

Integration and Perceptual Decision Making

Decision Making

(writ "small")

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 - **perception and psychophysics** (e.g., *Sperling task*)
 - **attention** (e.g., *Stroop task*, *Posner paradigm*)
 - **short term memory** (e.g., *Sternberg paradigm*, *Brown-Petersen paradigm*)
 - **long term memory** (e.g., *priming*, *familiarity effects*, etc.)

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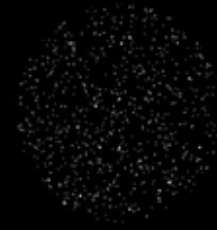
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- What are the *dynamics* that underlie these decisions...
and how are the *controlled*?

Outline

- **Simple behavioral task:**
 - Two alternative forced choice (2AFC) decision task
- **Current “state of play:”**
 - Behavioral findings
 - *(Some informative)* neurobiological findings
 - PDP models
- **Formal analysis:**
 - Drift diffusion model (DDM)
 - Sets the stage for:*
 - Control as optimization

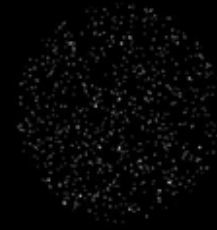
Two Alternative Forced Choice Task

Are the dots moving left or right?



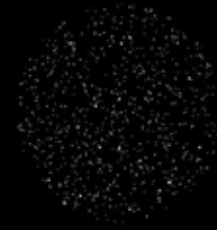
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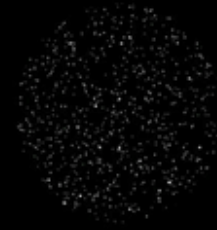
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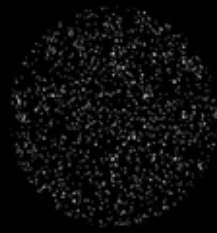


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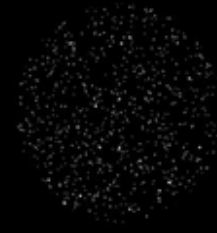
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High coherence →



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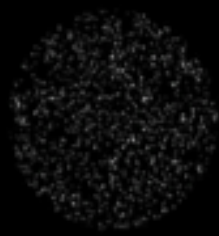
Low coherence →

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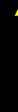
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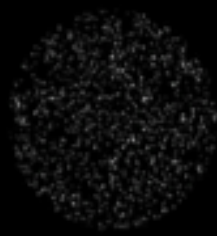


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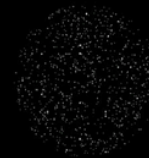
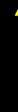


High coherence →



Low coherence →

See dots moving left (●),
press the left button

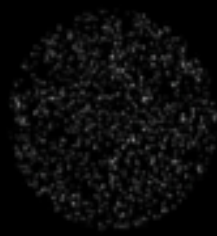


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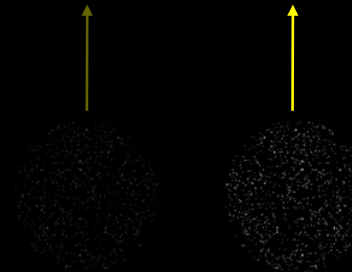
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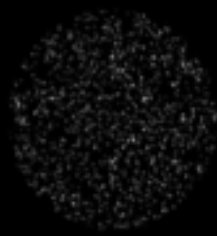


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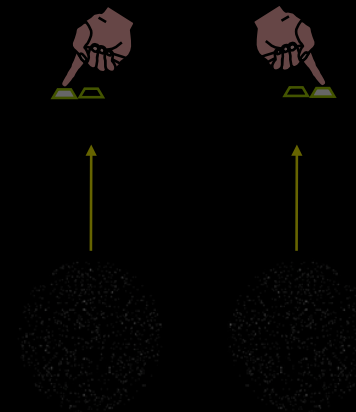
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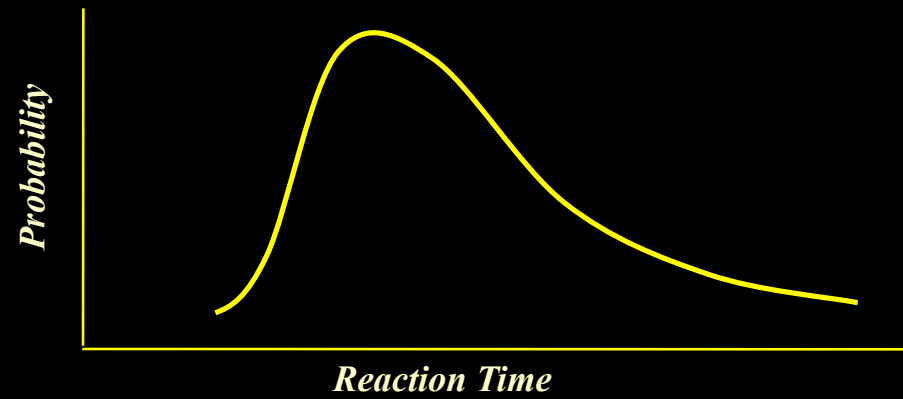
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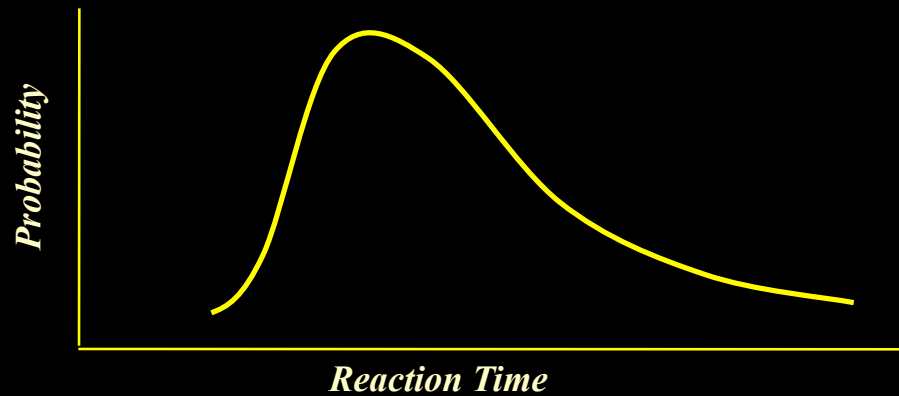
Measure reaction time (RT) and accuracy

Behavioral Findings



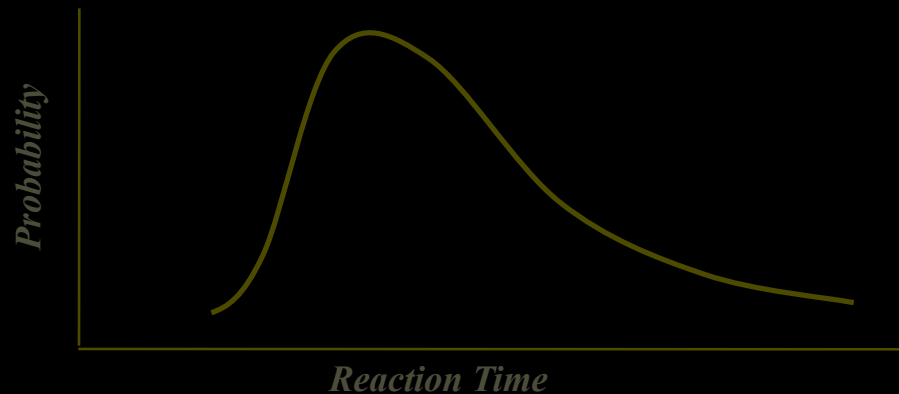
Behavioral Findings

- Characteristically skewed RT distribution:



Behavioral Findings

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- **Speed/accuracy tradeoff:**
 - faster response → less accurate
 - more accurate → slower response

Neural Findings



Neural Findings

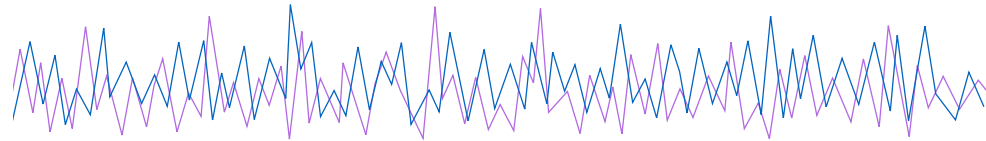


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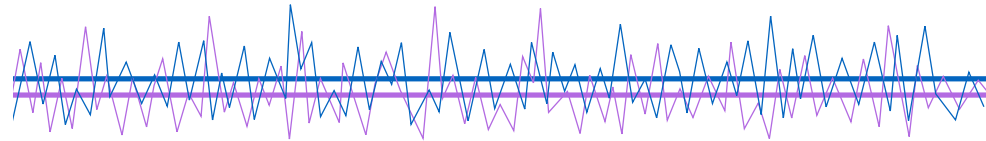
Which was higher, the blue or the purple?

Neural Findings



Which was higher, the **blue** or the **purple**?

Neural Findings

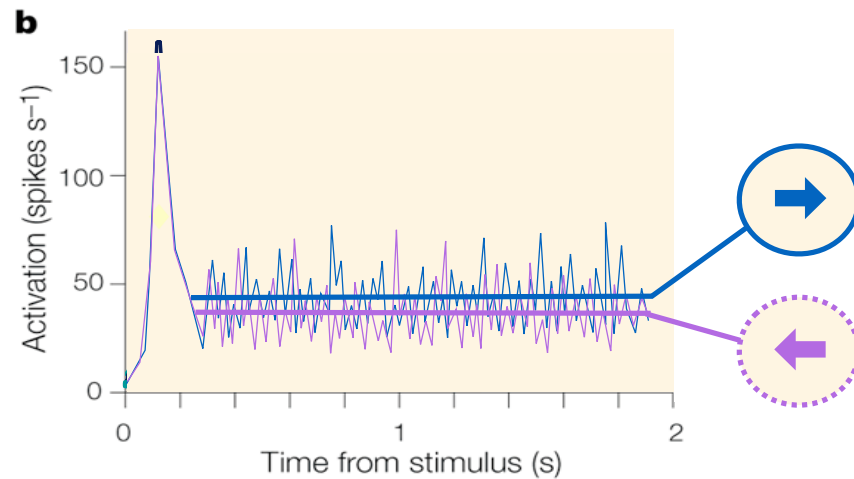


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Neural Findings

Motion Detection:

Area MT
(temporal cortex)
motion sensitive
visual cortex

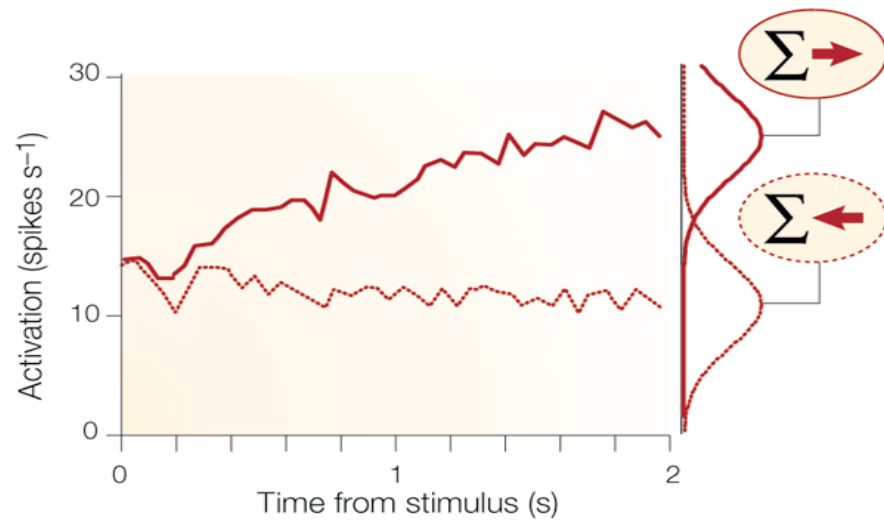


Shadlen & Newsome, 1998

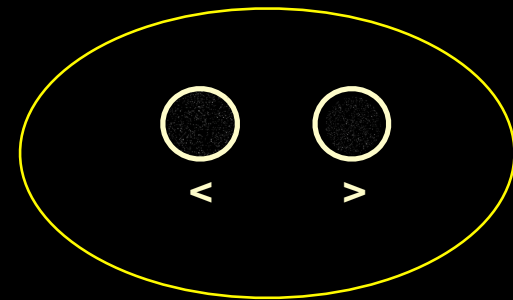
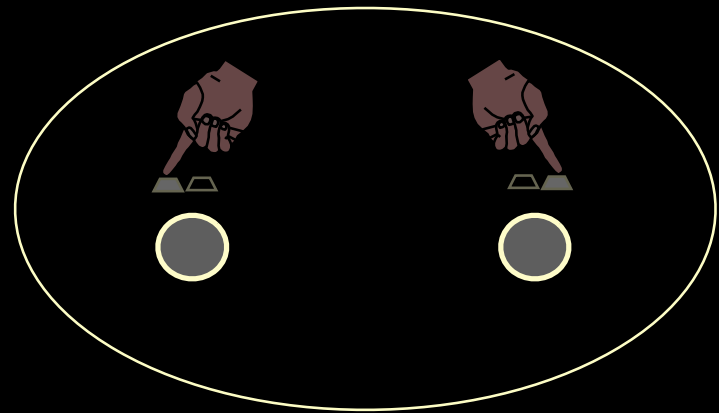
Neural Findings

Integration:

Areas LIP
(parietal cortex)
and SEF
(supplementary eye fields):
control of
eye movements

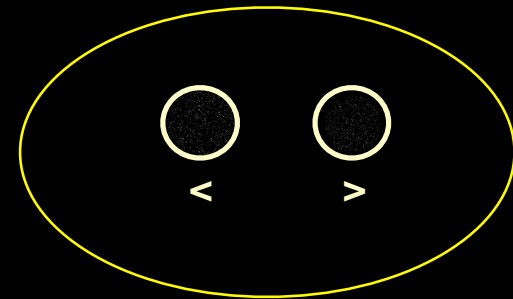
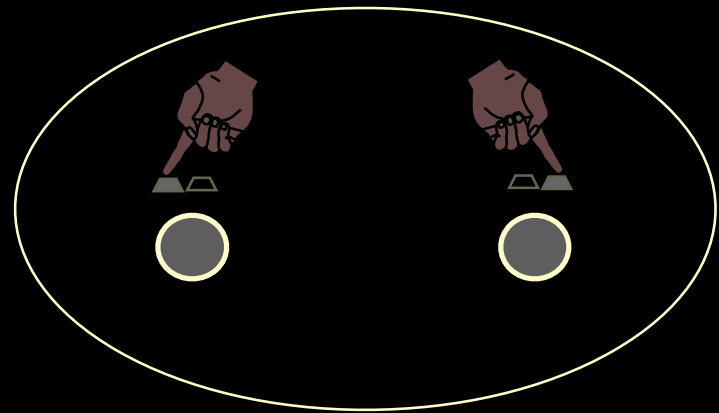


