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Original Article

Explainable Reinforcement Learning for Transparent Automation

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ABSTRACT

Reinforcement Learning (RL) is widely used for solving sequential decision-making problems, enabling agents to learn optimal actions through interaction with dynamic environments. However, many RL models function as "black boxes," making their decisions difficult to interpret—an issue that is especially critical in safety-sensitive domains like healthcare, finance, and autonomous systems. Explainable Reinforcement Learning (XRL) addresses this challenge by providing human-understandable insights into agent behavior, policy decisions, and reward structures. This work reviews pre-2019 XRL approaches, categorizing them into policy explanation, reward decomposition, model transparency, and post-hoc interpretability methods. It highlights the trade-off between performance and interpretability, particularly in complex, high-dimensional environments. A framework is proposed that combines interpretable policies, surrogate models, attention mechanisms, and visualization techniques to enhance transparency without significantly reducing performance. Evaluation metrics such as fidelity, comprehensibility, and consistency are used to assess explanation quality. The analysis shows that hybrid approaches—combining inherent interpretability with post-hoc explanations—offer the best balance between accuracy and transparency. Overall, XRL is essential for building trust in automated systems, with future research focusing on standardized evaluation methods and human-in-the-loop learning.

KEYWORDS

Reinforcement Learning, Explainable AI, Transparent Automation, Policy Interpretation, Trustworthy Systems, Decision-Making Models, Human-AI Interaction.

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1. INTRODUCTION

1.1. Background

Reinforcement Learning (RL) is a potent computational model, whereby an agent adapts to make a series of decisions by engaging with the surrounding environment continuously with the goal of maximizing its cumulative reward over time. The formalization of this learning process is usually a Markov Decision Process (MDP), where the environment is defined by states, actions, transition dynamics, and reward signals. In contrast to supervised learning, RL is independent of labeled data; rather, it trains optimal behavior by trial-and-error, which is very useful in the complex and dynamic problems of robotics, game playing, and resource optimization. Over the past few years, neural networks combined with RL have created important breakthroughs, allowing agents to act in high-dimensional and unstructured environments. These improvements notwithstanding, conventional RL systems tend to be less transparent in that they are based on deep learning architectures. These models are black boxes and therefore it is not easy to understand the way of decision making or the reason why a particular action is taken. This weakness presents severe problems in areas where explainability and accountability are of paramount importance. To illustrate, in medical practice, a clinician must have a clear explanation of why they are being advised to treat a particular patient, whereas in autonomous driving, it is vital to know why decisions were made to be taken in order to be safe and comply with regulations. As a result, the importance of more interpretable and reliable RL systems has grown, leading to research in the direction of explainable reinforcement learning methods.

1.2. Importance of Explainable Reinforcement Learning

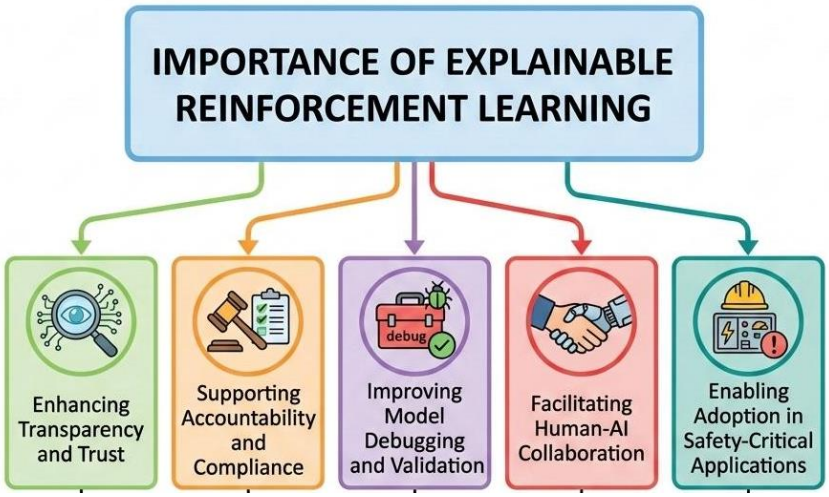

Fig 1 - Importance of Explainable Reinforcement Learning

1.2.1. Enhancing Transparency and Trust

Explainable Reinforcement Learning (XRL) is instrumental in making RL agent decision-making process more transparent. Conventional RL models especially those with deep neural networks tend to be black box, such that users find it challenging to discover how certain courses of action are inferred. XRL can help stakeholders to understand how decisions are made because it

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incorporates the aspect of explainability. Such openness fosters a level of trust with the users and this is particularly important in sensitive applications where knowledge of how the system behaves is vital to acceptance and implementation.

