# A Coupled Fokker-Planck Model for Collective Decision-Making

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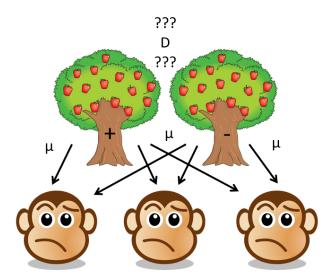
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# Background

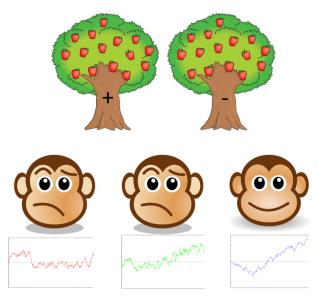
Imagine that you are a monkey.



You are looking to scope out possible foraging spots with companions. For simplicity, suppose we break this endeavor into a sequence of decisions between two trees.



How do **you** make a decision, using both your **own** evidence along with knowledge about companions' previous decisions?



#### Big Question: How to Maximize Collective Reward Rate?

- Where do you set your own decision thresholds?
- How much of a kick to your own decision state do you take from others' decisions? Their decisions are quicker, but are they reliable?
- How do these considerations depend on the amount of reward you expect from each choice, assuming it is the correct choice?
- Can a group with appropriately-chosen parameters achieve a higher average reward rate than individuals?

# First, a Single-Agent Model

$$dX = \mu dt + \sqrt{2D} dW(t), \qquad X(0) = 0$$

$$\updownarrow$$

$$\frac{\partial c}{\partial t} = -\mu \frac{\partial c}{\partial x} + D \frac{\partial^2 c}{\partial x^2}, \qquad c(-L, t) = c(H, t) = 0$$

- X(t): current decision state (decision thresholds set at X = H and X = -L)
- $\mu$ : environmental drift
- D: strength of environmental noise/uncertainty
- c(x, t): probability density function



# Single-Agent Reward Rate

$$RR = \frac{\langle r \rangle}{\langle T \rangle + T_I}$$

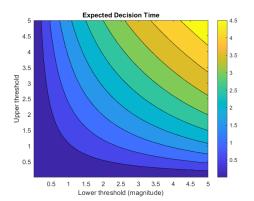
- ullet Assume a  $\mu=\pm 1$  environment with probability  $rac{1}{2}$
- $\langle T \rangle$ : expected decision time
- $\bullet$   $\langle r \rangle$ : expected amount of reward per decision
- T<sub>I</sub>: transient time between sequential decisions
  - Needs to be large enough!
  - We use  $T_I = 5$



## Single-Agent Expected Time

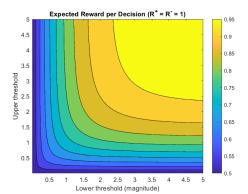
$$\langle T \rangle = \langle T | \mu = 1 \rangle P(\mu = 1) + \langle T | \mu = -1 \rangle P(\mu = -1)$$

$$= \frac{1}{2} \frac{(1 - e^L)(1 - e^H)(L + H)}{e^{L + H} - 1}$$

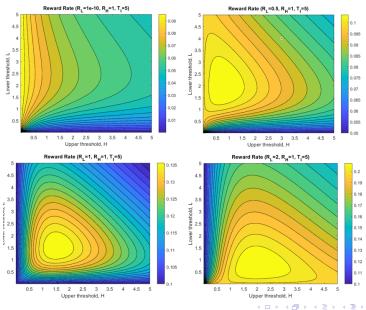


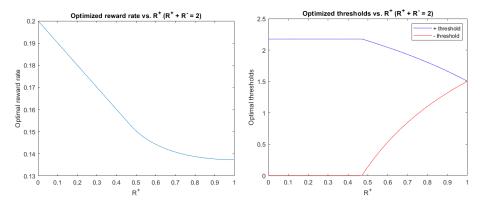
### Single-Agent Expected Reward

$$\begin{split} \langle r \rangle &= R^+ \cdot P(\text{decides at } H \,|\, \mu = 1) P(\mu = 1) \\ &\quad + R^- \cdot P(\text{decides at } -L \,|\, \mu = -1) P(\mu = -1) \\ &= \frac{1}{2} \frac{R^+(e^L - 1)e^H + R^-(e^H - 1)e^L}{e^{L+H} - 1} \end{split}$$



#### Putting it All Together





Notice how immediate decision is optimal for a range of reward ratios.

