Modelling the dynamics of decision-making

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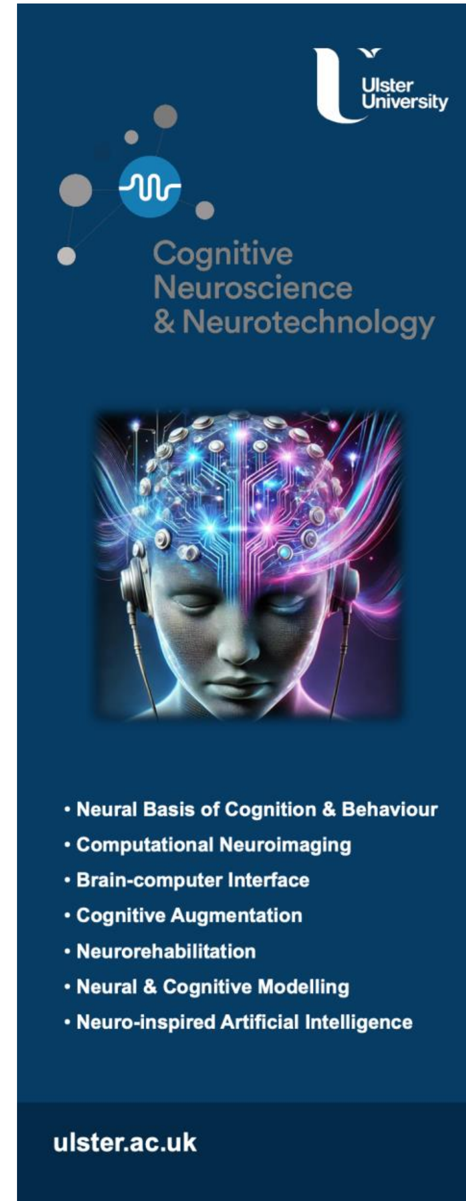

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27 Aug 2025

Perceptual decision making (under uncertainty)

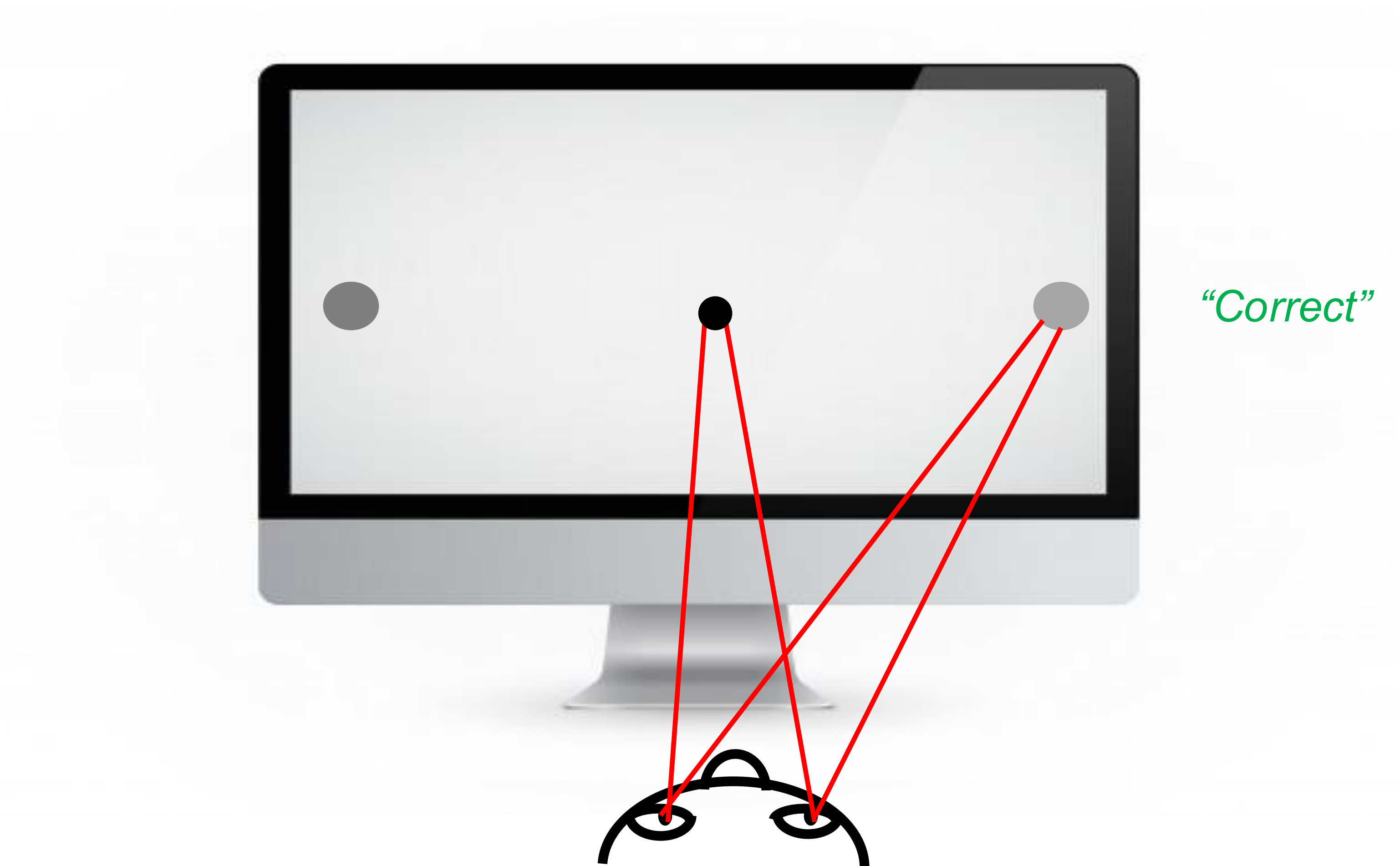
- *Integrate sensory information*
- *Select an action/choice among alternative competing options*
- *Respond quickly and/or accurately*

Sensory perception as a disturbance that passed along nerve fibres to the brain – a **mechanistic** machine. But **deterministic** reflex!

- René Descartes (1629) *Treatise of Man.*
- Sir Charles Sherrington (1906) *The Integrative Action of the Nervous System*

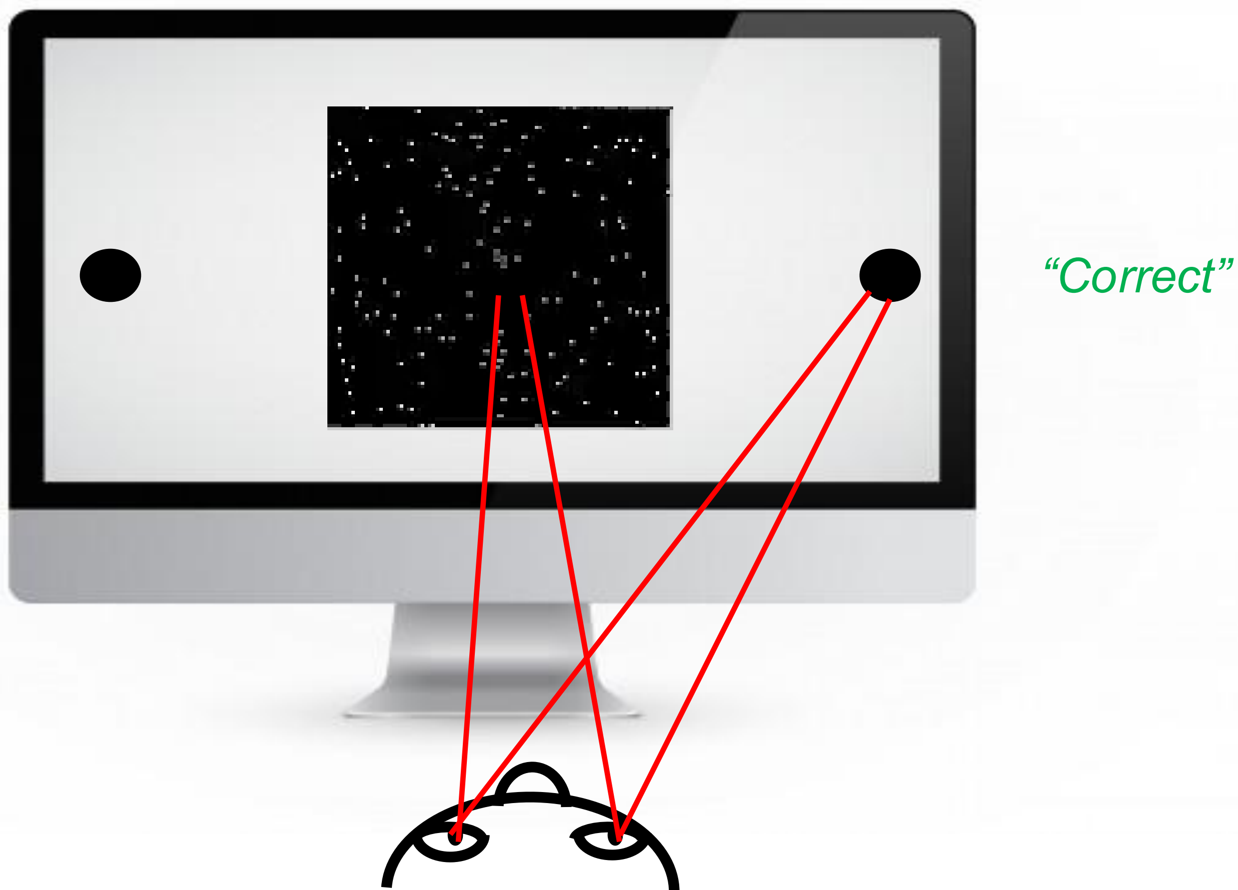
A colour/brightness discrimination task

Experimentalist controls difference in colours/brightness



Lab: A visual motion direction discrimination task

Experimentalist controls % of dots moving in the same direction (e.g. more rightward than leftward)



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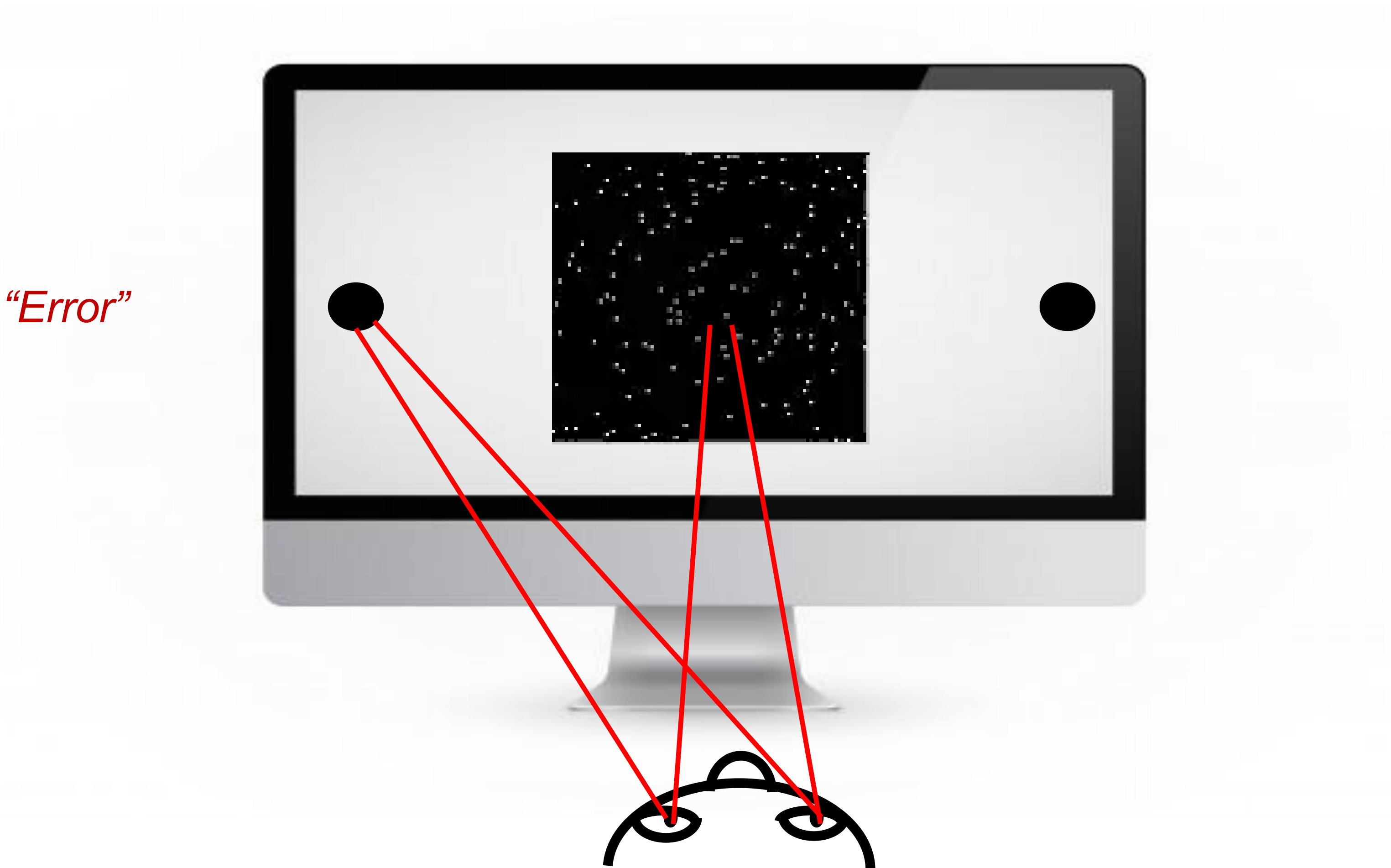
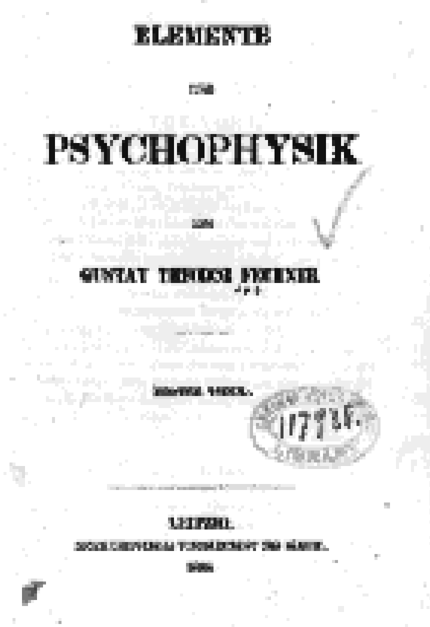


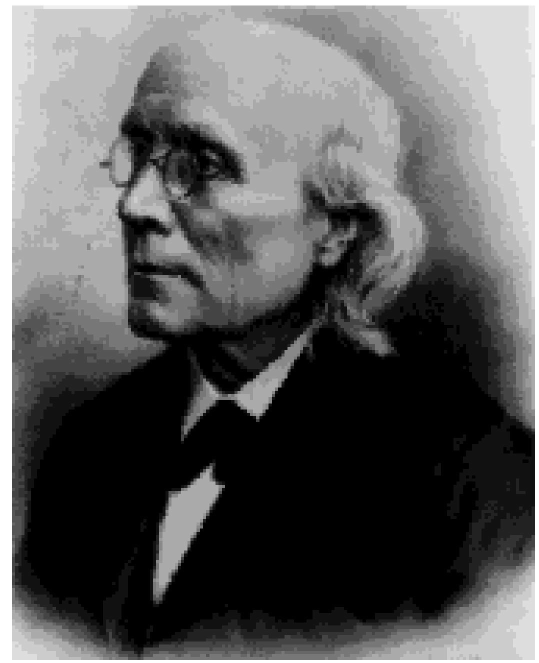
Psychophysics

… the analysis of perceptual processes by studying the effect on a subject's experience or behaviour of systematically varying the properties of a stimulus along one or more physical dimensions.


ELEMENTE

PSYCHOPHYSIK

Publication of Fechner's *Elemente der Psychophysik* (1860) is generally considered to mark the formal beginning of experimental psychology.



Gustav Theodor Fechner (1801-1887).

→ Mathematical/quantitative formulation of perception

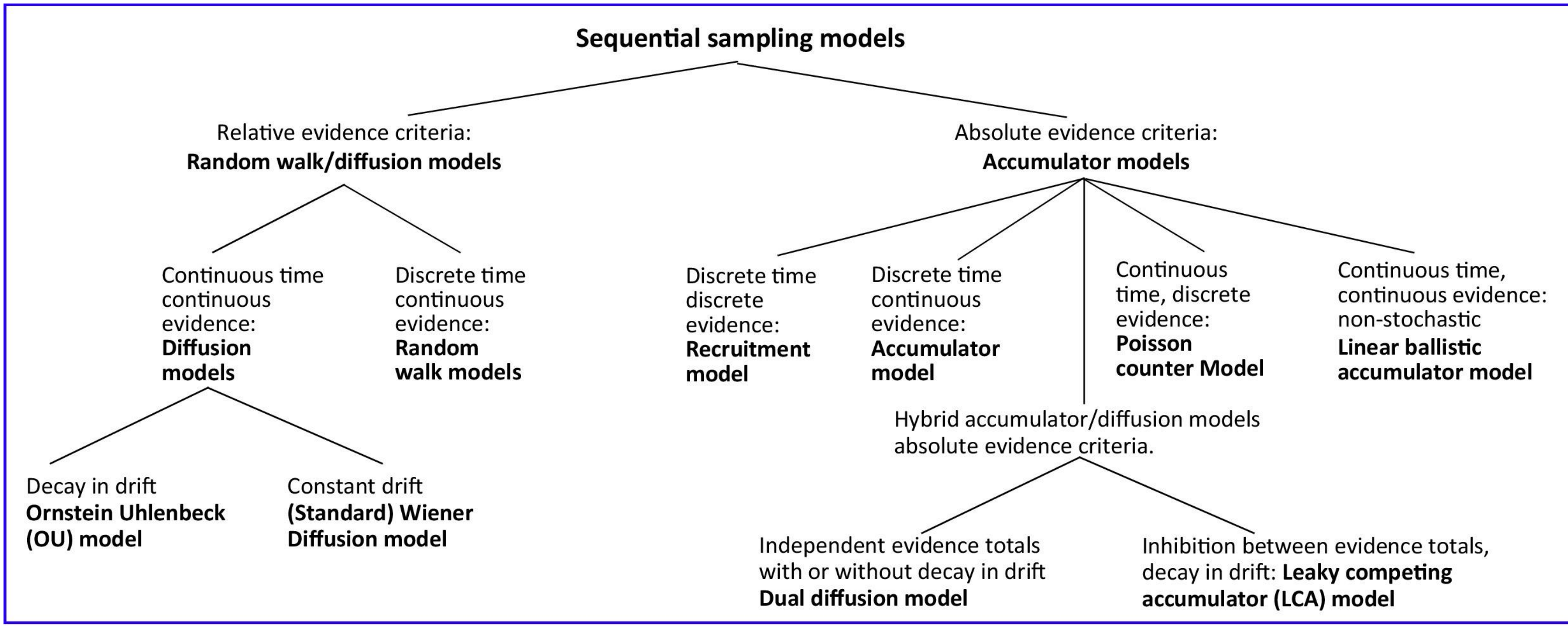
Golden age of Mathematical Psychology (1940's) …

Coinciding with the maturation of some mathematical (information-theoretic and probabilistic) frameworks to describe individual's choice behaviour and response times.

… & birth of Decision Sciences

- *Abraham Wald (1947) Sequential analysis.*
- *Jacob Wolfowitz (1949) Sequential decision.*
- *R. Duncan Luce (1959) Individual choice behavior: a theoretical analysis.*
- *Mervyn Stone (1960) Models for choice reaction time. Psychometrika.*
- *Donald R. J. Laming (1968) Information theory of choice-reaction times.*
- *Roger Ratcliff (1978) A theory of memory retrieval. Psychol. Rev.*
- *R. Duncan Luce (1986) Response times: their role in inferring elementary mental organization.*

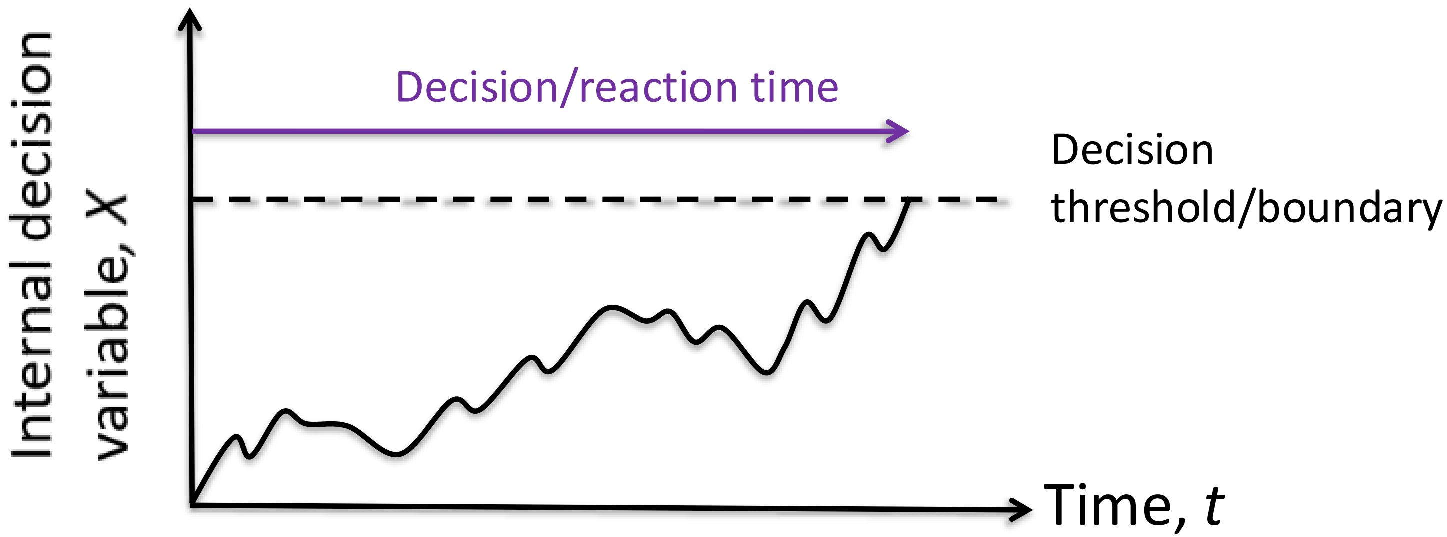
Models in Mathematical Psychology of decision-making



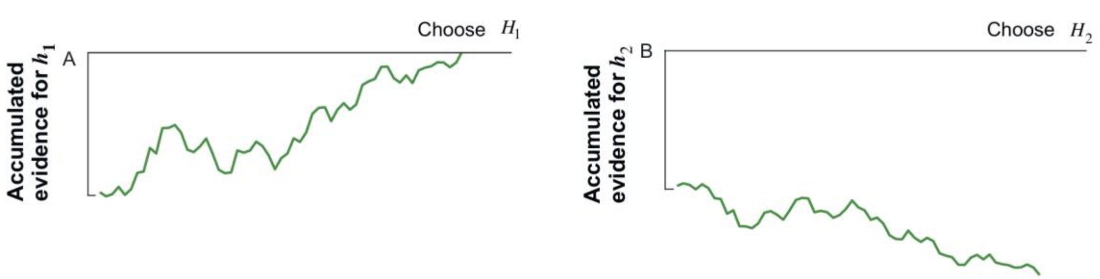
Ratcliff et al., Trends Cog. Sci. (2016)

Common feature in cognitive models: Evidence accumulation

Sequential sampling model framework

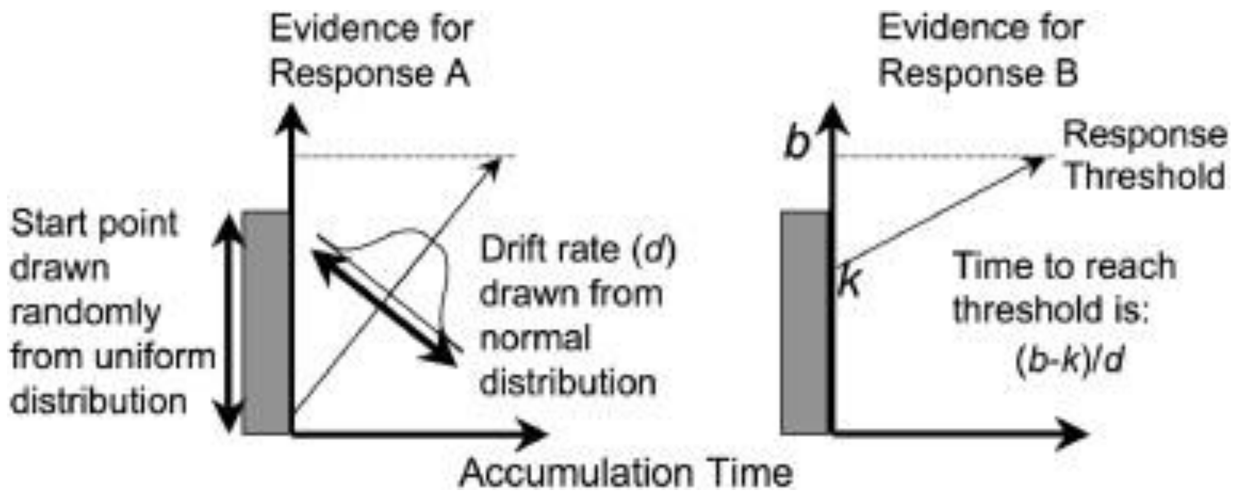


Race model



Common feature in cognitive models: Evidence accumulation

Linear Ballistic Accumulator (LBA) Model



Brown & Heathcote (2008)

https://itsdfish.github.io/SequentialSamplingModels.jl/dev/lba/

Elements of a decision: a probabilistic formalism

- Often, perceptual decisions are uncertain or comes with various forms of noise.
- Choice behaviour becomes non-deterministic and probabilistic.
- What is the (unknown) state of the world given noisy data from sensory systems?
- Select among competing hypotheses h_1, h_2, h_3, … h_n. WLOG, we focus on $n = 2$.

Definitions:

- Prior probability, $P(h_i)$: Probability before obtaining any evidence e.
- Likelihood, $P(e|h_i)$: Values that e can attain when h_i is true.
- Decision variable (DV): Accrual of all sources of priors, evidence, and values into a quantity interpreted by decision rule to produce a choice H_i (associated with hypothesis h_i).

Goal in decisions: achieve desired outcomes (correct) and avoid undesired ones (incorrect).

Signal detection theory (SDT)

SDT prescribes a process to **convert a single observation** of **noisy evidence** into **a categorical choice** (Green and Swets, 1966).

For binary decisions, the decision variable DV is related to the **ratio of the likelihoods** of h_1 and h_2 given e:

$$l_{12}(e) = \frac{P(e|h_1)}{P(e|h_2)}$$

Then impose a decision rule (criterion or threshold) to make a choice.

E.g. Choose h_1 if and only if $l_{12}(e) \geq \beta$, where β is some constant. Hence, variety of goals can be implemented.

Sequential analysis (SA) framework: extension to SDT

Accommodates multiple pieces of evidence observed over time $(t_1, \ldots t_n)$**.**

A simple DV is the logarithm of the likelihood, i.e. logLR, from multiple, independent pieces of evidences $e_1, e_2, \ldots, e_n$

$$logLR_{12} = log\frac{P(e_1,\ \ e_2, \ldots, e_n|h_1)}{P(e_1,\ \ e_2, \ldots, e_n|h_2)}$$
$$= \sum_{i=1}^{n} log\frac{P(e_i|h_1)}{P(e_i|h_2)}$$

A simple stopping rule: Update DV with new evidences till reaching some upper or lower bound.

Sequential analysis framework

$$e_0 \rightarrow f_0(e_0) \Rightarrow \begin{smallmatrix}\textit{Stop}\\ \textit{or}\end{smallmatrix}$$

$$\swarrow$$

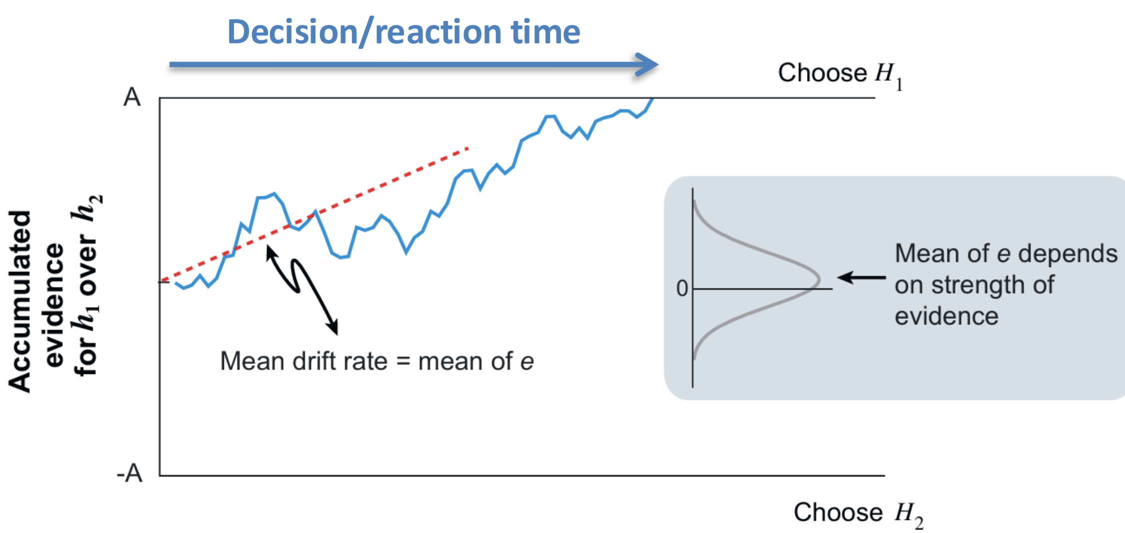
$$e_1 \rightarrow f_1(e_0, e_1) \Rightarrow \begin{smallmatrix}\textit{Stop}\\ \textit{or}\end{smallmatrix}$$

$$\swarrow$$

$$e_2 \rightarrow f_1(e_0, e_1, e_2) \Rightarrow \begin{smallmatrix}\textit{Stop}\\ \textit{or}\end{smallmatrix}$$

$$\vdots$$

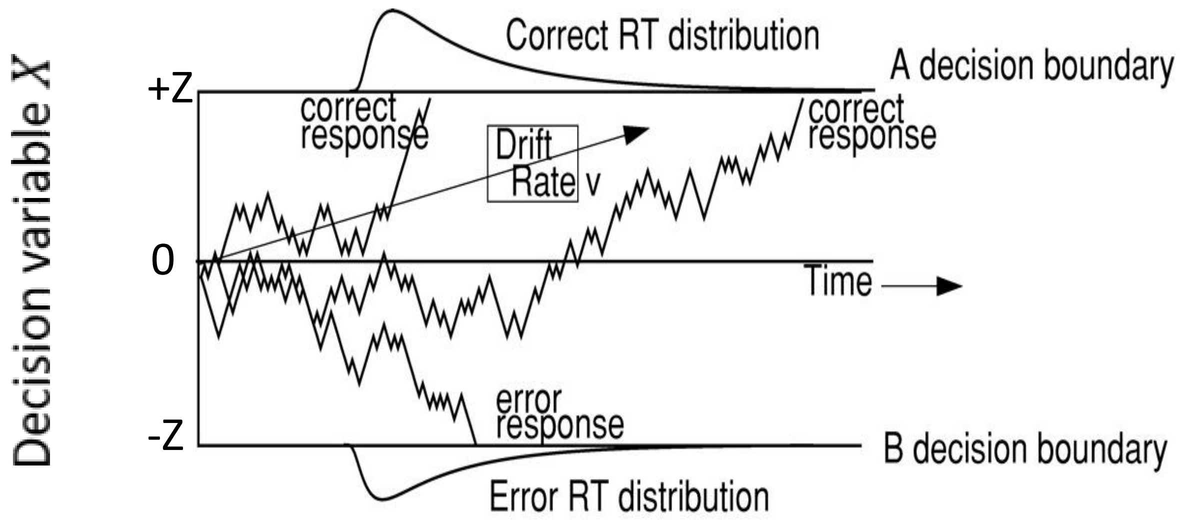
$$e_n \rightarrow f_1(e_0, e_1, \ldots, e_n) \Rightarrow \ldots$$



Gold & Shadlen (2007)

This process comprise the **Sequential Probability Ratio Test (SPRT) – most efficient test by achieving *a desired error rate (accuracy) with smallest number of samples*** (Wald & Wolfowitz, 1947) – speed-accuracy trade-off. Marian Adam Rejewski, Alan Turing et al. used this approach to break the German enigma cipher in WWII.

