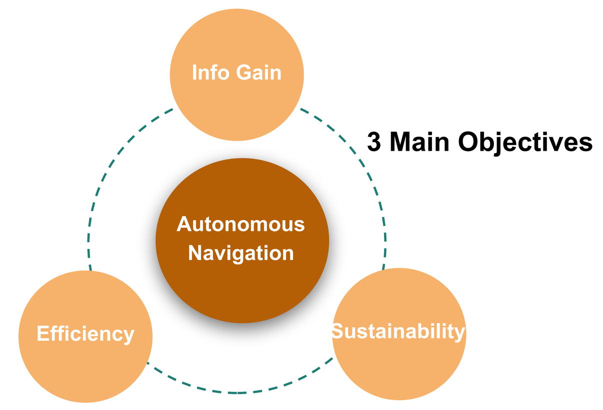
An Active Inference Approach to Autonomous Navigation

Introduction

Autonomous Navigation

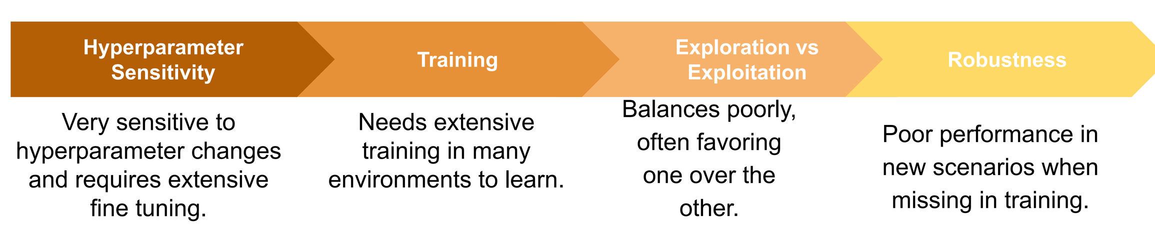
Autonomous Navigation: ability of an agent to navigate an environment on its own.

Objectives:
- Balancing **exploration** vs **exploitation**
- Robustness/Handling uncertain environments.
- Avoiding **myopic**, or inefficient behavior.



Reinforcement Learning

Reinforcement Learning: Dominant machine learning approach. Often used for autonomous navigation. Certain behaviors are rewarded to train agent.

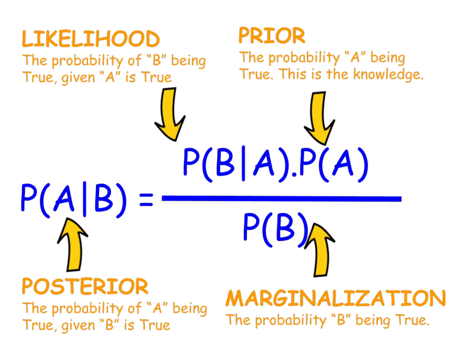


Active Inference

If training data is unavailable, where do we begin?

Predictive Processing: Biological creatures aim to build beliefs about the world that are as accurate as possible to reduce their surprise or uncertainty, which helps maintain stability.

Predictive processing is rooted in Bayesian principles as belief updates rely on Bayes' Theorem and the Law of Total Probability. Directly calculating this for numerous amounts of states requires increasing amounts of computational power.



(Taken from Chana 24)

Free Energy Principle: That's why living beings approximate surprise with a value called **variational free energy**.

$$\underbrace{\Im(y|m)}_{\text{Surprise}} = -\ln \underbrace{P(y|m)}_{\text{Model evidence}} \le \underbrace{D_{KL}[Q(x)\,||\,P(x|y,m)] - \ln P(y|m)}_{\text{Variational free energy}}$$

