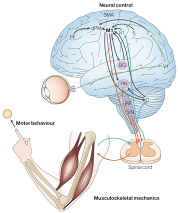
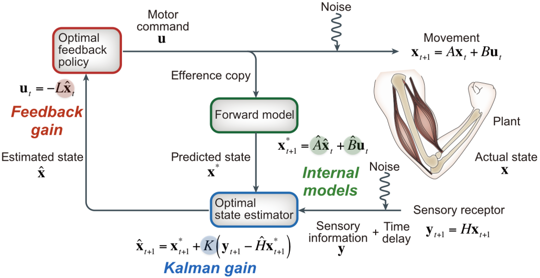
Neuromechanics of Human Motion

Decision-Making and Action Selection

Joshua Cashaback, PhD

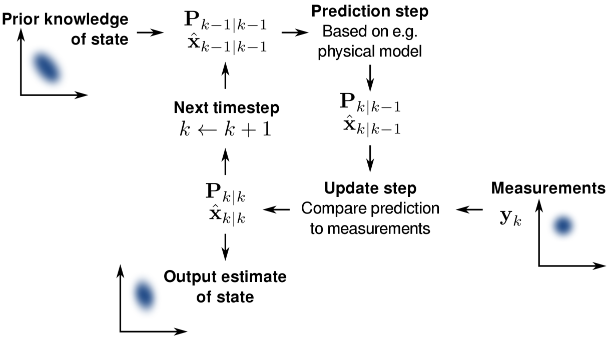
Recap — OFC


Neural control
SMA
dPM
M1
S1
PF
BG
V1
RN
RF
VN
Motor behaviour
Spinal cord
Musculoskeletal mechanics

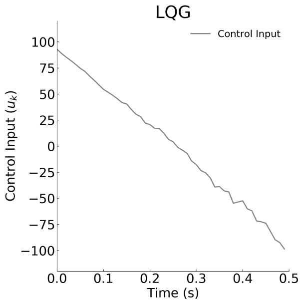

Optimal feedback policy
Motor command
$\mathbf{u}$
Noise
Movement
$\mathbf{x}_{t+1} = A\mathbf{x}_t + B\mathbf{u}_t$
Efference copy
$\mathbf{u}_t = -L\hat{\mathbf{x}}_t$
Feedback gain
Forward model
Plant
$\mathbf{x}^*_{t+1} = \hat{A}\hat{\mathbf{x}}_t + \hat{B}\mathbf{u}_t$
Estimated state
$\hat{\mathbf{x}}$
Predicted state
$\mathbf{x}^*$
Internal models
Noise
Actual state
$\mathbf{x}$
Optimal state estimator
Sensory receptor
Sensory information
$\mathbf{y}$
+
Time delay
$\mathbf{y}_{t+1} = H\mathbf{x}_{t+1}$
$\hat{\mathbf{x}}_{t+1} = \mathbf{x}^*_{t+1} + K\left(\mathbf{y}_{t+1} - \hat{H}\mathbf{x}^*_{t+1}\right)$
Kalman gain

Recap — OFC

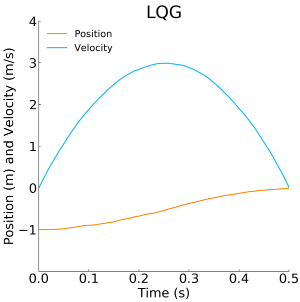
$$J = \sum_{k=0}^{N-1} \left(x_k^T Q x_k + u_k^T R u_k \right)$$



Recap — OFC



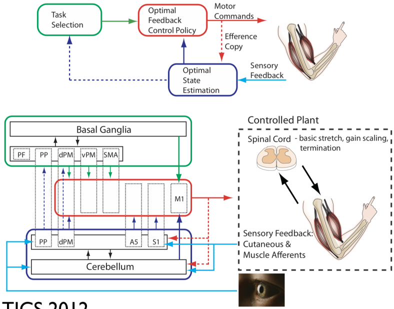
LQG
Control Input
Control Input (u_k)
100
75
50
25
0
−25
−50
−75
−100
0.0
0.1
0.2
0.3
0.4
0.5
Time (s)



LQG
Position
Velocity
Position (m) and Velocity (m/s)
4
3
2
1
0
−1
0.0
0.1
0.2
0.3
0.4
0.5
Time (s)

Recap — OFC

What task (i.e., action) do we decide to select?



