Individual variability of neural computations underlying flexible decisions

Hodivoianu Anamaria, Uceanu Alexandra, Gavrila Alexandru
University of Bucharest
Faculty of Mathematics and Informatics

May 14, 2025

Study Overview

- Better understanding of how the brain makes context-dependent decisions.
- Design an experiment with rats to study how they adapt their behavior based on task context.
- Key finding: Neural strategies vary across individuals, even when performing the same task successfully.
- Continuation of a similar study on monkeys: Context-dependent computation by recurrent dynamics in prefrontal cortex.

Context-Dependent Decision-Making

- The ability to flexibly change responses based on context.
- Requires selecting and integrating relevant sensory evidence while ignoring irrelevant input.

Why Monkeys and Rats?

Because they are **model organisms**. Model organisms are non-human species used to study biological processes that are conserved across species.

Monkeys:

- Closest analogs to human cognitive circuitry.
- Have a highly developed prefrontal cortex (PFC).

Rats:

- Cost-effective, trainable, and widely used in neuroscience.
- Rats allowed precise, large-scale recordings of neural dynamics during context-dependent decisions.

Prefrontal Cortex in Monkeys and Rats

The PFC is the front part of the frontal lobe, responsible for high-level cognitive functions like planning, decision-making, and context switching.

Monkeys:

- **FEF** (frontal eye fields) – responsible for eye movements and motor planning.

Rats:

- **FOF** (frontal orienting fields) – controls orienting responses and decision output.

Line Attractor: Concept & Intuition

- A stable trajectory in a neural dynamic system.
- Can only evolve along a 1D direction.
- Maintains its state when no new input is present.
- Decision making: brain accumulates evidence along a choice axis (line attractor).

Line Attractor: The Math Behind It

- Neural activity in the brain evolves over time according to:

$$\frac{d\vec{r}}{dt} = M\vec{r}$$

- $\vec{r}$: vector of neural activity (system state) M: dynamics matrix (how activity evolves)
- To understand this system, we look at its:
  - **Eigenvectors** – directions the system moves in
  - **Eigenvalues** – how fast it moves or decays along those directions
- A **line attractor** appears when:
  - One eigenvalue $= 0 \rightarrow$ system is stable along that direction (no decay)
  - All other eigenvalues $< 0 \rightarrow$ other directions fade over time
- Result: the system stays on a line in neural space and accumulates input there $\rightarrow$ **decision axis**

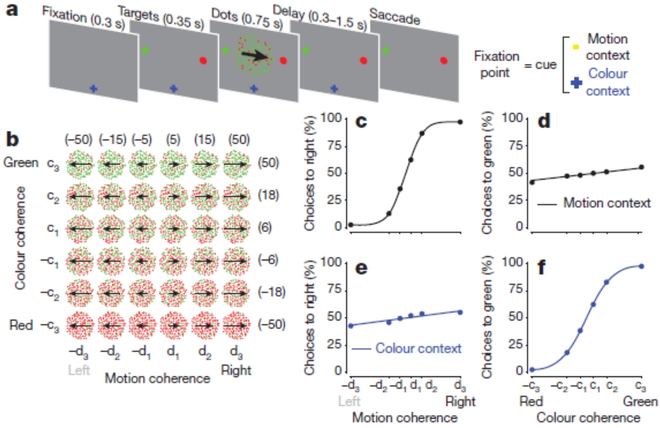
Selection Vector

$$\Delta\text{choice} = \vec{s} \cdot \vec{i}$$

- The brain receives input from many sources (motion, color, etc.).
- The **selection vector** $\vec{s}$ tells the system which input to care about.
- The input $\vec{i}$ is a pulse (e.g., motion or color).
- The dot product $\vec{s} \cdot \vec{i}$ decides how much that input moves the system along the decision line (line attractor).

The Monkey Study (Mante et al., 2013)

- Task: motion vs color, cued by context.
- Inputs from both dimensions entered PFC.
- Explained by: **line attractor** + **selection vector**.



Recurrent Neural Networks (RNNs) in the Monkey Study

- Trained RNNs to replicate the monkey's task.
- RNNs received streams of motion and color input and a context cue.
- The trained RNNs:
  - Learned to integrate only the relevant input (motion or color) based on context.
  - Developed internal dynamics with a **line attractor** and context-specific **selection vectors**.

