Modular Object-Oriented Games: A Task Framework for Reinforcement Learning, Psychology, and Neuroscience

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In recent years, trends towards studying simulated games have gained momentum in the fields of artificial intelligence, cognitive science, psychology, and neuroscience. The intersections of these fields have also grown recently, as researchers increasing study such games using both artificial agents and human or animal subjects. However, implementing games can be a time-consuming endeavor and may require a researcher to grapple with complex codebases that are not easily customized. Furthermore, interdisciplinary researchers studying some combination of artificial intelligence, human psychology, and animal neurophysiology face additional challenges, because existing platforms are designed for only one of these domains. Here we introduce Modular Object-Oriented Games, a Python task framework that is lightweight, flexible, customizable, and designed for use by machine learning, psychology, and neurophysiology researchers.

1. Introduction

In recent years, trends towards studying object-based games have gained momentum in the fields of artificial intelligence, cognitive science, psychology, and neuroscience. In artificial intelligence, interactive physical games are now a common testbed for reinforcement learning (François-Lavet et al., 2018; Leike et al., 2017; Mnih et al., 2013; Sutton and Barto, 2018) and object representations are of particular interest for sample efficient and generalizable AI (Battaglia et al., 2018; Greff et al., 2020; van Steenkiste et al., 2019). In cognitive science and psychology, object-based games are used to study a variety of cognitive capacities, such as planning, intuitive physics, and intuitive psychology (Chabris, 2017; Ullman et al., 2017). Developmental psychologists also use object-based visual stimuli to probe questions about object-oriented reasoning in infants and young animals (Spelke and Kinzler, 2007; Wood et al., 2020). In neuroscience, object-based computer games have recently been used to study decision-making and physical reasoning in both human and non-human primates (Fischer et al., 2016; McDonald et al., 2019; Rajalingham et al., 2021; Yoo et al., 2020).

Furthermore, a growing number of researchers are studying tasks using a combination of approaches from these fields. Comparing artificial agents with humans or animals performing the same tasks can help constrain models of human/animal behavior, generate hypotheses for neural mechanisms, and may ultimately facilitate building more intelligent artificial agents (Hassabis et al., 2017; Lake et al., 2017; Willke et al., 2019).

However, building a task that can be played by AI agents, humans, and animals is a time-consuming undertaking because existing platforms are typically designed for only one of these purposes. Professional game engines are designed for human play and are often complex libraries that are difficult to customize for training AI agents and animals. Reinforcement learning platforms are designed for AI agents but are often too slow or inflexible for neuroscience work. Existing psychology and neurophysiology platforms are too limited to easily support complex interactive games.

In this work we offer a game engine that is highly customizable and designed to support tasks that can be played by AI agents, humans, and animals.
2. Summary

The Modular Object-Oriented Games library is a general-purpose Python-based platform for interactive games. It aims to satisfy the following criteria:

- Usable for reinforcement learning, psychology, and neurophysiology. MOOG supports DeepMind dm_env and OpenAI Gym (Brockman et al., 2016) interfaces for RL agents and an MWorks interface for psychology and neurophysiology.
- Highly customizable. Environment physics, reward structure, agent interface, and more can be customized.
- Easy to rapidly prototype tasks. Tasks can be composed in a single short file.
- Light-weight and efficient. Most tasks run quickly, almost always faster than 100 frames per second on CPU and often much faster than that.
- Facilitates procedural generation for randomizing task conditions every trial.

3. Intended Users

MOOG was designed for use by the following kinds of researchers:

- Machine learning researchers studying reinforcement learning in 2.5-dimensional (2-D with occlusion) physical environments who want to quickly implement tasks in Python.
- Psychology researchers who want more flexibility than existing psychology platforms afford.
- Neurophysiology researchers who want to study interactive games yet still need to precisely control stimulus timing.
- Machine learning researchers studying unsupervised learning, particularly in the video domain. MOOG can be used to procedurally generate video datasets with controlled statistics.

MOOG may be particularly useful for interdisciplinary researchers studying AI agents, humans, and animals (or some subset thereof) all playing the same task.

