## Intro to EAM

@47th ECVP 2025 Mainz

Margherita Calderan

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#### Perception into action

Evidence Accumulation Models assume that, upon stimulus presentation, the decision maker:



#### What is "evidence"?

Neural signals reflecting sensory or internal information relevant to a choice.

"Are dots moving to the right or to the left?"

- Neurons fire in proportion to motion direction & strength.
- These firing rates = momentary evidence.
- Noisy and varies trial-to-trial.



# How does the brain accumulate evidence?

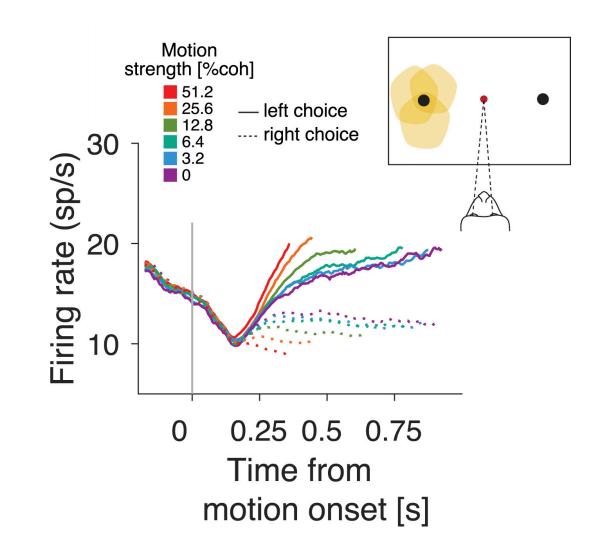


## Integrator neurons receive this input

- Neurons in LIP, dlPFC, or striatum ramp up/down over time.
- Reflects accumulated evidence

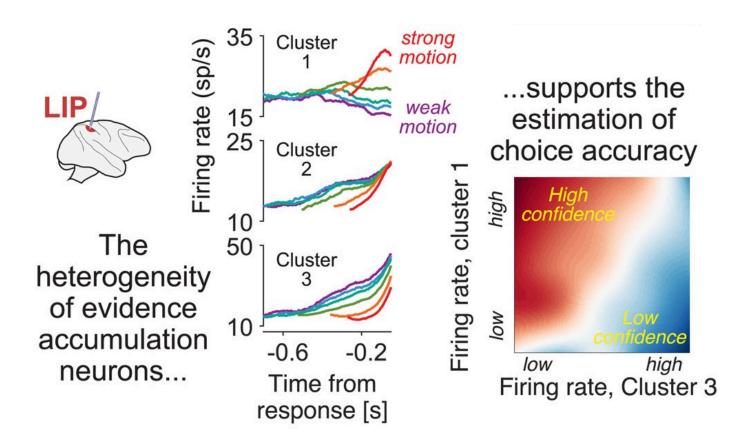


Zylberberg & Shadlen, 2025





## Threshold crossing triggers a decision



Zylberberg & Shadlen, 2025



## Brain computation of decisions

Cognitive Term	Neural Interpretation	
Evidence	Sensory neuron firing rates	
Accumulation	Integration in parietal/frontal areas	
Noise	Trial-to-trial neural variability	
Bound	Decision threshold in firing/activity	



# Latent Cognitive Parameters



## Sequential processing assumption

Total Response Time (RT) is modeled as the sum of three sequential stages:

- 1. Stimulus encoding
- 2. Evidence accumulation (decision-making)
- 3. Motor response execution

Stages (1) and (3) are captured in the nondecision time (Ter) parameter.



#### EAMs decompose decisions into:

- Drift rate
- Threshold



#### **Drift Rate**

#### Reflects evidence strength

- 1 Drift: fast & accurate decisions
- **J** Drift: slow, error-prone

Manipulated by stimulus discriminability/task difficulty



#### **Thresholds**

Set before stimulus onset

Reflect response caution/cognitive control/bias/preference

- 1 Threshold: Slower but more accurate
- **\** Threshold: Faster but error-prone

Manipulate via pre-trial cues or instructions.

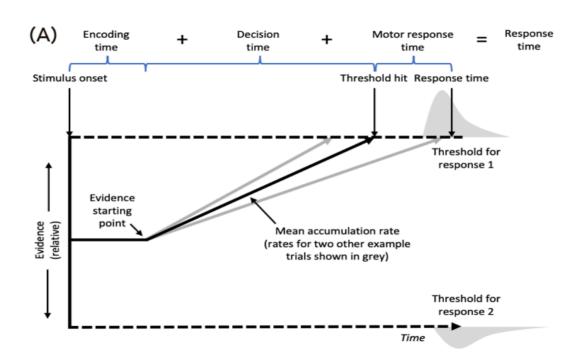


#### **Relative Evidence Models**

In **relative evidence models** (e.g., Wiener process, Diffusion Decision Model):

 Decision is based on the difference in accumulated evidence between two options.





