ATTRACTION-BASED REINFORCEMENT LEARNING:
A REAL-TIME APPROACH USING TECHNIQUES BASED ON ANIMAL BEHAVIOR

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MOTIVATION AND INSPIRATION

- Machine Learning Challenges:
  - Replicating ideal behavior for tasks.
  - Complex behaviors with fast response.
  - Real-time learning.

- Animals exhibit instinctive behaviors based on their needs:
  - Attraction to food.
  - Repulsion from predators.
  - Pursuit of prey.
  - Evasion.

MOTIVATION AND INSPIRATION

- Simulating animal behavior in virtual environments provides a unique opportunity to design agent-based systems that mimic real-world dynamics.

- These physical rules are useful not only for controlling agents but also for optimizing strategies through machine learning, improving decision-making in dynamic environments.

Games

Real World

OBJECTIVES

- Introduce a machine learning algorithm based on attraction/repulsion using the Unscented Kalman Filter (UKF) to predict and learn opponent behavior in real-time.
- Show the algorithm's effectiveness in dynamic environments, outperforming traditional Q-learning methods, particularly in low-frame conditions.
- Provide a framework for enhancing predictions and facilitating learning in complex, real-world scenarios.

PROBLEM STATEMENT

- Low-Frame Environment Challenges:
  - The low-frame environments, these methods often suffer from reduced accuracy and performance, as they struggle to predict opponent behavior efficiently.

- Need for Improved Approach:
  - There is a clear need for an approach that can combine learning with predictive modeling to optimize both movement and decision-making in real time.

- Parameter Tweaking Issues:
  - The existing techniques for simulating agent behaviors often involve significant parameter tweaking, limiting their practical application in real-world scenarios.

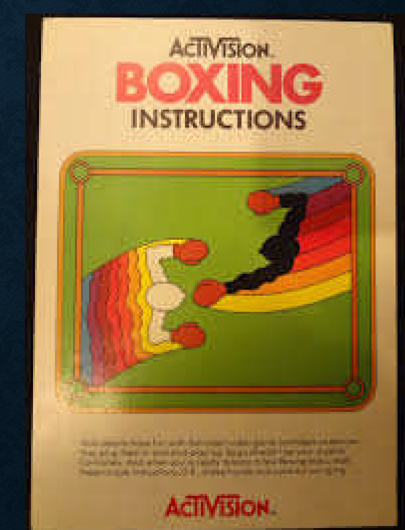
PROPOSED SOLUTION

- Dynamic Learning:
  - This approach allows agents to learn from their environment, adjusting attraction and repulsion parameters to optimize their strategies dynamically.

- Enhanced Predictions:
  - The combination of attraction rules with machine learning enables more robust predictions and learning processes compared to traditional methods like Q-learning.

