

Coordination of Distributed Agents through Stochastic Policies in a Cooperative Jamming Scenario

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How Russia Is Trying To Complicate Ukraine's Drone Defenses

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The Invisible War in Ukraine Being Fought Over Radio Waves

How drone combat in Ukraine is changing warfare

FEATURES

- Wide frequency coverage
- Simultaneous coverage of several drone ranges;
- Simple, intuitive controls
- VSWR and thermal protection
- Small size and weight

JAMMING OF SIGNALS IN THE RANGE FROM 428 MHZ TO 5800MHZ

USING

- Airports
- Military
- Police
- Prisons
- Protection of VIPs
- Support during special operations

PORTABLE ANTI-DRONE CONTROL SYSTEM 3 OR 5 CHANNELS

Portable 5-channel jammer. It can be used with both omnidirectional and directional antennas mounted on a rifle mount.

Designed for jamming signals in the range from 428 MHz to 5800 MHz.

5
Bands Jamming

2 000 m
Action Distance

2 hour
Working Time

DETECTION
DETECTION 5000 m. IS AN ADDITIONAL OPTION

TACTICAL KIT
THREE ANTI-DRONE GUNS AND ONE DRONE DETECTOR CREATE A CONTROL LINE OF 8000 M AND A DEPTH OF 2000 M

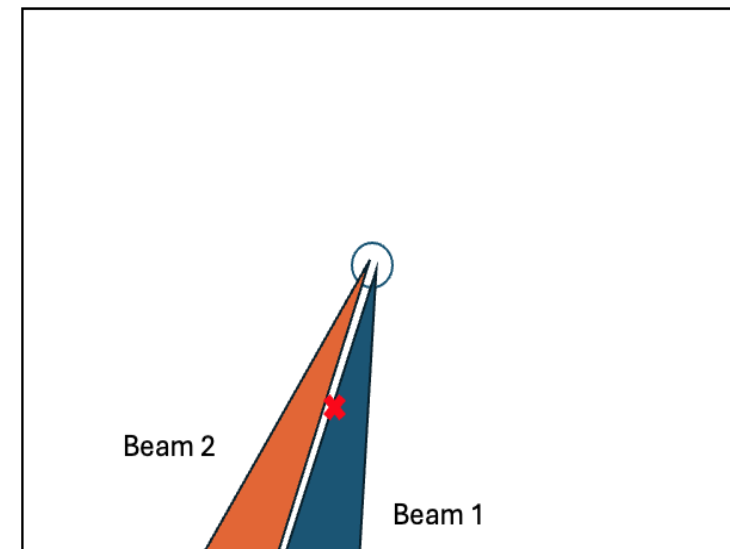
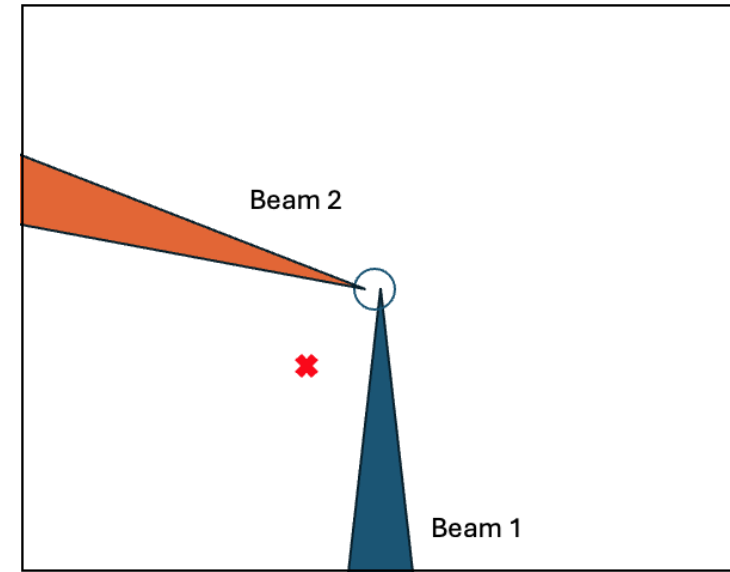
USABILITY
INTUITIVE AND QUICK TRAINING TO USE THE SYSTEM.

<https://piranha-tech.net>

How can agents coordinate their actions without direct communication in a cooperative jamming scenario?

