A Survey on Explainable Reinforcement Learning: Concepts, Algorithms, Challenges

YUNPENG QING, Zhejiang University, China
SHUNYU LIU, Zhejiang University, China
JIE SONG, Zhejiang University, China
MINGLI SONG, Zhejiang University, China

Reinforcement Learning (RL) is a popular machine learning paradigm where intelligent agents interact with the environment to fulfill a long-term goal. Driven by the resurgence of deep learning, Deep RL (DRL) has witnessed great success over a wide spectrum of complex control tasks. Despite the encouraging results achieved, the deep neural network-based backbone is widely deemed as a black box that impedes practitioners to trust and employ trained agents in realistic scenarios where high security and reliability are essential. To alleviate this issue, a large volume of literature devoted to shedding light on the inner workings of the intelligent agents has been proposed, by constructing intrinsic interpretability or post-hoc explainability. In this survey, we provide a comprehensive review of existing works on eXplainable RL (XRL) and introduce a new taxonomy where prior works are clearly categorized into model-explaining, reward-explaining, state-explaining, and task-explaining methods. We also review and highlight RL methods that conversely leverage human knowledge to promote learning efficiency and final performance of agents while this kind of method is often ignored in XRL field. Some open challenges and opportunities in XRL are discussed. This survey intends to provide a high-level summarization and better understanding of XRL and to motivate future research on more effective XRL solutions. Corresponding open source codes are collected and categorized at https://github.com/Plankson/awesome-explainable-reinforcement-learning.

CCS Concepts:
• Computing methodologies → Reinforcement learning;
• General and reference → Surveys and overviews.

Additional Key Words and Phrases: Deep Learning, Deep Reinforcement Learning, Explainability, Interpretability.

ACM Reference Format:
Yunpeng Qing, Shunyu Liu, Jie Song, and Mingli Song. 2022. A Survey on Explainable Reinforcement Learning: Concepts, Algorithms, Challenges. J. ACM 1, 1, Article 1 (January 2022), 36 pages. https://doi.org/XXXXXXX.XXXXXX

1 INTRODUCTION

Reinforcement learning [193] is inspired by human trial-and-error paradigm [143]. It is based on the fact that interacting with environment is a common way for human learning without the guidance of others [98]. From the interaction, human gains information about cause and effect, the results of actions, and how to achieve goals in the environment. This kind of information is implicitly utilized to construct our mental model [155, 218, 225] and more such information will make this mental model more precise [22, 171]. RL is similarly about goal-directed learning from interacting with environments to be acutely aware of how the environment responds to our behavior and purposefully influences future events. More precisely, RL learns to map from environment state to action so as to maximize a numerical reward signal [189]. In recent years, the...
fast development of deep learning [15, 194] promotes the fusion of deep learning and reinforcement learning. Therefore, Deep Reinforcement Learning (DRL) [44, 60, 134, 135, 177] occurs as a new RL paradigm. With the powerful representation capability of the deep neural network [7, 51, 230], DRL has achieved considerable performance in many domains [17, 24, 29, 37, 114, 121, 184], especially in game tasks like AlphaZero [184] and OpenAI Five [17], DRL-based methods successfully defeat human professional player. Nonetheless, for more complicated tasks in real-world scenarios such as autonomous driving [25, 39, 79, 213, 214] and power system dispatch [109, 115, 226, 227, 239], not
only high performance but also user-oriented explainability should be considered for the concern of security and reliability. This requirement of explainability is the main bottleneck for employing DRL in real worlds instead of the simulated environment.

Conventional DRL methods are limited by low explainability owing to the intricate backbone of deep neural network (DNN) [67, 100, 185, 195]. It is intractable to track and explain each parameter within a neural and scale up to the entire network. Therefore, we have no idea about which implicit features the DNN takes into consideration and how the DNN handles these features. This drawback leads to the fact that DRL model is becoming a black box [84, 232] where experts cannot understand how the agent knows about the environment or why the agent chooses a specific action. Such intransparency limits the application of DRL since most people will not trust the agent easily especially when the agent does exactly the opposite of their expectation without explaining the reason for the decision-making process. For example, in auto-navigation task [32, 156], people may feel confused by the abnormal guidance made by the navigator agent without telling them the reason which may be just for avoiding traffic jams. Furthermore, the lack of explainability also causes obstacles for inserting human knowledge and guidance into the training process [62, 166]. Although human knowledge is pre-given in specific forms [56, 57, 181, 233, 236], the agents are unable to extract effective information and benefit from it.

