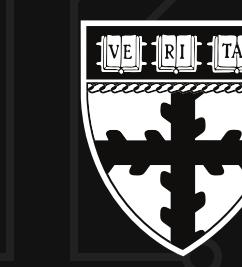
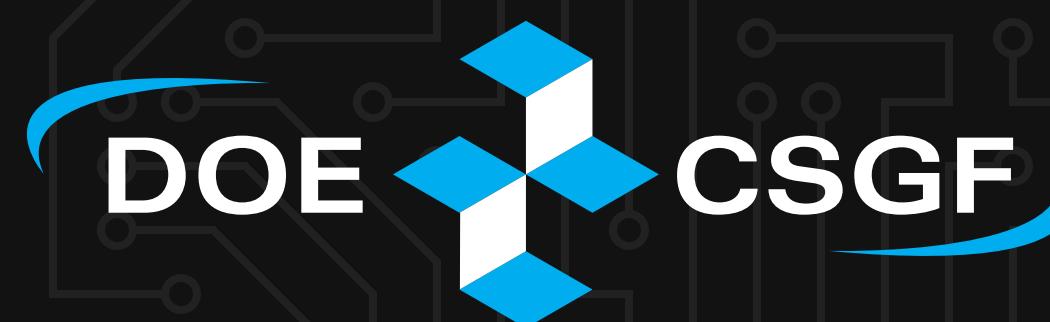


# Bayes Bots:

## Bayesian Decision-Making for Robot Swarms

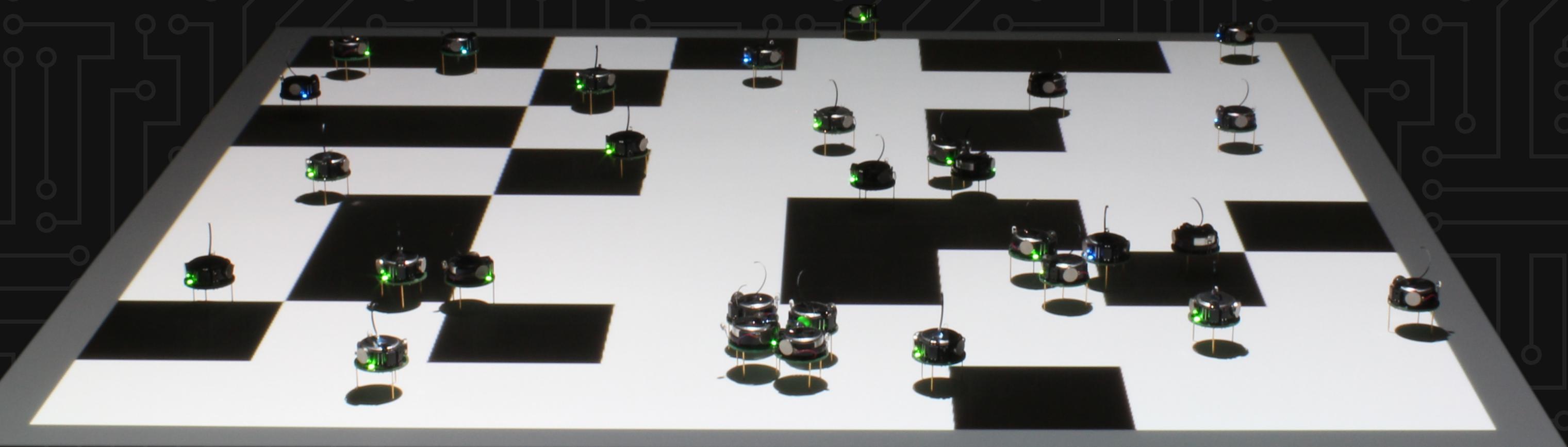
Julia Ebert,<sup>1</sup> Melvin Gauci,<sup>1,2</sup> and Radhika Nagpal<sup>1,2</sup>

<sup>1</sup>Harvard University, <sup>2</sup>Wyss Institute



Harvard John A. Paulson  
School of Engineering  
and Applied Sciences

WYSS INSTITUTE



## Background

### GENERAL PROBLEM

How can a swarm of robots collectively make accurate and fast decisions about features of their environment?

