DeepCrawl: Deep Reinforcement Learning for Turn-based Strategy Games

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Abstract

In this paper we introduce DeepCrawl, a fully-playable Roguelike prototype for iOS and Android in which all agents are controlled by policy networks trained using Deep Reinforcement Learning (DRL). Our aim is to understand whether recent advances in DRL can be used to develop convincing behavioral models for non-player characters in videogames. We begin with an analysis of requirements that such an AI system should satisfy in order to be practically applicable in video game development, and identify the elements of the DRL model used in the DeepCrawl prototype. The successes and limitations of DeepCrawl are documented through a series of playability tests performed on the final game. We believe that the techniques we propose offer insight into innovative new avenues for the development of behaviors for non-player characters in video games, as they offer the potential to overcome critical issues with classical approaches.

1 Introduction

Technological advances in gaming industry have resulted in the production of increasingly complex and immersive gaming environments. However, the creation of Artificial Intelligence (AI) systems that control non-player characters (NPCs) is still a critical element in the creative process that affects the quality of finished games. This problem is often due to the use of classical AI techniques that result in predictable, static, and not very convincing NPC strategies. Reinforcement learning (RL) can help overcome these issues providing an efficient and practical way to define NPC behaviors, but its real application in production processes has issues that can be orthogonal to those considered to date in the academic field: how can we improve the gaming experience? How can we build credible and enjoyable agents? How can RL improve over classical algorithms for game AI? How can we build an efficient ML model that is also usable on all platforms, including mobile systems?

At the same time, recent advances in Deep Reinforcement Learning (DRL) have shown it is possible to train agents with super-human skills able to solve a variety of environments. However the main objective of DRL of this type is training agents to surpass human players in competitive play in classical games like Go (Silver et al. 2016) and video games like DOTA 2 (OpenAI 2019). The resulting, however, agents clearly run the risk of being too strong, of exhibiting artificial behavior, and in the end not being a *fun* gameplay element.

Video games have become an integral part of our entertainment experience, and our goal in this work is to demonstrate that DRL techniques can be used as an effective *game design* tool for learning compelling and convincing NPC behaviors that are natural, though not superhuman, while at the same time provide challenging and enjoyable gameplay experience. As a testbed for this work we developed the DeepCrawl Roguelike prototype, which is a turn-based strategy game in which the player must seek to overcome NPC opponents and NPC agents must learn to prevent the player from succeeding. We emphasize that our goals are different than those of AlphaGo and similar DRL systems applied to gameplay: for us it is essential to limit agents so they are beatable, while at the same time training them to be convincingly competitive. In the end, playing against superhuman opponents is not *fun*, and neither is playing against *trivial* ones. This is the balance we try to strike.

With this paper we propose some requirements that a Machine Learning system should satisfy in order to be practically applied in videogame production as an active part of game design. We also propose an efficient DRL system that is able to create a variety of NPC behaviors for Roguelike games only by changing some parameters in the training set-up; moreover the reduced complexity of the system and the particular net architecture make it easy to use and to deploy to systems like mobile devices. Finally we introduce a new game prototype, tested with a series of playability tests, that can be a future benchmark for DRL for videogame production.

2 Related work

Game AI has been a critical element in video game production since the dawn of this industry; agents have to be more and more realistic and intelligent to provide the right challenge and level of enjoyment to the user. However, as game environments have grown in complexity over the years, scaling traditional AI solutions like Behavioral Trees (BT) and

Finite State Machines (FSM) for such complex contexts is an open problem (Yannakakis and Togelius 2018).

Reinforcement Learning (RL) (Sutton et al. 1998) is directly concerned with the interaction of agents in an environment. RL methods have been widely used in many disciplines, such as robotics and operational research, and games. The breakthrough of applying DRL by DeepMind in 2015 (Mnih et al. 2015) brought techniques from supervised Deep Learning (such as image classification and Convolutional Neural Networks) to overcome core problems of classical RL. This combination of RL and neural networks has led to successful application in games. In the last few years several researchers have improved upon the results obtained by DeepMind. For instance, OpenAI researchers showed that with an Actor Critic (Konda and Tsitsiklis 2003) algorithm such as Proximal Policy Optimization (PPO) (Schulman et al. 2017) it is possible to train agents to superhuman levels that can win against professional players in complex and competitive games such as DOTA 2 (OpenAI 2019) and StarCraft (DeepMind 2019).