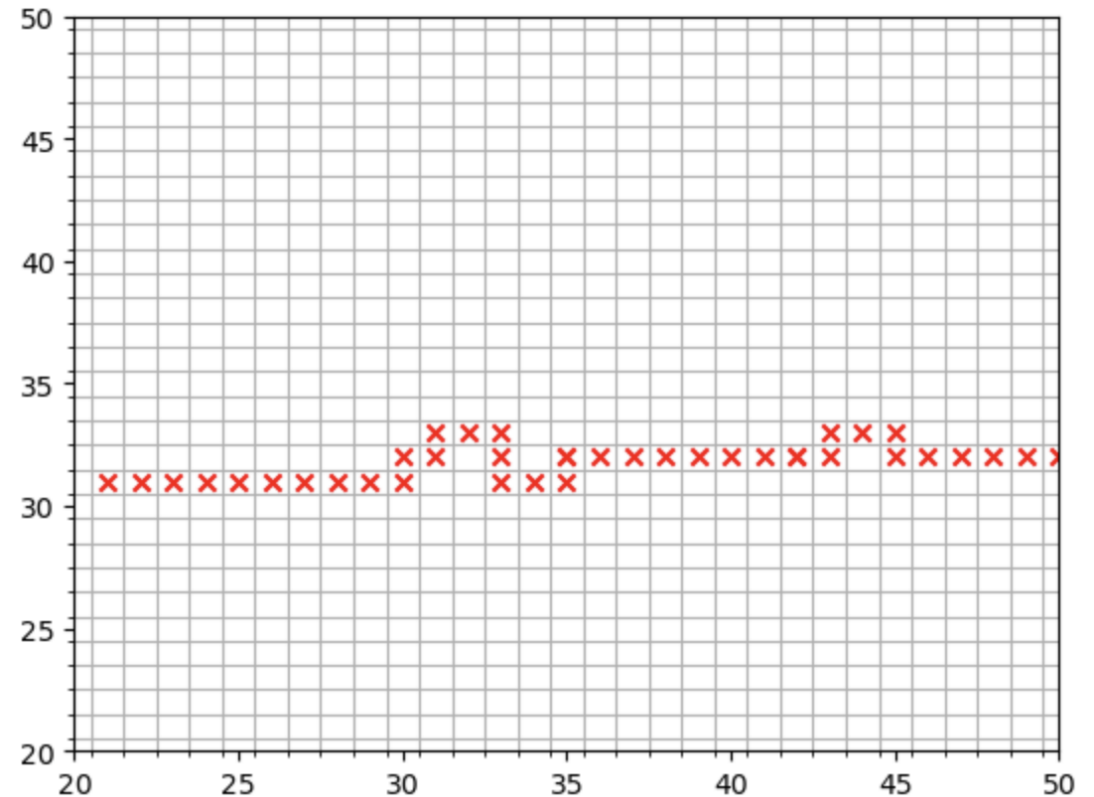
SYSTEM MODEL — JAMMING AGENTS

- Multiple agents at fixed locations in a region they are tasked to protect
- Each agent has a fixed-beam directional antenna modelled as a single lobe of width B°
- Fixed beamwidth with main lobe
- If adversary is in main lobe from any agent, it is jammed
- Consider discrete angular positions at each antenna dividing covered area into $\frac{360^\circ}{B^\circ}$ subsections
- Each agent learns resulting adversary position and beam position of fellow agents after choosing their own action



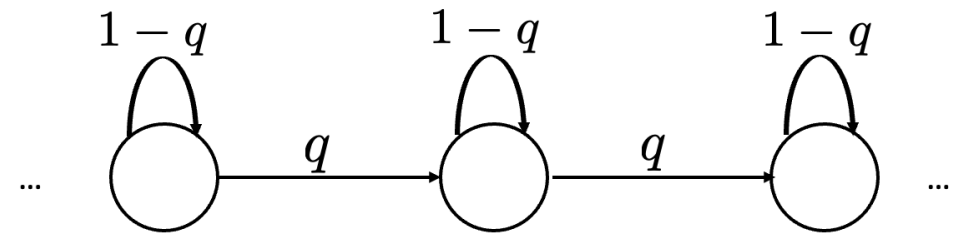
SYSTEM MODEL — ADVERSARY

- Consider movement on gridded space with discrete actions: up, down, left, right, stationary
- Momentum parameter, μ , equal to probability agent repeats previous action
- Smaller momentum probability corresponds to more evasive maneuvers/stochasticity
- General pattern of left-to-right and then right-to-left

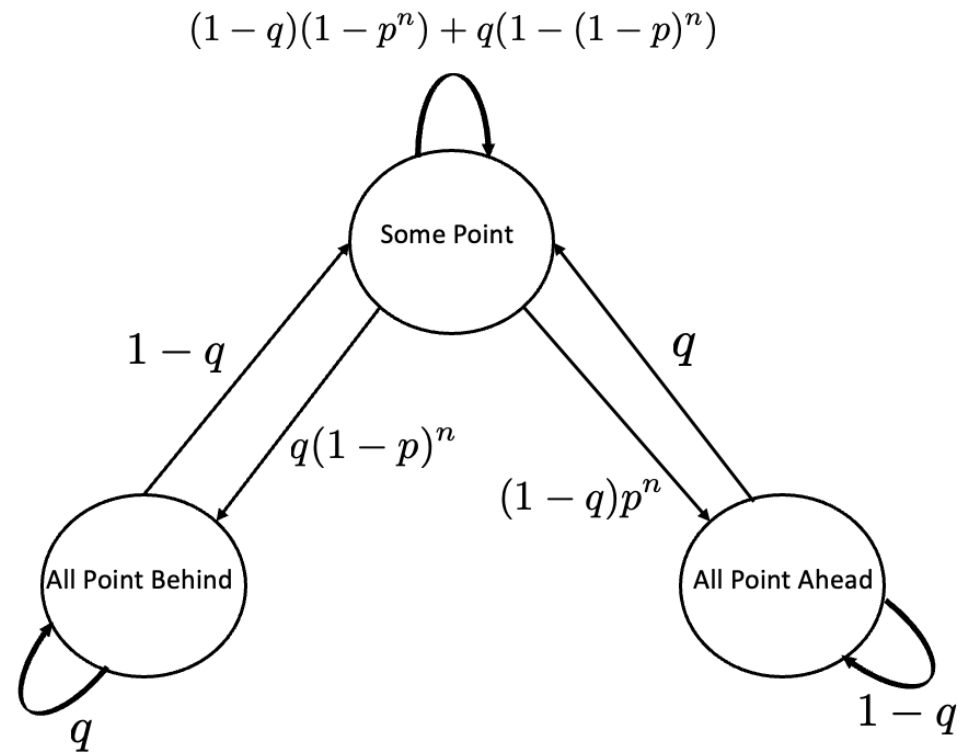


MOTIVATING ANALYSIS — ONE-D INFINITE MARKOV MOTION MODEL

- Consider simplified 1-D, unidirectional motion model on infinite quantized line
- Adversary moves with probability q , remains with probability $1-q$
- Assume agents begin by pointing at adversary
- Let agents point at the next state with probability p , or continue pointing at current state with $1 - p$
- Agents have knowledge of q
- If there are $N-1$ agents, choose p to **maximize probability of at least one agent pointing at adversary**



