Comparing Observation and Action Representations for Reinforcement Learning in μRTS

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Overview

RTS Games

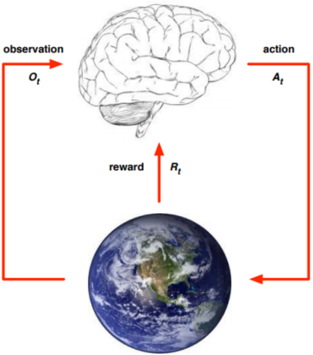
Figure: StarCraft II (PC, 2010)

https://youtu.be/yaqeZ9Snt4E?t=13

RTS Games

- RTS Games have the characteristics of:
    - Real-time decision making
    - Extremely large branching factor for search-based approaches
    - Partially-observable

Reinforcement Learning



- At each step t the agent:
  - Executes action A_t
  - Receives observation O_t
  - Receives scalar reward R_t
- The environment:
  - Receives action A_t
  - Emits observation O_{t+1}
  - Emits scalar reward R_{t+1}
- t increments at env. step

Problem Statement

- **Problem**: how do we design observation and action representation of RTS games for DRL (Deep Reinforcement Learning)?
  - Observations
    - Raw pixels?
    - Discretized states (A binary array of attributes "haveBarracks", "haveRanged", "isAttacking")?
  - Actions
    - Mouse clicks and key strokes?
    - For each unit, give a command (soilder1: attack, soilder2: noop)?

Problem Statement

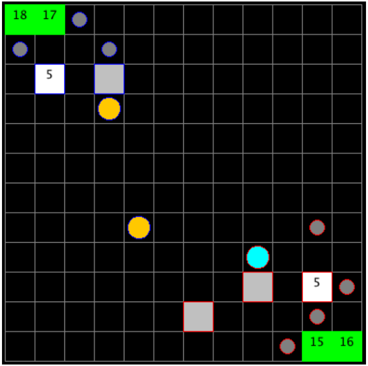
- **Problem**: how do we design observation and action representation of RTS games for DRL (Deep Reinforcement Learning)?

This paper:

- We compared two intuitive representations:
  - a *global* representation where the agent *sees* everything and *controls* an interested unit at each timestep.
  - a *local* representation where the agent becomes an unit at each timestep, *sees* everything that is some distance away from it and *controls* itself.

μRTS

- Open-source https://github.com/santiontanon/microrts
- Minimalistic
- Deterministic
- Fully or partially-observable options
- Available AI techniques: UCT, NaiveMCTS, Portfolio greedy search, AHTN, ...



Existing Work

RL techniques in RTS games:

- Alisp to specify a list of commands, and Q-learning to tune the parameters [Marthi et al., 2005] in Wargus.
- Q-learning to learn a policy for each class of units (peasants, knights, barracks, etc) [Jaidee and Muñoz-Avila, 2013] in Wargus.
- Option framework and heuristic algorithms to simplify the game space [Tavares and Chaimowicz, 2018].

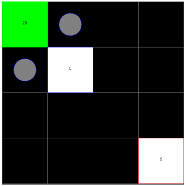
Existing Work

Recent development utilizing neural networks with RL:

- Provide feature maps and low-level actions to train agents. [Vinyals et al., 2017]
- High-level actions and curriculum. training [Tian et al., 2017, Sun et al., 2018, Lee et al., 2018]
- HRL (Hierarchical Reinforcement Learning) [Liu et al., 2019].
- Multi-Agent representation [Samvelyan et al., 2019]

Global Representation

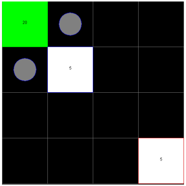
- Let the observation represents the whole game state



$$\rightarrow \underbrace{\begin{bmatrix} 1 & 4 & 0 & 0 \\ 4 & 2 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 2 \end{bmatrix}}_{\text{Unit type feature map}} \rightarrow \underbrace{\begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}}_{\text{One-hot-encoded array}}$$

Global Representation

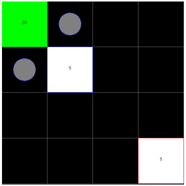
- We have 5 feature maps: hit points, resources, ownership, unit type, and unit actions



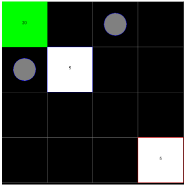
$$\rightarrow \underbrace{\begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 10 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 10 \end{bmatrix}}_{\text{Hit points feature map}} \rightarrow \underbrace{\begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}}_{\text{One-hot-encoded array}}$$

Global Representation

- Let the RL agent chooses which unit to issue actions to, and which actions to execute.

