PenQuestEnv: A Reinforcement Learning Environment for Cyber Security

Sebastian Eresheim[1,2][a], Simon Gmeiner[2][b], Alexander Piglmann[2], Thomas Petelin[1], Robert Luh[2][c], Paul Tavolato[1][d] and Sebastian Schrittwieser[1,3][e]

[1] *University of Vienna, Faculty of Computer Science, Austria*

[2] *St. Poelten UAS, Institute for IT-Security Research, Austria*

[3] *Christian Doppler Laboratory for Assurance and Transparency in Software Protection, Austria*

Keywords: Reinforcement Learning, Machine Learning, Cyber Security.

Abstract: We present PenQuestEnv, a reinforcement learning environment for the digital board game PenQuest. PenQuest is a cyber security strategic attack and defense simulation game that enables players to carry out cyber attacks and defenses in specific scenarios, without the need for technical know-how. Its two-player setup is highly customizable and allows to model a versatile set of scenarios in which players need to find optimal strategies to achieve their goals. This environment enables the training of reinforcement learning agents for finding optimal attack and defense strategies in a variety of different scenarios and multiple different game options. With this work we intend to ignite future research on multipurpose cyber security strategies, where a single agent is capable of finding optimal strategies against a versatile set of opponents in different scenarios.

1 INTRODUCTION

Navigating the complex world of IT risk management poses demanding challenges. Identifying and prioritizing potential risks, necessitates a nuanced understanding of evolving threats and vulnerabilities. Compound this difficulty with the inherent uncertainty surrounding cyber threats, as adversaries continually adapt their tactics in response to defensive measures. Moreover, communicating these risks to higher management stakeholders can present substantial hurdles, particularly when conveying technical intricacies in a digestible manner.

PenQuest (Luh et al., 2022; Luh et al., 2020), a high level cyber attack - defense simulation game, is one approach to close this gap where complex situations intermixed with complicated measures are clearly displayed. PenQuest is built upon cyber security frameworks like MITRE ATT&CK®[1], MITRE D3FEND®[2] and NIST SP 800-53 (NIST, 2020) for close to realistic game mechanics. Finding optimal strategic decisions in every situation, however, is a non-trivial task that requires a deep understanding of the game and its dynamics.

In response to these challenges, there arises a pressing demand for innovative methodologies in IT security, risk assessment and strategic modelling. Traditional approaches often struggle to capture the dynamic and adversarial nature of cyber-attacks, leading to suboptimal resource allocation and vulnerability management. In recent years the advent of reinforcement learning (RL) (Sutton and Barto, 2018) has opened promising avenues for addressing these deficiencies. By harnessing the principles of machine learning, RL empowers the development of adaptive strategies that can learn and evolve amidst evolving environments and adversaries. Indeed, the application of RL techniques to specific domains has created substantial research progress, spanning from autonomous vehicle navigation (Dosovitskiy et al., 2017), over computer games (Bellemare et al., 2013; OpenAI et al., 2019; Vinyals et al., 2017; Vinyals et al., 2019) to financial trading (Liu et al., 2020).

Recognizing the potential of RL in the domain

[a] https://orcid.org/0000-0001-7620-8391
[b] https://orcid.org/0009-0007-2880-5547
[c] https://orcid.org/0000-0001-6536-6706
[d] https://orcid.org/0009-0004-4641-8653
[e] https://orcid.org/0000-0003-2115-2022

[1] https://attack.mitre.org/

[2] https://d3fend.mitre.org/

Eresheim, S., Gmeiner, S., Piglmann, A., Petelin, T., Luh, R., Tavolato, P. and Schrittwieser, S.
PenQuestEnv: A Reinforcement Learning Environment for Cyber Security.
DOI: 10.5220/0013122700003899