### CHALLENGE

Robots only have local observations and communication

### CASE STUDY

Kilobots deciding whether an environment is mostly black or mostly white

### SOLUTION

Robots maintain Bayesian model of environment, update with observations, and apply decision rule.

Bayesian decision-making provides a leaderless, mathematically-grounded decision framework that can be applied across robot and environment complexities.

## Agent Model & Algorithm

### BAYESIAN MODEL

Prior distribution of fill ratio  $f$ :

$$f \sim \text{Beta}(\alpha, \beta)$$

Likelihood of color  $C$ :

$$C \sim \text{Bernoulli}(f)$$

Posterior after observing color:  $f | C \sim \text{Beta}(\alpha + C, \beta + (1 - C))$

### 1. MOVEMENT

Continuous pseudo-random walk in bounded arena

### 2. OBSERVATION

Observe black/white color  $C$  after observation interval

### 3. POSTERIOR UPDATE

Update posterior with own and received observations

### 4. DECISION

Commit when sufficient credible interval (credible threshold) of posterior is above or below 0.5

### 5. COMMUNICATION

- Transmit most recent observation OR decision
- Receive observations from other robots and update posterior

## Simulations

### SETUP

100 Kilobot robots in 2.4 m x 2.4 m arena in the Kilosim simulator  
100 trials per condition (5,280 parameter combinations)

### PARAMETER SWEEPS

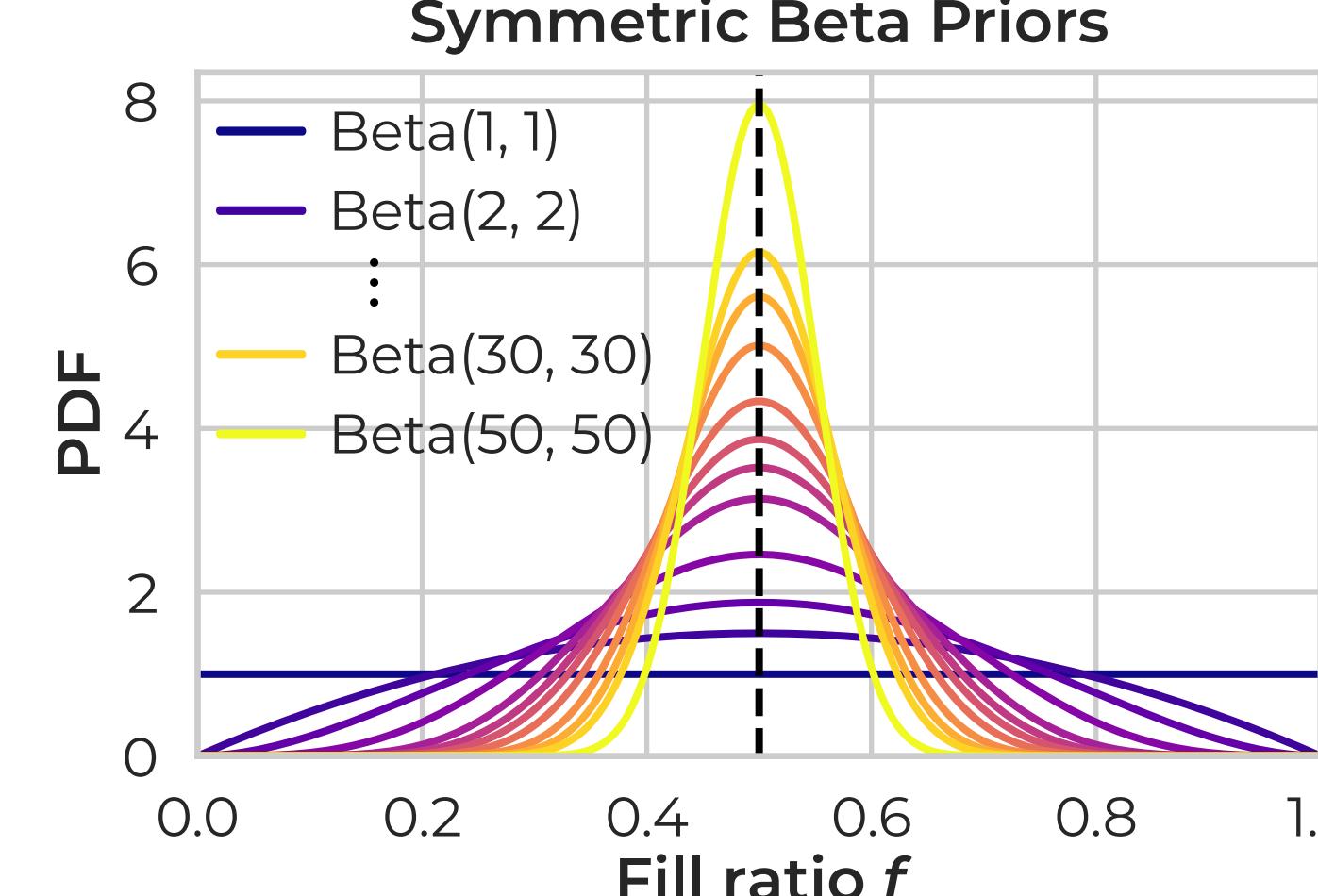
Symmetric Beta prior: {1, 2, 3, 5, 8, 10, 12, 15, 25, 30}

