Reinforcement Learning Applied to RTS games

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PUCRS

Introduction

Introduction

- Reinforcement learning focuses on maximizing the total reward of an agent through repeated interactions with an environment.
- In traditional approaches an agent must explore a substantial sample of the state-space before convergence
    - Thus, traditional approaches struggle to converge when faced with large state-spaces ($\geq 10k$ states).
    - Most "real world" problems have much larger state-spaces. E.g. chess.
- Alternatively, we can generate hypotheses of state features and try to generalize the reward function
    - However, this depends on good features and a good function hypothesis

Introduction

- Intuition of behind our work:
    - Compress traditional state representations domain-independently
    - Use traditional reinforcement learning on the compressed state-space
    - Aggregate experience from multiple, similar agents
- Main challenges:
    - How do we create a faithful representation of the states?
    - How do we address combinatorial explosion of multiple, parallel agent actions?
- Technical approach:
    - Learn a compressed state representation using deep auto-encoders
    - Reduce combinatorial explosion of RTS games by learning for individual unit types (in lieu of solving a Dec-MDP)

Background

MicroRTS

- Real Time Strategy (RTS) games are a very challenging gaming environment for AI control (**branching factor** on the order of 10^{50})
- MicroRTS is an abstract simulation environment with similar rules to fully fledged RTS games (e.g. StarCraft, Command and Conquer).
  - Much simpler to modify and test
  - Only 4 types of units and 2 structures
  - Open AI integration API
  - Used as testbed for AI planning and MCTS approaches for RTS control

MicroRTS

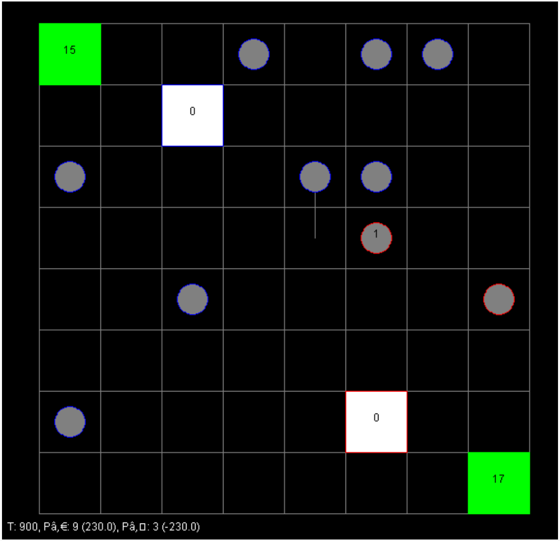


Figure 1: MicroRTS game state.

Approach

Approach

We use two key techniques to converge to a policy in RTS games:

- Train a deep auto-encoder to mitigate the state-space size
- Unit Q-Learning to mitigate the branching factor

Deep auto-encoders

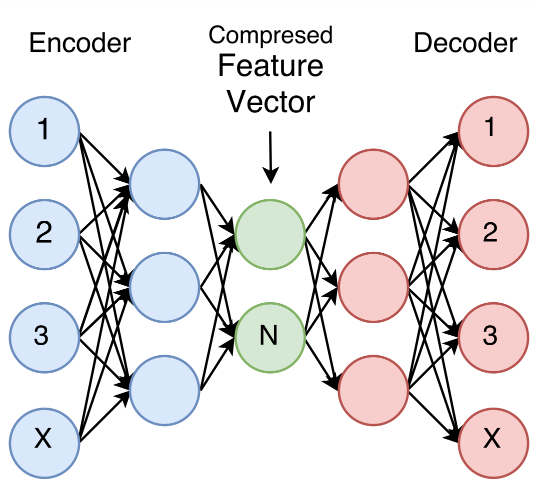


Figure 2: Deep auto-encoder.