4. Design

The core philosophy of MOOG is "one task, one file." Namely, a task should be implemented with a single configuration file. This configuration file is a short “recipe” for the task, containing as little substantive code as possible, and should define a set of components to pass to the MOOG environment. See Figure 1 for a schematic of these components.

A MOOG environment receives the following components (or callables returning them) from the configuration file:

- **State.** The state is a collection of sprites. Sprites are polygonal shapes with color and physical attributes (position, velocity, angular velocity, and mass). Sprites are 2-dimensional, and the state is 2.5-dimensional with z-ordering for occlusion. The initial state can be procedurally generated from a custom distribution at the beginning of each episode. The state is structured in terms of layers, which helps hierarchical organization. See state_initialization for procedural generation tools.
- **Physics.** The physics component is a collection of forces that operate on the sprites. There are a variety of forces built into MOOG (collisions, friction, gravity, rigid tethers, ...) and additional custom forces can also be used. Forces perturb the velocity and angular velocity of sprites, and the sprite positions and angles are updated with Newton’s method. See physics for more.
Figure 1 | **Components of a MOOG environment.** See main text for details.

- **Task.** The task defines the rewards and specifies when to terminate a trial. See tasks for more.
- **Action Space.** The action space allows the subject to control the environment. Every environment step calls for an action from the subject. Action spaces may impart a force on a sprite (like a joystick), move a sprite in a grid (like an arrow-key interface), set the position of a sprite (like a touch-screen), or be customized. The action space may also be a composite of constituent action spaces, allowing for multi-agent tasks and multi-controller games. See action_spaces for more.
- **Observers.** Observers transform the environment state into an observation for the subject/agent playing the task. Typically, the observer includes a renderer producing an image. However, it is possible to implement a custom observer that exposes any function of the environment state. The environment can also have multiple observers. See observers for more.
- **Game Rules** (optional). If provided, the game rules define dynamics or transitions not captured by the physics. A variety of game rules are included, including rules to modify sprites when they come in contact, conditionally create new sprites, and control phase structure of trials (e.g. fixation phase to stimulus phase to response phase). See game_rules for more.

Importantly, all of these components can be fully customized. If a user would like a physics force, action space, or game rule not provided by MOOG, they can implement a custom one, inheriting from the abstract base class for that component. This can typically be done with only a few lines of code.

The modularity of MOOG facilitates code re-use across experimental paradigms. For example, if a user would like to both collect behavior data from humans using a continuous joystick and train RL agents with discrete action spaces on the same task, they can re-use all other components in the task configuration, only changing the action space.

For users interested in doing psychology or neurophysiology, we include an example of how to run MOOG through MWorks, a platform with precise timing control and interfaces for eye trackers, HID devices, electrophysiology software, and more.

### 5. Example Tasks

See the example_configs for a variety of task config files. Four of those are shown in Figure 2. See the demo documentation for videos of them all and instructions for how to run them with a Python gui.

The MOOG codebase contains libraries of options for each of the components in Section 4, so implementing a task involves only combining the desired ingredients and feeding them to the environment. For an example, the following code fully implements a navigate-to-goal task, where the subject must move an agent via a joystick action space to a goal location:
Figure 2 | **Example tasks.** Time-lapse images of four example tasks. Left-to-right: (i) Pong - The subject aims to catch the yellow ball with the green paddle, (ii) Red-Green - The subject tries to predict whether the blue ball will contact the red square or the green square, (iii) Pac-Man - The subject moves the green agent to catch yellow pellets while avoiding the red ghosts, (iv) Collisions - the green agent avoids touching the bouncing polygons.

```python
"""Navigate-to-goal task."""

import collections
from moog import action_spaces, environment, observers, physics, sprite, tasks

# Initial state is a green agent in the center and red goal in the corner
def state_initializer():
    # Goal is a red square with side-length 0.1 at position (0.1, 0.1)
    # Color channels are [c0, c1, c2] arguments
    goal = sprite.Sprite(x=0.1, y=0.1, shape='square', scale=0.1, c0=255)
    # Agent is a green circle at position (0.5, 0.5)
    agent = sprite.Sprite(x=0.5, y=0.5, shape='circle', scale=0.1, c1=255)
    state = collections.OrderedDict([(
        'goal', [goal]),
        ('agent', [agent]),
    ])
    return state

# Physics is a drag force on the agent to limit velocity
phys = physics.Physics((physics.Drag(coef_fictric=0.25), 'agent'))

# Task gives a reward 1 when the agent reaches the goal, and a new trial begins
# 5 timesteps later.
task = tasks.ContactReward(1., 'agent', 'goal', reset_steps_after_contact=5)

# Action space is a joystick with maximum force 0.01 arena widths per timestep^2
action_space = action_spaces.Joystick(0.01, 'agent')

# Observer is an image renderer
obs = observers.PILRenderer(image_size=(256, 256))

# Create the environment, ready to play!
env = environment.Environment(
    state_initializer=state_initializer,
    physics=phys,
    task=task,
    action_space=action_space,
    observers={'image': obs},
)
```