In *Proceedings of the 11th International Conference on Information Systems Security and Privacy (ICISSP 2025) - Volume 1*, pages 217-224
ISBN: 978-989-758-735-1; ISSN: 2184-4356

of IT security, in this paper, we introduce *PenQuestEnv*, an open-source extension to the adversarial security game PenQuest[3]. It provides a reinforcement learning environment for PenQuest and enables agents to learn to attack and defend assets in the cyber domain. Based on multiple information security standards combined with well-known industry frameworks and vocabularies, PenQuestEnv provides attack-defense simulations that focus on the strategic components of cyber security. Offensive agents must progress through the cyber kill chain, gaining control of the defender's assets to enable lateral movement or achieve a specific malicious objective. Defensive agents must balance preventive, detective and counter-active measures to protect their network. The setting poses a complex RL challenge due to partial state observation, aligning short-term actions with long-term strategies, and uncertain infrastructure hierarchies.

As our key contributions, we:

- provide *PenQuestEnv* consisting of an open-source extension to the existing game,
- provide an API to choose from a versatile collection of information security scenarios as well as several game options that customize the gameplay,
- provide two rule-based, opponent bots, which are able to play both roles, attack and defense, and
- showcase several promising research avenues made possible by this environment.

The remainder of this work is structured as follows: section 2 discusses previous work, related to PenQuestEnv and why it fills a previously empty niche, section 3 explains the main concepts of the game PenQuest, section 4 dives deeper into the environment around the game, section 5 highlights the potential research directions that we hope to address with this environment, before section 6 concludes the paper.

2 MOTIVATION AND RELATED WORK

CyberBattleSim (Microsoft-Defender-Research-Team., 2021) explores the use of autonomous agents in a simulated enterprise environment to study the application of reinforcement learning in cybersecurity. It focuses on lateral movement within a cyber network in a post-breach scenario from an attacker's point of view. Kunz et al. (2022) extend the CyberBattleSim framework by incorporating defensive agents and Walter et al. (2021) explore the integration of deceptive elements such as decoys and honeypots. In contrast, PenQuestEnv incorporates actions and equipment for both attackers and defenders and it includes more advanced cyber security concepts like information gathering and lateral movement.

Hammar and Stadler (2020) present a model that simulates interactions between attackers and defenders as a Markov game. The authors utilizie reinforcement learning and self-play to autonomously evolve strategies on a small, static, simulated infrastructure. It highlights the ongoing challenge of achieving consistent policy convergence even on a small infrastructure. PenQuestEnv on the other hand includes a versatile set of scenarios that include network infrastructures of differing shapes and sizes.

Besides these simulation environments, a few specialised agents have been developed using RL, for example for cross side scripting (Caturano et al., 2021) or Denail-of-Service attacks (Sahu et al., 2023). However, they operate for their particular setting only, lacking more advanced concepts of cyber security, like reconnaissance or lateral movement.

To the best of our knowledge, there is no reinforcement learning environment, that may be used to train agents for cyber attack-defence battles that:

- leverages the full cyber kill chain, and therefore contains at least actions for reconnaissance, initial foot holding, elevating privileges and lateral movement,
- incorporates different scenarios as well as different infrastructure networks of different sizes and shapes,
- includes customisable roles for attackers and defenders
- is based on existing cyber security frameworks (e.g. MITRE ATT&CK) and industry conventions and
- contains bots for baseline evaluation.

3 PenQuest

PenQuest (Luh et al., 2020; Luh et al., 2022), is a digital, turn-based attacker–defender board game in the field of information security. It was built with cyber security frameworks (e.g. MITRE ATT&CK, MITRE D3FEND and NIST SP 800-53 (NIST, 2020)) in mind for real-world resembling game mechanics. Its game board consists of interconnected digital as-

[3]https://www.pen.quest

sets (depicted in Figure 1) that can form complex interdependencies. Each turn, both players use action cards to interact with and manipulate these assets. Actions model certain activities associated with the corresponding role. The success and visibility of each action is probabilistically evaluated, where any event of the previous game history may influence the evaluation outcome. The attacker's goal in the game varies by scenario and may range from gaining knowledge about potential future targets, to stealing confidential industry secrets from a database, or taking multiple application servers offline. The defender's goal in the game is always to prevent the attacker from reaching their specific goal and thus successfully defending the network as a whole.