## Coupled Two-Agent Drift-Diffusion Model

$$dX_1 = \mu_1 dt + \sqrt{2D} dW_1(t) + G_2 q_{\pm} \delta(t - t_2), \qquad X_1(0) = 0,$$
  $dX_2 = \mu_2 dt + \sqrt{2D} dW_2(t) + G_1 q_{\pm} \delta(t - t_1), \qquad X_2(0) = 0$ 

- t<sub>i</sub>: the time at which agent i decides
- $G_i$ : sign of the threshold at which agent i makes decision
- ullet  $q_{\pm}$ : "kick" size in  $\pm$  direction after other agent's decision
- Assume an undecided agent is forced to decide at the nearest threshold *immediately* after first decision
- Assume  $\mu_1 = \mu_2$  in any given environment

#### Reward Considerations

For simplicity, we try to minimize the number of parameters in the reward rate optimization problem with the following reward methods:

- "Agent-symmetric" rewards
  - $R_1^+ = R_2^+ \text{ and } R_1^- = R_2^-$
  - ▶ Optimal strategy gives  $H_1 = H_2$  and  $L_1 = L_2$
- "Agent-asymmetric" rewards
  - $R_1^+ = R_2^-$  and  $R_1^- = R_2^+$
  - ▶ Optimal strategy gives  $H_1 = L_2$  and  $L_1 = H_2$

# The Agent-Symmetric Case: Reward Rate

$$RR = \frac{2\langle r \rangle}{\langle T \rangle_F + T_I}$$

•  $\langle T \rangle_F$ : expected time for the **first** agent to decide

$$egin{aligned} \langle T 
angle_{F} &= \langle T_{i} \, | \, \mu = 1 \ ext{and} \ t_{i} < t_{j} 
angle P(\mu = 1) \ &+ \langle T_{i} \, | \, \mu = -1 \ ext{and} \ t_{i} < t_{j} 
angle P(\mu = -1) \end{aligned}$$

•  $\langle r \rangle$ : a bit more complicated than before!

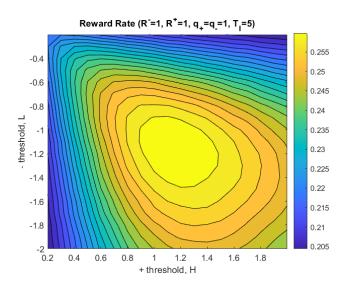
$$\langle r \rangle = R^+ \cdot P(i \text{ decides at } H \,|\, \mu = 1) P(\mu = 1) \\ + R^- \cdot P(i \text{ decides at } -L \,|\, \mu = -1) P(\mu = -1)$$

where

$$\begin{split} &P(i \text{ decides at } x \mid \mu) \\ &= P(i \text{ decides at } x \mid \mu \text{ and } t_i < t_j) P(t_i < t_j \mid \mu) \\ &+ P(i \text{ inst. crosses } x \mid \mu \text{ and } t_i > t_j) \big(1 - P(t_i < t_j \mid \mu)\big). \end{split}$$

By symmetry, we have  $P(t_i < t_j \mid \mu = 1) = \frac{1}{2}$ .

# Two-Agent Reward Rate Example



#### Future Work

- $\bullet$  Generate figures similar to those the single-agent plots above, keeping  $R^+ + R^- = 2$ 
  - Is there still a nontrivial region of rewards for which agents should decide immediately?
  - ▶ Does the two-agent model outperform the single-agent model, i.e. should you listen to your companions under this model?
- Allow diffusion after first decision instead of enforcing "immediate interrogation."

Thank you!