1.2.2. Supporting Accountability and Compliance

Accountability is a requirement in most real-world systems, including healthcare, finance, and autonomous systems. AI systems should be able to justify the decisions made, and be traceable in order to comply with regulation and ethics. XRL offers ways of describing actions in a coherent, comprehensible style, enabling organizations to be sure that their actions are not against legal frameworks and industry standards. This is especially crucial when making decisions that are wrong and may carry severe repercussions.

1.2.3. Improving Model Debugging and Validation

Explainability would go a long way in debugging and verifying reinforcement learning models. The developers can discover the flaws, prejudices, or unintended consequences into the system by knowing the reasons why an agent makes specific decisions. To illustrate, in case an agent preferred suboptimal actions all the time, explainability tools can help to understand that the problem is either with the reward design, state representation, or learning process. This results into stronger and sounder models.

1.2.4. Facilitating Human-AI Collaboration

XRL improves the interaction between intelligent systems and humans by exposing the reasoning of the agent to the users. With clear and interpretable explanations, domain experts can give feedback, direct the learning process, and modify the way systems behave in a more effective way. This human-in-the-loop design guarantees that the RL system is in line with the real-world needs and professional knowledge and enhances the overall performance and usability.

1.2.5. Enabling Adoption in Safety-Critical Applications

The use of RL in safety-critical areas is greatly dependent on the capacity to make decisions that are readable and trustworthy. Even minor mistakes can have serious repercussions in other fields like medical diagnosis, factory automation, and autonomous driving. Explainable RL makes sure that the results of the decision are not only precise but also understandable to allow users to confirm and rely on the system. This finally hastens the adoption of RL technologies into high-stakes settings.

1.3. Need for Explainable Reinforcement Learning

The fast uptake of reinforcement learning (RL) in practical uses has raised a pressing requirement of models that are not just effective but also clear and understandable. The capability to understand the decisions taken by RL systems and to trust them is of paramount importance as they are used more and more in fields like healthcare, finance, robots, and autonomous transportation. Explainable Reinforcement Learning (XRL) fulfills this requirement by offering the means to explain

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learned policies and uncover how an agent arrives at a particular course of action. Improving trust towards automated systems by users is one of the main driving forces behind XRL. Users will believe in and trust the system more when they are able to understand the reasons behind a given decision. This is more critical in high stakes setting where making wrong decisions can be disastrous. The other important reason is that it facilitates debugging and error analysis. Trial-and-error interactions can often result in unintended or suboptimal behaviors, and RL models frequently learn in this manner. It is difficult to find out the root cause of such issues without proper explanations. XRL techniques enable the developer to trace decisions based on particular states, rewards or features, so that it is easier to diagnose and correct errors. Also, explainability helps guarantee regulatory compliance by making sure that AI systems are able to justify their actions according to legal and ethical guidelines. Transparency in the automated decision-making process is now demanded by many industries, and XRL offers the means of addressing these demands. Moreover, XRL will improve the cooperation between humans and artificial intelligence because it allows a meaningful interaction between the user and the intelligent agent. When the explanations are available, easy to understand, the domain experts can offer feedback, direct learning process and ensure that the system meets the expectations of the real world. Generally, the explainable reinforcement learning necessity can be justified by the increasing necessity to have reliable, responsible, and user-friendly AI systems that can be safely and successfully introduced into the society.