To remedy the low-explainability problem, many pieces of explainable research have been conducted in several machine learning fields like explainable face recognition [43, 85, 165, 219] in computer vision (CV) and explainable text classification [8, 119, 186] in natural language process (NLP). Explainable machine learning aims to generate explanations in different forms to make the model explainable and transparent to experts and even laymen. It looks inside the black-box agent model, extracting or generating explanations automatically for why the agent chooses this action or gives out this conclusion at each timestep. The form of explanation can be various like natural language [38, 53, 66], saliency map [54, 83], or video [178]. With explainable models, the agents can be able to find out the potential flaw and explain these to experts to make further improvements.

For XRL field, many preliminary studies have been done to construct explainable reinforcement learning (XRL) model and have gained certain achievements in producing explanations. To have a complete view of them and summarize current XRL techniques, several surveys of XRL have been conducted [33, 49, 74, 158, 208, 217]. Heuillet et al. [74] review the approaches focusing on the explanation and user types. They simply divide the approaches into two types based on the way how explanations are generated. This classification is a preliminary one and needs to be further improved. Puiutta and Veith [158] followed traditional explainable AI taxonomy that is based on the time and scope of explanation. They only describe some representative methods and do not aim to present a comprehensive overlook of XRL. Wells and Bednarz [217] also enumerate varieties of XRL approaches. But they only focus on the visualization technique that can be utilized for XRL field. Vouros [208] limit the scope into the state-of-art XRL approaches and give an architectural symbolic paradigm for XRL while the explanation content can be divided into agent preference and goal’s influence. Dazeley et al. [33] proposed a conceptual architecture called causal XRL framework that explains how XRL can generate explanations for behaviors by focusing on causal behavior. This theoretical architecture is clear and rigorous, which takes not only perception, action, and event, but also the goal, expectation, and disposition into account. However, current XRL frameworks can only focus on perceptions and action causes for the outcome of an event, which means that the existing XRL technique can only be represented by a much simpler form of causal XRL framework. Glanois et al. [49] make a clear bound between explainability and interpretability. They divide the approaches into three types: explainable inputs, transition model, and preference model. It inspired us to focus on the process and structure of RL for XRL paradigm. All of these surveys propose
new taxonomy on XRL, while most of them are not based on RL paradigm. Also, from the surveys above we can find that XRL field is still lacking standard criteria especially for its definition and evaluation approaches while many of them proposed their own criteria for XRL [116, 131, 138, 208], but none of them are accepted by the whole DRL community. As for current XRL frameworks, most of them do not consider the impact of human participation, and only a few papers try to extend human knowledge-based paradigm into XRL field, whose results strongly prove that it is an effective way to obtain both high explainability and performance [237].

To make further development for the whole XRL architecture, we systematically review current XRL frameworks and surveys. We specify the concepts of XRL model explainability and summarize evaluation metrics of it. Based on these proposed XRL frameworks, we propose a new XRL taxonomy that is more fitted for RL. Since making the whole RL paradigm explainable is currently difficult, all of the works turn to get partial explainability on components of RL paradigms. We categorize current XRL works according to the target explainable part: model, reward, state, and task. The goal of these four part-explaining methods is to generate explanation to the action of agent. This taxonomy is much more advanced for RL than the general intrinsic/post-hoc and global/local. Considering the few number of human knowledge-based XRL work and its importance, we separate it out and make an attempt on summarizing these works and organizing them into our taxonomy. As we know, few researchers do summarization of this field that both includes human knowledge and XRL. Our work can be summarized below:

- We give a detailed summarization of model explainability in XRL based on existing literature on explainable RL and explainable machine learning. Current evaluation metrics for XRL are also included in this summarization.
- A new taxonomy is introduced for current XRL works based on the explainability of different parts of reinforcement learning framework: model, reward, state, and task. The taxonomy can be viewed in Figure 2.
- Noticing that currently human knowledge-based XRL is an unpopular direction that has only a few works and the remarkable result of them, we separate it as one of the main parts of our paper to give a systematic review of these approaches that combines XRL frameworks with human knowledge to get higher performance and better explanation.