Simple PDP Model of Two Alternative Decision Task



Usher & McClelland, 2001

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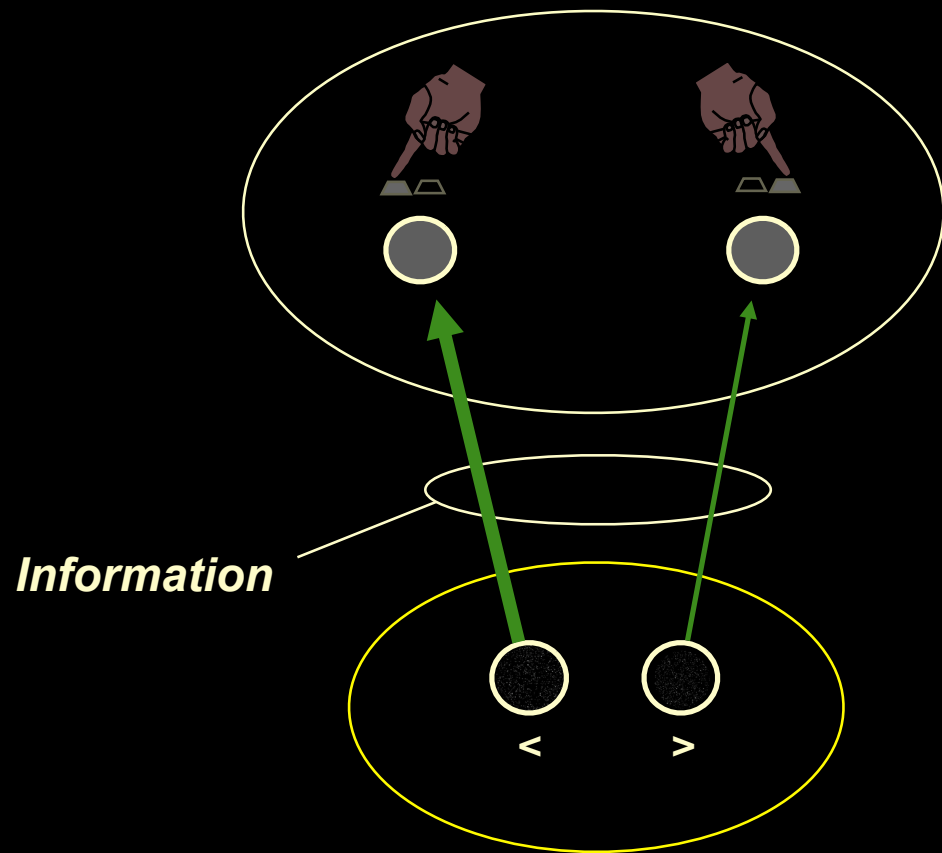


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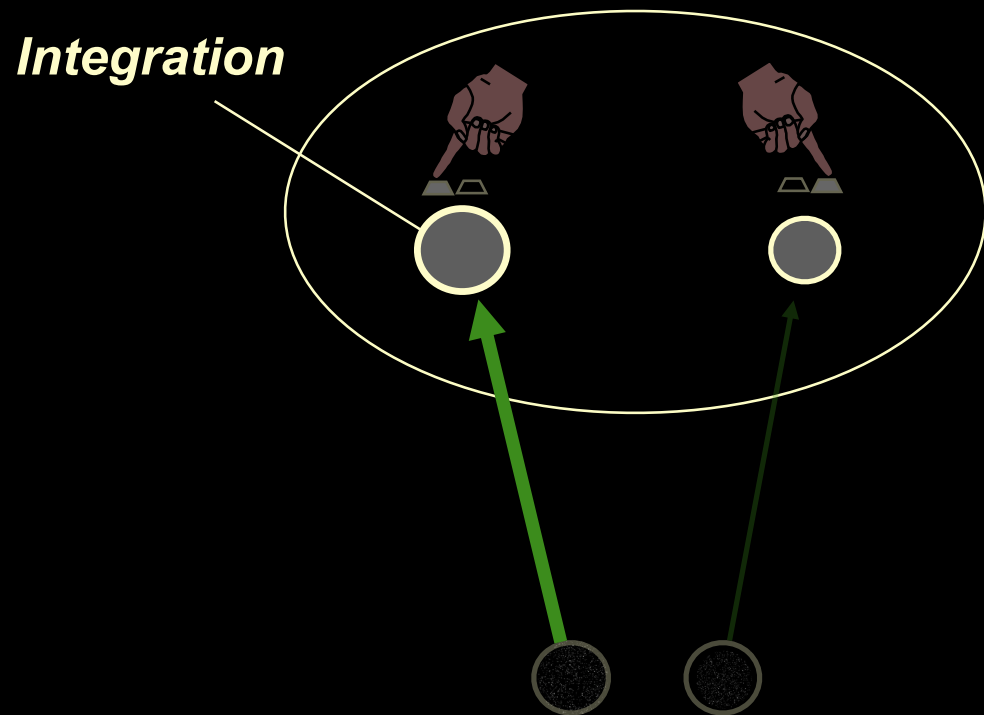


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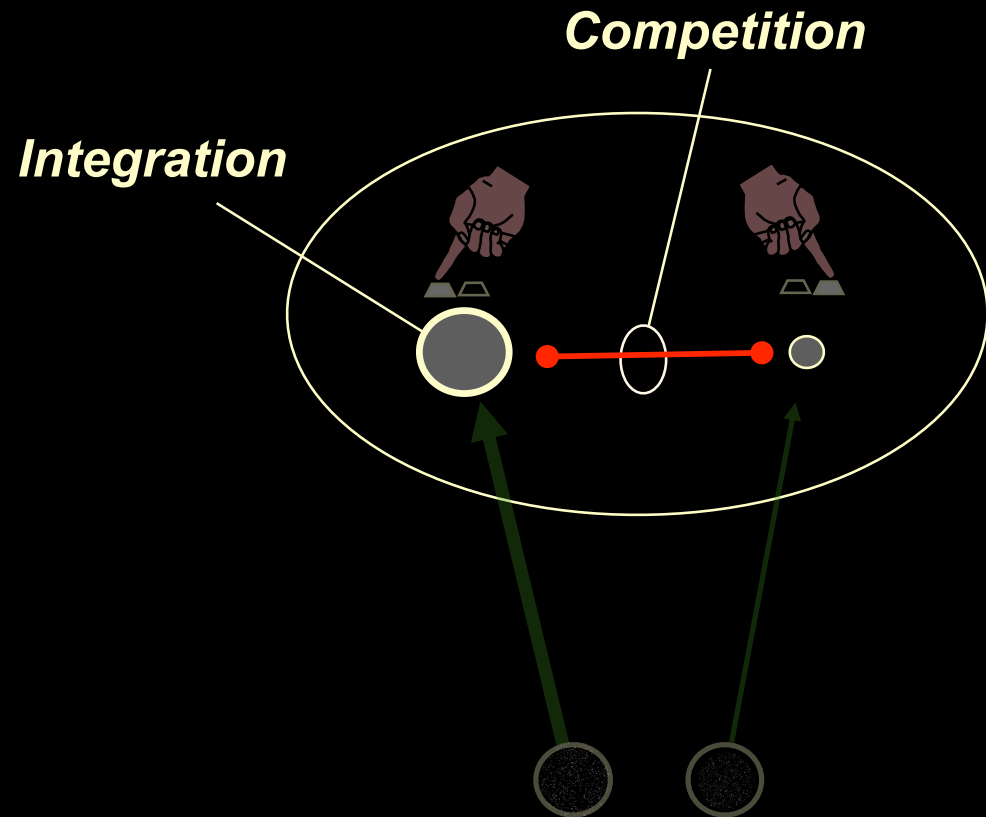
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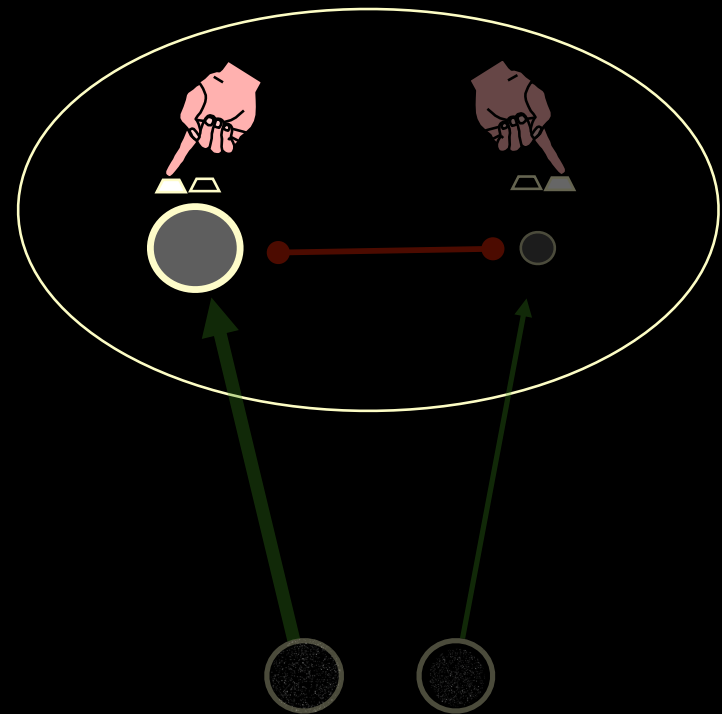
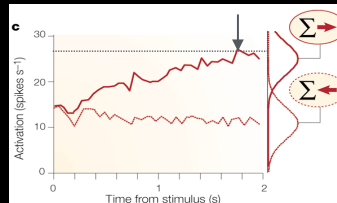
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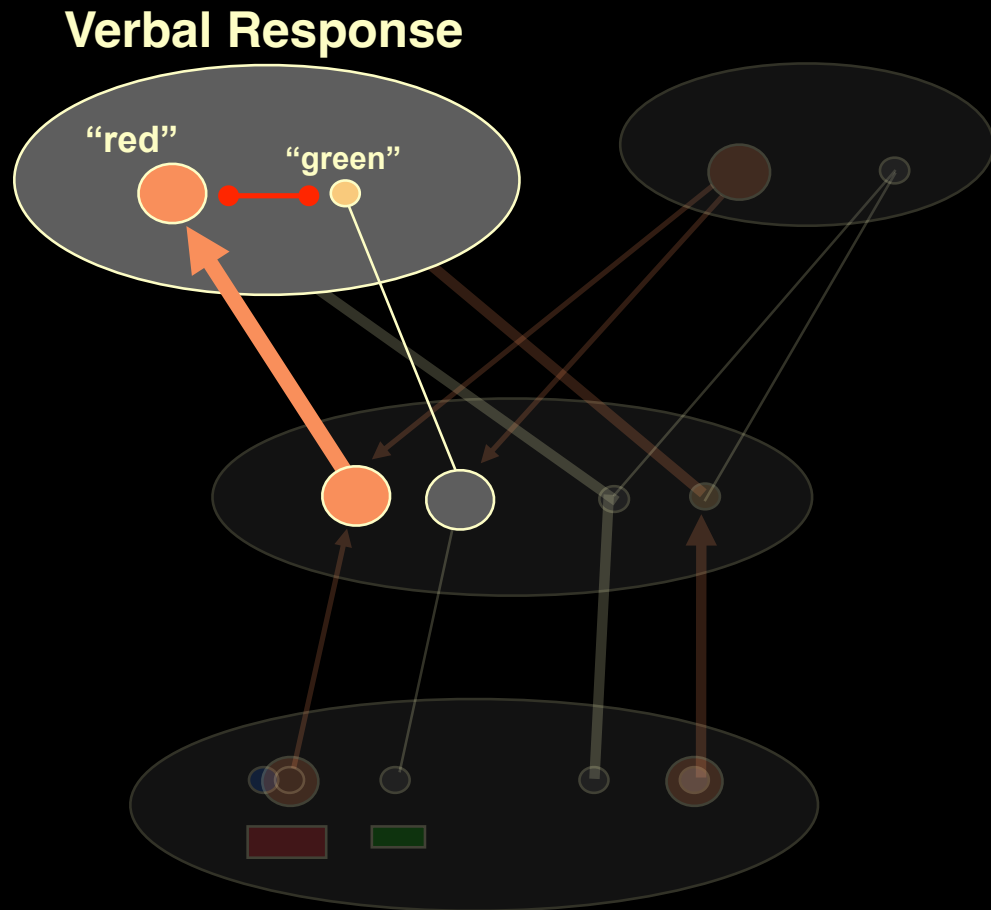
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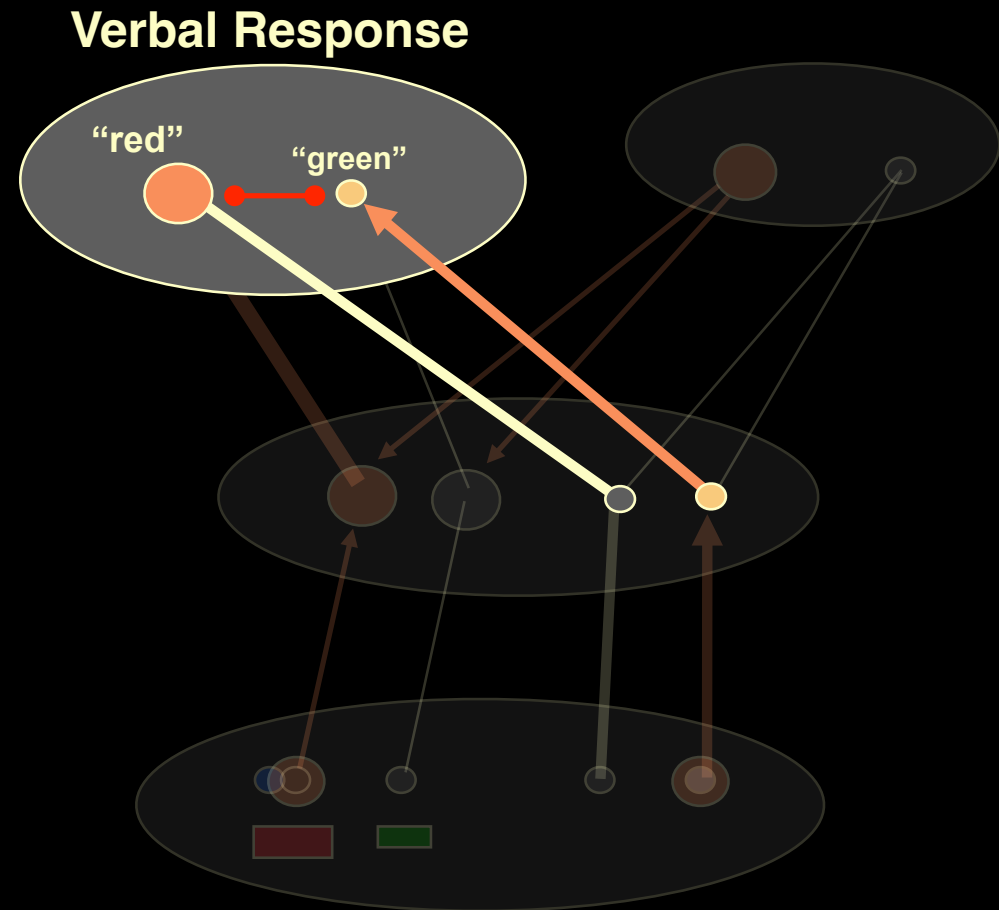
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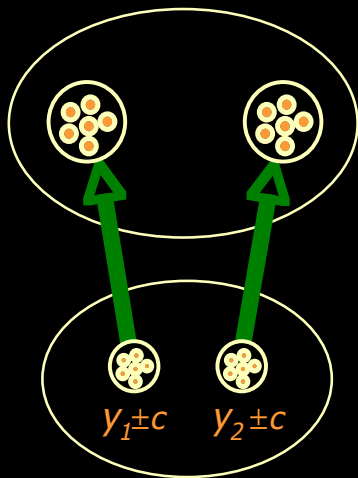
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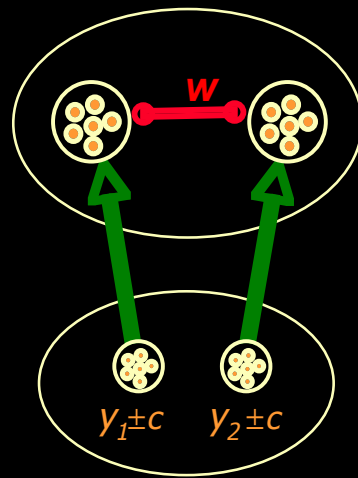
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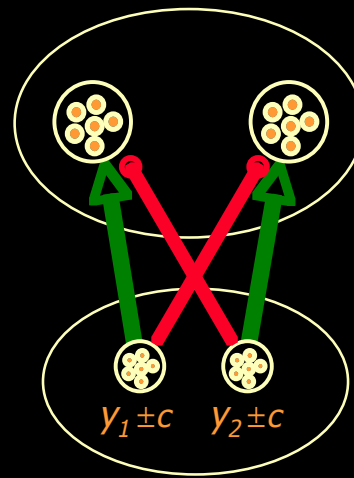
Race/Accumulator
(No Inhibition)
(LaBerge, 1962)