Rat Task

Rats solve a context-dependent task

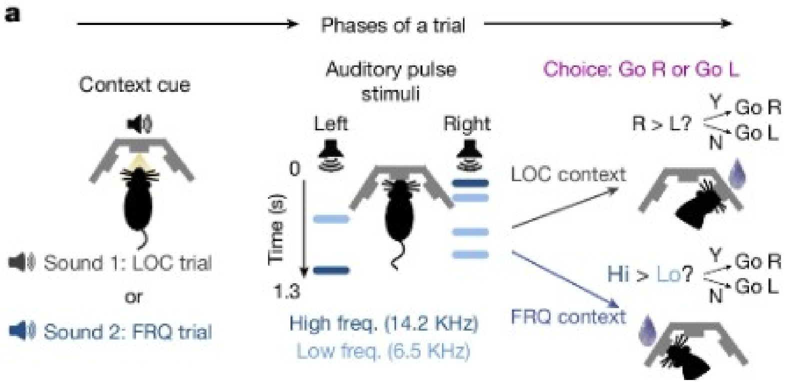


Figure: Experiment Design

Frontal Orienting Fields

Measuring neural activity in FOF:

- Irrelevant information is not gated out
- Same choice axis in both contexts
- Similar results in monkeys

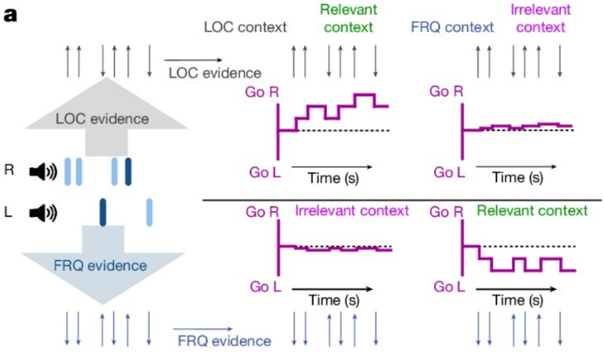


Figure: Pulses of Evidence Have Greater Influence When Relevant

Theorethical Framework

How is the impact of a pulse of evidence controlled?
Hypothesis: Choice axis = Line attractor
Implication: Change in position along the choice axis = $s \cdot i$
Condition: The product should be greater in the relevant context
Across contexts:

- Modify input vector i
- Modify selection vector s

Three Components(1)

DIM (direct input modulation) - change in input vector parallel to choice axis, immediate difference across contexts

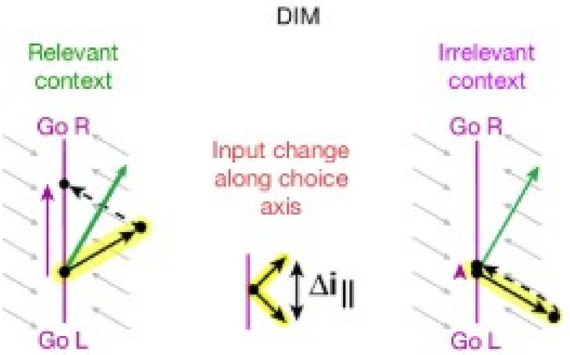


Figure: DIM
Pink - Choice Axis, Green - Selection Vector, Black - Input Vector

Three Components(2)

IIM (indirect input modulation) - change in input vector orthogonal to choice axis, gradual difference across contexts

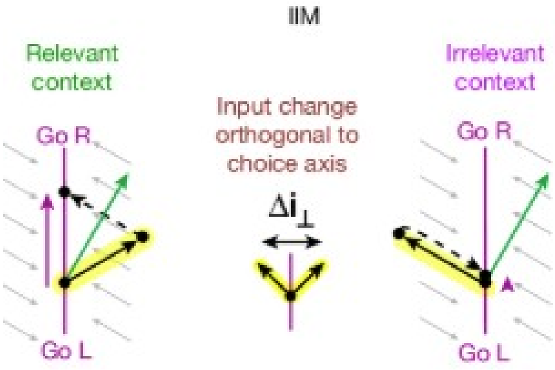


Figure: IIM

Three Components(3)

SVM (selection vector modulation) - recurrent dynamics change to adjust to relevant/ irrelevant information, gradual difference across contexts

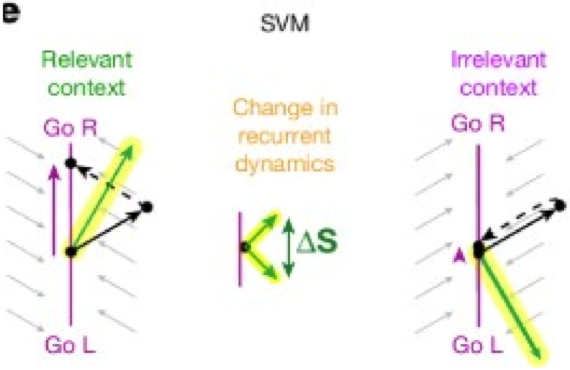


Figure: SVM

Variability

- All combinations are possible
- Theory matched experimental data
- Rats used different combinations of DIM, IIM, SVM
- All lead to good performance

