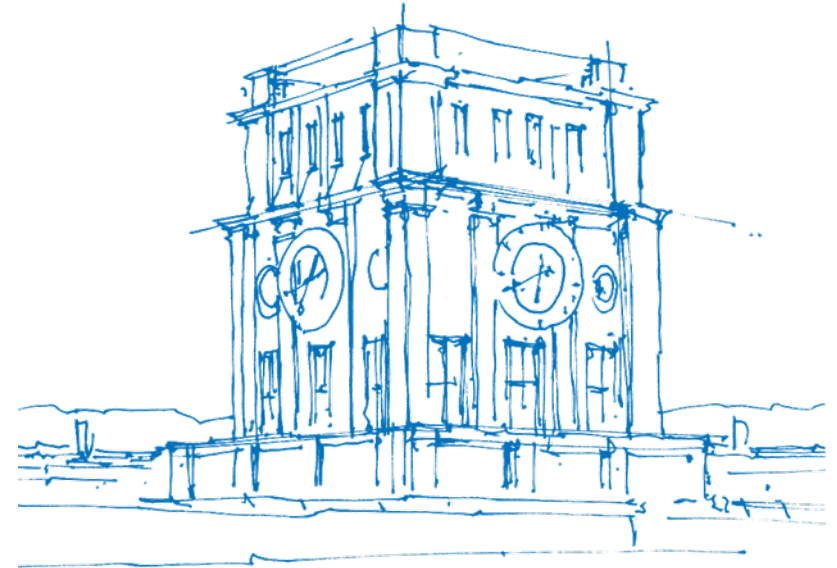


Checkmate with AI

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TUM Uhrenturm

Introduction

Supervised

Data: (x,y)

x is the data, y is the label

Goal: Learn function to map
 $x \rightarrow y$

Apple Example:



This object is an apple

UnSupervised

Data: (x,y)

x is the data, no labels!

Goal: Learn underlying structure

Apple Example:



This object is like
the other object

Reinforcement Learning

Data: State Action Pairs

Goal: Maximize future rewards

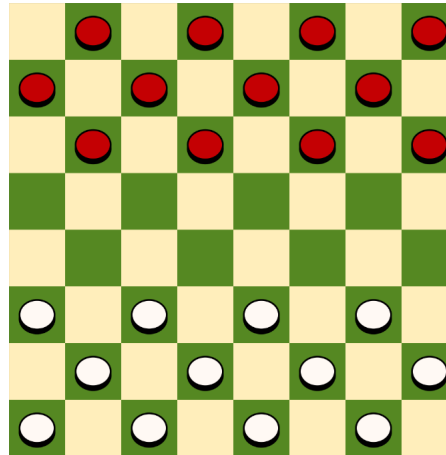
Apple Example:



Eat this thing because
it will keep you alive

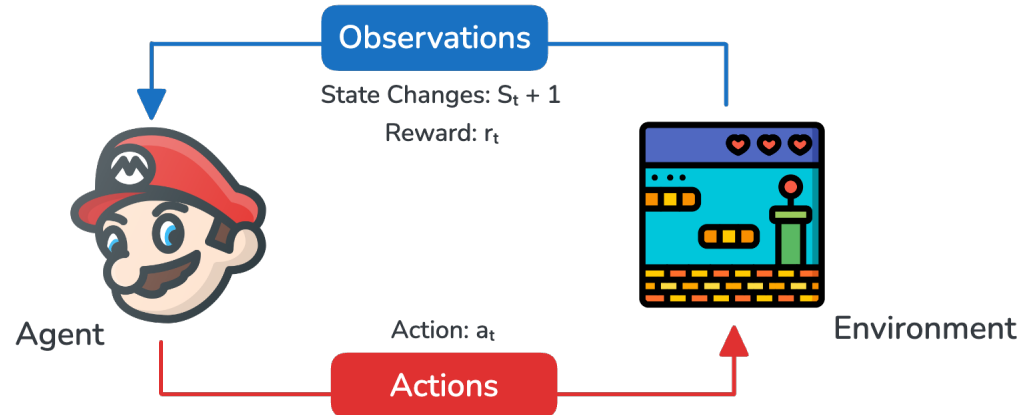
Introduction

- Checkers is a strategy game involving diagonal moves of pieces and captures by jumping over opponent pieces
- The objective of the project is to create an AI player using reinforcement learning
- Techniques: Q-learning and Deep Q-Networks (DQN)



