Deep Q-learning for Active Recognition of GERMS: Baseline performance on a standardized dataset for active learning

Mohsen Malmir, Karan Sikka, Deborah Forster, Javier Movellan, and Garrison W. Cottrell

Presented by Ruohan Zhang
The University of Texas at Austin

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Outline

The Active Object Recognition (AOR) Problem

- The **recognition** module: what is this?
- The **control** module: where to look?
- Goal: find a sequence of sensor control commands that maximizes recognition accuracy and speed.

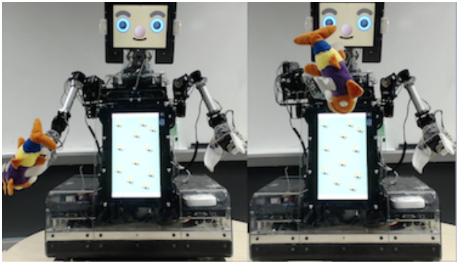


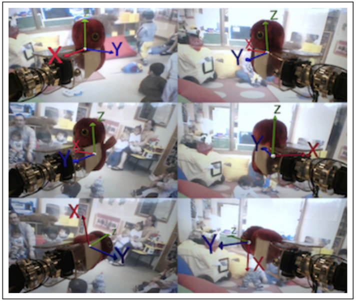
Figure : The AOR problem for the RUBI robot [Malmir et al.,].

Motivation

- A benchmark dataset for the AOR research
  - more difficult than previous ones, e.g. [Nayar et al., 1996].
  - without the need to have access to a physical robot.
- A baseline method and its performance
  - combines deep learning and reinforcement learning: deep Q-learning.

Data Collection

- The RUBI project at UCSD Machine Perception Lab.
- Six configurations for each object, two arms and three axes.
- RUBI brings the object to its center of view, rotate object by 180°.



Data Statistics

- Data format: [image][capture time][joint angles].
- Joint angles: 2-DOF head , 7-DOF arms X 2.
- 136 objects, 1365 videos, 30fps, 8.9s on average.
- Bound boxes are annotated manually.

Examples

Figure : Left: the collage of all 136 objects. Right: some ambiguous objects that require rotation to disambiguate.

Example Videos

The videos for the left arm and for the right arm.

The goal: what to do in a state?

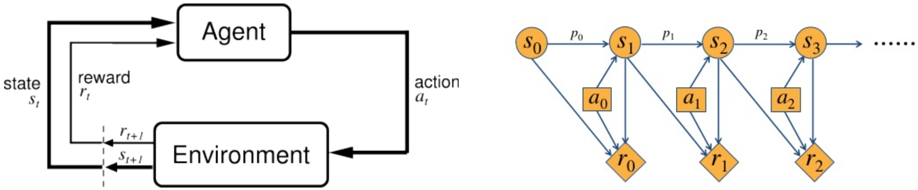


Figure : The agent-environment interaction and Markov decision process (MDP).

Markov Decision Process (MDP)

Definition

A tuple $\langle \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma \rangle$, where

- $\mathcal{S}$ is a finite set of states.
- $\mathcal{A}$ is a finite set of actions.
- $\mathcal{P}$ is a state transition probability matrix. $\mathcal{P}^a_{ss'} = \mathbb{P}[s'|s, a]$.
- $\mathcal{R}$ is a reward function, $\mathcal{R}^a_s = \mathbb{E}[r|s, a]$.
- γ is a discount factor, $\gamma \in [0, 1)$.

Policy and Value Function

Policy

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Goal of reinforcement learning

Find optimal policy:

$$\pi^*(s, a) = \begin{cases} 1 & \text{if } a = \arg\max_{a \in \mathcal{A}} Q(s, a) \\ 0 & \text{otherwise} \end{cases}$$

Therefore, if we know $Q(s, a)$, we find the optimal policy.

Bellman Equations

Action-value function recursive decomposition

$Q^\pi(s,a) = \mathbb{E}_\pi[r_{t+1} + \gamma Q^\pi(s_{t+1}, a_{t+1}) | s_t = s, a_t = a]$

Dynamic programming to solve MDP

Assumption: environment model $\mathcal{P}, \mathcal{R}$ is fully known.

Model-free Reinforcement Learning: Q-learning

The Q-learning algorithm [Sutton and Barto, 1998]

Initialize $Q(s, a)$ arbitrarily
Repeat (for each episode):
  Initialize s
  Repeat (for each step):
    Choose a from s
    Take action a, observe r, s'
    $Q(s, a) \leftarrow Q(s, a) + \alpha[r + \gamma \max_{a'} Q(s', a') - Q(s, a)]$
    $s \leftarrow s'$
  until s is terminal

Remark

$r + \gamma \max_{a'} Q(s', a')$ can be seen as a supervised learning target, but it is changing.

Deep Reinforcement Learning?

The basic Q-learning

Assumptions: discrete states and actions (lookup Q-table); manually defined state space.

The deep Q-learning

Using a deep neural network to approximate the Q function.

