DeepMind Lab

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Abstract

DeepMind Lab is a first-person 3D game platform designed for research and development of general artificial intelligence and machine learning systems. DeepMind Lab can be used to study how autonomous artificial agents may learn complex tasks in large, partially observed, and visually diverse worlds. DeepMind Lab has a simple and flexible API enabling creative task-designs and novel AI-designs to be explored and quickly iterated upon. It is powered by a fast and widely recognised game engine, and tailored for effective use by the research community.

Introduction

General intelligence measures an agent's ability to achieve goals in a wide range of environments (Legg and Hutter, 2007). The only known examples of general-purpose intelligence arose from a combination of evolution, development, and learning, grounded in the physics of the real world and the sensory apparatus of animals. An unknown, but potentially large, fraction of animal and human intelligence is a direct consequence of the perceptual and physical richness of our environment, and is unlikely to arise without it (e.g. Locke, 1690; Hume, 1739). One option is to directly study embodied intelligence in the real world itself using robots (e.g. Brooks, 1990; Metta et al., 2008). However, progress on that front will always be hindered by the too-slow passing of real time and the expense of the physical hardware involved. Realistic *virtual* worlds on the other hand, if they are sufficiently detailed, can get the best of both, combining perceptual and physical near-realism with the speed and flexibility of software.

Previous efforts to construct realistic virtual worlds as platforms for AI research have been stymied by the considerable engineering involved. To fill the gap, we present DeepMind Lab. DeepMind Lab is a first-person 3D game platform built on top of id software's Quake III Arena (id software, 1999) engine. The world is rendered with rich science fiction-style visuals. Actions are to look around and move in 3D. Example tasks include navigation in mazes, collecting fruit, traversing dangerous passages and avoiding falling off cliffs, bouncing through space using launch pads to move between platforms, laser tag, quickly learning and remembering random procedurally generated environments, and tasks inspired by Neuroscience experiments. DeepMind Lab is already a major research platform within DeepMind. In particular,

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it has been used to develop asynchronous methods for reinforcement learning (Mnih et al., 2016), unsupervised auxiliary tasks (Jaderberg et al., 2016), and to study navigation (Mirowski et al., 2016).

DeepMind Lab may be compared to other game-based AI research platforms emphasising pixels-to-actions autonomous learning agents. The Arcade Learning Environment (Atari) (Bellemare et al., 2012), which we have used extensively at DeepMind, is neither 3D nor first-person. Among 3D platforms for AI research, DeepMind Lab is comparable to others like VizDoom (Kempka et al., 2016) and Minecraft (Johnson et al., 2016; Tessler et al., 2016). However, it pushes the envelope beyond what is possible in those platforms. In comparison, DeepMind Lab has considerably richer visuals and more naturalistic physics. The action space allows for fine-grained pointing in a fully 3D world. Compared to VizDoom, DeepMind Lab is more removed from its origin in a first-person shooter genre video game. This work is different and complementary to other recent projects which run as plugins to access internal content in the Unreal engine (Qiu and Yuille, 2016; Lerer et al., 2016). Any of these systems can be used to generate static datasets for computer vision as described e.g., in Mahendran et al. (2016); Richter et al. (2016).

Artificial general intelligence (AGI) research in DeepMind Lab emphasises 3D vision from raw pixel inputs, first-person (egocentric) viewpoints, fine motor dexterity, navigation, planning, strategy, time, and fully autonomous agents that must learn for themselves what tasks to perform by exploration of their environment. All these factors make learning difficult. Each are considered frontier research questions on their own. Putting them all together in one platform, as we have, is a significant challenge for the field.

DeepMind Lab Research Platform

DeepMind Lab is built on top of id software's Quake III Arena (id software, 1999) engine using the ioquake3 (Nussel et al., 2016) version of the codebase, which is actively maintained by enthusiasts in the open source community. DeepMind Lab also includes tools from q3map2 (GtkRadiant, 2016) and bspc (bspc, 2016) for level generation. The bot scripts are based on code from the OpenArena (OpenArena, 2016) project.

Tailored for machine learning

A custom set of assets were created to give the platform a unique and stylised look and feel, with a focus on rich visuals tailored for machine learning.

A reinforcement learning API has been built on top of the game engine, providing agents with complex observations and accepting a rich set of actions.

