Deep Goal Reasoning: An Analysis



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Disclaimer: Any opinion, findings and conclusions or recommendations in this presentation are those of the authors and are not necessarily those of NSF





A direct **extension** of HDQN -T. D. Kulkarni, K. Narasimhan, A. Saeedi, and J. Tenenbaum, "Hierarchical deep reinforcement learning: Integrating temporal abstraction and intrinsic motivation," in Advances in neural information processing systems, 2016, pp. 3675–3683



The goal selector

- receives as input the state s and additional inputs i
- generates the next goal g



The Actor takes action based on:

- the goal g
- the state s
- possibly other inputs i'.

How is the GoalAct architecture situated relative to the goal reasoning paradigm?



Aha, David W. "Goal reasoning: Foundations, emerging applications, and prospects." *AI Magazine* 39, no. 2 (2018): 3-24.

GoalAct Architecture





- Observe refers to raw sensor readings from the environment
- Represented in GoalAct as a state s, possibly partially observed
- The state can be an an snapshot image of what the agent sees or a simple vector representing a map annotated with the current location of the agent



- The orient steps focuses the agent's attention. For example:
 - Goal-driven autonomy generates expectations X of the outcome of its actions
 - These expectations are then matched against the observed state, o(s) (e.g., X = o(S))
 - This determines if the goals are to be changed
- The orient step is completely bypassed in existing implementations of GoalAct.



- Decide selecting which goals to manage and among those managed which goals to pursue.
- In GoalAct: there is only one goal that is pursued at any point of time.
- The list of all possible goals remains fixed for the lifetime of the system.
- In principle, any changes in the list will require to re-learn by running the system on all episodes experienced so far



- Once a goal has been decided, the control of the agent is given to the Actor, which takes actions in order to achieve the goal.
- The effects of each action causes the environment to transition from one state to the next.
- Current implementations: The Actor continues to take actions until either the goal is achieved or a fixed number of steps is taken.

Taxonomy of Goals

Conditions	Condition 1	Condition 2
Declarative vs Procedural	\checkmark	\checkmark
Concrete vs Abstract	\checkmark	
Static-time vs Durative	\checkmark	\mathbf{O}
Knowledge vs regular goals		\checkmark
Interruptible vs non-i goals		\checkmark

van Riemsdijk, M. B.; Dastani, M.; and Winikoff, M. 2008. Goals In Agent Systems: A Unifying Framework. In Proceedings of the Seventh International Conference on Autonomous Agents and Multi-Agent Systems, 713–720. New York What kinds of outputs is the GoalAct architecture capable of generating?

GoalAct Architecture



Cox et al.' goal formulation rule:

$$\beta(s,g) \to g'$$

Cox, Michael, Dustin Dannenhauer, and Sravya Kondrakunta. "Goal operations for cognitive systems." *Proceedings of the AAAI Conference on Artificial Intelligence*. Vol. 31. No. 1. 2017.

$$eta(s,g) o g'$$
 (Cox et al.) $eta(s,_) o g_{\cdot}$ (H-DQN)

eta(s,g) o g' (Cox et al.) $eta(s,_) o g$ (H-DQN) $eta(s, ilde{s}) o g$ (FUNS)

"list of previously visited states"

Vezhnevets, A. S.; Osindero, S.; Schaul, T.; Heess, N.; Jaderberg, M.; Silver, D.; and Kavukcuoglu, K. 2017. Feudal networks for hierarchical reinforcement learning. In Proceedings of the 34th International Conference on Machine Learning-Volume 70, 3540–3549

$$\begin{split} \beta(s,i) &\to g & \text{(Direct generalization)} \\ \beta(s,g) &\to g' & \text{(Cox et al.)} \\ \beta(s,_) &\to g & \text{(H-DQN)} \\ \beta(s,~\tilde{s}) &\to g & \text{(FUNS)} \\ \end{cases}$$
sited states" Vezhnevets, A. S.; Osindero, S.; Schaul, T. Jaderberg, M.; Silver, D.; and Kavukcuogl

"list of previously visited states"

Vezhnevets, A. S.; Osindero, S.; Schaul, T.; Heess, N.; Jaderberg, M.; Silver, D.; and Kavukcuoglu, K. 2017. Feudal networks for hierarchical reinforcement learning. In Proceedings of the 34th International Conference on Machine Learning-Volume 70, 3540–3549

$$\beta(s,i) \to g$$



$$\beta(s,i) \to g$$

$$\beta(s,i) \to g$$

 $i \ s \ \langle \text{GOAL} \rangle \rightarrow i \ s \ g \ \langle \text{ACT} \rangle$

$$\beta(s,i) \to g$$

$$i \ s \ \langle \text{GOAL} \rangle \to i \ s \ g \ \langle \text{ACT} \rangle$$