A cognitive model: Drift-diffusion model (DDM)



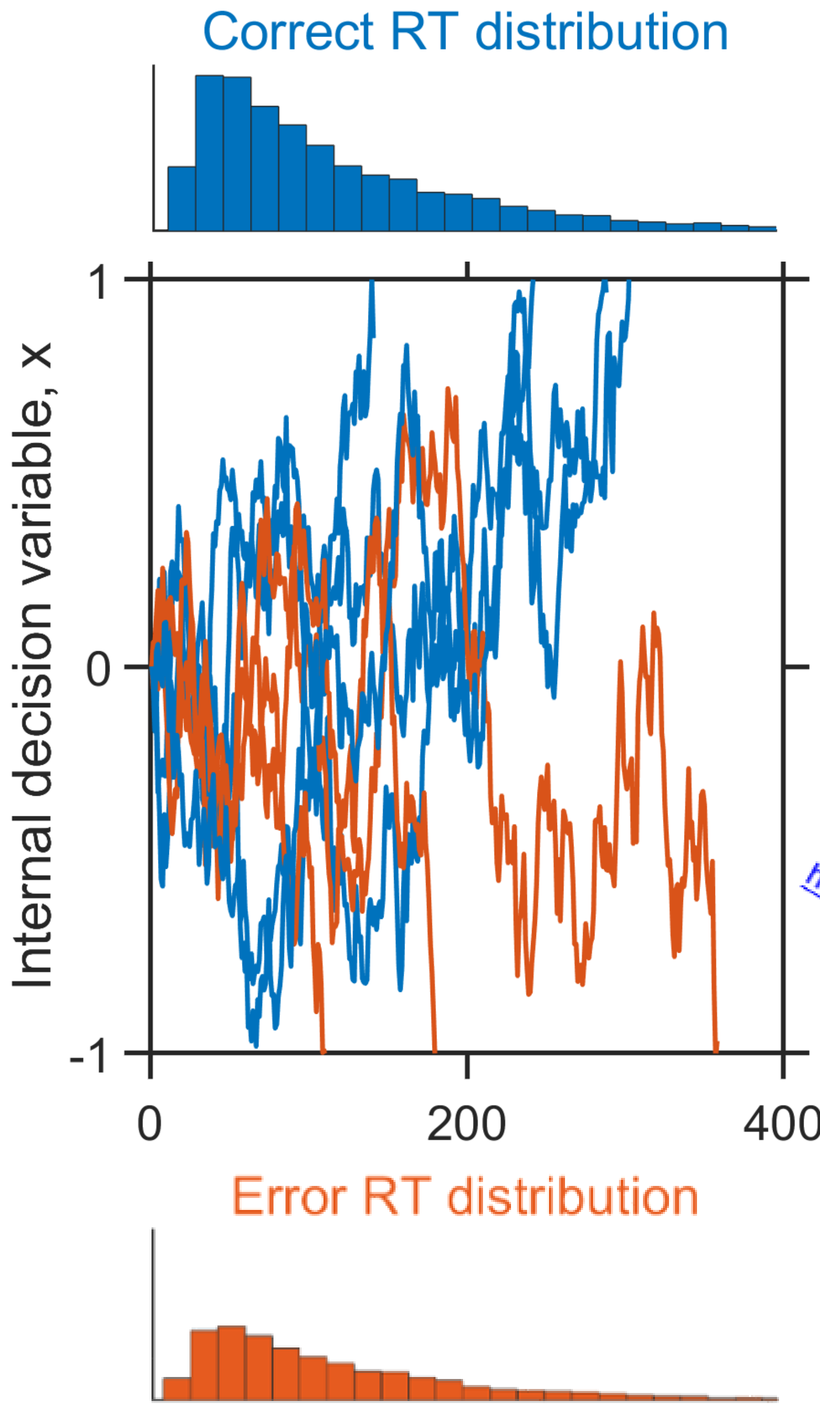
1D stochastic dynamics for 2-choice tasks

$$X = \int dX = \int v\,dt + \sigma\,dW$$

$$= \text{signal difference} + \text{noise}$$

Computer simulations over several trials

With upward drift rate (signal)



Reaction time (RT)

Accuracy = (No. corrects) / (Total no. choices)

https://www.ejwagenmakers.com/EZ.html

https://github.com/murraylab/PyDDM

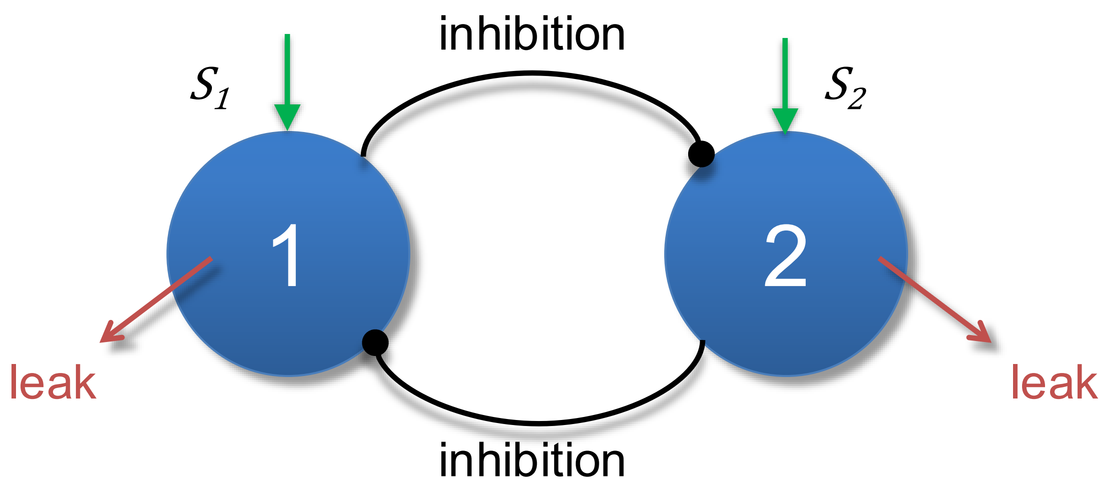
A simple neural network (connectionist) model

Leaky Competing Accumulator (LCA) model

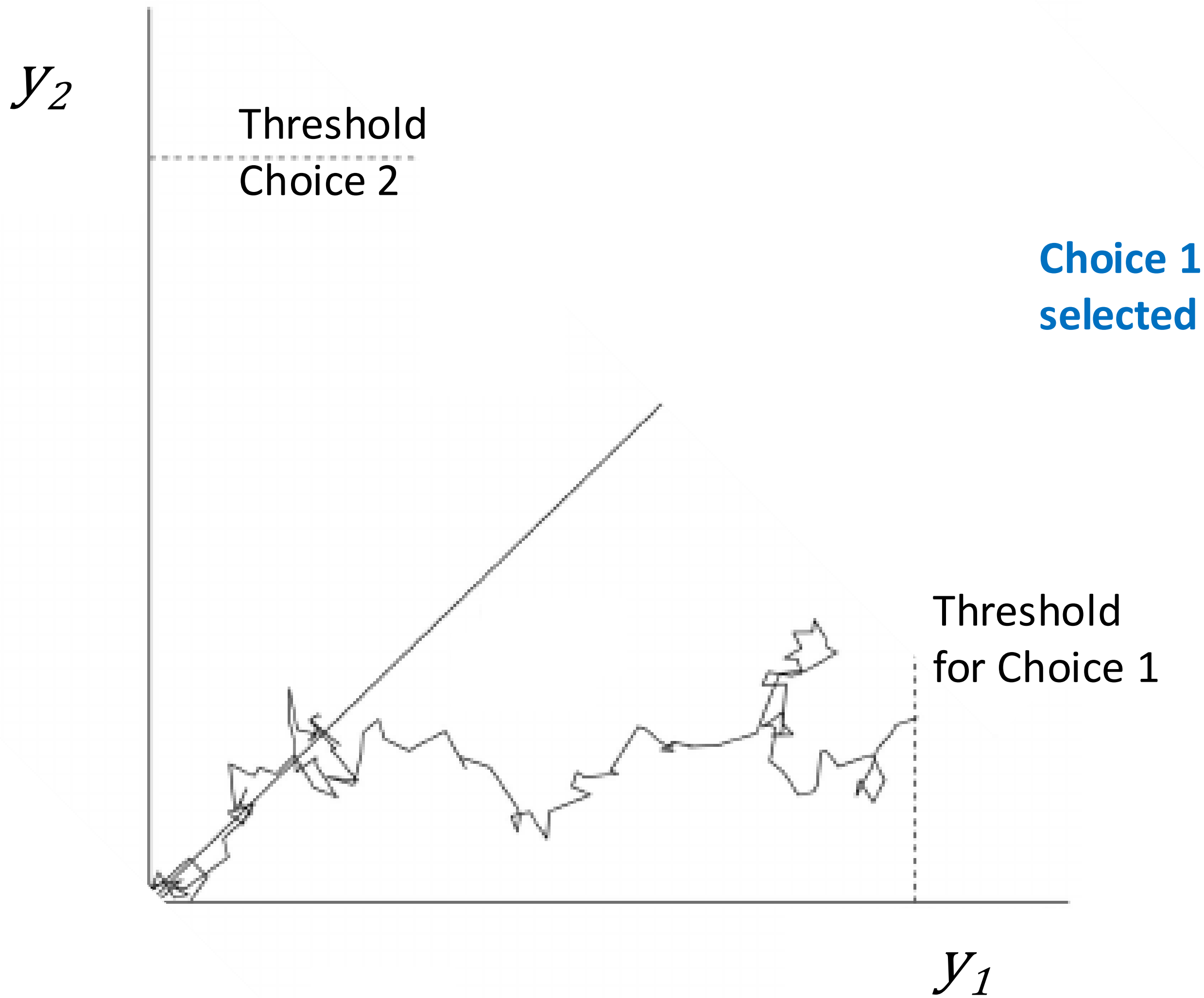
The decision process as the integration of evidence by competing accumulators – *winner-take-all* behaviour to facilitate process, or there will be conflict and indecisiveness.

$$
\begin{aligned}
dy_1 &= [-\gamma\, y_1 + f(-\beta\, y_2) + s_1]\, dt + \sqrt{D}\, dW_1 \\
dy_2 &= \underbrace{[-\gamma\, y_2}_{\text{leak}} + f\underbrace{(-\beta\, y_1)}_{\text{inhibn}} \underbrace{+\, s_2]}_{\text{stim}}\, dt + \underbrace{\sqrt{D}\, dW_2}_{\text{noise}}
\end{aligned}
$$

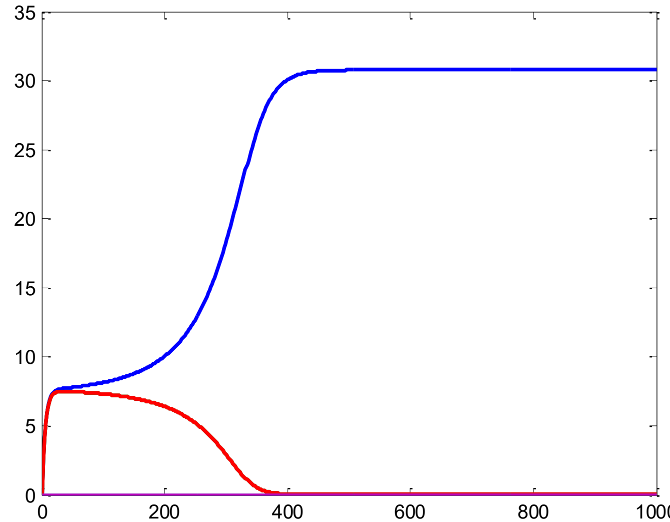
Usher & McClelland (1995, 2001)



Sample simulated trajectory of nonlinear LCA model in activity (phase/state) space

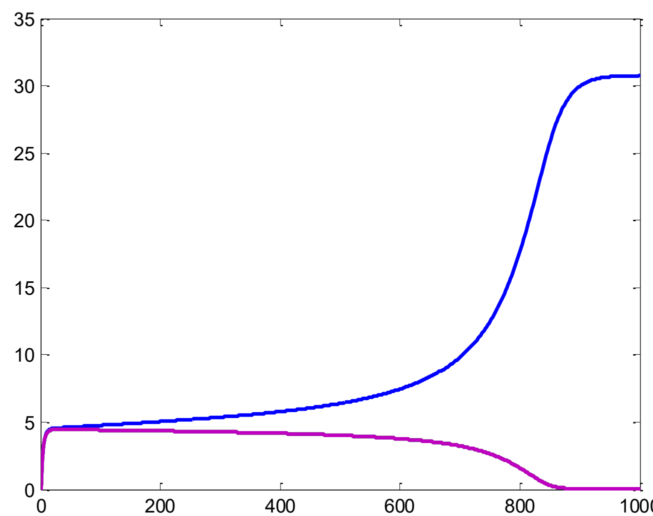


A multi-population winner-take-all network model



With 2 choices (short latency or response time)

Note: The other neural population follows the same dynamics as purple



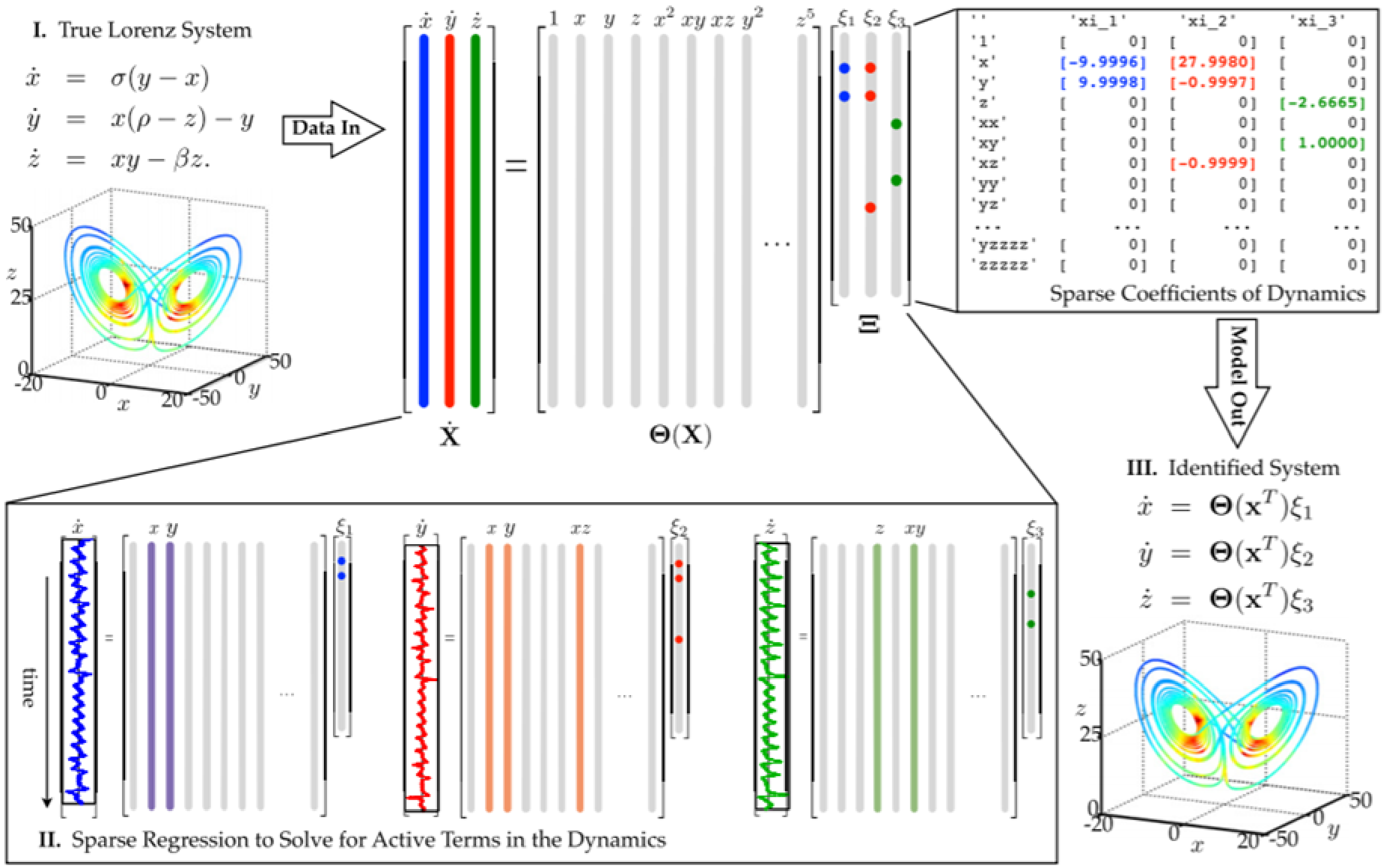
With 5 choices (long latency or response time)

Note: The other 3 neural populations follow the same dynamics as purple

Hick's or Hick–Hyman law*: Describes the time it takes for a person to make a decision as a result of the possible choices: increasing the number of choices will increase the decision time logarithmically*

All model parameter values remain the same in both cases.

Using machine learning (symbolic regression) to uncover dynamical equations of low-dimensional state trajectory

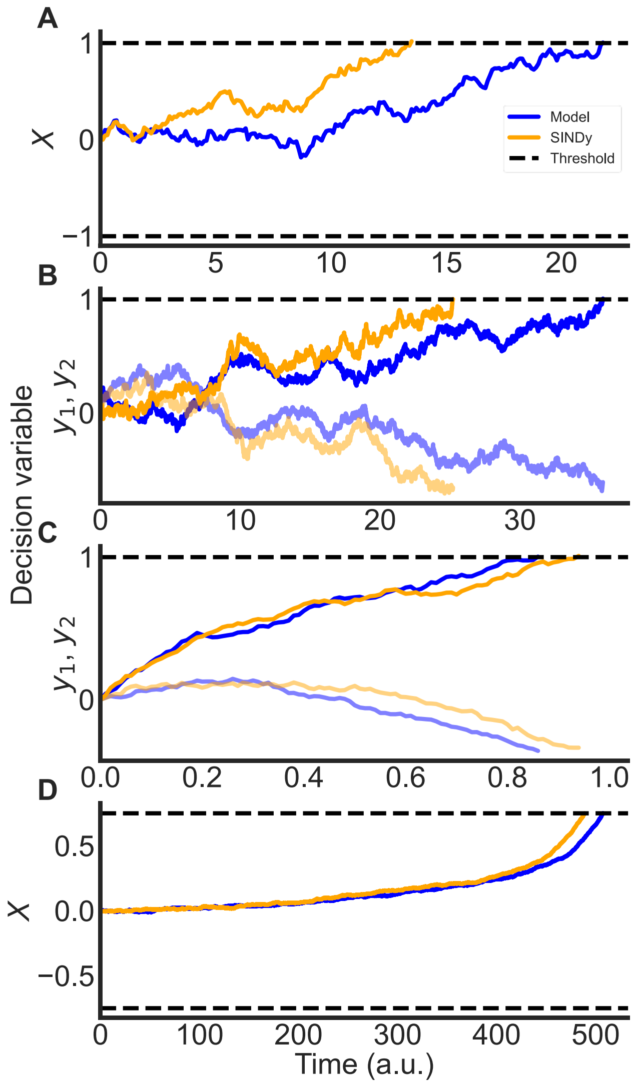


Sparse identification of nonlinear dynamics (SINDy) to rediscover governing equations

Brunton, Proctor & Kutz, PNAS (2016)

Using machine learning (symbolic regression) to uncover dynamical equations of low-dimensional neural trajectory

Single-trial examples



Decision models

Drift-diffusion model (DDM)

Leaky competing accumulator (LCA) model approx. DDM with fine-tuning (LCA-DDM)

LCA model with saddle fixed point

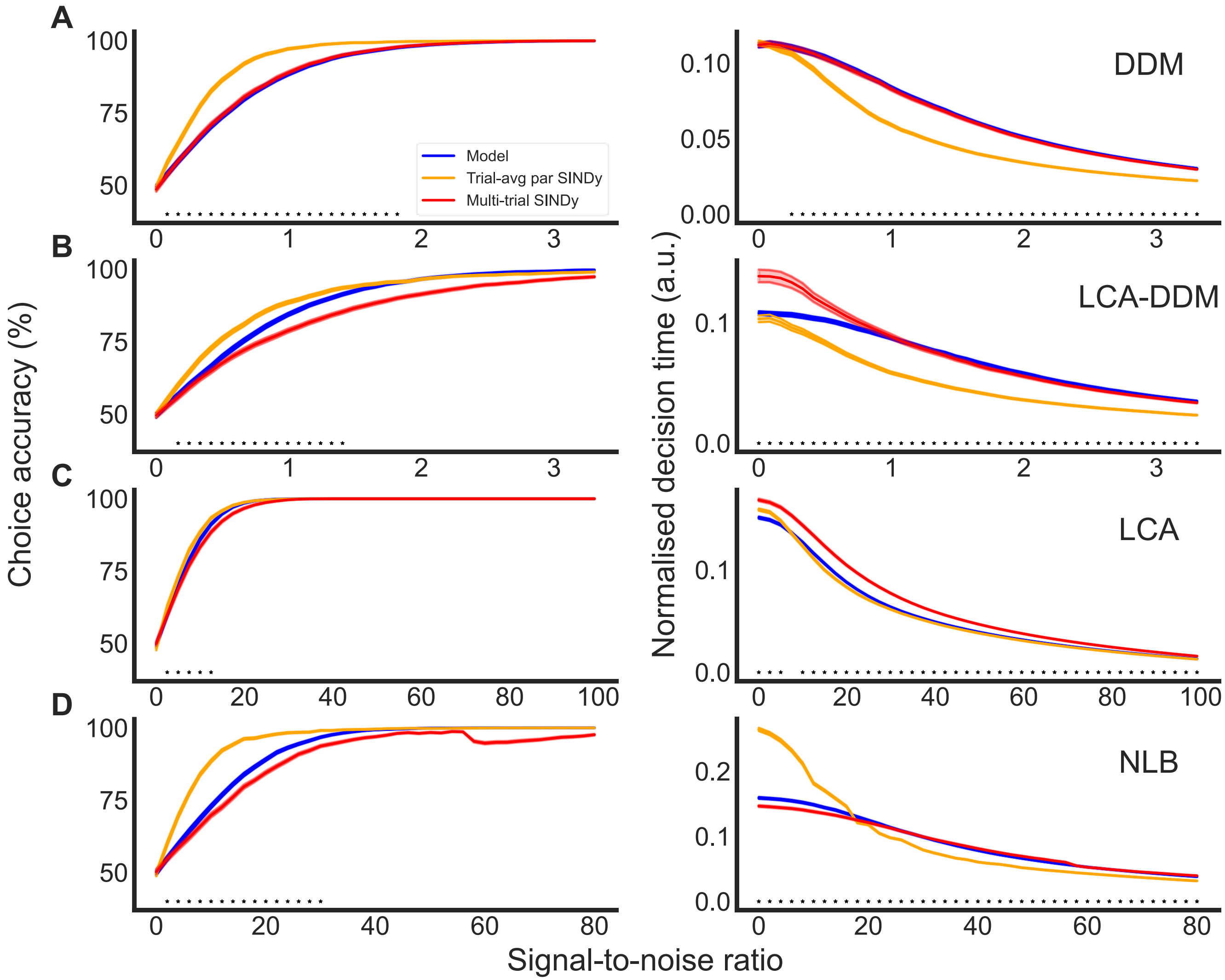
Nonlinear bistable model (NLB)

Brendan Lenfesty

Lenfesty, Bhattacharyya & Wong-Lin, (2025)

Using machine learning (symbolic regression) to uncover dynamical equations of low-dimensional neural trajectory

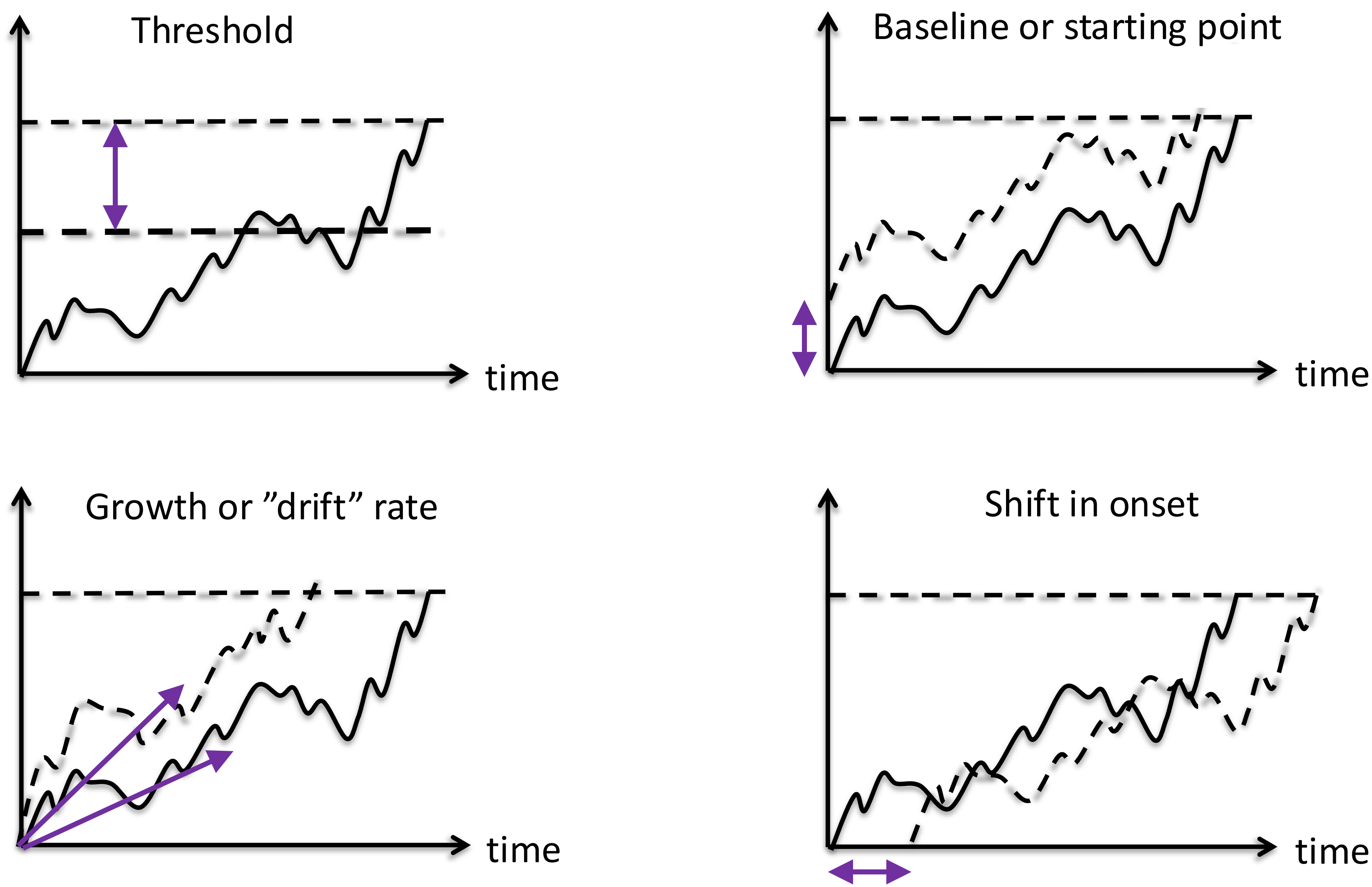
Trial-averaged approaches



Brendan Lenfesty

Lenfesty, Bhattacharyya & Wong-Lin, (2025)

“Biases” or “controls” in decision making

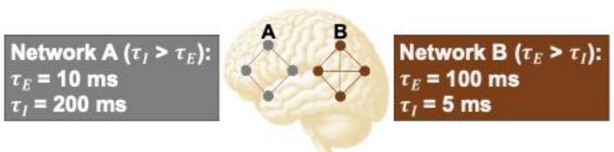


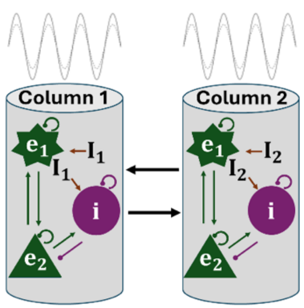
Speed-accuracy tradeoff (SAT)

“Biases” or “controls” in decision making

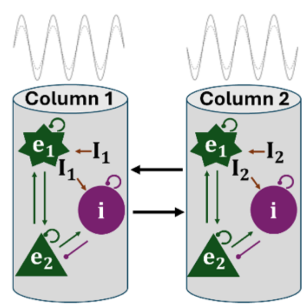
Neural oscillations

Neural oscillation as a selective modulatory mechanism on decision confidence, speed and accuracy → violate SAT

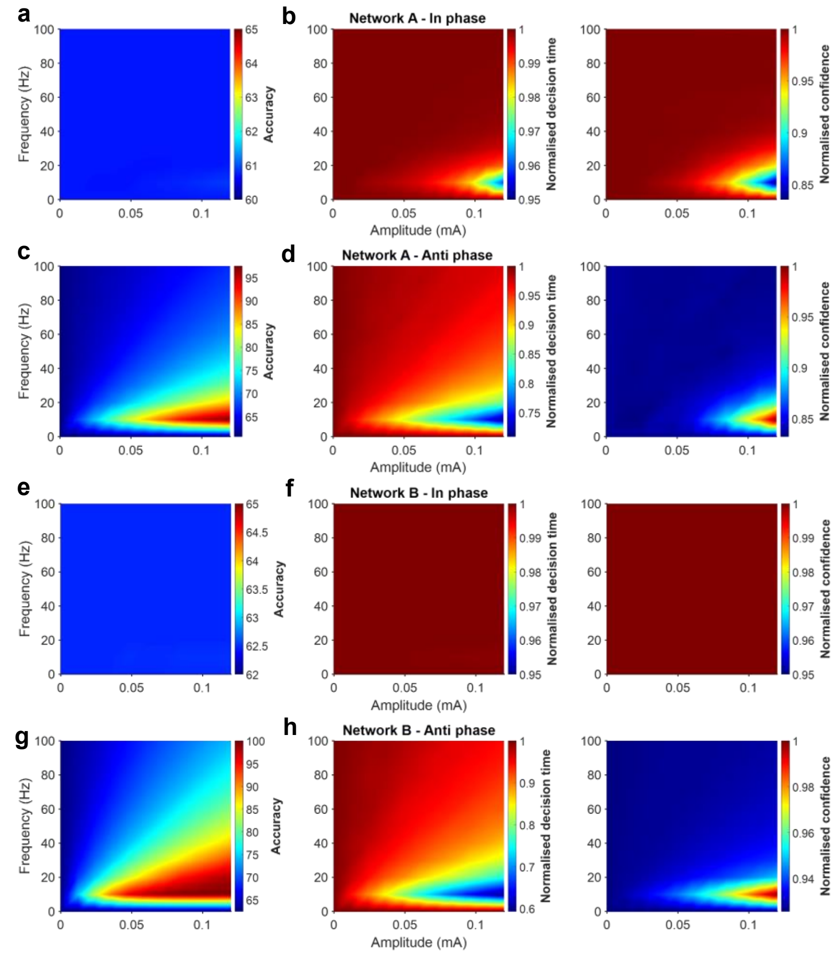




In-phase modulation



Anti-phase modulation



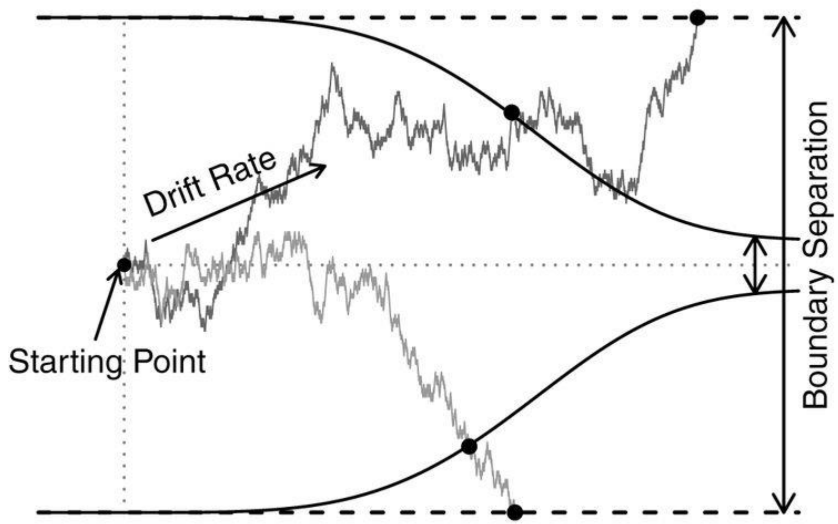
Amin Azimi

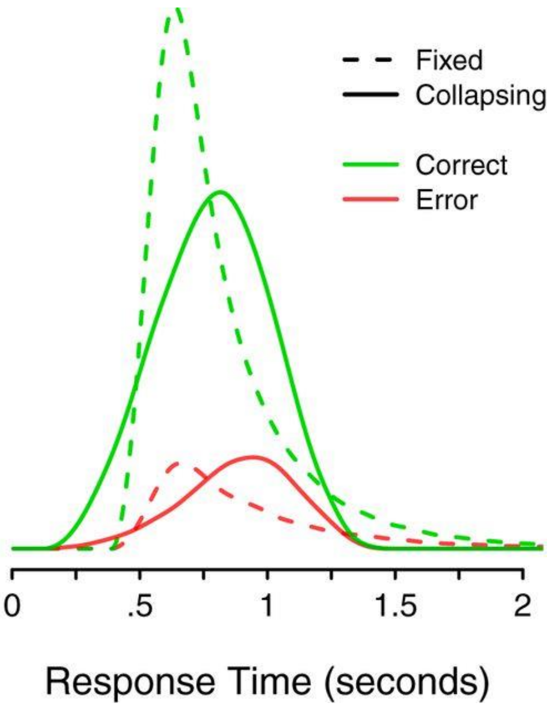
Azimi & Wong-Lin (2025; Submitted)

“Biases” or “controls” in decision making

*Threshold, drift rate, noise can be **time-dependent**, e.g. urgency*

Collapsing bound over time can lead to faster correct than error decisions in DDM



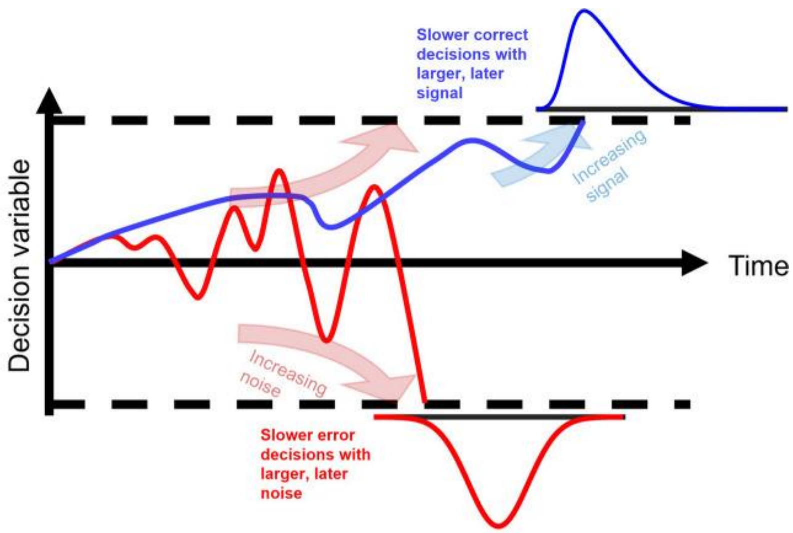


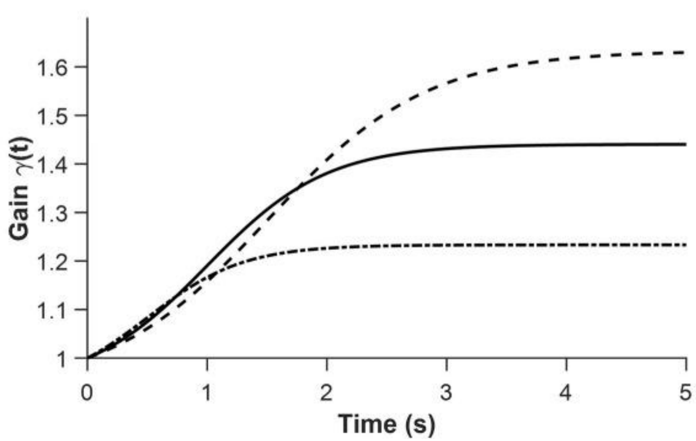
Churchland et al. (2008); Hawkins et al. (2015)