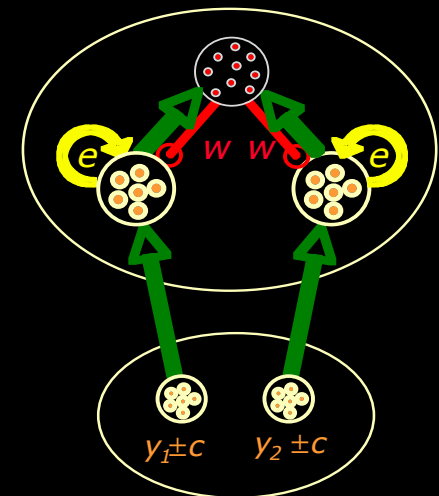
Mutual Inhibition
(Usher & McClelland, 2001)



Feedforward Inhibition
(Shadlen & Newsome, 2001)

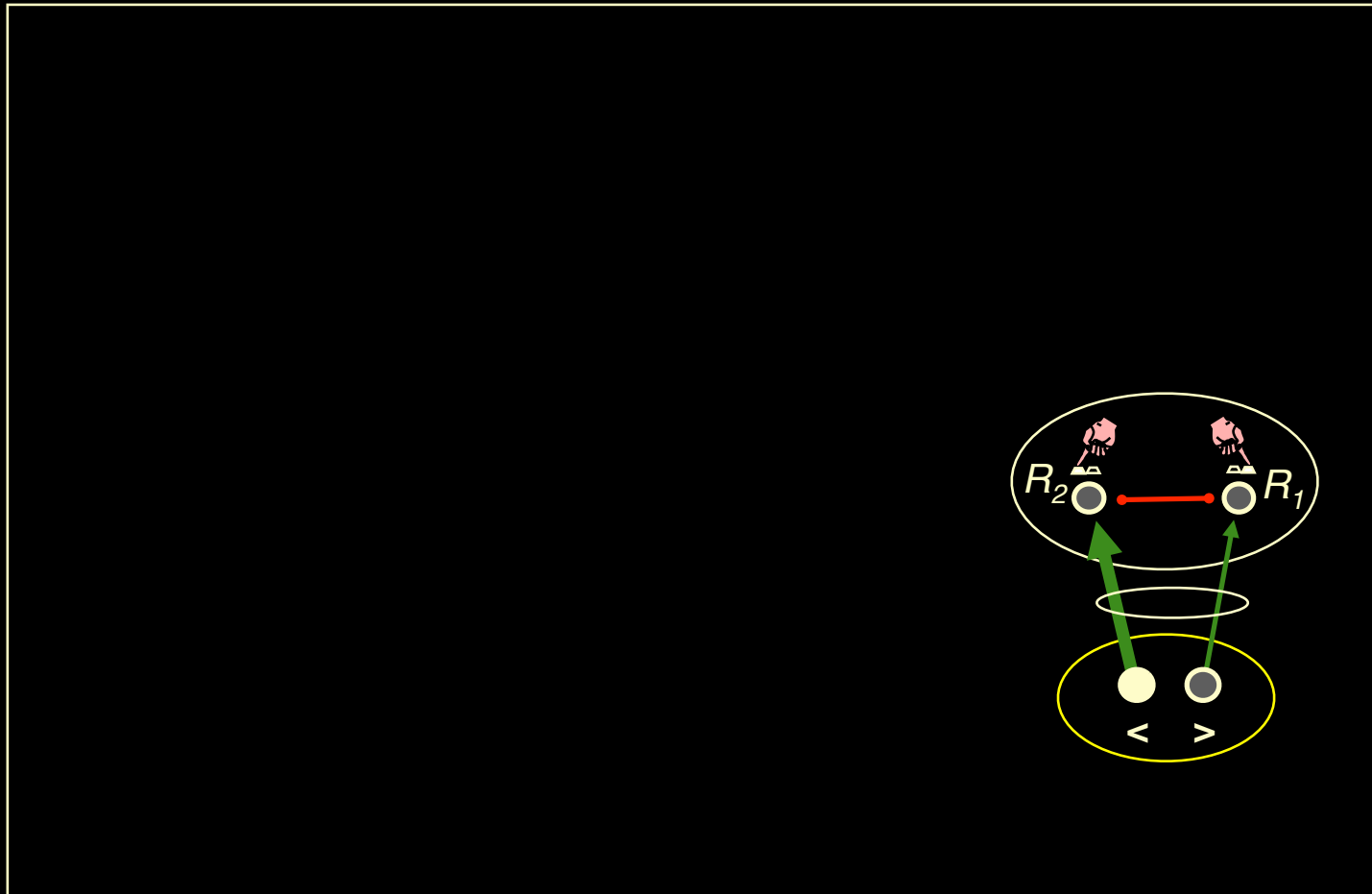


Pooled Inhibition
(Wang, 2001)