Scott, TICS 2012

Basal ganglia (i.e., internal global paladis [GPi] and external global paladis[[GPe]), prefrontal (PF), dorsal premotor (dPM), parietal (PP; i.e., lateral intraparietal [LIP] and medial intraparietal [MIP])

Lecture Objectives — Decision-making

Decision paradigms

a. dot coherence task
    i. behaviour, neural basis
b. tokens task
    i. behaviour, neural basis

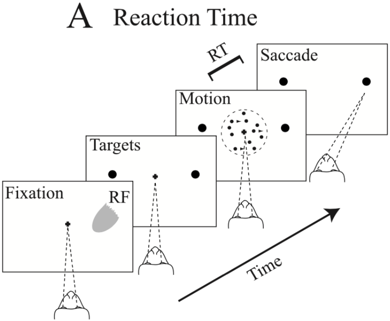
Decision-making models

a. drift diffusion model
b. urgency gating
c. Trueblood model
d. recurrent neural networks

Interplay of Decisions and Action

Dot Coherence Task

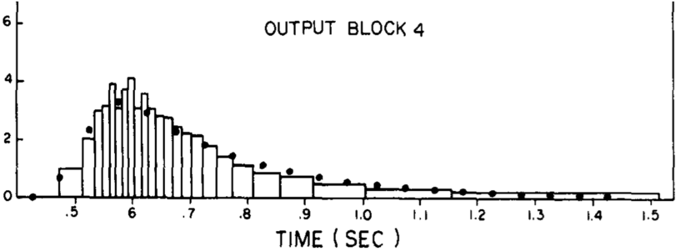
Dot Coherence Task



Roitman (2002)

constant evidence

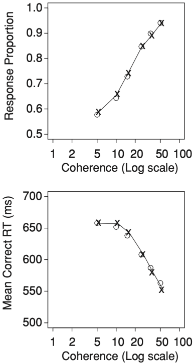
Dot Coherence Task — Behaviour



Ratcliff (1979)

Skewed reaction / decision times for a particular coherence

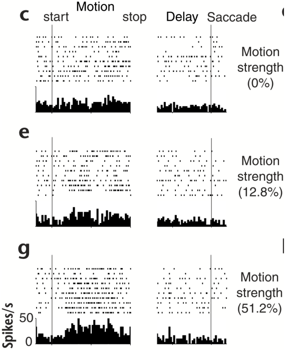
Dot Coherence Task — Behaviour



Ratcliff (1979)

Changes in accuracy and mean decision time with a change in coherence

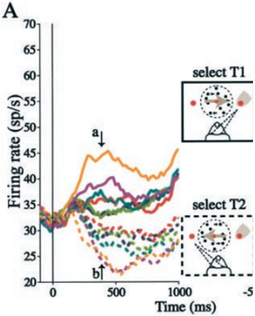
Dot Coherence Task — Neural Basis



Roitman (2002)

Dorsolateral Prefrontal Cortex represents evidence (dot motion)

Dot Coherence Task — Neural Basis

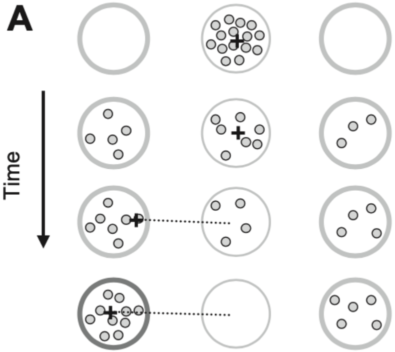


Roitman (2002)

Lateral Intraparietal (LIP; shown) and Medial Intraparietal (MIP; shown) represents evidence accumulation (i.e., integration)