MOTIVATING ANALYSIS — MARKOV CHAIN MODEL FOR AGENTS' STATE



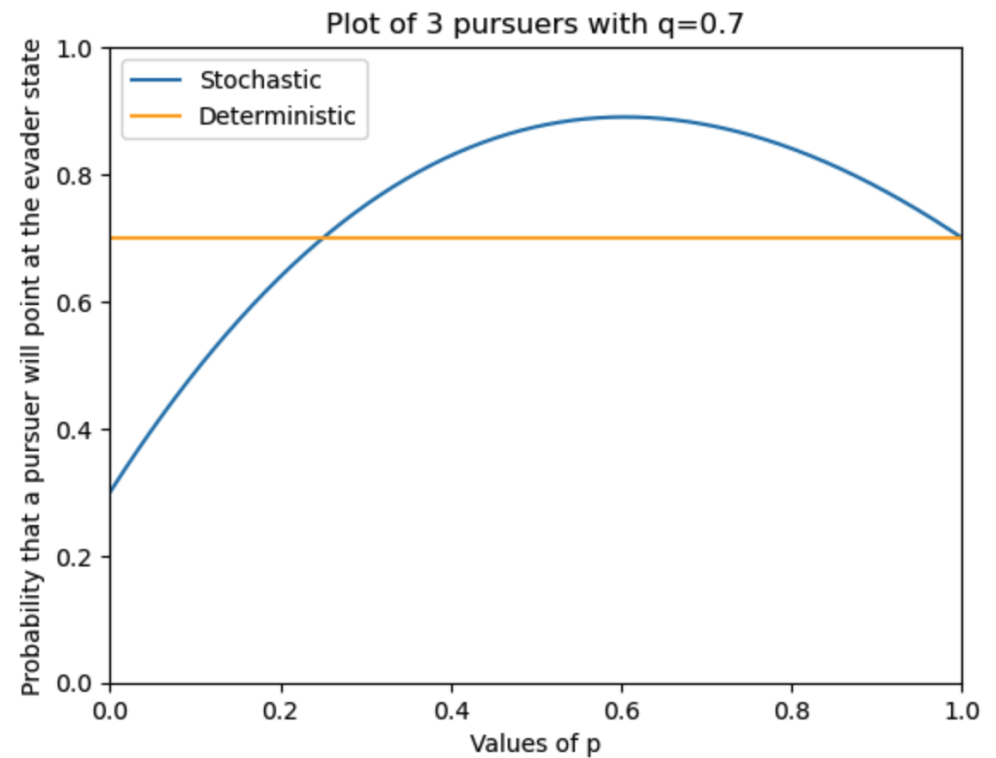
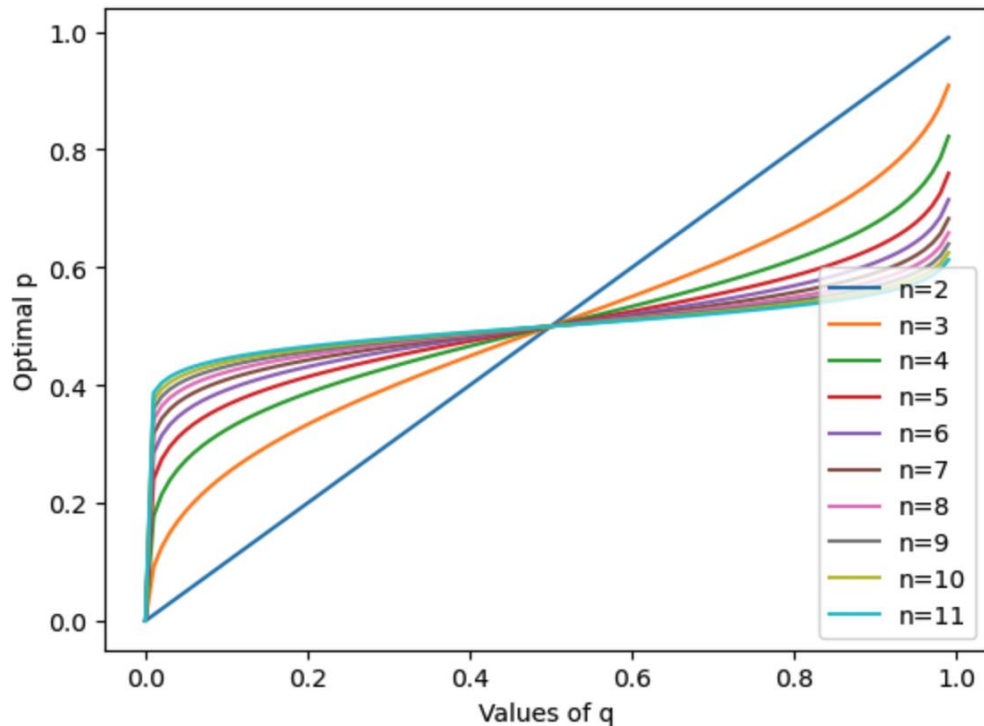
- Can model state of agents' jamming as simple finite-state Markov chain
- If an agent points behind the adversary, it deterministically moves to the next position to "catch up"
- If an agent points ahead of the adversary, it deterministically remains stationary to wait for the adversary to "catch up"

