DQN Reinforcement Learning

Advancing Deep Q-Networks for Optimal Navigation in Frozen Lake:
Evaluating Adaptability and Performance in Dynamic Environments

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Introduction

History

- 1992 Q-learning algorithm introduced by Watkins
- 2013 DQN introduced by DeepMind in the paper 'Playing Atari with Deep Reinforcement Learning' at NIPS
- 2015 Comprehensive DQN paper 'Human-level control through deep reinforcement learning' published in Nature
- 2018 Rainbow DQN algorithm introduced, combining several improvements

DeepMind

Google DeepMind is a research company owned by Google that focuses on artificial intelligence (AI) and machine learning.

DQN In A Nutshell

DQN is a reinforcement learning algorithm that combines Q-Learning with deep neural networks to learn how to act in an environment.

- **Key Concepts:**
  - States: Environment configurations.
  - Actions: Possible moves.
  - Rewards: Feedback signals.
- **Applications:** Video games (Atari), robotics, finance (trading strategies).
- **Advantages:** Handles high-dimensional state spaces, effective for complex policy learning.
- **Challenges:** Requires extensive training data, tuning for stability.
- **Purpose:** It aims to enable an agent to make decisions that maximize cumulative rewards over time.

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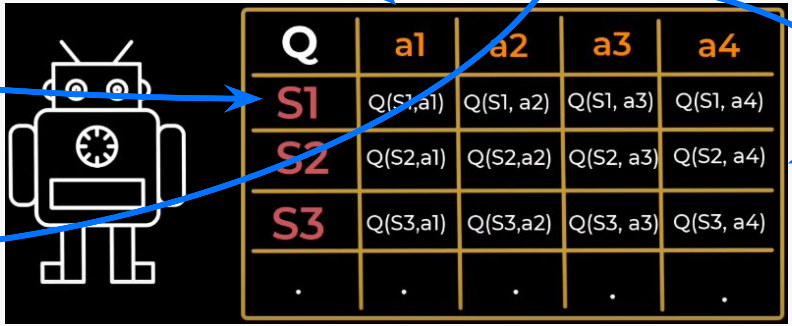
Architecture

Architecture

<u>RL agents policy (π):</u>

In each **State** the Agent know which **Action** to do, based on **Q-Table** to achieve the maximum **Reward**



The DQN replace the Q-table with a neural network instead

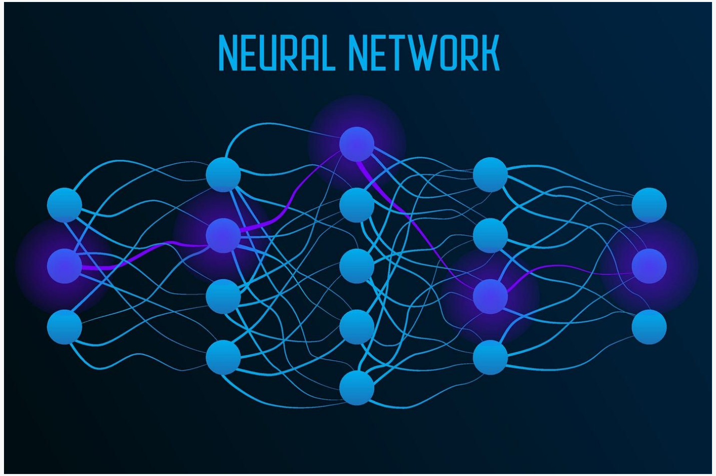
Architecture

DQN:

The DQN Replace Q–Table with NN prediction.
Performing with more robust and scalable solution rather than using a big action–state table

State

Action



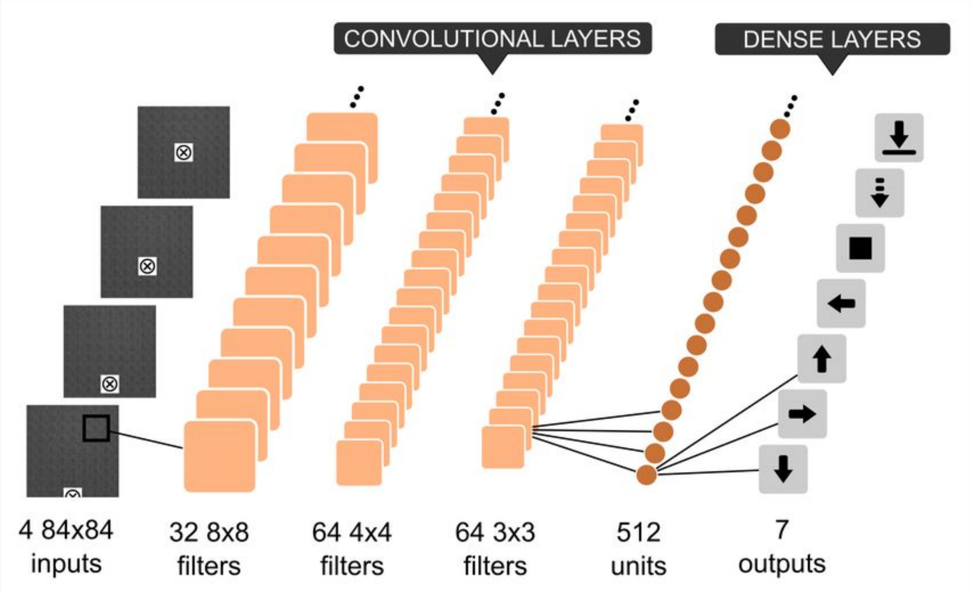
Q–Value

```
self.agent.replay_memory.store(state, action, next_state, reward)
```