Tokens Task

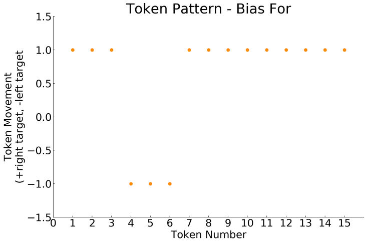
Tokens Task

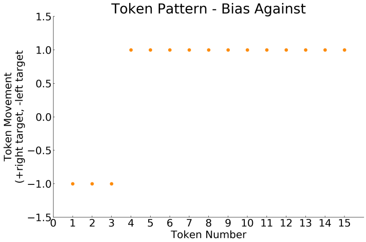


Cisek (2009)

dynamic evidence that changes over time

Token Patterns

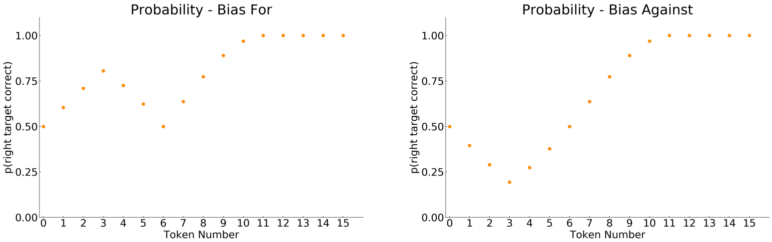




Bias for: First three tokens in right target, next three in left, remainder in right

Bias against: First three tokens in left target, next three in right, remainder in right

Token Patterns — Probability

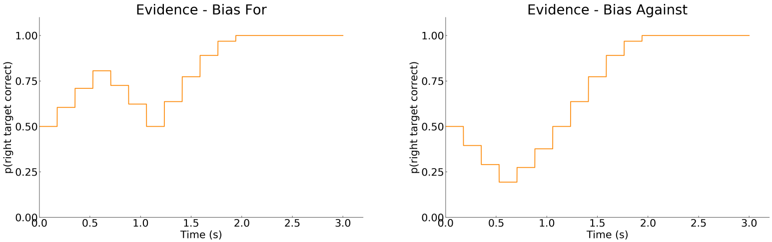


$$p(R|N_R, N_I, N_C) = \frac{N_C!}{2^{N_C}} \sum_{k=0}^{min(N_C,7-N_L)} \frac{1}{k!(N_C-k)!}$$

N_R (tokens in right target)
N_L (tokens in left target)
N_C (tokens in the center)
! (factorial)

Note: add 0.5 probability at time 0 (i.e., prior without any evidence) on figure.

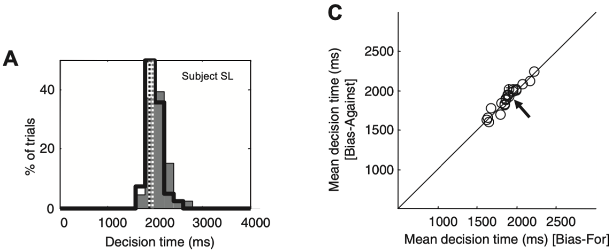
Token Patterns — Current Evidence



Current evidence (E) is p(right) discretized over time

(step size: h = 0.001 s)

Tokes Task — Behaviour



Cisek (2009)

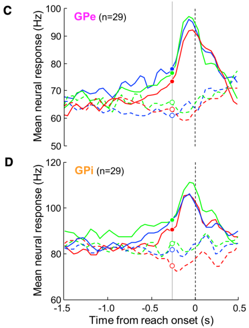
Same decision time for bias for and bias against

Urgency gating hypothesis: evidence is multiplied by a growing signal related to the urgency to respond.

I.e., make decisions based on current evidence, where the nervous system more heavily weights current evidence later in time.

Note evidence accumulation (i.e., integration) does not predict this finding.

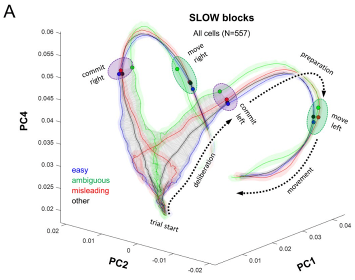
Tokes Task — Neural Basis



Thura & Cisek (2017)

Basal Ganglia (external Globus Pallidus [GPe] and internal Globus Pallidus [GPi]) provide an urgency signal.

Tokes Task — Neural Basis



Thura & Cisek (2022)

"Neural manifold" low-dimensional representations of neural population activity across recorded brain regions.

Pros: considers all neurons and brain regions (PMd, M1, dlPFC, GPe, GPi) simultaneously.