“Biases” or “controls” in decision making

*Threshold, drift rate, noise can be **time-dependent**, e.g. urgency*

Time-variant gain in noise but not signal leads to slower error decisions in DDM



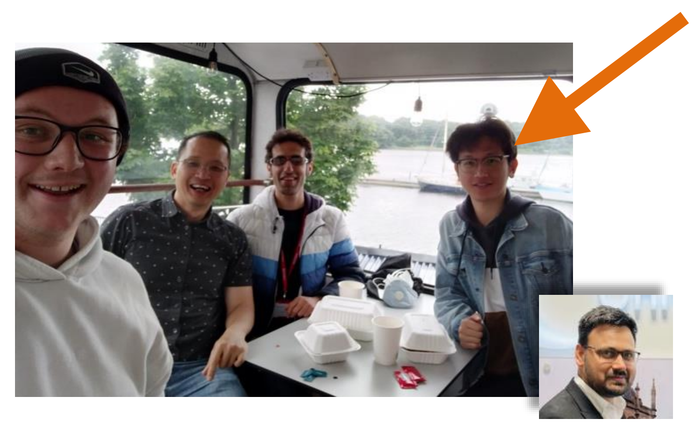


Type A

$$dX = v\,\gamma(t)\,dt + \sigma\,dW$$

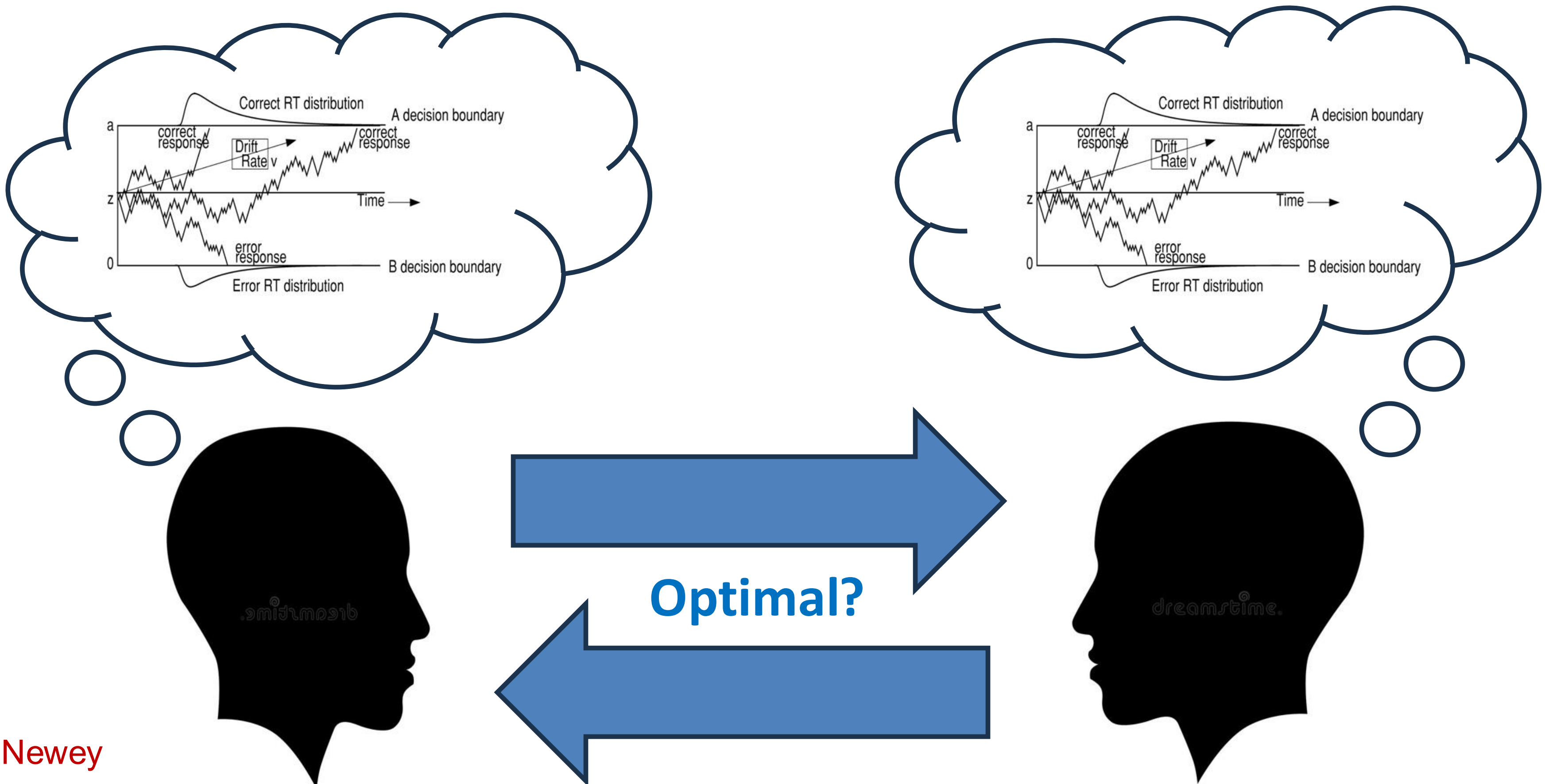
Type B

$$dX = v\,dt + \sigma\,\gamma(t)\,dW$$



Tan, Faraz, Lenfesty, Asadpout & Wong-Lin (2023); Asadpour, Tan, Lenfesty & Wong-Lin (2024)

Coupling DDMs (“digital brains”) for group decision-making



Toby Newey

Srivastava & Leonard (2015)
Newey et al. (2025)

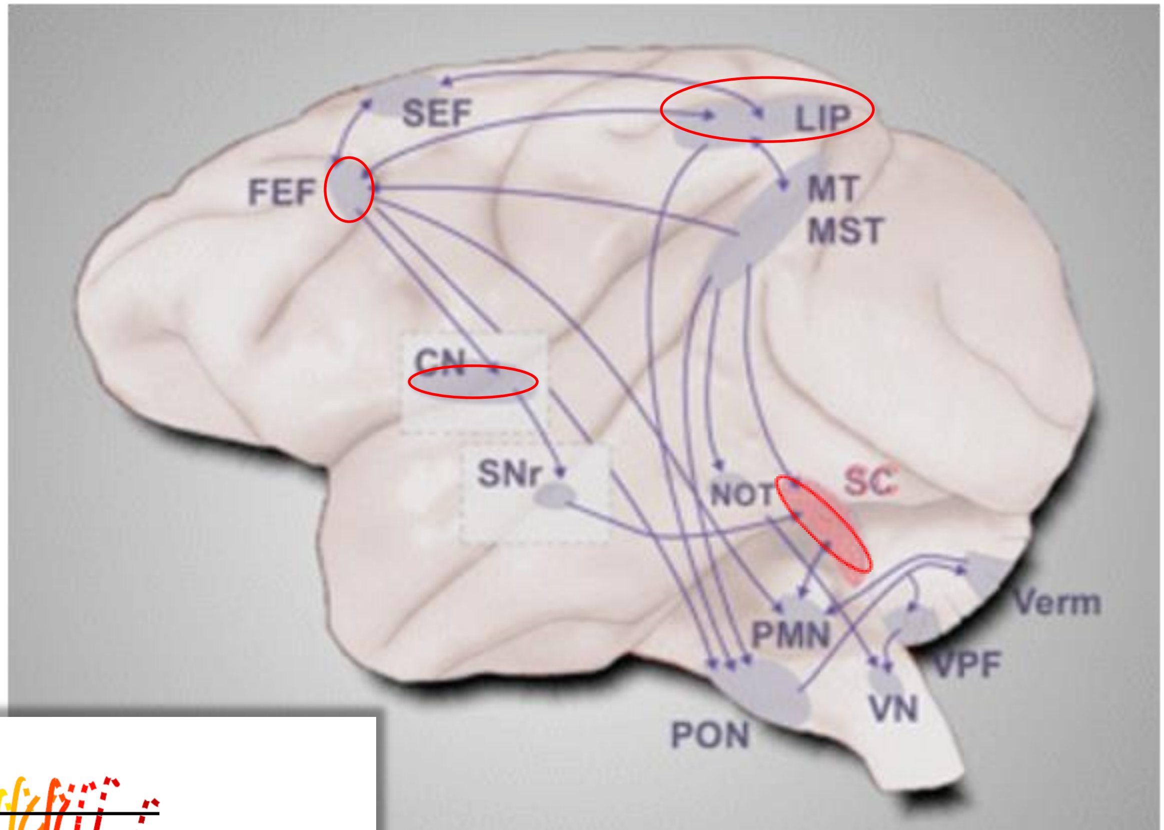
Is there evidence in brain physiology of such processes in perceptual decision-making?

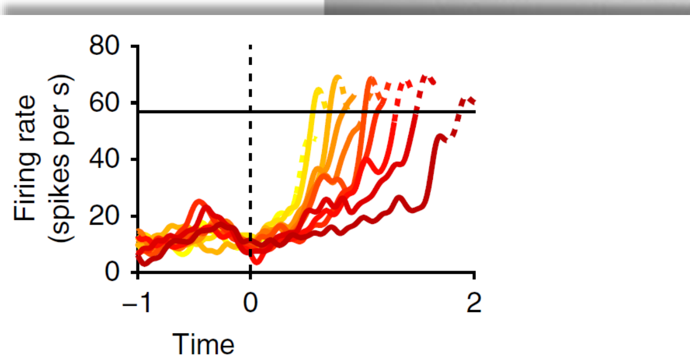
Neural correlates of perceptual decision making

Psychological process	Sensory processing Direction of motion	→	Decision making Right or left	→	Motor execution Initiate eye movement to report a choice
Neural correlate e.g. visual perceptual decisions	Sensory cortex MT, MST, etc regions	→	?	→	Movement related SC, SMA, etc regions

Brain circuitry controlling (saccadic) eye movements

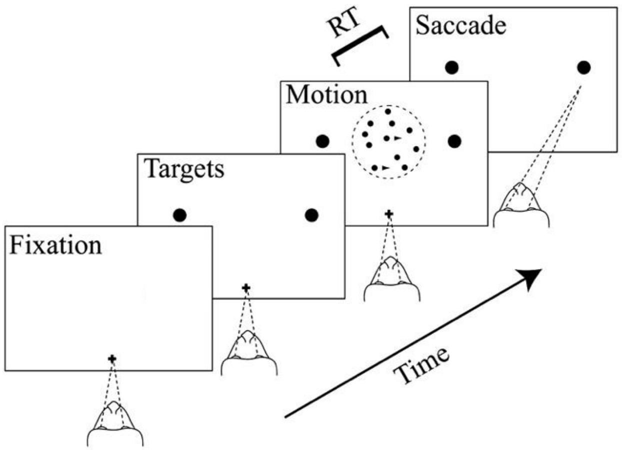
The search for “neural integrators” in the brain

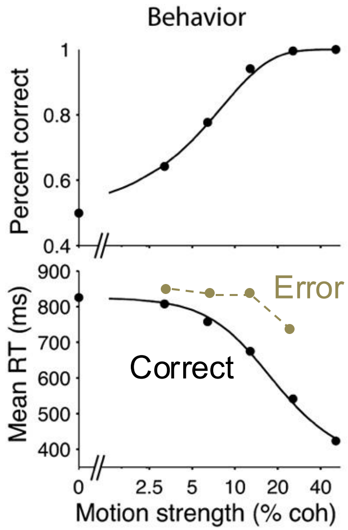


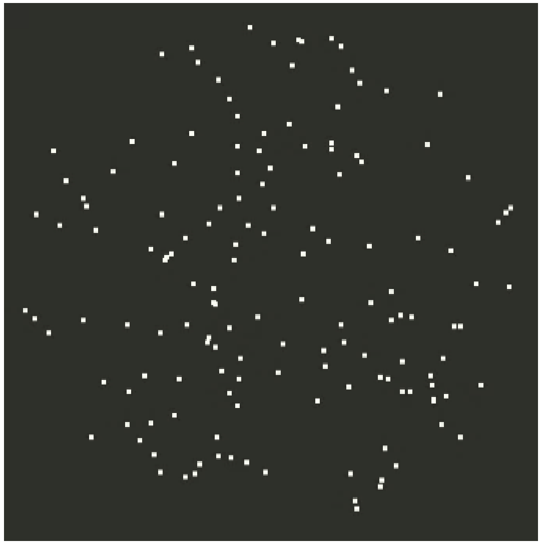


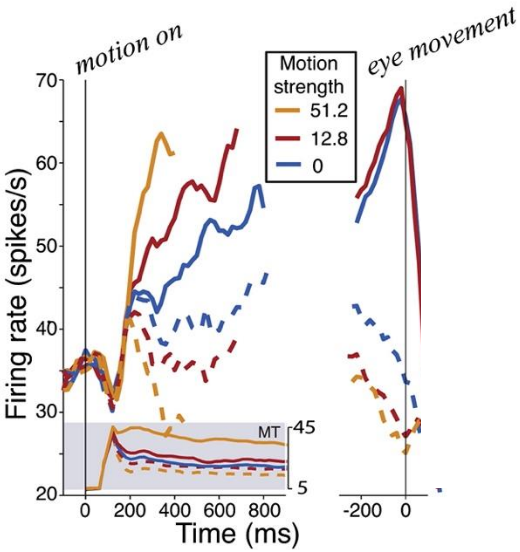
$$\int \ldots dt$$

Classic experiment





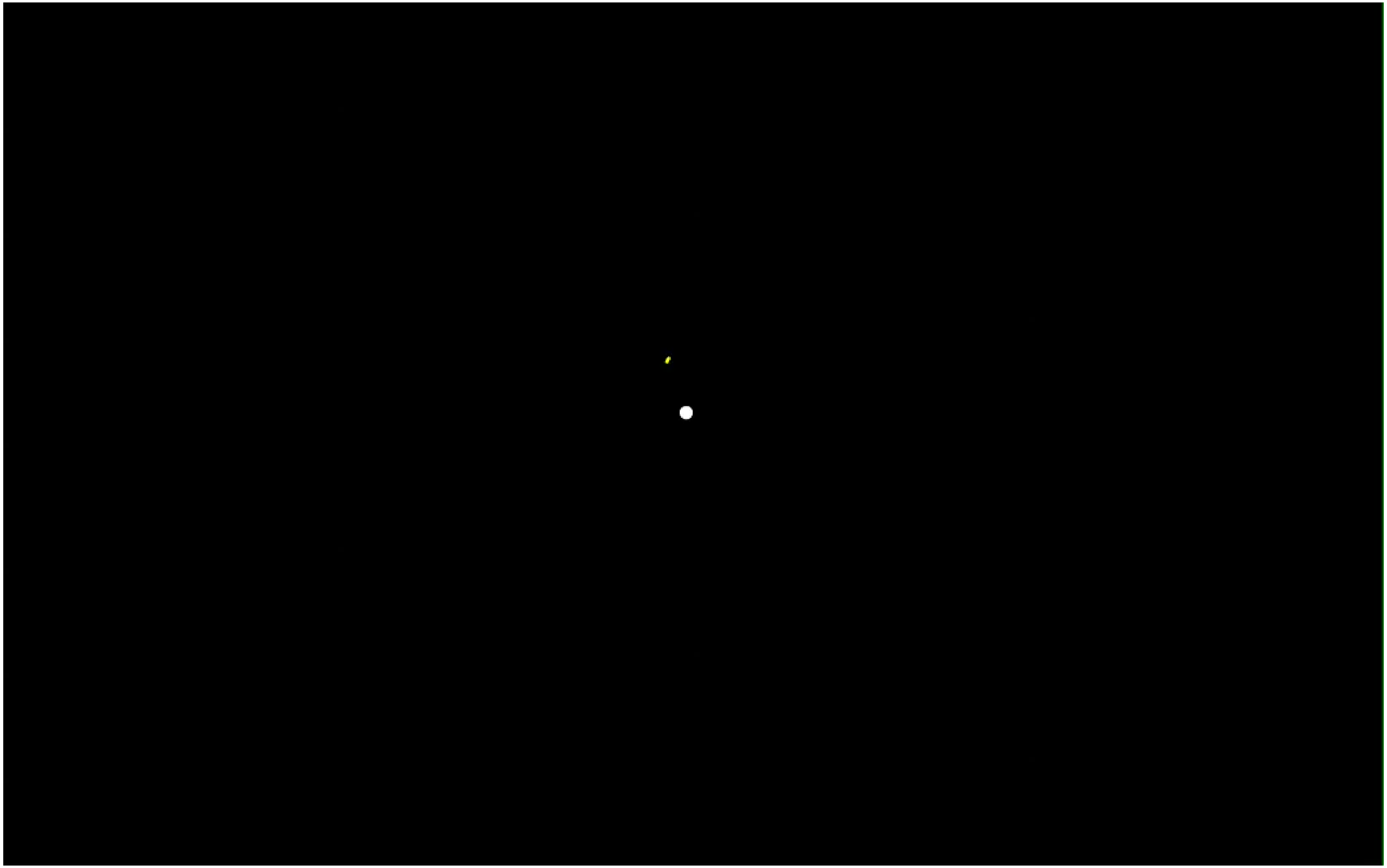




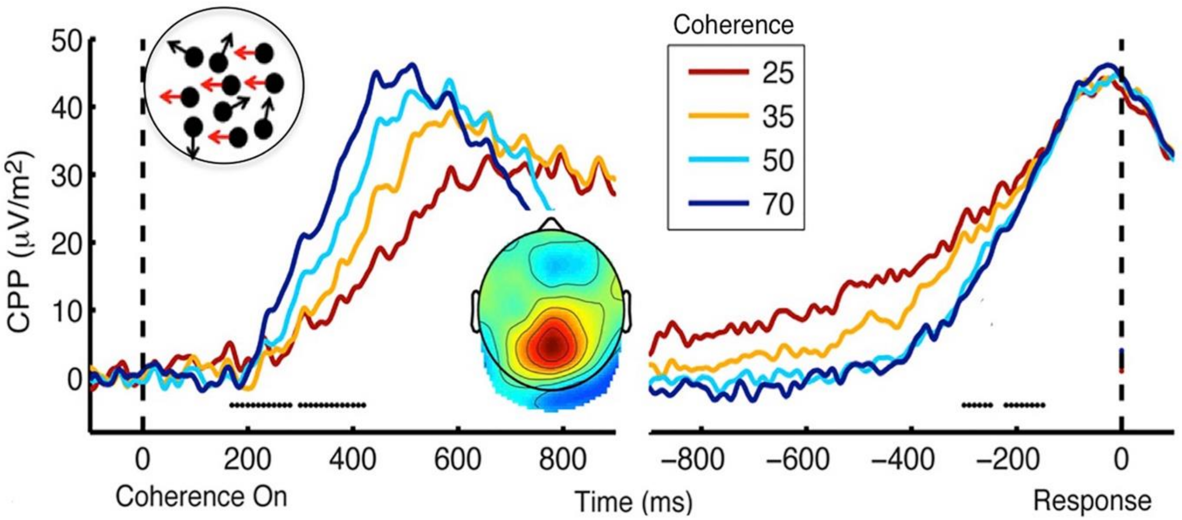
Neuronal population in area LIP (lateral intraparietal area)

Roitman & Shadlen, J. Neurosci. (2002)

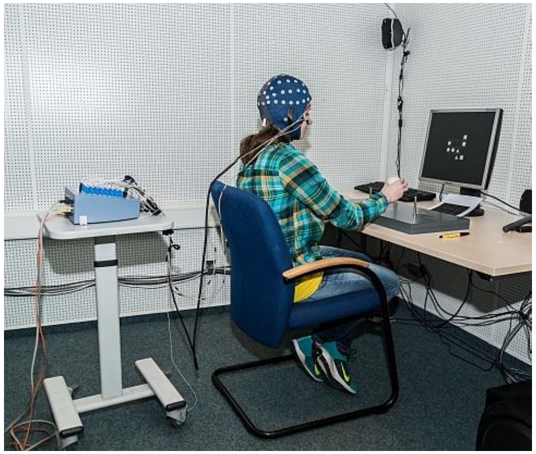
Recording of a particular (LIP) brain cell in a non-human primate performing motion discrimination task



Similar macroscale brain activity dynamics in humans



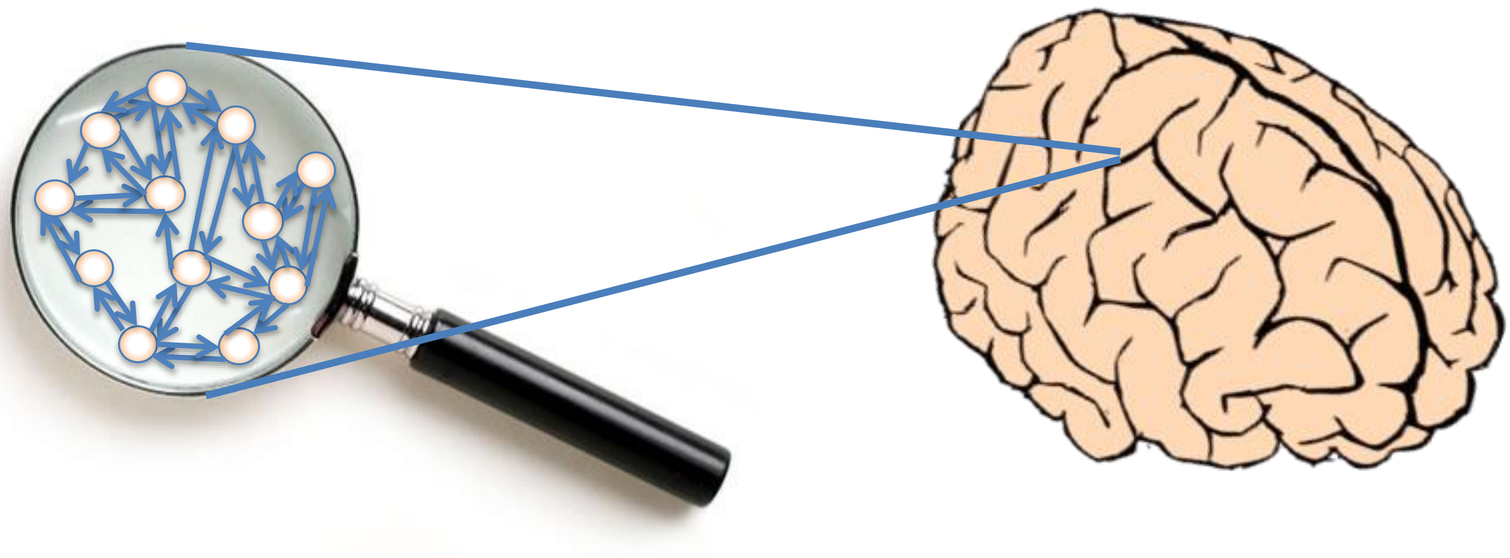
Kelly & O'Connell, J. Neurosci. (2013)



Electroencephalography (EEG) measures ensembles of neural activity with high temporal resolution

How to link cognitive models to elements of the brain, i.e. brain cells (neurons) and their connections (synapses)?

A network of neurons and emergent behaviour

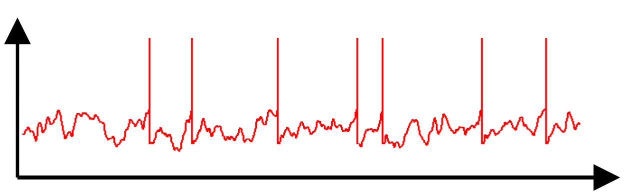


Spiking activity from a single model neuron, and network of connected neurons

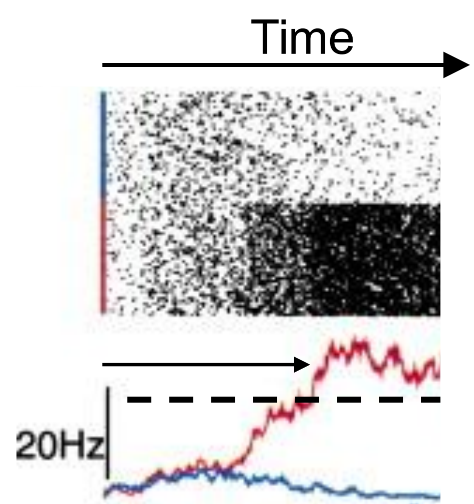
Leaky Integrate-and-fire neuronal model
with realistic synaptic dynamics

$$dV/dt = -g_L(V-E_L) + I_e - \Sigma\, g_s s(t)\, (V-E_s)$$

Neuronal
membrane
Potential, V



Time



X-J Wang (2002)

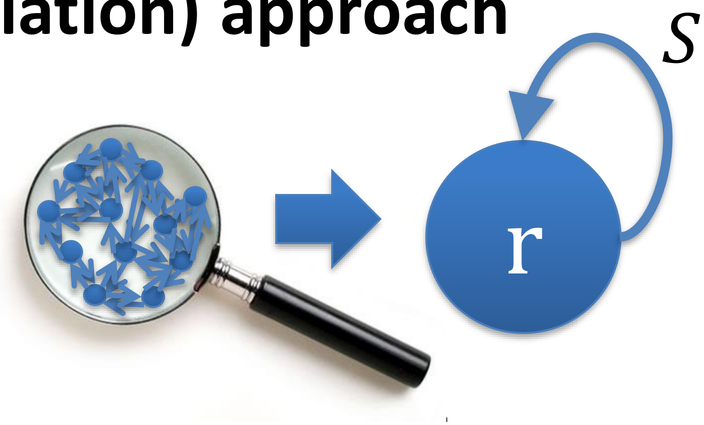
Key mechanisms in this model?

Simulate this model more efficiently?

What is the link to cognitive models?

Model reduction

A "mean-field" (neural population) approach



Neural population dynamics described by

$$\tau \frac{dr}{dt} = -r + \varphi(I)$$

$$\boxed{\varphi(I) = \frac{c\,I - I_0}{1 - exp\left(-g\,(c\,I - I_0)\right)}}$$

an approximation of a first passage time formula for LIF neurons (via Fokker-Planck approach), and I is averaged total input to a neuron,

$$I = W\,S + I_{stimulus} + I_{noise}$$

where W is the synaptic (connectivity) strength, and

$$\boxed{\tau_{noise} \frac{dI_{noise}}{dt} = -I_{noise} + \eta\sqrt{\tau_{noise}\,\sigma_{noise}^2}}$$

(Ornstein-Uhlenbeck process)

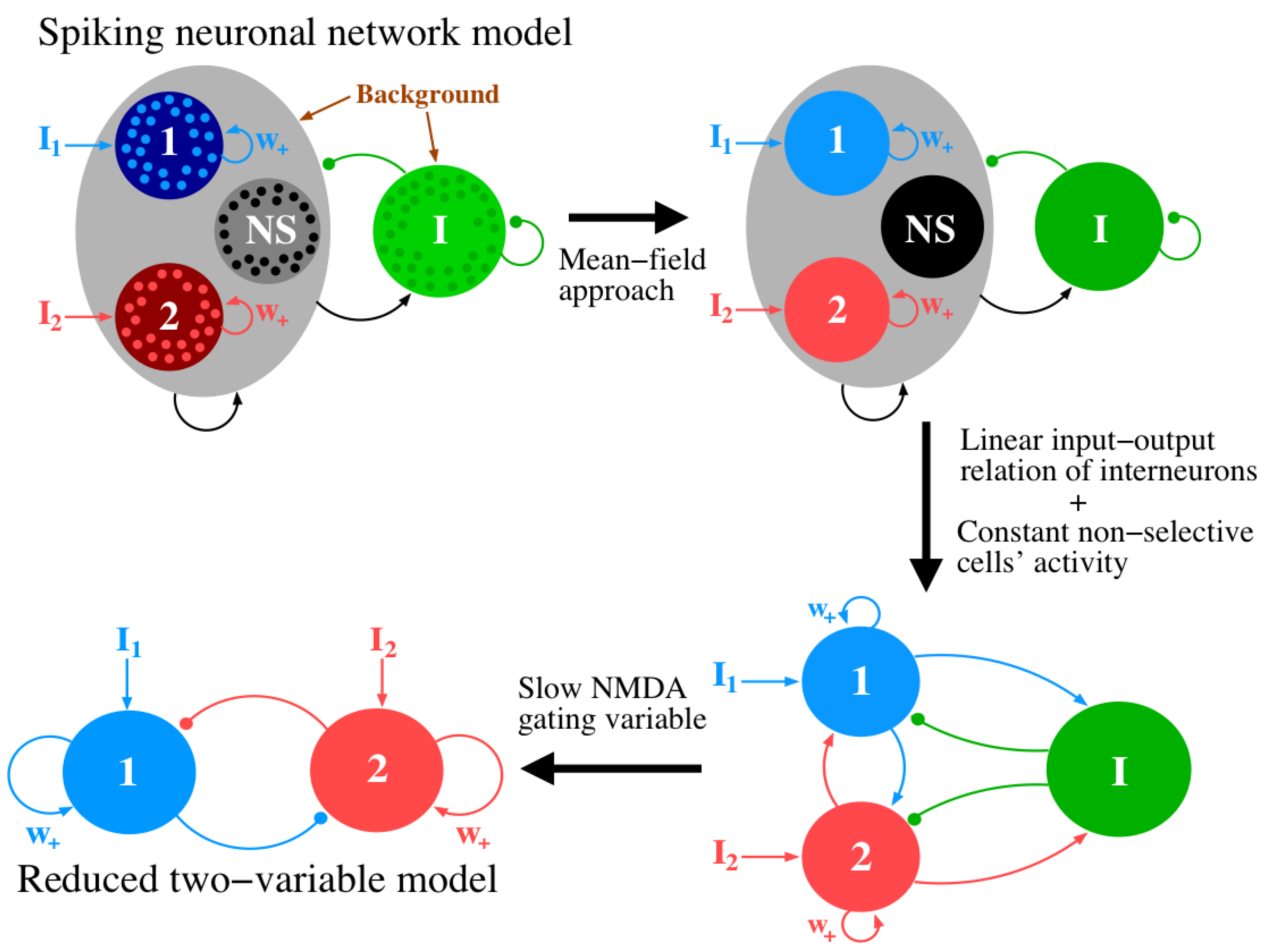
Dynamics describing the averaged (slow) synaptic dynamics for the neural population

$$\boxed{\frac{d\,S}{dt} = -\frac{S}{\tau_S} + (1 - S)\,\gamma\,r}$$

(with interspike interval distribution ~ Poisson)

Wong & Wang, J. Neurosci. (2006)

Reducing a biophysical model of decision-making

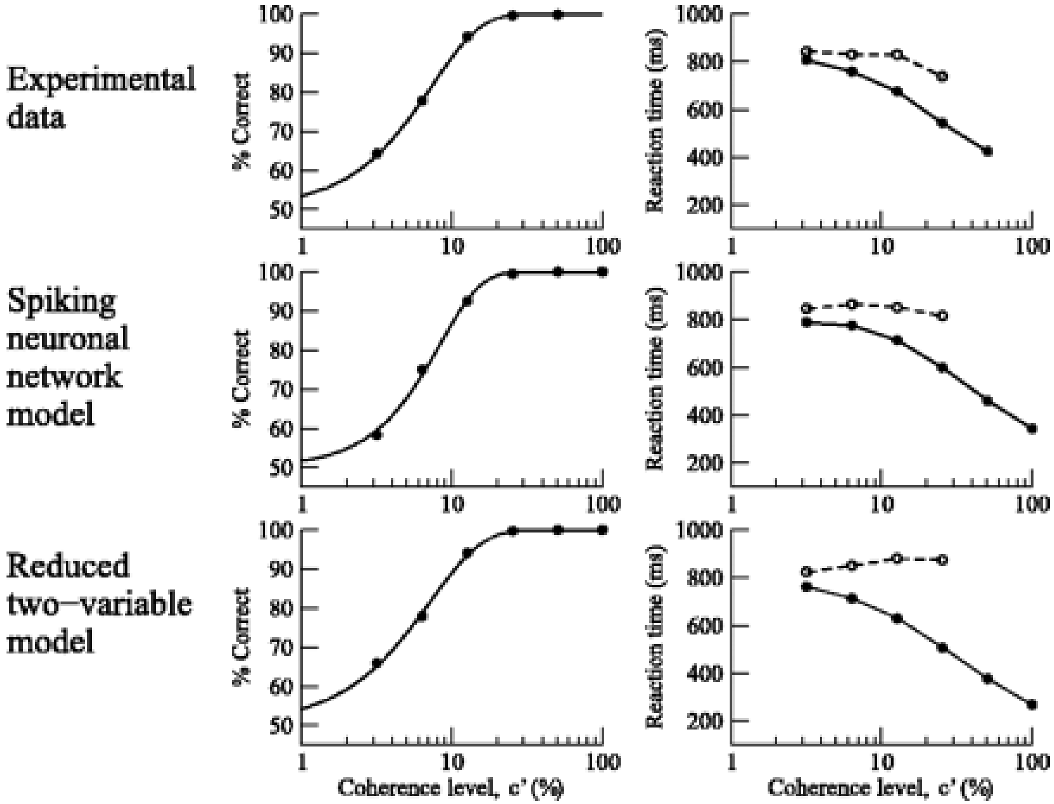


Dynamical equations described by population-averaged of slow NMDA-mediated synaptic dynamics:

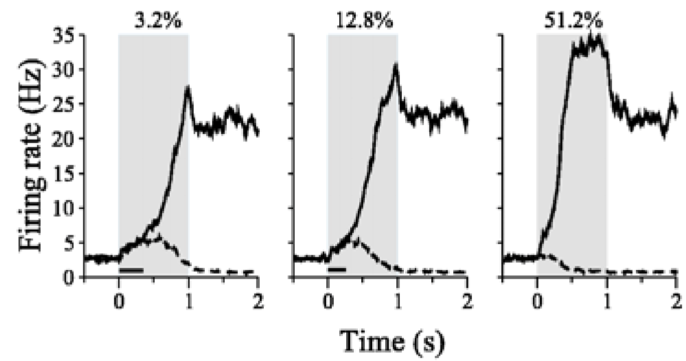
$$dS_1/dt = -S_1/\tau_S + (1 - S_1)\, F(W_+S_1 - W_-S_2 + I_1 + I_{noise})$$
$$dS_2/dt = -S_2/\tau_S + (1 - S_2)\, F(W_+S_2 - W_-S_1 + I_2 + I_{noise})$$

Wong & Wang, J. Neurosci.(2006)

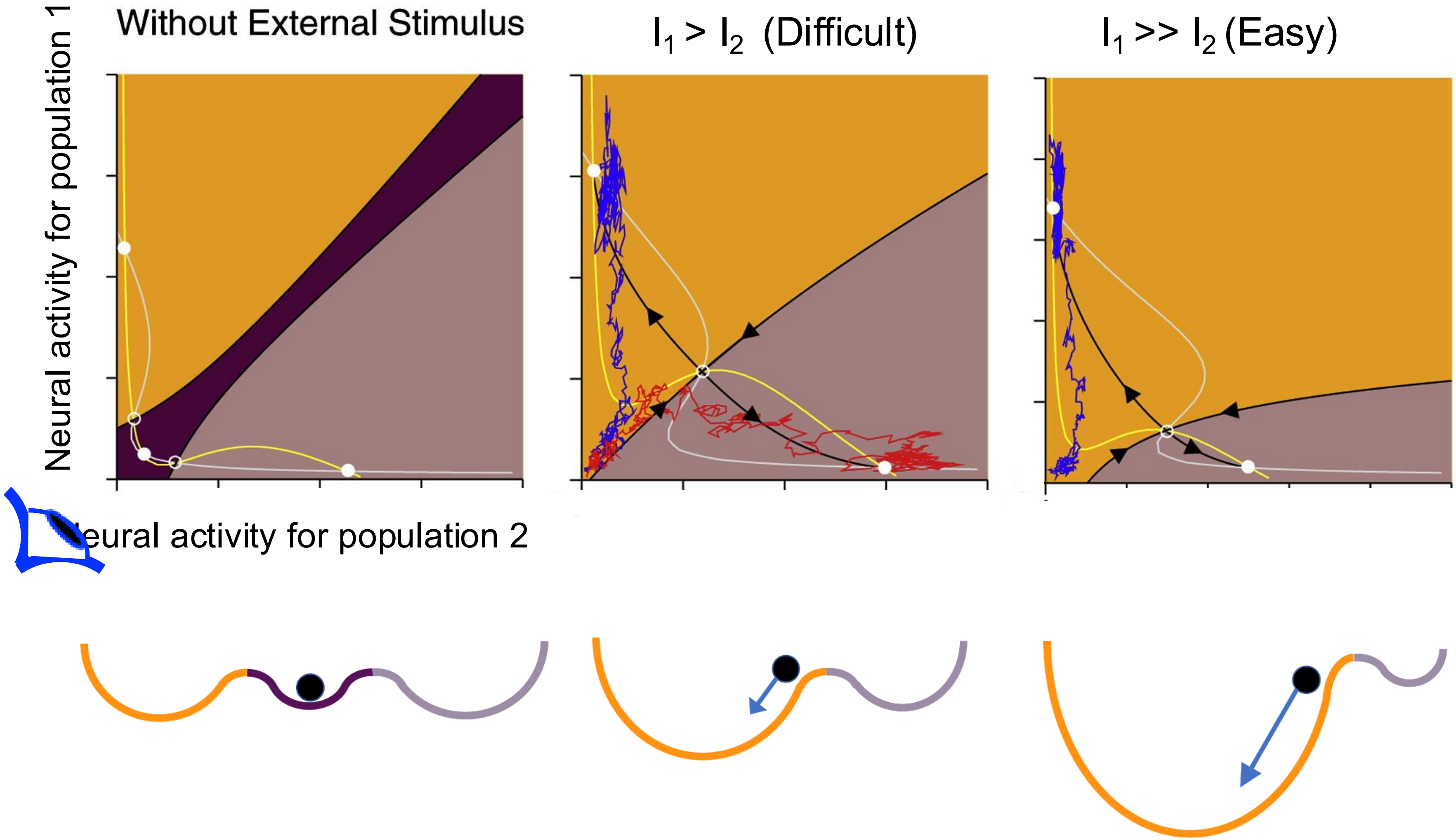
A reduced (attractor) neural network model with strong positive feedback