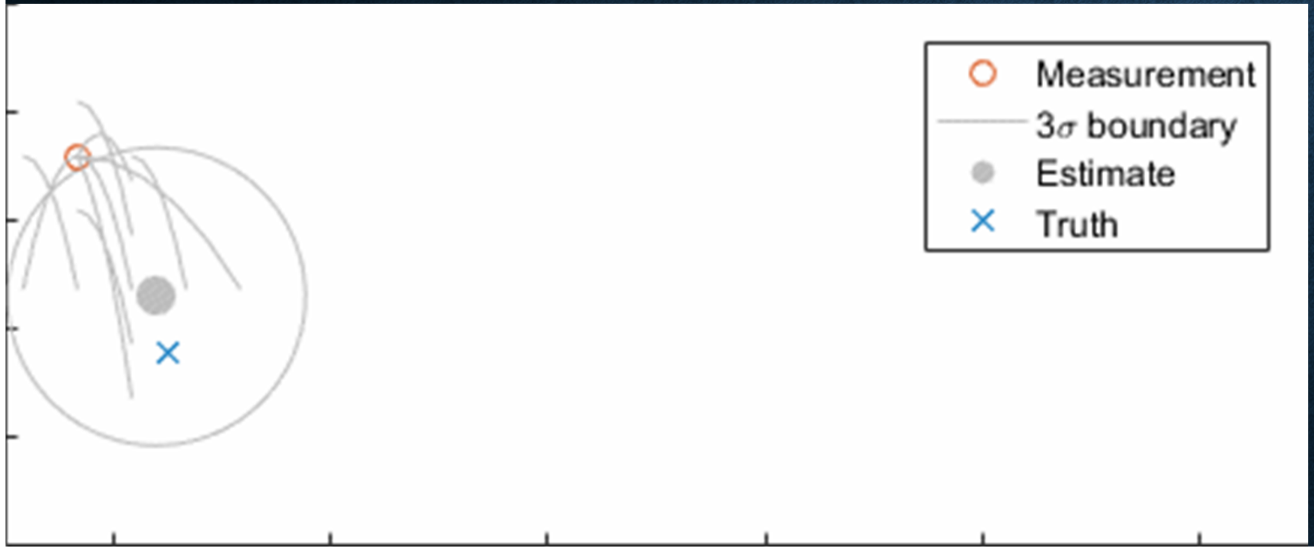
MATERIALS AND METHODS

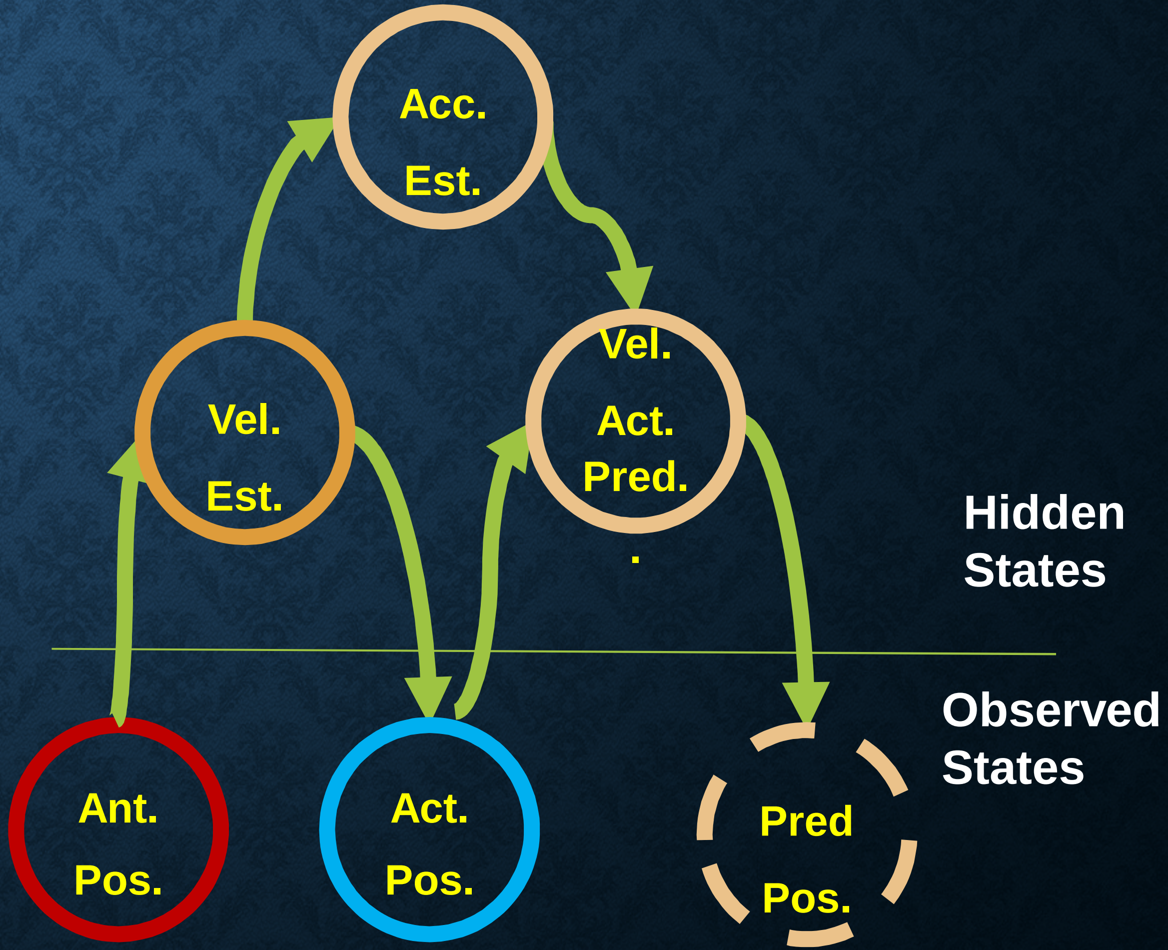
- Atari Emulator provided by OPENAI:
  - Allows the use of games by accessing inputs (buttons) and analyzing the screen output.
  - Enables the simulation of specific scenarios.
  - Provides memory access for reading and writing data for modifications.



