PsyRTS: a Web Platform for Experiments in Human Decision-Making in RTS Environments

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***Abstract*— This paper presents PsyRTS: an open-source web-platform designed to create psychological experiments using a dynamic environment based on real-time strategy games. This platform has characteristics present in Real-Time Strategy (RTS) games and allows the researcher to manipulate variables regarding visibility, resource availability and presence of other agents while at the same time enabling human participation through existing online platforms.**

***Keywords*— decision-making, exploration-exploitation, heuristics, player modeling, crowdsourcing.**

I. Introduction

Exploration and exploitation represent two mutually exclusive goals associated with choices within an environment: search too little and the lack of information will make it difficult to distinguish good from bad options penalizing the agent in the long run (exploiting) or search too much and suffer an excessive pursuit of information leading to sub optimal performance in the short term (exploring). Striking a balance between exploiting (i.e. current information gains) and exploring (i.e. seeking out new information) requires the learner to behave optimally in variety of different environments (e.g. static, dynamic) [1]-[3]. Managing this exploration-exploitation trade-off is an important process of our lives but isn't completely understood from a cognitive science perspective.

In psychological research, understanding foraging behaviors (in human and non-human animals) provides a potential approach to understanding spatial exploration that extends to gameplay experiences in video games. Moreover, a recent novel experimental approach to examining the application of models of explorative behavior involves using real-time strategy (RTS) games to examine how participants explore dynamic environments with partial information and stochastic actions in a competitive setting. However, while this type of approach is of obvious value, often the current application of this approach is restricted to laboratory-based methods, which means that participants must be recruited to take part in the study in a controlled environment in a laboratory in front of a computer in order to capture in-game data, which limits the ways in which experiments can be conducted as well as raising concerns about the reliability and robustness of findings from small participant samples common to these typical lab-based studies. Cognitive science and experimental psychology are increasing their use of web-platforms to reach wider pools of participants than has been previously feasible with lab-based methods [4]. Crowdsourcing platforms [4] like Amazon MTurk [5] and Prolific Academic [6] have been developed as a response to solve the problem of recruiting enough participants. These platforms circumvent the practical issues of typical lab-based data collection, allowing more creative methods of experimentation, as well as addressing concerns about the reliability and robustness of these findings.

The purpose of this paper is two-fold. Firstly, the aim here is to expose the availability of flexible platforms to run experiments in the field of dynamic decision-making for which exploration is key [7] and where RTS's are a perfect testbed for this purpose. Secondly, to introduce PsyRTS, a web-platform that we have developed to fill this gap by making possible online experimentation using dynamic environment based on simple real-time strategy scenarios. The PsyRTS uses technologies that enable researchers to acquire a wider pool of participants from all around the world which can facilitate the generation of new knowledge in understanding how humans learn and make decisions in these types of environments.

II. Related Work

A. Dynamic environments

Go and chess are examples of games situated in static environments. They share two characteristics that are worth mentioning: the full game state (pieces on board) is observable, and the decision maker can think about the next move while the environment remains static. Dynamic environments, on the other hand, change the state of the world while the decision maker acts, which is closer to many real-world decision-making scenarios [7]. Under these conditions using explorative behaviors to gain new information could be more important than exploiting the current knowledge to acquire rewards; though the optimum level of exploration is nuanced to the dynamic environment the decision-maker is in [8]. The dilemma between information gathering (exploration) and reward seeking (exploitation) is a fundamental problem for reinforcement learning agents that has long been recognized as a central issue in the field of reinforcement learning [9]. However, how humans resolve this dilemma is still an open question, because experiments have provided diverging evidence about the underlying strategies used by humans. Even if humans don't often reach optimality in the decisions made, much of the work in the decision sciences suggests that choice behavior is still reasonable to sufficiently within a dynamic environment to effectively achieve desirable goals over time [10].

B. Real-Time Strategy as dynamic environments

RTS games are computer games where players need to build an economy in an environment in which other agents

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(artificial or human) are present, and they can introduce competition for resources (competitors), or they can pose threats to the player (adversaries). The RTS genre has attracted significant attention in the AI research community because these environments are a toy analogue of real-world dynamic environments [11][12]. For instance, DeepMind introduced a platform to create bots [13] in order to tackle the "new grand challenge in AI" as they coined it [14]. To 'win' in these environments, the human player needs to continually switch strategies between exploration and exploitation that are relevant for learning about the environment, as well as control dynamic elements of the game in order to gain resources to win the game [15][16]. Unlike chess and Go, in RTS games the environment is dynamic (e.g., there are moving elements in the game that change over time) and partially observable (e.g., through fog-of-war) combined with the fact the camera that exposes the game environment to the player is not able to show the entire game environment at once. Additionally to these characteristics action and state space are bigger in RTS games than board games such as Chess and Go[11]. Balancing the amount of information search strategies (exploration) that are implemented over time, and the amount of resources gain strategies (exploitation) that are enacted determines the extent to which players are characterized as strategic and tactical, as well as the extent to which they have good situational awareness.

