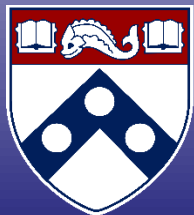




Predictive Simulation For UAV Flight Planning

- ATR Center Summer Workshop
- 9,10 August 2017



Penn
UNIVERSITY of PENNSYLVANIA

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Motivation & Objective

- **Motivation**

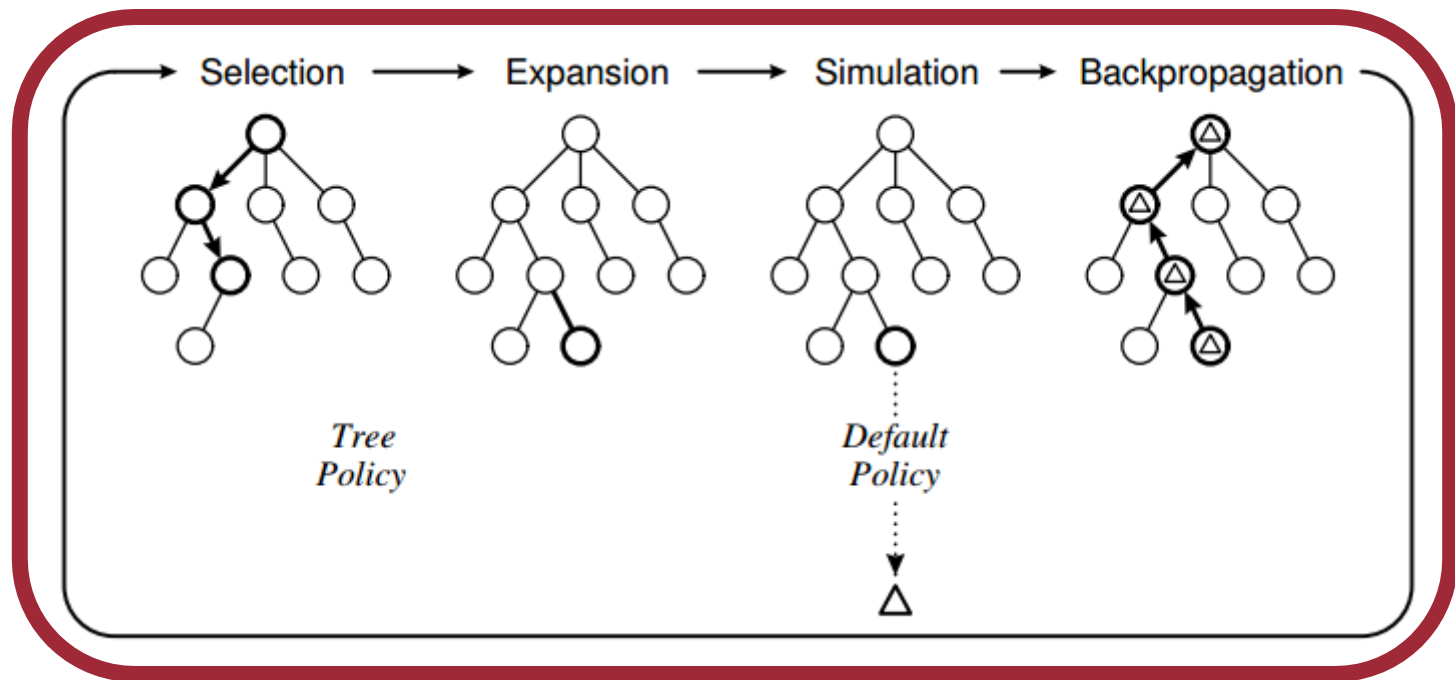
- Google DeepMind's AlphaGo defeated a human professional player at the game of Go

- **Objective**

- Explore the modifications made to Monte Carlo Tree Search (MCTS) in AlphaGo to determine if any such algorithm could be viable when applied to flying one or many Unmanned Aerial Vehicles (UAVs)