Note that PenQuest's underlying framework has been previously published (Luh et al., 2022), which may still serve as a reference for the more detailed and theoretical aspects of PenQuest's meta model. The game is still regularly updated, therefore more recent publications might be available.

Gameplay. PenQuest is a turn-based game where both players play action cards in sequence. Each turn is separated into two distinct phases: attack, and defense, where each player plays during their corresponding phase while the other waits for their turn.

Actors. Each game contains two actors, an attacker and a defender, both are defined by mostly the same attributes. These attributes model different capabilities and influence the game-play as well as the outcome of the game:

- **Skill** (1-5) - capabilities of the actor; determines which and how many actions in the deck can be used.
- **Determination** (1-5) - motivation and drive of the actor; determines how many action cards a player can choose from every turn.
- **Wealth** (1-5) - financial means of the actor; influences the actor's overall budget.
- **Insight** (0-15) - level of knowledge about the opponent actor; influences the success of future actions.
- **Initiative** (0-15) - financial and mental endurance of the attacker; if it is 0, the defender wins.

Assets. Assets are the core component of the game board. They model any desired IT component, ranging from physical computers to docker containers, or individual services. The state of each asset is tracked via a three dimensional damage scale where each dimension corresponds to one edge of the infamous *CIA triad*, confidentiality, integrity and availability. Each scale ranges from 0 to 3, where 3 damage points depict the maximum damage achievable. The effect – in gameplay terms – depends on the type of impact:

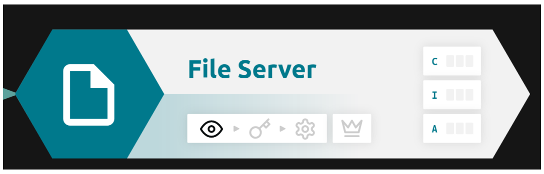


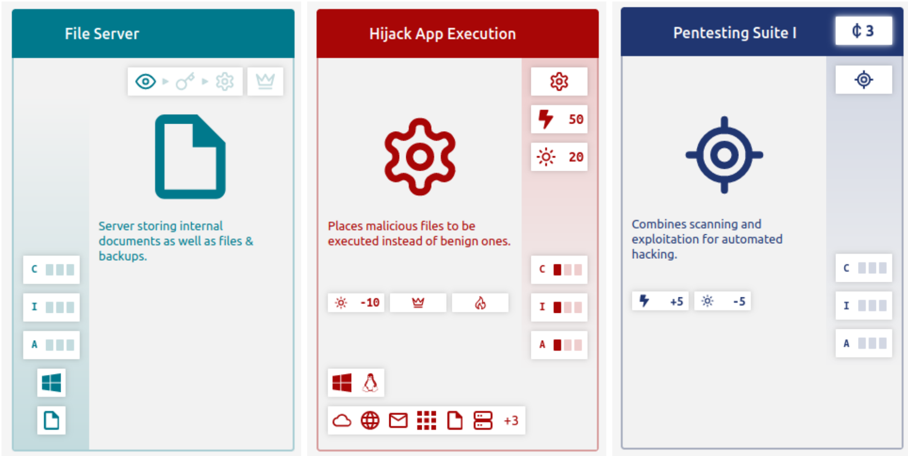
Figure 1: An asset of the game board. On the lower level the attacker's progress within our simplified cyber kill chain (Reconnaissance - eye, Initial Access - key, Execution - gear) is depicted - currently only the Reconnaissance phase is unlocked. Right next to it is the indicator whether the attacker has gained administrator privileges (crown). On the right side the 3 dimensional damage scale is visible, C for confidentiality, I for integrity and A for availability.

- **Confidentiality:** the attacker has retrieved all relevant information or data from the asset (e.g. passwords, files, configuration, etc.), which gets them additional Insight.
- **Integrity:** the attacker managed to modify data, configuration, settings, etc. on the asset, thereby gaining full control. As an effect, the actor can now use this asset for lateral movement and attack assets that where previously unreachable.
- **Availability:** the attacker has successfully taken services (or the asset a whole) offline, making it unavailable to legitimate users. Since the asset is offline, the attacker can no longer utilize actions targeting this asset. The defender, however, still may attempt recovery.