MATERIALS AND METHODS

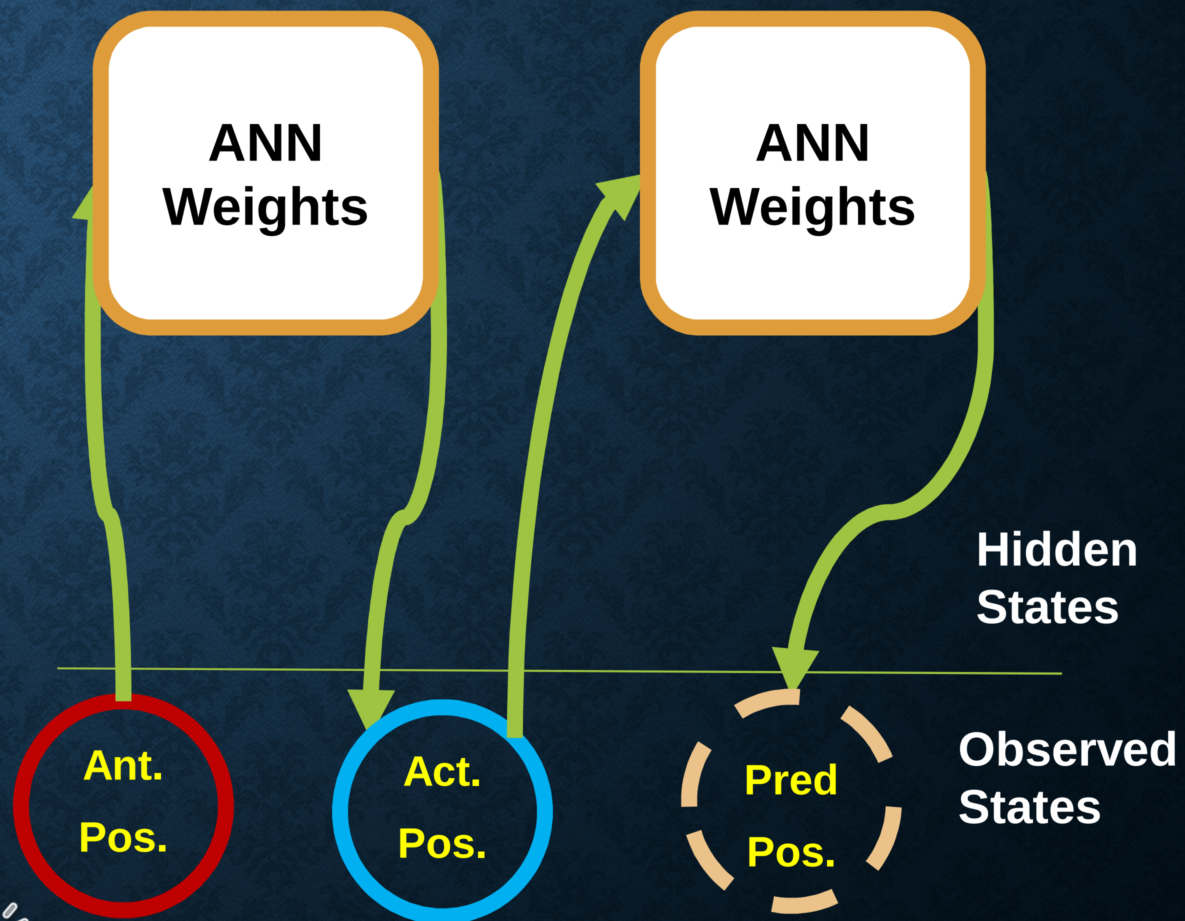
- Discrete Kalman Filter (DKF):
  - Can estimate hidden states, such as velocity and acceleration.
  - Helps eliminate data noise, such as false position measurements.