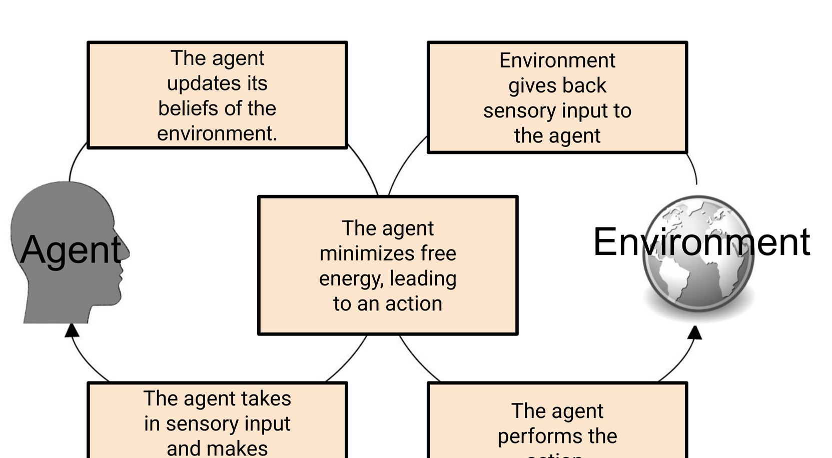
It has two main parts:
- A comparison between predicted states and actual states
- Evidence, a probability distribution encompassing existing information and its likelihood of being true, resulting from agent's beliefs

During **predictive processing**, the model attempts to minimize **future** uncertainty, considering both exploitation (pragmatic value) and exploration (information gain)

$$G(\pi) = \underbrace{-\mathbb{E}_{\tilde{Q}}[D_{KL}[Q(\tilde{s}|\tilde{o},\pi)\,||\,Q(\tilde{s}|\pi)]]}_{\text{Information gain}} - \underbrace{\mathbb{E}_{\tilde{Q}}[\ln P(\tilde{o}|C)]}_{\text{Pragmatic value}}$$

Active Inference: Unified neuroscience framework of sentient behavior that encompasses these principles.

Can be applied to **AI Agents:**
- No training required
- Sustainability - learns and adapts over the long-term.



(Modified from: Parr et al. 22)

Areas of Research

1) How does Active Inference compare with Reinforcement Learning in autonomous systems navigating unknown environments, while avoiding myopic behavior, thereby balancing exploration and exploitation, while mitigating uncertainty?
2) How does the Free Energy Principle contribute to efficient autonomous navigation, particularly in unknown environments?

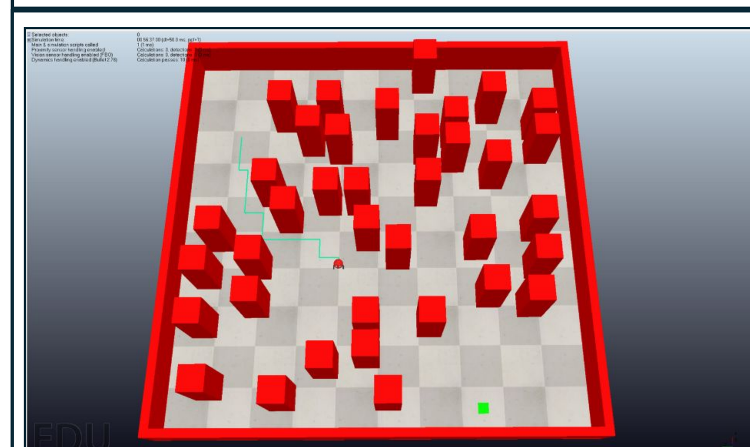
Methods

Environment/Task

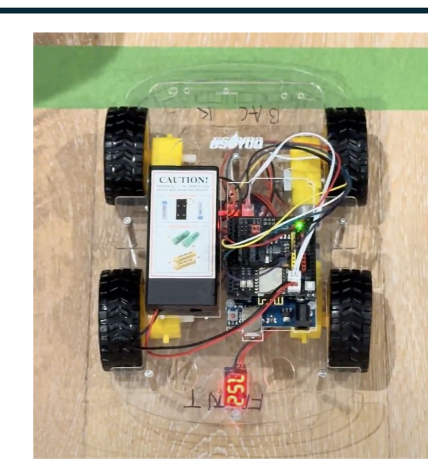
Environment: CoppeliaSim based 3D environment with walls, obstacles, and a goal.