ANALYSIS—OPTIMALITY

- Solve for the optimal p in terms of q and n

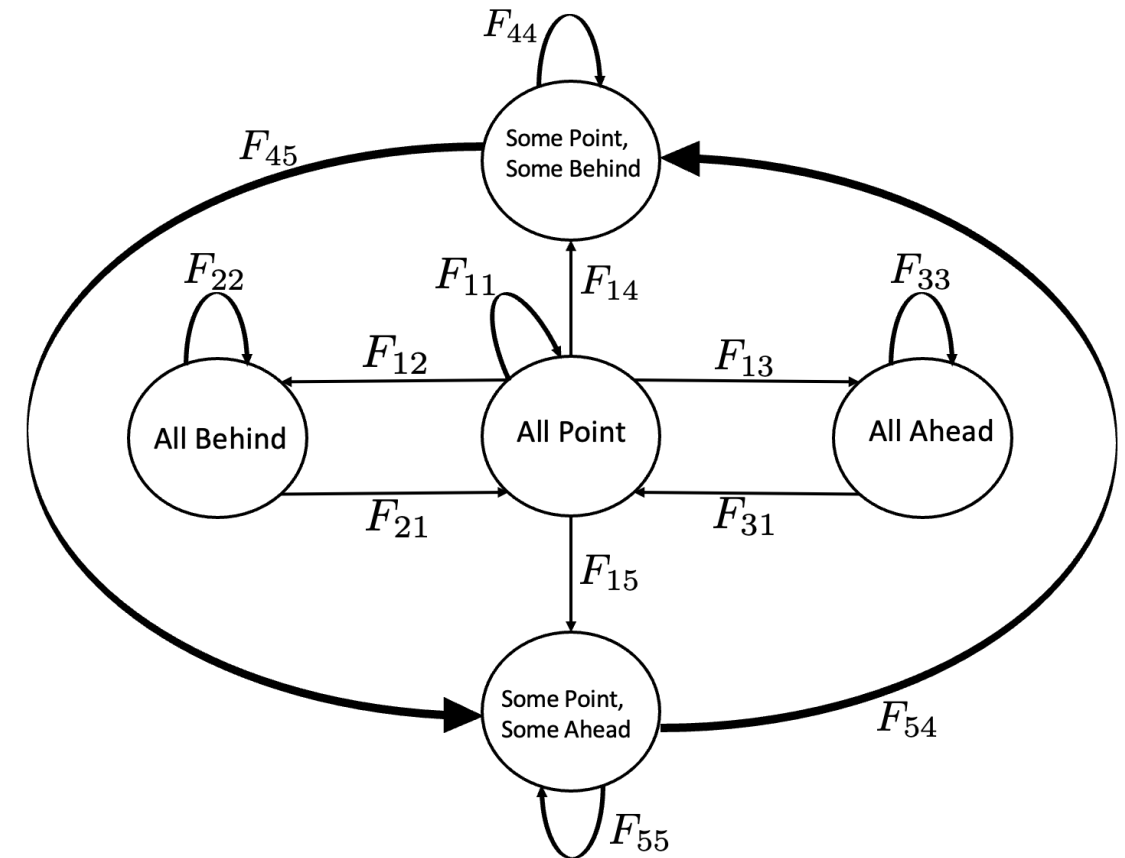
$$p_{opt} = \frac{\frac{q}{1-q} \frac{1}{n-1}}{1 - \frac{q}{1-q} \frac{1}{n-1}}$$

- Note that as the number of agents rises, p becomes more random to eliminate redundancy



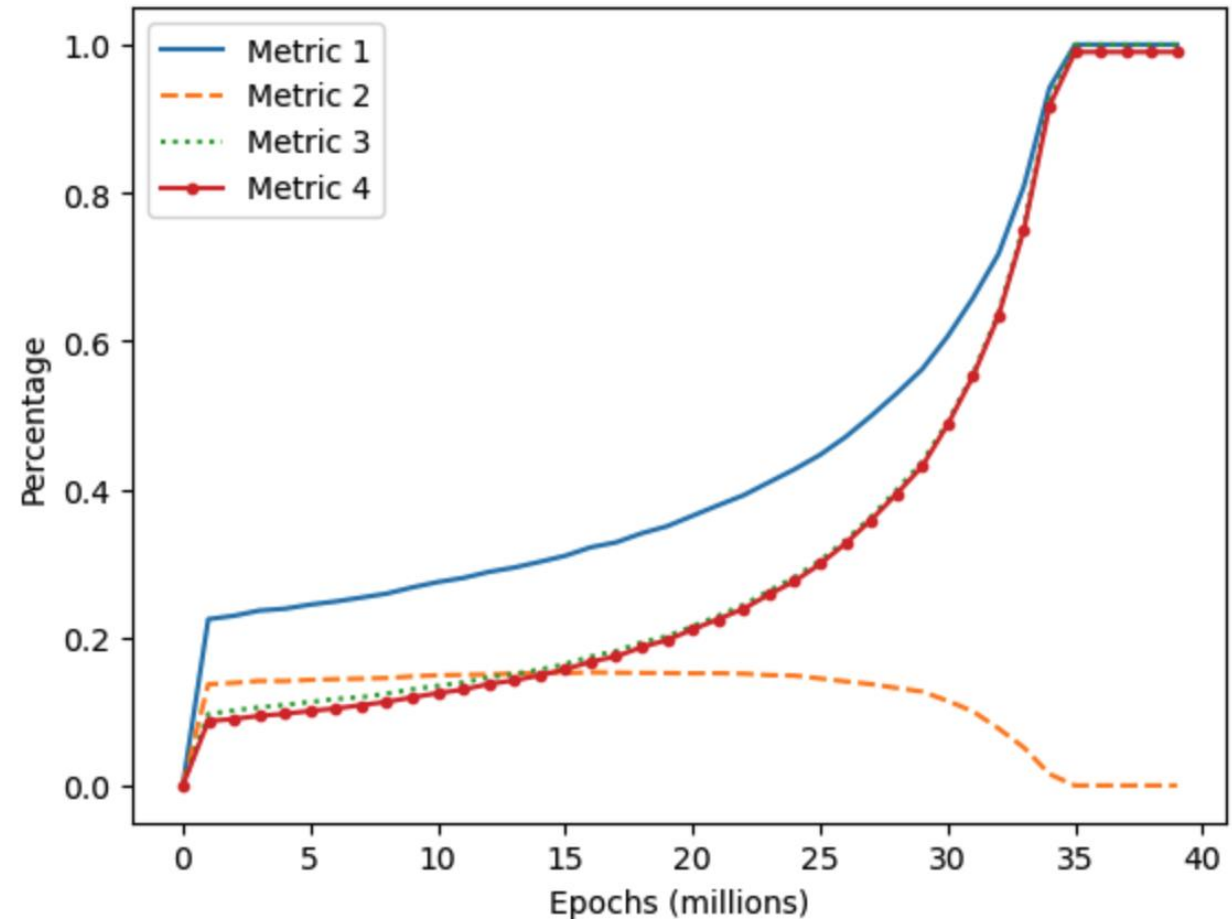
MOTIVATING ANALYSIS — EXPANSION OF MARKOV CHAIN