Storage of decision in memory (hysteresis) for different task difficulties

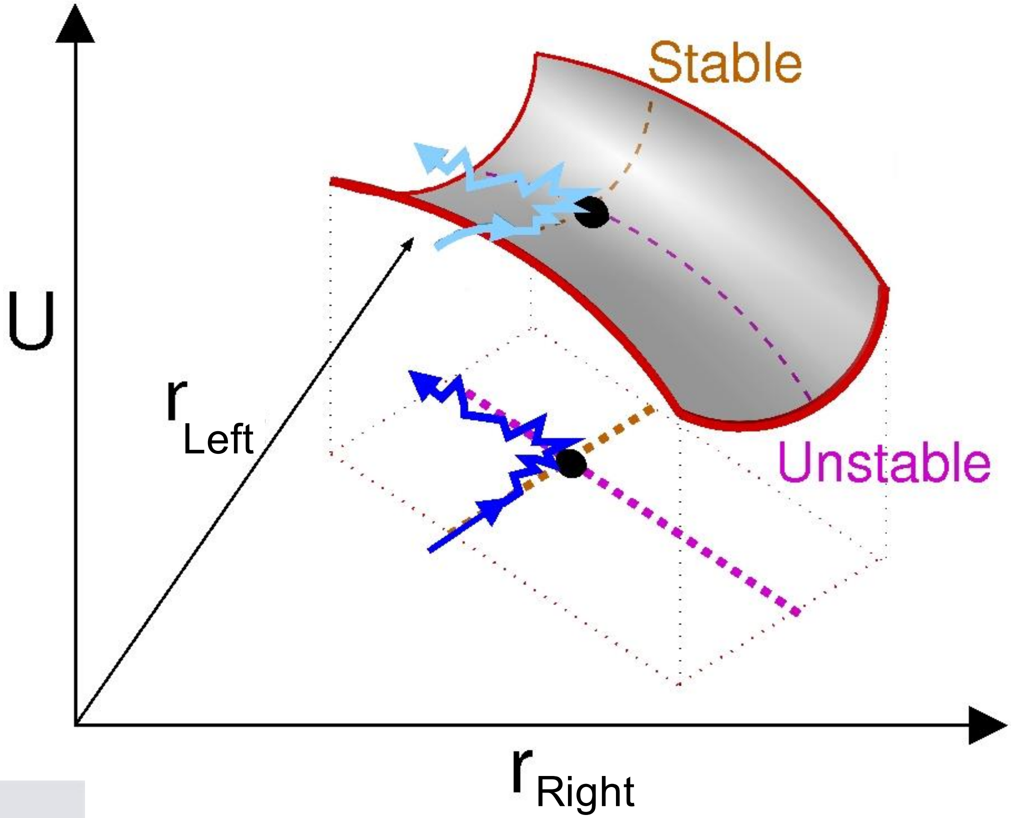


Phase-plane analysis of attractor network model

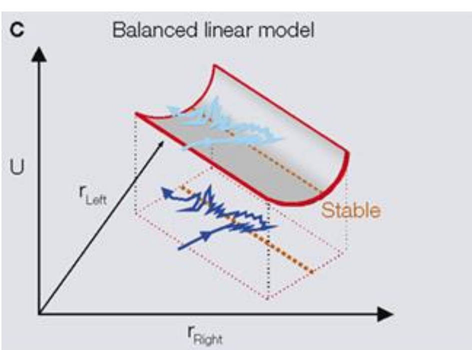


Wong & Wang, J. Neurosci. (2006), adapted

“Potential energy” landscape in phase space



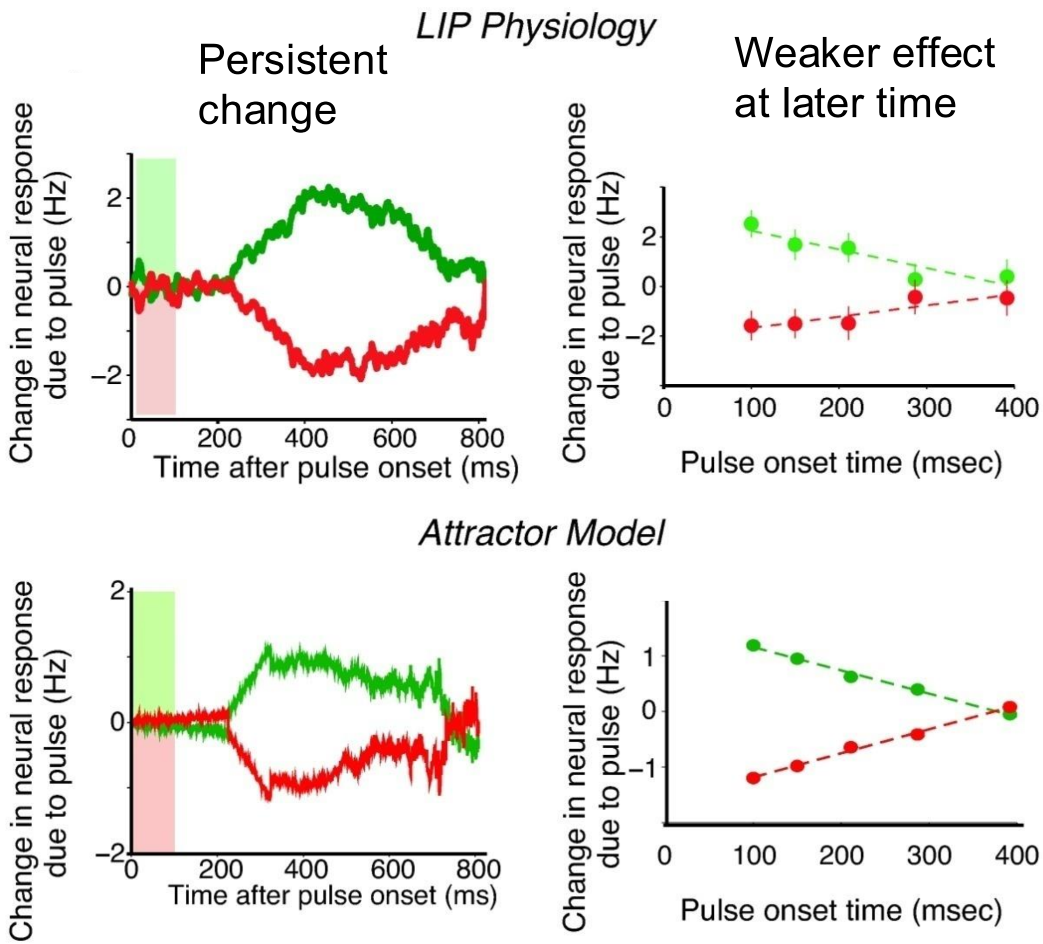
In the vicinity of the unstable “**saddle**” steady state

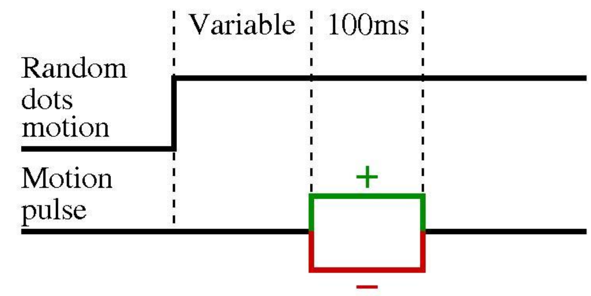


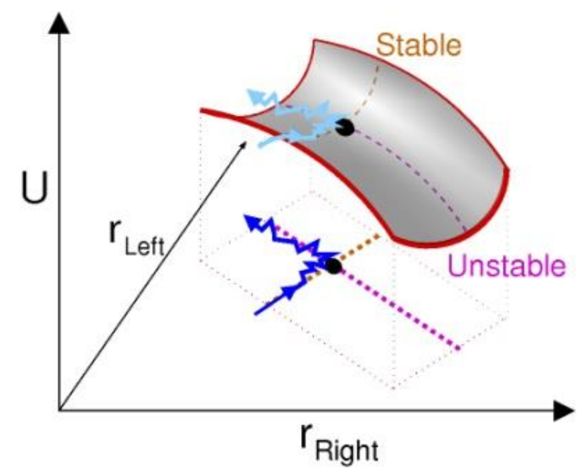
Wong & Huk, Front. Neurosci. (2008)

Bogacz et al., Psychol. Rev. (2006)

Model prediction: Attractor network model with “runaway” temporal integration can account for weaker perturbative effects at later times



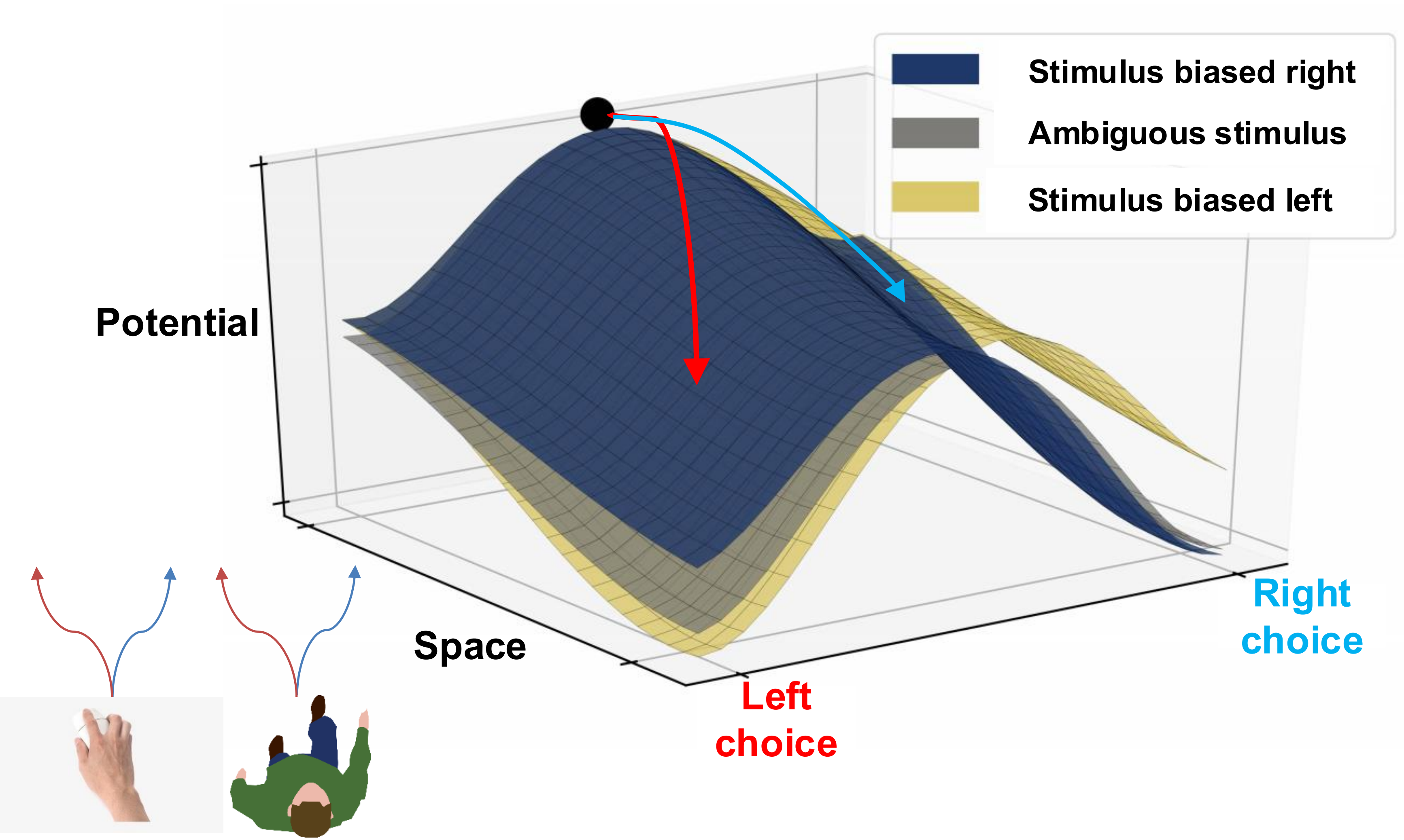




Wong, Huk, Shadlen & Wang (2007)

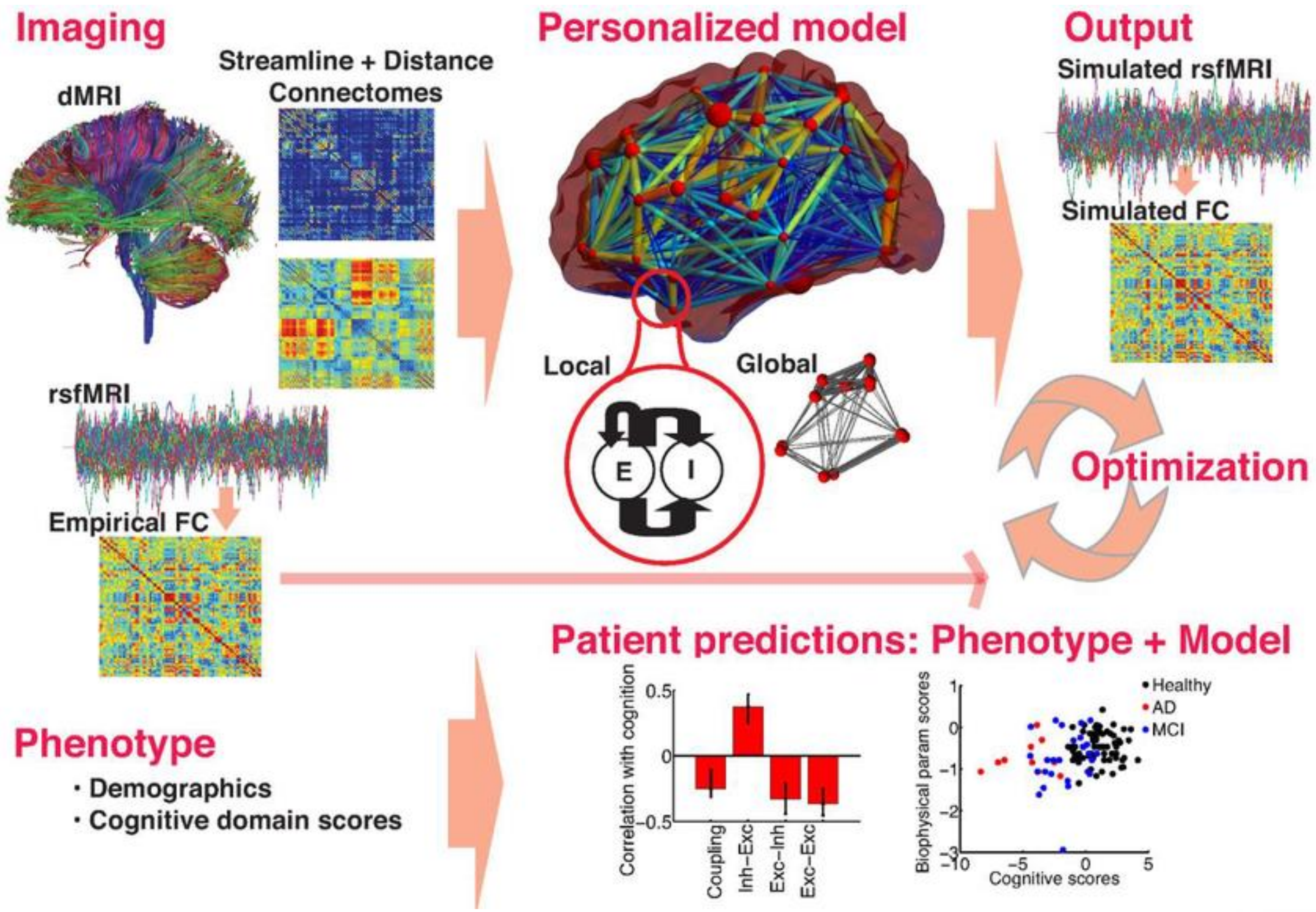
"Potential energy" landscape in space

Reconstructed from walking or computer mouse trajectories



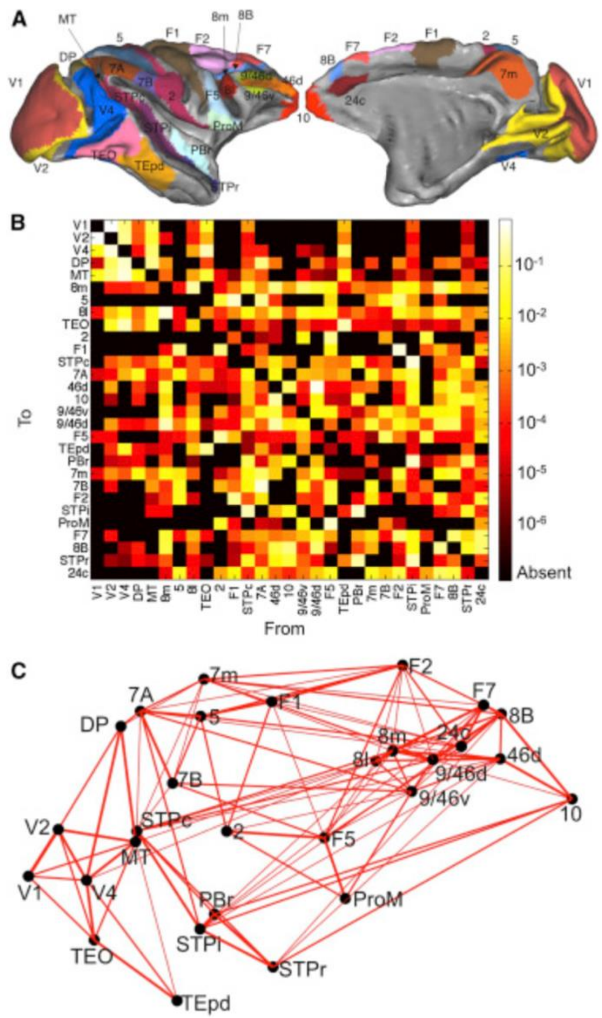
Adapted from Zgonnikov, Atiya, O'Hora, Rano & Wong-Lin (2019)

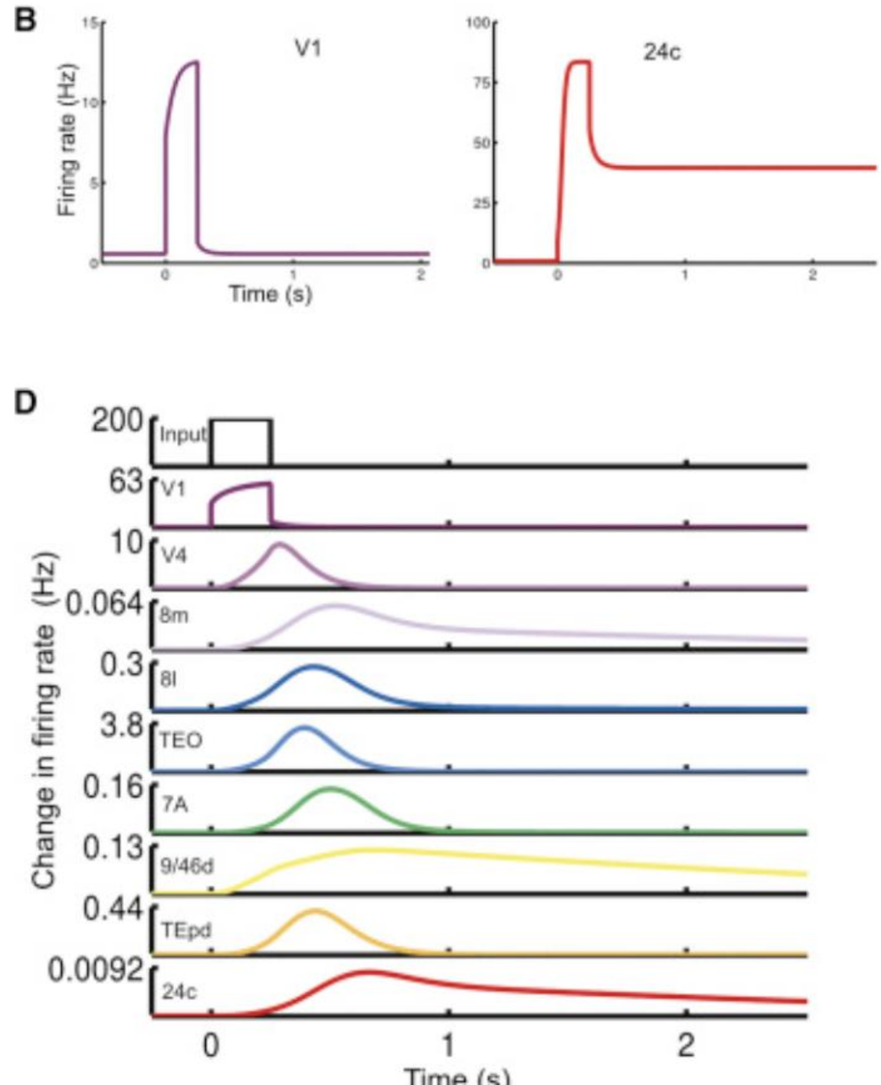
Off-track: Mean-field model in The Virtual Brain (TVB)



Sanz-Leon et al. (2013; 2015)

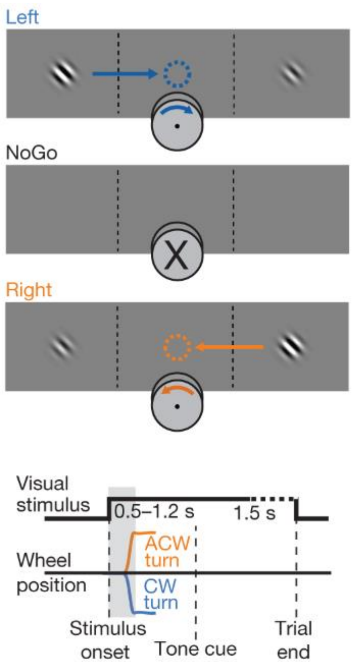
Off-track: Mean-field model in monkey brains

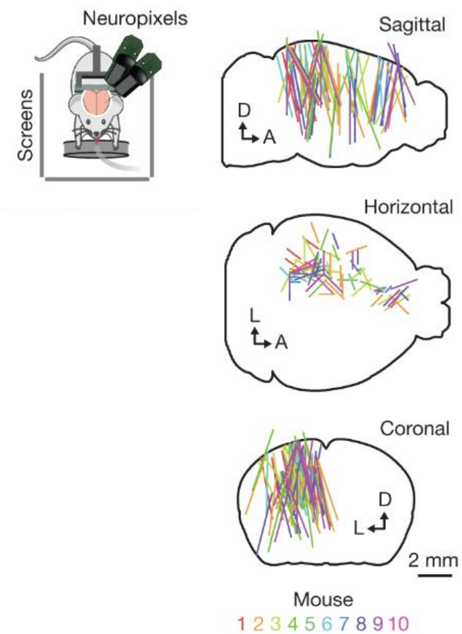


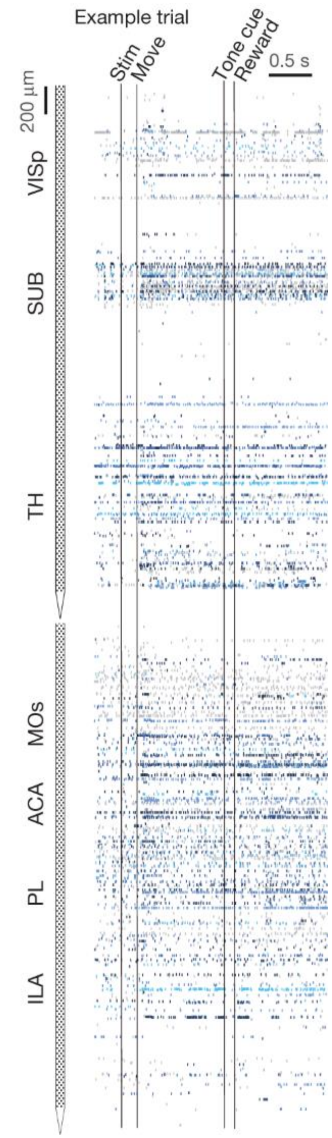


Chaudhuri et al. (2015)

Neural dynamics in higher dimensions from simultaneously recorded neurons



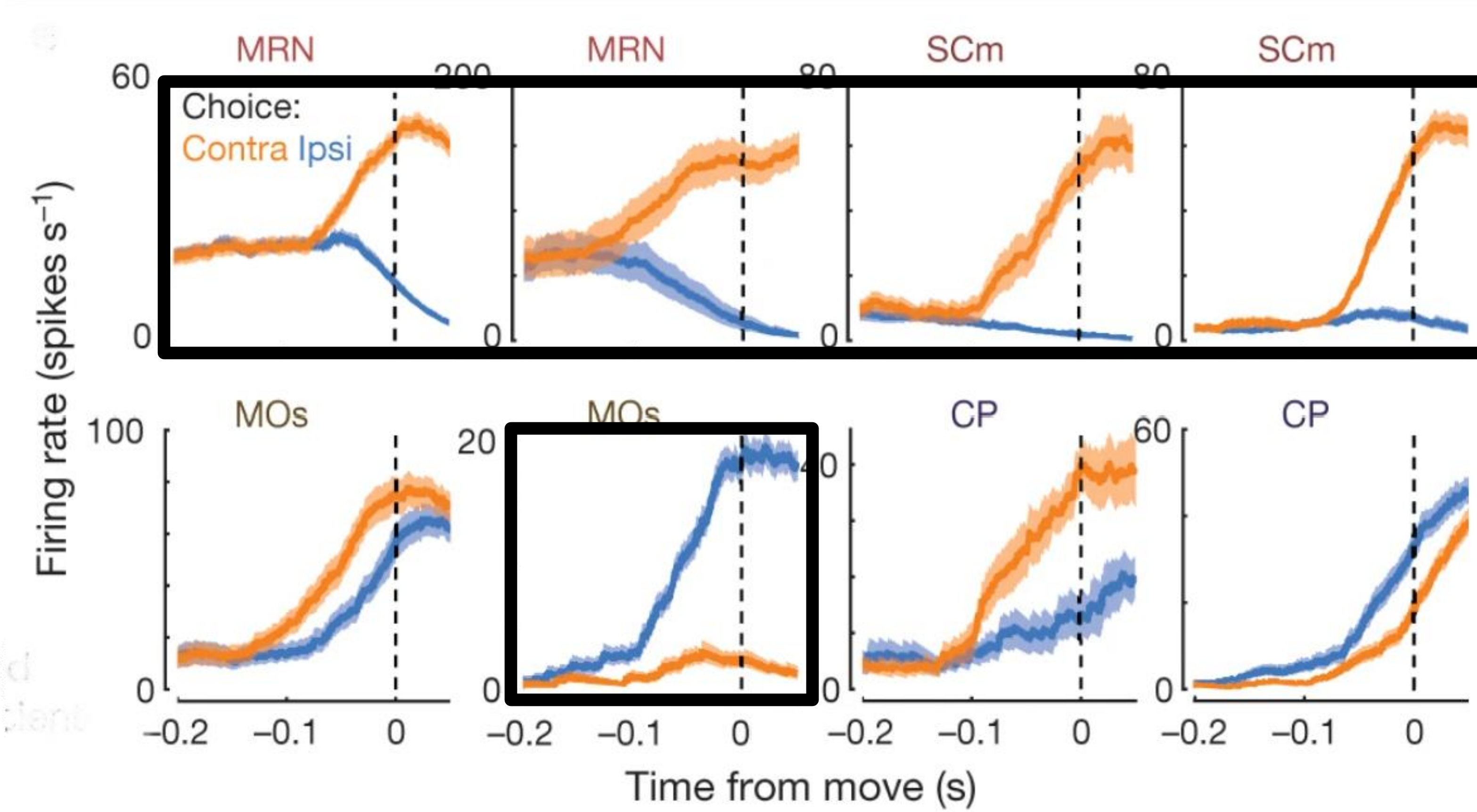




Steinmetz et al., Nature (2019)

Neural dynamics in higher dimensions from simultaneously recorded neurons

Some sample neuronal activities encoding choice information exhibit winner-take-all behaviour

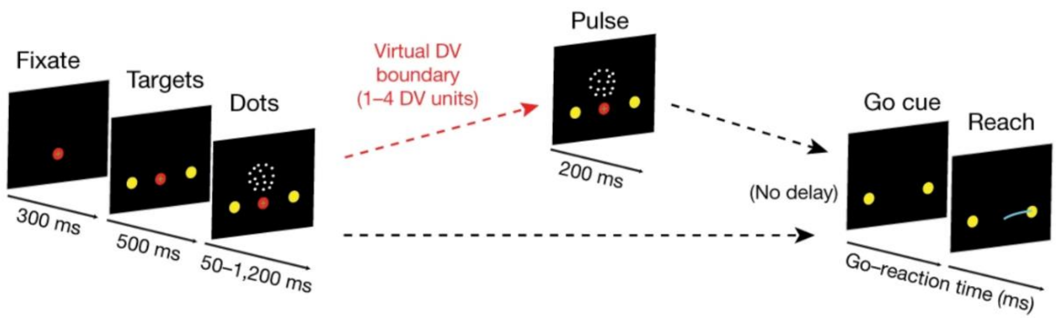


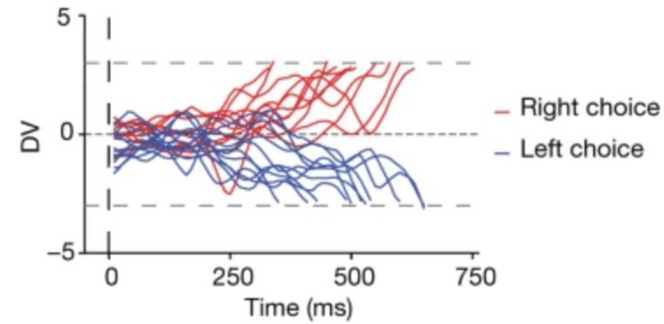
Activities averaged across experimental trials and aligned from movement onset

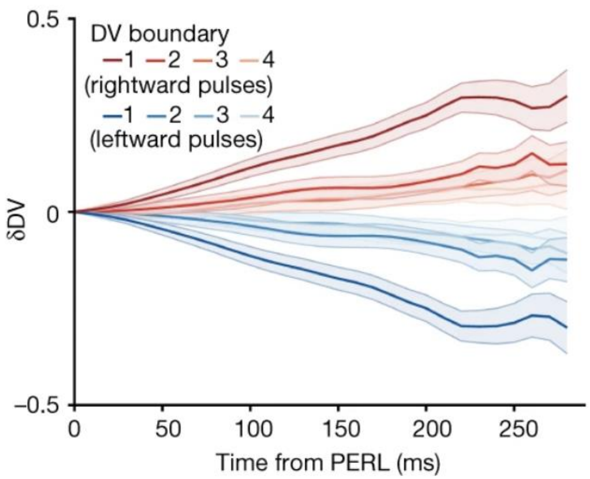
Steinmetz et al., Nature (2019)

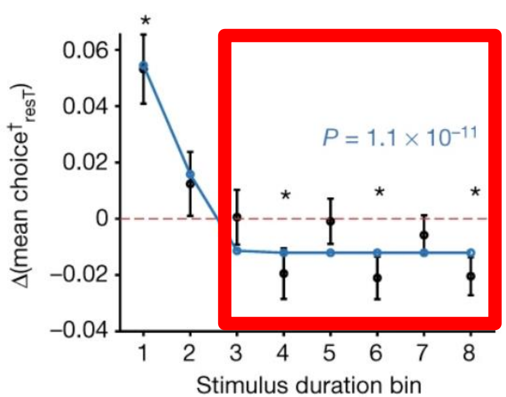
Neural dynamics in higher dimensions from simultaneously recorded neurons

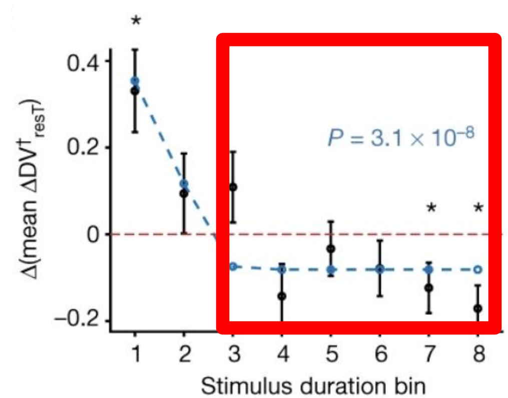
Peixoto et al., Nature (2021)







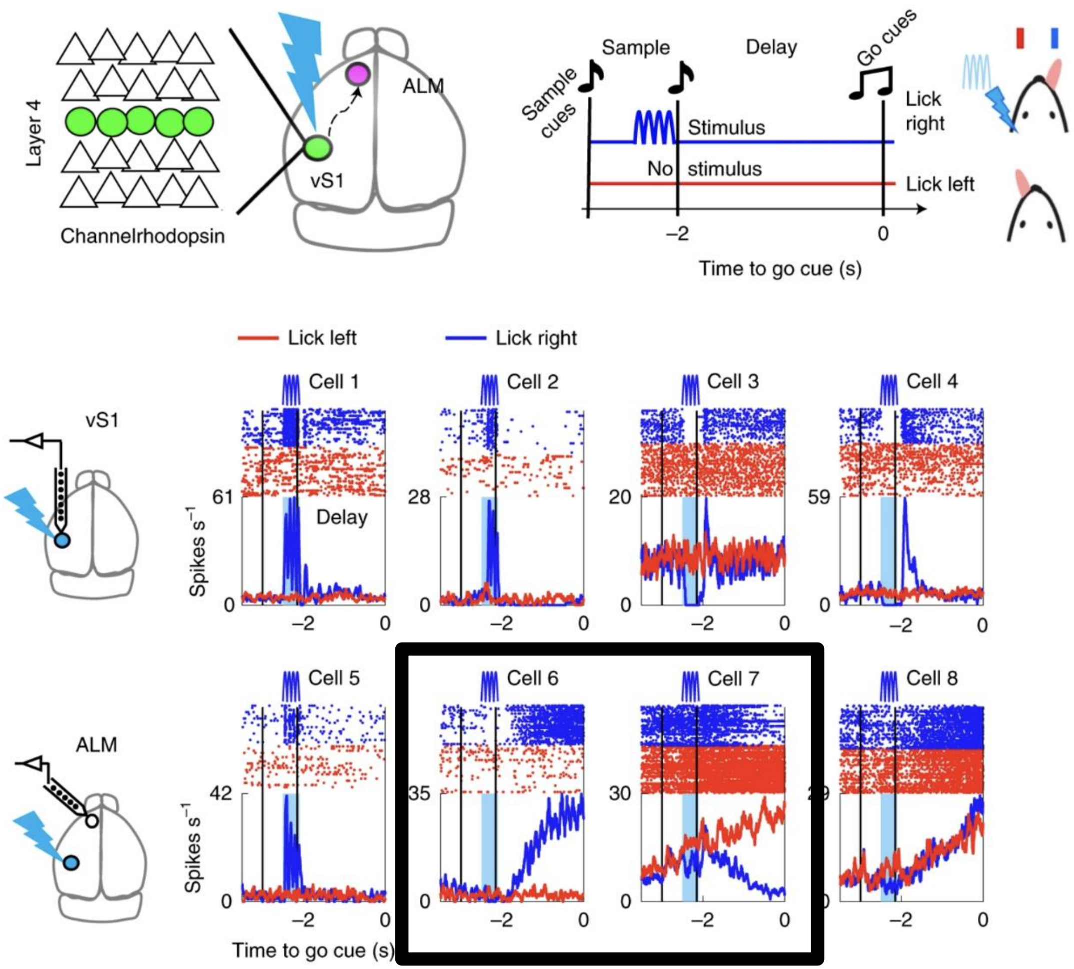




Neural dynamics in higher dimensions from simultaneously recorded neurons

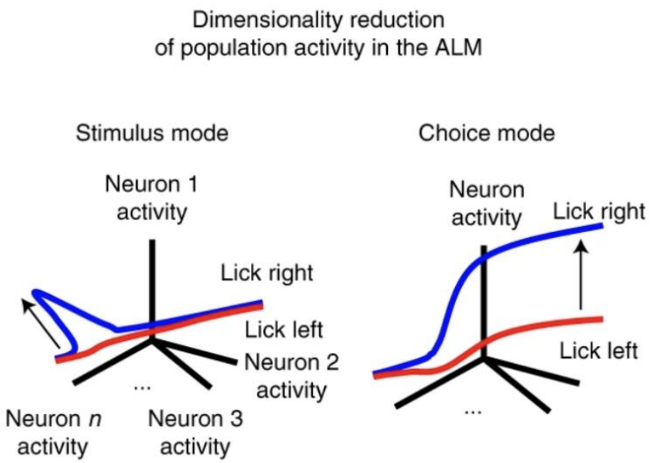
Finkelstein et al., Nat. Neurosci. (2021)