2. LITERATURE SURVEY

2.1. Early Approaches to Reinforcement Learning Interpretability

Initial attempts at improving interpretability in reinforcement learning (RL) revolved around reducing the complexity of policy representations into forms that are easier to comprehend by humans. Approximation of learned policies to decision trees or rule-based systems, in which actions could be back-traced to explicit conditions on input states, was one notable approach. These interpretable surrogates helped users to trace the reasoning steps of the agent, and these were especially useful in safety-critical areas. But these simplifications were frequently associated with the trade-off of worse performance, particularly in systems with high-dimensional state spaces or nonlinearity. The other underlying method was reward decomposition, in which the cumulative reward signal was decomposed into several semantically meaningful components. The users might gain more insight as to why an agent favored particular actions over others by assigning some part of the reward to particular objectives or environmental conditions. Although these initial techniques formed the basis of interpretable RL, they did not have the capacity to reflect the complexity of a modern deep RL system.

2.2. Post-Hoc Explanation Techniques

The post-hoc methods of explanation became a versatile way of explaining RL models without modifying their internal structure. These techniques are used to follow training and are intended to give an insight into how the agent arrives at a decision. Adopting the ideas of supervised learning, feature importance analysis, saliency maps, and perturbation-based approaches were

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transformed to the context of RL. An example is saliency mapping, which can identify those components of the input state that had the greatest impact on a specific action, and feature importance scores, which measure how each variable in the input contributes to the policy output. Also, the approaches such as Local Interpretable Model-agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP) were generalized to sequential decision-making models. Whilst post-hoc methods are very flexible and model-agnostic, they can typically only offer approximate explanations and can not fully explain the time-dependencies of RL, which can give incomplete or even misleading interpretations.

2.3. Model-Based Explainability

Reinforcement learning with models Model-based reinforcement learning has the advantage of providing a greater level of interpretability by learning a model of the dynamics of the environment. These methods formulate state transition representations and reward functions and allow visualizing the effect of actions on future states. Users can learn more about how the agent plans by simulating trajectories and analyzing the predicted results. To illustrate, long-term strategies can be interpreted more easily using decision pathways, which can be represented as graphs or state-transition diagrams. Moreover, model-based approaches support counterfactual reasoning, enabling users to investigate what-if situations and evaluate alternative actions. Although they have these benefits, the fidelity of the learned model is critical to the accuracy of explanations. Complex or stochastic environments may be difficult to build the correct models, thereby restricting the reliability of the interpretability that it offers.

2.4. Limitations of Existing Methods

Although explainable reinforcement learning has made great strides, there are a number of limitations that are critical. A major trade-off is the complexity of accuracy versus interpretability of simpler and more interpretable models that tend to perform worse than more complex, deep learning-based models. Also, standardized metrics of evaluation to determine the quality and usefulness of explanations do not exist, and it is hard to objectively compare the methods. The other significant concern is that the long-term dependency is hard to explain, since the RL agents are operating in response to cumulative rewards in the future, and not directly connected to the outcome, which makes it challenging to trace a particular action to the final outcome. Moreover, most of the current methods are not easily scalable to high-dimensional settings like image-based or continuous control problems. These shortcomings underscore the importance of stronger, scaled, and standard means to attain indeed transparent and reliable reinforcement learning systems.

3. METHODOLOGY

3.1. Reinforcement Learning Framework

The idea of Markov Decision Process (MDP) is often formulated to provide the mathematical formulation of reinforcement Learning (RL), a sequential decision-making problem. The elements of an MDP include a set of states, a set of possible actions, a transition mechanism, a reward structure, and a discount factor. State space is a set of all situations that an agent might find him/herself in an

