Learning to Navigate in Complex Environments

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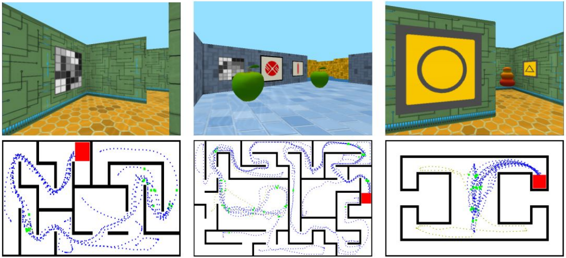
Outline

Motivation

Navigational abilities acquisition by policy learning

- In complex environments, navigational abilities could emerge as the by-product of an agent learning a policy that maximizes reward
- Game episode
  - 1, Random start 2, Find the goal (+10)
  - 3, Teleport randomly 4, Re-find the goal (+10) 5, Repeat 3 to 5 (limited time)
  - Fruit reward (apple (+1), strawberry (+2))
- demo: https://youtu.be/INoaTyMZsWI



Motivation

Challenges

- Rewards are often sparsely distributed in the environment
- Environments often comprise dynamic elements, requiring the agent to use memory at different timescales
  - Rapid one-shot memory for the goal location
  - Short term memory for visual observations
  - Longer term memory for constant aspects of the environment (e.g. boundaries, cues)
- These two challenges make the learning process inefficient

Motivation

Accelerate reinforcement learning through auxiliary losses

- Auxiliary tasks have often been used to facilitate representation learning[1]
- In deep RL, auxiliary tasks also works
  - Fit a recurrent model better by predicting next observed state [2]
  - The DQN agent in first-person shooter game is enhanced by an enemy-detection task [3]
- Derive spatial knowledge from auxiliary tasks
  - Depth prediction
  - Local loop closure prediction

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[1] Suddarth, Steven C. et. al. "Rule-injection hints as a means of improving network performance and learning time." Neural Networks. Springer, 1990.

[2] Li, Xiujun, et al. "Recurrent reinforcement learning: a hybrid approach." arXiv preprint arXiv:1509.03044 (2015).

[3] Lample, et. al. "Playing FPS games with deep reinforcement learning." Thirty-First AAAI Conference on Artificial Intelligence. 2017.

Motivation

Depth prediction and local loop closure prediction

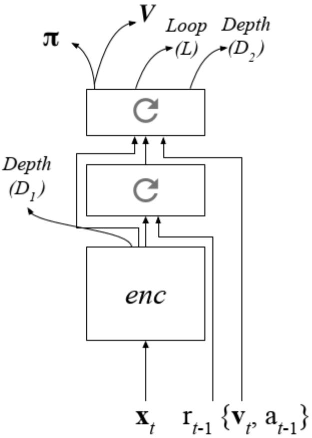
- Depth prediction
  - The depth information might supply valuable information about the 3D structure of the environment.
  - The primary input to the agent is in the form of RGB images
  - A single frame can be enough to predict depth [4]
- Local loop closure prediction
  - Loop closure is to recognize a previously-visited location and update beliefs accordingly
  - Local loop closure is valuable for a navigating agent, since can be used for efficient exploration and spatial reasoning

[4] Eigen, et. al. "Depth map prediction from a single image using a multi-scale deep network." Advances in neural information processing systems. 2014.