Architecture

Agent & NN

1. **Input Layer:**
   - State representation (game screen pixels)
2. **Convolutional Neural Networks (CNNs):**
   - Extract spatial features from inputs
3. **Fully Connected Layers:**
   - Combine features to predict Q-values
   - ReLU Activation function
4. **Output Layer:**
   - Q-values for each possible action



Architecture

Optimal Q action-value function

s – state (observation)
a – action
r – reward
t – index for step
γ – discount
π – policy P(action|state)

$$Q^*(s,a) = \max_{\pi} \mathbb{E}\left[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \ldots \middle| s_t = s,\ a_t = a,\ \pi\right]$$

The data for the NN

The data is the states and actions that were happened in the environment

e – experience
t – index for step
Dt – collection of e, data set

$$e_t = (s_t, a_t, r_t, s_{t+1})$$

$$D_t = \{e_1, \ldots, e_t\}$$

Architecture

Loss function

i – index for iteration
θ – weights
U(D) – unified the data set

s′ – state, s – previous state
a′ – action, a – previous action
r – reward
γ – discount
Q – action-value function

$$L_i(\theta_i) = \mathbb{E}_{(s,a,r,s') \sim \mathrm{U}(D)} \left[\left(r + \gamma \max_{a'} Q(s', a'; \theta_i^-) - Q(s, a; \theta_i) \right)^2 \right]$$

Optimization algorithm

SGD – stochastic gradient descent

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Articles

Articles

Human-level control through deep reinforcement learning

LETTER

doi:10.1038/nature14236

Human-level control through deep reinforcement learning

Volodymyr Mnih[1]*, Koray Kavukcuoglu[1]*, David Silver[1]*, Andrei A. Rusu[1], Joel Veness[1], Marc G. Bellemare[1], Alex Graves[1], Martin Riedmiller[1], Andreas K. Fidjeland[1], Georg Ostrovski[1], Stig Petersen[1], Charles Beattie[1], Amir Sadik[1], Ioannis Antonoglou[1], Helen King[1], Dharshan Kumaran[1], Daan Wierstra[1], Shane Legg[1] & Demis Hassabis[1]

Playing Atari with Deep Reinforcement Learning

Playing Atari with Deep Reinforcement Learning

Volodymyr Mnih   Koray Kavukcuoglu   David Silver   Alex Graves   Ioannis Antonoglou
Daan Wierstra   Martin Riedmiller
DeepMind Technologies

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Environment

Froze Lake

1. **Game Description:**
   - Frozen Lake is a grid-based game where an agent must navigate from a start point to a goal point on a slippery surface, avoiding holes.

2. **Environment Setup:**
   - Grid Layout: Typically an $n \times n$ grid (4x4 or 8x8)
     - S: Start point
     - G: Goal point
     - H: Holes (fall into one, and the game is over)
     - F: Frozen surface (safe to walk on)

3. **Borders:**
   - The grid is bounded, meaning the agent cannot move outside the grid.
   - Actions attempting to move out of bounds result in no movement.

Froze Lake

4. States and Actions:

- States (S): Each cell in the grid represents a unique state.
- Actions (A): Four possible actions – left, right, up, down.
- Rewards (R):
  - +1 for reaching the goal.
  - 0 for all other transitions (including falling into a hole).

5. Slippery Surface Dynamics:

- **Slippery Nature:** Due to the slippery surface, actions do not always result in moving to the intended adjacent cell. Instead, there is a chance the agent will slide to an unintended cell, adding randomness to the game and increasing the complexity of navigation.

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METHODOLOGY

Project Goal

Train an AI agent using Deep Q-Networks (DQN) to navigate the Frozen Lake environment and successfully reach the goal state while avoiding falling into holes.

Topic	OBJECTIVE
Problem Definition	• Train DQN agent to navigate Frozen Lake, reaching goal while avoiding holes.
Environment Setup	• Define Frozen Lake grid with start, goal, holes, and frozen surfaces.
State and Action Representation	• States: Agent's grid position; Actions: Left, right, up, down movements.
DQN Implementation	• Use neural network for Q-function approximation.
Training Process	• Implement DQN model
Evaluation and Testing	• Assess agent's performance: average reward, success rate.
Hyperparameter Tuning	• Optimize parameters like learning rate, discount factor.

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Project Plans

Project Stages

Implement RL:
DQN model and Environment

Stage 1

Train and Test RL Model

Stage 2

Collect and Analyze
Results

Stage 3

Thanks

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