- Previous Markov chain can be expanded to reveal recurrent subchain (outer states)
 - In this subchain, at least one agent is always pointing at the adversary, resulting in optimum performance
- Reaching recurrent states requires stochastic policy
- Deterministic agents make same decision & thus can never reach this optimal configuration
- Note that in this recurrent subchain, agents may still switch their roles (which ones advance where they point and which ones are stationary)

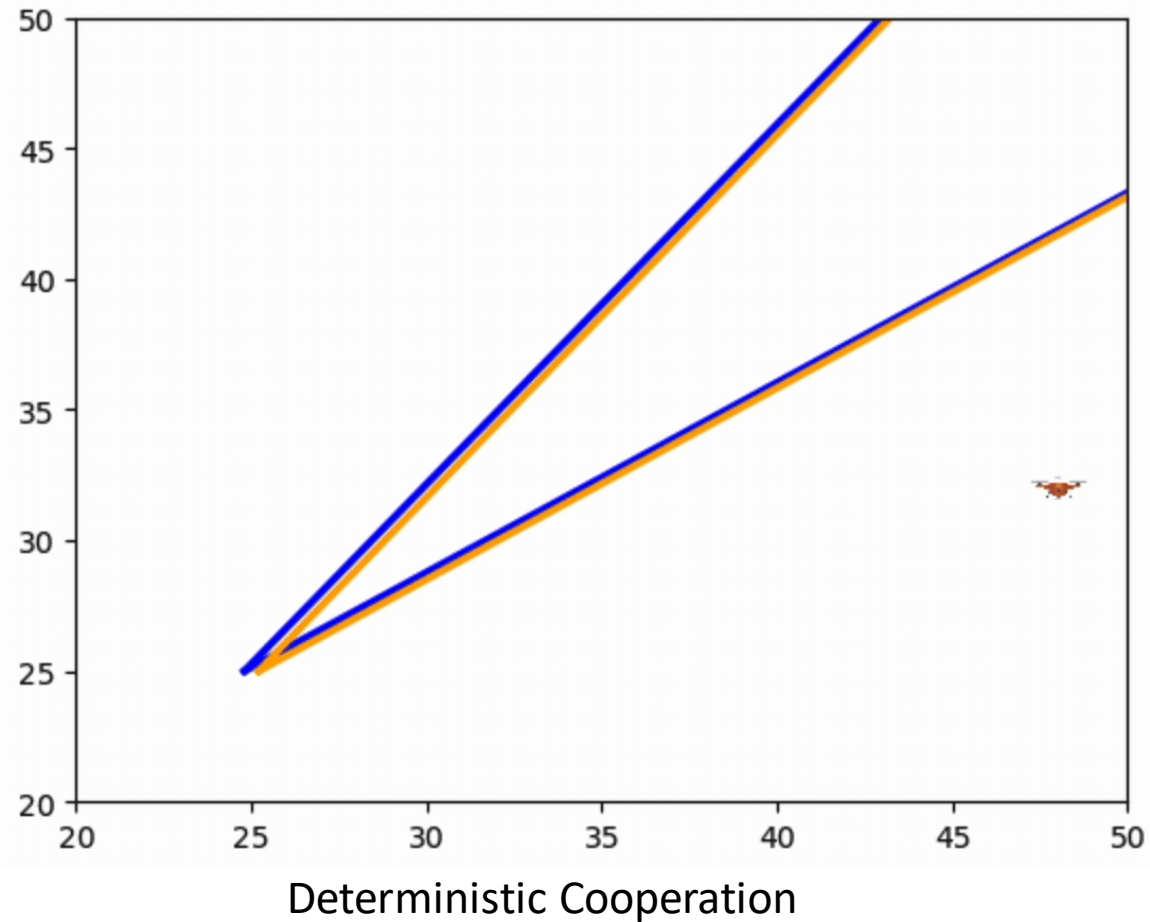


SIMULATION—FINITE MARKOV CHAIN

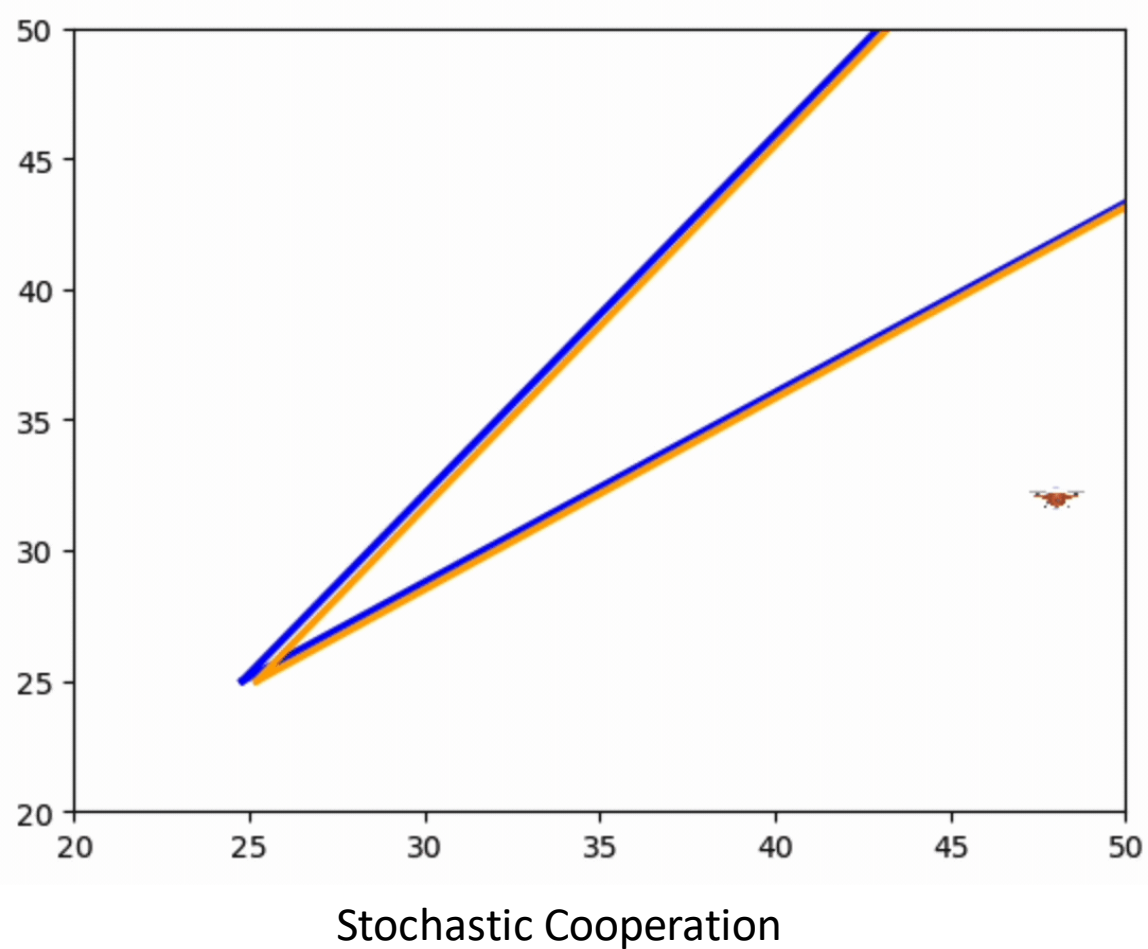
- Simulation is completed of the expanded Markov chain
- Reinforcement learning to see if the agents could learn optimal policy
- Four metrics (%):
 - 1) An agent points at the adversary
 - 2) The agents are in the same state
 - 3) A deterministic policy is used
 - 4) The agents are in the absorbing states



