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Deep W-Networks: Solving Multi-Objective Optimisation Problems With Deep Reinforcement Learning

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Multi-Objective Optimisation Problems

Background

- **These problems require balancing trade-offs between objectives to find a compromise solution that satisfies all constraints.**
- **Many real world problems can be formulated as a multi-objective optimisation problem:**
  - Radio resource management;
  - infectious disease control;
  - marketing optimization in advertising;
  - energy management of sensor networks.

Pareto Front

Background

- **Is defined as the set of non-dominated solutions;**
- **Each objective is considered as equally good;**
- **Provides a way to visualize the trade-offs.**

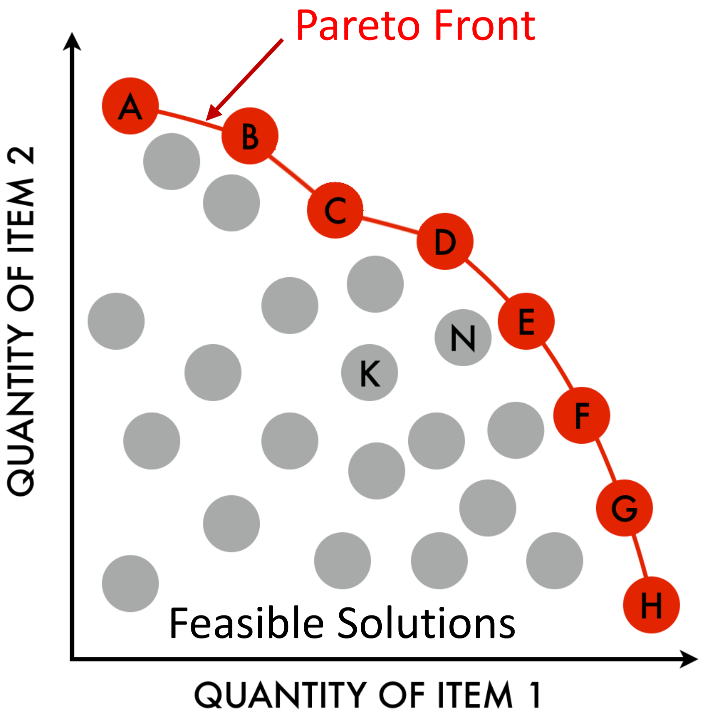


Image taken from: Wikipedia

W-Learning

Solution to Resolve Multi-Objective Problems

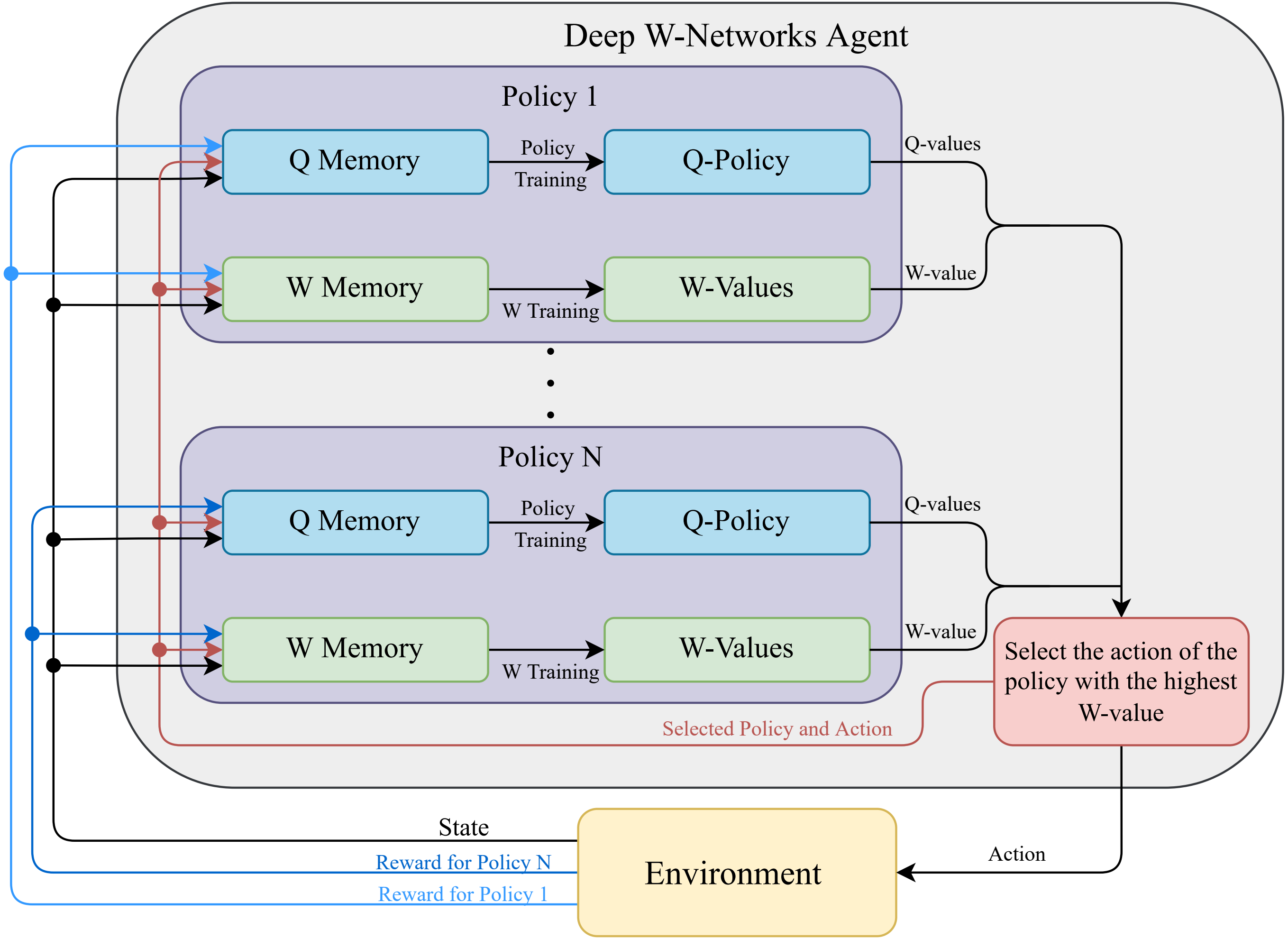
- **Developed in the 1990s [1] to find the optimal policy for a multi-objective problems.**
- **Resolves competition between different policies, with the winner policy being the one that is most likely to suffer the most if it does not win.**
- **Each policy is implemented with a tabular Q-learning, and W-values representing the W weight.**
- **Computationally efficient, intuitive, versatile applicability, etc.**

[1] Humphrys, M. (1995). W-learning: Competition among selfish Q-learners.

Aims and Objectives of Our Work

Contributions

- **We propose a Deep W-Networks (DWN), a deep learning extension to W learning algorithm;**
- **DWN resolves the competition between greedy single-objective policies by relying on W-values;**
- **We show the modularity of DWN.**


Deep W-Networks Agent
Policy 1
Q Memory
Policy
Training
Q-Policy
Q-values
W Memory
W Training
W-Values
W-value
Policy N
Q Memory
Policy
Training
Q-Policy
Q-values
W Memory
W Training
W-Values
W-value
Select the action of the policy with the highest W-value
Selected Policy and Action
State
Reward for Policy N
Reward for Policy 1
Environment
Action