Success in RTS games is strongly based on resource gathering. With enough resources the player can fulfil other criteria for success in the game such as create buildings, training units, increasing defense capabilities, and expanding the territory under the player's control [16]. Another feature of success in RTS games is survival against other competitors as well as adversaries (through micro-management). Decisions that players' make in response to competitors and predators in RTS games is analogous to the patterns of behavior that have been modelled in foraging tasks based on work in ecology and biology [17]-[20].

Clearly there is value in work on RTS game in revealing important features of the way humans and artificial agents learn and make decisions in complex environments, and that this in turn provides insights to other disciplines (e.g., ecology, biology, psychology, machine learning). Current trends in artificial intelligence research examining RTS makes use of machine learning techniques applied to massive datasets of human replays but given that the settings are usually complex and often using commercial games, there are limits to the kind of experimental manipulations that can be introduced. In case that these manipulations are able to be included in experimental designs through mod plugins, API's like BWAPI [21] or creation tool, the lack of tools to expose these platforms through online exposition mean that these experiments need to be run in laboratory-based settings, facing problems with small samples sizes and their reliability.

C. Psychological experiments in web-based platforms.

Recent advances in web technologies allowed researchers to use web-browsers as a platform to find participants for their psychological experiments [4]. Experiments conducted in Gorilla [22], PsyToolkit [23], Pavlovia hosting PsycoPy [24] and OpenSesame [25] are the typical examples.

These platforms are optimized for behavioral tasks, but they aren't suited to run experiments using dynamic environments containing the kind of complex features present in RTS games. In the remainder of this article we present our toolkit, developed to overcome these difficulties.

III. Toolkit

A. Overview

From our review of the literature, Psychlab from DeepMind come closest to fill the gap between psychological experiments with humans and artificial intelligence tests with agents, but the main limitation of the Psychlab platform is the scalability of human experiments, for the reason that, as identified before, they are lab-based. Psychlab was built with the idea of applying methods form cognitive psychology to study behaviors or artificial agents in controlled environments and to compare performance between humans and agents on tasks from cognitive psychology and psychophysics [26].

One principle that motivated the creation of the PsyRTS toolkit which we present here is the advantage for recruiting participants through existing crowdsourcing platforms such as Amazon MTurk, Prolific or Gorilla, and so an easy integration with these online sites was a priority and therefore popular technologies for implementing web projects like html5 and JavaScript were selected for this platform. Secondly, we wanted to focus on the dynamic decision-making paradigm (for review see [7]) – which has used RTS-like games. As an interesting avenue to explore we examined the impact of uncertainty on decision-making by varying the visibility the player has of the environment because this would enable the investigation of the exploration-exploitation trade-off in a dynamic environment where different information search strategies might be needed depending on what parts of the environment were visibly exposed. In addition, RTS games like StarCraft I and II have been a test bed for AI researchers given that they combine micro-actions with the need for strategical planning and execution, and so these were a source of inspiration for the RTS set up used in PsyRTS. The PsyRTS environment created contained the following properties for examining several cognitive behaviors:

- It is a multiagent system where agents compete for resources resembling foraging in nature. (Value-based decision-making)
- It is an imperfect information game and the environment is partially observable, so that the player must actively reposition the camera in order to acquire and integrate new information as they explore the environment. (Information foraging).
- Players experience "fog-of-war", that is by obscuring the unvisited regions of the map makes them unknowable to the player (until they enter into that area), so it´s not only a matter of repositioning the camera, but the player must commit resources to explore the environment in order to increase knowledge of the state of the world and the potential presence of other agents within. (Decision-making under uncertainty). See figure 1 and figure 2 for examples of environments making use of this concept.
- The player executes actions, but the state of the world is changing independent of direct human intervention. (Dynamic decision-making).

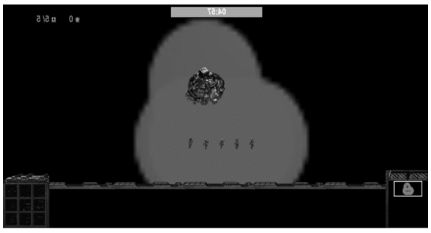

Fig. 1. Initial position for a condition with fog-of-war.

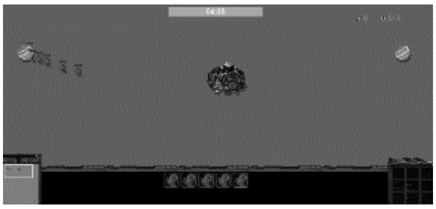

Fig. 2. Experimental condition without fog-of-war.

B. Behavioral Data

Given the features of the RTS we devised, we outline here the specific behavioral data that were recorded in the game:

- State of the world: Time, resources in the world, presence of fog-of-war or not.
- Demographics.
- Position and state of each unit in the world, whether user´s units, competition or threats.
- History of units, competitors and threats positions during the whole experiment.
- Type of mouse clicks and keyboard events that users performed interacting with the environment.