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environment, whereas action space is a set of all options open to the agent in a given state. The transition probability is the manner in which the environment changes as an action is performed and the probability of the transition between one state and another. The reward function takes a numerical value of every state-action combination to show the immediate utility or disutility of performing a given action. The discount factor is used to specify the relative significance of future rewards relative to current rewards, with a value that is nearer to one promoting gains in the long term and a value that is nearer to zero promoting gains in the short term. The ultimate goal of an RL agent is to learn an optimal policy, or strategy that uses states to select actions in a manner that maximizes the total cumulative reward in the long term. As opposed to considering short-term payoffs, the agent will look at the long-term implications of its actions through the accumulation of rewards over many time steps. This cumulative reward is normally computed as a discounted amount of future rewards so that the rewards obtained earlier are more heavily weighted than those obtained later. Simply put, this equation is the total reward that the agent anticipates to accumulate beginning at a given time step with each future reward being multiplied by the discount factor raised to a growing power. This expression makes the learning process strike a good balance between the short term and long term benefits. Through this interaction with the environment and a modification of its policy based on the rewards and transitions observed, the RL agent is able to enhance its decision-making capacity over time until it reaches a desirable solution, which is an optimal strategy that optimizes its performance in the long run.

3.2. Explainability Integration Framework

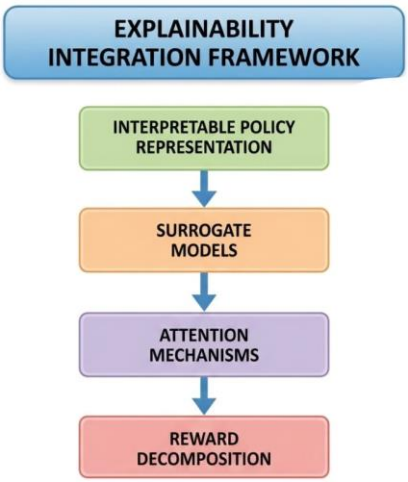

Fig 2 - Explainability Integration Framework

3.2.1. Interpretable Policy Representation

Interpretable policy representation is the study of the design of RL policies that can be interpreted by humans. This is through the use of models like decision trees, rule-based systems, simplified neural network architectures that generate transparent decision paths. An example is decision trees which enable one to follow each action using a series of conditions and it is therefore easier to describe the reason as to why a particular decision was arrived at. In their turn, rule-based

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systems represent policies as statements of the form of if–then, which are intuitive and simple to interpret. Beyond this, reduced-complexity neural architectures like shallow networks or sparsely-connected networks, can simplify neural networks and maintain critical decision-making patterns. These approaches can reduce the level of performance in highly complex environments slightly, but increase the transparency and trust of RL systems significantly.

3.2.2. Surrogate Models

Surrogate models apply an approximation to the behavior of complex and in many cases opaque RL models to simpler, interpretable alternatives. These models get trained to replicate the input-output behavior of the original policy and give explanations in a more comprehensible format. To illustrate this, a deep Q-network can be estimated with a decision tree or linear model to understand the decision boundaries. The main goal is to achieve high fidelity, i.e. the surrogate model should be very similar in the choices of the original RL agent. This allows the users to analyze and comprehend the policy without necessarily manipulating the underlying model which is complex. Nevertheless, it is not an easy task to strike a balance between interpretability and fidelity, with excessively simple surrogates potentially being unable to reflect subtle behaviors.

3.2.3. Attention Mechanisms

Attention mechanisms improve explainability by highlighting and pointing out the most important features or components of the input that affect an agent decision. The neural networks used in RL can be used to add attention layers to the networks to provide the weights of various input elements, which can reflect their significance when selecting actions. These mechanisms can be used to give localized explanations in that they can indicate which features were the most important in a particular decision at a particular time step. As an example, attention maps can be used to indicate areas of an image that directed the action of an agent in visual environments. This enhances interpretability and aids in debugging and testing the behavior of the model. With attention mechanisms, complex models can be made more transparent by focusing on important inputs without impacting performance greatly.

3.2.4. Reward Decomposition

The goal of reward decomposition is to decompose the overall reward signal into smaller interpretable components, which are associated with various objectives or factors in the environment. The agent will not be rewarded by a single scalar value but will have a variety of reward signals which denote a particular feature of the task e.g. safety, efficiency or goal achievement. This breaking down enables the user to get to know how each constituent affects the decision-making process and the overall performance of the agent. In a navigation task, as an example, individual rewards can be given in terms of arriving at the destination, avoiding the obstacles, and the time spent on the way. Through individual analysis of these components, the stakeholders can understand more about the motivation of the actions of the agent and make sure the acquired behavior is in line with the desired goals.