As already discussed in the introduction, most of the works in DRL aim to build agents replacing human players either in old-fashioned games like Go or chess (Silver et al. 2016; Asperti, Cortesi, and Sovrano 2018) or in more recent games such as Doom or new mobiles games (OpenAI 2019; Vinyals et al. 2017; Oh et al. 2019; Kempka et al. 2016; Juliani et al. 2019). Our objective, however, is not to create a new AI system with superhuman capabilities, but rather to create ones that constitute an active part of the game design: our work has a similar conetxt to (Zhao et al. 2019), while (Amato and Shani 2010) tried to use simple RL to build a variety of NPC beahviors.

3 Game design and desiderata

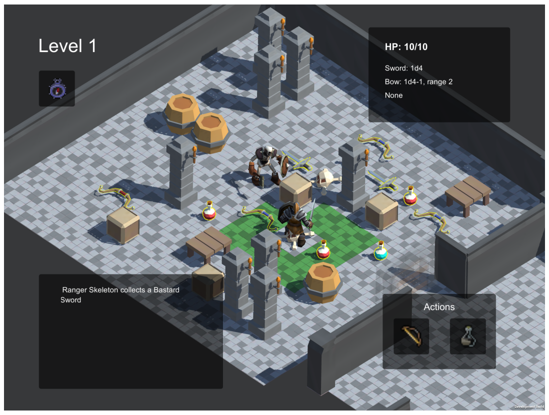
In this section we describe the main gameplay mechanics of DeepCrawl and the requirements that the system should satisfy in order to be used in a playable product. The DeepCrawl prototype is a fully playable Roguelike game and can be downloaded for Android and iOS [1]. In figure 1 we give a screenshot of the final game.

Gameplay mechanics

We decided to build a *Roguelike* as there are several aspects of this type of games that make them an interesting testbed for DRL as a game design tool, such as the *procedurally created environment*, the *turn-based* system and the *non-modal* characteristic that makes available every action for actors regardless the level of the game. In fact, Roguelikes are often used as a proving ground game genre specifically because they involve a limited set of game mechanics, which allows game designers to concentrate on emergent complexity of gameplay as a combination of the relatively simple set of possibilities given to the player.

The primary gameplay mechanics in DeepCrawl are defined in terms of several distinct, yet interrelated elements.

[1]Android Play: http://tiny.cc/DeepCrawl
App Store: http://tiny.cc/DeepCrawlApp



Ranger Skeleton collects a Bastard Sword

Figure 1: Screenshot of the final version of DeepCrawl. Each level of the game consists of one or more rooms, in each of which there is one or more agents. To clear a level the player must fight and win against all the enemies in the dungeon. The game is won if the player completes ten dungeon levels.

Actors. Success and failure in DeepCrawl is based on direct competition between the player and one or more agents guided by a deep policy network trained using DRL. Player and agents act in procedurally generated rooms, and player and agents have exactly the same characteristics, can perform the same actions, and have access to the same information about the world around them.

Environment. The environment visible at any instant in time is represented by a random grid with maximum size of 10×10 tiles. Each tile can contain either an agent or player, an impassible object, or collectible loot. Loot can be of three types: melee weapons, ranged weapons, or potions. Moreover, player and agent are aware of a fixed number of personal characteristics such as HP, ATK, DEX, and DEF. Agents and player are also aware of their inventory in which loot found on the map is collected. The inventory can contain at most one object per type at a time, and a new collected item replaces the previous one. The whole dungeon is composed of multiple rooms, where in each of them there are one or more enemies. The range of action of each NPC agent is limited to the room where it spawned, while the player is free to move from room to room.