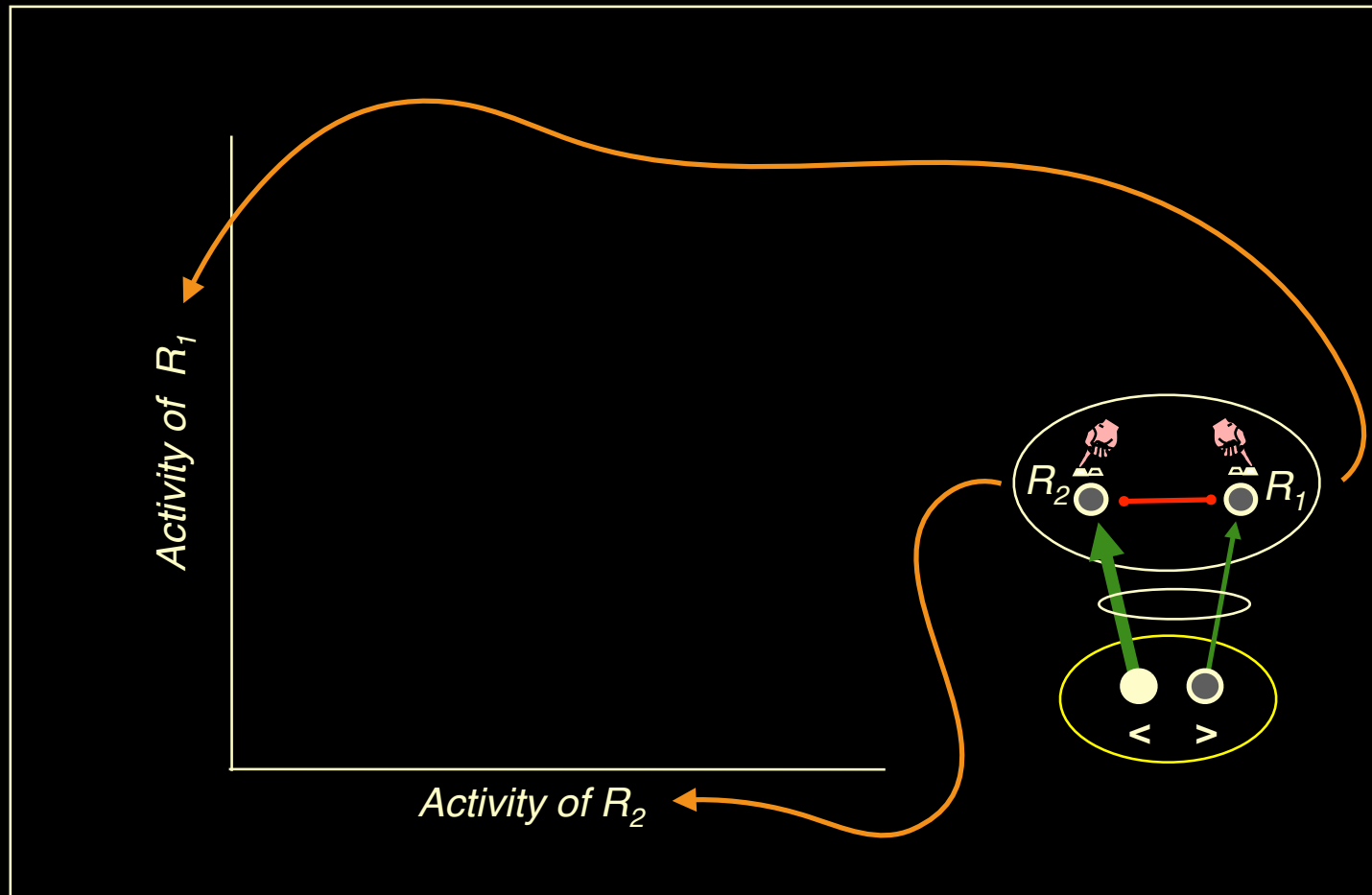
Simplification & Analysis

Step 1: Construct geometric representation of model's behavior



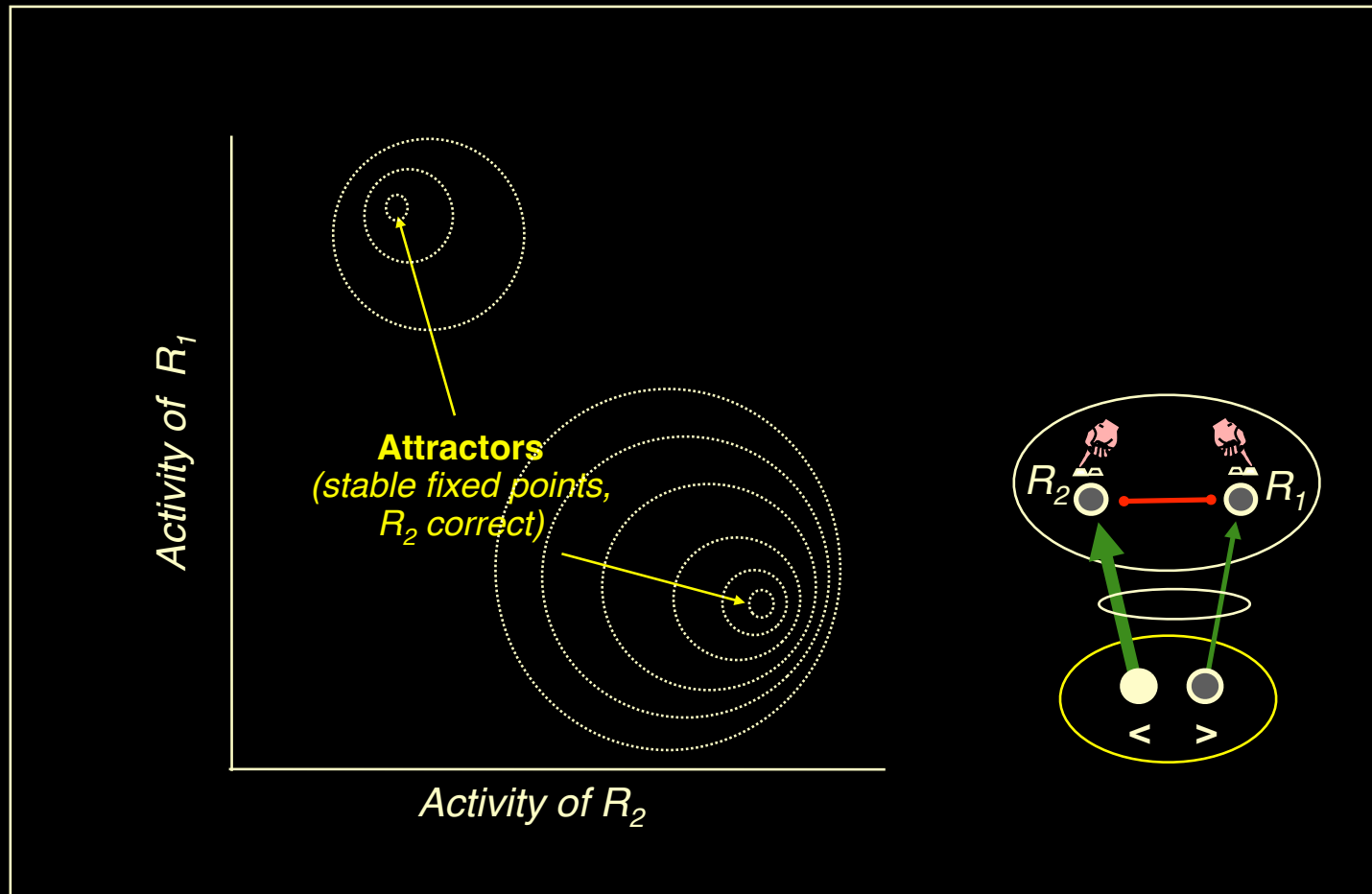
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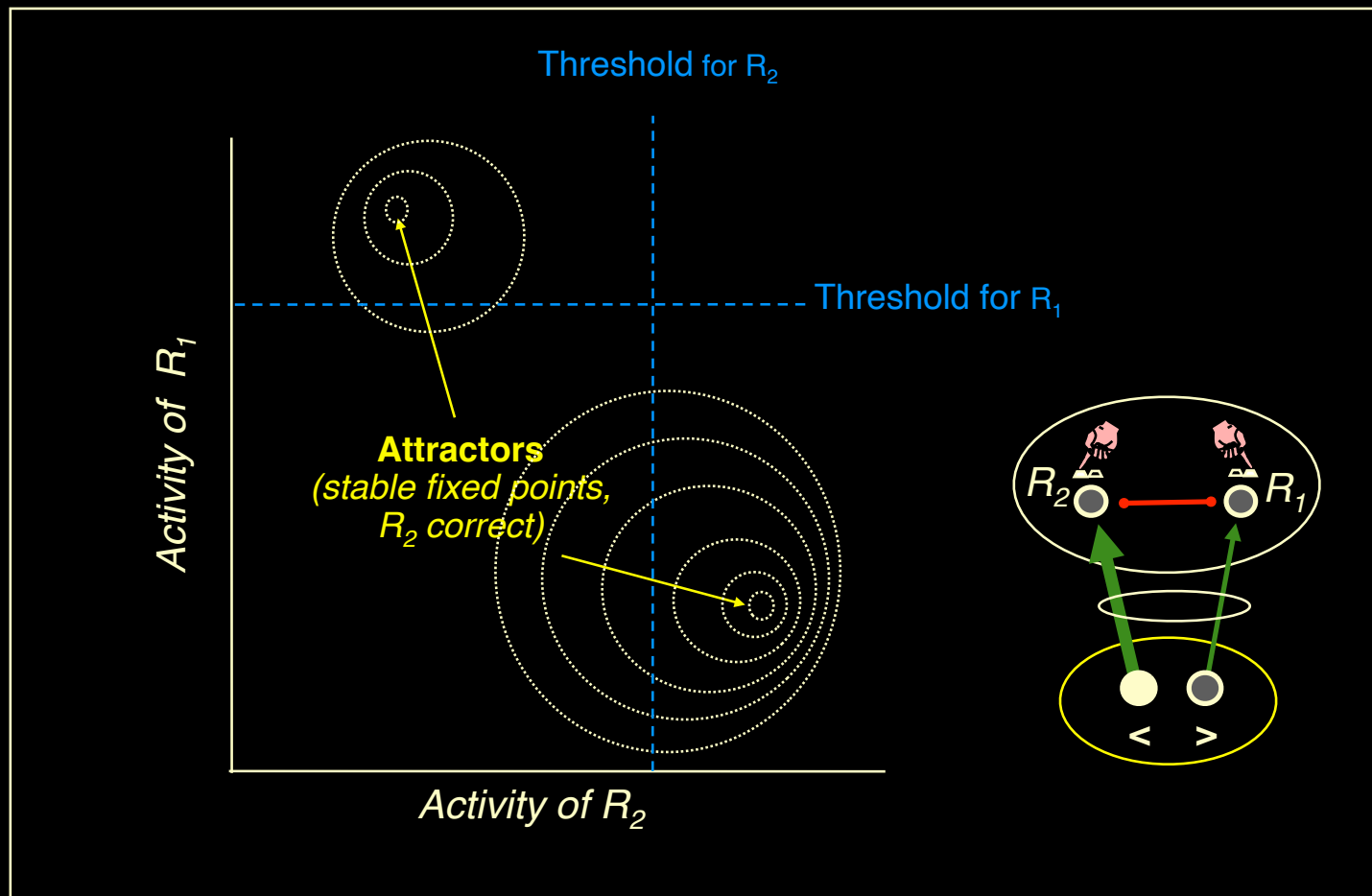
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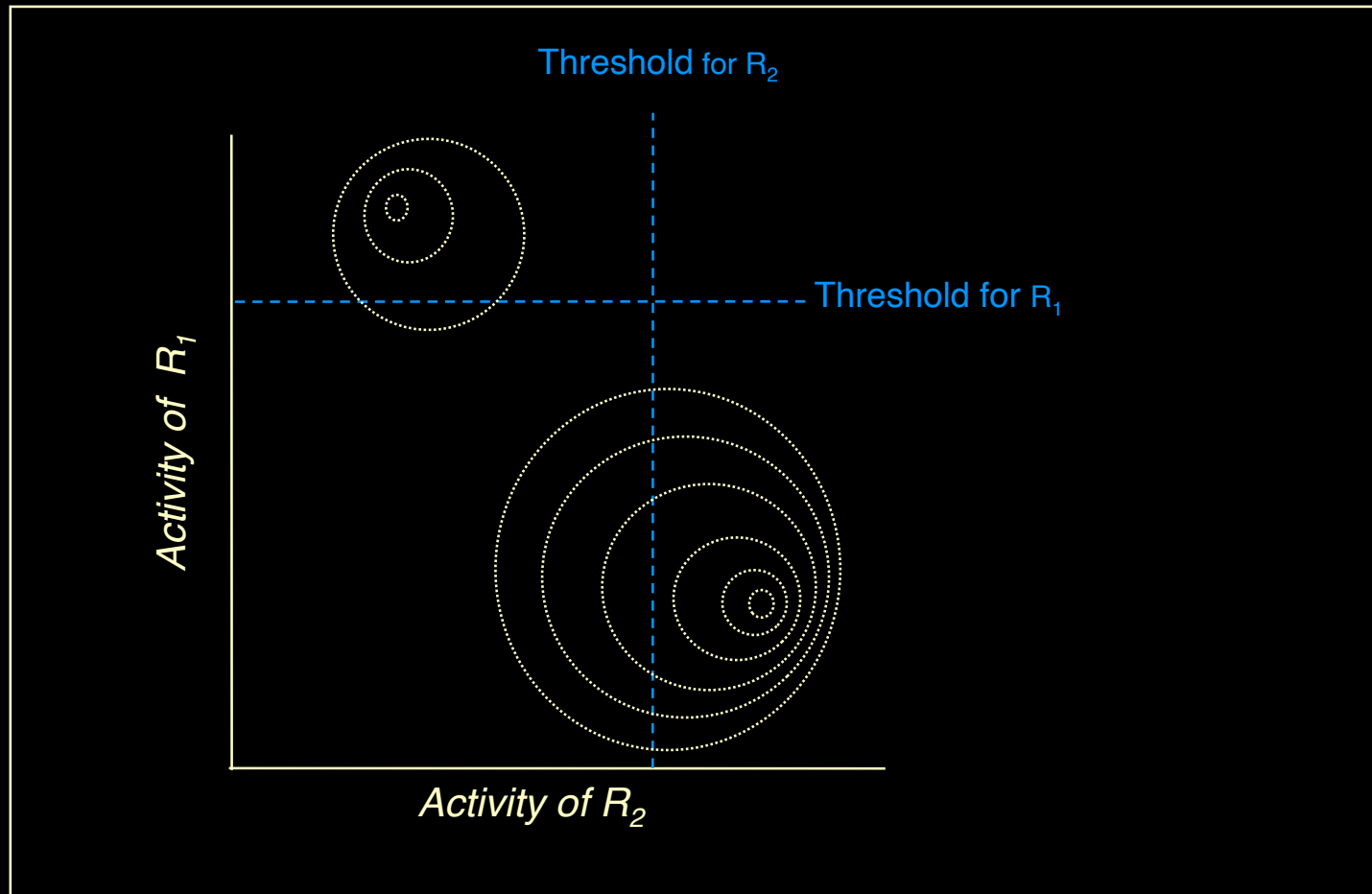
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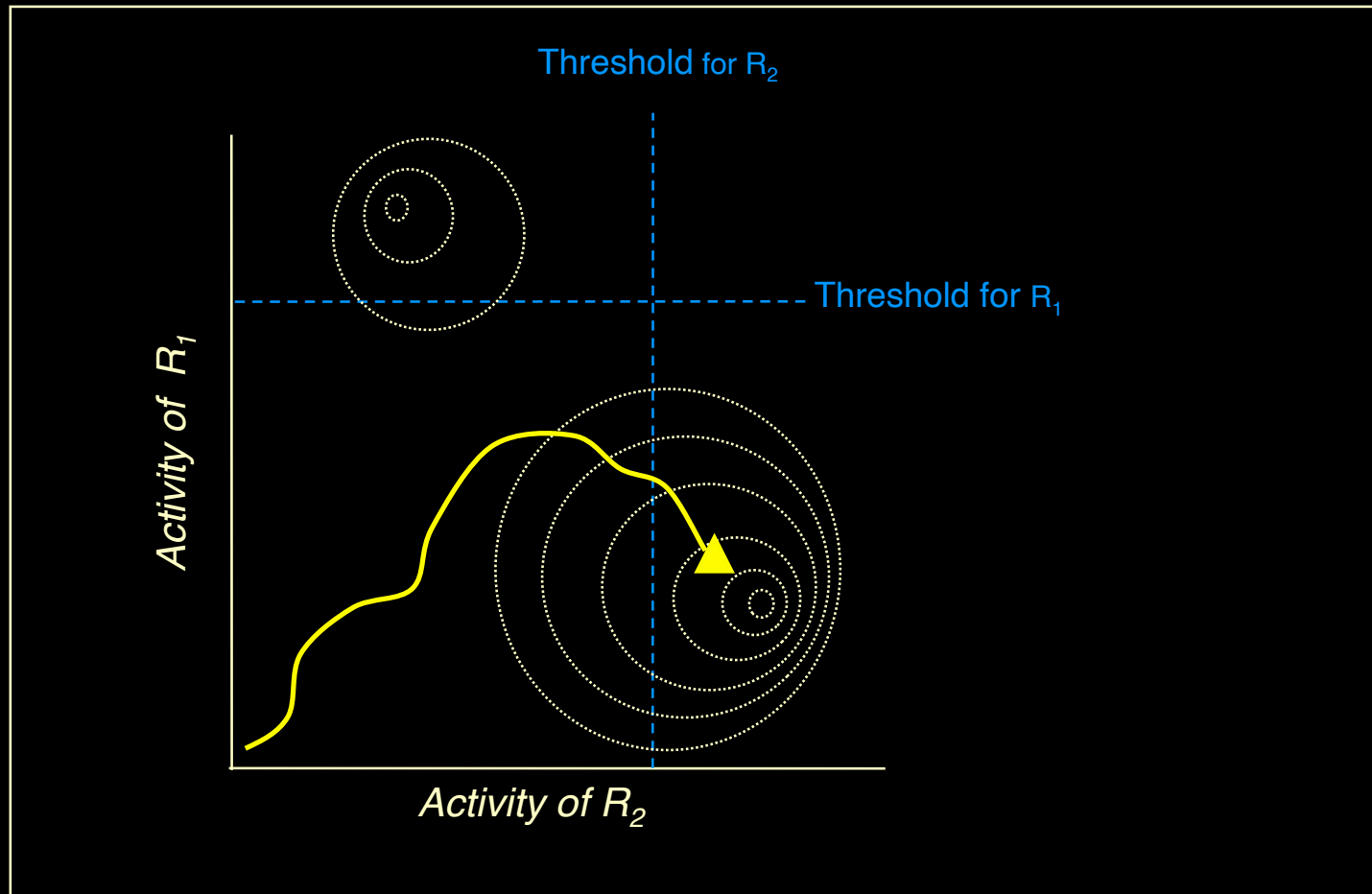
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Step 2: Examine Dynamics