This is an extremely simple task, but by complexifying the state initializer and adding additional forces and game rules, a **wide range of complex tasks** can be implemented with few lines of code.
6. Limitations

Users should be aware of the following limitations of MOOG before choosing to use it for their research:

- **Not 3D.** MOOG environments are 2.5-dimensional, meaning that they render in 2-dimensions with z-ordering for occlusion. MOOG does not support 3D sprites.
- **Very simple graphics.** MOOG sprites are monochromatic polygons. There are no textures, shadows, or other visual effects. Composite sprites can be implemented by creating multiple overlapping sprites, but still the graphics complexity is very limited. This has the benefit of a small and easily parameterizable set of factors of variation of the sprites, but does make MOOG environments visually unrealistic.
- ** Imperfect collisions.** MOOG’s collision module implements Newtonian rotational mechanics, but it is not as robust as professional physics engines (e.g. can be unstable if objects are moving very quickly and many collisions occur simultaneously).

7. Related Software

Professional game engines (e.g. Unity and Unreal) and visual reinforcement learning platforms (e.g. DeepMind Lab (Beattie et al., 2016), Mujoco (Todorov et al., 2012), and VizDoom) are commonly used in the machine learning field for task implementation. While MOOG has some limitations compared to these (see above), it does also offer some advantages:

- **Python.** MOOG tasks are written purely in Python, so users who are most comfortable with Python will find MOOG easy to use.
- **Procedural Generation.** MOOG facilitates procedural generation, with a library of compositional distributions to randomize conditions across trials.
- **Online Simulation.** MOOG supports online model-based RL, with a ground truth simulator for tree search.
- **Psychophysics.** MOOG can be run with MWorks, a psychophysics platform.
- **Speed.** MOOG is fast on CPU. While the speed depends on the task and rendering resolution, MOOG typically runs at 200fps with 512x512 resolution on a CPU, much faster than DeepMind Lab and Mujoco and at least as fast as Unity and Unreal.

Python-based physics simulators, such as PyBullet (Coumans and Bai, 2016–2019) and Pymunk, are sometimes used in the psychology literature. While these offer highly accurate collision simulation, MOOG offers the following advantages:

- **Customization.** Custom forces and game rules can be easily implemented in MOOG.
- **Psychophysics, Procedural Generation, and Online Simulation, as described above.**
- **RL Interface.** A task implemented in MOOG can be used out-of-the-box to train RL agents, since MOOG is Python-based and has DeepMind dm_env and OpenAI Gym interfaces.

Psychology and neurophysiology researchers often use platforms such as PsychoPy (Peirce et al., 2019), PsychToolbox (Kleiner et al., 2007), and MWorks. These allow precise timing control and coordination with eye trackers and other controllers. MOOG can interface with MWorks to leverage all of those features and offers the following additional benefits:

- **Flexibility.** MOOG offers a large scope of interactive tasks. Existing psychophysics platforms are not easily customized for game-like tasks, action interfaces, and arbitrary object shapes.
• **Physics.** Existing psychophysics platforms do not have built-in physics, such as forces, collisions, etc.

• **RL Interface,** as described above.

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