Deep W-Networks

Algorithm

- **We employ two DQNs for each objective.**
- **The agent takes the action suggested by the policy associated with the highest W-value:**

$$W_j(t) = \max\left(\{W_1(t), \ldots, W_N(t)\}\right).$$

Deep W-Networks

Training W-values

- **W-values are updated similarly to Q-values:**

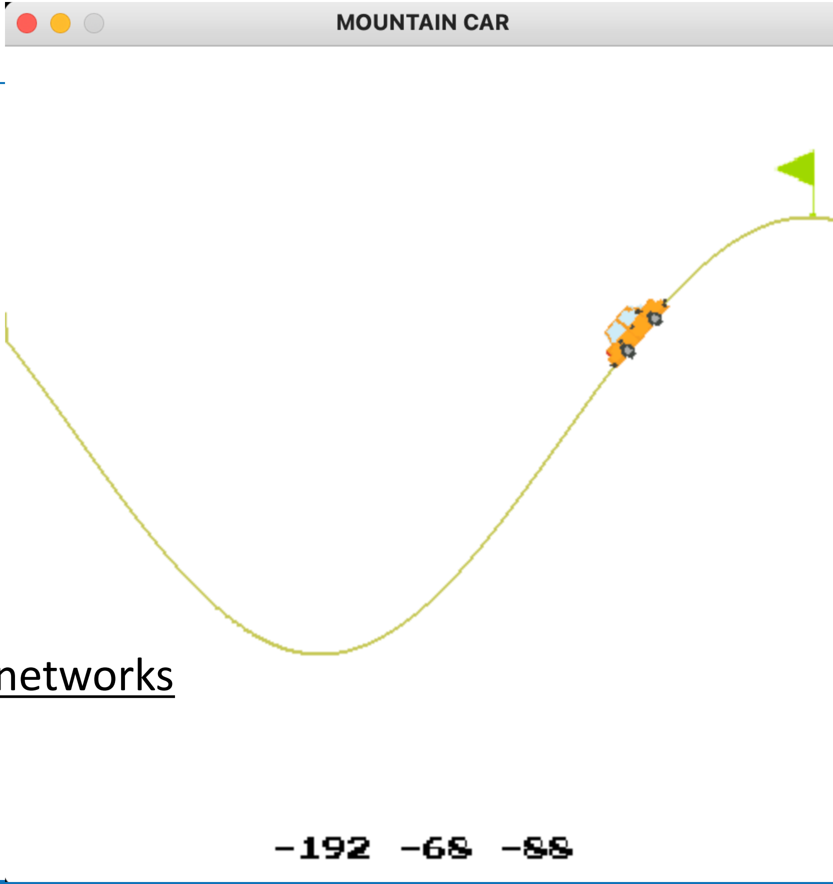
$$W_i(t) \leftarrow (1-\alpha)W_i(t) + \alpha\left[Q(s(t), a_j(t)) - (R_i(t) + \gamma \max_{a_i(t+1)\in\mathcal{A}} Q(s(t+1), a_i(t+1))\right].$$