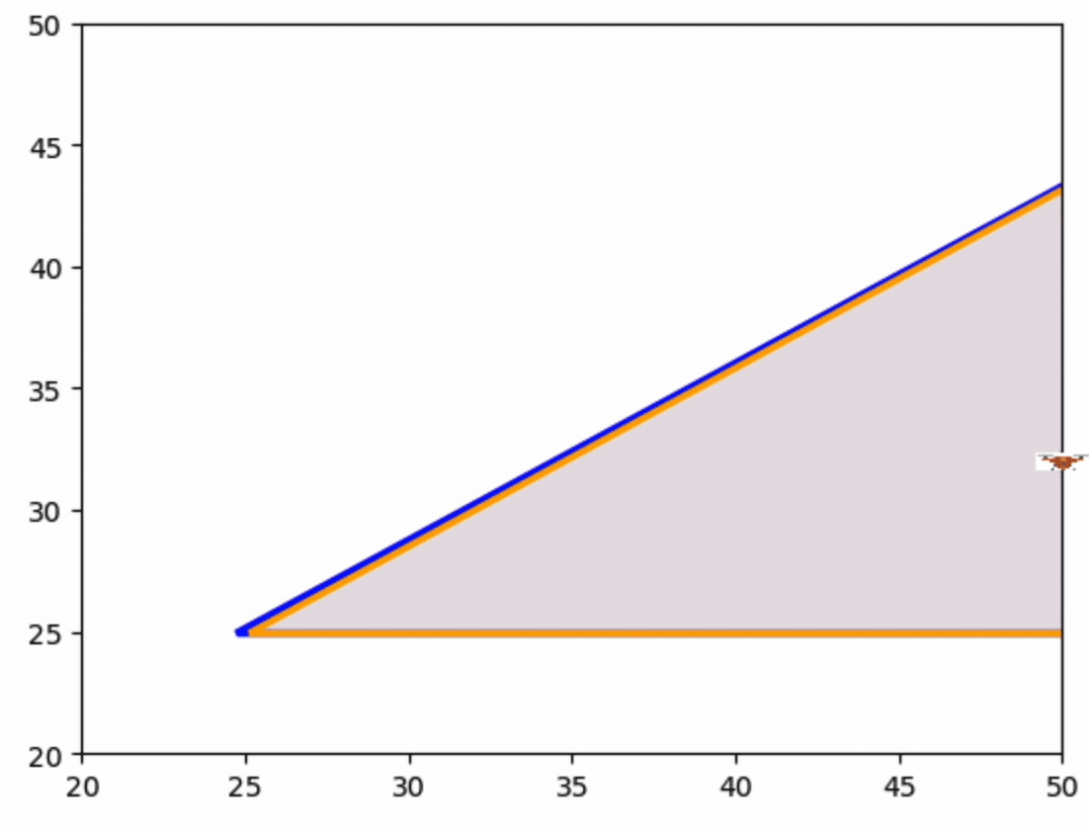
TRAINED Q-TABLE EXAMPLE



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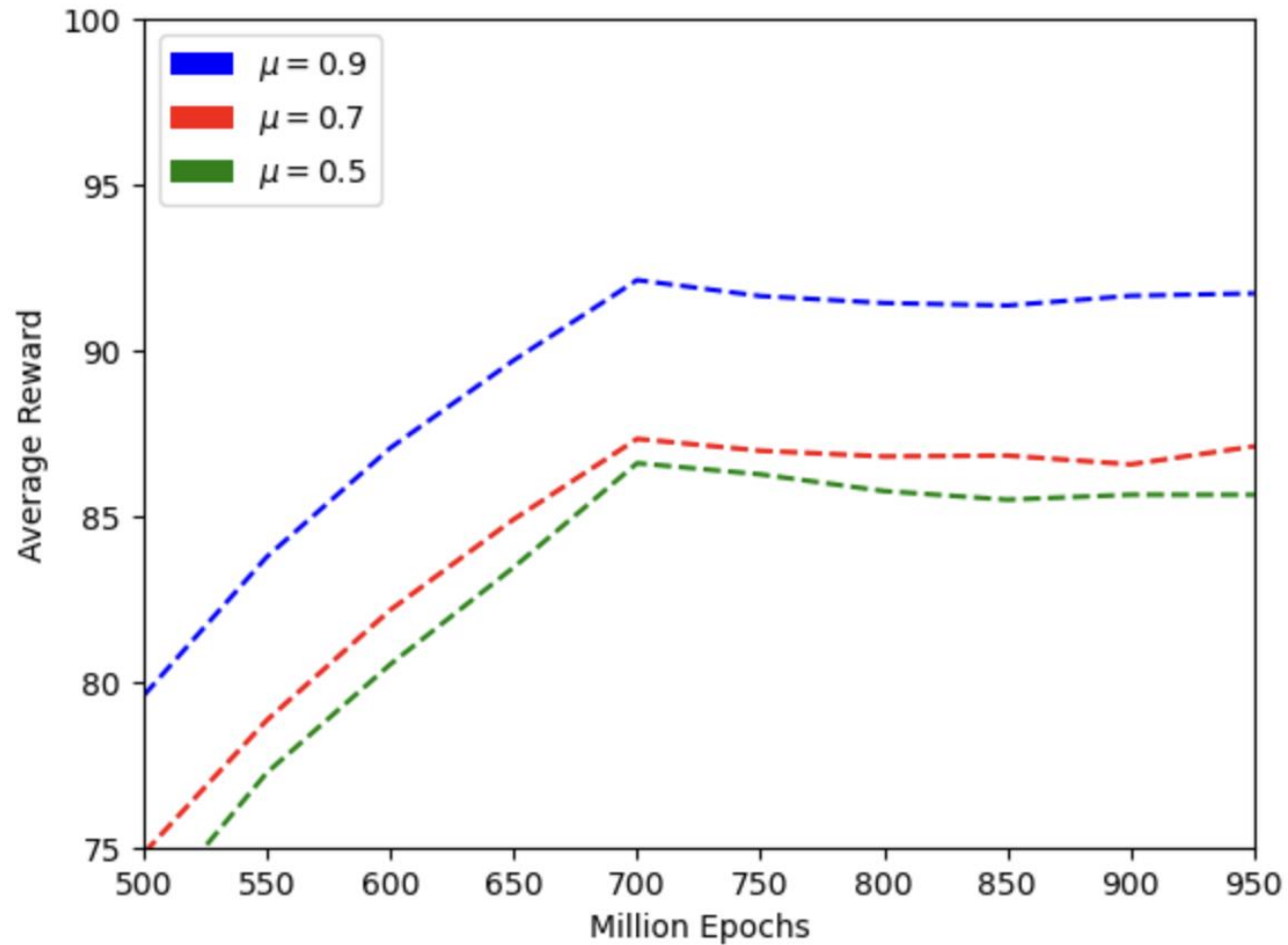
Stochastic Cooperation with Two Antenna Beamwidths

SIMULATION—SYSTEM MODEL

- Two agents adjacently placed near the center of the environment
- Beamwidths of 36° with 10 distinct radial positions
- Two action space strategies:
 - Three deterministic-only pmfs (e.g. [1.0,0.0,0.0])
 - Thirteen stochastic and deterministic pmfs (e.g. [0.7,0.3,0.0])
- Simulation run for three values of adversary momentum:
 $\mu = 0.9, \mu = 0.7, \mu = 0.5$