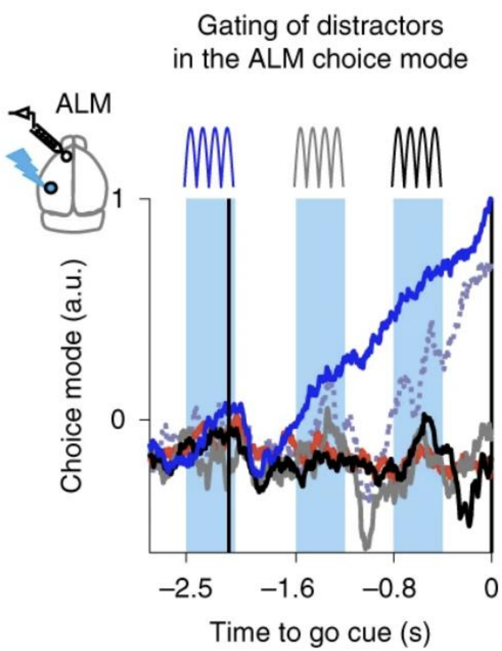
Direct cortical photostimulation in tactile decisions

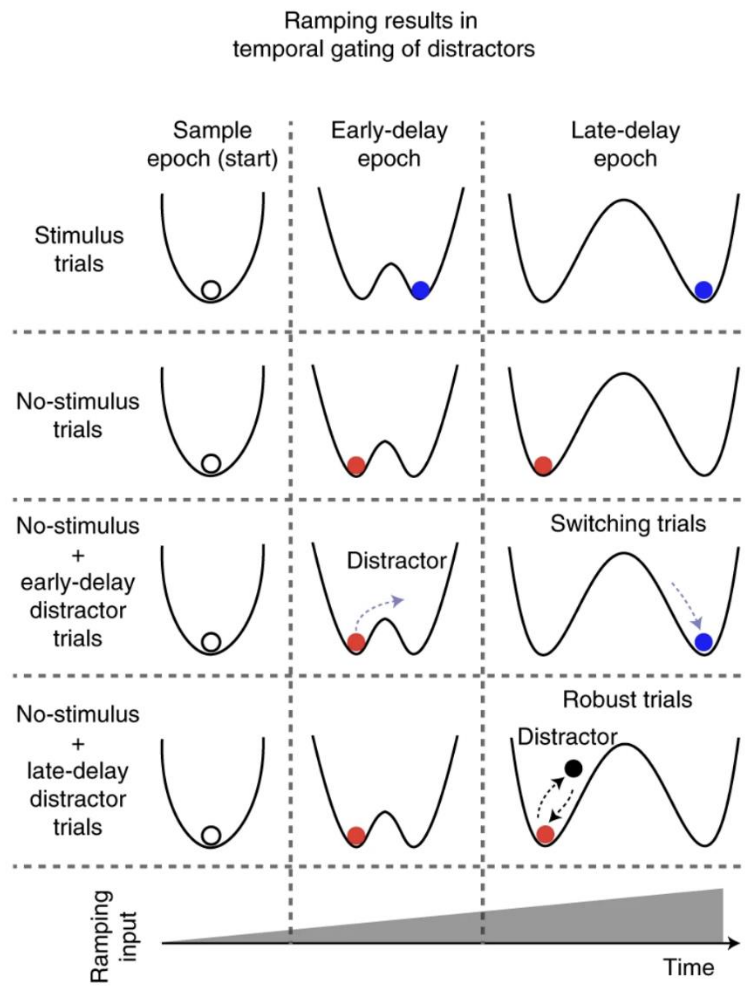


Neural dynamics in higher dimensions from simultaneously recorded neurons

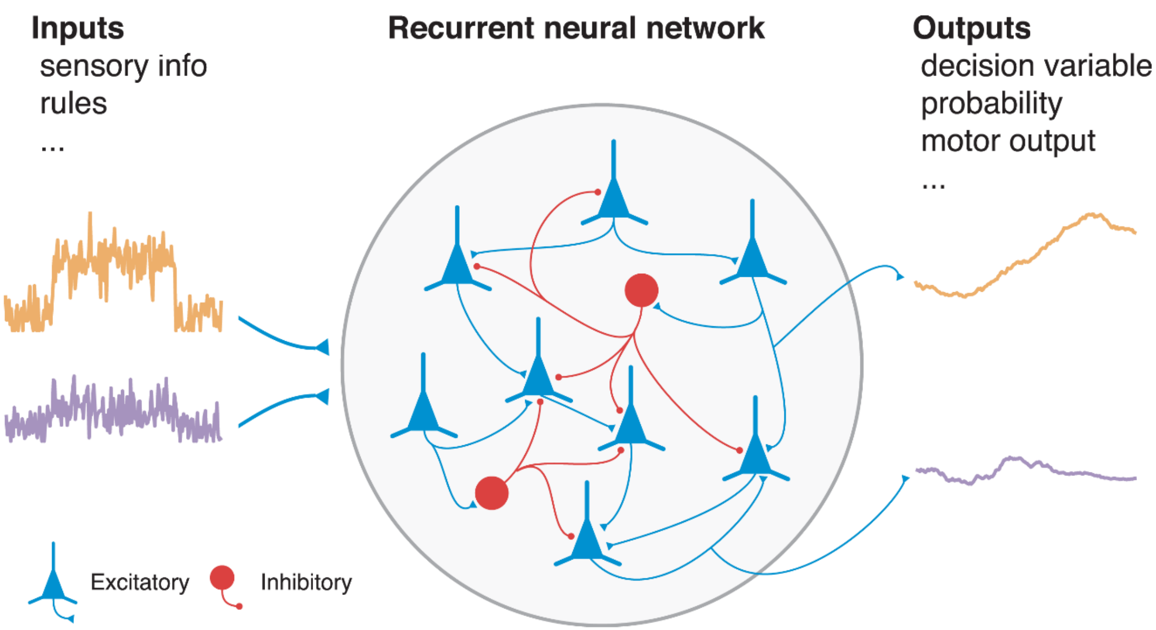
Finkelstein et al., Nat. Neurosci. (2021)

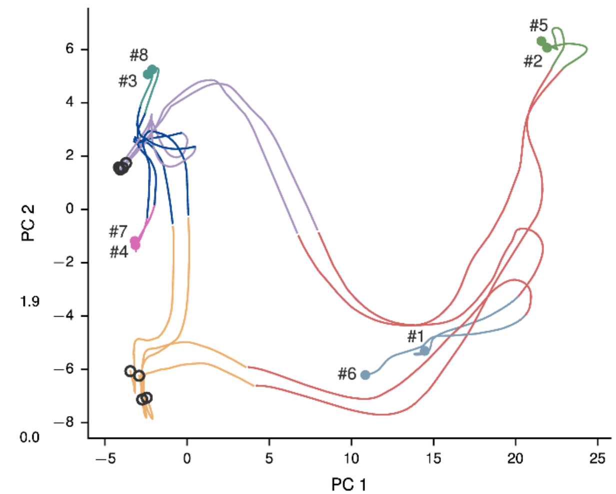


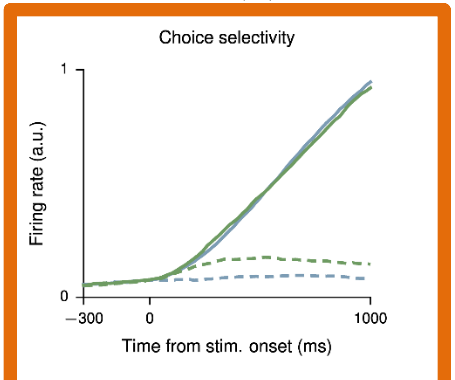


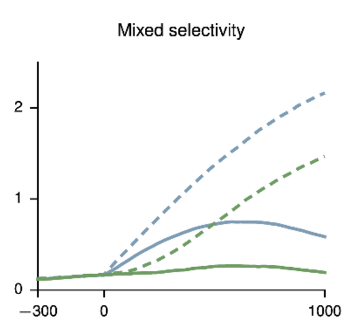


Training excitatory-inhibitory recurrent neural network (RNN) model in decision-making tasks





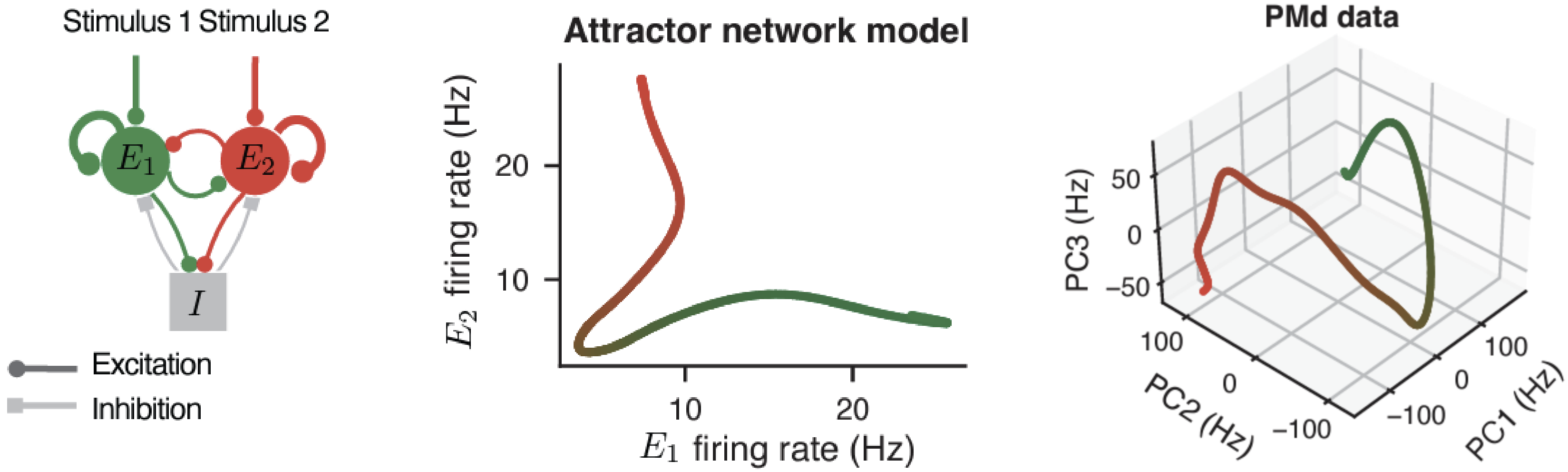




*Neural units embedded in trained RNN with **time integration & winner-take-all behaviour** (amongst others)*

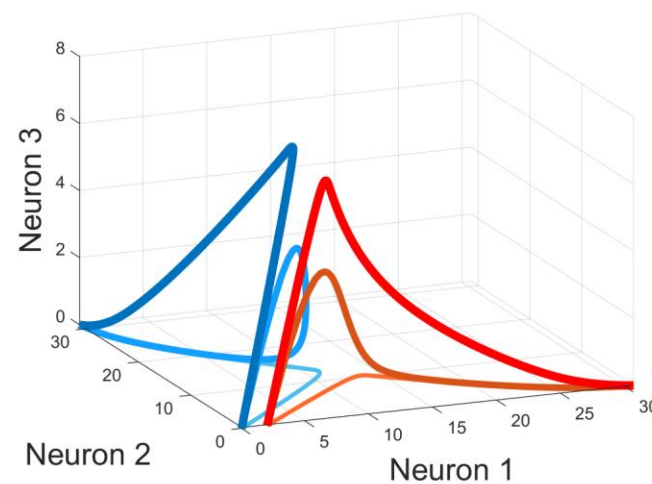
Song, Yang & Wang, PLoS Comput. Biol. (2016)

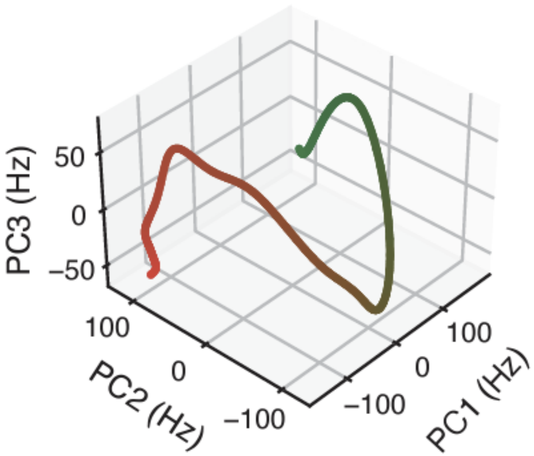
Additional neuron causes neural trajectories to traverse into additional dimension



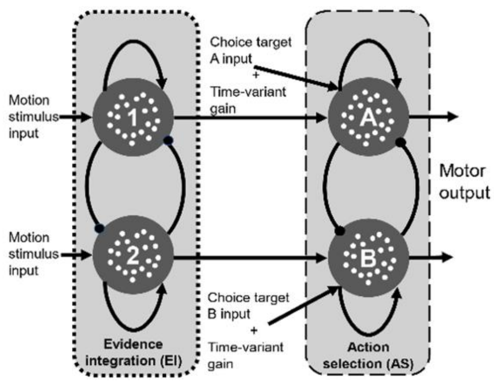
Genkin, Shenoy, Chandrasekaran & Engel, Nature (2025)

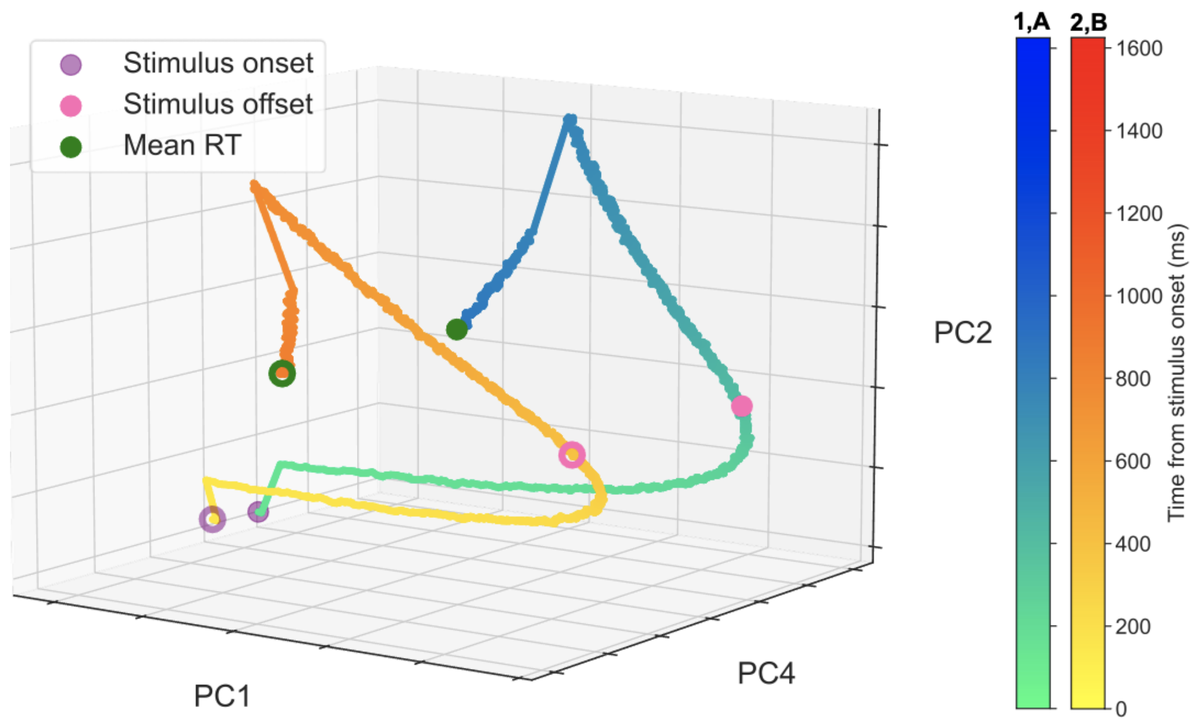
As neuron 3 gradually receives stronger stimulus input, neural trajectories pass through additional dimension (darker colours) (unpublished)





Neural trajectory with 4 neural units (2 evidence integration + 2 action selection)



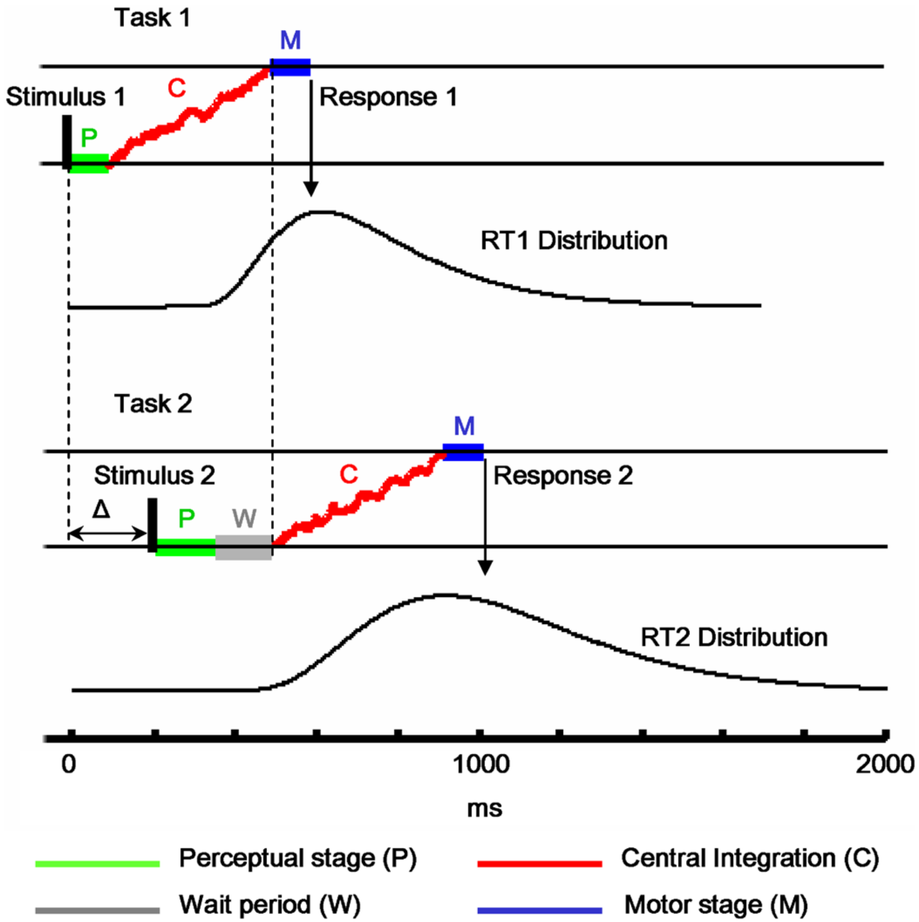


Brendan Lenfesty

Lenfesty et al. (In preparation)

Decision-making as a central bottleneck process

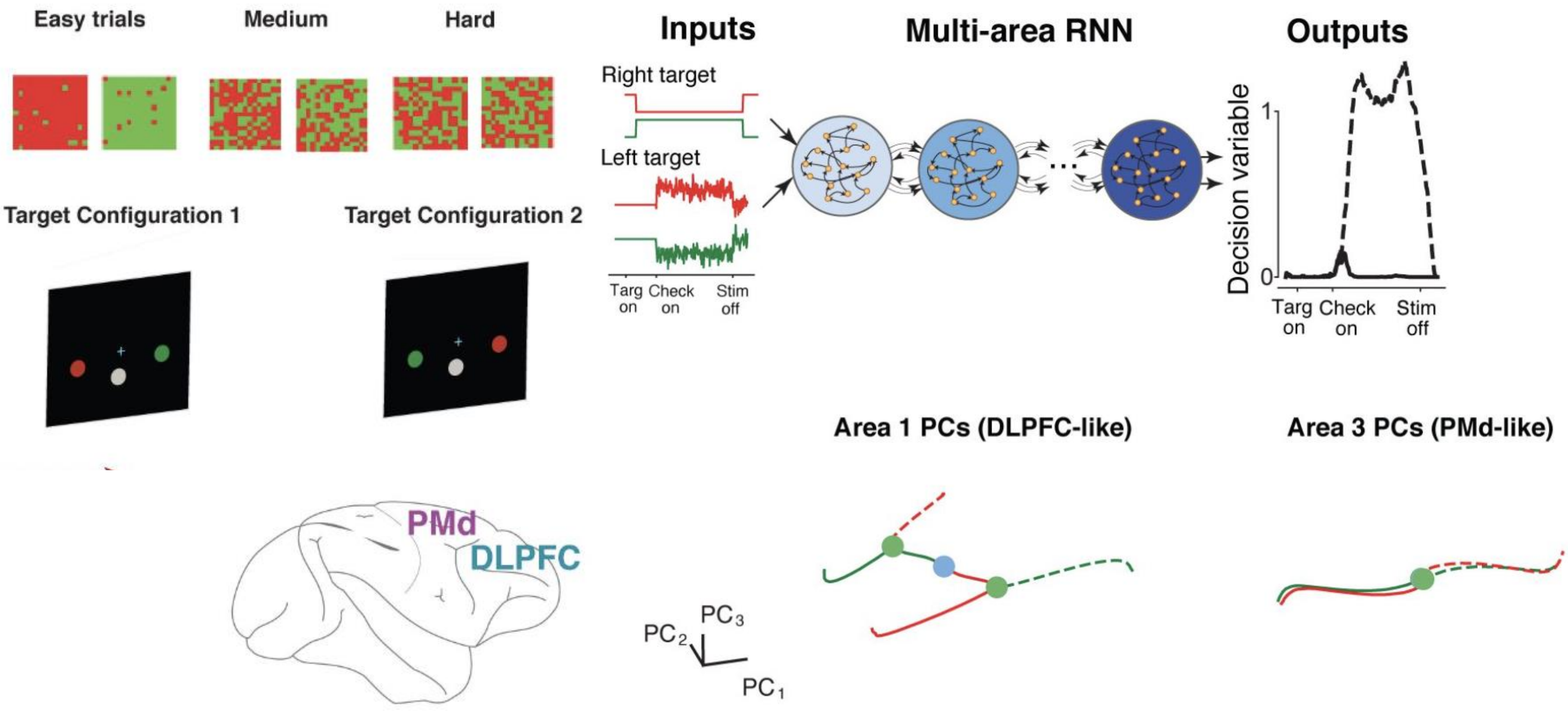
Behavioural evidence



Sigman & Dehaene (2005)

Decision-making as a central bottleneck process

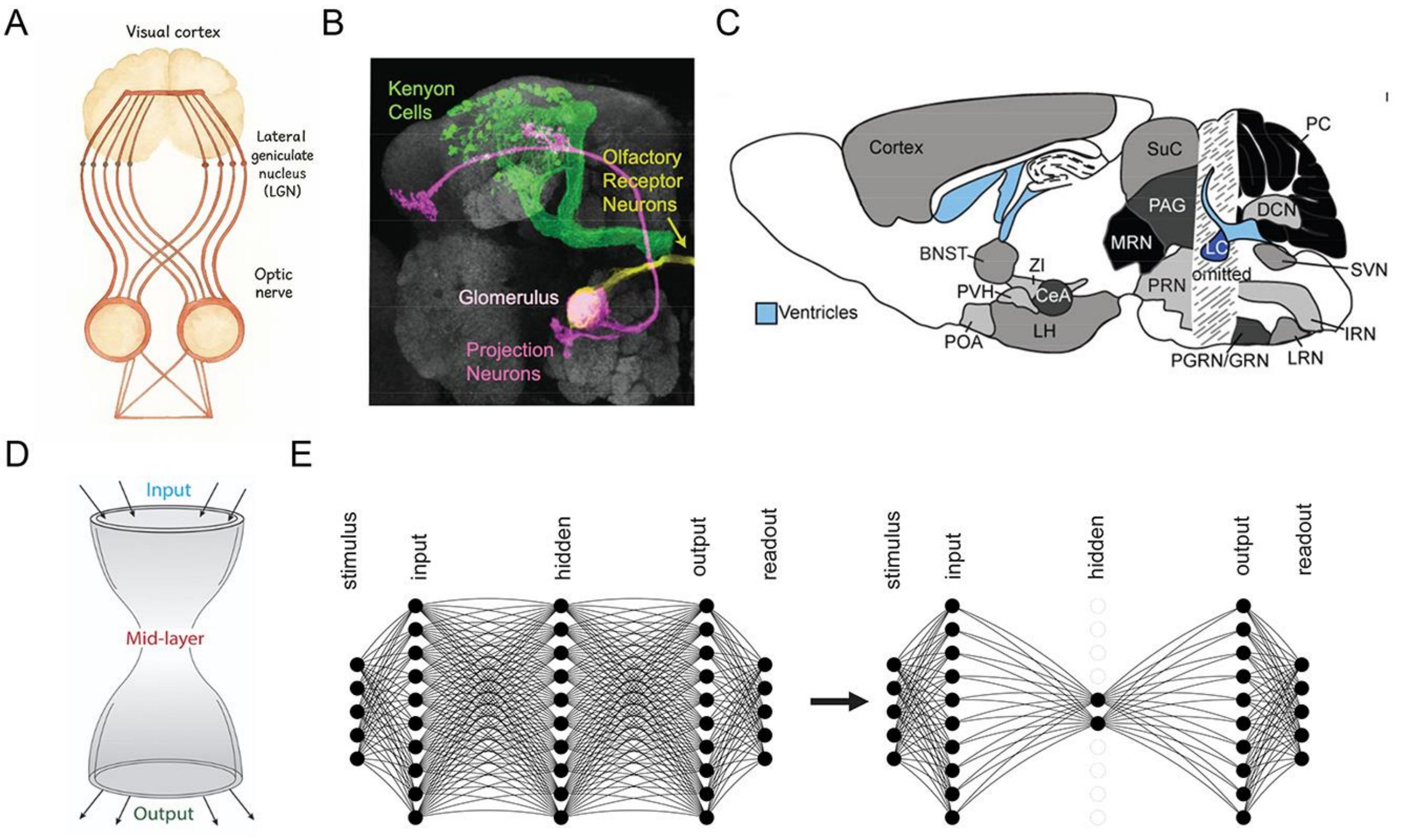
Neural evidence and RNN model



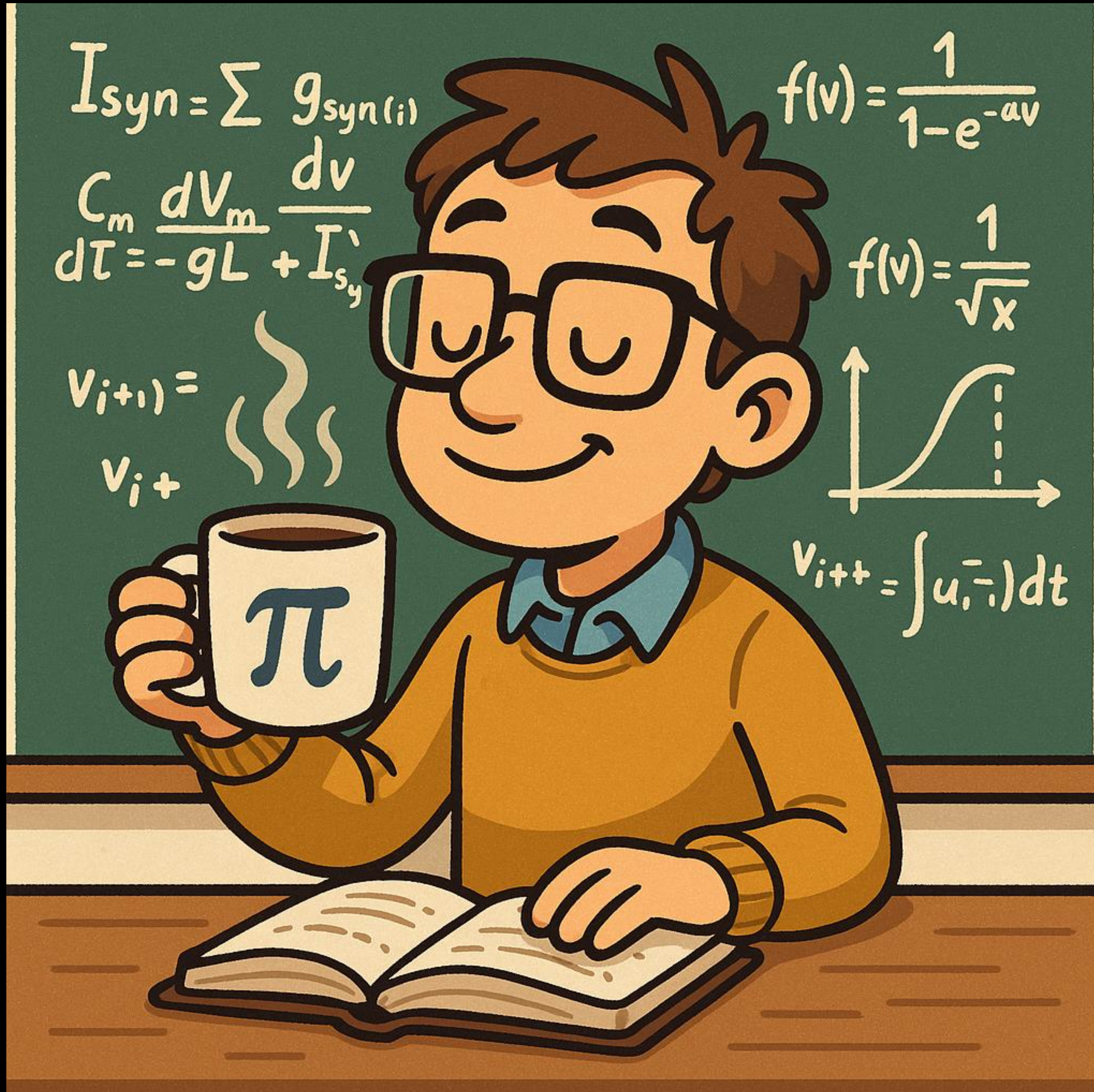
Kleinman et al. (2025)

Decision-making as a central bottleneck process

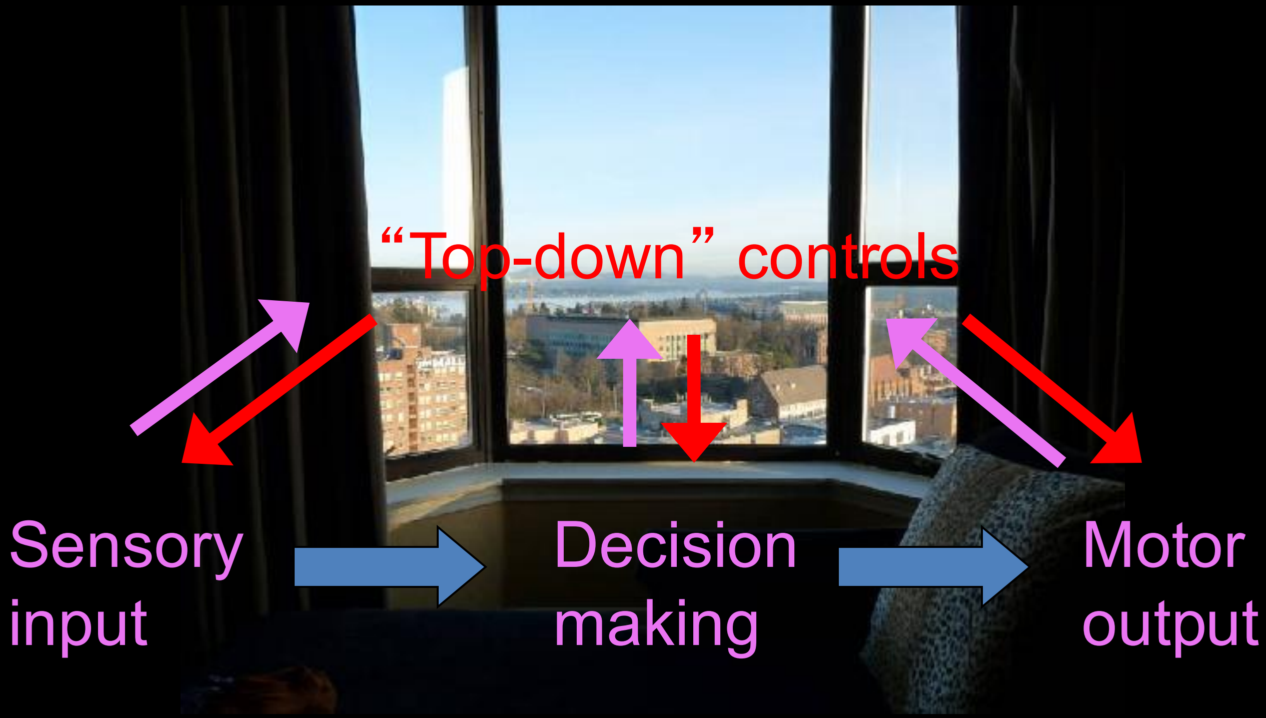
ANN evidence (with non-negative connectivity)



Liu, Du, Wong-Lin & Wang (2025)


Isyn = ∑ gsyn(i)
f(v) = 1 / 1−e−av
Cm dVm dv
dτ = −gL + Isy
f(v) = 1 / √x
vi+1) =
vi +
vi++ = ∫u,−,)dt
π