The remaining of this survey is organized as follows. In Section 2, we recall the necessary basic knowledge of reinforcement learning. Next, we discuss the definition of XRL model explainability as well as giving some possible evaluation aspects for explanation and XRL approaches in Section 3. In Section 4, we describe our categorization as well as provide works of each type and sub-type in detail, the abstract figure of our taxonomy can be viewed in Figure 2. Then we discuss XRL works that are combined with human knowledge according to our taxonomy in Section 5. After that, we summarize current challenges and promising future directions of XRL in Section 6. Finally, we give a conclusion of our work in Section 7. The structure of this paper and our taxonomy work is shown in Figure 1.

2 BACKGROUND

Reinforcement Learning paradigm considers the problem of how an agent interacts with the environment to maximize the cumulative reward, where the reward is a feedback signal according to the response action of the agent in different states. Concretely, the interaction process can be formalized as a Markov Decision Process (MDP) [40]. An MDP is described as a tuple $M = \langle S, A, P, R, \gamma \rangle$, where $S$ is the state space, $A$ is the action space, $P : S \times A \times S \rightarrow [0, 1]$ is the state transition function, $R : S \times A \rightarrow \mathbb{R}$ is the reward function, and $\gamma \in [0, 1]$ is a discount factor. At each discrete time step $t$, the agent observes the current state $s_t \in S$ and chooses an action $a_t \in A$.  

J. ACM, Vol. 1, No. 1, Article 1. Publication date: January 2022.
This causes a transition to the next state $s_{t+1}$ drawn from the transition function $P(s_{t+1}|s_t, a_t)$. Moreover, the agent can receive a reward signal $r_t$ according to the reward function $R(s_t, a_t)$. The core object of the agent is to learn an optimal policy $\pi^*$ that maximizes the expected discounted return $E_\pi [G_t] = E_\pi [\sum_{i=0}^{\infty} y^i r_{t+i}]$. To tackle this problem, existing reinforcement learning methods can be mainly categorized into two classes: value-based methods and policy-based ones.

### 2.1 Value-based Methods

The value-based methods [135] tend to assess the quality of a policy $\pi$ by the action-value function $Q^\pi$ defined as:

$$Q^\pi(s, a) = E_\pi[\sum_{i=0}^{\infty} y^i r_{t+i}|s_t = s, a_t = a],$$

which denotes the expected discounted return after the agent executes an action $a$ at state $s$. A policy $\pi^*$ is optimal if:

$$Q^{\pi^*}(s, a) \geq Q^\pi(s, a), \forall \pi, s \in S, a \in A.$$

There is always at least one policy that is better than or equal to all other policies [193]. All optimal policies share the same optimal action-value function defined as $Q^*$. It is easy to show that $Q^*$ satisfies the Bellman optimality equation:

$$Q^*(s, a) = E_{a' \sim P(\cdot|s, a)} \left[ R(s, a) + y \max_{a' \in A} Q^*(s', a') \right].$$

To estimate the optimal action-value function $Q^*$, Deep Q-Networks (DQN) [135] uses a neural network $Q(s,a;\theta)$ with parameters $\theta$ as an approximator. We optimize the network of DQN by minimizing the following temporal-difference (TD) loss:

$$\mathcal{L}(\theta) = E_{(s,a,r,s') \sim \mathcal{D}} \left[ (y - Q(s,a;\theta))^2 \right],$$

where $\mathcal{D}$ is the replay buffer of the transitions, $y = r + y \max_{a' \in A} Q(s', a'; \theta^-)$ and $\theta^-$ represents the parameters of the target network. After the network converges, the final optimal policy can be obtained by a greedy policy $\pi(s) = \arg\max_{a \in A} Q(s, a; \theta)$. Due to the encouraging results accomplished by DQN, several follow-up works [14, 27, 30, 65, 73, 129, 136, 174, 204, 215] progressively enlarged the family of DQN and has recently demonstrated extraordinary capabilities in multiple domains [26, 117, 150, 205]. However, while these value-based methods can handle high-dimensional observation spaces, they are restricted to problems with discrete and low-dimensional action spaces.