Action space. Each character can perform 17 different discrete actions:

- **8 movement actions** in the horizontal, vertical and diagonal directions; if the movement ends in a tile containing another agent or player, the actor will perform a melee attack: this type of assault deals random damage based on the melee weapon equipped, the ATK of the attacker, and the DEF of the defender;
- **1 use potion action**, which is the only action that does not end the actor's turn. DeepCrawl has two buff potions available, one that increases ATK and DEF for a fixed number of turns, and heal potion that heals a fixed number of HP; and

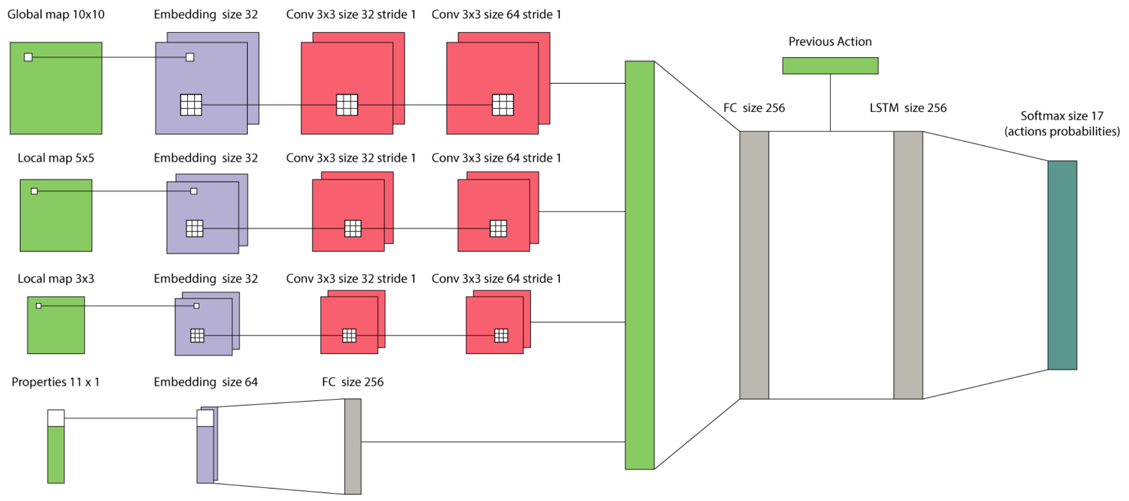


Figure 2: The policy network used for NPCs in DeepCrawl. See section 4 for a detailed description.

- **8 ranged attack actions**, one for each possible direction. If there is another actor in selected direction, a ranged attack is performed using the currently equipped ranged weapon. The attack deals a random amount of damage based on the ranged weapon equipped, the DEX of the attacker, and the DEF of the defender.

Desiderata

As defined above, our goals were to create a playable game, and in order to do this the game must be enjoyable from the player's perspective. Therefore, in the design phase of this work it was fundamental to define the requirements that AI systems controlling NPCs should satisfy in order to be generally applicable in videogame design:

Credibility. NPCs must be *credible*, that is they should act in ways that are predictable and that can be interpreted as intelligent. The agents must offer the right challenge to the player and should not make counterintuitive moves. The user should not notice that he is playing against an AI.

Imperfection. At the same time, the agents must be *imperfect* because a superhuman agent is not suitable in a playable product. In early experiments we realized that it was relatively easy to train *unbeatable* agents that were, frankly, no fun to play against. It is important that the player always have the chance to win the game, and thus agents must be beatable.

Prior-free. Enemy agents must be *prior-free* in that developers do not have to manually specify strategies – neither by hard-coding nor by carefully crafting specific rewards – specific to the game context prior the training. The system should extrapolate strategies independently through the trial-and-error mechanism of DRL. Moreover, this prior-free system should generalize to other Roguelike games sharing the same general gameplay mechanics.

Variety. It is necessary to have a certain level of *variety* in the gameplay dynamics. Thus, it is necessary to support multiple agents during play, each having different behaviors. The system must provide simple techniques to allow agents to extrapolate different strategies in the training phase.

4 Proposed model

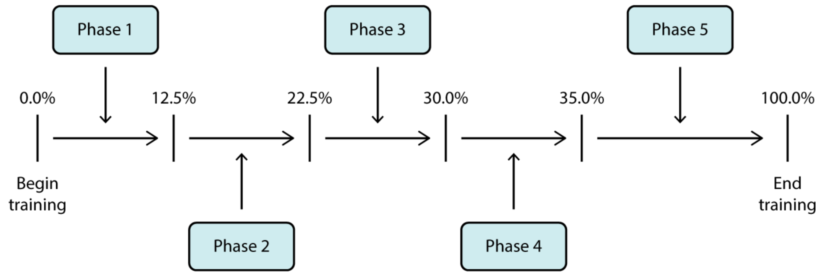
Here we describe in detail the main elements of the DRL model that controls the agent in DeepCrawl, with particular attention to the neural network architecture and the reward function.