Cons: Observational and it is somewhat obvious there will be a lower dimension (e.g., similar to 'muscle synergies')

Decision-Making Models

a. drift diffusion model
b. urgency gating
c. Trueblood model
d. recurrent neural networks

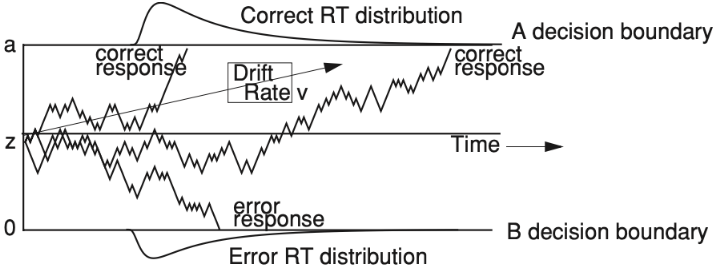
Drift Diffusion Model with Leak

$$\frac{dDV}{dt} = g \cdot E(t) - L \cdot DV(t)$$
$$E(t) = p(R|N_R, N_I, N_C) - 0.5 + N(t)$$
$$-T \geq DV \geq +T$$

DV: decision variable
$g(1500)$: gain (i.e., integrates / accumulates evidence)
E: evidence (specific to tokens task)
$L(0.5)$: leak (i.e., memory loss)
$N = \mathcal{N}(\mu = 0, \sigma = 3.0)$
$T(+500\ \&\ -500)$: decision threshold and choice (left vs. right)
$h = 0.001$

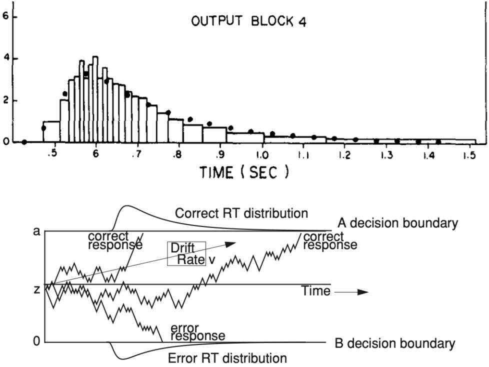
Note: there are many other variants of the drift diffusion model.

Drift Diffusion Model



Ratcliff (1979)

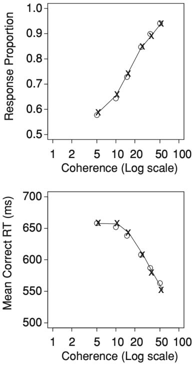
Drift Diffusion Model (Skewed Reaction Times)



Ratcliff (1979)

Captures skewed reaction times

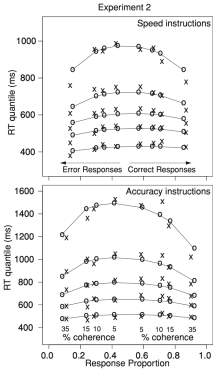
Drift Diffusion Model (Mean accuracy and correct response time)



Ratcliff (1979)

data are o's, drift diffusion model are x's

Drift Diffusion Model (Decision - Speed Accuracy Tradeoff)



Ratcliff (1979)

data are o's, drift diffusion model are x's

Higher accuracy with slower decision speed.

Drift Diffusion Model
(Hick's Law)

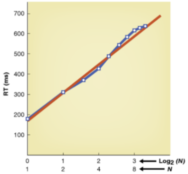
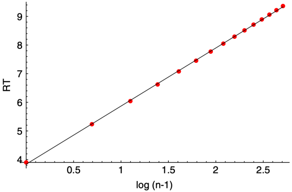


FIGURE 2.7 Hick's Law: The relation between choice RT and number of S-R alternatives (N) is replotted using Merkel's data from figure 2.6, with choice RT as a function of $\mathrm{Log}_2(N)$.

Reprinted by permission from Schmidt and Lee 2011; Data from Merkel 1885.

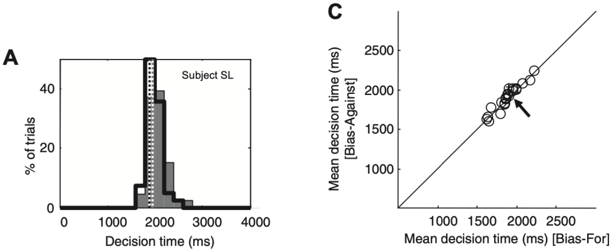


McMillen (2006)

Drift diffusion model can be extended using multiple coupled racers to explain Hick's Law.