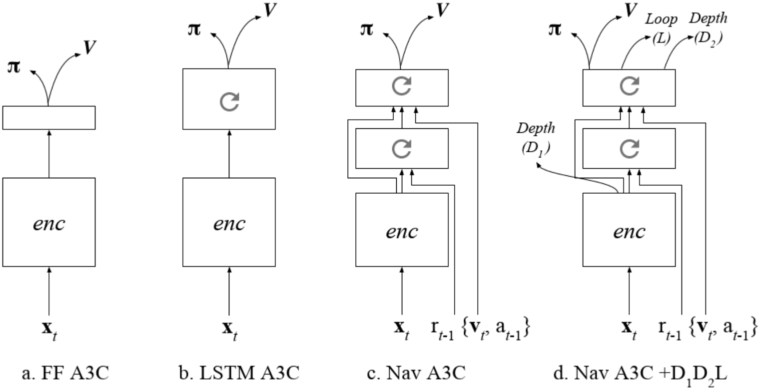
Approach

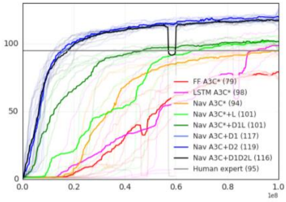
A end-to-end learning framework

- Convolutional encoder and RGB inputs
- Stacked LSTM
- Additional inputs (reward, action and velocity)
- Auxiliary task 1: Depth prediction
- Auxiliary task 2: Loop closure prediction
- The reinforcement learning problem is addressed with A3C algorithm
- Reward clipping is used to stabilize learning: A3C*

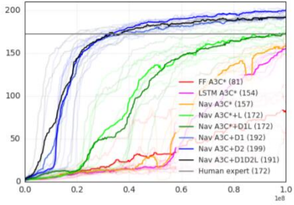


Approach
Variations in architecture

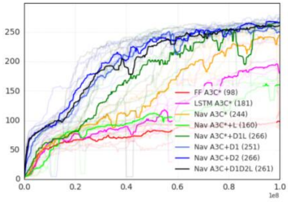




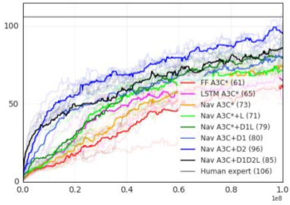
(a) Static maze (small)



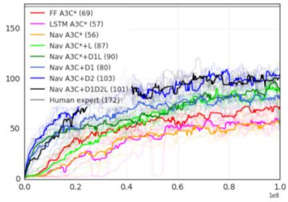
(b) Static maze (large)



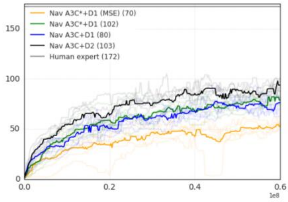
(c) Random Goal I-maze



(d) Random Goal maze (small)



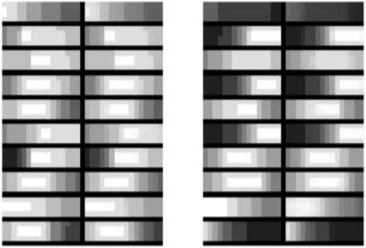
(e) Random Goal maze (large)

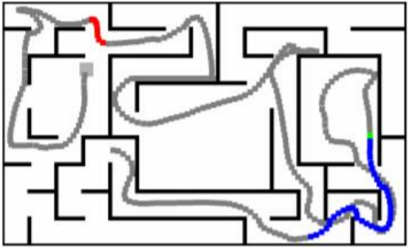


(f) Random Goal maze (large): different formulation of depth prediction

[5] star in the label indicates the use of reward clipping

- Left: Example of depth prediction (pairs of ground truth and predicted depth)
- Right: Example of loop closure prediction