Next to damage, the progress of the attacker along an asset's cyber kill chain is of key importance. Successfully playing an action of a preceding phase unlocks the next phase in the sequence, progressing the overall attack. For accessibility's sake, PenQuest simplifies known models to 3 primary stages:

- **Reconnaissance:** the attacker gathers information about the target(s). More information lead to likelier future successes.
- **Initial Access:** the attacker establishes an initial foothold on the system.
- **Execution:** the attacker has access to the asset and is free to wreak havoc.

Assets come with three additional properties: privilege level, operating system, and category. Some actions require elevated privileges in order to be executed, while others grant them. Operating system and asset category serve as constraint and need to match the action used on the asset.



(a) Asset (b) Action (c) Equipment

Figure 2: Detailed views of examples of (a) assets, (b) actions and (c) equipment.

Actions. Actions[4] are the means by which players interact with assets. Each action represents an offensive or defensive activity the player exhibits. This e.g., includes system scans, code injection attacks, or account remediation measures. While attack actions progress the cyber kill chain as well as inflict damage points, defense actions remove damage points, apply supporting effects, or shield assets. Each action has both a base success chance as well as detection chance, which are influenced by a multitude of factors during the game (e.g. actors' Skill ratings, Insight). Optimising the own chance of success while staying covert and decreasing the opponent's success chance is a main strategic goal of PenQuest (similar to real-world cyber security actions/measures). Actions are additionally constrained by compatible operating systems and the aforementioned asset categories. They also may have effects that impact the game in different ways such as providing elevated privileges, shielding future potential damage or granting equipment to the player.

Equipment. Equipment typically provides bonuses in regard to success and detection chances, although an equipment can also be a prerequisite to play an action. Attack equipment is split into Attack Tools, Credentials, Exploits and Malware, where Attack Tools are permanent lasting equipment that provide passive buffs. Other equipment types must be used alongside an action card. Similarly, defense equipment is distinguished into Security Systems, Policies, Fixes and Analysis Tools, where Security Systems provide permanent passive buffs.

[4] A full list of actions is accessible at https://www.pen.quest/wp-content/uploads/2024/07/Actionlists.pdf

Scenarios. PenQuest allows game administrators to build different scenarios, where nearly all components (assets, actions, etc.) are independently configurable. This includes attacker goals, an overarching narrative, and a multitude of game options to tune most of the game's inherent mechanics.

4 PenQuestEnv

4.1 Main Components

PenQuestEnv[5] is built on top of the Farama Gymnasium (Towers et al., 2023) framework, which itself builds on top of the widely used OpenAI Gym framwork (Brockman et al., 2016). Therefore, observation- and action-spaces build upon spaces contained in these frameworks.

State & Observations. A *state* in PenQuestEnv contains the full game information. This includes all role attributes of both players, all assets, all previously played actions and their outcomes, effects and damage dealt, all purchased equipment of both players, all action cards on the players hands and common turn information. However, an *observation* only includes public information such as the current turn and game phase, or player-owned specific information, like the players action cards, detected assets or purchased equipment. It does not include opponent information like the opponent's action cards. The observation space of the environment is a multi-level, dictionary space that resembles the logical model of

[5] https://github.com/seresheim/penquest-env

the game, where keys are strings and the values again different gymnasium spaces depending on the property they model. The following snippet shows the highest level observation space:

```
{
    "turn": Discrete(1e10),
    "phase": Discrete(6),
    "actor_id": Discrete(64),
    "actor_connection_id": Discrete(64),
    "roles": Sequence(...),
    "hand": Sequence(...),
    "equipment": Sequence(...),
    "board": Sequence(...),
    "shop": Sequence(...),
    "selection_choices": Sequence(...),
    "selection_amount": Discrete(20)
}
```

Each value of the dictionary space either consists of a discrete space containing a number of different discrete values provided, or a sequence space, containing variable size lists where each element is also again a dictionary space. For more information, please visit the documentation.