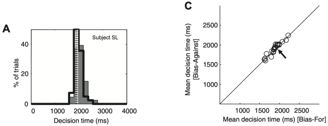
University of Delaware

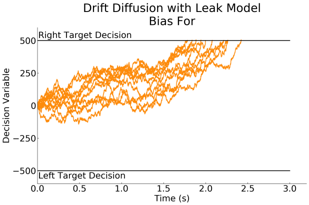
Drift Diffusion Model (Dynamic Evidence)

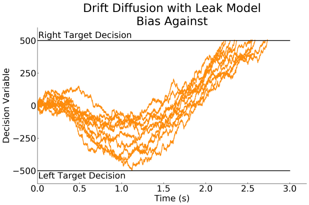


Same decision time for bias for and bias against

Drift Diffusion Model (Dynamic Evidence)







Same decision time for bias for and bias against

Drift diffusion model does not predict this result

(but could with collapsing bound)

IC: $DV_0 = 0.0$

Urgency Gating Model with Low Pass Filter

$$DV = g \cdot E(t) \cdot u(t)$$

$$\frac{dE(t)}{dt} = \frac{-E(t) + [p(R|N_R, N_I, N_C) - 0.5 + N(t)]}{\tau}$$

$$u(t) = t$$

$$-T \geq DV \geq +T$$

DV: decision variable

$g(1000)$: gain on evidence

E: evidence

u: urgency signal

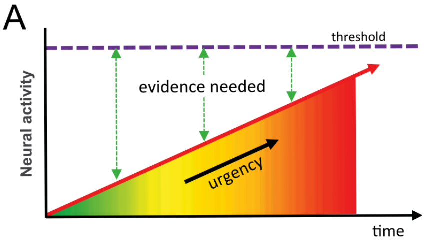
$N = \mathcal{N}(\mu = 0, \sigma = 0.7)$

$\tau(0.05)$: low-pass filter on evidence

$T(+500 \ \& \ -500)$: decision threshold

$h = 0.001$: time step

Urgency Gating Model (Dynamic Evidence)

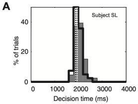


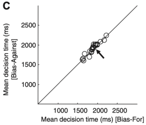
Carland (2019)

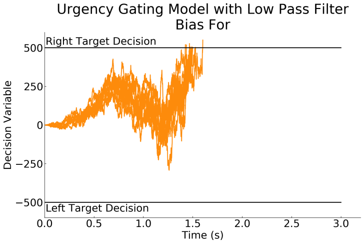
Increasing urgency signal over time

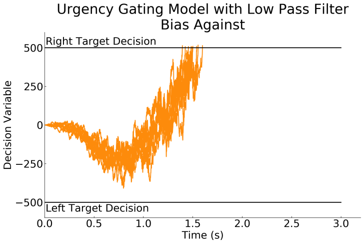
urgency may scale as a function of reward, effort, and time.

Urgency Gating Model (Dynamic Evidence)









Urgency-gating model captures decision times with dynamic evidence.

IC: $E_0 = 0.0$

Urgency Gating Model

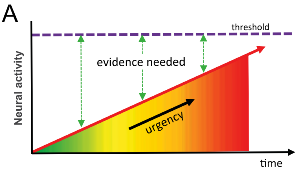
1. Skewed reaction times
2. Mean accuracy and correct response time
3. Speed / accuracy tradeoff (reward rate)
4. Hicks Law (not done but could with interacting racers)
5. Dynamic evidence

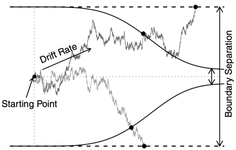
MODEL SIMILARITIES

Drift diffusion model and urgency gating model turn out to be mathematically very similar.

1. urgency signal ≈ collapsing bound
2. low pass filter ≈ evidence accumulation (both integrators)

Yet different perspectives of how decisions are made





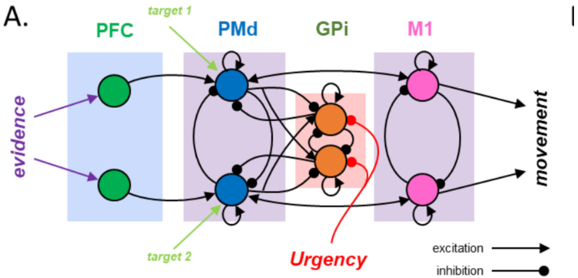
Hawkins (2015)

Trueblood 2021

Trueblood, J. S., Heathcote, A., Evans, N. J., & Holmes, W. R. (2021). Urgency, leakage, and the relative nature of information processing in decision-making. Psychological Review, 128(1), 160-186.