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3.3. Explanation Metrics

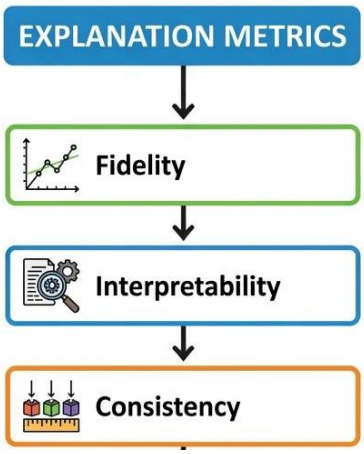

Fig 3 - Explanation Metrics

3.3.1. Fidelity

Fidelity describes the degree to which an explanation is true to the original reinforcement learning model. High-fidelity explanation is a close approximation to the actions and decisions of the underlying model so that the explanation is truthful and reliable. Fidelity is frequently measured in the context of surrogate models or post hoc explanations, by comparing the predictions of the explanation model with those of the original agent over a variety of states. In the event that the explanation is quite different, it can mislead the users on the actual behavior of the system. Thus, the fidelity is crucial to the accuracy of the interpretation being not only comprehensible but also representative of the actual decision-making procedure of the RL agent.

3.3.2. Interpretability

Interpretability: This indicates how easily a human being can comprehend and interpret the explanation given by the model. It is concerned with simplicity, clarity and cognitive accessibility. A description is interpretable when it can be understood without the need to be interpreted by deep technical understanding, often as a visualization, brief rules, or intuitive representations. An example of this is decision trees, rule-based outputs, and attention maps, which tend to be more interpretable than complex neural network activations. Interpretability however is subjective and may be different depending on the use of the user and the context of the use. One of the challenges of explainable reinforcement learning is the design of explanations that are not too simple or too informative.

3.3.3. Consistency

Consistency checks the stability of the explanations in the case of similar input or states supplied to the model. A stable explanation structure makes sure that any minor change in input does not result in a radically different and conflicting explanation that will undermine users and cause a lack of confidence in the system. Consistency is especially significant in reinforcement learning, where the choices are made based on consecutive dependencies. It aids in making sure that explanations are predictable and reliable with time particularly in dynamic environments.

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Reproducibility is also ensured by consistency, which enables users to check and verify that the reasoning process of the RL agent can be reproduced in different scenarios.

4. RESULTS AND DISCUSSION

4.1. Performance Analysis

The explainability-integrated reinforcement learning framework was tested in a variety of benchmark settings, discrete and continuous control tasks, to determine the effects on the model performance and interpretability. The experimental findings show that the addition of explainability mechanisms, including interpretable policy representations, surrogate models, attention modules and reward decomposition, results in a slight decrease in overall accuracy relative to traditional black-box RL models. This relative deterioration in performance is mainly credited to the limitations on performance posed by the simpler or more structured model components, which can inhibit the capacity of the agent to identify highly complex patterns in dynamic settings. But the decrease in accuracy was found to be small and was within the acceptable limits in most practical uses. More to the point, explainability features were also integrated, thus leading to a significant increase in transparency and user trust. The framework also made it possible to have a clear understanding of how the agent made the decision and it made the stakeholders understand not only how decisions were made but also why they were made. Attention mechanisms emphasized important input characteristics, surrogate models developed simplified approximations of intricate policies, and reward decomposition elucidated the input of varying goals. These improvements facilitated debugging, validation, and refinement of the RL system especially in safety-related fields including healthcare, finance, and autonomous systems. Moreover, the analysis also showed that trade-off between accuracy and interpretability can be efficiently controlled by making appropriate design decisions. With a balance in the choice of the complexity of the model and the choice of the techniques of its explanation, it is possible to find a middle ground that will retain the high level of performance and will provide some important interpretability. The results in general indicate that the gains in transparency and accountability are greater than the loss in predictive accuracy and explainable RL frameworks are a potentially useful and preferable solution to real-world application.