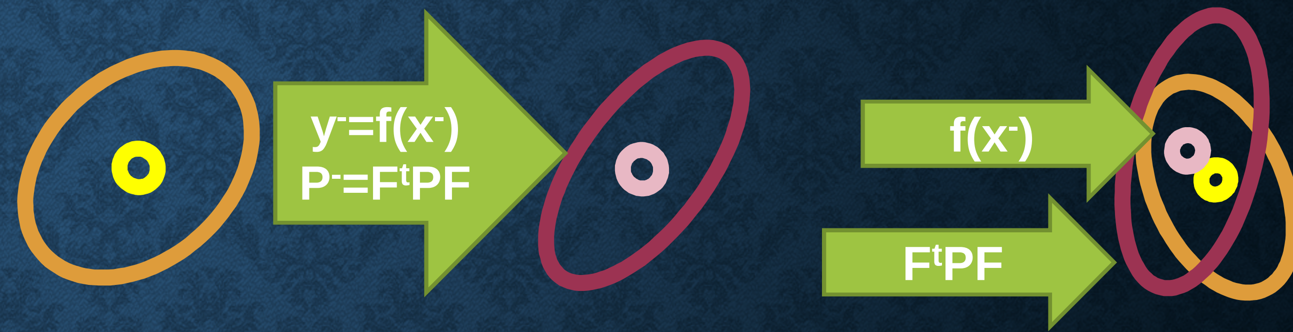
MATERIALS AND METHODS

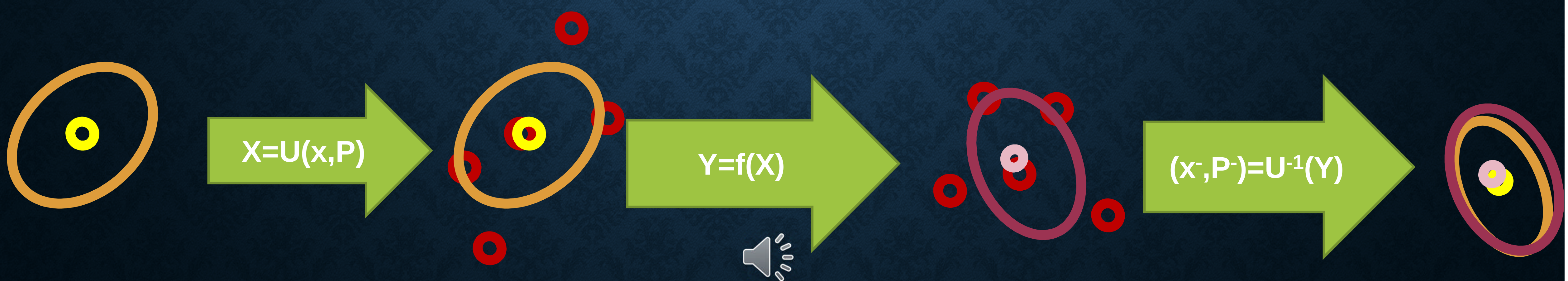
- Extended Kalman Filter (EKF):
  - An extension that uses partial derivatives to handle nonlinearities.
  - When combined with artificial neural networks (ANN), it allows for better state estimation.
  - Can be used to enable an ANN to learn in real-time.



MATERIALS AND METHODS

- Unscented Kalman Filter (UKF):
  - A filter used for nonlinear systems.
  - It includes an improvement with sigma points for better mapping of the intrinsic variances of the states.