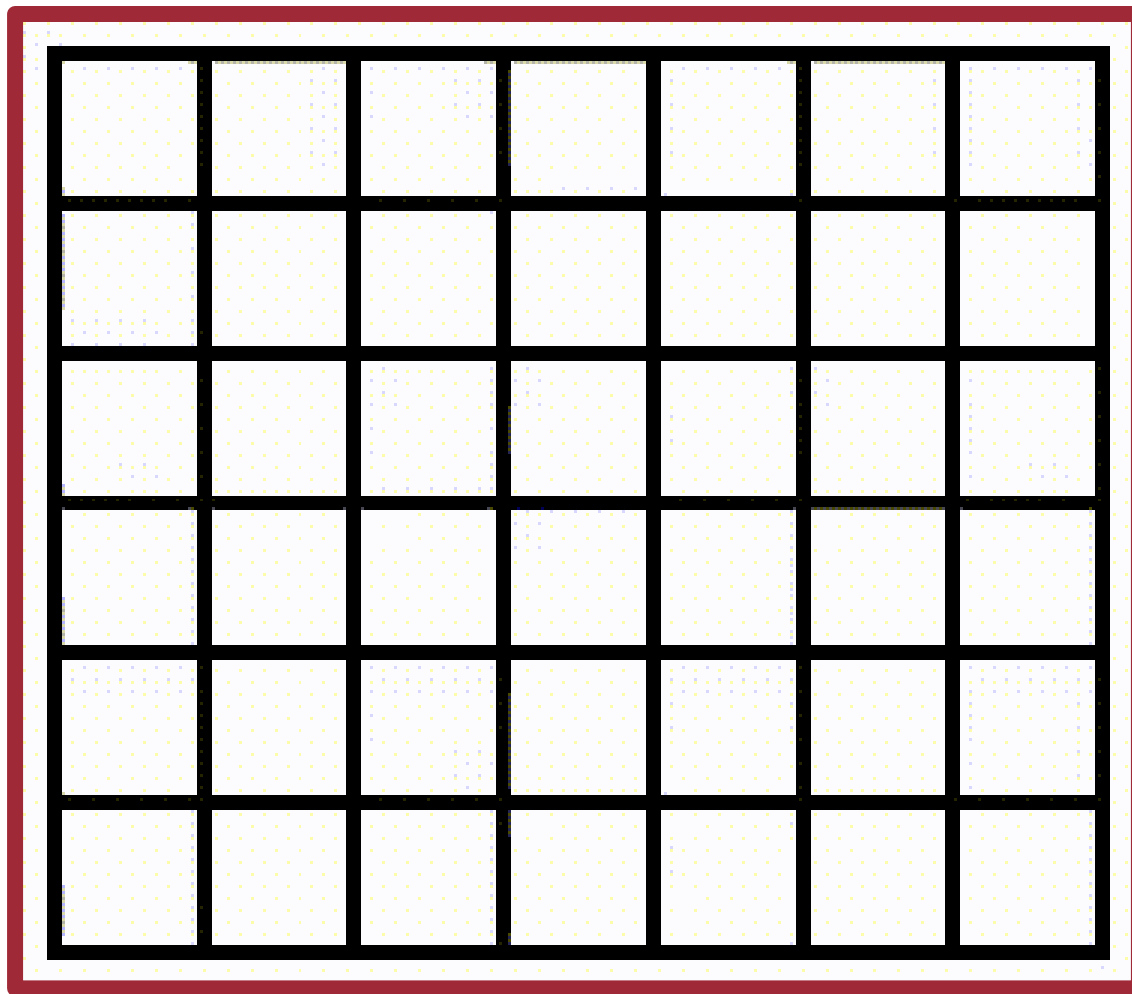
Monte Carlo Tree Search (MCTS)



For each iteration of the MCTS algorithm, a tree policy (in this case, Upper Confidence Bounds for Trees, or UCT) is used to **select** a non-terminal node in the current tree. The node is **expanded** by adding a random child, a **simulation** is run from the child to a terminal state to obtain a reward, and **backpropagation** updates the tree with the reward. Each such iteration is called a playout.