Policy network and state representation

We used a policy-based method to learn the best strategy for agents controlling NPCs. For these methods, the network must approximate the best policy. The neural network architecture we used to model the policy for NPC behavior is shown in figure 2. The network consists of four input branches:

- the first branch takes as input the whole map of size 10×10, with the discrete map contents encoded as integers:
  - 0 = impassable tile or other agent;
  - 1 = empty tile;
  - 2 = agent;
  - 3 = player; and
  - 4+ = collectible items.

  This input layer is then followed by an embedding layer which transforms the $10 \times 10 \times 1$ integer input array into a continuous representation of size $10 \times 10 \times 32$, a convolutional layer with 32 filters of size 3×3, and another 3×3 convolutional layer with 64 filters.
- The second branch takes as input a local map with size 5×5 centered around the agent's position. The map encoding is the same as for the first branch and an embedding layer is followed by convolutional layers with the same structure as the previous ones.
- The third branch is structured like the second, but with a local map of size 3×3.



	agent HPs	enemy HP	loot quantity
Phase 1	20	1	20%
Phase 2	[5, 20]	10	20%
Phase 3	[5, 20]	[10, 20]	20%
Phase 4	[5, 20]	[10, 20]	[10%, 20%]
Phase 5	[5, 20]	[10, 20]	[5%, 20%]

Figure 3: Curriculum used for training all agents. Left: a training timeline showing how long each curriculum phase lasts as a percentage of total training steps. Right: the changing generation parameters of all the curriculum phases. The numbers in parentheses refer to a random number in that; the loot quantity depends on the number of empty tiles in the room (e.g. 20% loot quantity indicates that the number of items in the room is equal to the 20% of empty tiles in that).

- The final branch takes as input an array of 11 discrete values containing information about the agent and the player:
  - agent HP in the range [0,20];
  - the potion currently in the agent's inventory;
  - the melee weapon currently in the agent's inventory;
  - ranged weapon in the agent's inventory;
  - a value indicating whether the agent has an active buff;
  - a value indicating whether the agent can perform a ranged attack and in which direction;
  - player HP in the range [0,20];
  - the potion currently in the player's inventory;
  - the melee weapon in the player's inventory;
  - the ranged weapon in the player's inventory; and
  - a value indicating whether the player has an active buff.

  This layer is followed by an embedding layer of size 64 and a fully-connected (FC) layer of size 256.

The outputs of all branches are concatenated to form a single vector which is passed through an FC layer of size 256; we add a *one-hot* representation of the action taken at the previous step, and the resulting vector is passed through an LSTM layer. The final output of the net is a probability distribution over the action space (like all policy-based methods such as PPO).

With this model we also propose some novel solutions that have improved the quality of agents behavior, overcoming some of the challenges of DRL in real applications:

- **Global vs local view**: we discovered that the use of both global and local map representations improves the score achieved by the agent and the overall quality of its behavior. The combination of the two representations helps the agent evaluate both the general situation of the environment and the local details close to it; we use only two levels of local maps, but for a more complex situation game developers could potentially use more views at different scales;
- **Embeddings**: the embedding layers make it possible for the network to learn continuous vector representations for the meaning of and differences between integer inputs. Of particular note is the embedding of the last branch of the network, whose inputs have their own ranges distinct from each other, which helps the agent distinguish the contents of two equal but semantically different integer values. For instance:
  - agent HP $\in [0, 20]$;
  - potion $\in [21, 23]$;
  - etc.
- **Sampling the output**: instead of taking the action with the highest probability, we sample the output, thus randomly taking *one of the most probable actions*. This behavior lets the agent make some mistakes during its interaction with the environment, guaranteeing *imperfection* and avoids the agent getting stuck in repetitive loops of the same moves.

Reward function

When defining the reward function for training policy networks, to satisfy the *prior-free* requirement we used an extremely sparse function:

$$R(t) = -0.01 + \begin{cases} -0.1 & \text{for an impossible move} \\ +10.0 * \text{HP} & \text{for the win} \end{cases}, \tag{1}$$

where HP refers to the normalized agent HPs remaining at the moment of defeating an opponent. This factor helps the system to learn as fast as possible the importance of HP: winning with as many HP as possible is the implicit goal of a general Roguelike game.