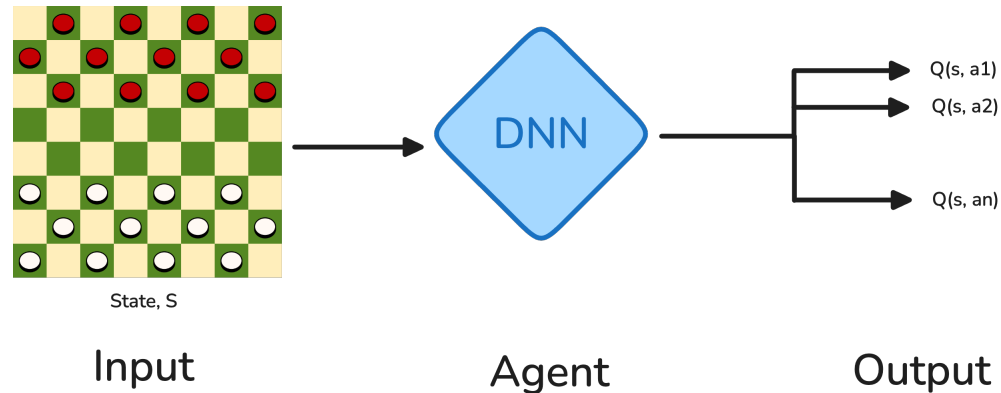
What is Reinforcement Learning?

- A machine learning paradigm focused on training agents to make sequences of decisions
- Key components:
 - **Agent**: Learns to act in an environment
 - **Environment**: The system with which the agent interacts
 - **Reward**: Feedback signal indicating the success of an action
- Goal: Maximize cumulative rewards over time



Deep Q-Learning

- reinforcement learning technique to find the optimal action-value function $Q(s, a)$
- It maps state-action pairs to their expected future rewards



Deep Q-Learning: Q-update rule

$$Q^{\text{new}}(s_t, a_t) \leftarrow Q(s_t, a_t) + \underbrace{\alpha}_{\text{learning rate}} \cdot \overbrace{\left(r_t + \underbrace{\gamma}_{\text{discount factor}} \cdot \underbrace{\max_a Q(s_{t+1}, a)}_{\text{estimate of optimal future value}} - \underbrace{Q(s_t, a_t)}_{\text{old value}} \right)}^{\text{temporal difference}}$$

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Challenge: Traditional Q-learning fails for large or continuous state spaces

Deep Q-Learning: Solution

Use a **Deep Neural Network** (DNN) as a function approximator for $Q(s, a)$ instead of a table

- **Input:** State s , **Output:** Q-values for all actions a
- **Target Network:** stabilizes training by holding fixed weights for a few updates
- **Experience Replay:** samples random batches of past experiences (s, a, r, s') to break correlation in training data

Deep Q-Learning Algorithm

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1. Initialize:

Q-Network $Q(s, a; \theta)$ and Target Network $Q'(s, a; \theta^-)$

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Use an ϵ – greedy policy to balance exploration vs. exploitation

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Add (s, a, r, s') to a replay buffer

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4. Train the Network:

- sample a minibatch from the buffer
- Compute target Q-values: $y = r + \gamma \max_{a'} Q'(s', a'; \theta^-)$
- Minimize loss: $L(\theta) = (y - Q(s, a; \theta))^2$

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5. Update Target Network:

Periodically copy weights: $\theta^- \leftarrow \theta$

Key Improvements and Applications

Improvements:

- **Double DQN:** Reduces overestimation of Q-values
- **Dueling DQN:** Separates value and advantage functions
- **Prioritized Experience Replay:** Samples important experiences more frequently