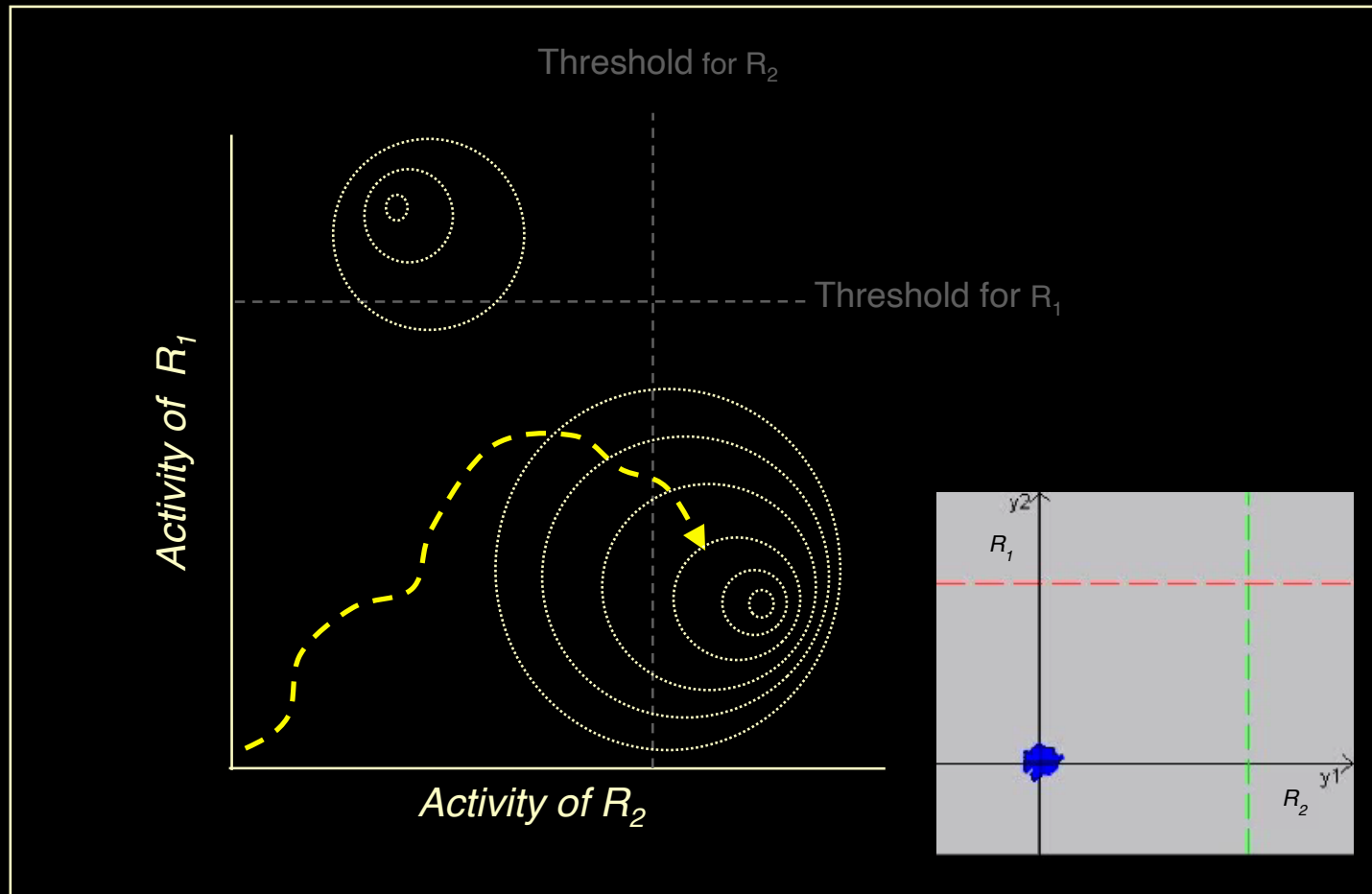
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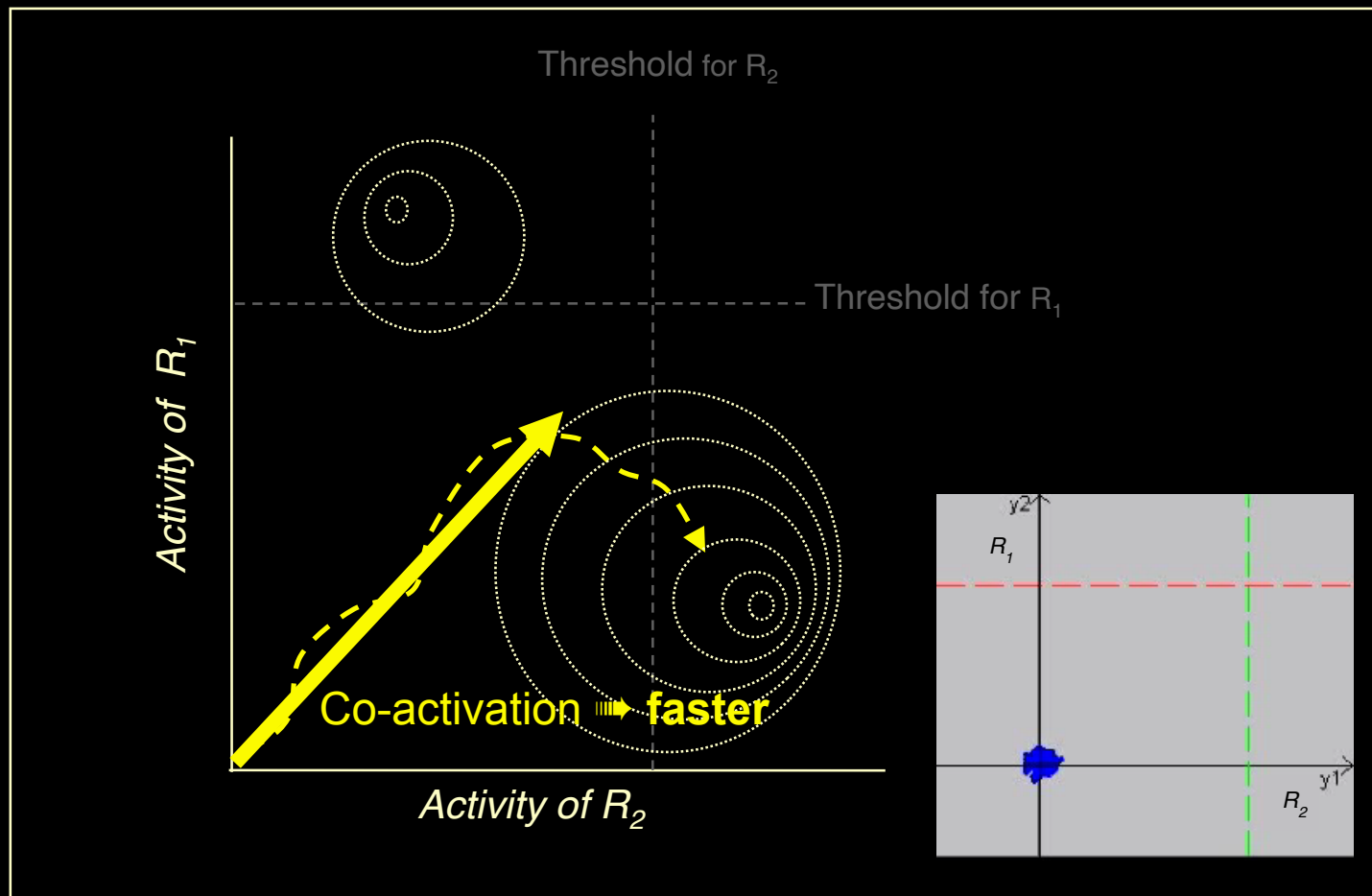
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Step 3: Note that there are two components of the trajectory...



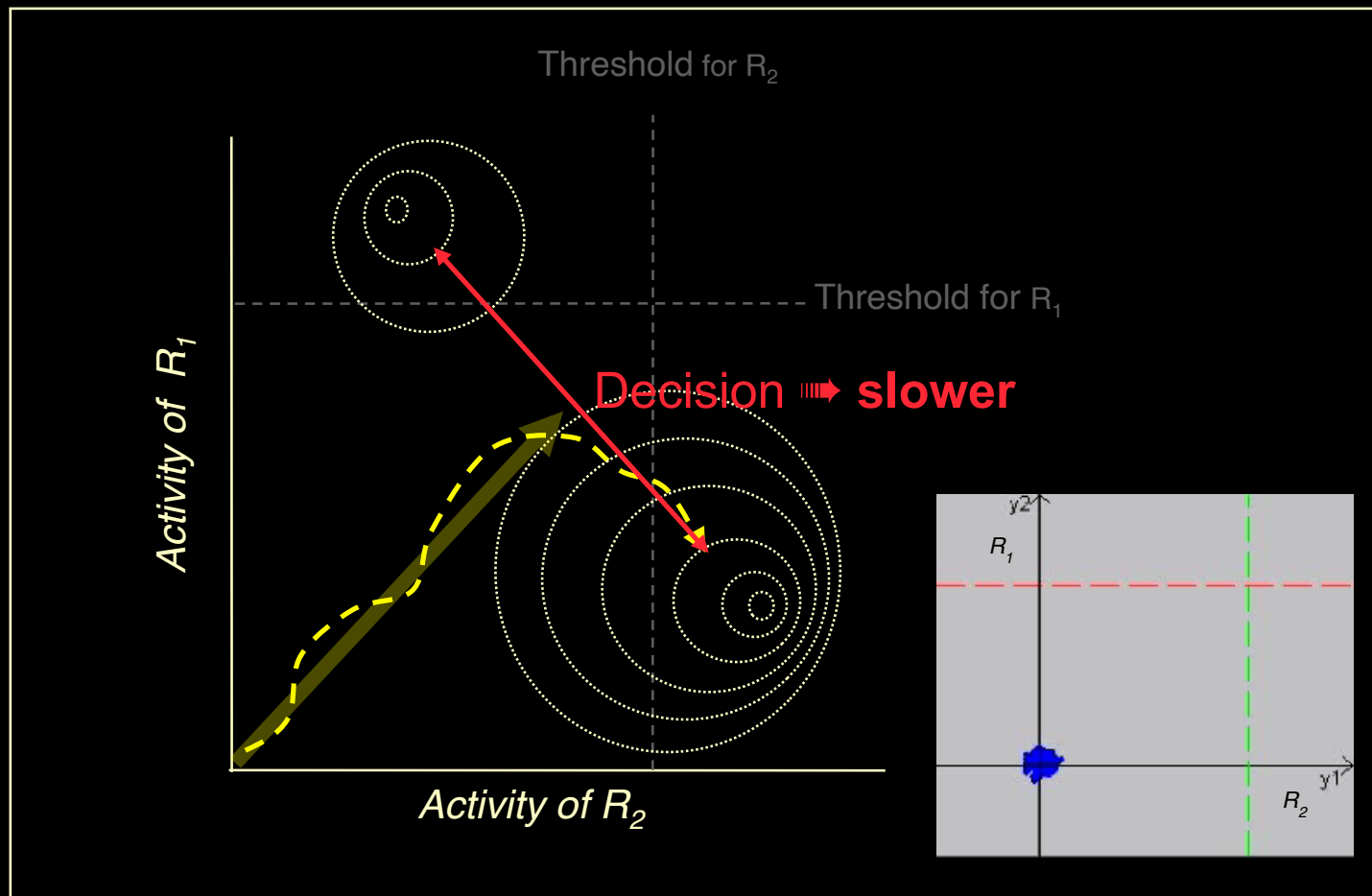
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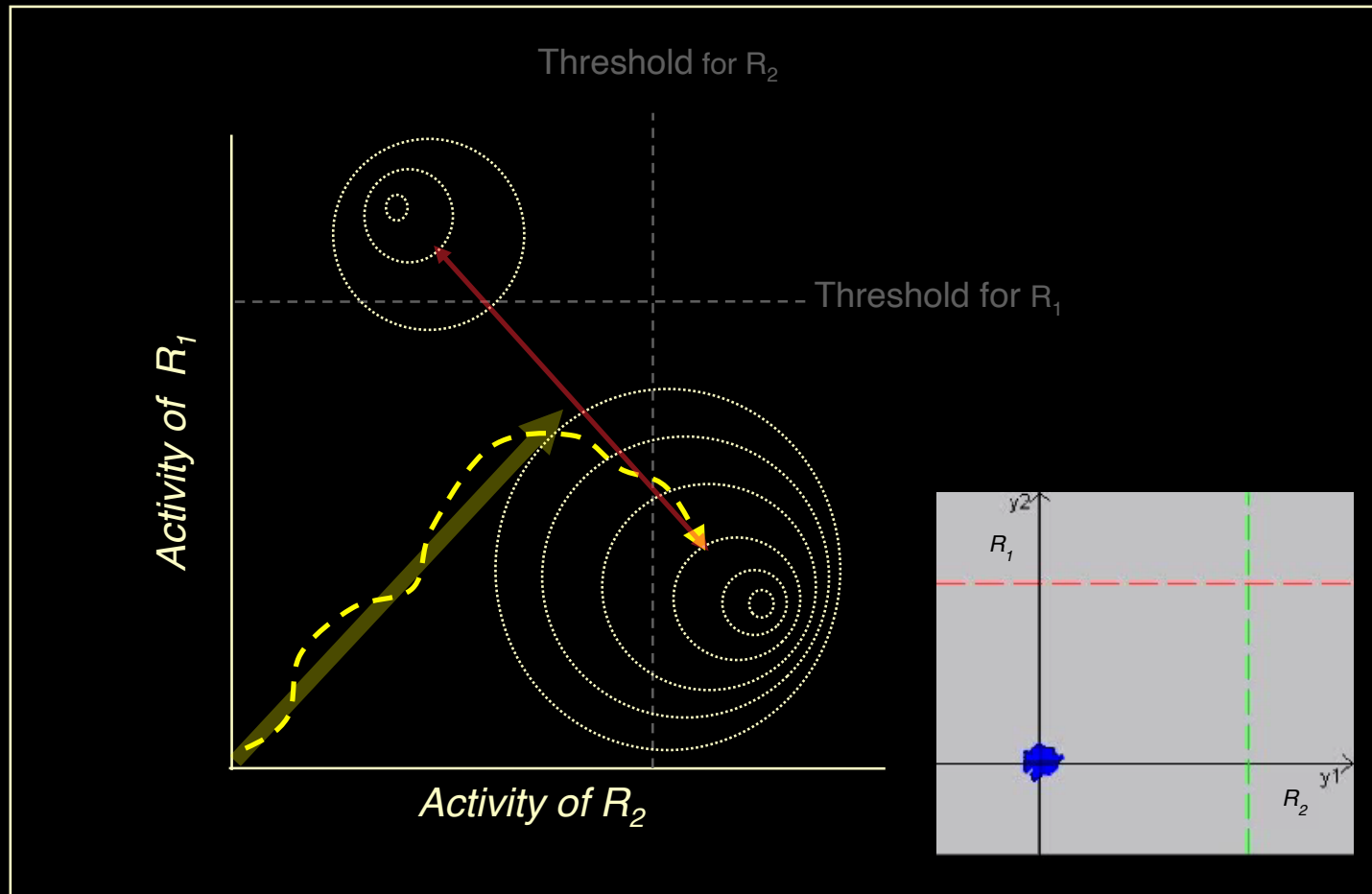
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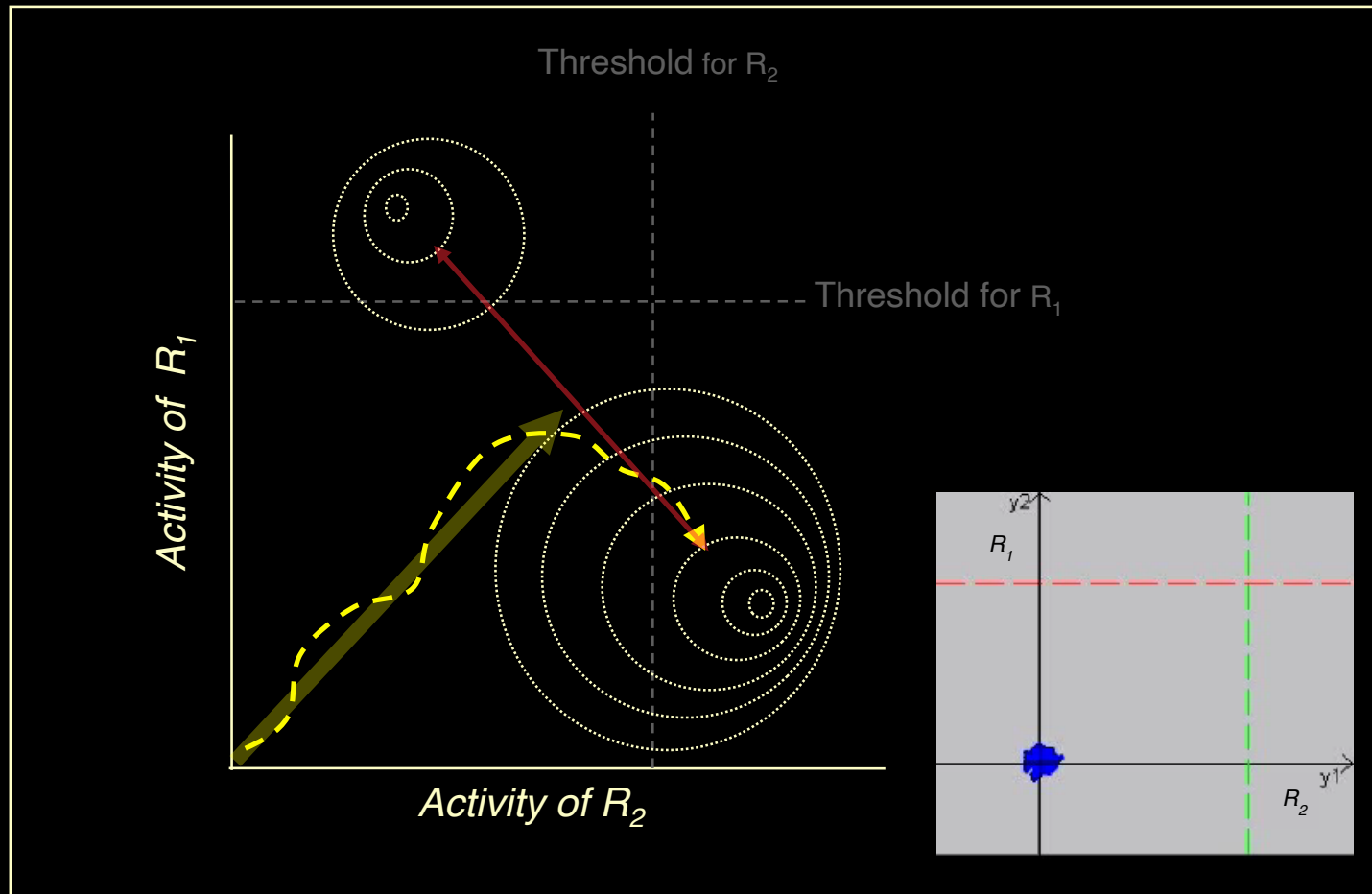
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and that they have different dynamics