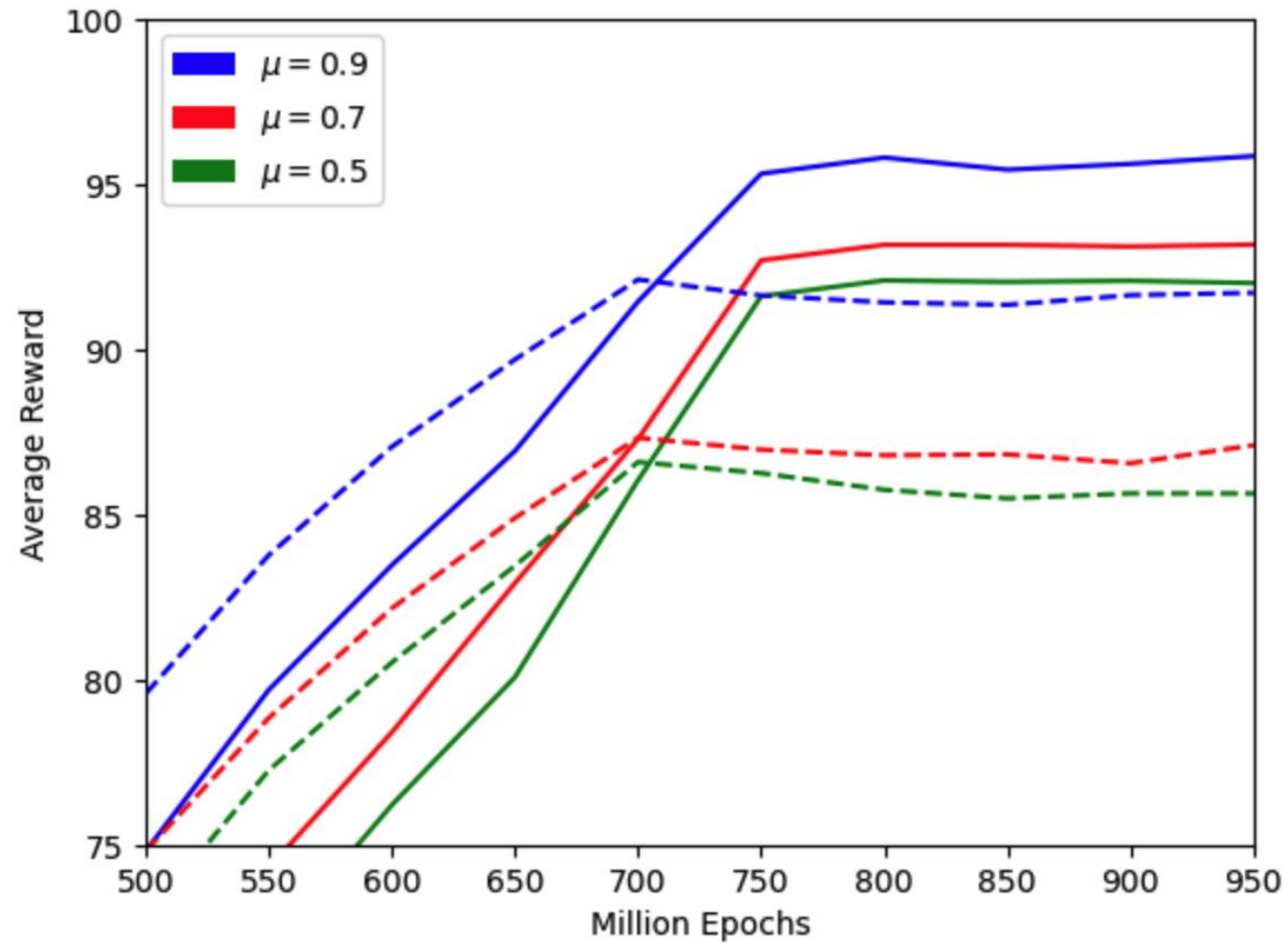
SIMULATION—RESULTS

- Consider deterministic policies first



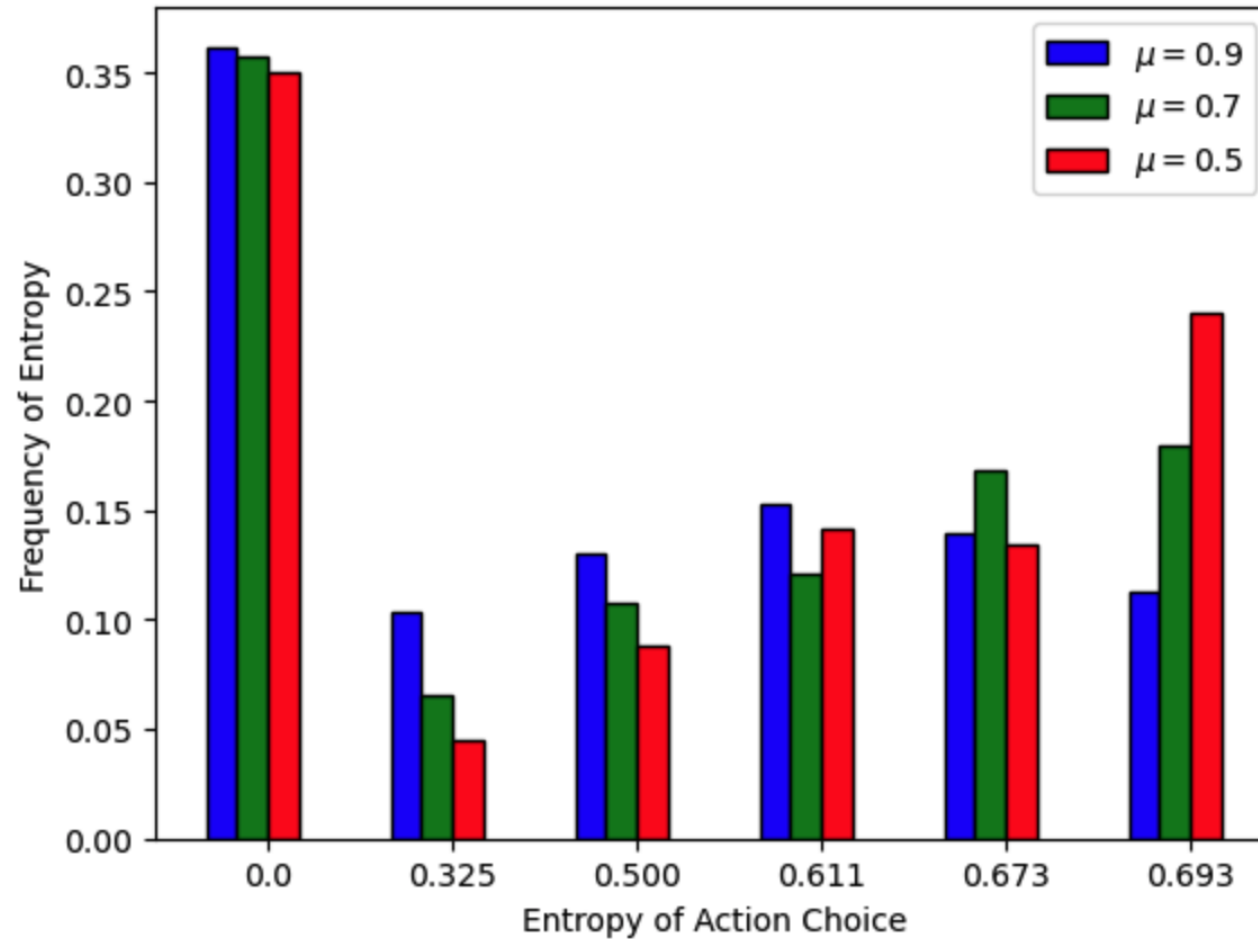
SIMULATION—RESULTS

- Now allow stochastic policies (solid lines):



SIMULATION - ENTROPY

- States where beams are in overlap and adversary momentum was leaving were collected to analyze trained decisions



Momentum	Entropy (Nats)
$\mu = 0.9$	0.363820
$\mu = 0.7$	0.387328
$\mu = 0.5$	0.402358



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