- **W policy saves the experience only when it was not selected.**

Mountain Car

Environment

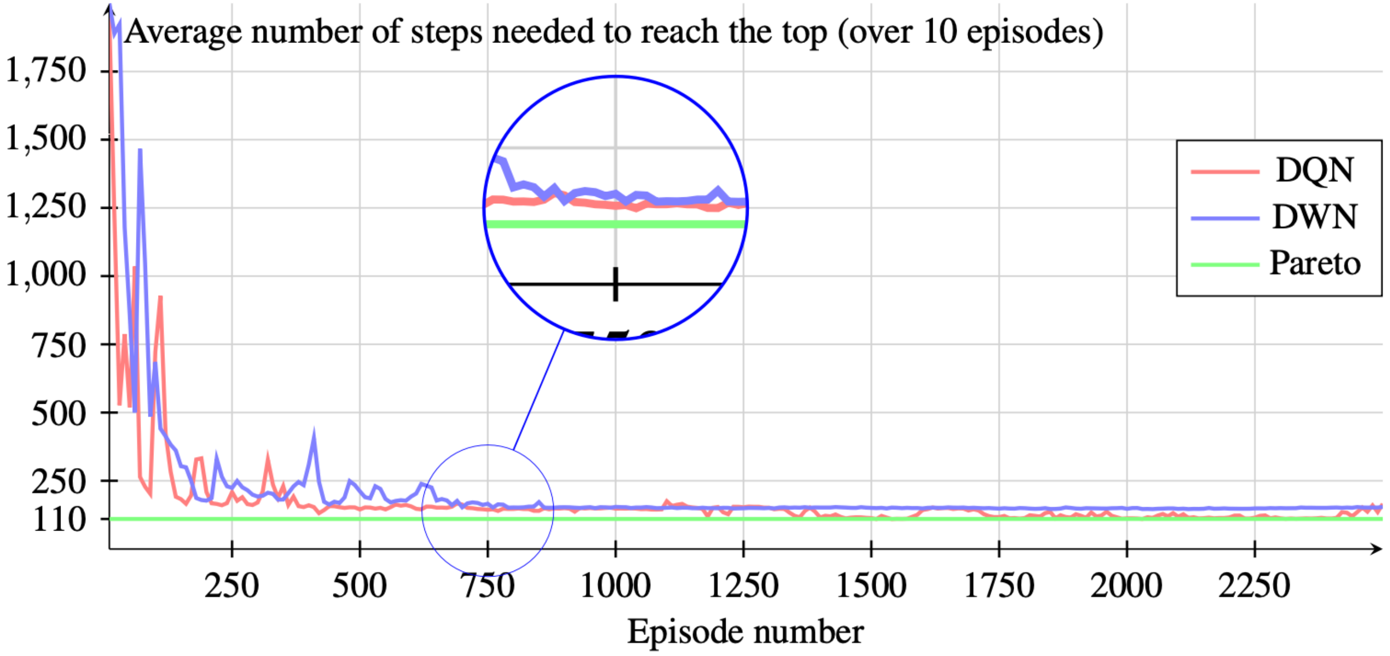
- **The environment has three different objectives:**
    - time penalty;
    - backward acceleration penalty;
    - forward acceleration penalty.