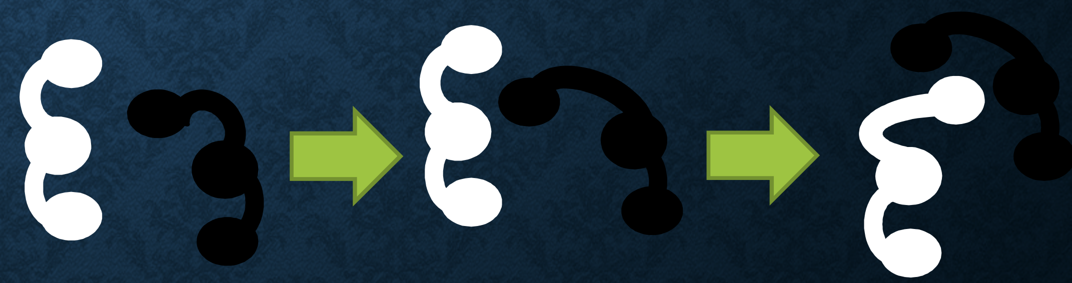




ATTRACTION-BASED MODEL

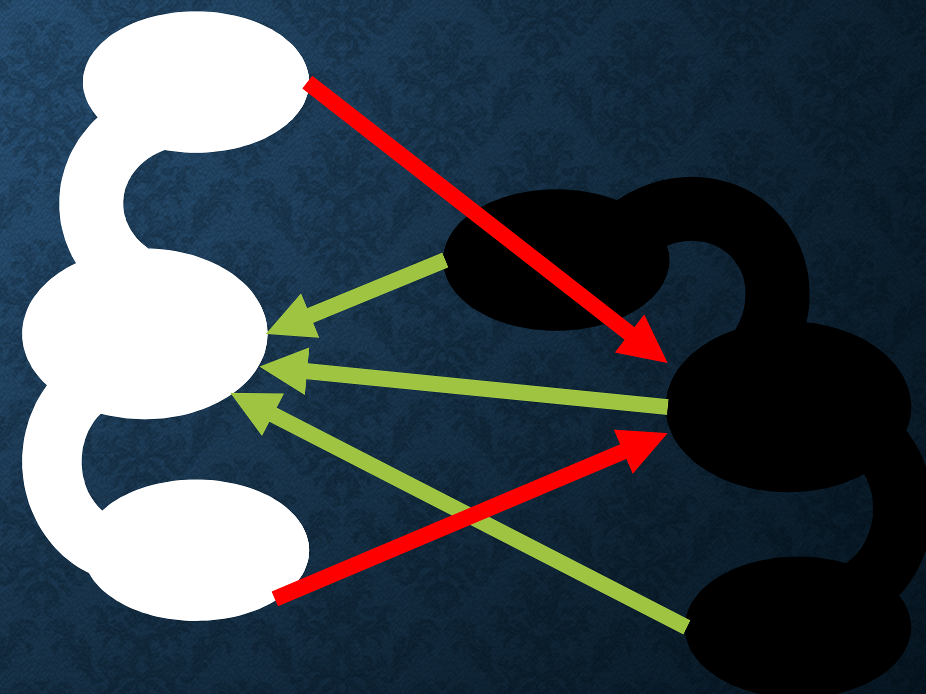
- Model based on attraction and repulsion techniques:
- The player's fighter is attracted to the CPU-controlled fighter.
- The fighter experiences repulsion from the opponent's glove.
- At a certain distance from the player's gloves and the CPU's head, the player throws a punch.

```
Player_pos=Attraction(Player_pos,CPU_pos,K_1);
Player_pos=Attraction(Player_pos,CPU_G_R_pos,-K_2);
Player_pos=Attraction(Player_pos,CPU_G_L_pos,-K_2);
```