Actions. The action space is a sequence space of discrete values, where the sequence length of the action depends on the currently required interaction type: *buy equipment*, *redraw action cards* and *play action cards*. For a *buy equipment* action, each element of the sequence is an index to the position an equipment currently holds in the shop. For example the action

```
a = (5, 17, 3)  # buy equipment
```

indicates to buy the 3rd, 5th and 17th equipment in the shop. An empty sequence indicates to buy no equipment this turn. *Redraw action cards* actions have the same structure, except the indices are entries into a list of (pre-selected) offered actions. The specific set of action cards for redrawing is configuarble via game options. *Play action cards* actions always contain six integers. Table 1 lists the exact meanings for each position of the *play action card* action. For example the action

```
a = (1, 22, 1, 4, 2, 0)  # play action card
```

means: 'Play the second action on the hand onto the asset with ID 22 with confidentiality damage supported by the fourth action on the hand and provided with the second equipment in hand'.

Rewards. Rewards are provided sparsely at the end of the game, +1 for winning or -1 for losing. On all intermediate steps the reward is 0.

Table 1: 'play action card' actions always consists of an integer sequence of length six. Each position has it's own meaning. Apart from the first position all other fields may be 0, indicating that this position is not required for this action. Because of this use of the value 0, integers at the positions 1-5 which indicate indices, start indexing from 1.

Position	Meaning
0	Index of action card that is played
1	ID of the asset the action targets
2	Index of damage scale
3	Index of support action card
4	Index of an equipment card
5	ID of a previously played action card, the current one tries to mitigate

Scenarios. Currently, PenQuestEnv encompasses nine scenarios, where each scenario contains a different infrastructure setup. Out of brefity we provide the following statistics about the number of assets across all scenarios: maximum: 34, average: 12.77, median: 10 and minimum: 6.

4.2 Playing the Game

Game Dynamics. The game is a non-cooperative, two-player game and non-deterministic, as each player can in most situations choose between a number of possible actions non-deterministically. Additionally, it also contains stochastic dynamics, as the success and detection of action cards depends on probabilities. PenQuestEnv is an imperfect and incomplete information game, due to invisible opponent actions as well as unknown opponent objectives and strategies. Only a very restricted set of information about the current game state is observed by the players; during the game, more parts of this information may become unveiled. This aspect of partial observability is most notable when both players are initially presented with their own view of the game board. Attackers do not know the full details of the network and defenders do not know the attacker's goal. Additionally, both players per default do not know the action cards the other player played, however both have the opportunity to detect some opponent actions during the game.

Game Options. Because it might be challenging for an agent to learn all game mechanics at once, game options introduce the possibility to customise aspects of the dynamics individually and allow to simplify the game across multiple dimensions. Besides others, this includes scenarios, attacker goals, seeds, making success and detection chances (individually) deterministic and turning on/off support actions and equipment.