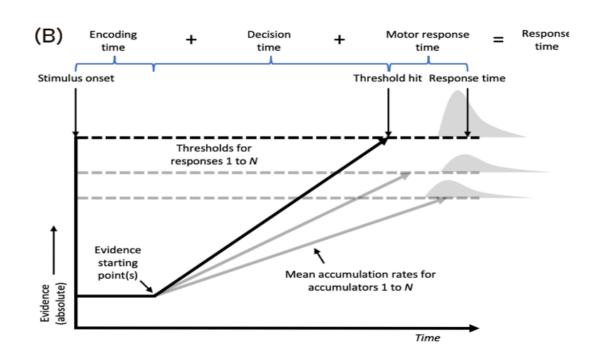
Boag, R. J., Innes, R. J., Stevenson, N., Bahg, G., Busemeyer, J. R., Cox, G. E., ... Forstmann, B. (2024, July 2). An expert guide to planning experimental tasks for evidence accumulation modelling.



#### **Absolute Evidence Models**

In racing accumulator models (e.g., LBA, RDM):

- Each option has its own accumulator tracking absolute evidence.
- Decision is made by the first accumulator to reach threshold.
- Can handle multiple alternatives (not just binary choices).



Boag, R. J., Innes, R. J., Stevenson, N., Bahg, G., Busemeyer, J. R., Cox, G. E., ... Forstmann, B. (2025) An expert guide to planning experimental tasks for evidence accumulation modelling.



## Noisy process

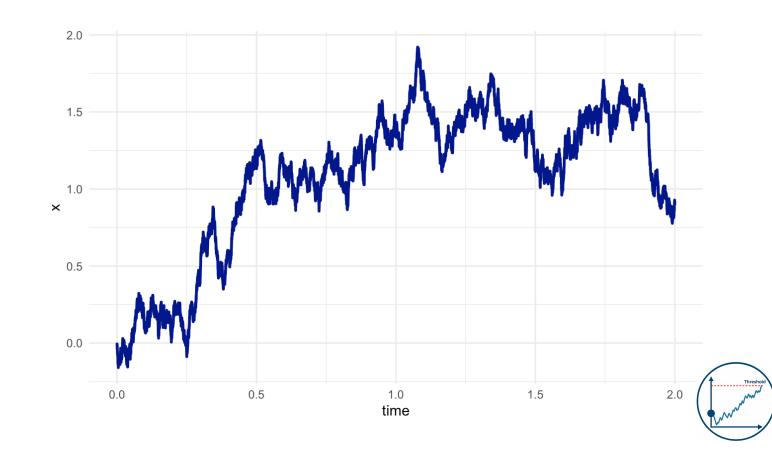


#### **Wiener Process**

The Wiener process (Brownian motion) is the foundation of many decision models (Smith & Ratcliff, 2024). It models the accumulation of evidence as a noisy process:

$$x(t) = z + vt + sW(t)$$

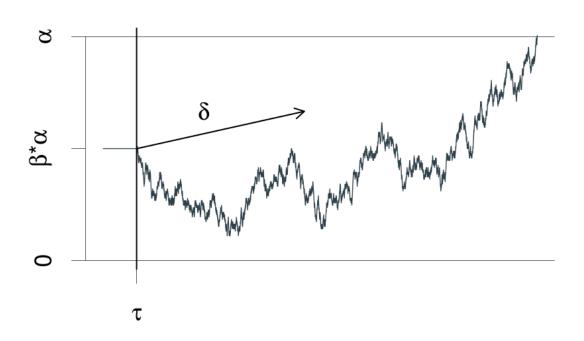
- x(t): accumulated evidence at time t
- z: starting point
- v: drift rate (signal strength)
- s: noise (standard deviation of the increments)
- W(t): standard Wiener process (Gaussian increments)



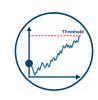


#### **Wiener Diffusion Model**

It is the expected distribution of the time until the process first hits or crosses one or the other boundary. This results in a bivariate distribution, over responses and hitting times.