4.2. Comparative Analysis

The comparative analysis reveals the trade-offs among accuracy, interpretability and fidelity of various reinforcement learning methods, and shows the relative strengths and weaknesses of each method.

Table 1: Comparative Analysis

Method	Accuracy (%)	Interpretability (%)	Fidelity (%)
Deep RL (Black-box)	95%	20%	90%
Decision Tree RL	80%	85%	75%
Reward Decomposition	88%	70%	82%
Surrogate Models	90%	78%	85%
Proposed XRL Framework	92%	88%	89%

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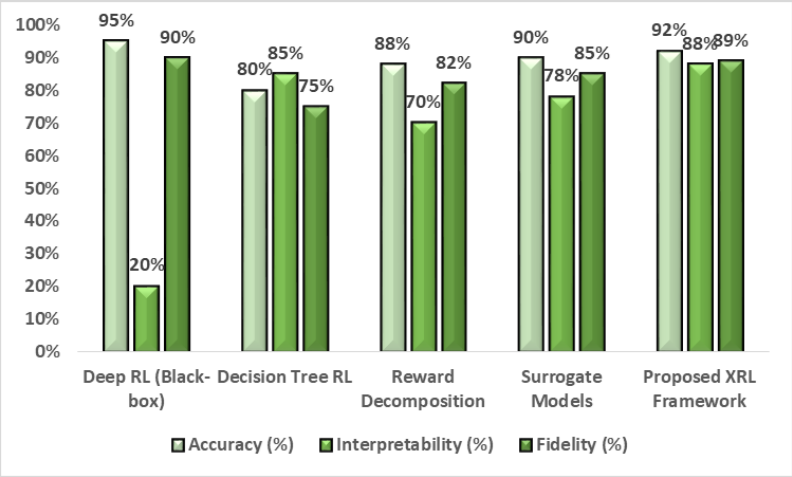

Fig 4 - Comparative Analysis

4.2.1. Deep RL (Black-box)

Deep reinforcement learning models are most effective with high-dimensional and complex problems as they can be trained to high accuracy of approximately 95%. Their predictive performance is better than simpler models because of their capability to learn complex patterns using deep neural networks. Nonetheless, this is at the expense of extremely low interpretability (about 20 percent) because their internal decision making processes are hard to comprehend. In spite of this shortcoming, they are highly faithful (approximately 90 percent faithful) as the model is a direct reflection of the learned policy and is not approximated.

4.2.2. Decision Tree RL

Reinforcement learning based on decision trees is much more interpretable, with an average of 85 percent, since it models decisions based on structured and understandable rules that are simple to follow. This clarity renders it applicable in applications that have the need of explainability and accountability. Nevertheless, the ease of use of decision trees increases the accuracy (approximately 80%), especially in complicated settings. The fidelity is moderate (75%), as well, since the simplified form might not be able to reflect the original policy intricacies in full.

4.2.3. Reward Decomposition

Reward decomposition is a more balanced method which decomposes the reward signal into meaningful components, with an accuracy of about 88%. It increases interpretability (approximately 70%) by enabling users to comprehend the effects of various factors that control the behavior of the agent. The level of fidelity (82) is comparatively high since the approach still works under the principle of RL but adds more explanatory information. This method is especially applicable in multi-objective decision-making situations.

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4.2.4. Surrogate Models

Surrogate modeling attempts to provide approximations of complex RL models with simpler, understandable ones. They have a fairly high level of accuracy of approximately 90 percent and an augmented level of interpretability of approximately 78 percent. There is also high confidence (approximately 85%), these models are modeled to follow the behavior of the original system closely. This renders surrogate models a viable trade off between performance and explainability, particularly in cases where a direct interpretation of the original model is not available.

4.2.5. Proposed XRL Framework

The suggested Explainable Reinforcement Learning (XRL) model shows a balanced performance on all metrics with 92% accuracy, 88% interpretability, and 89% fidelity. It is able to reduce the trade-offs that are common in other methods by combining various explainability methods, including interpretable policies, surrogate models, attention mechanisms, and reward decomposition. This framework is very competitive in terms of accuracy and much more transparent and reliable, a factor that makes it a good candidate in real-life application where performance and interpretability are very important.