Network and training complexity

All training was done on an NVIDIA 1050ti GPU with 4GB of RAM. On this modest GPU configuration, complete training of one agent takes about two days. However, the reduced size of our policy networks (only about 5.5M parameters in the policy and baseline networks combined) allowed us to train multiple agents in parallel. Finally, the trained system needs about 12MB to be stored. We remind though that more agents of the same type can use the same model: therefore this system does not scale with the number of enemies, but only with the number of different classes.

5 Implementation

In this chapter we describe how the DeepCrawl policy networks were trained. We used two type of technologies to build both the DRL system and the game:

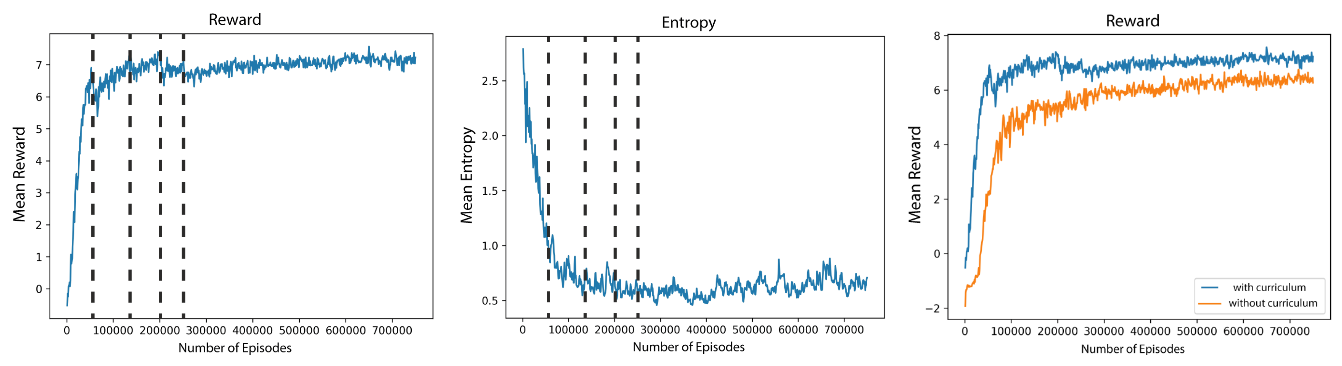


Figure 4: Plots showing metrics during the training phase for the warrior class as a function of the number of episodes. From left to right: the evolution of the mean reward, the evolution of the entropy, and the difference between the training with and without curriculum. The dashed vertical lines on the plots delineate the different curriculum phases.

Tensorforce. Tensorforce (Kuhnle, Schaarschmidt, and Fricke 2017; Schaarschmidt et al. 2018) is an open-source DRL framework built on top of Google's TensorFlow framework, with an emphasis on modular, flexible library design and straightforward usability for applications in research and practice. Tensorforce is agnostic to the application context or simulation, but offers an expressive state- and action-space specification API. In particular, it supports and facilitates working with multiple state components, like our global/local map plus property vector, via a generic network configuration interface which is not restricted to simple sequential architectures only. Moreover, the fact that Tensorforce implements the entire RL logic, including control flow, in portable TensorFlow computation graphs makes it possible to export and deploy the model in other programming languages, like C# as described in the next section.

Unity and Unity ML-Agents. The DeepCrawl prototype was developed with Unity (Unity 2019) and Unity Machine Learning Agents Toolkit (Unity ML-Agents) (Juliani et al. 2018), that is an open source plugin available for the game engine that enables games and simulations to serve as environments for training intelligent agents. This framework allows external Python libraries to interact with the game code and provides the ability to use pre-trained graph directly within the game build thanks to the TensorFlowSharp plugin (Icaza 2019).

Training setup

To create agents able to manage all possible situations that can occur when playing against a human player, a certain degress of randomness is required in the procedurally-generated environments: the shape and the orientation of the map, as well as the number of impassable and collectible objects and their positions are random; the initial position of the player and the agent is random; and the initial equipment of both the agent and the player is random.