Positive feedback: {0, 1}

Observation interval (s): {1, 5, 10, 15, 30, 45, 60, 90, 120, 150, 200}

Credible threshold: {0.9, 0.95, 0.98, 0.99}

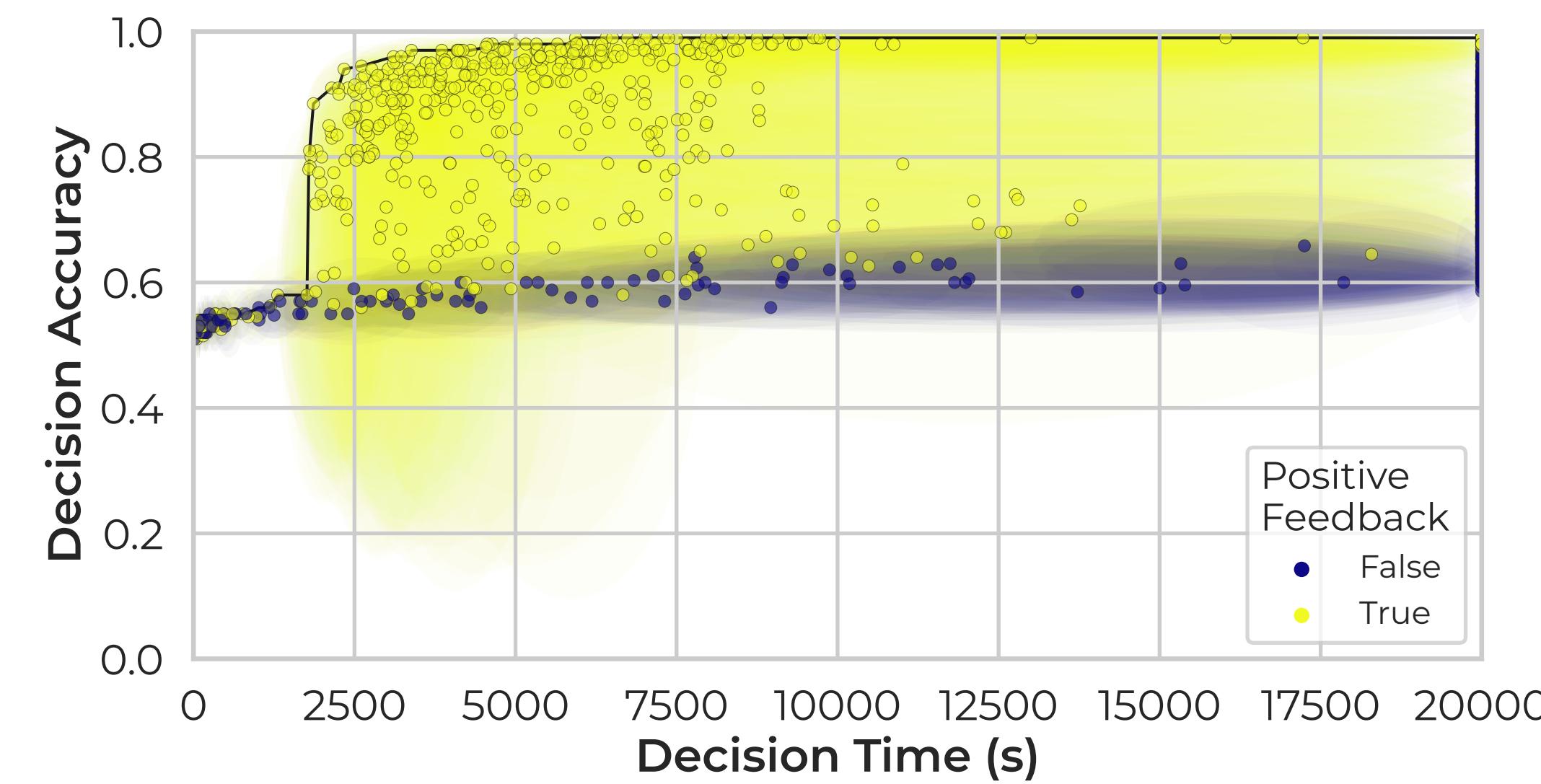
Fill ratio: {0.52, 0.55, 0.6, 0.7, 0.8}