The interaction with the platform is lock-stepped, with the engine stepped forward one simulation step (or multiple with repeated actions, if desired) at a time, according to a user-specified frame rate. Thus, the game is effectively paused after an observation is provided until an agent provides the next action(s) to take.

Observations

At each step, the engine provides reward, pixel-based observations and, optionally, velocity information (figure 1):
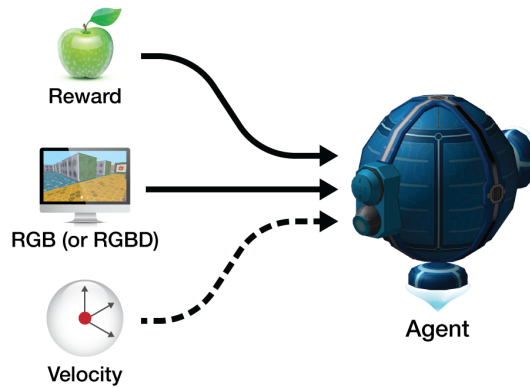
Figure 1: Observations available to the agent. In our experience, reward and pixels are sufficient to train an agent, whereas depth and velocity information can be useful for further analysis.
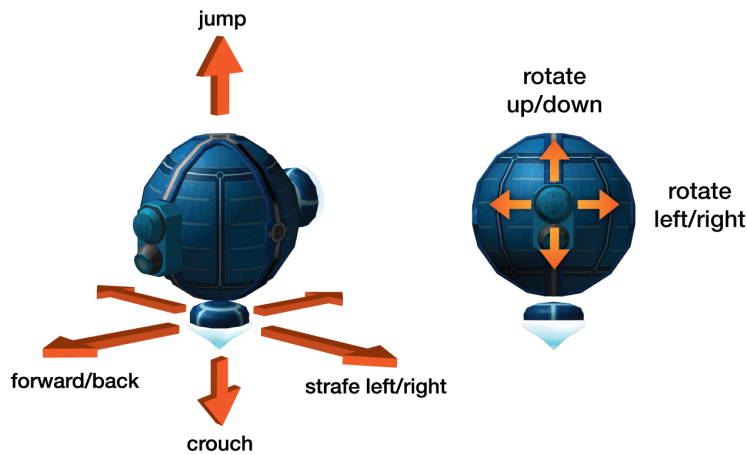

Figure 2: The action space includes movement in three dimensions and look direction around two axes.

1. The reward signal is a scalar value that is effectively the score of each level.

2. The platform provides access to the raw pixels as rendered by the game engine from the player's first-person perspective, formatted as RGB pixels. There is also an RGBD format, which additionally exposes per-pixel depth values, mimicking the range sensors used in robotics and biological stereo-vision.

3. For certain research applications the agent's translational and angular velocities may be useful. These are exposed as two separate three-dimensional vectors.

Actions

Agents can provide multiple simultaneous actions to control movement (forward/back, strafe left/right, crouch, jump), looking (up/down, left/right) and tagging (in laser tag levels with opponent bots), as illustrated in figure 2.

Example levels

Figures 7 and 8 show a gallery of screen shots from the first-person perspective of the agent. The levels can be divided into four categories:

1. Simple fruit gathering levels with a static map (seekavoid_arena_01 and stairway_to_melon). The goal of these levels is to collect apples (small positive reward) and melons (large positive reward) while avoiding lemons (small negative reward).

2. Navigation levels with a static map layout (nav_maze_static_0$\{1, 2, 3\}$ and nav_maze_random_goal_0$\{1, 2, 3\}$). These levels test the agent's ability to find their way to a goal in a fixed maze that remains the same across episodes. The starting location is random. In the random goal variant, the location of the goal changes in every episode. The optimal policy is to find the goal's location at the start of each episode and then use long-term knowledge of the maze layout to return to it as quickly as possible from any location. The static variant is simpler in that the goal location is always fixed for all episodes and only the agent's starting location changes so the optimal policy does not require the first step of exploring to find the current goal location. The specific layouts are shown in figure 3.

3. Procedurally-generated navigation levels requiring effective exploration of a new maze generated on-the-fly at the start of each episode (random_maze). These levels test the agent's ability to explore a totally new environment. The optimal policy would begin by exploring the maze to rapidly learn its layout and then exploit that knowledge to repeatedly return to the goal as many times as possible before the end of the episode (three minutes).