Key Improvements and Applications

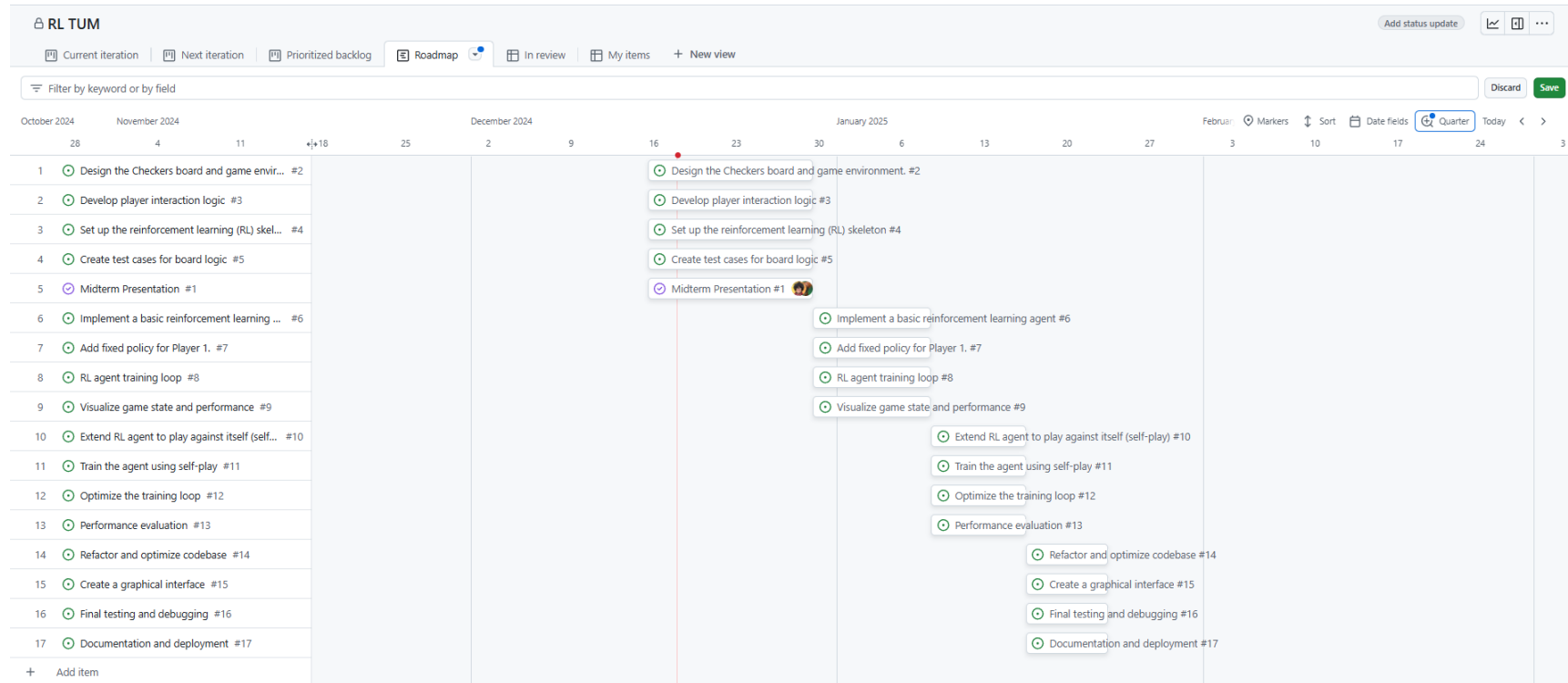
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Applications:

- Games
- robotics
- autonomous systems

Project Planning & Timeline



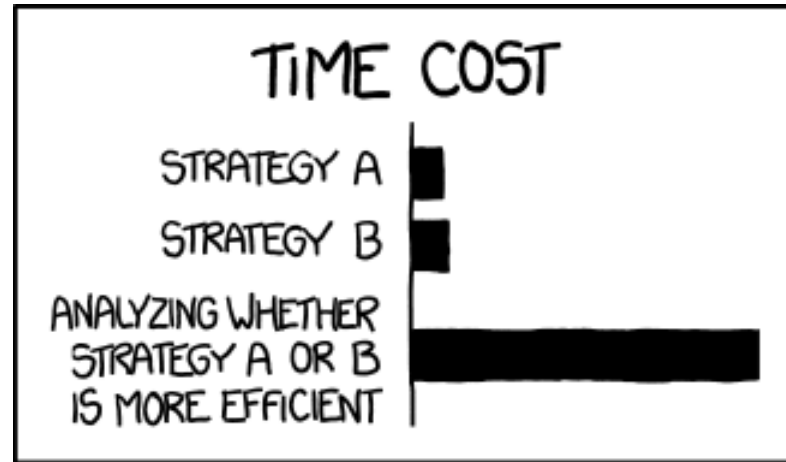
Software Stack

- Python
- numpy (for matrix calculations)
- pygame (fast UI)
- Web frameworks
- tensorflow (for ML implementation)

Future Work

- Fine-tuning the DQN model for improved decision-making
- Incorporating advanced techniques like Double DQN and Dueling DQN
- Testing against human players to evaluate real-world performance
- Extending the approach to other board games or strategy games (some side-projects)

Thank You



THE REASON I AM SO INEFFICIENT

xkcd 1445