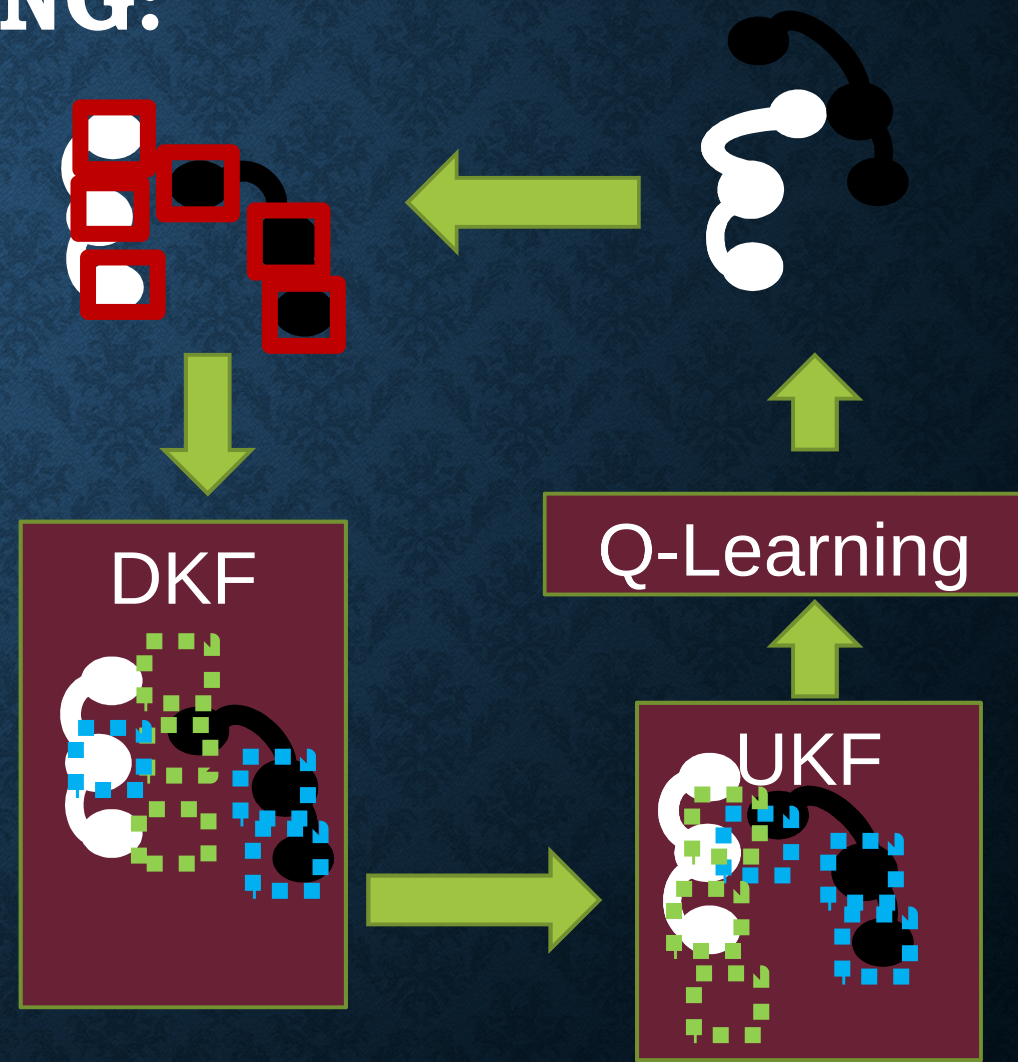
ATTRACTION-BASED LEARNING

- Learns the degrees of repulsion and attraction between certain sprite positions using the DKF and UKF.
- It is done in real-time.
- The reaction time starts from the moment the coefficient values are assigned.



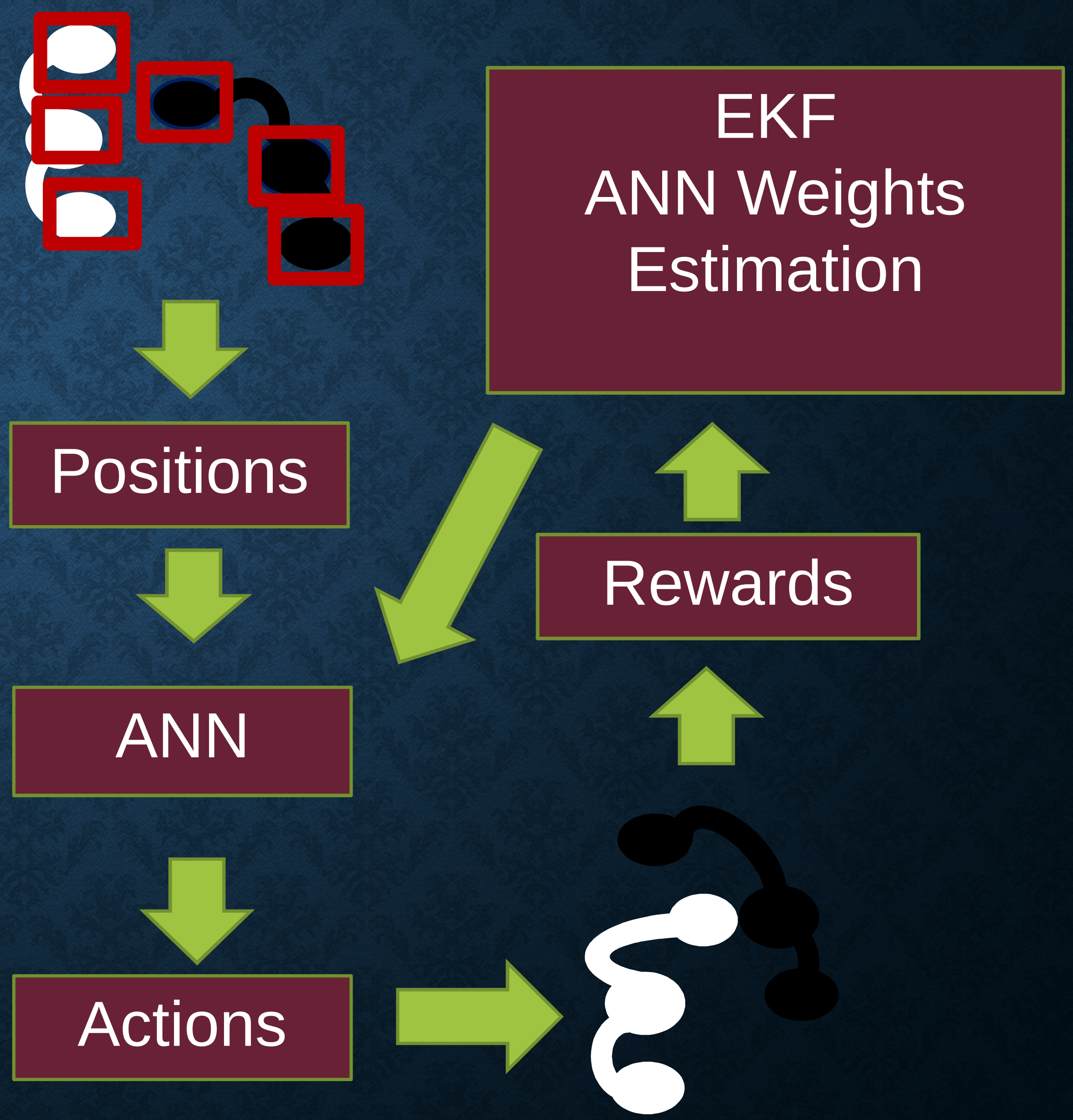
ATTRACTION-BASED REINFORCEMENT LEARNING:

- We perform a linear prediction of the future position of the sprites using the DKF.
- We use attraction-based learning to better determine the sprites' positions in future steps.
- The learning process is enhanced by adding an objective through rewards.

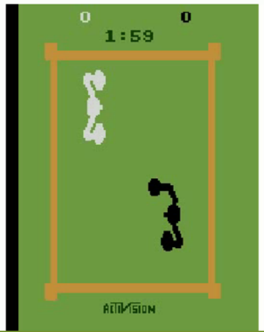


NOT TOO DEEP Q-LEARNING USING EKF

- We use the EKF to train the neural network in real-time.
- It replaces the heavy processing used in Deep Q-Learning by already having the sprites' positions.
- The neural network has fewer neurons and fewer layers, making it less complex.
- This allows training with the lowest possible error.



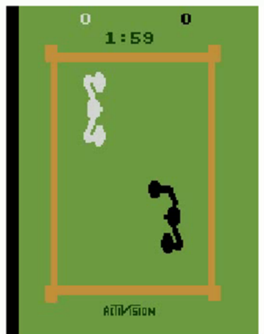
RESULTS



UK
F

Q-Learning

EKF



UKF+Q-Learning

UKF + EKF

Algorithms	Score	Remaining Time	Total Rewards
Programmed	KO x 74	34 s	45,422
UKF	79 x 78	0 s	27,670
Q-learning	KO x 97	3 s	33,361
EKF + RN	24 x 58	0 s	-18,241
UKF + Q-learning	95 x 96	0 s	30,871
UKF + EKF	13 x 59	0 s	-42,262

CONCLUSIONS

- Integrated Approach: The integration of attraction and repulsion rules with the Unscented Kalman Filter presents a promising solution for real-time decision-making in dynamic environments.
- Enhanced Learning: The proposed method enhances the learning process by refining predictions about agent movements and behaviors, leading to more robust strategies.
- Improved Reliability: Compared to traditional Q-learning and EKF-based approaches, the UKF offers a more reliable and adaptive framework, particularly in low-frame-rate conditions where fast, real-time decisions are required.
- Demonstrated Potential: The results demonstrate the potential of combining physical interaction models with machine learning to improve both prediction accuracy and agent performance in complex environments.

FUTURE WORKS

- Model Refinement:
  - Future improvements will focus on refining the attraction and repulsion models to incorporate more complex behaviors and interactions, such as environmental factors and multi-agent dynamics.
- Real-World Testing:
  - The next steps include testing the algorithm on video data of real-world players to enhance the model's ability to predict human behavior.
- Sports Analytics Application:
  - Applying this algorithm to other fields, such as sports analytics, could provide new insights by analyzing player movements and strategies in real-time
- Robotics Exploration:
  - Further exploration into robotics is planned, particularly in areas such as real-time

AUTHORS THANKS

- The authors would like to thank the Federal University of Technology – CP/PR and Federal University of São João del Rei for the financial support provided for this research.

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