C. Implementation

Well-tested web technologies like html5, JavaScript and AJAX (Asynchronous Javascript And Xml) were selected for this project. JSON (Javascript Object Notation) objects were used to save all the information present in the environment. Using AJAX invocations, the objects are stored in a web server using PHP for the interaction. The complete data is sent to a MYSQL database where these objects are stored as UTF strings. The only external library used is SurveyJS, that is used to create surveys.
The platform also includes artificial agents that can behave like competitors or adversaries (i.e. threats). When an artificial agent is acting like competitor (competitor mode) it starts with a wandering behavior around the environment, in which the agent selects a random point and moves toward it. If the artificial agent (acting as competitor) detects resources within its range of vision then it engages in a gatherer behavior, where it forages resources until depletion. In that case the artificial agent is a threat (predator mode), the agent is fixed in one position, maintaining an idle behavior until some other agent that is either a human agent or an artificial competitor is detected in its range of vision. In this case the agent acting like a threat in the environment switches to a pursuit mode until one of the following conditions holds: a) the prey is eliminated or b) the prey is out of its range of vision. In both cases the behavior switches back to idle behavior. Human agents in this version of the framework are limited to be foragers and not threats for other agents in the environment.

D. Parameters

The system has around sixteen tunable parameters that modify the visibility, range of vision, size of the environment, number of seconds in each trial, how often the system takes a snapshot of the world state, the position of each agent in the environment as well as their internal state, among others.

E. Repository

The source code, database scripts and documentation are currently hosted on a private GitHub site: https://github.com/oruburos/ExpPsyRTS, where the project is being actively updated and will be released to a public repository in the short-term future. The website also includes python scripts that help in data extraction, data cleaning and data analysis of data used experiments performed.

F. Case of use: a psychology experiment in exploration under threats and competition.

Several empirical studies have used dynamic environments to explore the exploration-exploitation trade-off [18][19].
In order to study the information foraging strategies adopted by human agents and how factors such as threats and competition affect explorative and exploitative behavior, we devised an experiment based on the presented toolkit where 248 participants were recruited through Prolific Academic using an opportunistic sampling method. Participants were presented with a simulated alien environment in which their main role was to command a group of 5 explorers (units that they controlled) in order to collect tokens, spread across the environment (See figure 3). In the experiment there were two main manipulations, the first being the level of visibility of the environment (full, partial) and the presence of other agents and the type of agents they were (competitors or predators). Some of the exploration patterns are presented in Figure 4. For further details see [27].

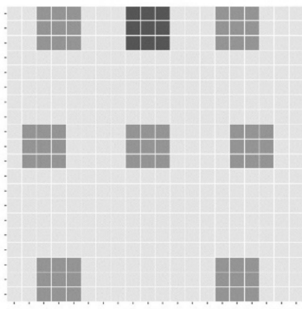

Fig. 3. Environment used in the experiment. Darker areas show presence of resources. Darkest area is the location where resources need to be stored.

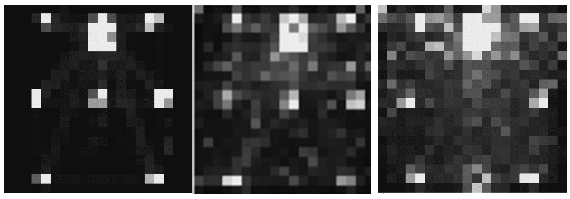

Fig. 4. Heatmaps of participants from conditions with total visibility and no other agents in the environment (Left), partial visibility and threats (Center) and partial visibility, threats and competition(Right).

IV. Conclusions and Future Work

This paper introduces PsyRTS, a novel web-based platform for examining behavior in dynamic environments with RTS characteristics. PsyRTS makes it easy to create experiments for examining decision-making and learning behaviors, and the major advantage is that is facilitates the recruitment of large samples of human participants through pre-existent online crowdsourcing platforms. The PsyRTS platform stores data including keystrokes, mouse movements, movement of units over time, game state of the world as well as demographic data for each participation, and easily allows further statistical analysis through python scripts. One of the main limitations is that researchers need programming skills to modify the source code to create new experiments, given that the platform doesn't expose the specific parameters through an interface nor do they use a specific file format to store and modify experiments to allow a data driven approach. Below we present possible extensions of the PsyRTS platform:

- Iterate for a data-driven design, allowing future researchers to create different experiments by modifying configuration files in plain text.
- Extend the functionality to allow researchers to mark explicitly what kinds of behavioral metrics are important to store.
- Create a GUI tool for creating experiments based on the two previous ideas, so that it is possible to expose what the system is capable of tracking and to automatically generate documents with a specific format selected for sharing new experimental designs.
- Expose the functionality through a REST API that will allow external bots to interact as participants in the experimental setting (e.g., General Video Game AI agents [45])

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