In preliminary experiments we noticed that agents learned very slowly, and so to aid the training and overcome the problem of the sparse reward function, we use curriculum learning (Bengio et al. 2009) with phases shown in figure 3. This technique lets the agent gradually learn the best moves to obtain victory: for instance, in the first phase it is very easy to win the game, as the enemy has only 1 HP and only one attack is needed to defeat it; in this way the model can learn to reach its objective without worrying too much about other variables. As training proceeds, the environment becomes more and more difficult to solve, and the "greedy" strategy will no longer suffice: the agent HP will vary within a range of values, and the enemy will be more difficult to defeat, so it must learn how to use the collectible items correctly and which attack is the best for every situation. In the final phases loot can be difficult to find and the HP, of both agent enemy, can be within a large range of values: the system must develop a high level of strategy to reach the end of the game with the highest score possible.

Agents opponent. The behavior of the enemies agents are pitted against is *of great importance*. To satisfy requirements defined in section 3, during training the agents fight against an opponent that always makes *random moves*. In this way, the agent sees all the possible actions that a user might perform, and at the same time it can be trained against a limited enemy with respect of human capabilities. This makes the agent beatable in the long run, but still capable of offering a tough and unpredictable challenge to the human player.

Training results

The intrinsic characteristic values for NPCs must be chosen before training. These parameters are not observed by the system, but offer an easy method to create different types of agents. Changing the agent's ATK, DEF or DEX obliges that agent to extrapolate the best strategy based on its own characteristics. For DeepCrawl we trained three different combinations:

- **Archer**: ATK = 0, DEX = 4 and DEF = 3;
- **Warrior**: ATK = 4, DEX = 0 and DEF = 3; and
- **Ranger**: ATK = 3, DEX = 3 and DEF = 3.

For simplicity, the opponent has always the same characteristics: ATK = 3, DEX = 3 and DEF = 3.

To evaluate training progress and quality, we performed some quantitative analysis of the evolution of agent policies. In figure 4 we show the progression of the mean reward and

Table 1: Results of the SEQ questionnaire. Players answered with a value between 1 (strongly disagree) and 7 (strongly agree).

N°	Question	μ	Mo	Md	σ
1	Would you feel able to get to the end of the game?	5.54	6	6	1.03
2	As the level increases, have the enemies seemed too strong?	4.63	4	5	0.67
3	Do you think that the enemies are smart?	5.72	5	6	0.78
4	Do you think that the enemies follow a strategy?	6.18	6	6	0.40
5	Do you think that the enemies do counterintuitive moves?	2.00	2	2	0.63
6	Do the different classes of enemies have the same behavior?	1.27	1	1	0.46
7	Are the meaning of the icons and writing understandable?	5.72	6	6	1.67
8	Are the information given by the User Interface clear and enough?	5.54	6	6	1.21
9	Are the level too big and chaotic?	2.00	1	2	1.34
10	Are the objects in the map clearly visible?	5.81	7	7	1.66
11	Do you think that is useful to read the enemy's characteristics?	6.90	7	7	0.30
12	How much is important to have a good strategy?	6.90	7	7	0.30
13	Give a general value to enemy abilities compared to other Roguelike games	6.00	6	6	0.77
14	Is the game enjoyable and fun?	5.80	6	6	0.87
15	Does the application have bugs?	1.09	1	1	0.30

entropy for the warrior class as a function of the number of training episodes. The other two types of agents follow the same trend. In the same figure we show the difference between training with and without curriculum learning. Without curriculum, the agent learns much slower compared to multi-phase curriculum training. With a curriculum the agent achieves a significantly higher average reward at the end of training.

PPO and hyperparameters

To optimize the policy networks we used the PPO algorithm. One agent rollout is made of 10 episodes, each of which lasts at most 100 steps, and it may end either achieving success (i.e. agent victory), a failure (i.e. agent death) or reaching the maximum steps limit. At the end of 10 episodes, the system updates its weights with the episodes just experienced. PPO is an Actor-Critic algorithm with two functions that must be learned: the policy and the baseline. The latter has the goal of a normal state value function and, in this case, has the exactly same structure as the policy network show in figure 4.