## Results

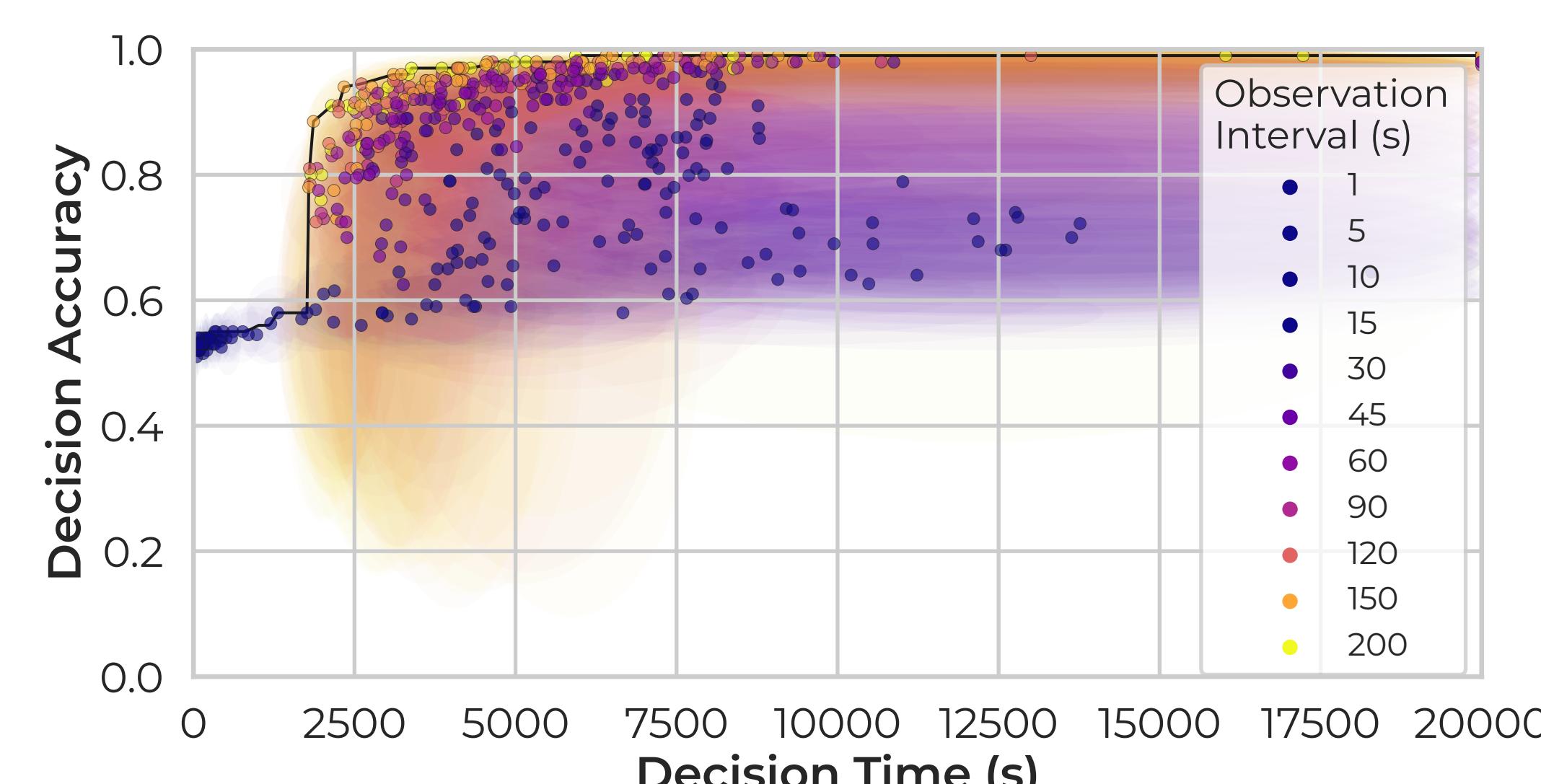
### GOAL

Understand the **speed/accuracy trade-off** in decision-making as a multi-objective optimization problem by comparing against the Pareto front for a fill ratio of 0.52.