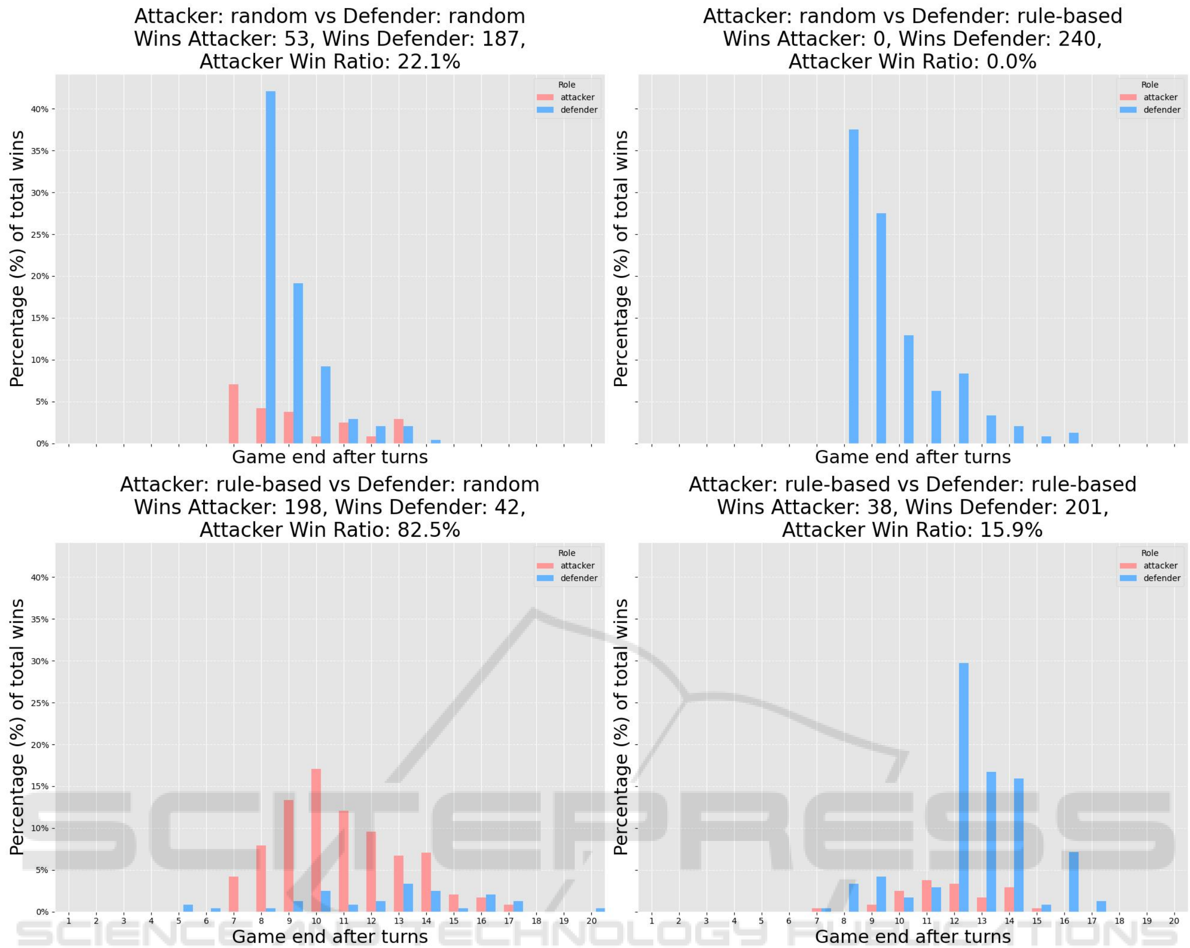


Figure 3: Shows the amount of turns it took a type of bot (rule-based or random) to achieve it's goal when matched against other specific bot types. Each plot shows the outcomes of 240 games, evaluated on scenario 'Medium 1'. A bar indicates the amount of games that were won at each turn by the player (red: attacker, blue: defender). The amount of games won, displayed as a fraction of total games played is shown on the y-axis, the final game turn on the x-axis. In total, the games were won by the attacker in 30.1% of games, and 69.9% by the defender. The performance difference between attacker and defender greatly depends on the complexity and depth of the chosen scenario. We have chosen a scenario with a slight bias towards favoring the defensive side, which appears more pronounced when looking at longer game-durations or the pairing of rule-based against rule-based bot, where the rule-based attacker only came out on top in 15.9% of games against the rule-based defender's reactive strategy. Note that both axes have the same scale for all plots.

4.3 Built-In Opponent Bots

The environment also currently controls opponent bots that can be used to challenge or evaluate RL agents. There are currently two kinds of opponent bots, a random bot, and a rule-based bot.