Most of the remaining hyper-parameters values were chosen after many preliminary experiments made with different configurations: the policy learning rate $lr_p = 10^{-6}$, the baseline learning rate $lr_b = 10^{-4}$, the agent exploration rate $\epsilon = 0.2$, and the discount factor $\gamma = 0.99$.

6 Playability evaluation

To evaluate the DeepCrawl prototype with respect to our desiderata, we conducted playability test as a form of qualitative analysis. The tests were administered to 10 candidates, all passionate videogamers with knowledge of the domain; each played DeepCrawl for sessions lasting about 60 minutes. Then, each player was asked to answer a Single Ease Question (SEQ) questionnaire. All the questions were designed to understand if the requirements laid out in section 3 had been met and to evaluate the general quality of DeepCrawl. Table 1 summarizes the results.

We reconsider here each of the main requirements we discussed above in section 3 in light of the player responses:

- **Credibility**: as shown by questions 3, 4, and 5, the agents defined with this model offer a tough challenge to players; the testers perceived the enemies as intelligent agents that follow a specific strategy based on their properties.
- **Imperfection**: at the same time, questions 1 and 2 demonstrate that players are confident they can finish the game with the proper attention and time. So, the agents we have trained seem far from being superhuman, but they rather offer the right amount of challenge and result in a fun gameplay experience (question 14).
- **Prior-free**: questions 5 and 12 show that, even with a highly sparse reward, the model is able to learn a strategy without requiring developers to define specific behaviors. Moreover, question 13 indicates that the agents implemented using DRL are comparable to others in other Roguelikes, if not better.
- **Variety**: the testers stated that the differences between the behaviors of the distinct types of agents were very evident, as shown by question 6. This gameplay element was much appreciated as it increased the level of variety and fun of the game, and improved the general quality of DeepCrawl.

7 Conclusions

In this we presented a new DRL framework for development of NPC agents in video games. To demonstrate the potential of DRL in video game production, we designed and implemented a new Roguelike called DeepCrawl that uses the model defined in this article with excellent results. The current versions of the agents work very well, and the model supports numerous agents types only by changing a few parameters before starting training. We feel that DRL brings many advantages to the table commonly used techniques like finite state machines or behavior trees.

The recent and highly-publicized successes of DRL in mimicking or even surpassing human-level play in games like DOTA have not yet been translated into effective tools for use in developing game AI. The DeepCrawl prototype is a step in this direction and shows that DRL can be used to develop credible – yet imperfect – agents that are prior-free and offer variety to gameplay in turn-based strategy games. We feel that DRL, with some more work towards rendering training scalable and flexible, can offer great benefits over classical, hand-crafted agent design that dominates the industry.

References

[Amato and Shani 2010] Amato, C., and Shani, G. 2010. High-level reinforcement learning in strategy games. In *Proceedings of the 9th International Conference on Autonomous Agents and Multiagent Systems: Volume 1 - Volume 1*, AAMAS '10, 75–82. Richland, SC: International Foundation for Autonomous Agents and Multiagent Systems.

[Asperti, Cortesi, and Sovrano 2018] Asperti, A.; Cortesi, D.; and Sovrano, F. 2018. Crawling in Rogue's dungeons with (partitioned) A3C. *arXiv e-prints* arXiv:1804.08685.

[Bengio et al. 2009] Bengio, Y.; Louradour, J.; Collobert, R.; and Weston, J. 2009. Curriculum learning. In *Proceedings of ICML*.

[DeepMind 2019] DeepMind. 2019. AlphaStar. Web page. Accessed: April 19, 2019.

[Icaza 2019] Icaza, M. 2019. Tensorflowsharp: Tensorflow API for .NET languages. Accessed: January 18, 2019.

[Juliani et al. 2018] Juliani, A.; Berges, V.-P.; Vckay, E.; Gao, Y.; Henry, H.; Mattar, M.; and Lange, D. 2018. Unity: A General Platform for Intelligent Agents. *arXiv e-prints* arXiv:1809.02627.

[Juliani et al. 2019] Juliani, A.; Khalifa, A.; Berges, V.-P.; Harper, J.; Henry, H.; Crespi, A.; Togelius, J.; and Lange, D. 2019. Obstacle Tower: A Generalization Challenge in Vision, Control, and Planning. *arXiv e-prints* arXiv:1902.01378.