Deep auto-encoder for state-space compression

Our approach to compressing the state-space consists of 3 steps:

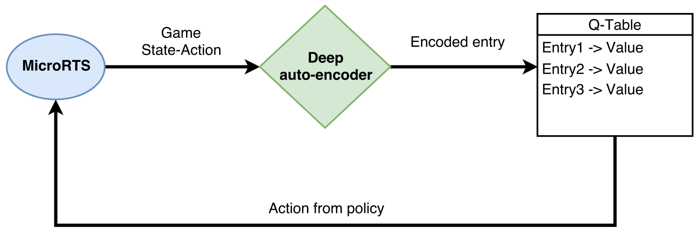
1. design a binary representation for the state space, the *raw encoding*;
2. design an auto-encoder that takes as input the raw encoding and narrows it into 15 neurons (bits), creating a *canonical encoding*; and
3. train the network using state-action pairs from the MicroRTS game.

Deep auto-encoder

Assuming a trained encoder $E(s, a)$, we modify the Q-learning update so that the tables are mapped through $E(s, a)$:

$$Q(E(s,a)) \leftarrow Q(E(s,a)) + \alpha(R(s) + \gamma \max_a Q(E(s', a')) - Q(E(s,a)))$$

- We train the auto-encoder offline with a fixed dataset of AI MicroRTS matches;
- Since we encode all updates through $E(s, a)$, the Q-table consists exclusively of encoded pairs.



Training the auto-encoder

- To train the auto-encoder, we first model all binary features of the MicroRTS game state, e.g.:
  - the position of all units from the player and the enemy;
  - health of the player and enemy bases; etc
- We use two Random strategies available from MicroRTS to generate a training dataset for the auto-encoder
  - These strategies execute random actions, generating multiple state-action pairs with each player's units scattered around the map
- Finally, we train the auto-encoder using this dataset

Unit Q-Learning

- Each player action in a MicroRTS game state is the combination of actions for all units on the map
  - Resulting in more than 3^5 actions turn
- To avoid dealing with this very large branching factor, we use independent learning, which analyzes the best action for each unit locally.
  - each unit generates an independent Q-Learning update.
  - the overall player action then becomes the group of the best action of each unit.
- At the end of each learning episode:
  - units of the same role share their experience, building a unified table for the role using the algorithm below

$$Q(s,a) = \frac{\sum_{i=0}^{agents} Q_i(s,a) * frequency(Q_i(s,a))}{frequency(Q(s,a))}$$

  - this table is used as the base for new episodes.

Unit Q-Learning

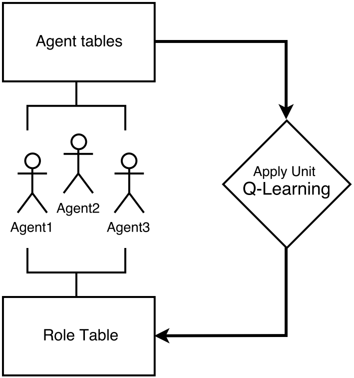


Figure 3: Unit Q-Learning process life cycle.

Experiments and Results

Experiment Setup

- All tests were made in the 8x8 grid scenario of MicroRTS.
- The computer used for the experiments has the following specifications:
  - Intel CPU I5 2.7ghz.
  - 8GB RAM.
  - Java VM 1024 GB.
  - 6M Cache.
- When matching against other strategies to evaluate our win rate, we trained using 200 games, and then played 20 games with learning disabled.

Separate Roles for Workers

- Workers in MicroRTS can be used for both harvesting resources and attacking other units.
- To avoid this problem when merging the tables, we separate workers in two types, the **harvesters** and the **attackers**.
- The difference is that the harvester workers are rewarded for gathering resources.
- Both are rewarded for attacking enemy units.
- Other units (heavy, light, ranged) are considered attackers.