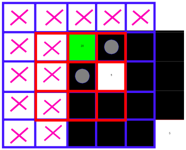


$$\rightarrow \quad \underbrace{\begin{bmatrix} 1 & 0 & 1 & 1 \end{bmatrix}}_{[a_t^x, a_t^y, a_t^{\text{action type}}, a_t^{\text{action param}}]} \quad \rightarrow$$



Local Representation

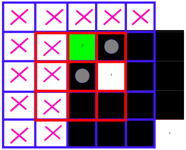
- Let the observation to be represented from the point of view of an individual unit. Introduce the parameter of window size w that specifies the observable distance away from the selected unit.



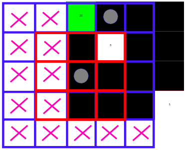
$$\rightarrow \underbrace{\begin{bmatrix} 0 & 2 & 5 \\ 0 & 5 & 3 \\ 0 & 1 & 1 \end{bmatrix}}_{\text{Unit Type feature map}} \rightarrow \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}}_{\text{One-hot-encoded array}}$$

Local Representation

- Let the RL agent picks actions for each unit independently.



$$\rightarrow \underbrace{\begin{bmatrix} 1 & 2 \end{bmatrix}}_{[a_t^{\text{action type}}, a_t^{\text{action param}}]} \rightarrow$$



Other Details and Insights

- If the action produced is invalid, then it will be replaced by an NOOP action.
- The agent can only issue one action to one unit at each timestep.
- The local representation rotates through units *one unit at a time* and asks the RL agent to produce actions for the selected unit only.

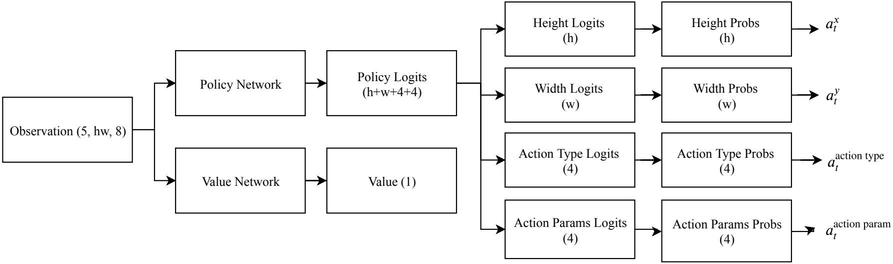
A2C

Algorithm 1 Advantage Actor Critic

Initialize policy function π with random weights θ
Initialize value function v with random weights θ'
for episode $= 1, M$ **do**
    Reset the game and get s_1
    for $t = 1, T$ **do**
        Sample action a_t from $\pi(s_t)$
        Execute action a_t and record reward r_t and state s_{t+1}
        If s_{t+1} is terminal, break
    end for
    for $t = 1, T$ **do**
        Calculate the value v_t
        Calculate the advantage $A = \sum_{i=1}^{T} \gamma^i r_t - v_t$
        $\theta = \theta + \alpha \nabla_\theta A \log \pi(a_t|s_t) + \pi_\theta(a_t|s_t) \log \pi_\theta(a_t|s_t)$
        $\theta' = \theta' + \beta \nabla_{\theta'} A^2$
    end for
end for

Specifics

How exactly do we input s_t to A2C and generate action a_t?



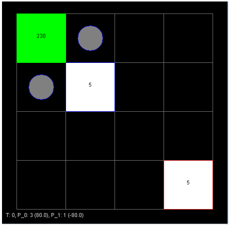
Specifics

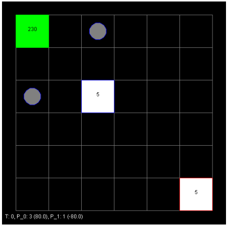
How exactly do we calculate $\log \pi_\theta(a_t|s_t)$ and $\pi_\theta(a_t|s_t)\log \pi_\theta(a_t|s_t)$?

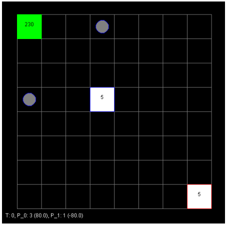
$$\begin{aligned}
\log \pi_\theta(a_t|s_t) &= \log \pi_\theta(a_t^{\text{x}}|s_t) \\
&+ \log \pi_\theta(a_t^{\text{y}}|s_t) \\
&+ \log \pi_\theta(a_t^{\text{action type}}|s_t) \\
&+ \log \pi_\theta(a_t^{\text{action param}}|s_t) \\
\pi_\theta(a_t|s_t)\log \pi_\theta(a_t|s_t) &= \pi_\theta(a_t^{\text{x}}|s_t)\log \pi_\theta(a_t^{\text{x}}|s_t) \\
&+ \pi_\theta(a_t^{\text{y}}|s_t)\log \pi_\theta(a_t^{\text{y}}|s_t) \\
&+ \pi_\theta(a_t^{\text{action type}}|s_t)\log \pi_\theta(a_t^{\text{action type}}|s_t) \\
&+ \pi_\theta(a_t^{\text{action param}}|s_t)\log \pi_\theta(a_t^{\text{action param}}|s_t)
\end{aligned}$$

Experimental Setup

- Task: harvest resources with different map sizes of 4×4, 6×6, and 8×8.
- It takes 10 timesteps to execute actions (move, harvest, return)
- When the agent harvested or returned the resources, it gets a reward of 10. Otherwise the reward is 0.