- **Github code:** https://github.com/deepwlearning/deepwnetworks

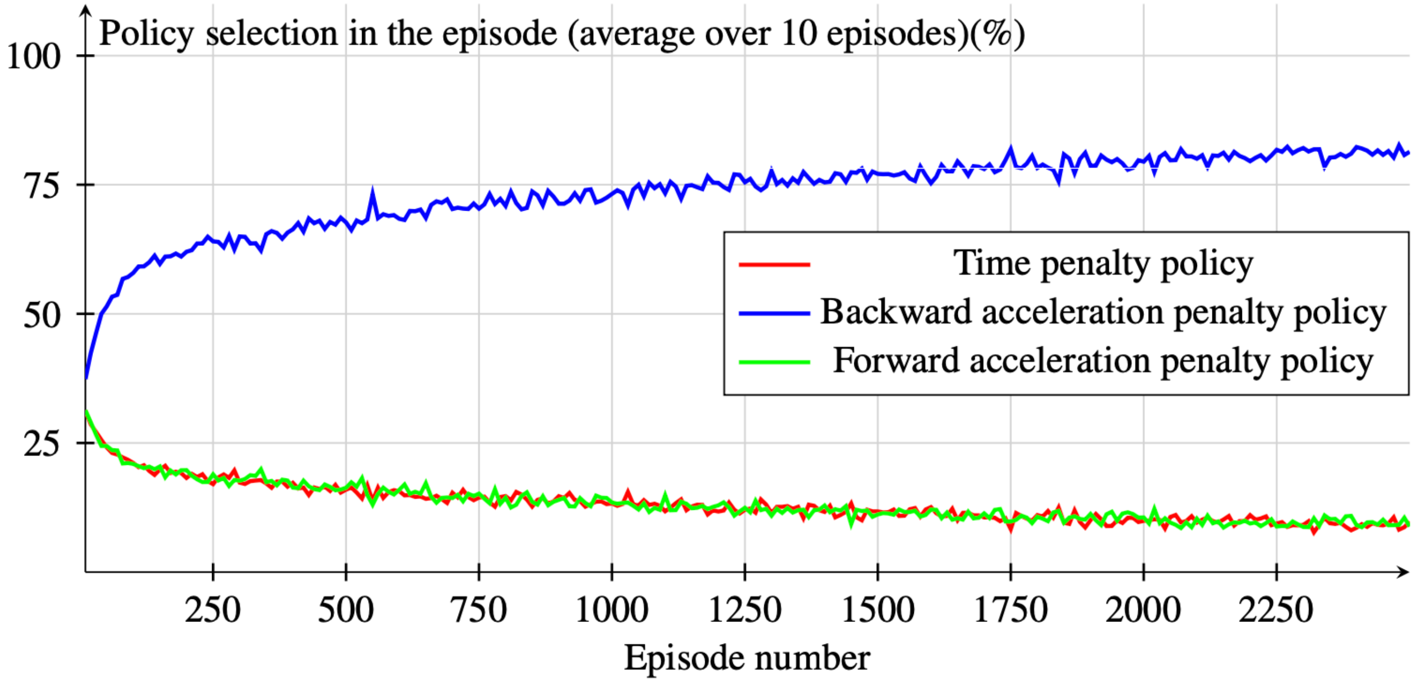
Mountain Car

The number of steps to finish the episode



Mountain Car

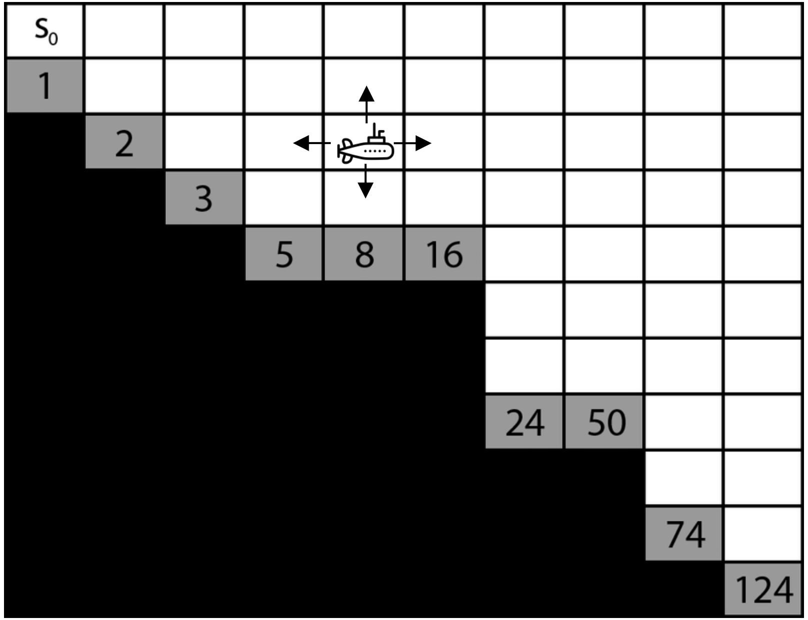
The percentage of each policy DWN agent selects in an episode,