- **Random Bot** - selects actions randomly from a pool of valid options.
- **Rule-based Bot** The rule-based bot has separate strategy sets for attack and defense. Its attacking strategy revolves around discovering the target asset(s) as quickly as possible by probing unexplored attack vectors (integrity attacks) and focusing the target directly once it is exposed. The defending rules focuses primarily on immediately responding to all harm done (response actions) and secondly pre-emptively securing assets from receiving damage (prevention actions).

To showcase the performance of the bots as well as typical game lengths (measured in game turns) we conducted multiple matches between the bot types. Figure 3 depicts the outcomes of 240 games for each pairing of bot type, with rule-based and random bot taking the role of attacker or defender. Note that the game lengths may increase if an attacking agent pays much care on it's intrusion attempts not being detected. These opponent bots can be used to evaluate RL agents or strategies.

5 PROMISING RESEARCH DIRECTIONS

5.1 Multiplayer Experiments

PenQuestEnv enables to train an agent against different opponents, one at a time. This style of training bears the potential to overfit on a specific opponent strategy where a specific weakness is exploited. This can result in winning against one specific (advanced) strategy but due to a lack of generalization at the same time loosing against a rather simple opponent. Such behaviour was already observed in other games where no single best strategy exists, like football (Kurach et al., 2020), or StarCraft2 (Vinyals et al., 2019). This non-transitivity of strategies is also characteristic for real-world cyber incidents, where an ever evolving arms race between attackers and defenders, constantly adapting to the opponents strategy, takes place. We therefore think that PenQuestEnv is a fitting opportunity to inspire research in this area, as little similar work currently exists in IT security in this manner.

5.2 Risk Assessment Experiments

Risk assessment in computer systems is a non-trivial task. By finding strategies in given scenarios that are most likely to succeed, trained agents can also be used to support decisions for risk assessment. Such agents may provide additional information for security management decisions on where to put resources like personnel attention or money. The insights gathered by these agents, adaptable to different risk-tolerances can be invaluable resources to decision makers. We believe PenQuestEnv provides a unique setting to enable future research into this area.

6 CONCLUSION

In this paper we introduced PenQuestEnv, a novel open source reinforcement learning environment extension to the partial-information, turn-based, digital, cyber security board game PenQuest. It is non-symmetric in its action choices, highly diverse and challenging to win against a wide variety of opponents. PenQuestEnv comes with a diverse set of different scenarios making it a fitting environment for training multipurpose cyber agents, as well as two baseline bots that help evaluating new RL agents. We expect that this environment will be useful to AI and security researchers alike to investigate current scientific challenges.

ACKNOWLEDGEMENTS

This research was primarily funded by the Austrian Science Fund (FWF) [P 33656-N]. Additionally the financial support by the Austrian Federal Ministry of Labour and Economy, the National Foundation for Research, Technology and Development and the Christian Doppler Research Association is gratefully acknowledged. For the purpose of open access, the author has applied a CC BY public copyright licence to any Author Accepted Manuscript version arising from this submission.

REFERENCES

Bellemare, M. G., Naddaf, Y., Veness, J., and Bowling, M. (2013). The arcade learning environment: An evaluation platform for general agents. *Journal of Artificial Intelligence Research*, 47:253–279.

Brockman, G., Cheung, V., Pettersson, L., Schneider, J., Schulman, J., Tang, J., and Zaremba, W. (2016). Openai gym.

Caturano, F., Perrone, G., and Romano, S. P. (2021). Discovering reflected cross-site scripting vulnerabilities using a multiobjective reinforcement learning environment. *Computers & Security*, 103:102204.

Dosovitskiy, A., Ros, G., Codevilla, F., Lopez, A., and Koltun, V. (2017). CARLA: An open urban driving simulator. In *Proceedings of the 1st Annual Conference on Robot Learning*, pages 1–16.

Hammar, K. and Stadler, R. (2020). Finding effective security strategies through reinforcement learning and self-play. In *2020 16th International Conference on Network and Service Management (CNSM)*, pages 1–9. IEEE.

Kunz, T., Fisher, C., La Novara-Gsell, J., Nguyen, C., and Li, L. (2022). A multiagent cyberbattlesim for rl cyber operation agents. In *2022 International Conference on Computational Science and Computational Intelligence (CSCI)*, pages 897–903. IEEE.

