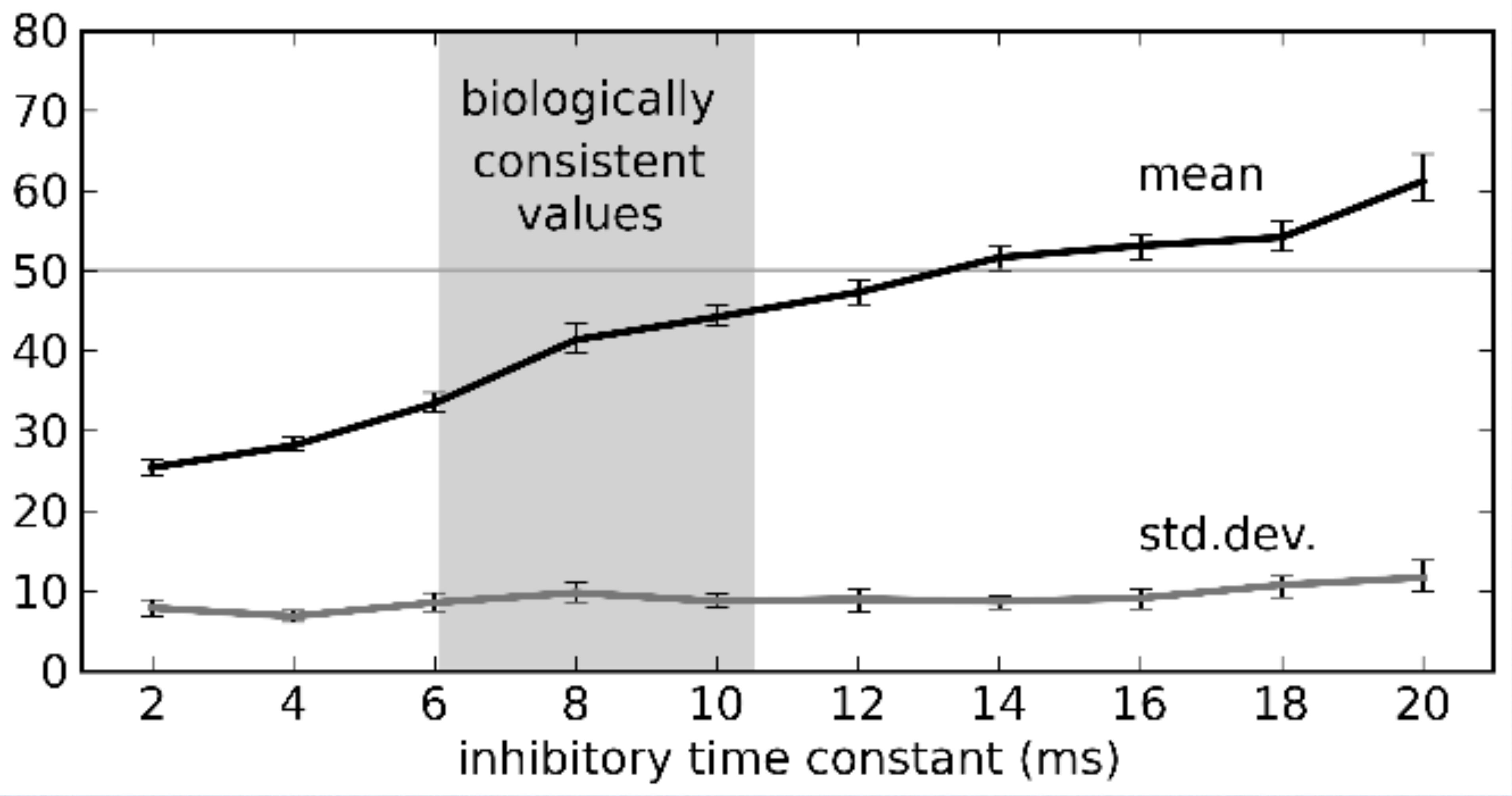
# SPA: Action selection




- **M** compares the cortical state with known SPs
- **$M_t$** maps selected action to cortical control states

# SPA: Action selection*

- Timing predictions based on GABA neurotransmitter time constant (simple actions)



# SPA: Control states

- Simple action selection isn't enough, we need to control the flow of information through the system
- A 'gating' operation is ubiquitous (e.g. attention, sequencing, prioritizing, etc.)
- The controlled integrator is a simple 1D example (when A is zero and 1)
- We can add content to the control signal with a convolution network

# SPA: Question answering

- Sentence: “There is a red circle and blue triangle”

$$\mathbf{S} = \mathbf{sentence} + \mathbf{red} \otimes \mathbf{circle} + \mathbf{blue} \otimes \mathbf{triangle}$$

- What is red?