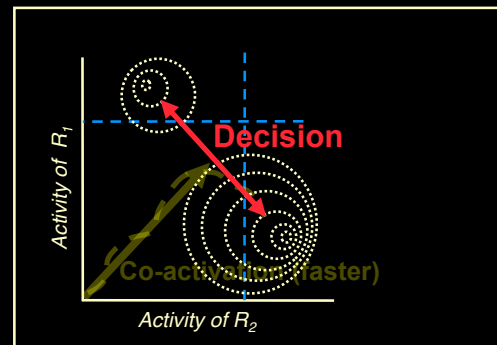
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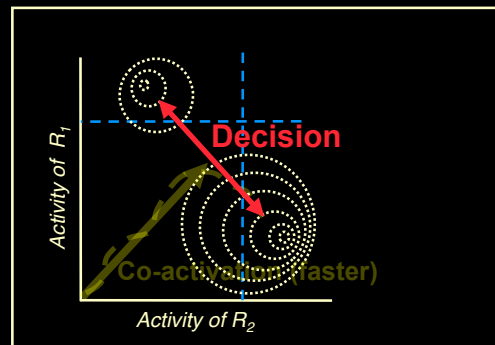
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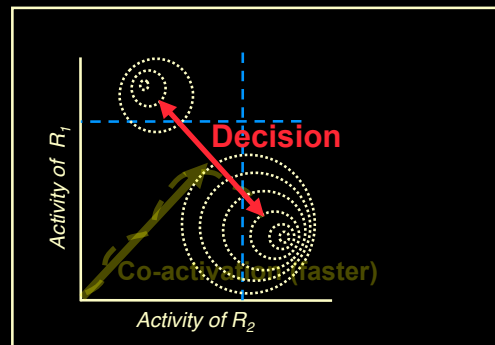
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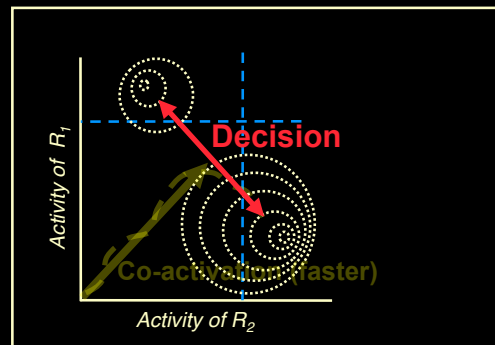
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Simplification & Analysis

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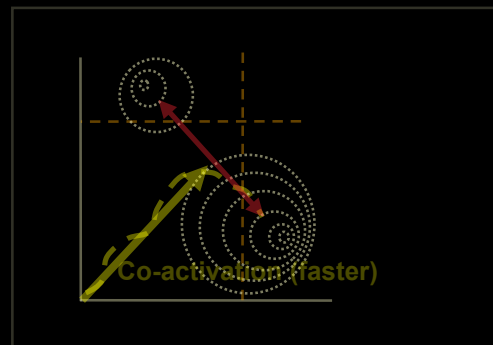
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Simplification & Analysis

Step 5: Linearization

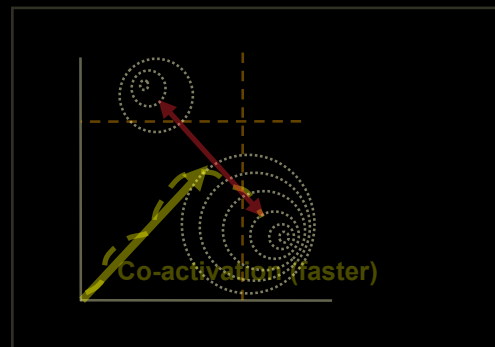
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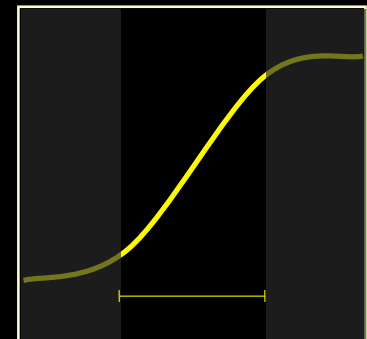
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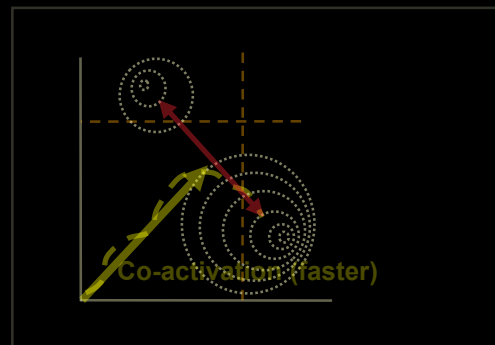
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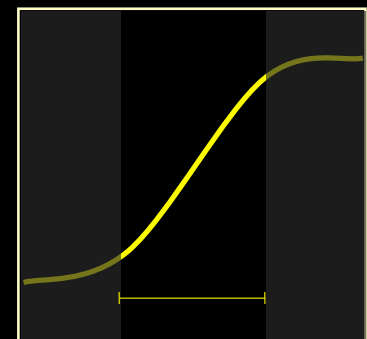
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- **Focus on linear range of function**
 - assume that units in the “focus of attention” are on the linear part of their activation function (i.e., most sensitive part of their dynamic range)
Cohen et al (Psychological Review, 1990)



Simplification

- Drift Diffusion Model (DDM):

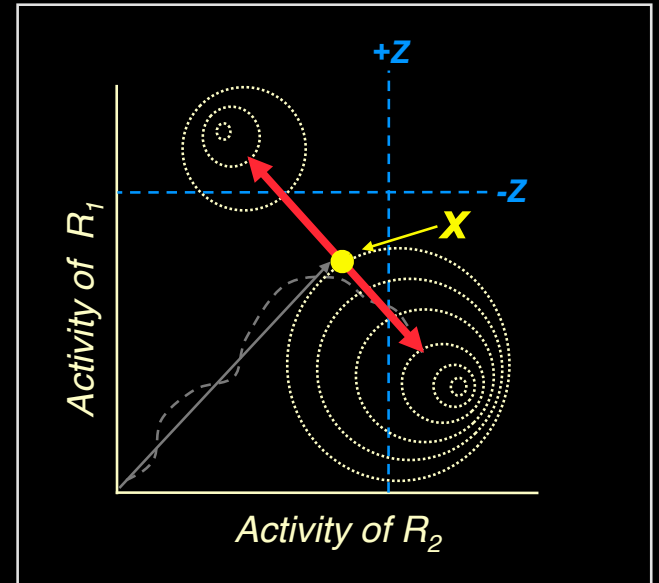
$$\dot{\mathbf{x}} = \mathbf{A} + \mathbf{c}$$

\mathbf{A} = drift rate

\mathbf{c} = noise

$$P(\mathbf{x}, t) = N(\mathbf{A}t, \mathbf{c}\sqrt{t})$$

Process ends when \mathbf{x} exceeds $\pm z$



Simplification

- **Drift Diffusion Model (DDM):**

$$\dot{x} = A + c$$

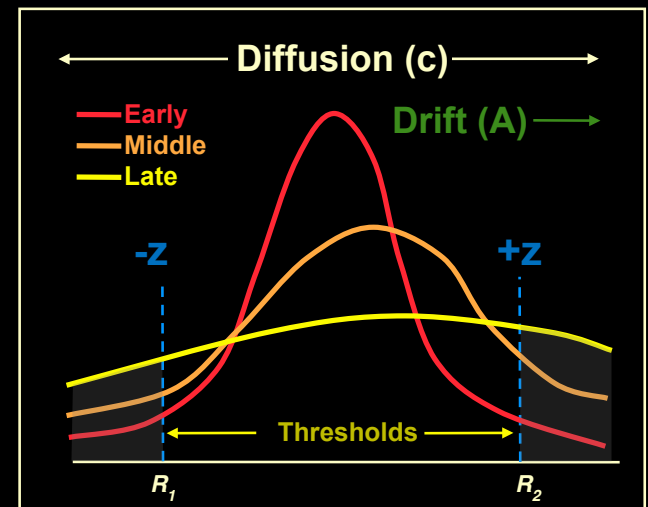
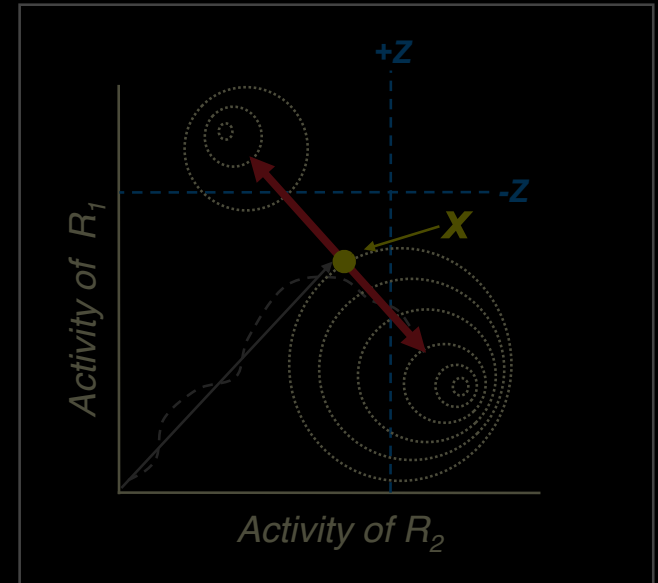
A = drift rate

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$$P(x,t) = N(Ax, c\sqrt{t})$$

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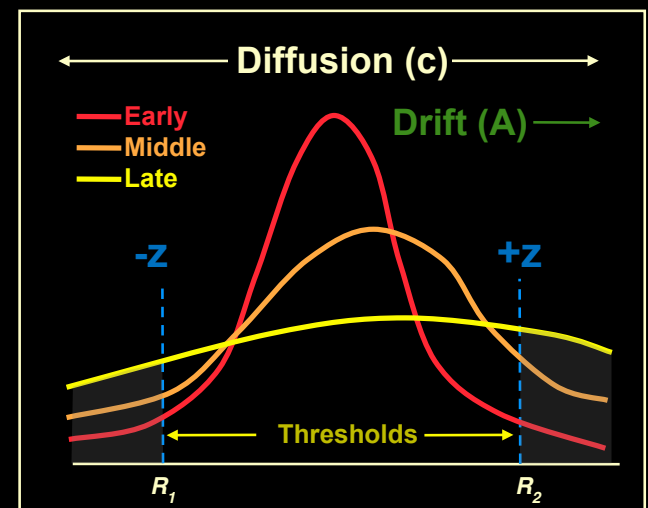
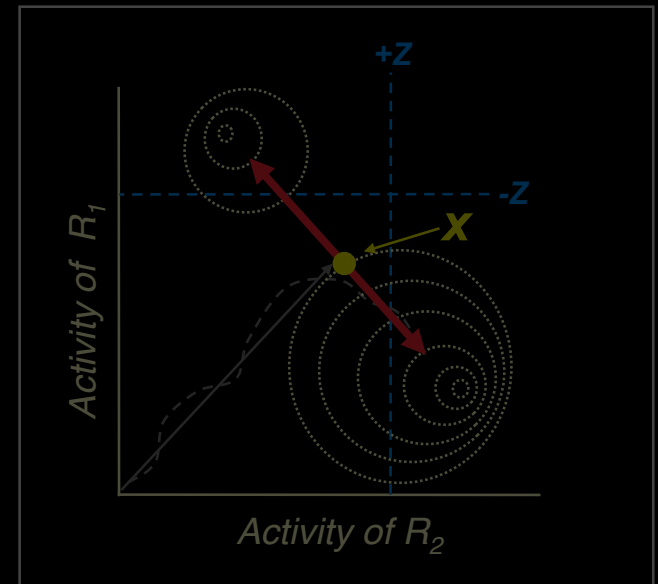
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= mathematical description of diffusion of an ideal gas