4. Laser-tag levels requiring agents to wield laser-like science fiction gadgets to tag bots controlled by the game's in-built AI (lt_horseshoe_color, lt_chasm, lt_hallway_slope, and lt_space_bounce_hard). A reward of 1 is delivered whenever the agent tags a bot by reducing its shield to 0. These levels approximate the usual gameplay from Quake III Arena. In lt_hallway_slope there is a sloped arena, requiring the agent to look up and down. In lt_chasm and lt_space_bounce_hard there are pits that the agent must jump over and avoid falling into. In lt_horseshoe_color and lt_space_bounce_hard, the colours and textures of the bots are randomly generated at the start of each episode. This prevents agents from relying on colour for bot detection. These levels test aspects of fine-control (for aiming), planning (to anticipate where bots are likely to move), strategy (to control key areas of the map such as gadget spawn points), and robustness to the substantial visual complexity arising from the large numbers of independently moving objects (gadget projectiles and bots).

Technical Details

The original game engine is written in C and, to ensure compatibility with future changes to the engine, it has only been modified where necessary. DeepMind Lab provides a simple C API and ships with Python bindings.
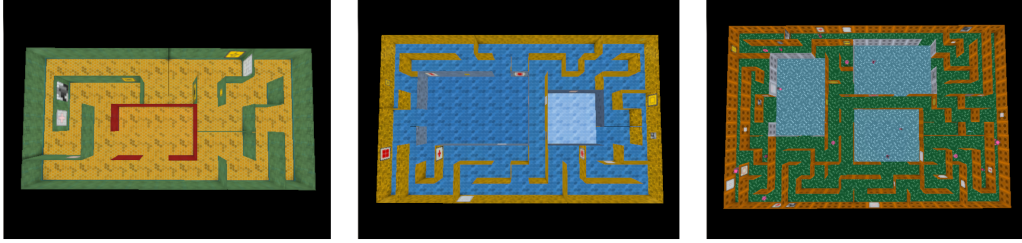
Figure 3: Top-down views of static maze levels. Left: nav_maze_static_01, middle: nav_maze_static_02 and right: nav_maze_static_03.

The platform includes an extensive level API, written in Lua, to allow custom level creation and mechanics. This approach has resulted in a highly flexible platform with minimal changes to the original game engine.

DeepMind Lab supports Linux and has been tested on several major distributions.

API for agents and humans

The engine can be run either in a window, or it can be run headless for higher performance and support for non-windowed environments like a remote terminal. Rendering uses OpenGL and can make use of either a GPU or a software renderer.

A DeepMind Lab instance is initialised with the user's settings for level name, screen resolution and frame rate. After initialisation a simple RL-style API is followed to interact with the environment, as per figure 4.

```python
1  # Construct and start the environment.
2  lab = deepmind_lab.Lab('seekavoid_arena_01', ['RGB_INTERLACED'])
3  lab.reset()
4
5  # Create all-zeros vector for actions.
6  action = np.zeros([7], dtype=np.intc)
7
8  # Advance the environment 4 frames while executing the action.
9  reward = env.step(action, num_steps=4)
10
11  # Retrieve the observations of the environment in its new state.
12  obs = env.observations()  # dict of Numpy arrays
13  rgb_i = obs['RGB_INTERLACED']
14  assert rgb_i.shape == (240, 320, 3)
```

Figure 4: Python API example.

Level generation

Levels for DeepMind Lab are Quake III Arena levels. They are packaged into .pk3 files (which are ZIP files) and consist of a number of components, including level geometry, navigation information and textures.

DeepMind Lab includes tools to generate maps from .map files. These can be cumbersome to edit by hand, but a variety of level editors are freely available, e.g.

GtkRadiant (GtkRadiant, 2016). In addition to built-in and user-provided levels, the platform offers Text Levels, which are simple, human-readable text files, to specify walls, spawn points and other game mechanics as shown in the example in figure 5. Refer to figure 6 for a render of the generated level.

```
1  map = [[
2  *************
3  *    *    *******
4  **        *     ***
5  *****    I     ***
6  *****    *     ***
7  *****    *******
8  *****      ******
9  ******H*******
10 *          I  P  *
11 *************
12 ]]
```