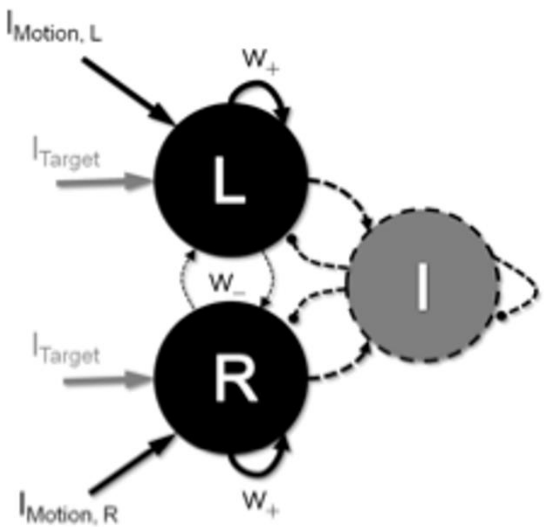
Perceptual decision making: a window to understanding higher cognition

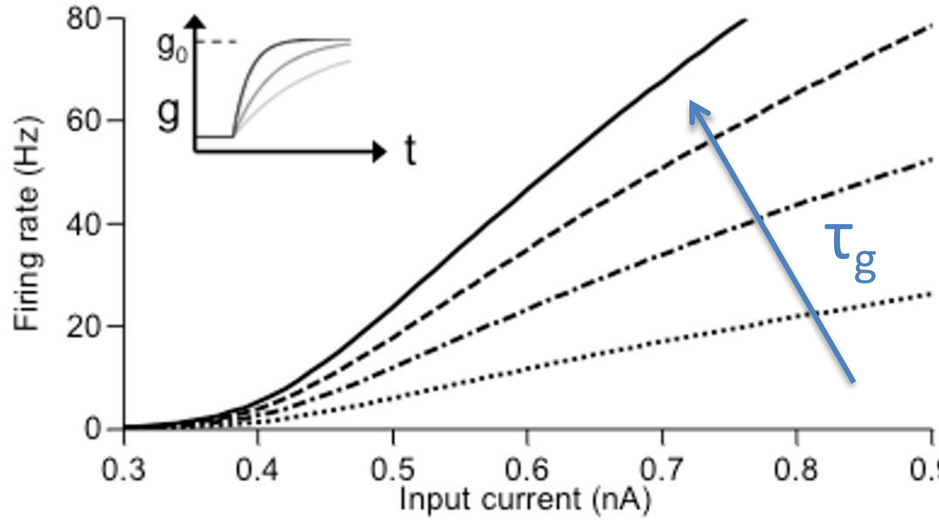


Dynamic gain modulation on excitatory and inhibitory neurons

Motivated by attention-induced and urgency studies

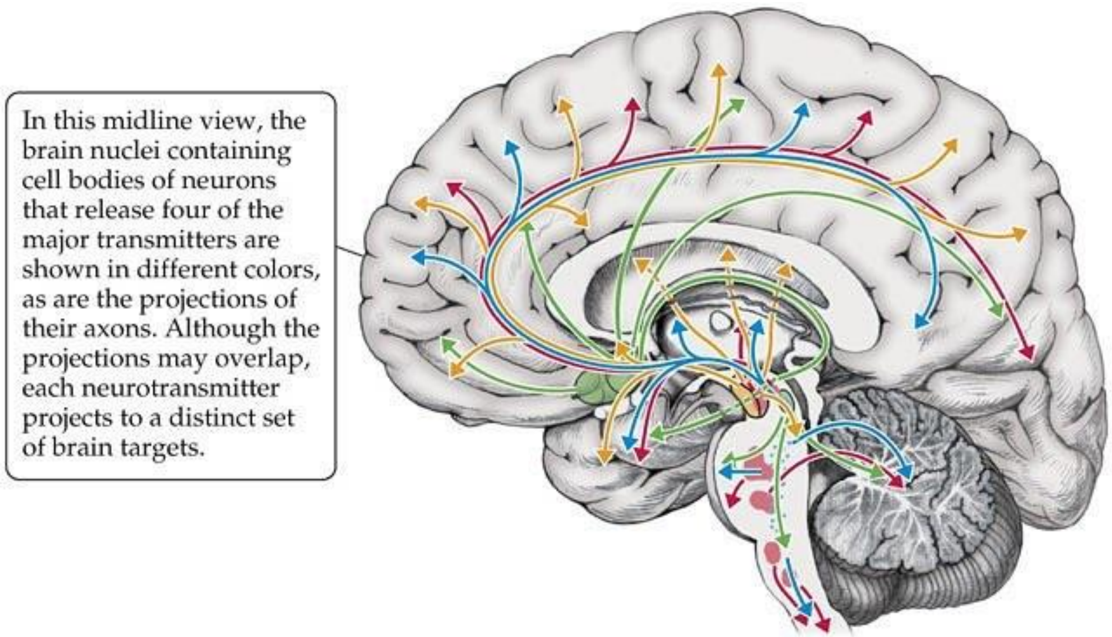
Single-cell input-output (response) function with different gains

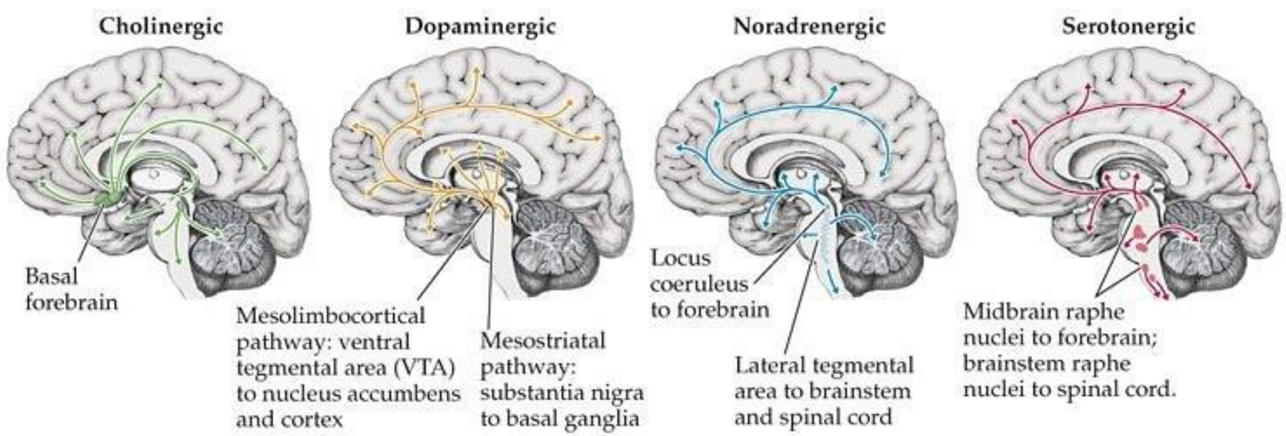




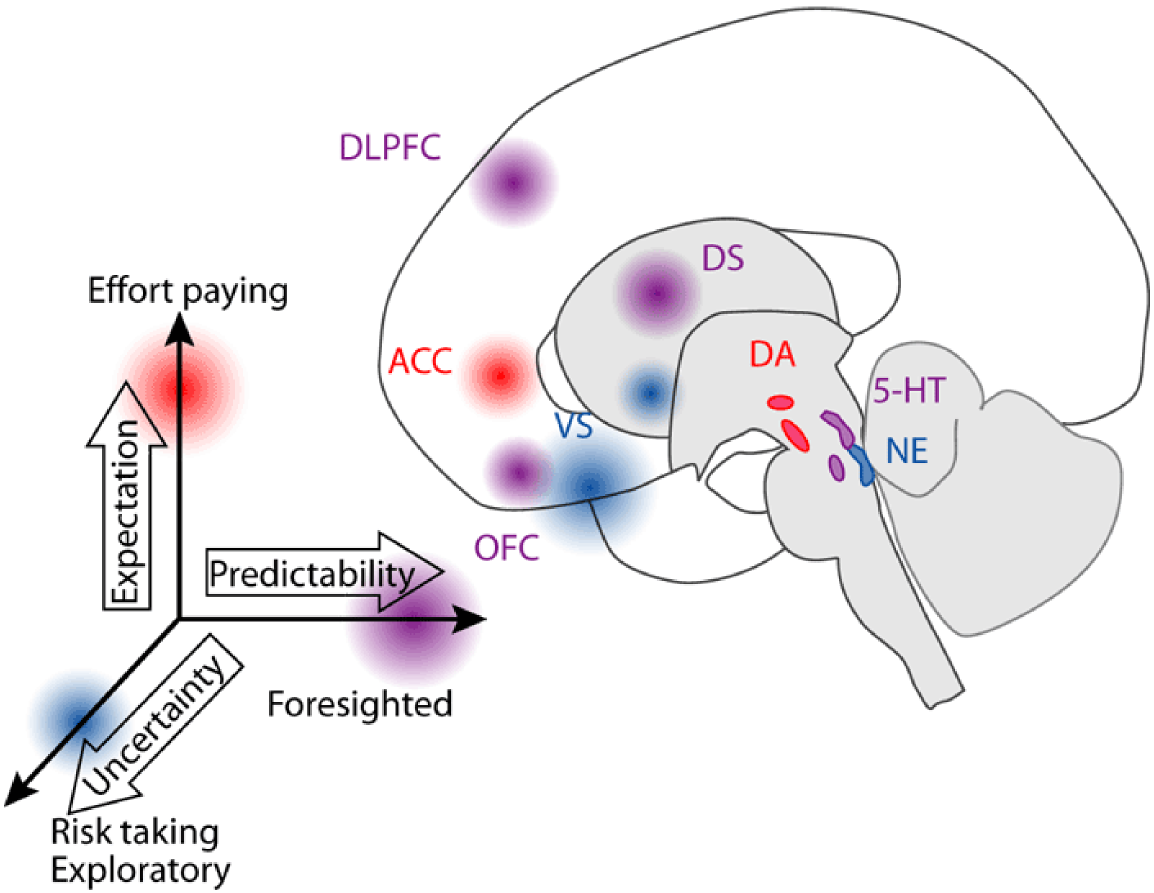
Niyogi & Wong-Lin, PLoS Comput. Biol. (2013)

Chemical neuromodulation





Theories of chemical neuromodulation on decision-making

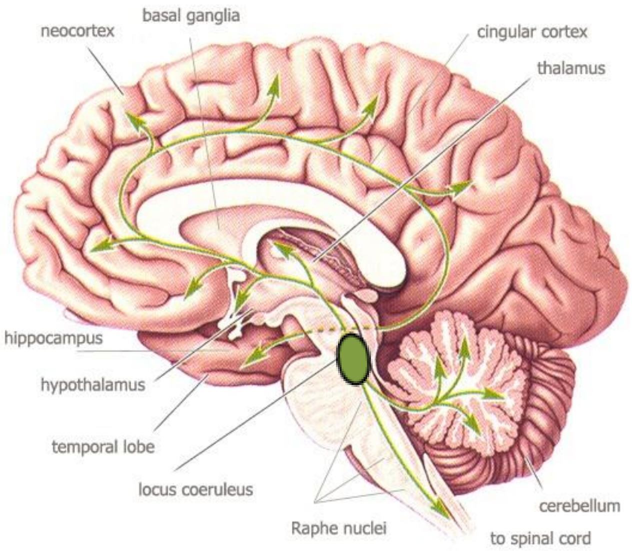


Kenji Doya, Modulators of decision making, Nat. Neurosci. (2008)

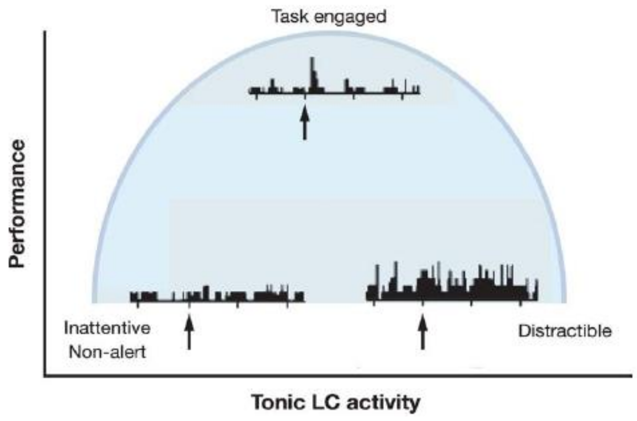
Norepinephrine / noradrenaline (NE / NA)

Involves in arousal, stress, “fight-or-flight” response, attention, etc

The locus coeruleus (LC) releases NE throughout the brain, modulating neural network.



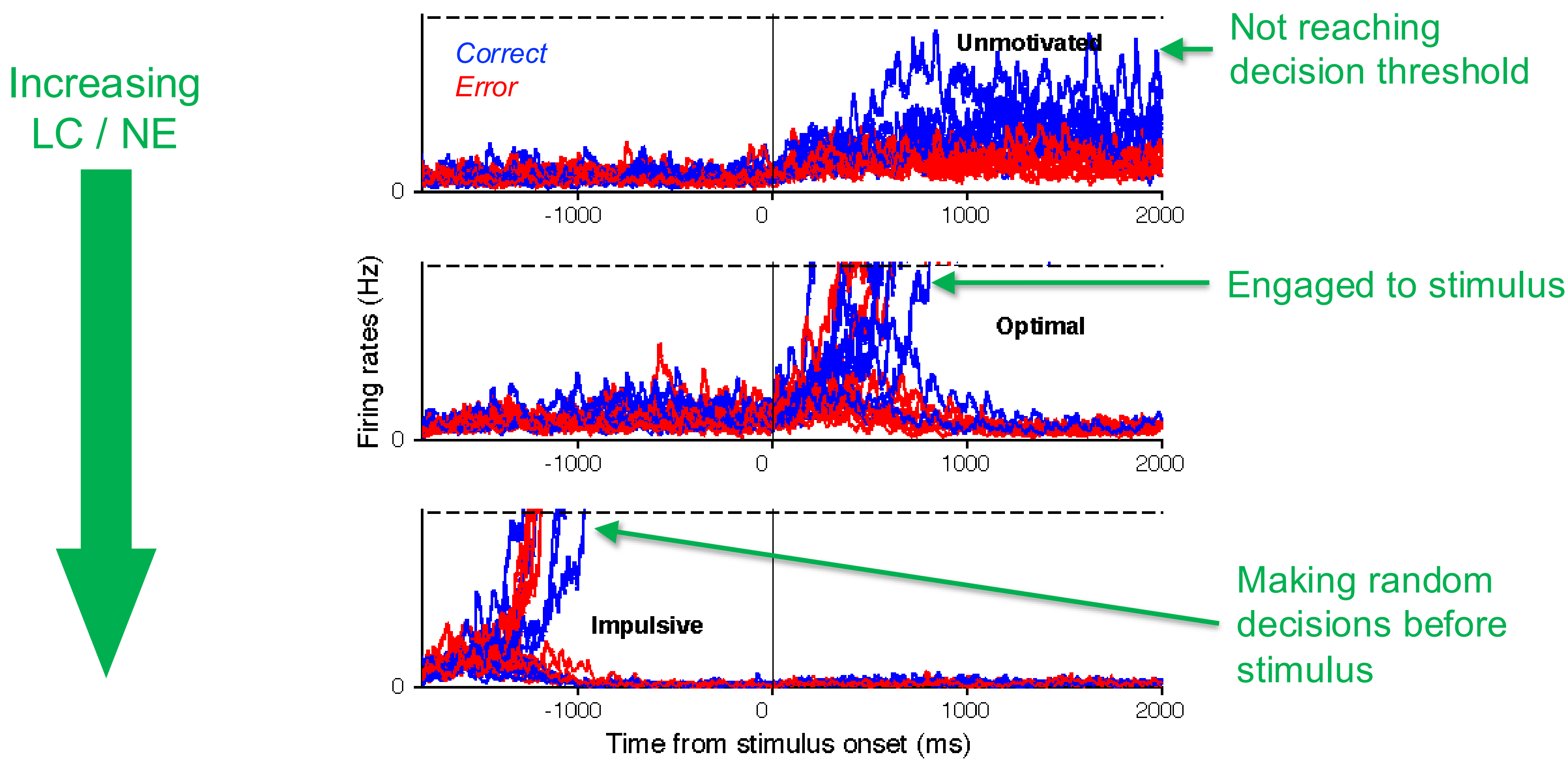
Different LC/NE levels are correlated with different behaviours



Aston-Jones et. al (1999); Aston-Jones and Cohen (2005)

Change in model decision dynamics under "chemical" modulation (of internal state)

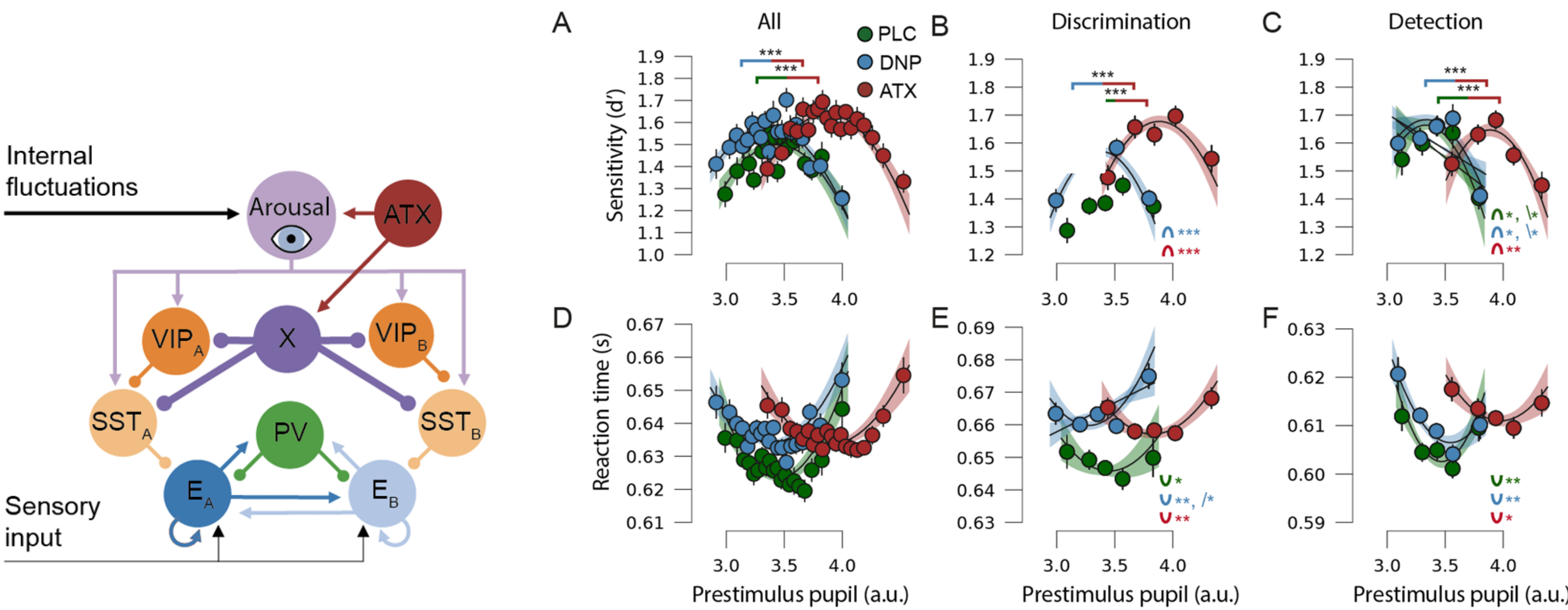
10 sample trials with the *same* external stimulus.



Eckhoff, Wong-Lin & Holmes, J. Neurosci. (2009)

Eckhoff, Wong-Lin & Holmes, SIADS (2011)

Change in model decision dynamics under "chemical" modulation (of internal state)



Atomoxetine is used to treat attention-deficit hyperactivity disorder (ADHD) in children, teenagers, and adults. It belongs to the group of medicines called selective norepinephrine reuptake inhibitors (SNRIs)

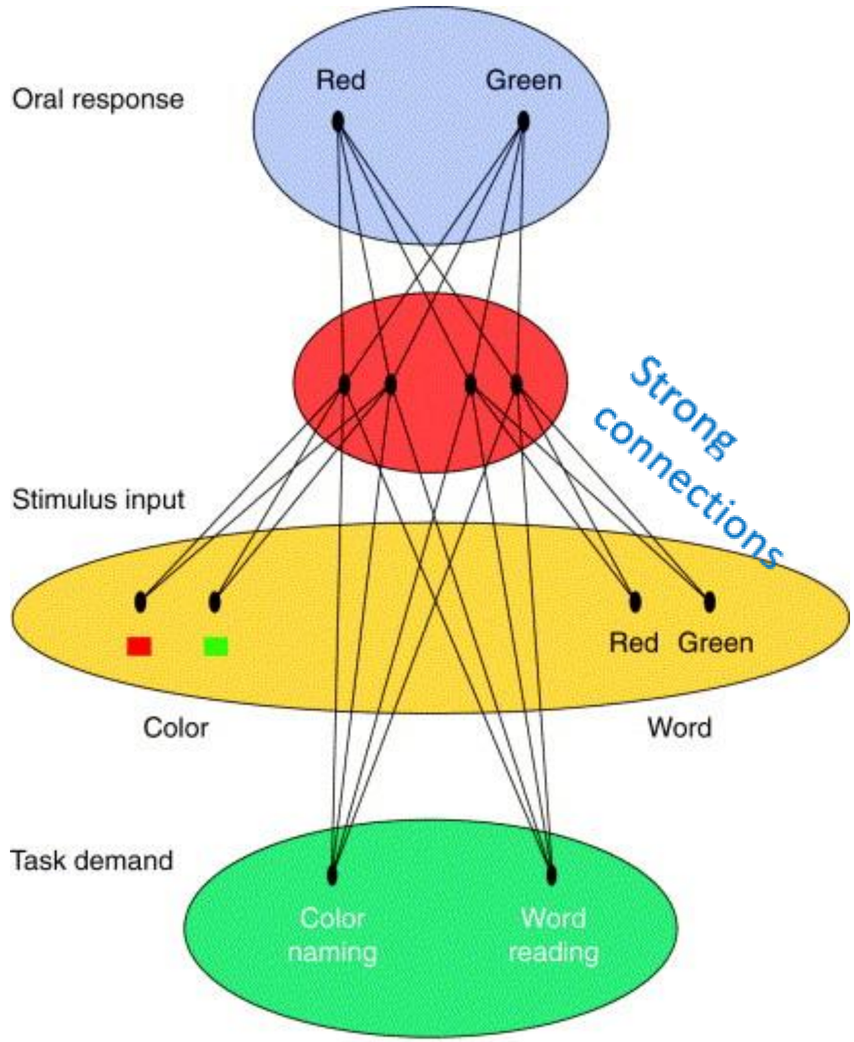
Beerendonk et al., PNAS (2025)

Rule-based decisions and flexible task-switching

Classic Stroop task and task switching: Word reading or colour naming.

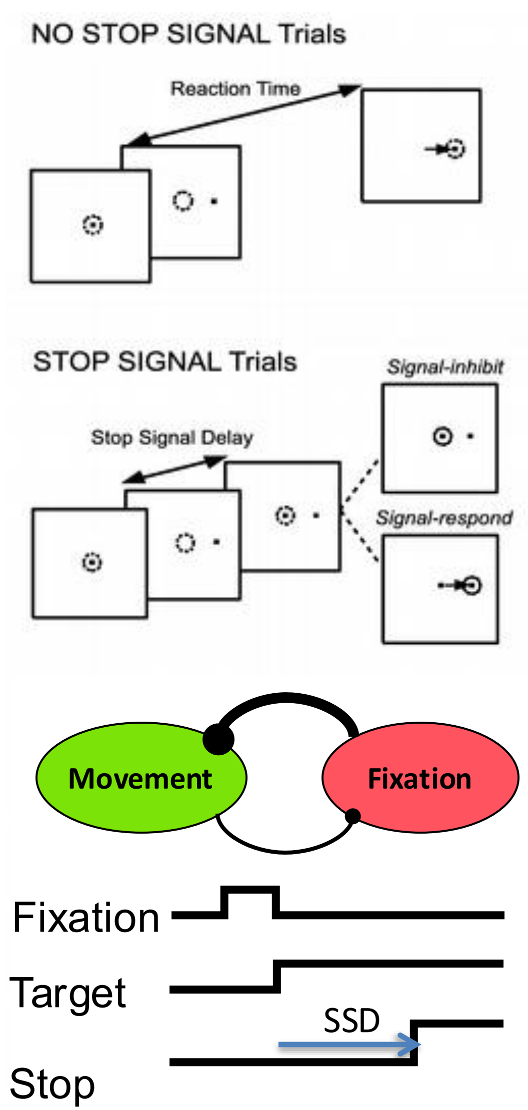
BLUE	GREEN	YELLOW
PINK	RED	ORANGE
GREY	BLACK	PURPLE
TAN	WHITE	BROWN

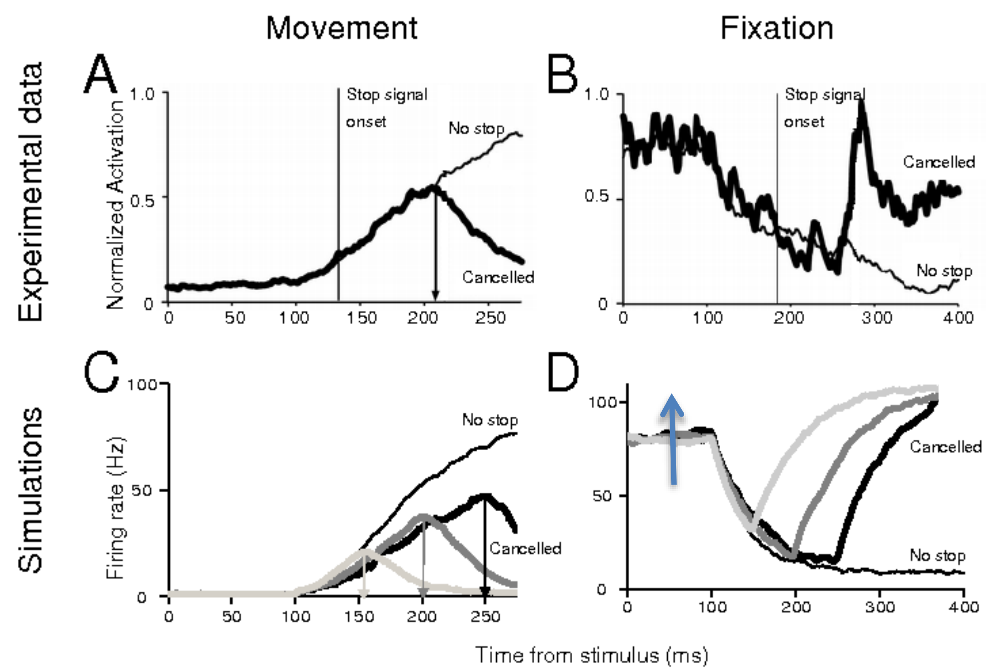
Guided activation theory: Network model with cognitive control for Stroop task



Cohen & Huston (1994)
Colin & MacDonald (2000)
Ito et al. (2022)

Proactive inhibition of an impending decision

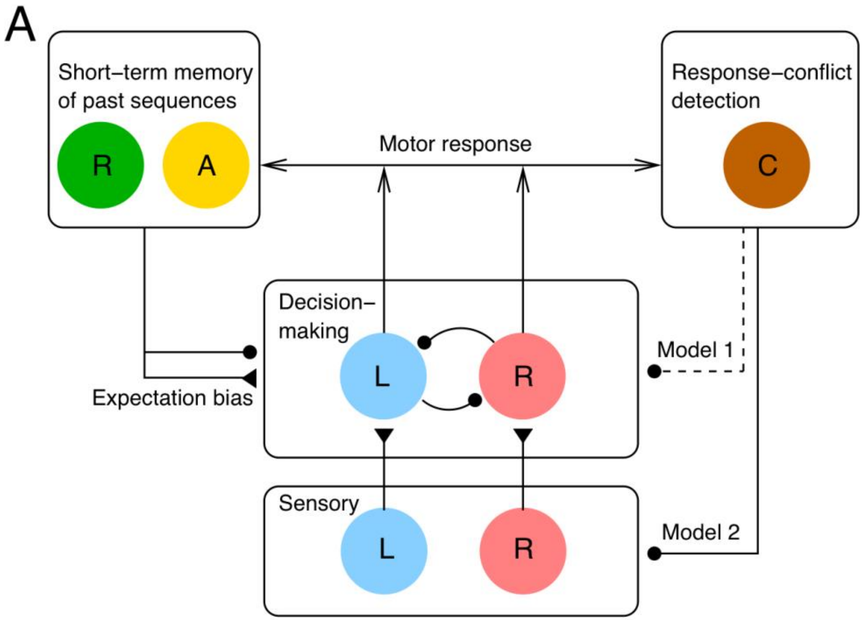


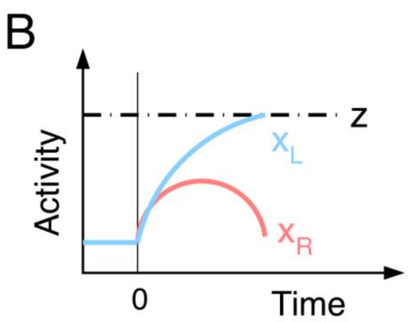


Wong-Lin, Eckhoff, Holmes & Cohen, Brain Res. (2010)

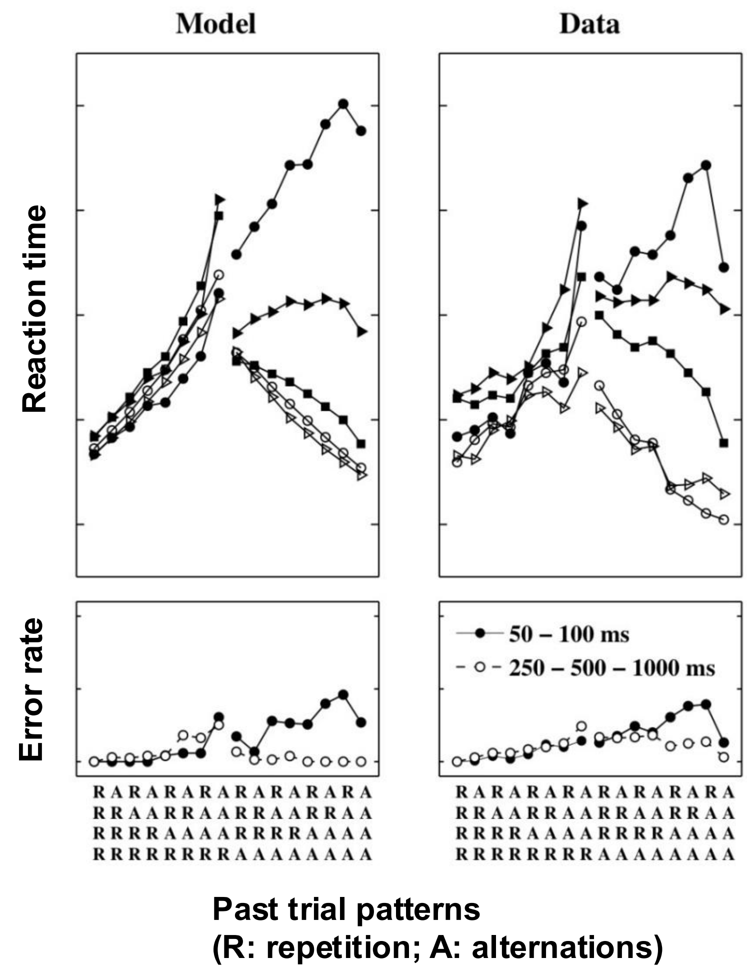
Yang, McGinnity & Wong-Lin, Front. Neuroeng. (2012)

Sequential effects in simple decisions



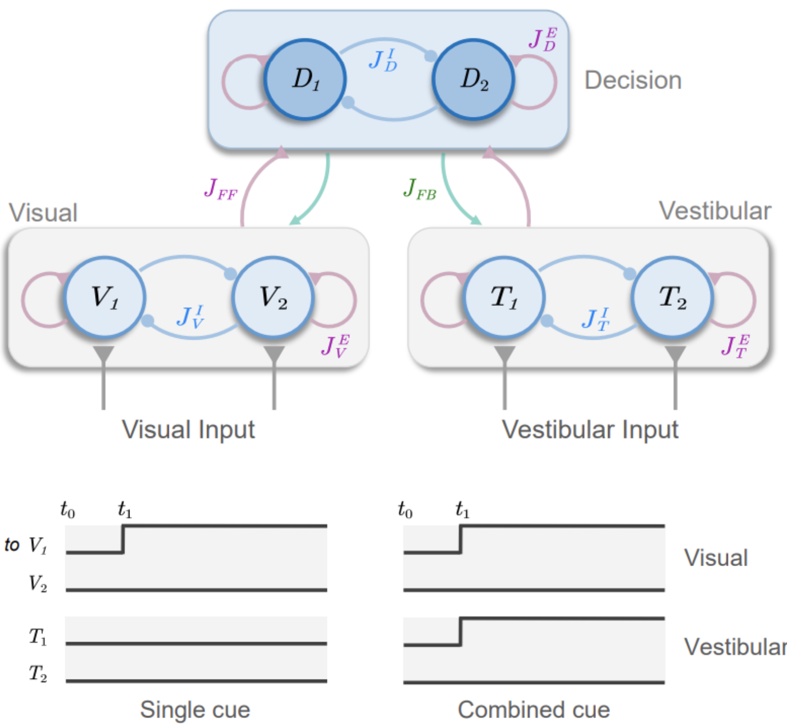


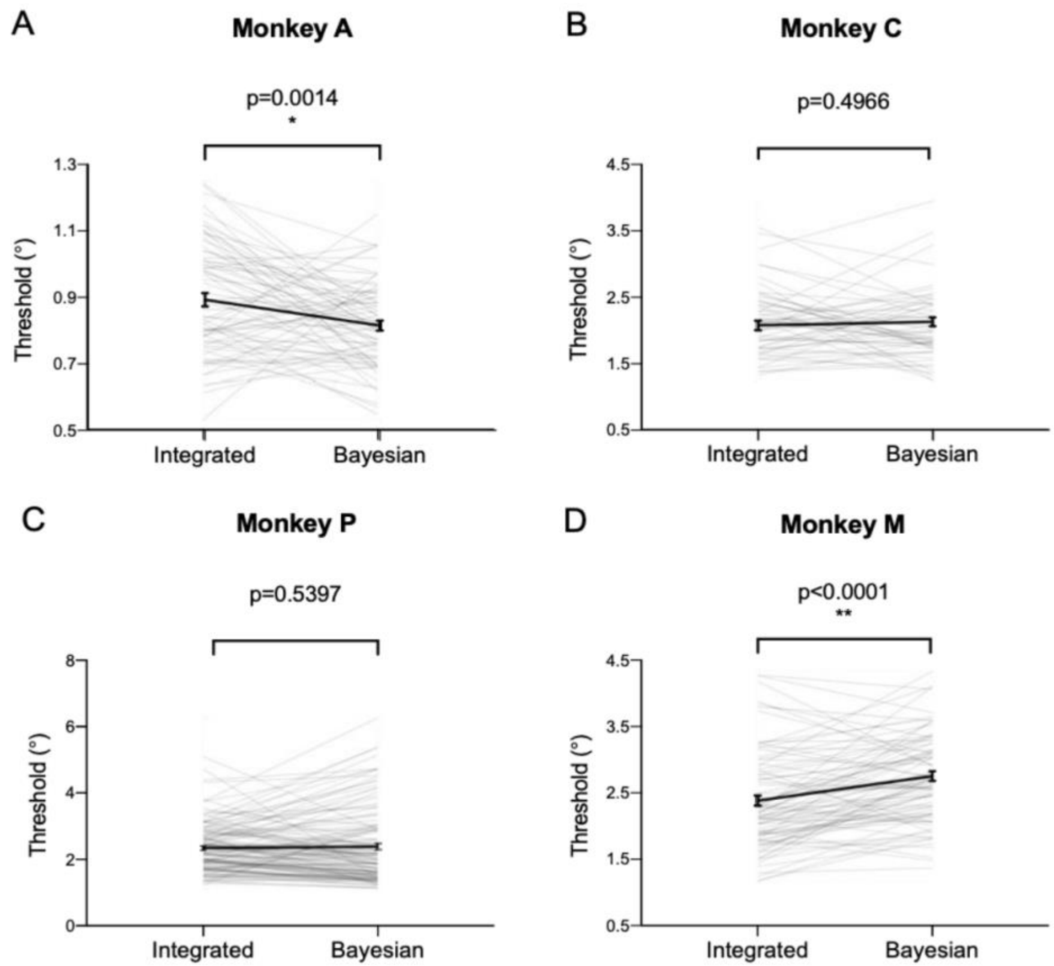
Modified LCA model
(2 biases in drift rate +
post-decision decay)