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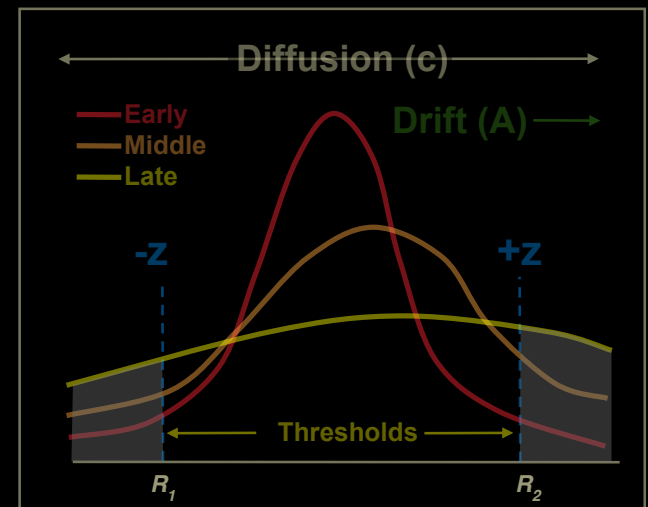
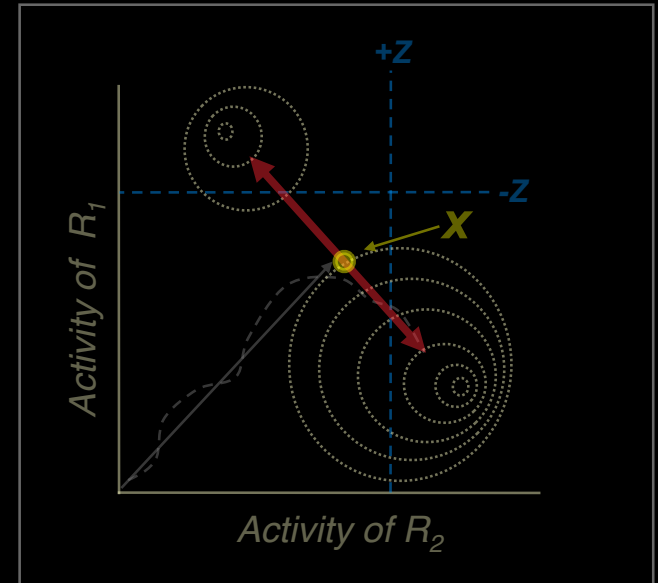
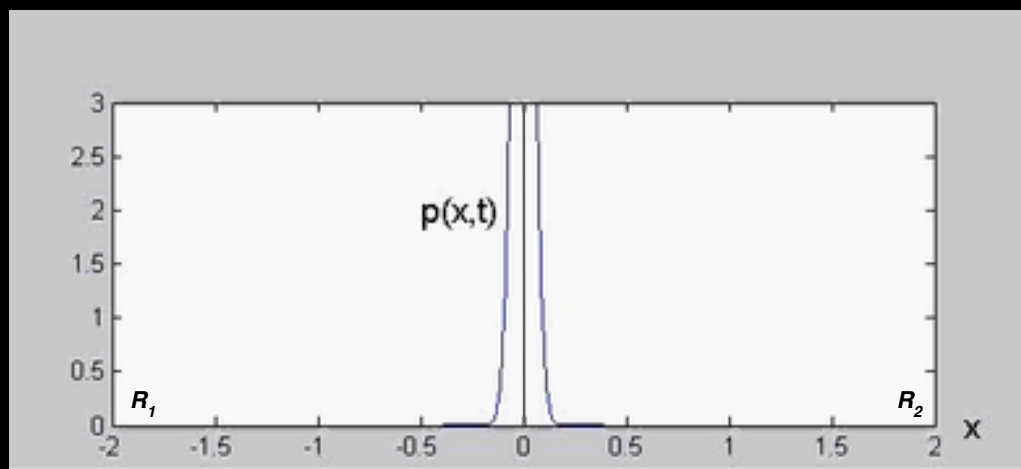
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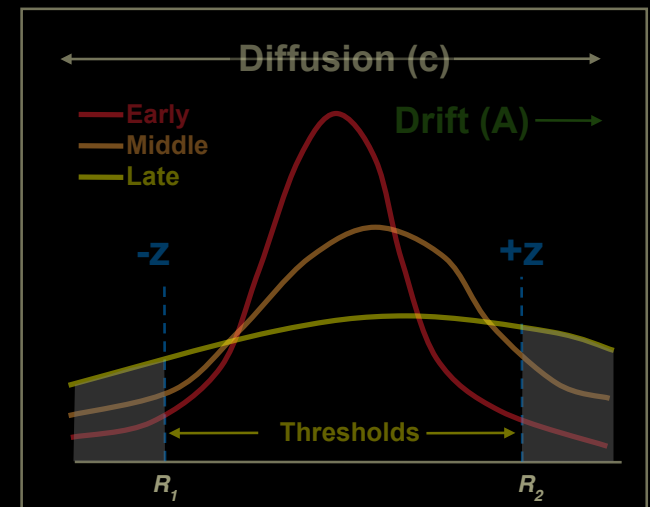
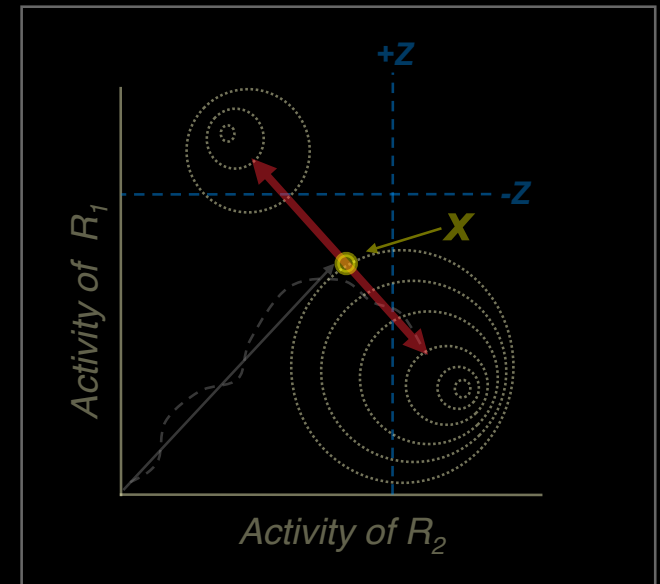
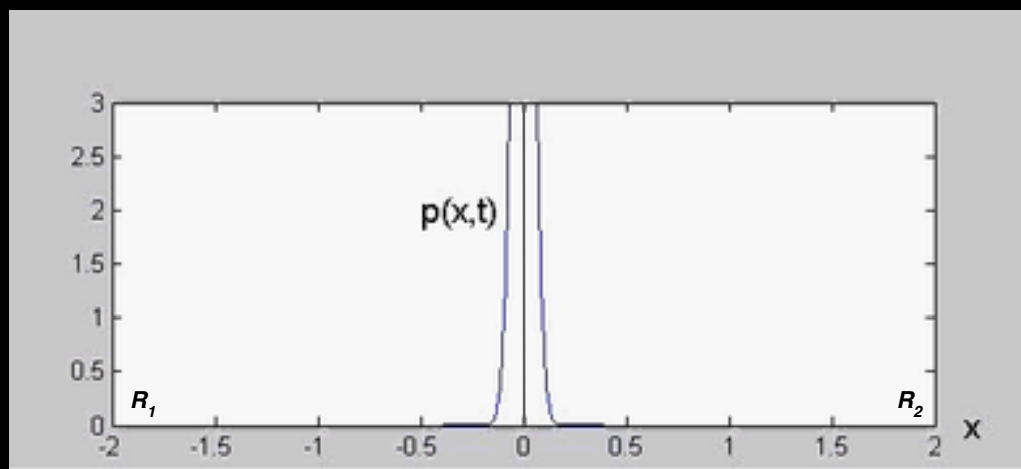
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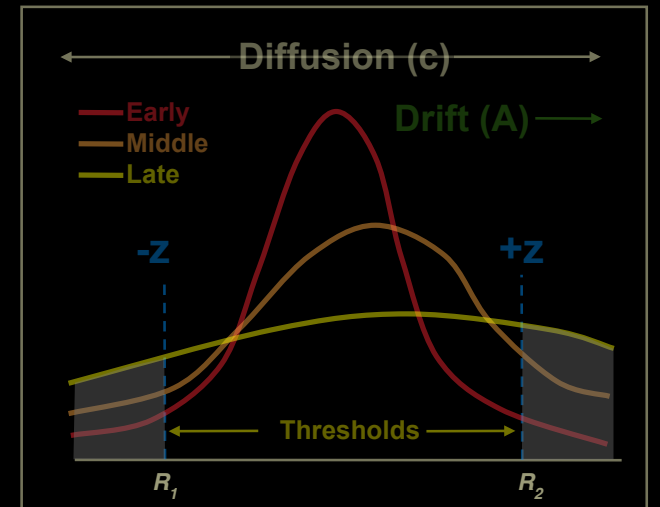
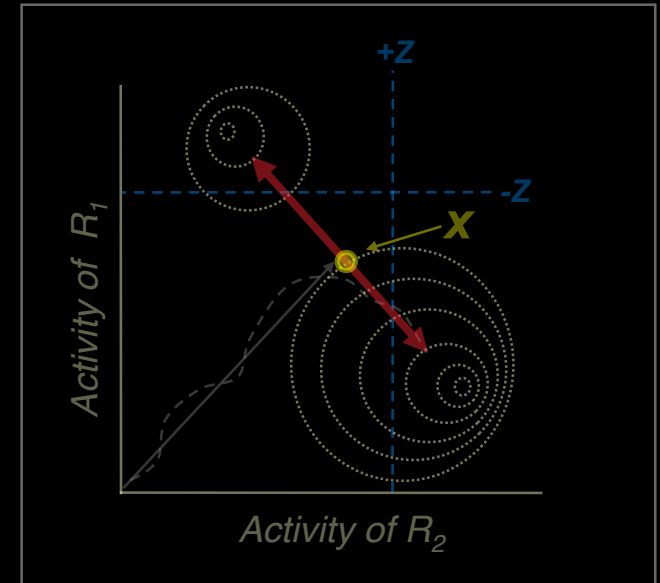
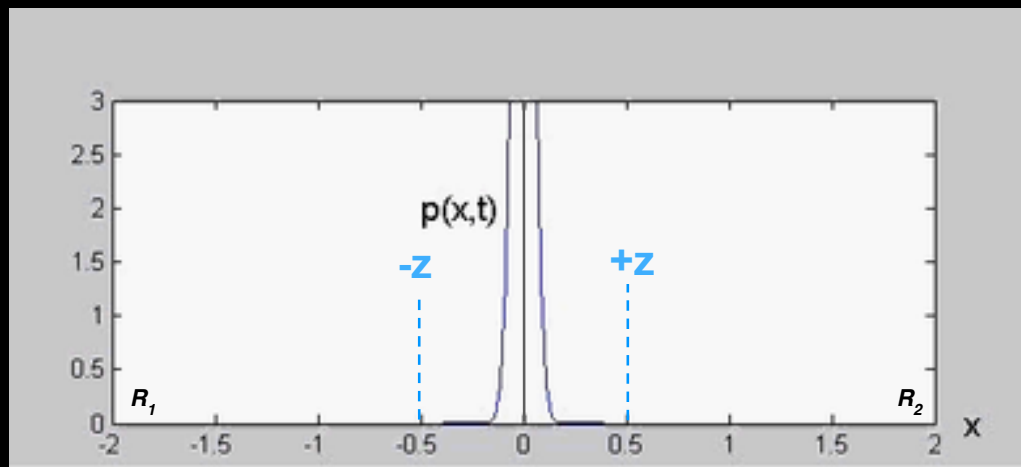
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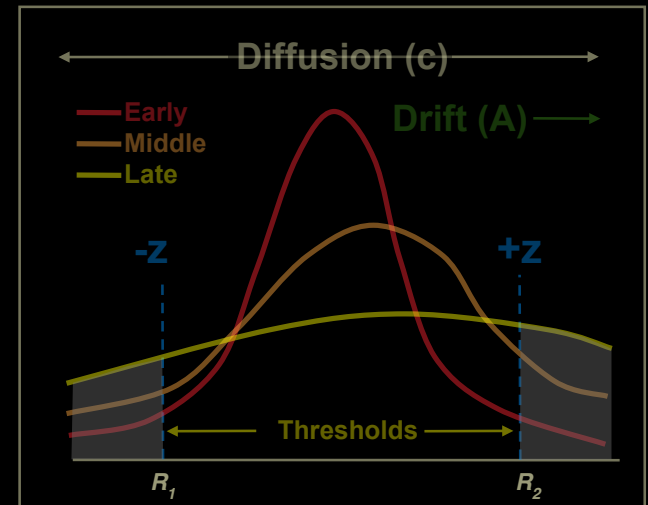
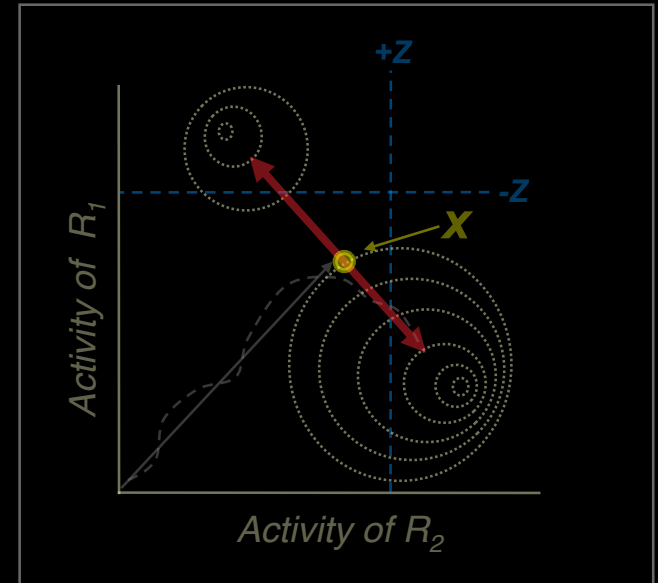
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- **Can analytically solve for Error Rate and Decision Time:**

$$\text{Error Rate (ER)} = \frac{1}{1 + e^{\frac{2 \cdot \text{Drift} \cdot \text{Threshold}}{\text{Noise}^2}}}$$

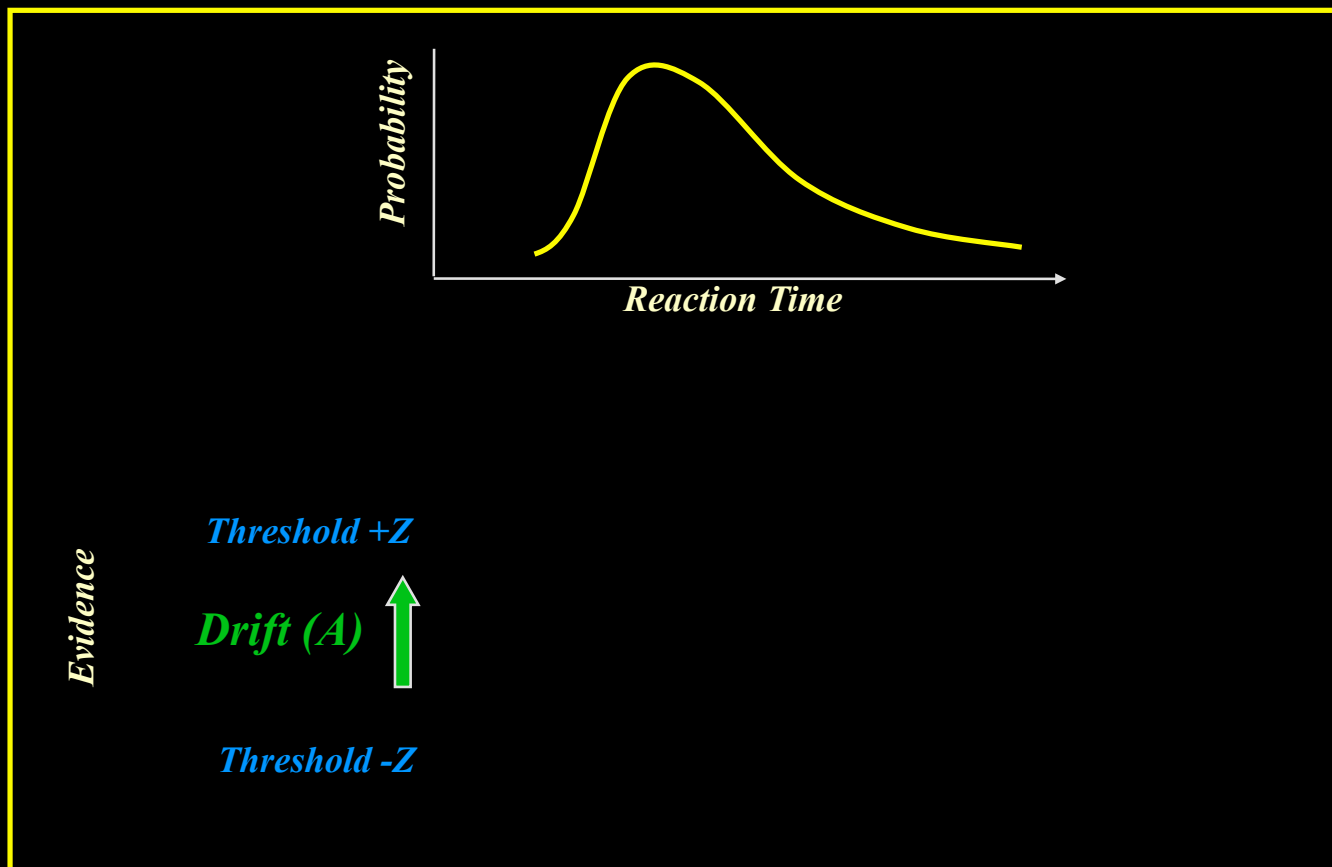
$$\text{Decision Time (DT)} = \frac{\text{Threshold}}{\text{Drift}} \text{Tanh}\left(\frac{\text{Drift} \cdot \text{Threshold}}{\text{Noise}^2}\right)$$