 $\beta(s,i) \to g$ $i \ s \ \langle \text{GOAL} \rangle \rightarrow i \ s \ g \ \langle \text{ACT} \rangle$

$$eta(s,i)
ightarrow g$$

 $i \, s \, \langle \text{GOAL}
angle
ightarrow i \, s \, g \, \langle \text{ACT}
angle$



$$eta(s,i)
ightarrow g$$

 $i \, s \, \langle ext{GOAL}
angle
ightarrow i \, s \, g \, \langle ext{ACT}
angle$

(H-DQN)



$$\begin{array}{c} (\text{H-DQN}) \\ \beta(s,i) \rightarrow g \\ is \langle \text{GOAL} \rangle \rightarrow is \, g \, \langle \text{ACT} \rangle \\ \end{array} \qquad \begin{array}{c} \beta(s,j) \rightarrow g \\ s \langle \text{GOAL} \rangle \rightarrow sg \langle \text{ACT} \rangle \end{array}$$

$$(\text{FUNS}) \\ \beta(s,\tilde{s}) \rightarrow g \\ \tilde{s}s \langle \text{GOAL} \rangle \rightarrow \tilde{s}sg \langle \text{ACT} \rangle \end{array}$$

Formal System Around these Rules (exemplified for H-DQN)



Formal System Around these Rules – **Basic GoalAct** (exemplified for H-DQN) (H-DQN) $\beta(s, _) \rightarrow g$ $S \rightarrow s_3 \langle \text{GOAL} \rangle$ $s(\text{GOAL}) \rightarrow sg(\text{ACT})$ $s_3 \langle \text{GOAL} \rangle \rightarrow s_3 g_6 \langle \text{ACT} \rangle$ $s_6 \langle \text{GOAL} \rangle \rightarrow s_6 g_0 \langle \text{ACT} \rangle$ $s_i g_j \langle \text{ACT} \rangle \rightarrow s_i s_j \langle \text{GOAL} \rangle \quad (1 \le i, j \le 6 \land i \ne j)$ $s_i g_0 \langle \text{ACT} \rangle \rightarrow s_i s_0 \quad (1 \le i \le 6)$ $s_i g_i \langle \text{ACT} \rangle \rightarrow s_i g_i \langle \text{ACT} \rangle \quad (1 \le i \le 6)$ (a) < (b)

 $S \rightarrow s_{3} \langle \text{GOAL} \rangle$ $s_{3} \langle \text{GOAL} \rangle \rightarrow s_{3} g_{6} \langle \text{ACT} \rangle$ $s_{6} \langle \text{GOAL} \rangle \rightarrow s_{6} g_{0} \langle \text{ACT} \rangle$ $s_{i} g_{j} \langle \text{ACT} \rangle \rightarrow s_{i} s_{j} \langle \text{GOAL} \rangle \quad (1 \leq i, j \leq 6 \land i \neq j)$ $s_{i} g_{0} \langle \text{ACT} \rangle \rightarrow s_{i} s_{0} \quad (1 \leq i \leq 6)$ $s_{i} g_{i} \langle \text{ACT} \rangle \rightarrow s_{i} g_{i} \langle \text{ACT} \rangle \quad (1 \leq i \leq 6)$

(a) ← _____ (b) ← _____



$$\begin{split} S &\to s_3 \langle \text{GOAL} \rangle \\ s_3 \langle \text{GOAL} \rangle &\to s_3 g_6 \langle \text{ACT} \rangle \\ s_6 \langle \text{GOAL} \rangle &\to s_6 g_0 \langle \text{ACT} \rangle \\ s_i g_j \langle \text{ACT} \rangle &\to s_i s_j \langle \text{GOAL} \rangle \quad (1 \leq i, j \leq 6 \land i \neq j) \\ \hline s_i g_0 \langle \text{ACT} \rangle &\to s_i s_0 \quad (1 \leq i \leq 6) \\ \hline s_i g_i \langle \text{ACT} \rangle &\to s_i g_i \langle \text{ACT} \rangle \quad (1 \leq i \leq 6) \end{split}$$
 When state reached is a terminal state

$$\begin{split} S &\to s_3 \langle \text{GOAL} \rangle \\ s_3 \langle \text{GOAL} \rangle &\to s_3 g_6 \langle \text{ACT} \rangle \\ s_6 \langle \text{GOAL} \rangle &\to s_6 g_0 \langle \text{ACT} \rangle \\ s_i g_j \langle \text{ACT} \rangle &\to s_i s_j \langle \text{GOAL} \rangle \quad (1 \leq i, j \leq 6 \land i \neq j) \\ s_i g_0 \langle \text{ACT} \rangle &\to s_i s_0 \quad (1 \leq i \leq 6) \\ \hline s_i g_i \langle \text{ACT} \rangle &\to s_i g_i \langle \text{ACT} \rangle \quad (1 \leq i \leq 6) \\ \end{split}$$

 $S \xrightarrow{1} s_3 \langle \text{GOAL} \rangle$ $\xrightarrow{2} s_3 g_6 \langle \text{ACT} \rangle$ $\xrightarrow{4} s_3 s_6 \langle \text{GOAL} \rangle$ $\xrightarrow{3} s_3 s_6 g_0 \langle \text{ACT} \rangle$ $\xrightarrow{5} s_3 s_6 s_0$ $\beta(s, _) \to g$