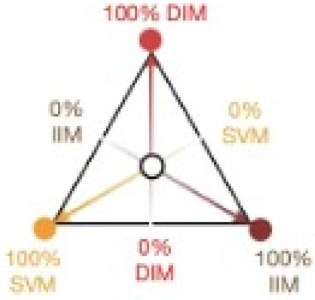


Figure: Space of Networks that Can Solve the Task Larger than Previously Thought

Biological Implications

Pulse effect:

- DIM: immediate
- IIM & SVM: changes with time (last pulse may have less influence)

Context-dependence handling:

- SVM: in decision-making regions
- DIM & IIM: outside decision-making regions, probably in:
  - sensory regions
  - pathways from sensory to decision-making regions

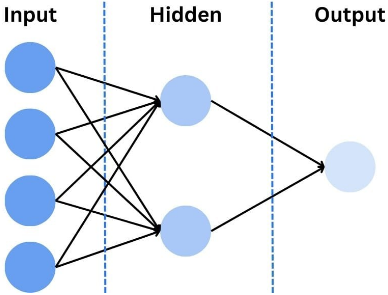
Pulse Analyses Distinguish Solutions

- Artificial model networks can be used to illustrate approaches to solving the task
  - Mante et al. in the monkey study developed an RNN and trained it
  - They observed important similarities in the experimental data and the trained RNNs
  - Upon further analysis the researchers found SVM as the leading candidate used in decision-making.
- Fast vs slow separation along the choice axis (immediate $=$ DIM; delayed $=$ IIM/SVM)

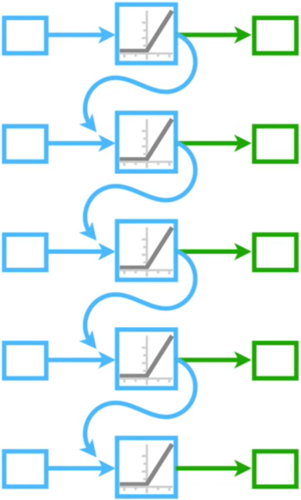
Introduction to RNNs

- What are RNNs?
- How do they work?
- Why use them?

Introduction to Recurrent Neural Networks(2)



Source: SimplyBlock



Source: StatQuest

New Observation in Linearization

- In the current study, Pagan et al. found that the results from Mante's study were biased because of the linearization used
- Activation-space hides input modulations because it linearizes before nonlinearity.
- Firing-rate-space linearizes after nonlinearity, revealing all three components.

RNN Training vs Engineering

- Trained many RNNs on the same rat task
  - Backpropagation-through-time (BPTT)
    - Sends trained RNNs to SVM corner
  - Engineered RNNs
    - Analytical construction via derived constraints

RNN Training vs Engineering(2)

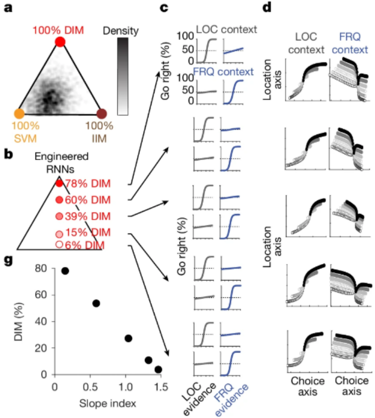


Figure: RNN Training Dispersion

Engineered RNNs

- Started by analyzing standard trained RNNs to understand their internal dynamics
- Derived mathematical equations that characterize how input and recurrent weights contribute to each component (DIM, IIM, SVM)
- Used these equations to construct new RNNs from scratch that lie at any desired point in the solution triangle

Linking Neural and Behaviour Variability

- Study based on relative weight that evidence presented across different time points of a trial has on the subject's choices
- If that is correct, then fast vs slow context-dependent effects on the choice axis should have corresponding behavioural correlates
- Tested the prediction on RNNs engineered to solve the task using different amounts of DIM.
- The RNNs data was tightly linked with rats experimental data.

Conclusion

- Individual variability arises from different mixes of DIM, IIM, SVM
- Neural differential pulse responses predict behavioral weighting of early vs late evidence
- Broader insight

Thank You!