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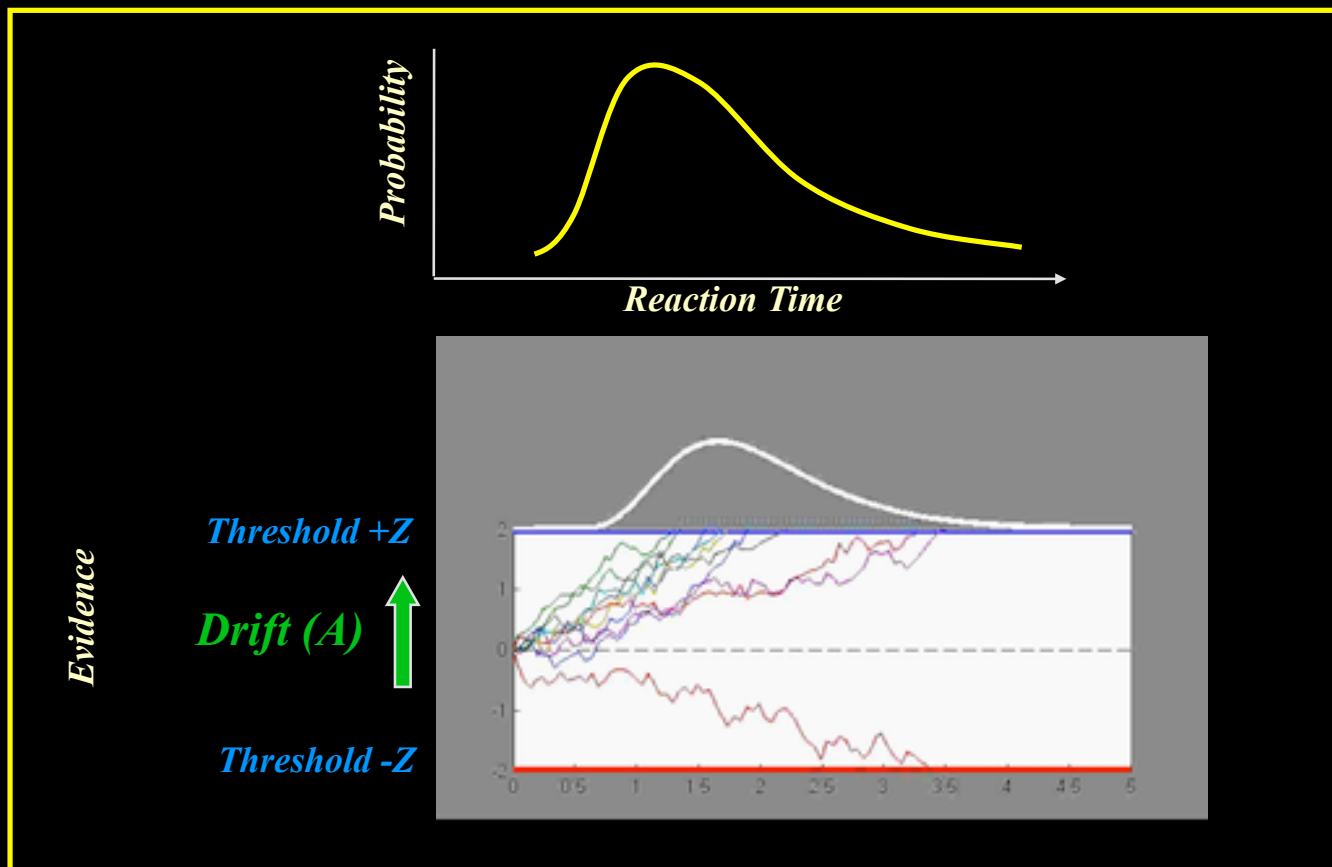
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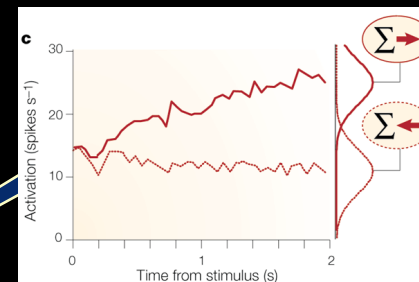
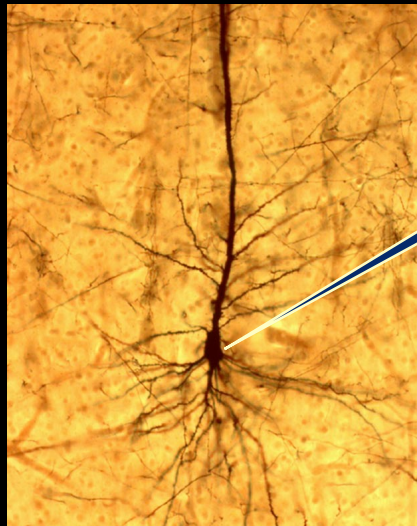
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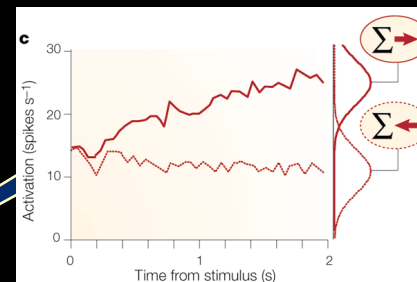
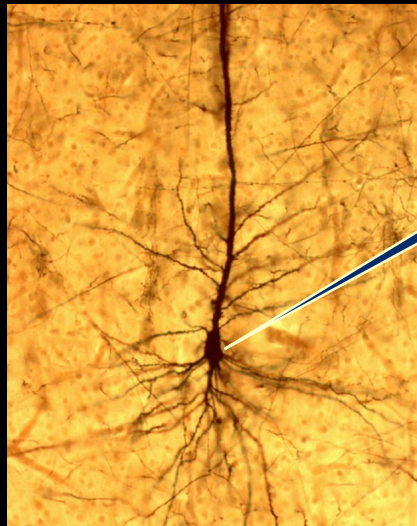
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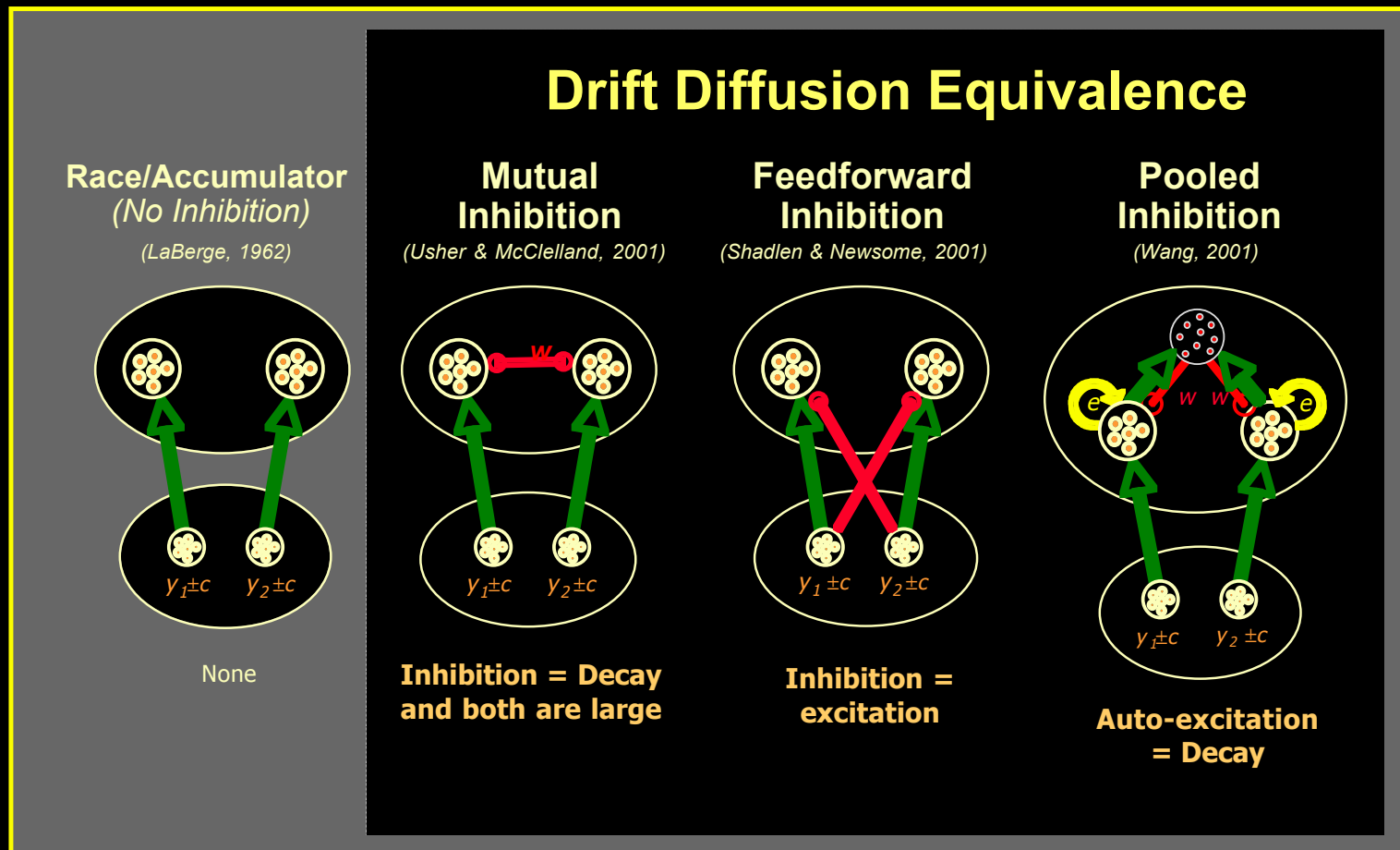
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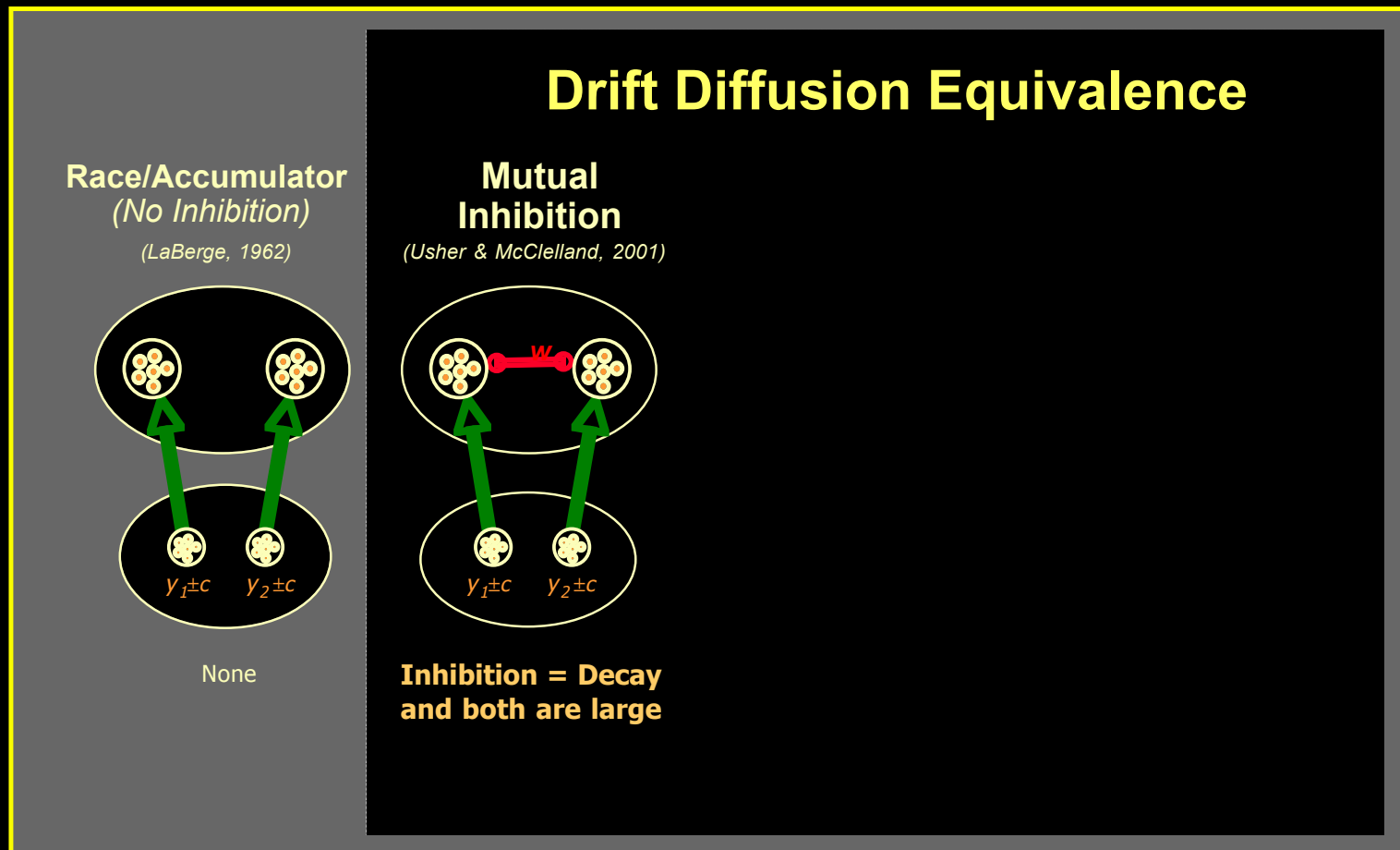
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 - Here is where ***control*** comes in...

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 - First, however, must define “*objective function*”
 - the function that control seeks to optimize