Convergence Results

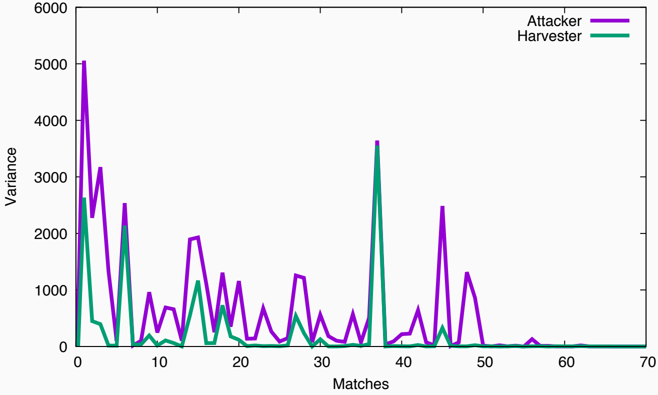


Figure 4: Convergence of Attacker and Harvester.

Q-table size Results

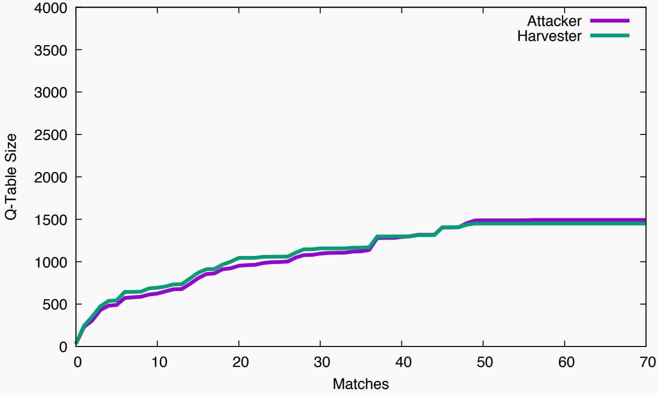


Figure 5: Q-Table size of Attacker and Harvester.

Comparison against other Strategies/Algorithms

Strategies	Wins	Draws	Losses	Win rate	Score
Passive	20	0	0	100%	+ 20
Random	20	0	0	100%	+ 20
Random Biased	20	0	0	100%	+ 20
Heavy Rush	20	0	0	100%	+ 20
Light Rush	20	0	0	100%	+ 20
Ranged Rush	20	0	0	100%	+ 20
Worker Rush	9	4	7	45%	+ 2
Monte Carlo	17	3	0	85%	+ 17
NaiveMCTS	6	6	8	40%	- 2

Experiments

Finally, we analyzed the time for each approach to execute 10 cycles, which is the shortest period for any action in MicroRTS.

Strategies	Average time (s)	Maximum time (s)
Passive	0s	0s
Random	∼0s	∼0s
Random Biased	∼0s	∼0s
Heavy Rush	0.001s	0.05s
Light Rush	0.001s	0.01s
Ranged Rush	0.001s	0.03s
Worker Rush	0.05s	0.1s
Monte Carlo	2.0s	2.303s
NaveMCTS	2.0s	2.545s
Our approach	0.3s	0.511s

Conclusion

Conclusion

- We developed an approach to play RTS games using traditional Q-learning distributed over multiple units with compressed Q-tables:
    - The combination of approaches obtained promising results in the MicroRTS;
    - Converged to a policy analogous to the best fixed strategy
- As future work:
    - Evaluate the performance using other auto-encoders, such as the denoising stacked auto-encoder.
    - Learn the reward function using inverse reinforcement learning on the already implemented strategies.

Thank You

Related Work

Distributed Reinforcement Learning

- Nair, A. et al. **Massively parallel methods for deep reinforcement learning.** 2015.
    - Nair presents a distributed RL architecture to play Atari games.
    - The state is the game image encoded by a deep neural network.
    - Multiple instances of the environment are used to accelerate the training.

Multi-agent Reinforcement Learning

- Zhang, C.; Lesser, V. **Coordinating multi-agent reinforcement learning with limited communication.** 2013.
    - Multiple agents acting in the same environment.
    - They learn independently.
    - Independent learning can not ensure convergence to an optimal policy.
    - Policy coordination is required to build a global policy.