### 2.2 Policy-based Methods

To solve the problems with continuous and high-dimensional action spaces, policy-based methods have been proposed as a competent alternative. One of the conventional policy-based methods is stochastic policy gradient (SPG) [193], which seeks to optimize a policy function $\pi_\phi : S \times A \rightarrow [0,1]$ with parameters $\phi$. SPG directly maximizes the expected discounted return as the objective $\mathcal{J}(\phi) = E_{\pi_\phi} [\sum_{t=0}^{\infty} y^t r_t]$. To update the policy parameters $\phi$, we can perform the gradient of this objective as follow:

$$\nabla_\phi \mathcal{J}(\pi_\phi) = E_{s \sim \rho^\pi, a \sim \pi_\phi} \left[ \nabla_\phi \log \pi_\phi(a|s)Q^\pi(s, a) \right],$$

where $\rho^\pi(s)$ is the state distribution and $Q^\pi(s, a)$ is the action value. To estimate the action value $Q^\pi(s, a)$, a simple and direct way is to use a sample discounted return $G$. Furthermore, to reduce the high variance of the action-value estimation while keeping the bias unchanged, a general method is to subtract an estimated state-value baseline $V^\pi(s)$ from return [193]. This yields the advantage function $A^\pi(s, a) = Q^\pi(s, a) - V^\pi(s)$, where an approximator $V(s; \theta)$ with parameters $\theta$ is used.
estimate the state value. This method can be viewed as an actor-critic architecture where the policy function is the actor and the value function is the critic [41, 52, 68, 134, 175–177, 223].

On the other hand, the policy in the actor-critic architecture can also be updated through the deterministic policy gradient (DPG) [44, 111, 183] for continuous control:

$$\nabla_{\phi} J(\mu_{\phi}) = \mathbb{E}_{s \sim \rho} \left[ \nabla_a Q^\mu(s, a) |_{a = \mu_{\phi}(s)} \nabla_{\phi} \mu_{\phi}(s) \right].$$

where $\mu_{\phi}(s) : S \rightarrow A$ with parameters $\phi$ is a deterministic policy. Moreover, we directly instead approximate the action-value function $Q^\mu(s, a)$ with a parameterized critic $Q(s, a; \theta)$, where the parameters $\theta$ are updated using the TD loss analogously to the value-based case. By avoiding a problematic integral over the action space, DPG provides a more efficient policy gradient paradigm than the stochastic counterparts [183].

3 EXPLAINABLE RL DEFINITIONS AND MEASUREMENT

This section sets the ground for enhancing RL framework with explainability. Although various papers in this field make their effort to give a precise definition of explainable RL, none of them have been accepted by the whole RL community and therefore no clear consensus has been reached. Meanwhile, a large number of current works view being explainable as a kind of subjective perception that is unnecessary to focus on. Such a vague definition will hinder the understanding of XRL papers and evaluation metrics of XRL frameworks seeking. After reviewing the existing literature, we make further detailed descriptions of explainable model’s concepts and summarize current evaluation metrics of XRL.

3.1 Definition of model explainability

XRL methods share lots of related words of similar meanings like explainability and interpretability since lacking an official definition of XRL. Many pieces of literature on XRL propose their criteria for these concepts. Miller [131] defines interpretability as the degree to which a person can understand the decision made by the model. Meanwhile, Kim et al. [94] asset that interpretability is the degree to which a person can consistently predict the result of the model. As for explainability, Lipton [116] believe explainability is a post-hoc property while Molnar [138] specifies it as the capability to provide explanation for individual predictions. Recent work [208] makes a reasonable distinction between interpretability and explainability: interpretability is the ability of a paradigm to utilize an interpretable model to provide explanation while explainability is the ability to provide a surface representation of interpretations. Summarizing these definitions, we can get the conclusion that there are two possible architectures of XRL: construct an interpretable agent or construct a mechanism that contains explainable logic and make it work together with the RL agent.

1) interpretability: The interpretable agent is corresponding to interpretability which means the capability of whether the decision-making and inner logic of the agent are transparent and easy to understand during the whole training and testing process.

2) explainability: The mechanism including explainable logic is related to explainability which represents the ability to output the aspects that the agent takes into account when producing action with a specific input state.

The relation of these two terms in XRL is like the relation between intrinsic and post-hoc: interpretability is a kind of capability that is determined while the model is constructed; as for explainability, it needs to have not only an accomplished model but also the input data and execution on it, which means explainability is a post-hoc property. The interpretability is at a higher level on the whole structure of the model, and explainability is much more concrete since it is based on the working process of the model. XRL field is constituted with such two kinds of explanation.
In the following of this paper, we use interpretability and explainability interchangeably since we will shift our focus from the explanation types to our new taxonomy and we will describe them in detail.