 $s \langle \text{GOAL} \rangle \rightarrow sg \langle \text{ACT} \rangle$



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 $s \langle \text{GOAL} \rangle \rightarrow sg \langle \text{ACT} \rangle$

 $\beta(s, _) \to g$





 $s \langle \text{GOAL} \rangle \rightarrow sg \langle \text{ACT} \rangle$

 $\beta(s, _) \to g$





 $s \langle \text{GOAL} \rangle \rightarrow sg \langle \text{ACT} \rangle$

 $\beta(s, _) \to g$





 $S \xrightarrow{1} s_3 \langle \text{GOAL} \rangle$ $\xrightarrow{2} s_3 g_6 \langle \text{ACT} \rangle$ $\xrightarrow{4} s_3 s_6 \langle \text{GOAL} \rangle$ $\xrightarrow{3} s_3 s_6 g_0 \langle \text{ACT} \rangle$ $\xrightarrow{5} s_3 s_6 s_0$

 $s \langle \mathrm{GOAL} \rangle \to sg \langle \mathrm{ACT} \rangle$





Formal System Around these Rules – Mnemonic GoalAct (exemplified for FUNS) (FUNS)

 $\beta(s, \tilde{s}) \rightarrow q$

$$S \rightarrow s_{3}\langle \text{GOAL} \rangle$$

$$s_{3}\langle \text{GOAL} \rangle \rightarrow s_{3}g_{6}\langle \text{ACT} \rangle$$

$$s_{3}s_{6}\langle \text{GOAL} \rangle \rightarrow s_{3}s_{6}g_{5}\langle \text{ACT} \rangle$$

$$s_{3}s_{6}\langle \text{GOAL} \rangle \rightarrow s_{3}s_{6}s_{5}g_{6}\langle \text{ACT} \rangle$$

$$s_{3}s_{6}s_{5}\langle \text{GOAL} \rangle \rightarrow s_{3}s_{6}s_{5}g_{6}\langle \text{ACT} \rangle$$

$$s_{3}s_{6}s_{5}s_{6}\langle \text{GOAL} \rangle \rightarrow s_{3}s_{6}s_{5}s_{6}g_{0}\langle \text{ACT} \rangle$$

$$s_{i}g_{j}\langle \text{ACT} \rangle \rightarrow s_{i}s_{j}\langle \text{GOAL} \rangle \quad (1 \leq i, j \leq 6 \land i \neq j)$$

$$s_{i}g_{0}\langle \text{ACT} \rangle \rightarrow s_{i}s_{0} \quad (1 \leq i \leq 6)$$

$$s_{i}g_{i}\langle \text{ACT} \rangle \rightarrow s_{i}g_{i}\langle \text{ACT} \rangle \quad (1 \leq i \leq 6)$$

$$(b) \leftarrow \blacksquare$$

Formal System Around these Rules – Mnemonic GoalAct (exemplified for FUNS) (FUNS)

Formal System Around these Rules – Mnemonic GoalAct (exemplified for FUNS) (FUNS)

$$\begin{split} S &\to s_3 \langle \text{GOAL} \rangle \\ s_3 \langle \text{GOAL} \rangle \to s_3 g_6 \langle \text{ACT} \rangle \\ s_3 s_6 \langle \text{GOAL} \rangle \to s_3 s_6 g_5 \langle \text{ACT} \rangle \\ s_3 s_6 s_5 \langle \text{GOAL} \rangle \to s_3 s_6 s_5 g_6 \langle \text{ACT} \rangle \\ s_3 s_6 s_5 s_6 \langle \text{GOAL} \rangle \to s_3 s_6 s_5 s_6 g_0 \langle \text{ACT} \rangle \\ s_i g_j \langle \text{ACT} \rangle \to s_i s_j \langle \text{GOAL} \rangle \quad (1 \leq i, j \leq 6 \land i \neq j) \\ s_i g_0 \langle \text{ACT} \rangle \to s_i s_0 \quad (1 \leq i \leq 6) \\ s_i g_i \langle \text{ACT} \rangle \to s_i g_i \langle \text{ACT} \rangle \quad (1 \leq i \leq 6) \end{split}$$

$$\tilde{s}s \langle \text{GOAL} \rangle \rightarrow \tilde{s}sg \langle \text{ACT} \rangle$$

 $\beta(s, \tilde{s}) \rightarrow g$



Results (1)

- We provide a characterization of the grammars generating the states sequences: k-mnemonic grammars
- Using this characterization we prove that Mnemonic GoalAct is strictly more expressive than Basic GoalAct
- This result is corroborated in empirical evaluation: corridor, Doom, Grid







Results (2)



Related Work - Inspirations

- DQN combines RL and DL
- DRQN combines RNN and DQN
- Options: a mechanism to jump between policies when certain states are reached
- Memory-based RL considers rewards based on states visited
- Subgoal learning: learns which goal to choose in a particular situation

Conclusion