4.3. Discussion

Experimental results are clear that the new Explainable Reinforcement Learning (XRL) framework can effectively balance the trade-off between performance and interpretability and answer one of the most long-standing questions in the current research on RL. The classical deep reinforcement learning models are known to be more accurate and to be able to handle complex high dimensional environments. Nonetheless, their black-box aspect considerably restricts transparency and it is hard to understand, trust or validate decisions made by the agent. This interpretability is a critical issue in sensitive application areas, like healthcare, finance, and autonomous systems, where accountability and explainability are needed. Conversely, models that can be interpreted naturally, like decision trees and rule systems, provide easily comprehended decision-making. The models enable users to follow actions up to logical rules or structured conditions thus enhancing trust and usability. Nonetheless, such transparency can be associated with a loss of performance, particularly in situations that involve the need to capture complex patterns and long-run dependencies. Therefore, the use of interpretable models alone might not be adequate in solving real life problems. The proposed XRL system fills this gap by implementing a hybrid model that combines various explainability methods to a high-performing RL system. The framework can improve the transparency without drastically reducing the accuracy by incorporating various features like surrogate models, attention mechanisms, interpretable policy structures, and reward decomposition. This integration enables users to have valuable information about the behavior of the agent without having to lose good decision-making powers. Moreover, the hybrid design makes sure that the explanations can be faithful to the original model as well as be user-friendly to human beings. On the whole, the findings indicate that there is no need to view performance and interpretability as antagonistic targets. Rather, through careful design and combination of complementary methods, one

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can create effective and transparent RL systems, which will open the door to the wider adoption of RL to real-world and high-stakes applications.

5. CONCLUSION

Explainable Reinforcement Learning (XRL) is an important and timely addition to the history of intelligent systems, especially in a time where transparency, accountability, and trust are gaining more importance than performance. The paper has given a thorough discussion of the XRL methods with a special focus on how it can be used to solve the problem of the obscurity inherent to the classical reinforcement learning models. The study presents insight by systematically examining current methods, including the initial methods of presenting interpretable policies up to the latest methodologies of post-hoc explanation and model-driven methods, to show the current improvements and the challenges that still lie ahead in developing actually explainable decision-making systems. The results support the notion that even though standard deep RL models are the best performers, their interpretability is a weakness that restricts their use in critical real-life settings. In a bid to overcome these shortcomings, the proposed methodology proposes a hybrid XRL framework that combines various explainability mechanisms, such as interpretable policy structures, surrogate modeling, attention mechanisms, and reward decomposition. This is a multi-faceted approach, which can be used to explain the behavior of the agent in more detail by giving both local and global explanations. Significantly, the framework shows that the improvement of transparency does not always mean a significant trade-off in performance. Rather, a high level of accuracy, fidelity and interpretability can be successfully traded off with careful design and integration. This statement is confirmed by the results of the experiment and the comparative analysis, which demonstrates that the proposed structure is more efficient than the traditional interpretable frameworks, as well as possesses a high degree of explainability. In the future, XRL has a number of promising avenues of future research. Among the urgent requirements, there is the establishment of the standard evaluation metrics and benchmarking frameworks that will help to objectively evaluate the quality and usefulness of explanations. Also, the main challenge is to enhance the scalability of explainability methods to real-time and high-dimensional settings. The other significant direction is the integration of human-in-the-loop strategies, in which experts in the domain actively participate in and direct the learning process, contributing to the increase in interpretability and system reliability. Additionally, ethical deliberations and mechanisms that consider fairness will be essential in the implementation of XRLs in order to achieve responsible AI usage. To sum up, it can be seen that the application of explainable reinforcement learning to real-world systems has the potential to change the way intelligent agents are created, implemented, and trusted. XRL will help to reduce the difference between performance and interpretability, creating more transparent, responsible, and ethically aligned AI systems that can be safely used in a wide range of applications.

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