### FEEDBACK

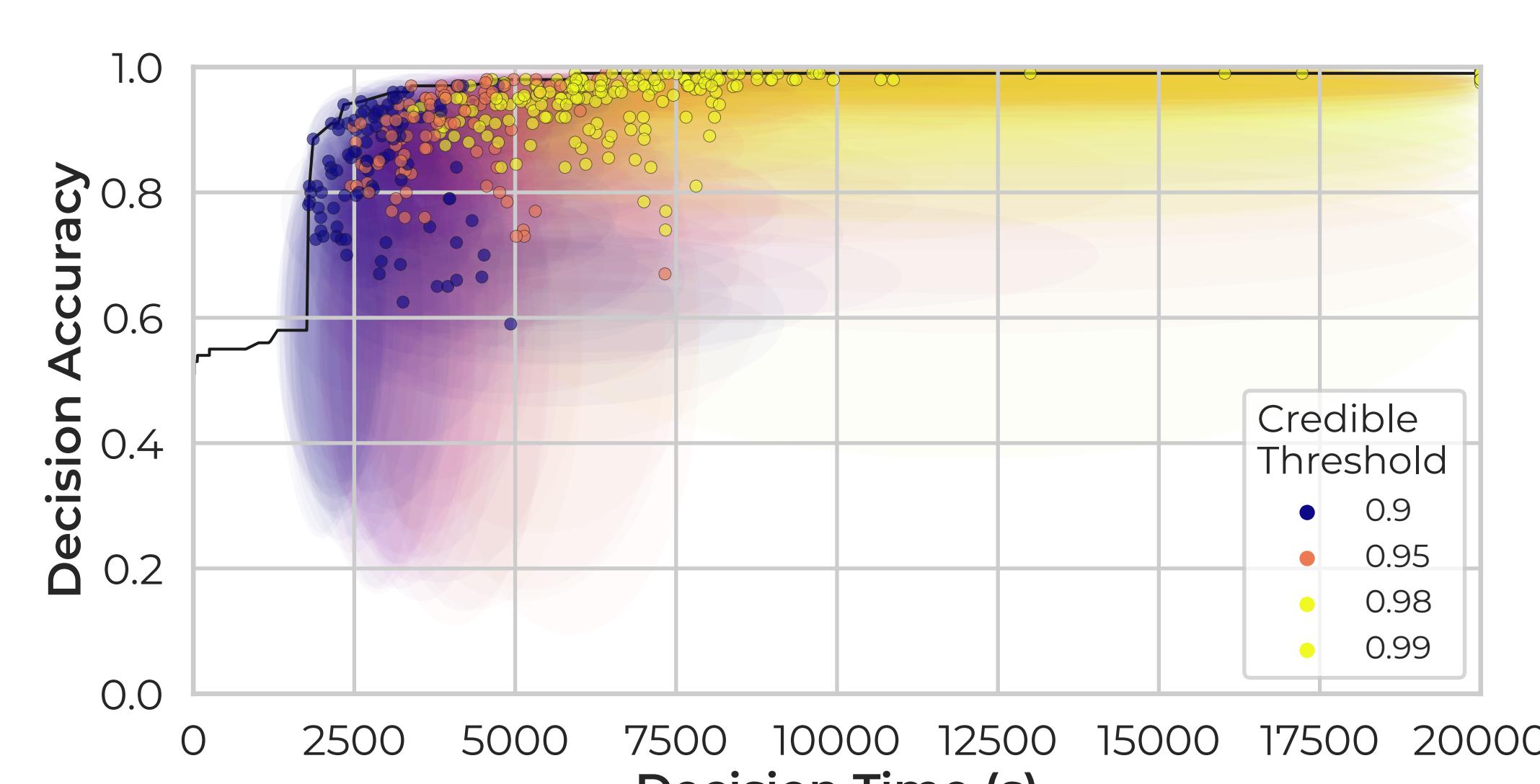
**Effect:** Using bio-inspired positive feedback results in dramatically faster and higher accuracy decisions



### OBSERVATION INTERVAL

**Effect:** Surprisingly, longer times between observations are closer to the Pareto front; increased spatial mixing decreases the total swarm decision time