Combines the ideas of urgency and evidence accumulation.

Recurrent Neural Networks

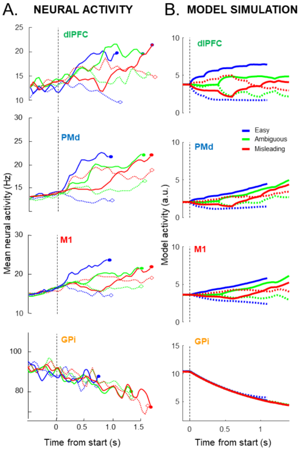


Mirzazadeh (2024)

Pros: closer to neural implementation

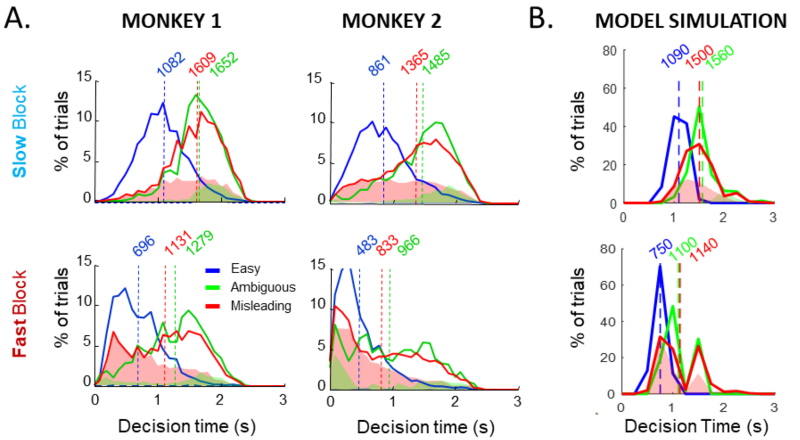
Cons: can fit anything and infinite architectures can explain the same result (what do you learn?)

Recurrent Neural Networks



Mirzazadeh (2024)

Recurrent Neural Networks



Mirzazadeh (2024)

Recurrent Neural Networks

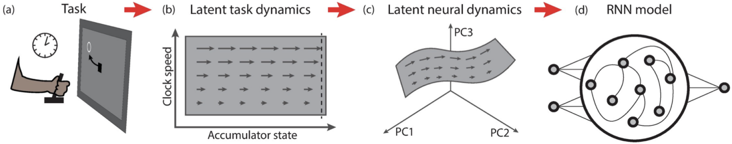


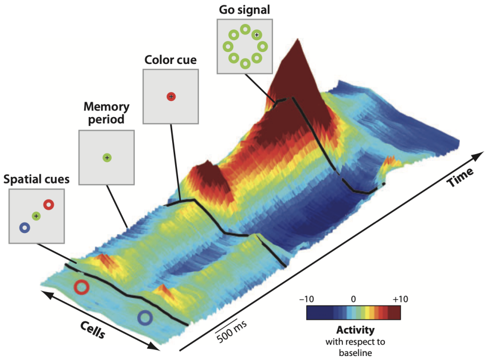
Fig 1. Embedding latent task dynamics into recurrent neural networks. a) A hypothetical task, adapted from [27]. The subject is instructed to produce a time interval by making a delayed movement. b) Latent task space over a manifold (gray rectangle) based on a clock-accumulator model [28]. The y-value reflects the speed of the clock, and the x-value reflects the state of the accumulator before movement initiation. In this model, the instruction sets the speed of the clock (length of the arrow) at which the accumulator evolves over time (faster for shorter intervals). Movement is initiated when the accumulator reaches a threshold (dashed line). c) A nonlinear embedding of the task manifold depicted in a neural state space spanned by the first three principal components of population activity. d) An RNN model to establish the desired nonlinear embedding.

Pollock (2020)

RNN can be used to map task-relevant dynamics onto low dimensional neural manifolds.