The Network Architecture

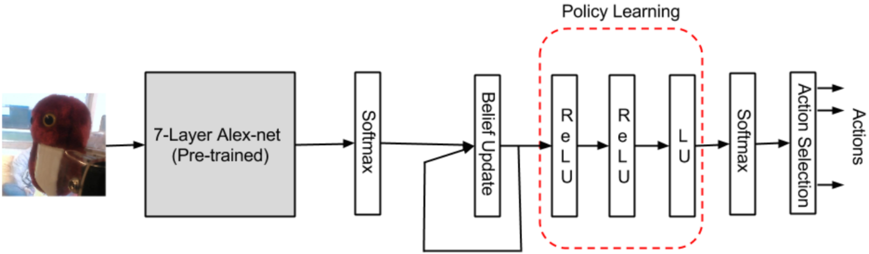

Figure : The deep network architecture in [Malmir et al.,].

The MDP in this Paper

MDP

- The state B_t : the output of softmax layer of the CNN at time t, i.e., the belief vector over object labels.
  - not the input image at time step t, as in [Mnih et al., 2013].
  - use Naive Bayes to accumulate belief from history.

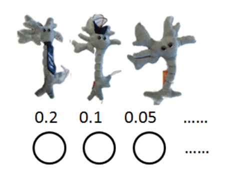

Figure : The state space representation in [Malmir et al.,].

The MDP in this Paper

MDP

- a_t : ten rotation commands $\{\pm\pi/64, \pm\pi/32, \pm\pi/16, \pm\pi/8, \pm\pi/4\}$.
- $\mathcal{P}$: transition matrix **unknown** (The reason they used Q-learning).
- $\mathcal{R}$: $+10$ for correct classification, -10 ow.
- γ : unknown.

The Training Algorithm

- Exactly the Q-learning algorithm.

$$Q(B_t, a_t) \leftarrow Q(B_t, a_t) + \alpha[r_t + \gamma \max_a Q(B_{t+1}, a) - Q(B_t, a_t)]$$

- For network weights update, use stochastic gradient descent:

$$W \leftarrow W - \lambda[r_t + \gamma \max_a Q(B_{t+1}, a) - Q(B_t, a_t)] \frac{\partial}{\partial W} Q(B_t, a_t)$$

- mini-batch update. This is a key trick to stabilize deep RL network. Otherwise, the learning target is changing rapidly and it will not converge.

Results

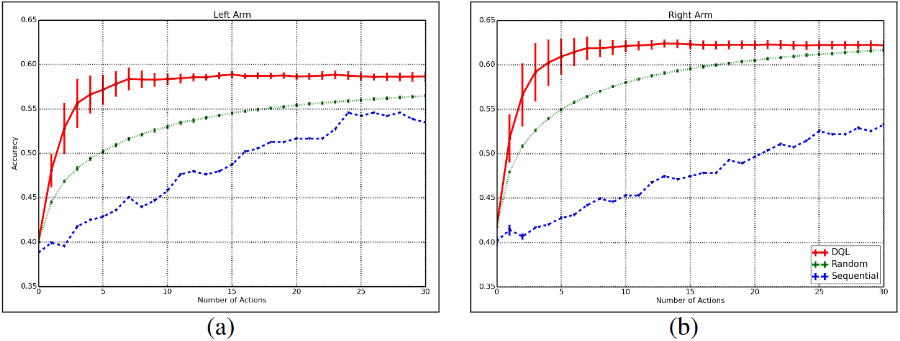

Figure : The experiment results on classification accuracy [Malmir et al.,].

Results

Method \ Prediction Accuracy(%)	48	53	55	58	62	
Sequential	18	30	-	-	-	**Right Arm**
Random	2	4	6	10	-	
DQL	**1**	**2**	**2**	**3**	**10**	
Sequential	15	24	-	-	-	**Left Arm**
Random	3	10	18	-	-	
DQL	**1**	**3**	**3**	**7**	-	

Figure : The number of steps required to achieve certain classification accuracy by different algorithms [Malmir et al.,].

Conclusions

- The GERMS dataset.
- The deep Q-learning for AOR, however, much space left for improvement:
    - performance-wise.
    - very basic version of deep Q-learning.

Discussions

- Right arm outperforms left arm.
- "Uncommon" objects for robotic tasks.
- Manual bounding box annotations is labor intensive.
- State representation (belief vector).
- The most representative frame?
- Any other similar datasets?
- Extension: using RNN to combine the two modules (control and recognition), e.g., **Recurrent models of visual attention** [Mnih et al., 2014].

Malmir, M., Sikka, K., Forster, D., Movellan, J., and Cottrell, G. W.
Deep q-learning for active recognition of germs: Baseline performance on a standardized dataset for active learning.
In *Proceedings of the British Machine Vision Conference (BMVC), pages*, pages 161–1.

Mnih, V., Heess, N., Graves, A., et al. (2014).
Recurrent models of visual attention.
In *Advances in Neural Information Processing Systems*, pages 2204–2212.

Mnih, V., Kavukcuoglu, K., Silver, D., Graves, A., Antonoglou, I., Wierstra, D., and Riedmiller, M. (2013).
Playing atari with deep reinforcement learning.
arXiv preprint arXiv:1312.5602.

Nayar, S., Nene, S., and Murase, H. (1996).
Columbia object image library (coil 100).
Department of Comp. Science, Columbia University, Tech. Rep. CUCS-006-96.

Sutton, R. S. and Barto, A. G. (1998).
Reinforcement learning: An introduction.
MIT press.