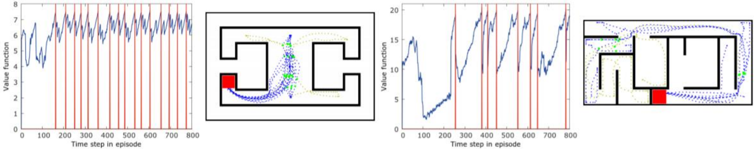
Experiment

Maze	Agent	Mean over top 5 agents AUC	Score	% Human	Highest reward agent Goals	Position Acc	Latency 1:>1	Score
I-Maze	FF A3C*	75.5	98	-	94/100	42.2	9.3s:9.0s	102
	LSTM A3C*	112.4	244	-	**100/100**	**87.8**	15.3s:3.2s	203
	Nav A3C*+$D_1 L$	169.7	266	-	**100/100**	68.5	10.7s:2.7s	252
	Nav A3C+D_2	**203.5**	**268**	-	**100/100**	62.3	**8.8s:2.5s**	**269**
	Nav A3C+$D_1 D_2 L$	199.9	258	-	**100/100**	61.0	**9.9s:2.5s**	251
Static 1	FF A3C*	41.3	79	83	100/100	64.3	8.8s:8.7s	84
	LSTM A3C*	44.3	98	103	100/100	88.6	6.1s:5.9s	110
	Nav A3C+D_2	**104.3**	**119**	**125**	100/100	**95.4**	**5.9s:5.4s**	122
	Nav A3C+$D_1 D_2 L$	102.3	116	122	100/100	94.5	**5.9s:5.4s**	**123**
Static 2	FF A3C*	35.8	81	47	100/100	55.6	24.2s:22.9s	111
	LSTM A3C*	46.0	153	91	100/100	80.4	15.5s:14.9s	155
	Nav A3C+D_2	**157.6**	**200**	**116**	100/100	**94.0**	10.9s:11.0s	**202**
	Nav A3C+$D_1 D_2 L$	156.1	192	112	100/100	92.6	11.1s:12.0s	192
Random Goal 1	FF A3C*	37.5	61	57.5	88/100	51.8	11.0:9.9s	64
	LSTM A3C*	46.6	65	61.3	85/100	51.1	11.1s:9.2s	66
	Nav A3C+D_2	**71.1**	**96**	**91**	**100/100**	**85.5**	**14.0s:7.1s**	**91**
	Nav A3C+$D_1 D_2 L$	64.2	81	76	81/100	83.7	11.5s:7.2s	74.6
Random Goal 2	FF A3C*	50.0	69	40.1	**93/100**	30.0	27.3s:28.2s	77
	LSTM A3C*	37.5	57	32.6	74/100	33.4	21.5s:29.7s	51.3
	Nav A3C*+$D_1 L$	62.5	90	52.3	90/100	51.0	17.9s:18.4s	106
	Nav A3C+D_2	**82.1**	**103**	**59**	79/100	72.4	**15.4s:15.0s**	**109**
	Nav A3C+$D_1 D_2 L$	78.5	91	53	74/100	**81.5**	15.9s:16.0s	102

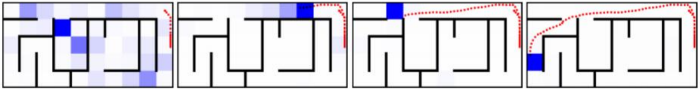
Analysis

Position decoding

- Trajectories of the agent



- Example of position decoding by the Nav A3C+D_2



Analysis

Different combination of auxiliary tasks

- comparison of reward prediction [6] and depth prediction.

Maze	Navigation agent architecture					
	Nav A3C*	Nav A3C+D_1	Nav A3C+D_2	Nav A3C+D_1D_2	Nav A3C*+R	Nav A3C+RD_2
I-Maze	143.3	196.7	**203.5**	197.2	128.2	191.8
Static 1	60.1	103.2	104.3	100.3	86.9	**105.1**
Static 2	59.9	153.1	**157.6**	151.6	100.6	155.5
Random Goal 1	45.5	57.6	71.1	63.2	54.4	**72.3**
Random Goal 2	37.0	66.0	**82.1**	75.1	68.3	80.1

Combining reward prediction and depth prediction (Nav A3C+RD_2) yields comparable results to depth prediction alone (Nav A3C+D_2); normalised average AUC values are respectively 0.995 vs. 0.981.

[6] Jaderberg, et. al. "Reinforcement learning with unsupervised auxiliary tasks",ICLR 2017

Summary

- They proposed a deep RL method,augmented with memory and auxiliary learning target.
- Their approach allows end-end learning, and their auxiliary losses do not rely on any form of replay.
- Whilst their best performing agents are relatively successful at navigation, their abilities would be stretched , due to the limited capacity of the stacked LSTM

Thank You for Your Attention!
Q&A