[Kempka et al. 2016] Kempka, M.; Wydmuch, M.; Runc, G.; Toczek, J.; and Jaśkowski, W. 2016. ViZDoom: A Doom-based AI research platform for visual reinforcement learning. In *IEEE Conference on Computational Intelligence and Games*. IEEE.

[Konda and Tsitsiklis 2003] Konda, V. R., and Tsitsiklis, J. N. 2003. On actor-critic algorithms. *SIAM J. Control Optim.* 42(4).

[Kuhnle, Schaarschmidt, and Fricke 2017] Kuhnle, A.; Schaarschmidt, M.; and Fricke, K. 2017. Tensorforce: a tensorflow library for applied reinforcement learning. Web page. Accessed: January 6, 2019.

[Mnih et al. 2015] Mnih, V.; Kavukcuoglu, K.; Silver, D.; Rusu, A. A.; Veness, J.; Bellemare, M. G.; Graves, A.; Riedmiller, M.; Fidjeland, A. K.; Ostrovski, G.; Petersen, S.; Beattie, C.; Sadik, A.; Antonoglou, I.; King, H.; Kumaran, D.; Wierstra, D.; Legg, S.; and Hassabis, D. 2015. Human-level control through deep reinforcement learning. *Nature* 518(7540).

[Oh et al. 2019] Oh, I.; Rho, S.; Moon, S.; Son, S.; Lee, H.; and Chung, J. 2019. Creating Pro-Level AI for Real-Time Fighting Game with Deep Reinforcement Learning. *arXiv e-prints* arXiv:1904.03821.

[OpenAI 2019] OpenAI. 2019. OpenAI 5. Web page. Accessed: January 6, 2019.

[Schaarschmidt et al. 2018] Schaarschmidt, M.; Kuhnle, A.; Ellis, B.; Fricke, K.; Gessert, F.; and Yoneki, E. 2018. LIFT: Reinforcement learning in computer systems by learning from demonstrations. *CoRR* abs/1808.07903.

[Schulman et al. 2017] Schulman, J.; Wolski, F.; Dhariwal, P.; Radford, A.; and Klimov, O. 2017. Proximal Policy Optimization Algorithms. *arXiv e-prints* arXiv:1707.06347.

[Silver et al. 2016] Silver, D.; Huang, A.; Maddison, C. J.; Guez, A.; Sifre, L.; van den Driessche, G.; Schrittwieser, J.; Antonoglou, I.; Panneershelvam, V.; Lanctot, M.; Dieleman, S.; Grewe, D.; Nham, J.; Kalchbrenner, N.; Sutskever, I.; Lillicrap, T.; Leach, M.; Kavukcuoglu, K.; Graepel, T.; and Hassabis, D. 2016. Mastering the game of Go with deep neural networks and tree search. *Nature* 529(7587).

[Sutton et al. 1998] Sutton; S., R.; Barto; and G., A. 1998. *Introduction to Reinforcement Learning*. MIT Press, 1st edition.

[Unity 2019] Unity. 2019. Unity game engine. Web page. Accessed: January 18, 2019.

[Vinyals et al. 2017] Vinyals, O.; Ewalds, T.; Bartunov, S.; Georgiev, P.; Sasha Vezhnevets, A.; Yeo, M.; Makhzani, A.; Küttler, H.; Agapiou, J.; Schrittwieser, J.; Quan, J.; Gaffney, S.; Petersen, S.; Simonyan, K.; Schaul, T.; van Hasselt, H.; Silver, D.; Lillicrap, T.; Calderone, K.; Keet, P.; Brunasso, A.; Lawrence, D.; Ekermo, A.; Repp, J.; and Tsing, R. 2017. StarCraft II: A New Challenge for Reinforcement Learning. *arXiv e-prints* arXiv:1708.04782.

[Yannakakis and Togelius 2018] Yannakakis, G. N., and Togelius, J. 2018. *Artificial Intelligence and Games*. Springer.

[Zhao et al. 2019] Zhao, Y.; Borovikov, I.; Beirami, A.; Rupert, J.; Somers, C.; Harder, J.; de Mesentier Silva, F.; Kolen, J.; Pinto, J.; and Pourabolghasem, R. 2019. Winning Isn't Everything: Training Human-Like Agents for Playtesting and Game AI. *arXiv e-prints* arXiv:1903.10545.