Task: Efficiently navigate towards a goal location while avoiding obstacles.

Observations Given: Current and goal location coordinates, and surrounding locations' colors within a 2-unit radius (red = danger, green = rewarding, white = safe).



Environment (CoppeliaSim)



Robot

Control Group

Deep-Q Network (DQN): Deep reinforcement learning model that combines deep neural networks with Q-learning. 29 neuron input.

Experimental Group

Active Inference: Created with 2-dimensional states (location and attribute - safe, dangerous, or rewarding)

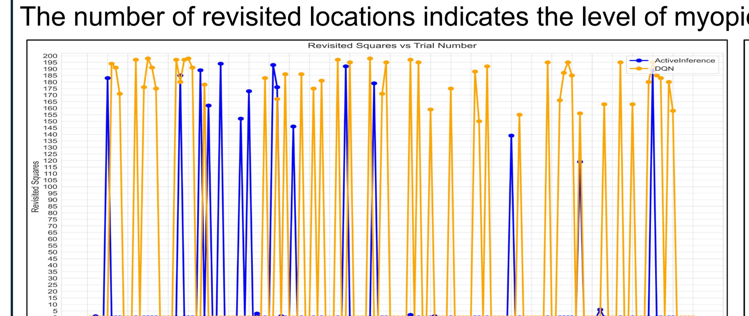
Data Metrics

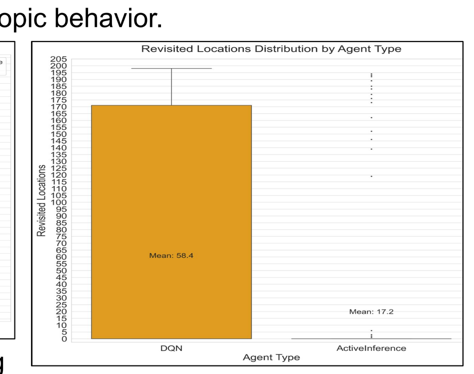
Conducted navigation in 150 unique trials and collected:

Results and Analysis

Myopic Behavior (Revisited Locations)

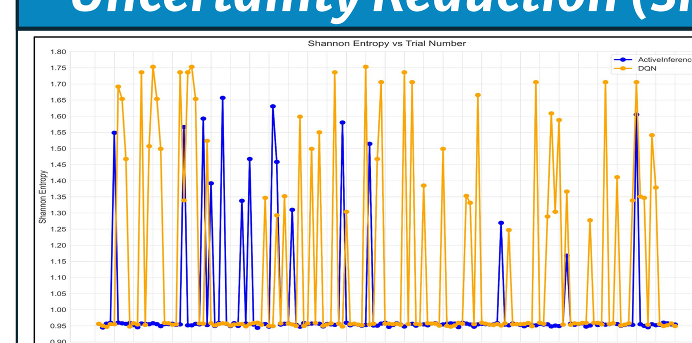
The number of revisited locations indicates the level of myopic behavior.

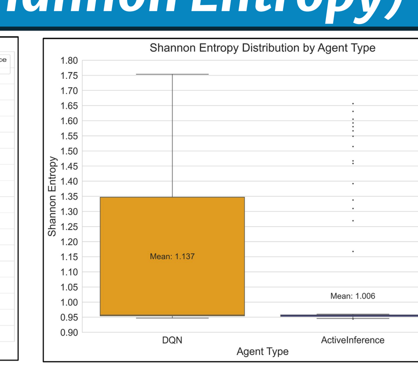




Bimodal distribution. The top cluster has failed trials / long navigation sequences. The bottom has successes.The DQN has more failed trials.
Active Inference performed better, being lower and near zero on average and having less failures.