Figure 5: Example text level specification, where '*' is a wall piece, 'P' is a spawn point and 'H' and 'I' are doors.
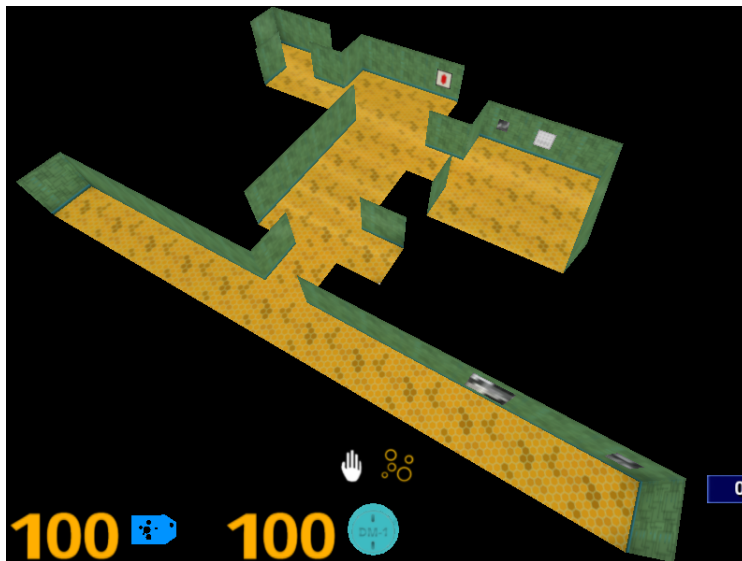
Figure 6: A level with the layout generated from the text in figure 5.

In the Lua-based level API each level can be customised further with logic for bots, item pickups, custom observations, level restarts, reward schemes, in-game messages and many other aspects.

Results and Performance

Tables 1 and 2 show the platform's performance at different resolutions for two typical levels included with the platform. The frame rates listed were computed by connecting an agent performing random actions via the Python API. This agent has insignificant overhead so the results are dominated by engine simulation and rendering times.

The benchmarks were run on a Linux desktop with a 6-core Intel Xeon 3.50GHz CPU and an NVIDIA Quadro K600 GPU.

	CPU		GPU	
	RGB	**RGBD**	**RGB**	**RGBD**
84 x 84	199.7	189.6	996.6	995.8
160 x 120	86.8	85.4	973.2	989.2
320 x 240	27.3	27.0	950.0	784.7

Table 1: Frame rate (frames/second) on nav_maze_static_01 level.

	CPU		GPU	
	RGB	**RGBD**	**RGB**	**RGBD**
84 x 84	286.7	263.3	866.0	850.3
160 x 120	237.7	263.6	903.7	767.9
320 x 240	82.2	98.0	796.2	657.8

Table 2: Frame rate (frames/second) on lt_space_bounce_hard level.

Machine learning results from early versions of the DeepMind Lab platform can be found in Mnih et al. (2016); Jaderberg et al. (2016); Mirowski et al. (2016).

Conclusion

DeepMind Lab enables research in a 3D world with rich science fiction visuals and game-like physics. DeepMind Lab facilitates creative task development. A wide range of environments, tasks, and intelligence tests can be built with it. We are excited to see what the research community comes up with.