Monte Carlo Tree Search (MCTS)



MCTS (Y) vs Human Player (R)
1000 playouts



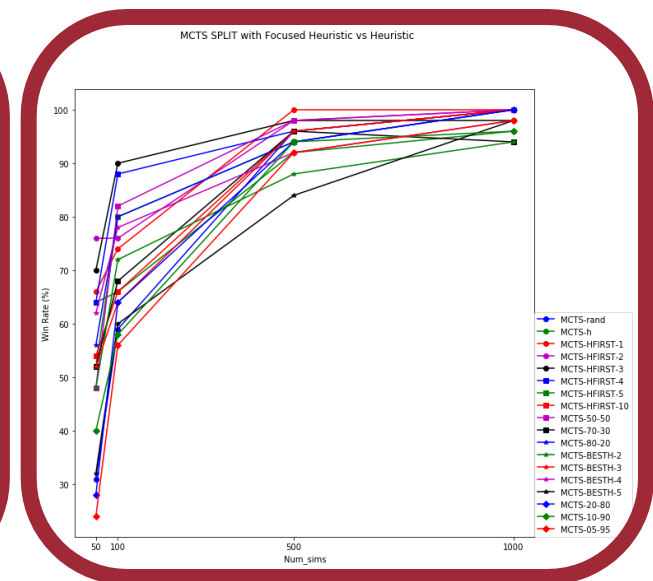
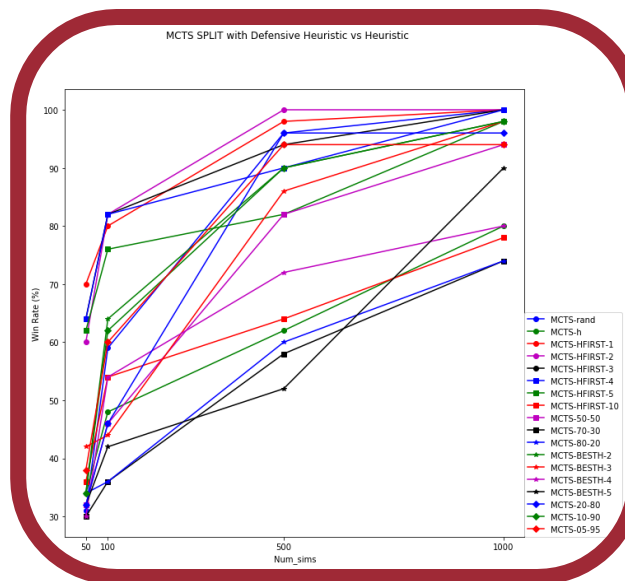
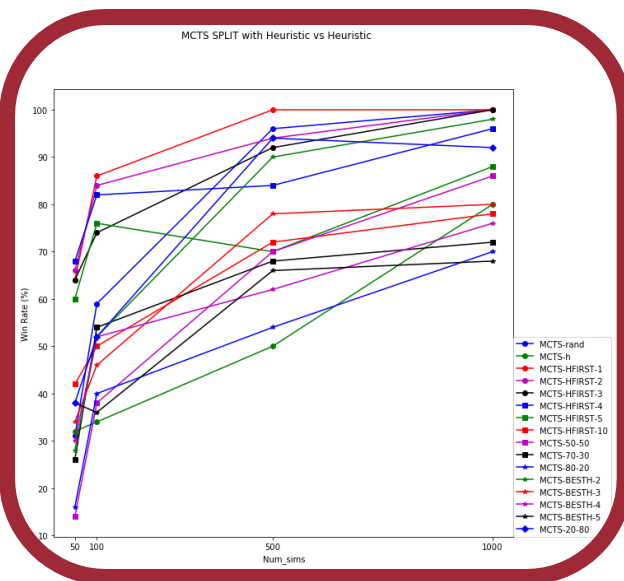
Playout Policies & Heuristics

	Description
HPOLICY	Uses the heuristic policy to select moves until the board state is terminal, then returns the reward
HFIRST POLICY(n)	Uses heuristic move selection for first n moves, then uses random moves to a terminal board state, and returns the reward
BESTH POLICY(n)	For each move in the rollout, generates a set of n random moves of the current set of possible moves, then chooses the best one using the heuristic. Continues this selection process until a terminal state is reached, then returns the reward
PERC PLAYOUTS(n)	Applies HPOLICY for n percent of the playouts, uses DEFAULTPOLICY the rest of the time

	Regular Heuristic	Defensive Heuristic	Focused Heuristic
Description	Picks a move by attempting to win, attempting to block, then selecting randomly, close to the center	Picks a move by attempting to block, attempting to win, then selecting randomly, close to the center	Picks a move by selecting randomly, close to the center