Kurach, K., Raichuk, A., Stańczyk, P., Zając, M., Bachem, O., Espeholt, L., Riquelme, C., Vincent, D., Michalski, M., Bousquet, O., et al. (2020). Google research football: A novel reinforcement learning environment. In *Proceedings of the AAAI conference on artificial intelligence*, volume 34, pages 4501–4510.

Liu, X.-Y., Yang, H., Chen, Q., Zhang, R., Yang, L., Xiao, B., and Wang, C. D. (2020). Finrl: A deep reinforcement learning library for automated stock trading in quantitative finance. In *Proceedings of the 34th Conference on Neural Information Processing Systems (NeurIPS 2020*.

Luh, R., Eresheim, S., Größbacher, S., Petelin, T., Mayr, F., Tavolato, P., and Schrittwieser, S. (2022). Penquest reloaded: A digital cyber defense game for technical education. In *2022 IEEE Global Engineering Education Conference (EDUCON)*, pages 906–914. IEEE.

Luh, R., Temper, M., Tjoa, S., Schrittwieser, S., and Janicke, H. (2020). Penquest: a gamified attacker/defender meta model for cyber security assessment and education. *Journal of Computer Virology and Hacking Techniques*, 16:19–61.

Microsoft-Defender-Research-Team. (2021). Cyberbattlesim. https://github.com/microsoft/cyberbattlesim. Created by Christian Seifert, Michael Betser, William Blum, James Bono, Kate Farris, Emily Goren, Justin Grana, Kristian Holsheimer, Brandon Marken, Joshua Neil, Nicole Nichols, Jugal Parikh, Haoran Wei.

NIST (2020). Security and privacy controls for information systems and organizations. Technical Report Federal Information Processing Standards Publications (FIPS PUBS) 140-2, Change Notice 5 December 10, 2020, U.S. Department of Commerce, Washington, D.C.

OpenAI, Berner, C., Brockman, G., Chan, B., Cheung, V., Dębiak, P., Dennison, C., Farhi, D., Fischer, Q., Hashme, S., Hesse, C., Józefowicz, R., Gray, S., Olsson, C., Pachocki, J., Petrov, M., de Oliveira Pinto, H. P., Raiman, J., Salimans, T., Schlatter, J., Schneider, J., Sidor, S., Sutskever, I., Tang, J., Wolski, F., and Zhang, S. (2019). Dota 2 with large scale deep reinforcement learning.

Sahu, A., Venkatraman, V., and Macwan, R. (2023). Reinforcement learning environment for cyber-resilient power distribution system. *IEEE Access*.

Sutton, R. S. and Barto, A. G. (2018). *Reinforcement learning: An introduction*. MIT press.

Towers, M., Terry, J. K., Kwiatkowski, A., Balis, J. U., Cola, G. d., Deleu, T., Goulão, M., Kallinteris, A., KG, A., Krimmel, M., Perez-Vicente, R., Pierré, A., Schulhoff, S., Tai, J. J., Shen, A. T. J., and Younis, O. G. (2023). Gymnasium.

Vinyals, O., Babuschkin, I., Czarnecki, W. M., Mathieu, M., Dudzik, A., Chung, J., Choi, D. H., Powell, R., Ewalds, T., Georgiev, P., et al. (2019). Grandmaster level in starcraft ii using multi-agent reinforcement learning. *Nature*, 575(7782):350–354.

Vinyals, O., Ewalds, T., Bartunov, S., Georgiev, P., Vezhnevets, A. S., Yeo, M., Makhzani, A., Küttler, H., Agapiou, J., Schrittwieser, J., et al. (2017). Starcraft ii: A new challenge for reinforcement learning. *arXiv preprint arXiv:1708.04782*.

Walter, E., Ferguson-Walter, K., and Ridley, A. (2021). Incorporating deception into cyberbattlesim for autonomous defense. *arXiv preprint arXiv:2108.13980*.