Deep Sea Treasure

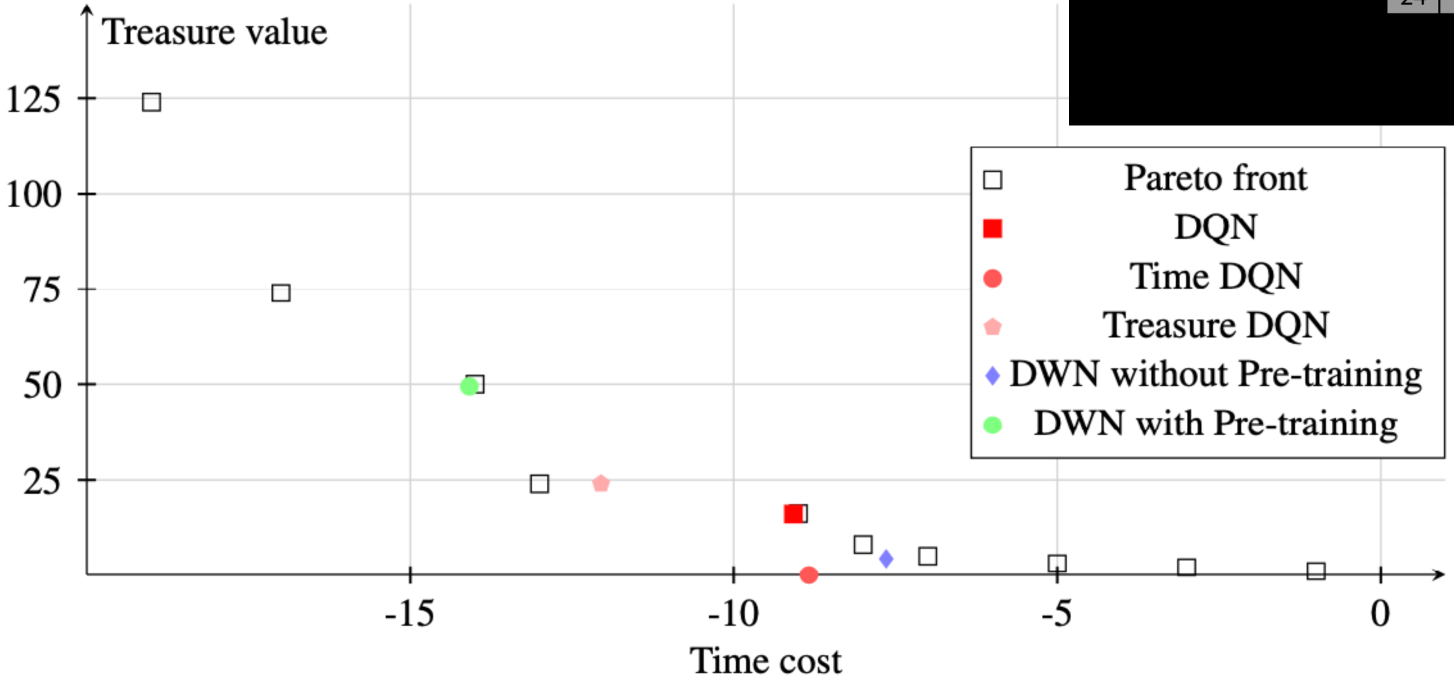
Environment

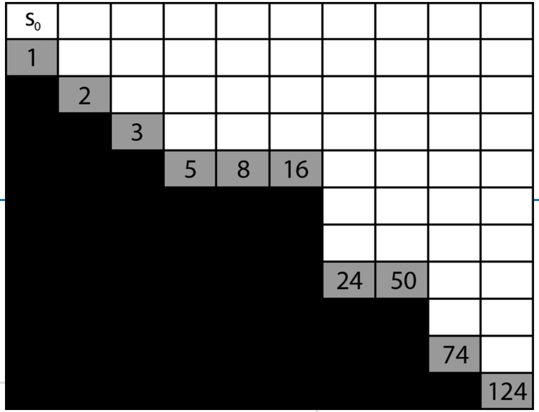
- **The environment has two objectives:**
  - Time penalty;
  - Collected treasure.
- **We use Convolutional Neural Network (CNN) structure in DWN Agent**



Deep Sea Treasure

Pareto Front





Conclusion
and Future Work

- **The proposed DWN is capable of finding the Pareto front.**
- **The main advantage of DWN is its ability to train multiple policies simultaneously.**
- **Future work:**
    - Improving the computational performance;
    - Evaluating in more complex environments.

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Thank you for your attention!

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