Policy & Heuristic Comparisons



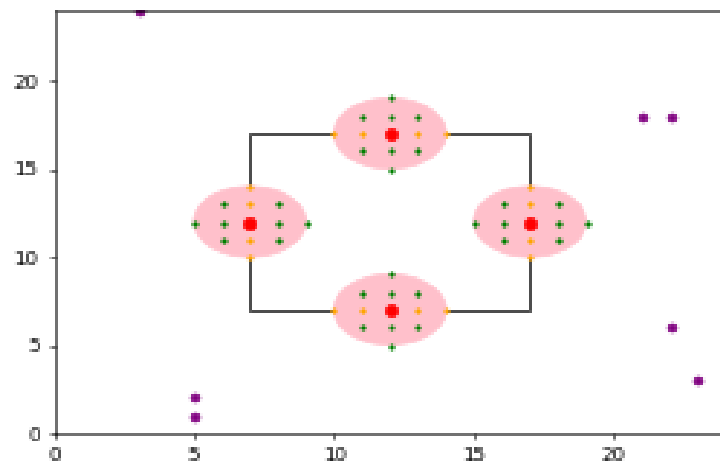
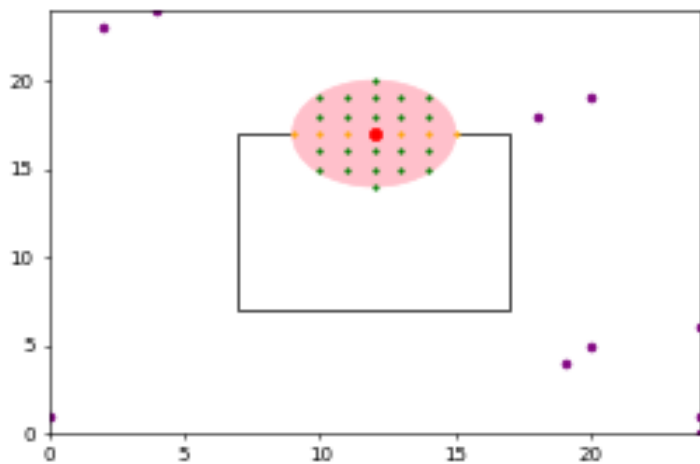
Connect Four Playout Policy Comparisons:
MCTS with Regular Heuristic – HFIRST-1
MCTS with Defensive Heuristic – HFIRST-2
MCTS with Focused Heuristic – HFIRST-3, HFIRST-1

Focused Heuristic has best performance alone



UAV Flight Planning

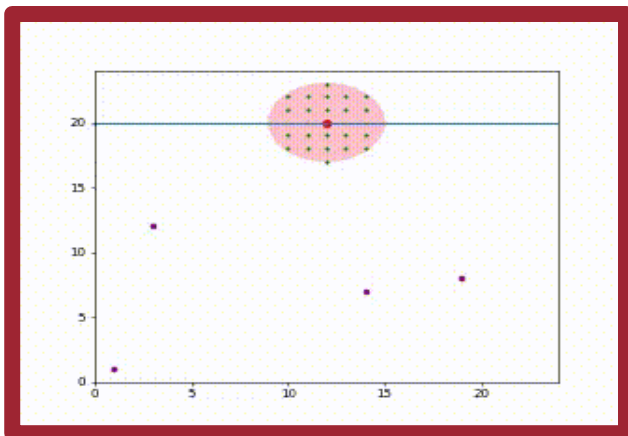
- Created a game to simulate a base being attacked
- Rewards determined by how many intruders were caught before an intruder reached the perimeter fence
- Made improvements by allowing multiple UAVs and preventing UAVs from having overlapping scanning zones