- $\alpha$ : threshold
- $\beta$ : initial bias (starting point)
- $\delta$ : quality of the stimulus (often v)
- $\tau$ : non-decision time



#### **Full Diffusion Decision Model**

The **Full DDM** accounts for more behavioral phenomena by allowing **trial-to-trial variability** in key parameters:

Drift rate
Starting point
Non-decision time



#### **Full DDM Parameters**

*a*: decision boundary

z: starting point

v: drift rate

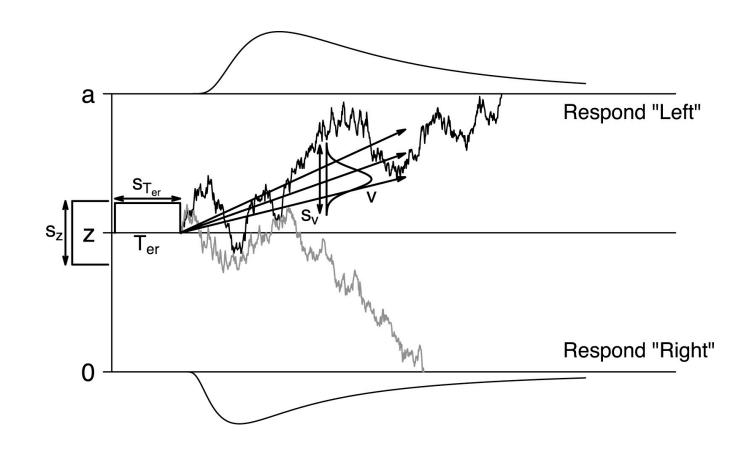
 $t_0$ : non-decision time

s: noise scale (usually fixed to 1)

 $\eta$ : SD of drift rate across trials

 $s_z$ : variability in start point

 $s_{t_0}$ : variability in non-decision time



Boehm, U., Annis, J., Frank, ... & Wagenmakers, E. J. (2018). Estimating across-trial variability parameters of the Diffusion Decision Model: Expert advice and recommendations. *Journal of Mathematical Psychology*, 87, 46-75. Ratcliff, R., & Rouder, J. N. (1998). Modeling Response Times for Two-Choice Decisions. Psychological Science, 9(5), 347-356.

## Purpose of variability

Adding variability improves the model's ability to:

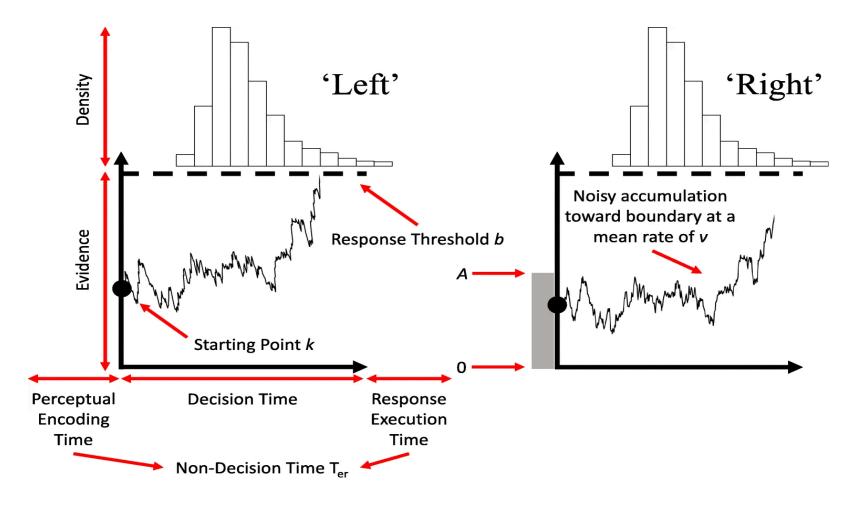
- Capture error RT differences
- Reflect trial-to-trial attention or difficulty changes

However, it increases computational demands.



#### **Racing Diffusion Model**

Instead of a single process choosing between boundaries, the RDM uses **multiple independent diffusion processes**, one per option. Each accumulator races toward its threshold. The first to cross **wins**. Tillman, Van Zandt, & Logan, 2020





## Summary

Model	Core Mechanism	Key Strengths
Wiener	Noisy accumulation	Simple FPT, binary outcomes
Full DDM	Accumulation + param variability	Realistic RTs, error patterns
Racing DM	Multiple accumulators	Handles multi-alternative decisions



## Core assumptions of the basic EAM

- Each decision = a single, continuous accumulation of evidence
- Culminates in a discrete response
- Evidence accumulates from stimulus onset to response



## Guidelines

Boag et al. 2025



### Within-Trial Stationarity

Model parameters are fixed within a trial

#### **Evidence accumulation:**

- Constant mean rate, though noisy
- No changes in stimulus evidence mid-trial

#### **Decision thresholds:**

- Set **before** stimulus onset
- Do not change during the trial



## Within-Condition Stationarity

Parameters are constant across same-type trials

#### **Assumes:**

- Trials of same condition reflect same cognitive settings
- Participant behavior is stable



### Free of contaminant processes

Data should reflect evidence accumulation!

#### Avoid:

- Random guessing
- Fast guesses
- Attention lapses or missing responses

Clean data = better model fit and interpretability.



# "All models are wrong, but some are useful" - G. Box



## Thank you!