Interplay of Decisions and Action

Neural Basis

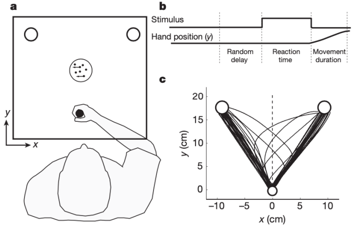


Cisek and Kalask (2010)

Premotor cortex (PMd) represent potential goals / motor plans.

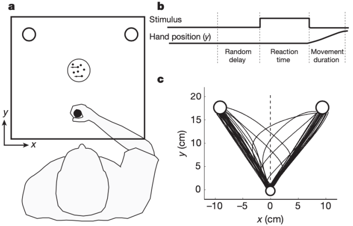
Decision and motor systems integrated!

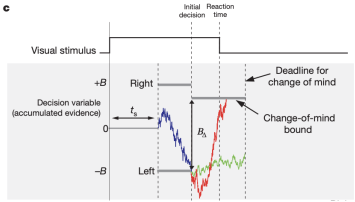
Decision → Action (Changes of Mind)



Resulaj (2009)

Decision → Action
(Changes of Mind)

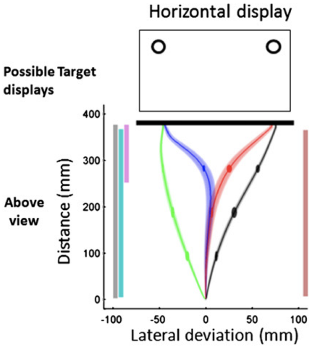




Resulaj (2009)

decision processing delays leads to 'changes of mind'

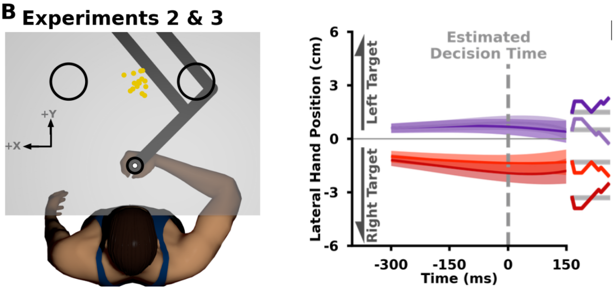
Decision $\rightarrow$ Action (Go-before-you-know)



Chapman (2010)

single, flexible vs. parallel average?

Decision → Action (Calalo)

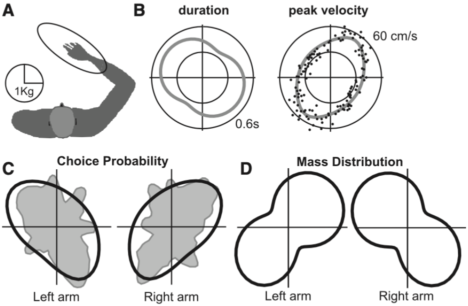


Calalo (2024)

Ongoing deliberation Influences online movement.

Decision circuits interact in real-time with motor circuits.

Decision ← Action (Biomechanics)



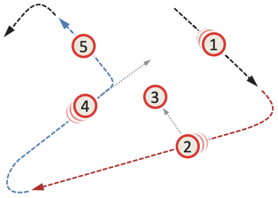
Wang (2012)

Humans choose more energetically efficient movements

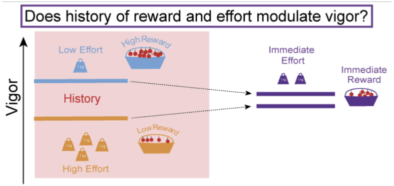
Decision & Action
Other Relevant Works

1. distractors (Song, 2006)
2. congruence (Finkbeiner, 2008)
3. language (Spivey, 2005)
4. deilberation in long-latency response (Selen, 2012)
5. target split paradigm (Kurtzer, 2020)

Sequence Tasks & Foraging



Michalski (2020)



Sukumar (2024)

Summary

Decision paradigms

a. dot coherence task
    i. behaviour, neural basis
b. tokens task
    i. behaviour, neural basis

Decision-making models

a. drift diffusion model
b. urgency gating
c. Trueblood model
d. recurrent neural networks

Interplay of Decisions and Action

Questions???

Next Class

Error-based Learning

1. one-state model
2. two-state model (Smith et al., 2006)
3. learning and forgetting
4. spontaneous recovery
5. savings

Other Considerations

1. Generalization
2. Variability
3. Learning vs. Adaptation

Homework

1. Last assignment!