Gao, Wong-Lin, Holmes, Simen & Cohen, Neural Comput. (2009)

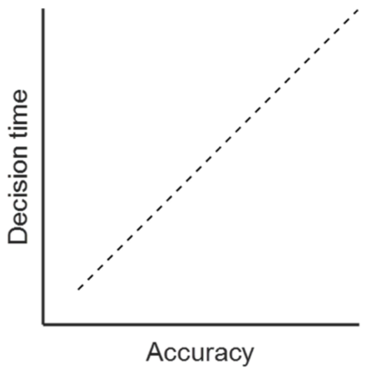
“Top-down” feedback effects on multisensory decisions

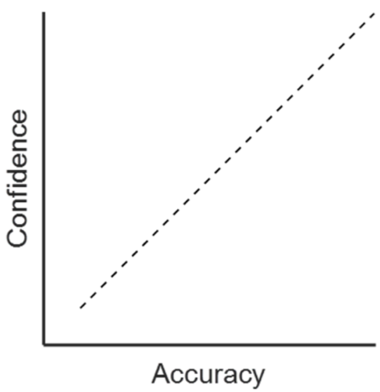


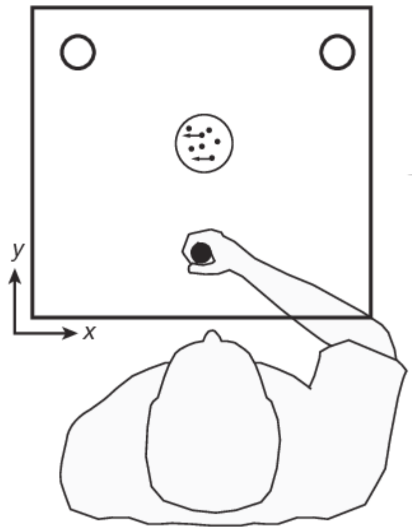


Dong, You, Shao, Gu, Wong-Lin & Wang, Neurosci Bull. (Accepted)

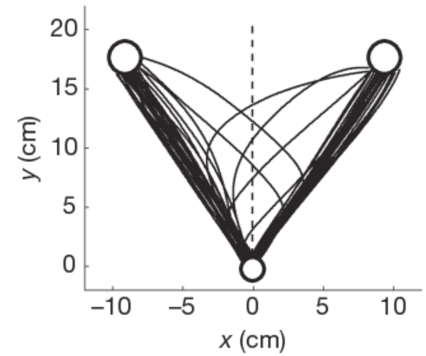
Decision confidence/uncertainty and change-of-mind



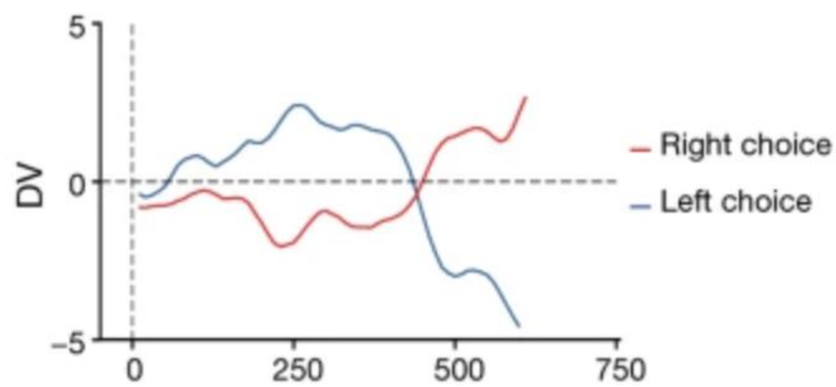




Motor or neural trajectories in addition to subjective confidence rating and reaction time

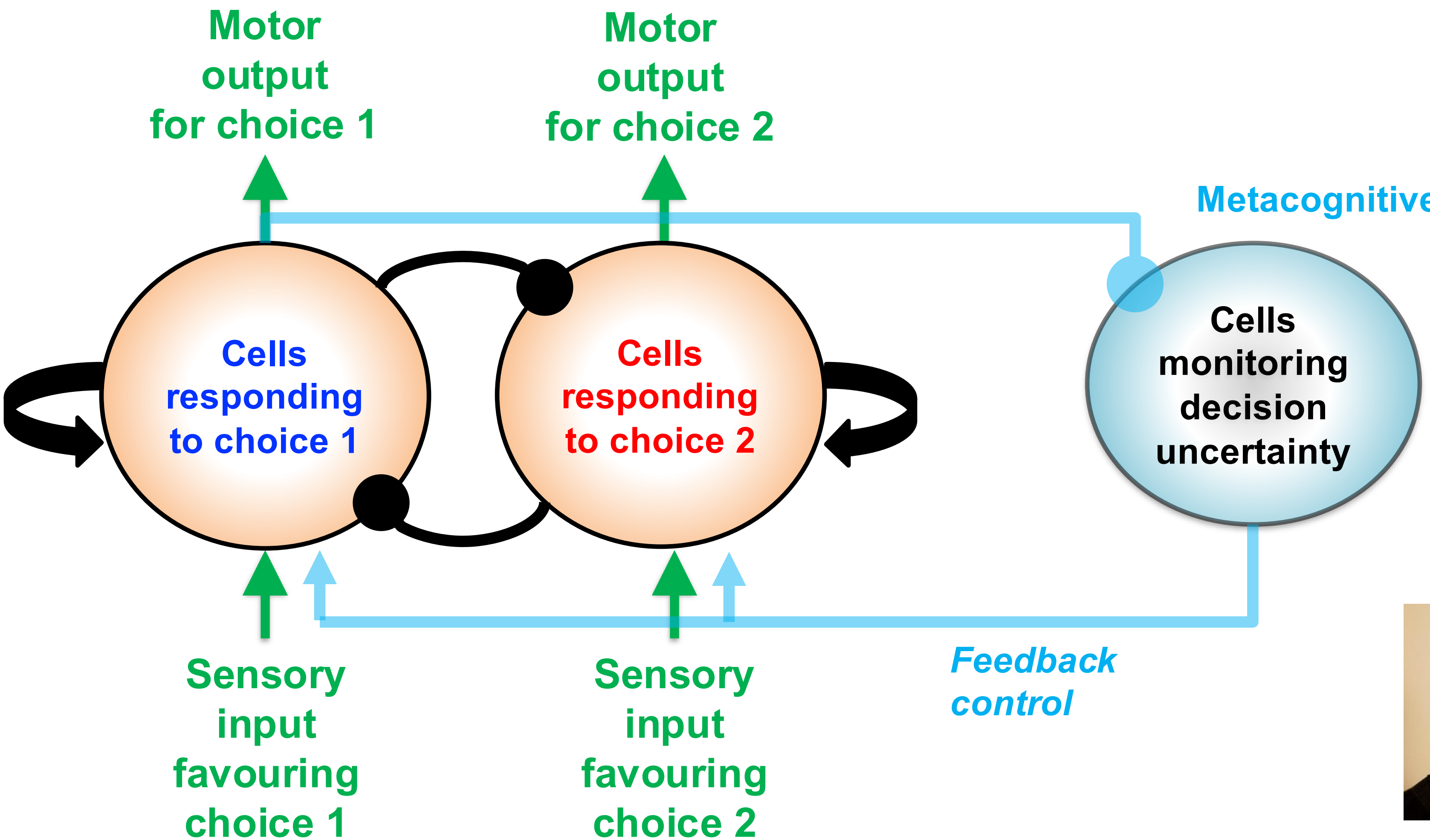


Resulaj, Kiani, Wolpert & Shadlen, Nature (2009)



Peixoto et al., Nature (2021)

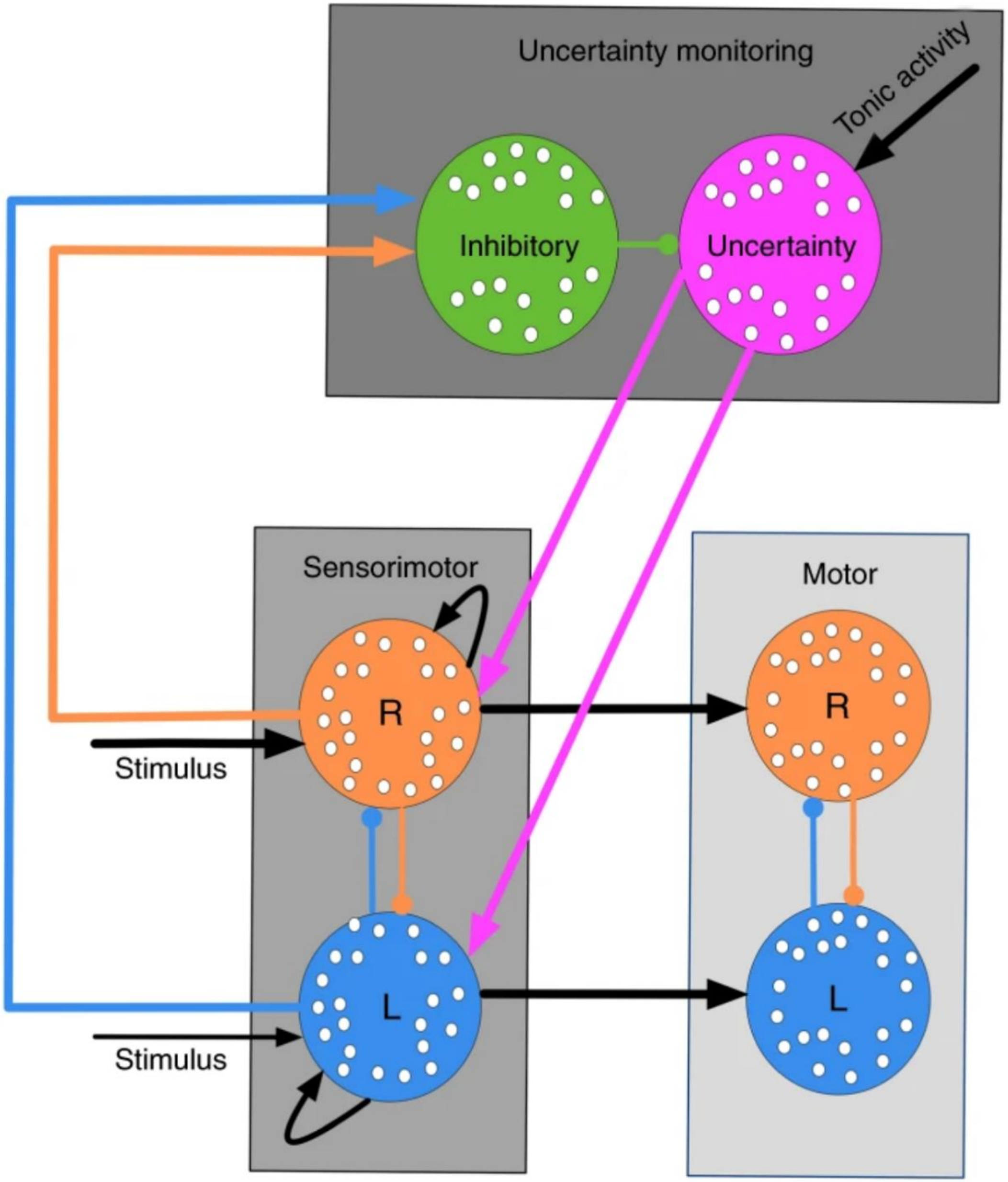
Real-time monitoring of decision uncertainty ("awareness") and change-of-mind

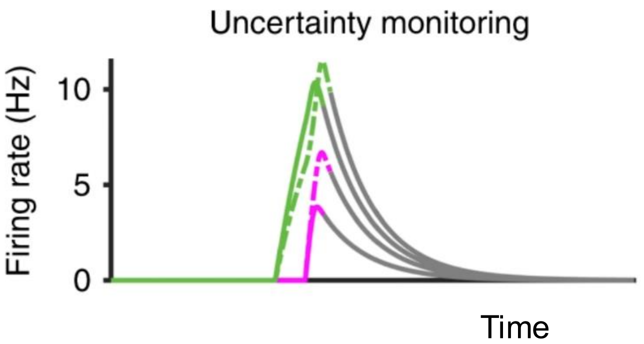


Nadim Atiya

Atiya, Rano, Prasad & Wong-Lin, Nat. Commun. (2019)

Atiya, Zgonnikov, O'Hora, Schoemann, Scherbaum & Wong-Lin, PLoS Comput. Biol. (2020)



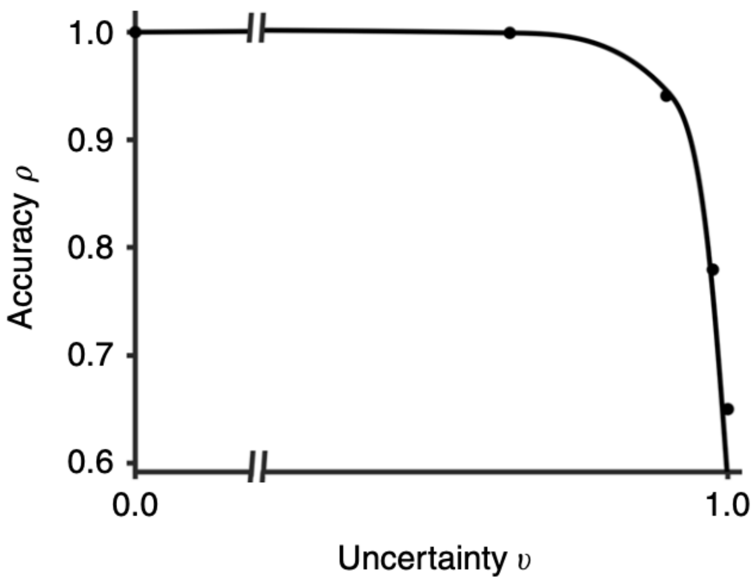


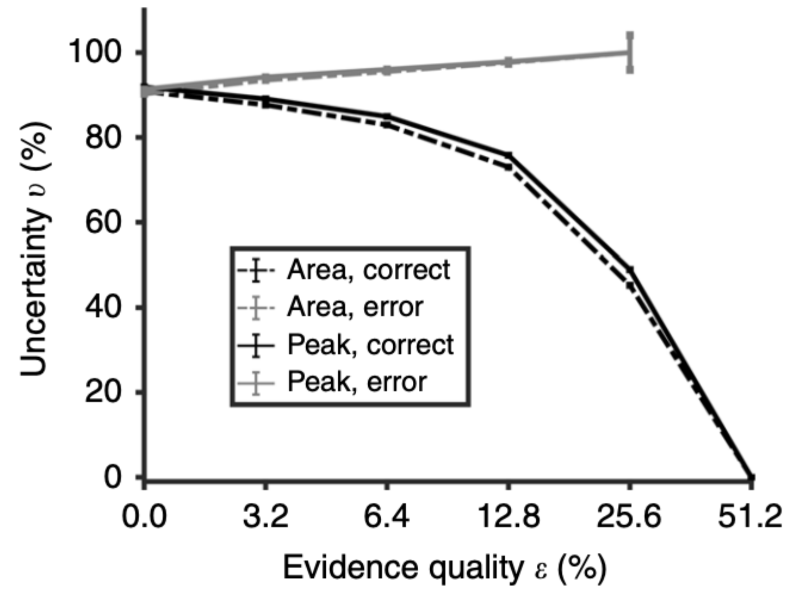
Dashed: Lower signal
Bold: Higher signal

Atiya, Rano, Prasad & Wong-Lin, Nat. Commun. (2019)

Model captures key characteristics of decision confidence/uncertainty

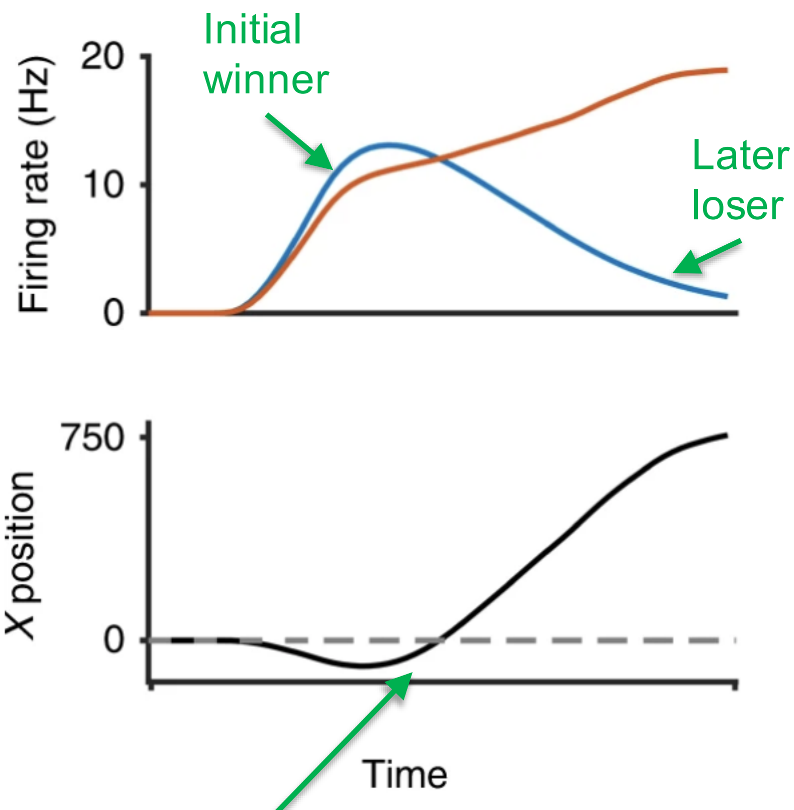
“<“ or “X-shaped”



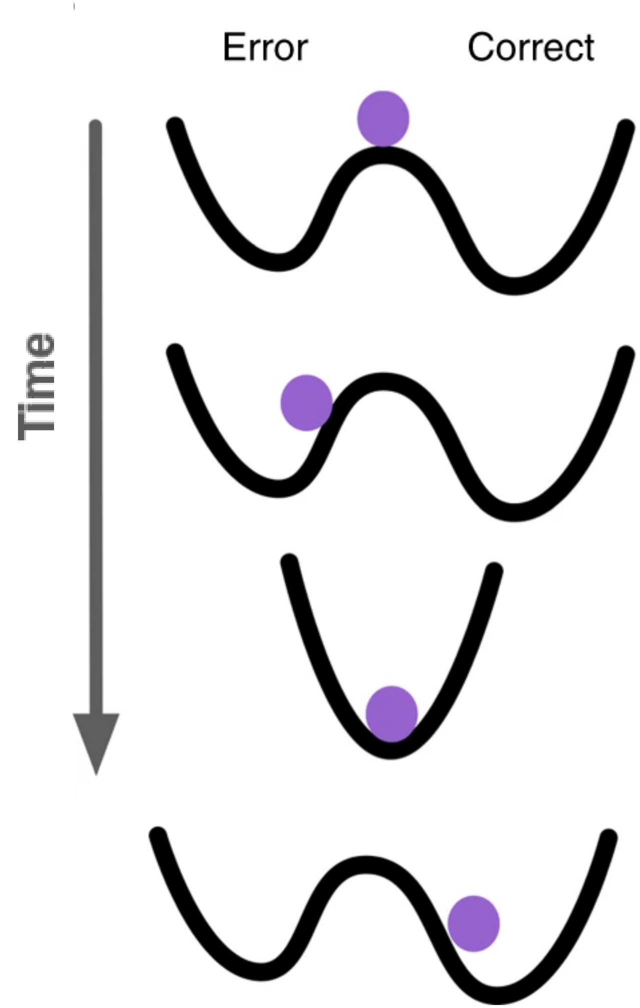


Atiya, Rano, Prasad & Wong-Lin, Nat. Commun. (2019)

Model provides an explanation for change-of-mind

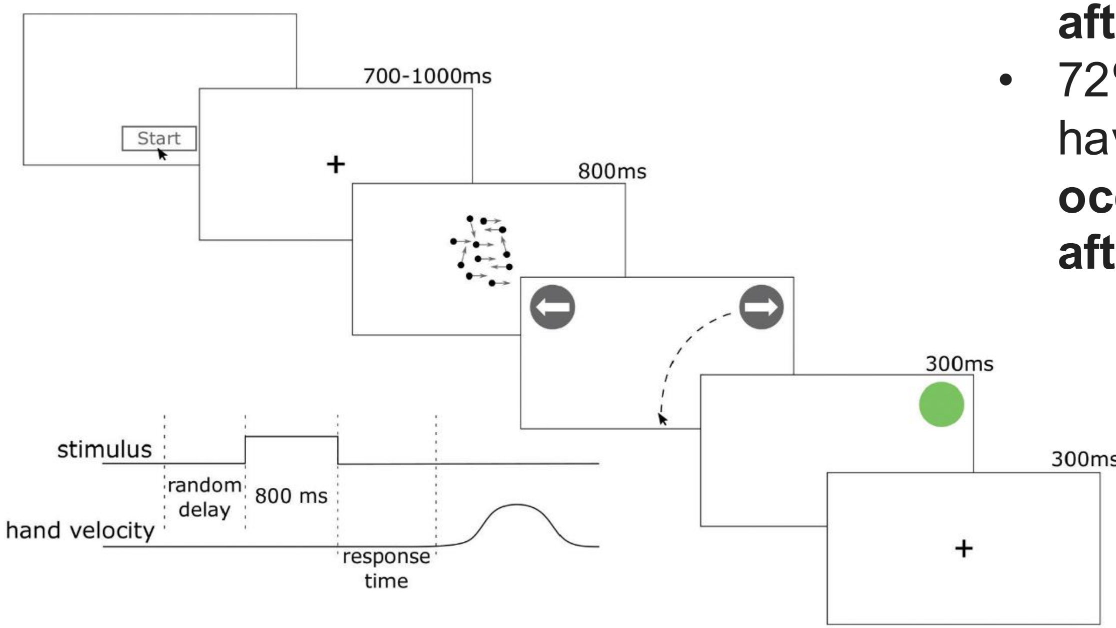


Change-of-mind
reflected in motor movement

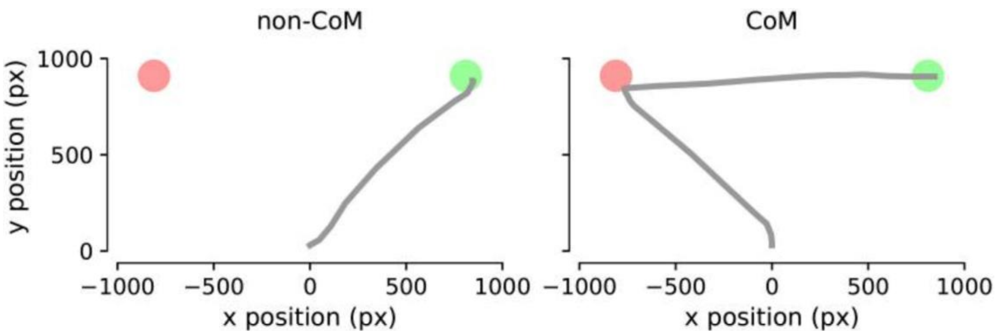


Atiya, Rano, Prasad & Wong-Lin, Nat. Commun. (2019)

Model prediction: Changes-of-mind can occur in the absence of additional evidence after initial decision



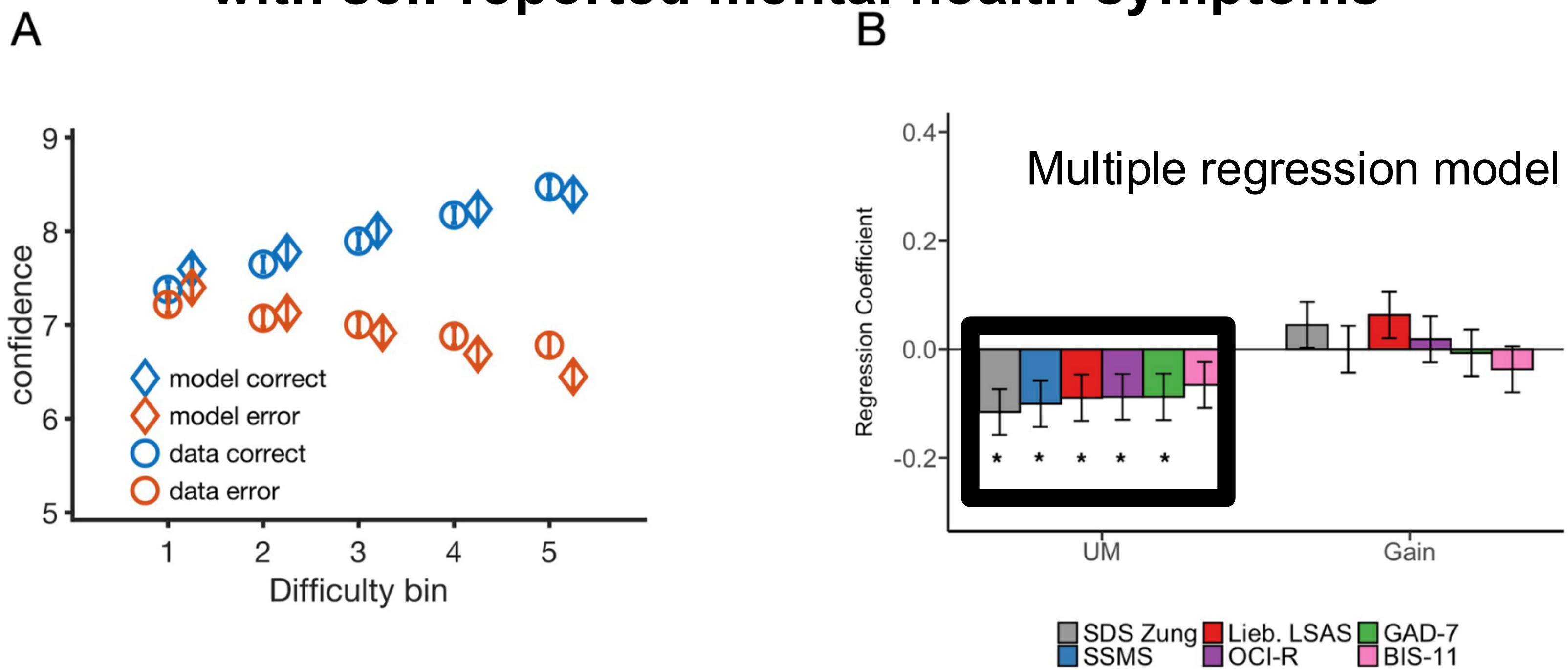
- Participants respond only **after** stimulus offset
- 72% change-of-mind trials have **decision reversal occurring later than 450ms after stimulus offset**



Atiya, Zgonnikov et al., PLoS Comput. Biol. (2020)

Model accounts for data in separate study:

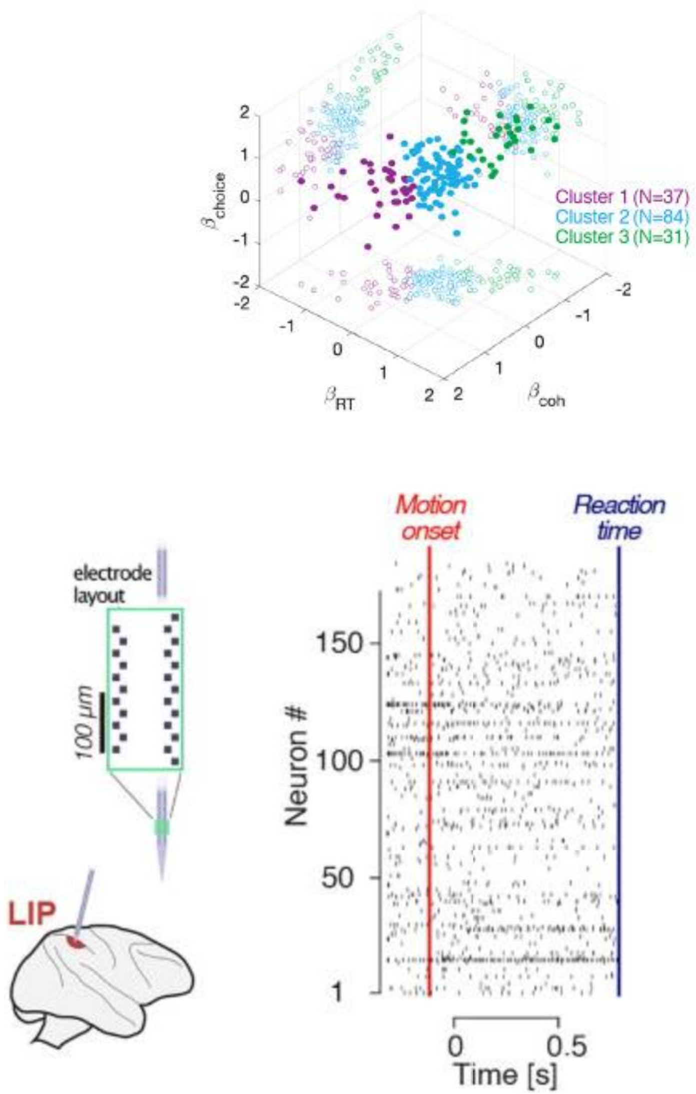
Weaker model uncertainty monitoring connectivity associated with self-reported mental health symptoms

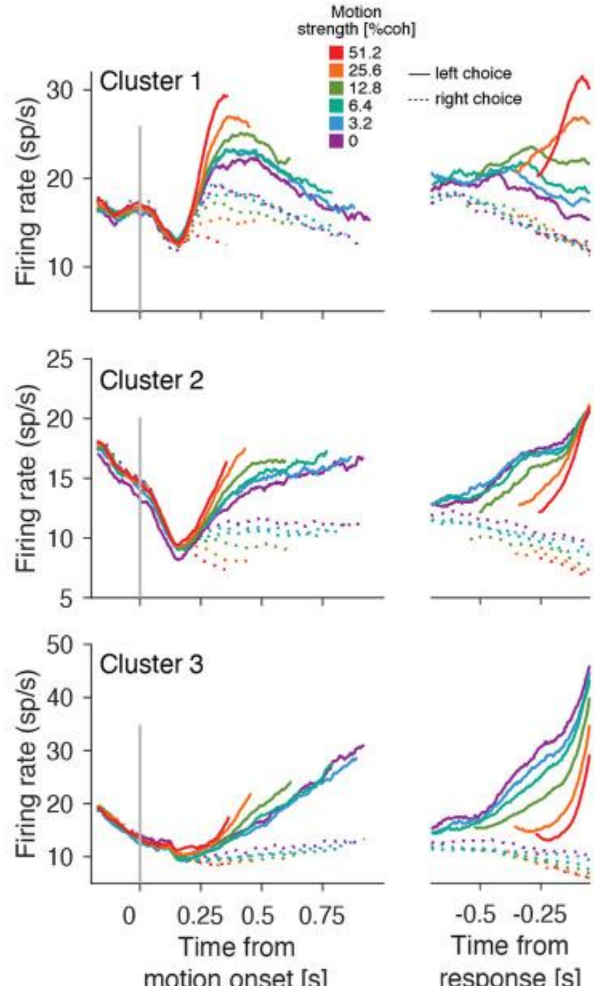


Atiya, Huys, Dolan & Fleming, PLoS Comput. Biol. (2021)

Self-report measures of depression, schizotopy, social anxiety, obsessive & compulsive symptoms & generalised anxiety associated with weaker uncertainty modulation but not impulsivity. No association with stimulus gain parameter.

Area LIP neuronal population encodes decision & confidence



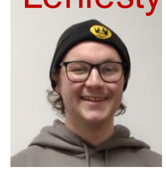


Memory of evidence, or decision confidence?

Sequential sampling to threshold

Decision uncertainty?