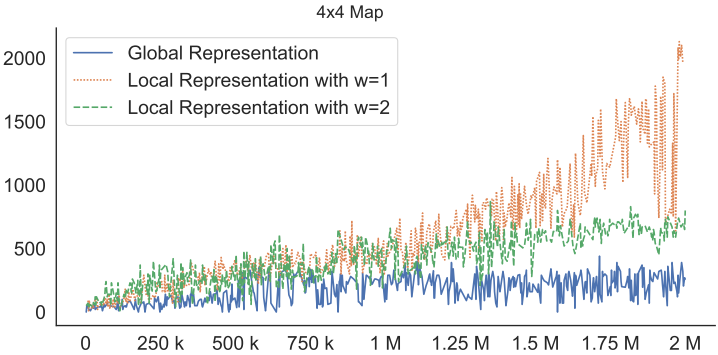






Episode Rewards

Episode rewards (y axis) as a function of training time steps (x-axis) for the 3 map sizes. (Higher is better)



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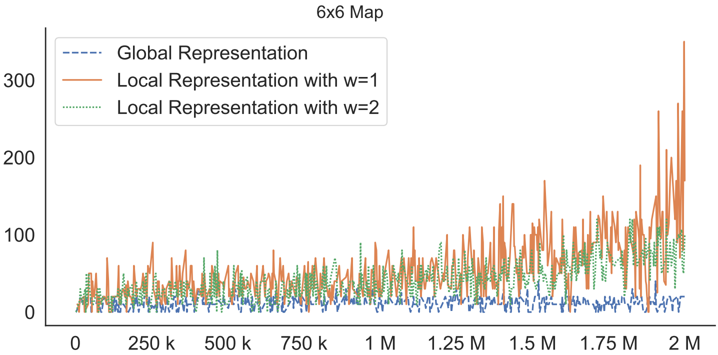

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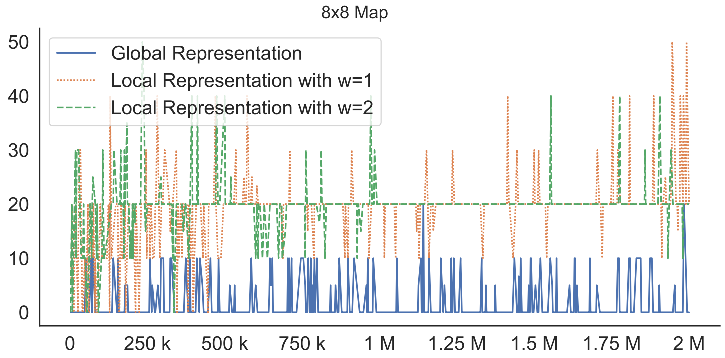


Metrics Evaluation

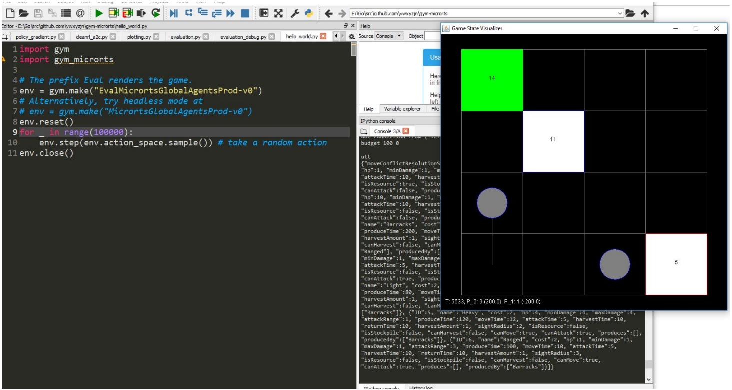
	map	$t_{\text{first harvest}}$	$t_{\text{first return}}$	r
RandomAI	4×4	51.33	142.67	11.87
Global	4×4	99.00	167.73	13.13
Local ($w = 1$)	4×4	29.87	172.47	67.20
Local ($w = 2$)	4×4	45.00	73.73	33.40
RandomAI	6×6	421.33	797.33	2.00
Global	6×6	533.33	1931.20	0.07
Local ($w = 1$)	6×6	59.20	567.40	3.53
Local ($w = 2$)	6×6	62.33	408.73	3.93
RandomAI	8×8	878.67	1480.67	0.87
Global	8×8	1464.53	-	0.00
Local ($w = 1$)	8×8	167.20	1844.20	0.20
Local ($w = 2$)	8×8	89.87	-	0.00