Acknowledgements

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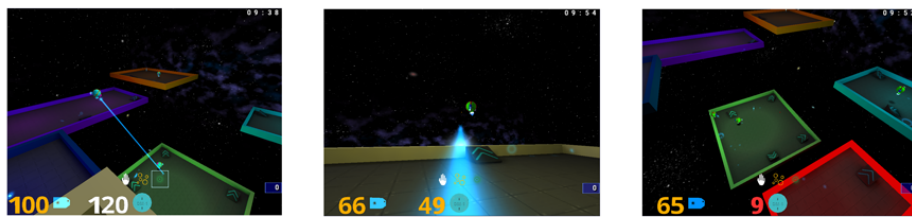
lt_chasm
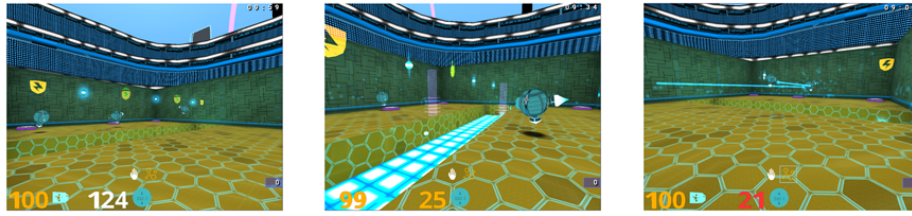
lt_hallway_slope
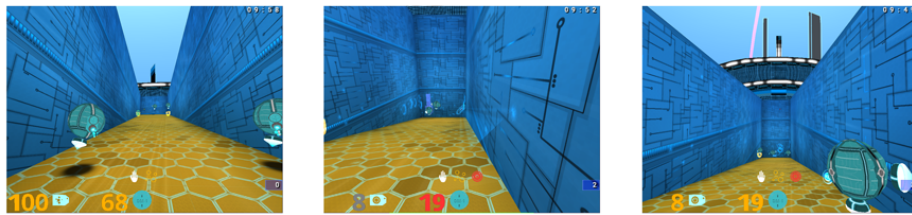
lt_horseshoe_color
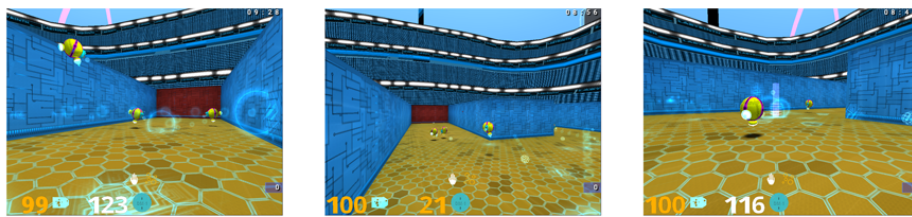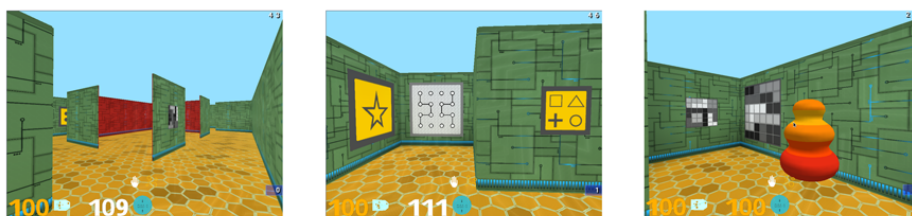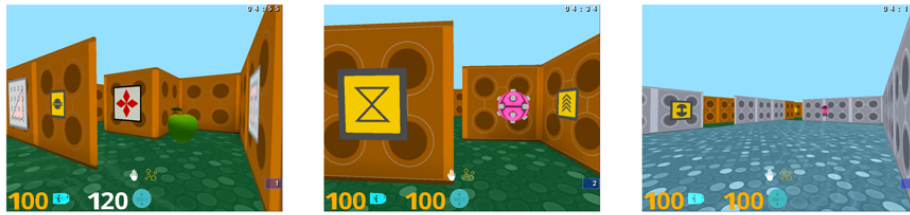

lt_space_bounce_hard

nav_maze*01

Figure 7: Example images from the agent's egocentric viewpoint from several example DeepMind Lab levels.
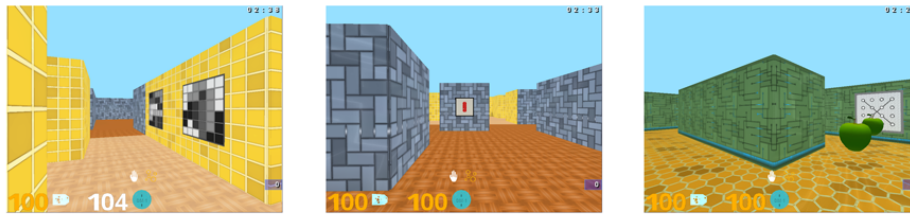
nav_maze*02
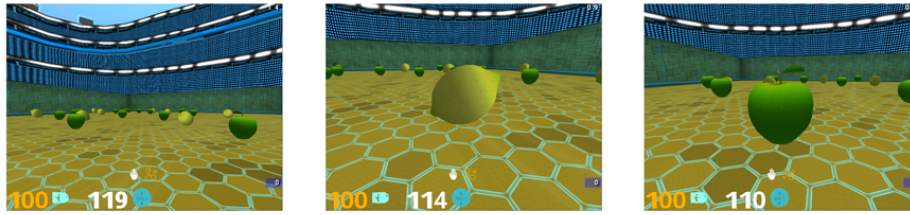

nav_maze*03

random_maze

seekavoid_arena_01

stairway_to_melon

Figure 8: Example images from the agent's egocentric viewpoint from several example DeepMind Lab levels.

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