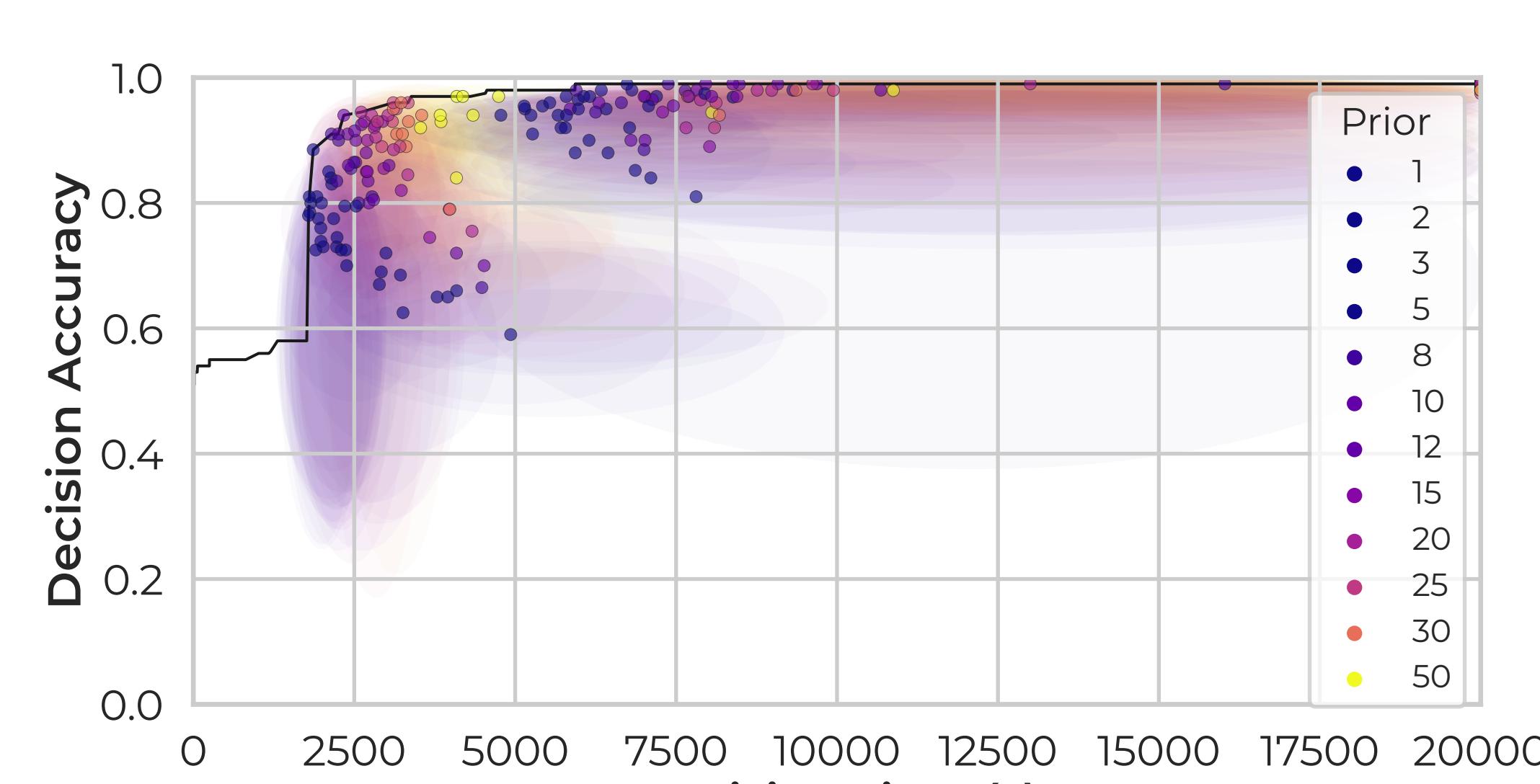
**Showing only:** Conditions with positive feedback



### CREDIBLE THRESHOLD

**Effect:** Lower credible threshold saves time with minimal accuracy cost

**Showing only:** Conditions with observation interval  $\geq 15$  s



### PRIOR

**Effect:** Lower credible thresholds are effective only if a regularizing prior prevents premature decisions

**Showing only:** Conditions with credible threshold of 0.9 and 0.99

## Discussion & Future Work

### SUMMARY

We show a "cheap lunch" effect with tunable (but non-intuitive) trade-offs:

- Positive feedback improves decision-making, rather than creating bifurcations
- Robots making fewer observations improves accuracy by reducing spatial effects
- Selecting a sufficient regularizing prior allow for a lower credible threshold with a small time cost

### FUTURE WORK

- Extend positive feedback mechanism to more complex informed communication
- Add informed movement (adaptive sampling) instead of random walks
- Extend to multiple features with multi-dimensional distributions (e.g., Dirichlet)
- Generalization to more complex robots and environmental features
- Compare to previous bio-inspired decision-making algorithms and ongoing theoretical work

### REFERENCES

JT Ebert, M Gauci, & R Nagpal (2018). "Multi-Feature Collective Decision Making in Robot Swarms." AAMAS.

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