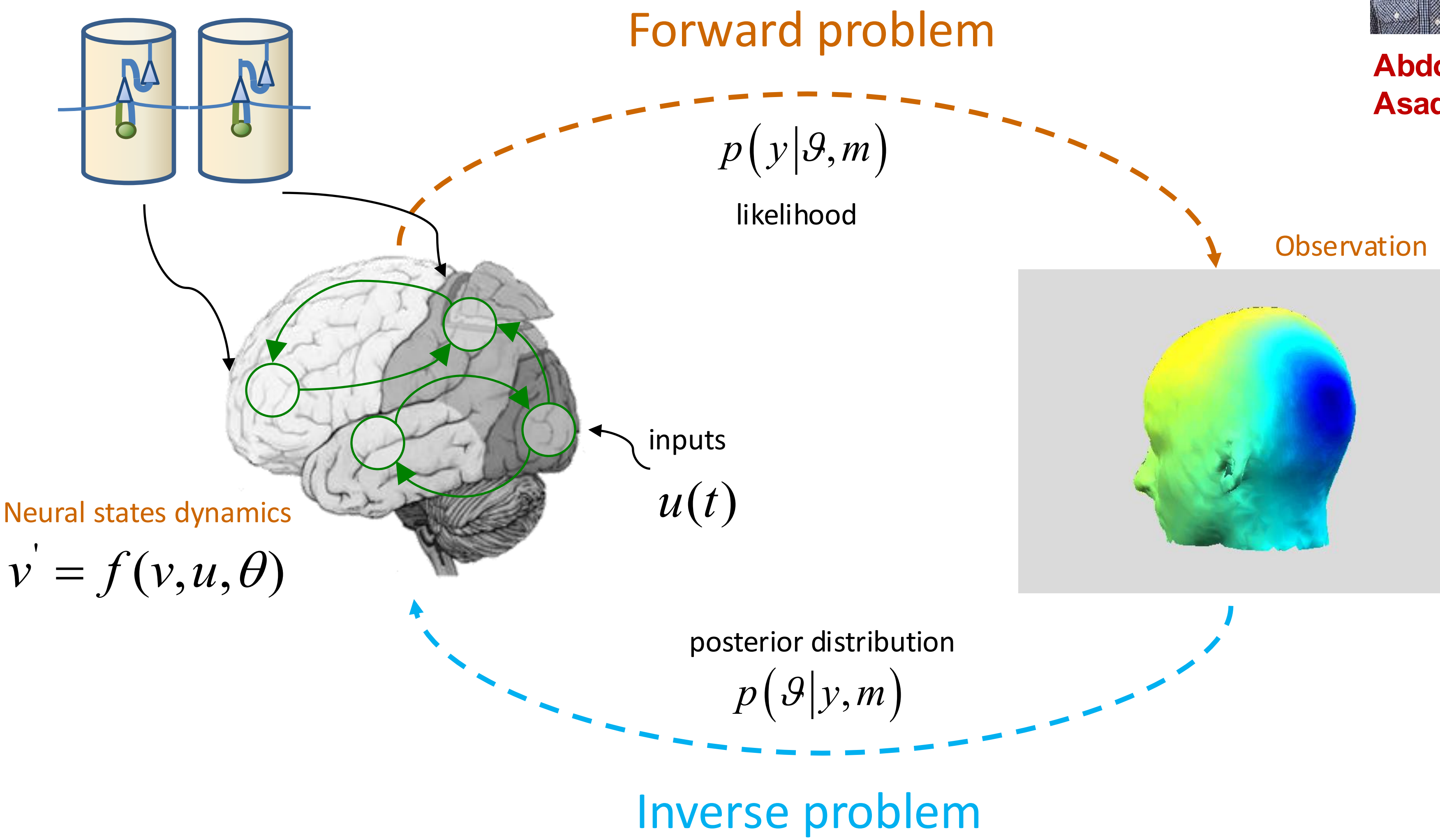
Brendan Lenfesty



Zylberberg & Shadlen, Cell Rep. (2025)

Dynamic causal modelling (DCM) to understand effective connectivity in human decision confidence

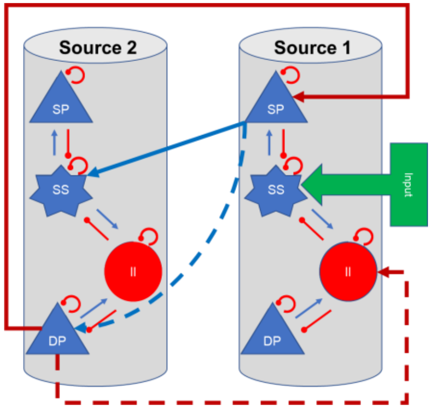
Abdoreza Asadpour



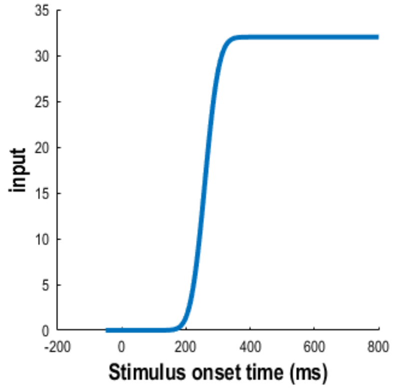
Friston group

fMRI informed EEG-DCM identifies different networks for early perceptual decision confidence, uncertainty and speed (and across cortical layers)

Common regions: left Middle Frontal Gyrus & left Precuneus



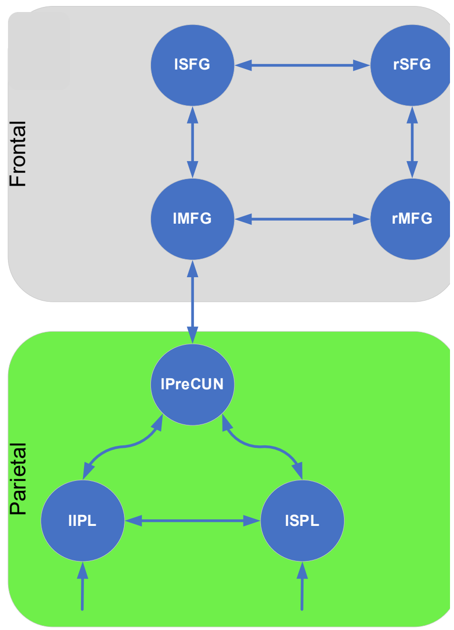
Canonical model

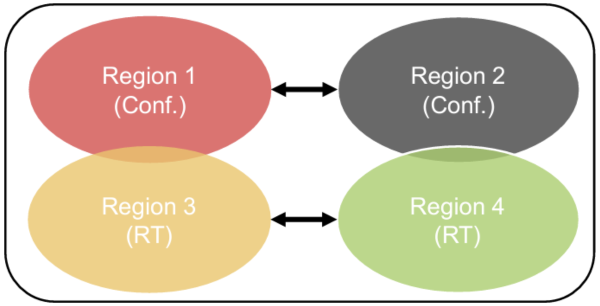


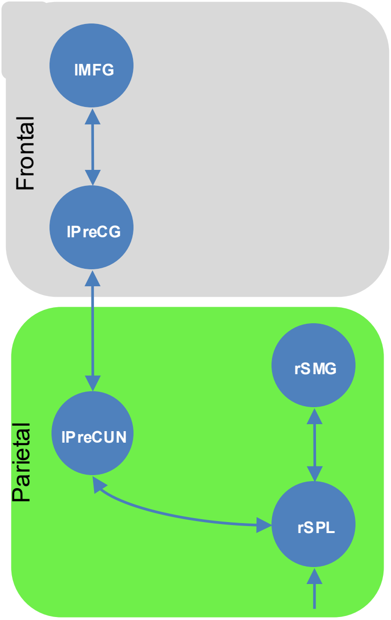
Model input

Low vs high confidence rating

Slow vs fast reaction time

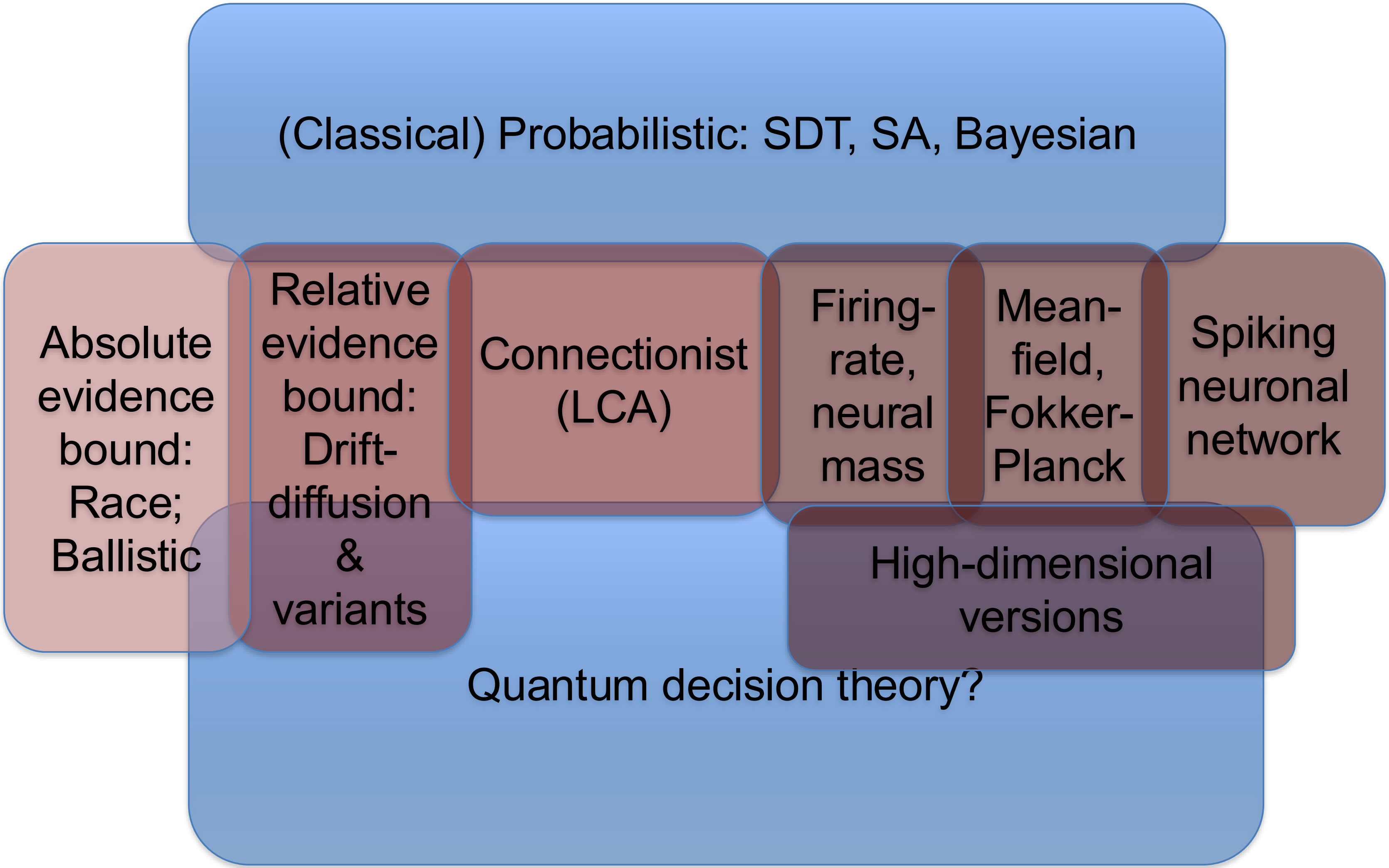




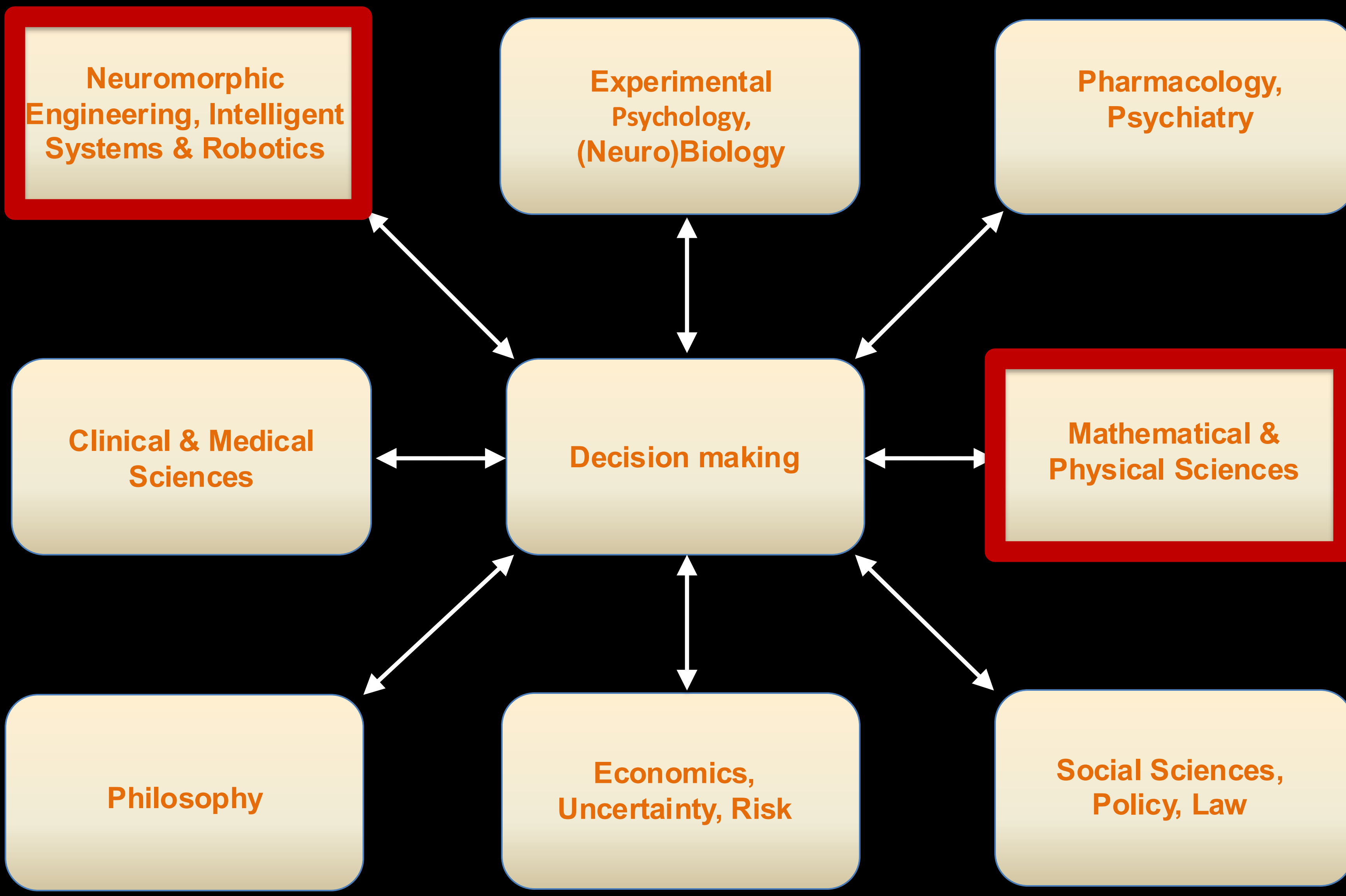


Asadpour & Wong-Lin, bioRXiv (2024); Asadpour & Wong-Lin (Submitted)

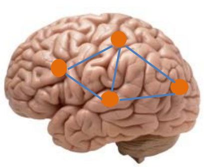
Taxonomy of decision models



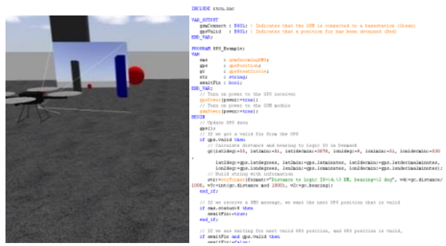
Wide Applications and Links of Decision Making



Applications to intelligent technologies



Computational cognitive neuroscience



Computational models, novel algorithms, & simulations

(Neuromorphic) Implementations in hardware for real-time applications

Implementation in physical intelligent machines & robots

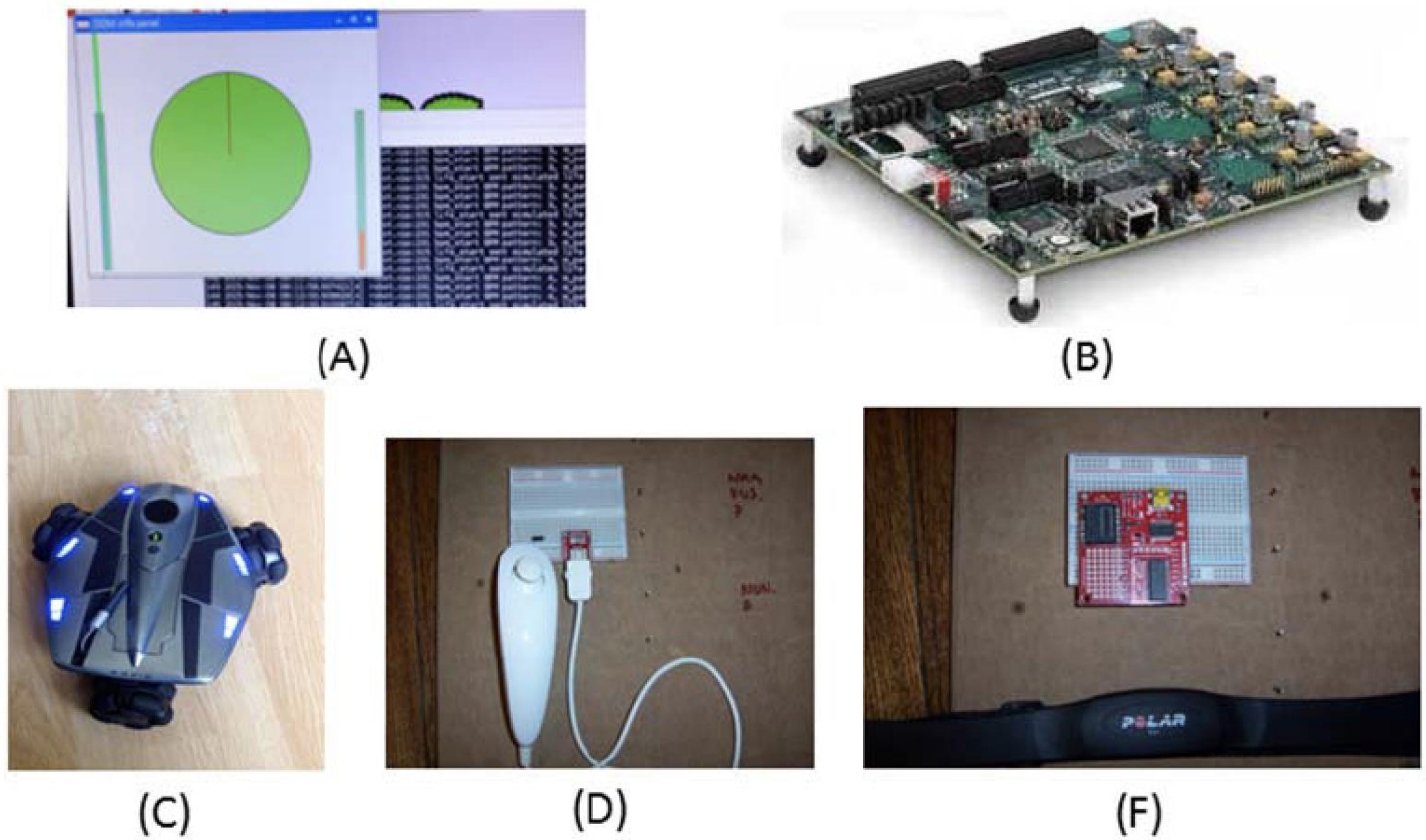
Decision making in AI / machines

A key component in AI and machine algorithms

E.g.

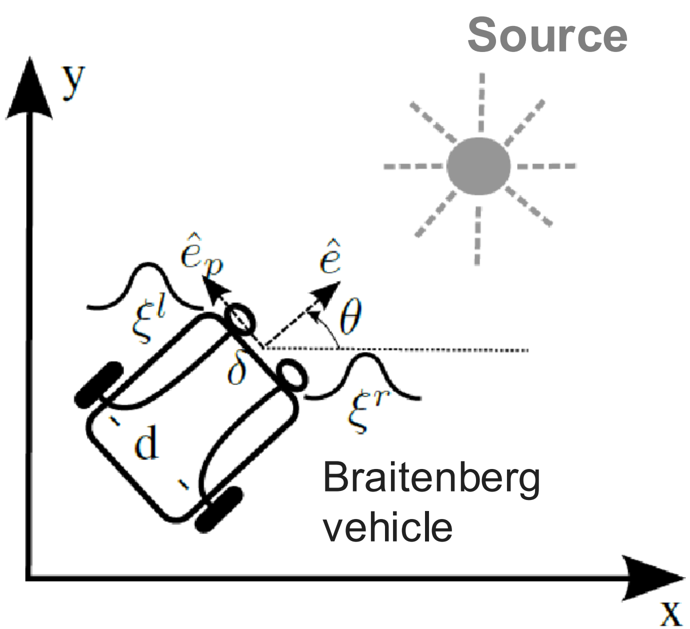
- Search
- Planning
- Probabilistic reasoning (uncertainty reasoning)
- Utility theory
- Probabilistic reasoning over time (e.g. HMM, Kalman filters)
- Utility theory
- Markov Decision Process (MDP)
- Game theory (multi-agent)
- Prediction (Classification, Regression, Reinforcement Learning)
- Association (Link analysis, Sequence analysis)
- Clustering

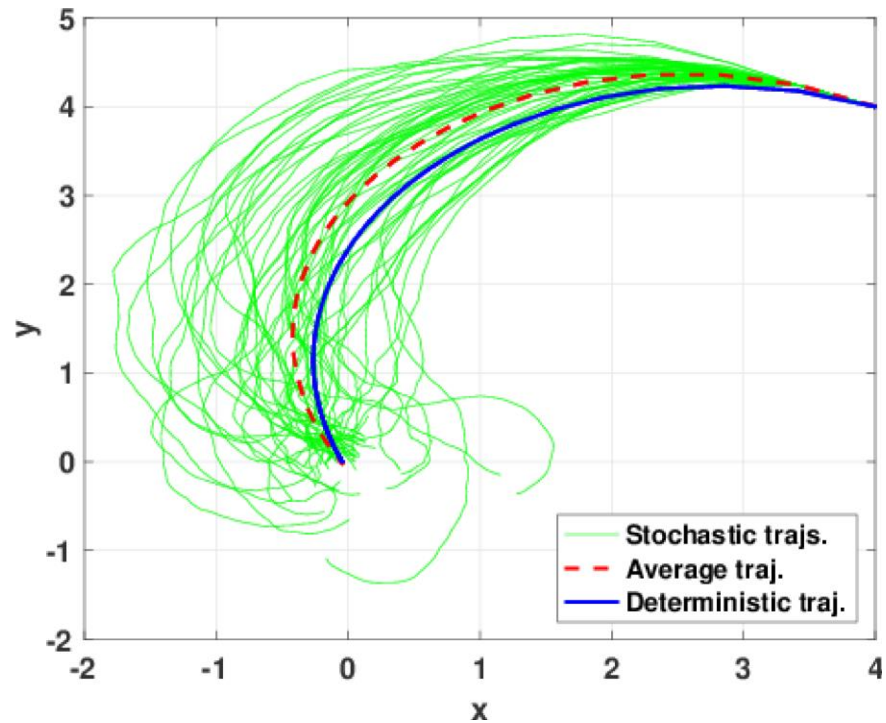
Sensor data fusion using DDM implemented in a single (FPGA) computing chip



Yang, Wong-Lin, Rañó & Lindsay (2017)

Source-seeking mobile robotic model (or heat avoidance of fruit fly) with noisy sensory information as a DDM process

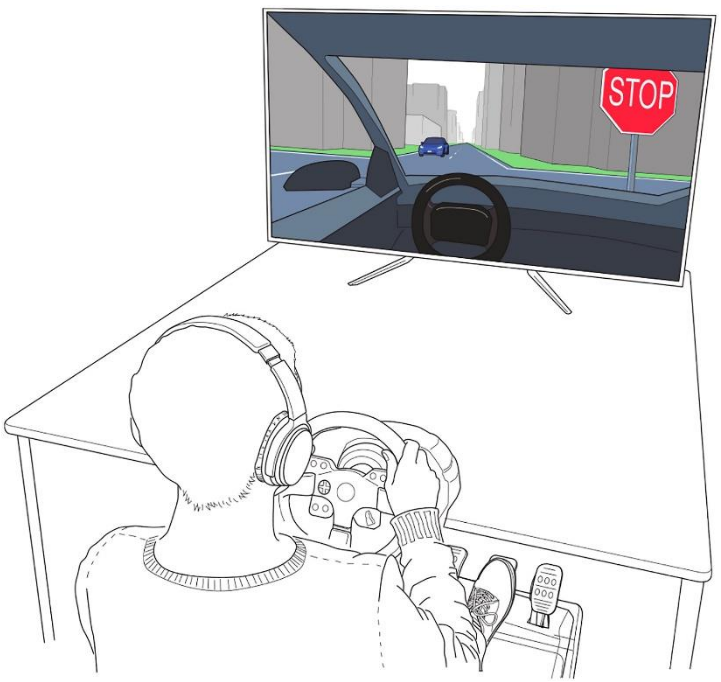


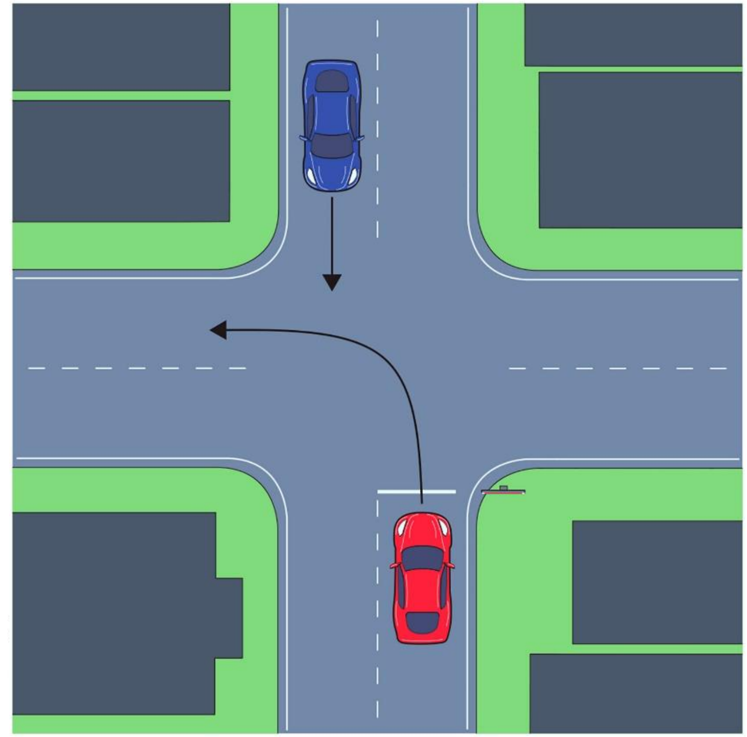


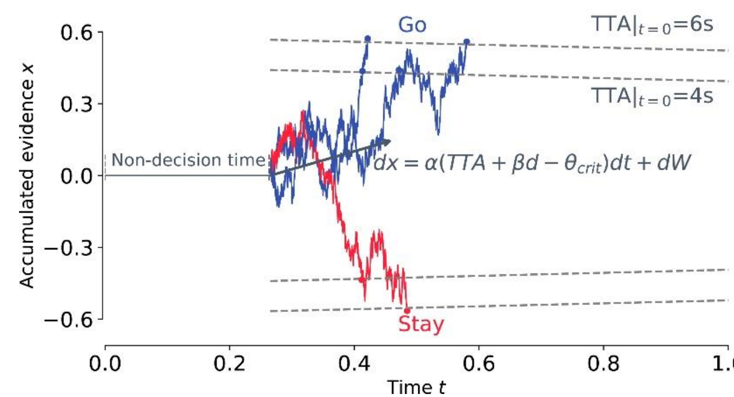
Rañó, Mehdi & Wong-Lin, ICRA (2017) A drift-diffusion model of biological source seeking for mobile robots.

Simoes et al., Nat. Commun. (2021) Robustness and plasticity in Drosophila heat avoidance

Real-time prediction of human decisions by automated vehicles & simulating realistic human-like decisions in virtual environments for automated vehicles



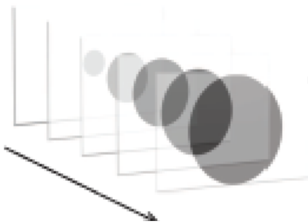




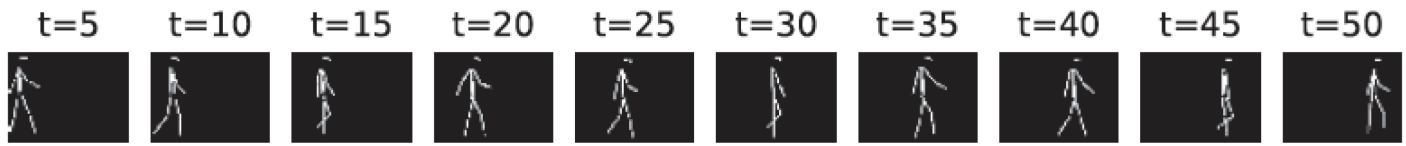
Zgonnikov et al., HFES (2022); Bontje & Zgonnikov, Comput. Brain Beh. (2024)

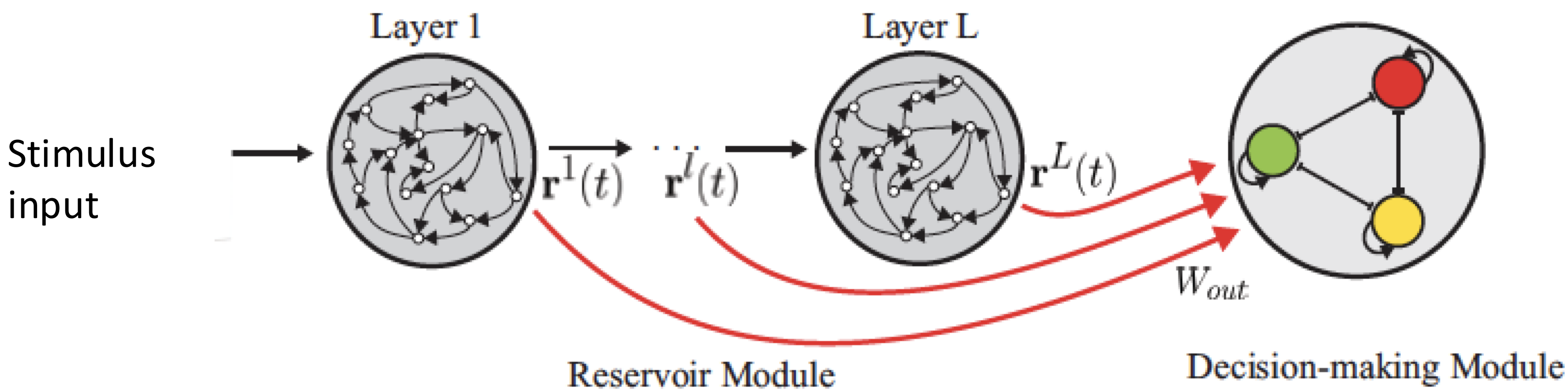
Few-shot machine learning in space & time outperforms state-of-the-art deep learning

Looming pattern detection



Individual's gait identification



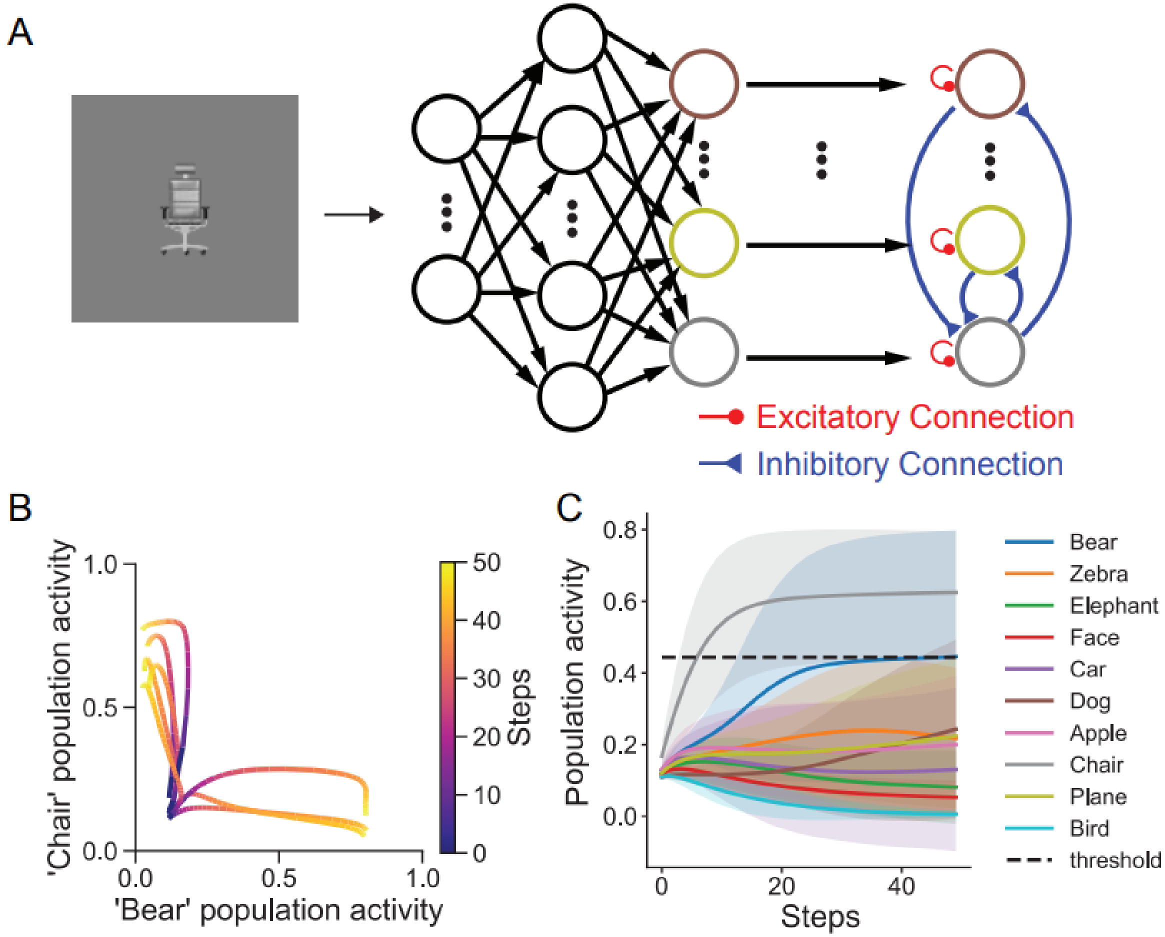


Spatiotemporal → Spatial features

*Spatial → **Temporal integration***

Lin, Zou, Ji, Huang, Wu & Mi Neural Netw. (2021)

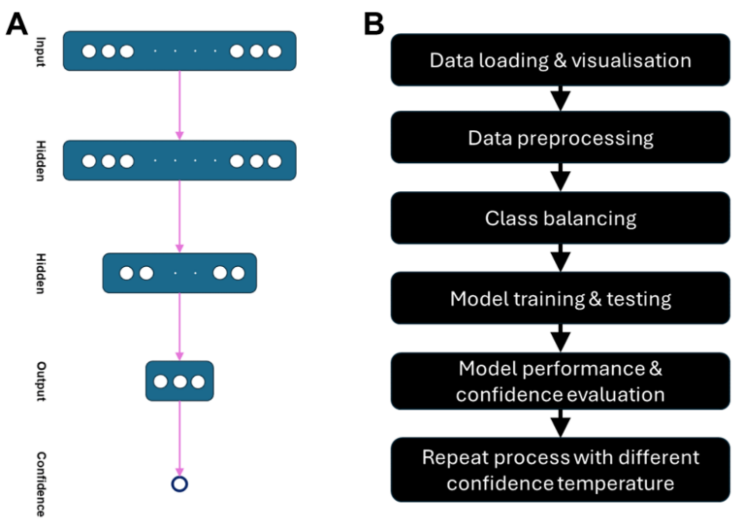
Neuro-inspired deep learning with evidence accumulation



Cheng, Rodriguez, Chen, Kar, Watanabe & Serre, NeurIPS (2024)

Neuro-inspired deep learning with decision confidence for detecting individual with Alzheimer's disease

→ Understand reliability of model's decision for better trust



$$\text{softmax}, \sigma(\boldsymbol{z})_i = \frac{e^{\beta z_i}}{\sum_{j=1}^{3} e^{\beta z_j}}$$

where $\beta = 1/(Temperature)$

Confidence temperature	0.5	1.0	1.5	2.0	2.5
Average classification accuracy	0.8448	0.8421	0.8320	0.8466	0.8476
SD accuracy	0.3621	0.3647	0.3739	0.3603	0.3594
Average confidence	0.8152	0.8066	0.7888	**0.8188**	0.8163
SD confidence	0.1628	0.1681	0.1678	0.1578	0.1613
TP confidence	0.8024	0.6723	0.9401	**0.8415**	0.6889
TN confidence	0.8152	0.7511	0.5369	**0.7839**	0.6621
FP confidence	0.8084	0.6538	0.6690	**0.6946**	0.6871
FN confidence	0.7288	0.7796	0.7783	**0.7238**	0.6297

TP, TN > FP, FN

Alausa, Sanchez-Bornot, Asadpour, McClean & Wong-Lin (2024)

Summary

- Network dynamics as representation and tools for understanding decision making
- Low-dimensional decision models can account for (and explain) key dynamics in neural and behavioural data
- More complex choice behaviour and dynamics can be built on simpler models, e.g. for cognitive control
- Neurodynamical models of brain-wide activities for distributed encoding of decision processing
- AI (machine learning) closely linked to decision-making → opportunities for brain-inspired intelligent technologies (NeuroAI)