Uncertainty Reduction (Shannon Entropy)





Penalized shannon entropy indicates agent's certainty about the states around it and efficiency of exploration, low entropy implies more uncertainty reduction by agent.

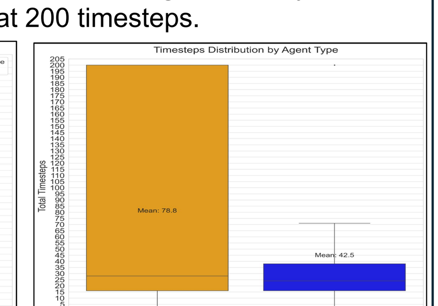
State Visit Entropy
$$H(S) = -\sum_{s \in S} P(s) \log P(s)$$

Coverage Penalty
$$CP = 1 - e^{\frac{(|X|/N - 0.5)^2}{0.1}}$$

Active Inference had lower shannon entropy than the DQN and less outliers.

Efficiency (Timesteps)

The number of timesteps took to reach the goal demonstrates the agent's ability to use information to get to the goal. Failed tests terminated at 200 timesteps.

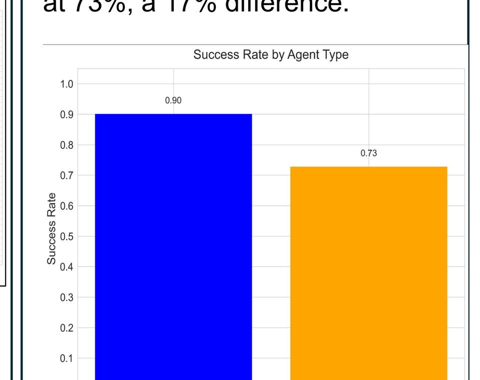


The distribution is bimodal with the top cluster including failures and bottom cluster having successes.

Based on mean and median, **Active Inference took less time steps to reach the goal**, and the DQN failed more often, reaching 200 timesteps.

Success Rate

Active Inference had a 90% success rate, while the DQN was at 73%, a 17% difference.



Summary

Overall, Active inference outperformed the Deep-Q Network across all metrics measured, demonstrating its efficiency, exploration and exploitation balance, and management of uncertainty.

Agent	Success Rate (%)	Median # of Timesteps	Mean # of Timesteps	Mean # of Revisited Locations	Mean Shannon Entropy
DQN	73	28.00	78.81	58.43	1.1369
Active Inference	90	24.00	42.50	17.23	1.0060

Conclusions

Findings

Active Inference outperforms Reinforcement Learning in unknown environments while avoiding myopic behavior, balancing exploration and exploitation, and mitigating uncertainty.

The Free Energy Principle heavily contributes to the Active Inference agent's ability to conduct efficient autonomous navigation as it inherently balances information gain and use, allowing it to balance exploration and exploitation.

Impacts/Applications

Autonomously navigating unknown environments has many applications in the real world, including:
- Disaster response, especially in unsafe and unknown environments.
- Rescue missions.
- Deep-sea and deep-space exploration where data is limited.
- And other environments where there is a lack of available training data.

Challenges

- Active Inference is computationally intensive, which leads to scaling issues without GPUs
- Hard to define for more complex environments.

Possible Improvements

- Code efficiency, particularly with functions with the simulation
- Movement accuracy with physical robot.

Future Research

- **More RL:** Testing against more RL models and methods
- **Complex Decision Making:** Active Inference has the capability to be used in ethics. For instance, it can be used for self driving car and human interactions in autonomous navigation.
- **Complex Environments:** Design more dynamic environments with moving obstacles and more tasks for exploitation.
- **Complex Inference:** More states than location and danger level like obstacle weight,
- **Real-World Implementation:** Move to a more realistic simulation (Ex: Carla). Implement all parts of active inference into a physical robot, not just actions, use sensors for gathering information for instance
- **Hybrid Models:** Use Active Inference as a fine-tuning mechanism for Reinforcement Learning models and as a perception unit for agents to better choose actions

Key References

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