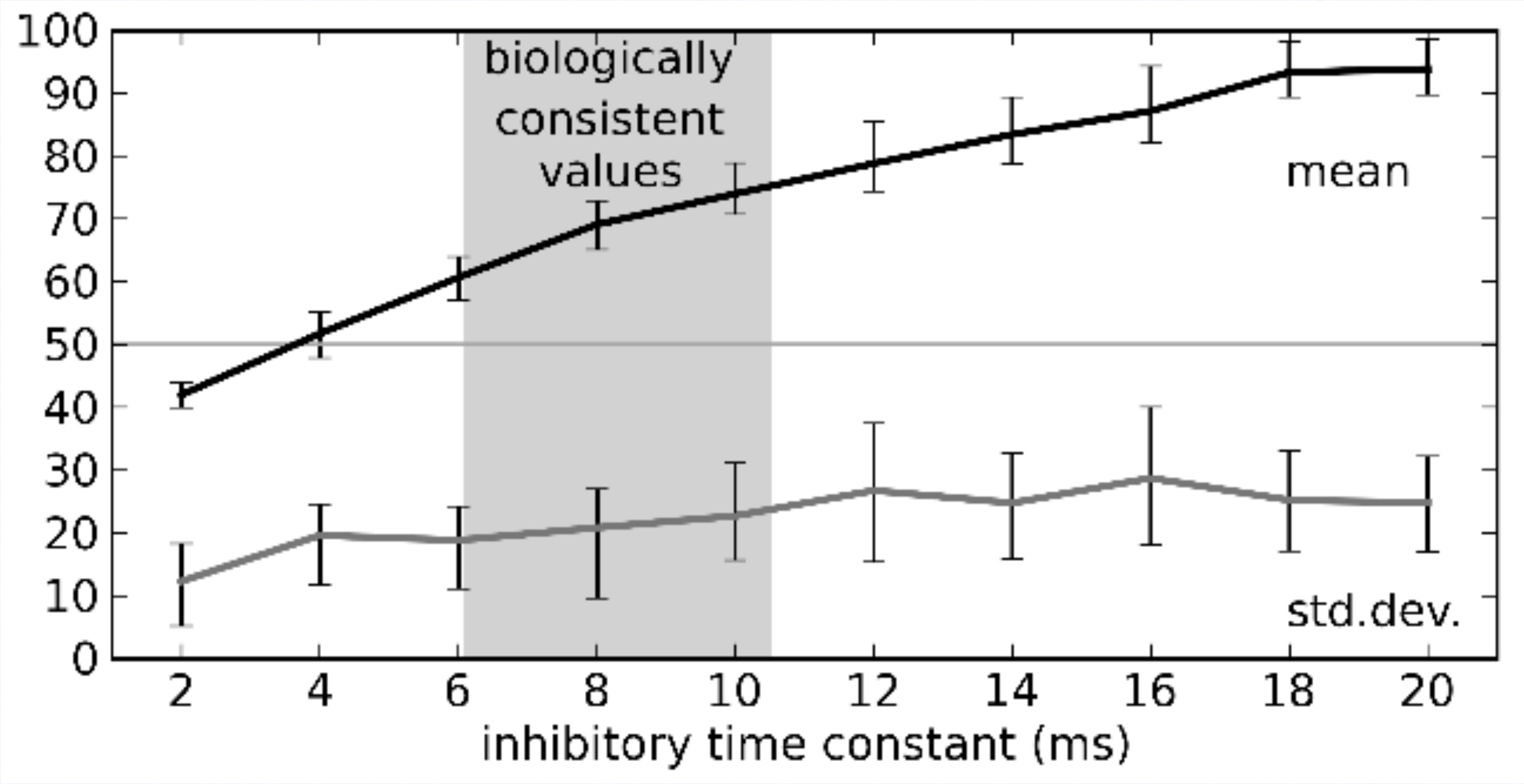
$$\mathbf{Ans} \approx \mathbf{red}' \otimes \mathbf{S}$$

- Transformation: make the red thing a square

$$\begin{aligned} \mathbf{convert} &= \mathbf{square} \otimes (\mathbf{red}' \otimes \mathbf{S})' \\ \mathbf{Ans} &\approx \mathbf{convert} \otimes \mathbf{S} \\ &\approx \mathbf{sentence} + \mathbf{red} \otimes \mathbf{square} + \mathbf{blue} \otimes \mathbf{triangle} \end{aligned}$$

# SPA: Control states*

- Timing predictions based on GABA neurotransmitter time constant (complex actions)



# Conclusion

- The SPA/NEF addresses several neurally realistic cognitive modelling challenges
  - High-dimensional processing, control, syntax, semantics, statistical inference, relation to single cell models, network and cellular dynamics, etc.
  - Scales very well (Stewart & Eliasmith, 2010)
- A nascent research approach that is flexible and unifying