Visualization of Agents

https://youtu.be/--BoBOwnF0s

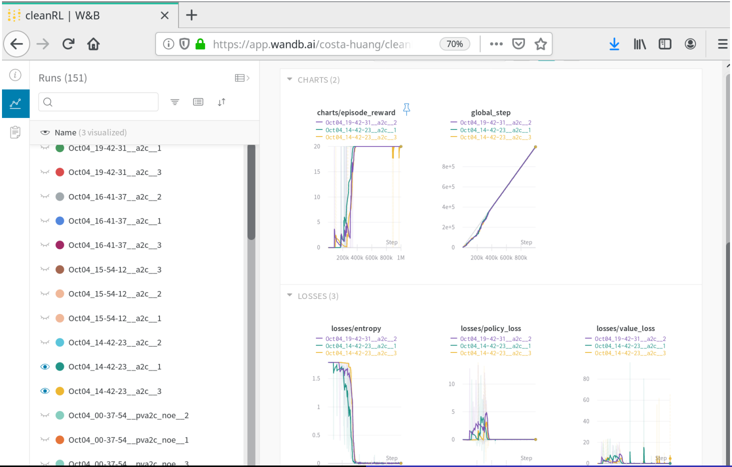
Gym environment

Our OpenAI Gym library is available at
`https://github.com/vwxyzjn/gym-microrts`



DRL Library (WIP)

Our RL library is available at `https://github.com/vwxyzjn/cleanrl`



Conclusions

- We compared two intuitive representations
  - a *global* representation that feeds the RL agent the entire game state, and require the agent to learn to locate the unit and control it.
  - a *local* representation that feeds the RL agent the localized game state that is around the selected unit, and require the agent to learn to control it
- We show that local representation generally performs the best but the training of agents becomes more difficult in larger maps, where the exploration and sparse rewards become a problem.

Future Work

- Frame skipping
- Parallel processing
- Larger maps
- DQN-based algorithms
- Partial observability and LSTM
- Self-play

Our Code

- https://github.com/vwxyzjn/gym-microrts
- https://github.com/vwxyzjn/cleanrl
- https://github.com/vwxyzjn/microrts

Thank you. Questions?

References I

Jaidee, U. and Muñoz-Avila, H. (2013).
Modeling unit classes as agents in real-time strategy games.
Proceedings of the 9th AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment, AIIDE 2013, pages 149–155.

Lee, D., Tang, H., Zhang, J. O., Xu, H., Darrell, T., and Abbeel, P. (2018).
Modular architecture for starcraft ii with deep reinforcement learning.
In *Fourteenth Artificial Intelligence and Interactive Digital Entertainment Conference*.

References II

Liu, R.-Z., Guo, H., Ji, X., Yu, Y., Xiao, Z., Wu, Y., Pang, Z.-J., and Lu, T. (2019).
Efficient reinforcement learning with a mind-game for full-length starcraft ii.
arXiv preprint arXiv:1903.00715.

Marthi, B., Russell, S. J., Latham, D., and Guestrin, C. (2005).
Concurrent hierarchical reinforcement learning.
In *IJCAI*, pages 779–785.

References III

Samvelyan, M., Rashid, T., de Witt, C. S., Farquhar, G., Nardelli, N., Rudner, T. G., Hung, C.-M., Torr, P. H., Foerster, J., and Whiteson, S. (2019).
The starcraft multi-agent challenge.
arXiv preprint arXiv:1902.04043.

Sun, P., Sun, X., Han, L., Xiong, J., Wang, Q., Li, B., Zheng, Y., Liu, J., Liu, Y., Liu, H., et al. (2018).
Tstarbots: Defeating the cheating level builtin ai in starcraft ii in the full game.
arXiv preprint arXiv:1809.07193.

References IV

Tavares, A. R. and Chaimowicz, L. (2018).
Tabular reinforcement learning in real-time strategy games via options.

2018 IEEE Conference on Computational Intelligence and Games (CIG), pages 1–8.

Tian, Y., Gong, Q., Shang, W., Wu, Y., and Zitnick, C. L. (2017).
Elf: An extensive, lightweight and flexible research platform for real-time strategy games.
In *Advances in Neural Information Processing Systems*, pages 2659–2669.

References V

Vinyals, O., Ewalds, T., Bartunov, S., Georgiev, P., Vezhnevets, A. S., Yeo, M., Makhzani, A., Küttler, H., Agapiou, J., Schrittwieser, J., et al. (2017).
Starcraft ii: A new challenge for reinforcement learning.
arXiv preprint arXiv:1708.04782.