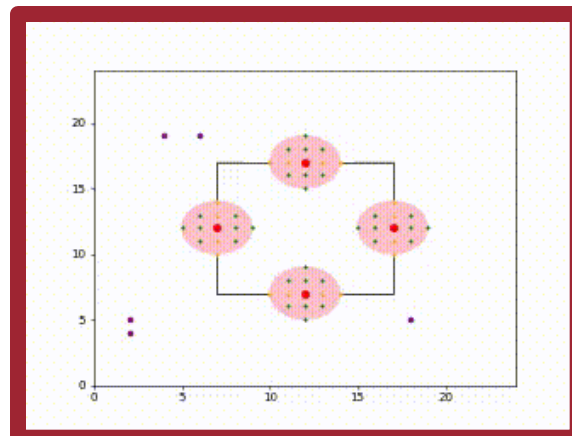


UAV Flight Planning

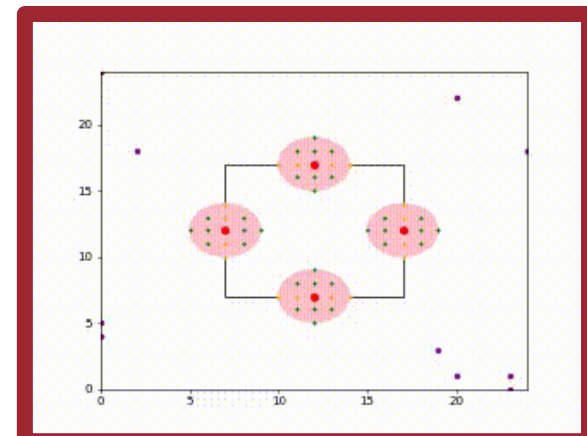
UAV Collisions Permitted:



1000 playouts, 4 opponents

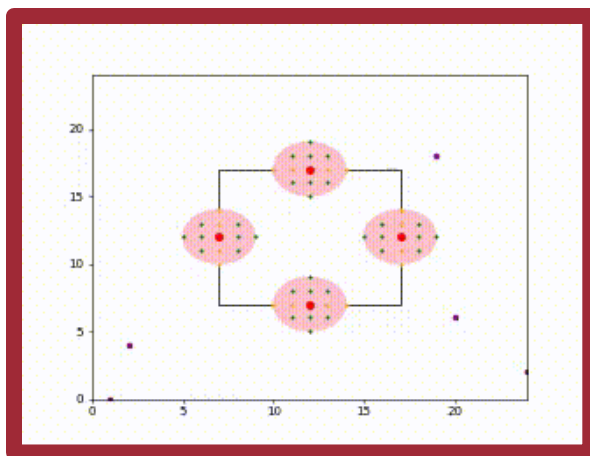


800 playouts, 5 opponents

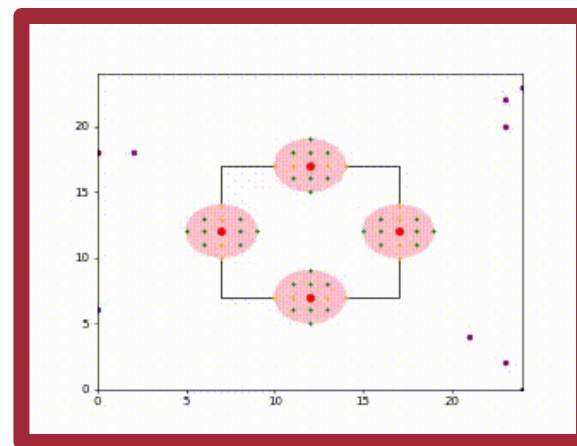


1000 playouts, 10 opponents

UAV Collisions Prohibited:



800 playouts, 5 opponents



800 playouts, 10 opponents



Contributions & Future Work



- **Contributions**

- Python codebase
 - General MCTS algorithm
 - Working Tic Tac Toe with MCTS AI
 - Working Connect Four with MCTS AI
 - Defend the Base simulation
 - Can change number of UAVs, UAV radius, base position, radius, and board size
 - Data-producing code to evaluate effectiveness of changes
- Data on effectiveness of different heuristics used in MCTS
- Videos, images, or text output from hundreds of games

- **Future Work**

- Evaluate capture rates of single UAV vs multiple on square, line, and circular boards
- Evaluate effects of changing board size or UAV radius on capture rate
- Adjust for uncertainty or partial information in intruder locations
- Real-life application:
 - Figure out how to coordinate movement among a swarm of UAVs using the MCTS algorithm
 - Test the algorithm with a swarm of UAVs



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References

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