### 3.2 Evaluation framework

After giving a clear description of explainability, we turn to the evaluation of XRL. Unfortunately, there is still no consensus about how to measure the explainability of RL framework. Some initial work has been made to formulate some approaches or aspects for evaluation. Doshi-Velez and Kim [35] proposed the idea that evaluates interpretability in three levels which include application, human, and function. Hoffman et al. [80], Mohseni et al. [137] make further contribution on giving reasonable metrics for explainable AI. We summarize their work and give an evaluation framework for explainable RL paradigm:

#### 3.2.1 subjective assessment

Subjective assessment performs evaluating explainable frameworks based on the view of humans. The human testers receive the explanation and construct their own understanding of the systems. Subjective assessment is aimed at recording and measuring how a person understands the process, event, or system. It is based on how humans understand the mode through explanation, which is subjective and also necessary for evaluation. The metrics that are significant for subjective assessment can be further divided into the types below:

1) Mental model: Mental model refers to how a person understands the model process and structure [155, 218, 225]. The generated explanation promotes the process of user building the mental model. Therefore conversely evaluating the mental model can be an optional aspect to verify the effectiveness of the explanation. It is hard to reconstruct the mental model of human testers in their mind, so current approaches for looking into the mental model are all in indirect ways. A quantitative way is to make testers predict the agent decision [92, 163, 164] or the model failure [10, 145] and then calculate the hit rate. The hit rate can be viewed as an evaluation of how accurate the mental model is. Likert-scale questionnaire method can also quantitatively evaluate the mental model [95, 101, 103, 160]. The participants rate the received information like input data and generated explanation in terms of user-believed importance, confidence, and relevancy, which are directly relevant to the mental model of users.

2) User-oriented properties: This aspect can be important to the implementation of explainable system in real life. To apply XRL in the real scene we must take user-oriented factors such as satisfaction, trust, and reliance of users into account [19]. These factors reflect the degree of complexity, transparency, and usefulness of explanation [47, 102]. The Likert-scale questionnaire method is still a feasible approach to measure such metrics [16, 31, 112, 113, 125]. Gedikli et al. [47], Lim et al. [113] also explore the efficiency and complexity of explanation by measuring the users’ response time in their explainable system. For trust and reliance aspects, many researchers [144, 157] track the action and intention of users in the explainable system to measure the user trust and reliance on the generated explanations.

#### 3.2.2 objective assessment

The over-reliance on human evaluation will lead to focusing on the persuasiveness of explanation rather than other more abstract aspects such as transparency of the system since humans prefer simple and effective explanations [72]. Therefore, Objective assessment does not rely on human evaluation. This evaluation type focuses on directly measuring the properties of explainable framework, which externs the breadth and depth of evaluation. The objective assessment can be divided as follows:
1) Model output performance: It is necessary to keep a balance between the performance and explainability since enhancing explainability to RL will lead to larger computing resource consumption [49]. Therefore we need to check whether the explainable system has the same or better performance than the explainable one. For deep learning methods, the metrics are about the success rate and certainty of the prediction [55, 99, 191]. For RL fields, the evaluation methods are focusing on total reward [13, 107, 197, 199, 207] and task success rate [18, 105, 140, 180, 229].

2) Explainer fidelity: Explainer fidelity refers to the correlation of the explanation to the true reason for agent decision-making [137]. Simulation experiment [163, 164] is a direct way to test the explainable framework in expert cases. Many researchers set the computational interpretability and generated qualitative explanation of the result as evidence for fidelity and correctness [146, 231, 232, 242]. Comparative method that makes explanation comparison between different explainable system is also an effective way for getting relatively fidelity [167, 173].

3) Sensitivity and robustness: Sensitivity refers to the capability of explanation to reflect the sensitivity of explainable system’s inner model with respect to the perturbation on the input feature space [97, 192]. Sensitivity can also be utilized to roughly measure robustness which stands for stability under small perturbation [4]. To measure sensitivity, current evaluation methods add perturbation on input [20, 20, 142] or model parameters [1, 2, 48], utilizing the difference of generated explanation to measure sensitivity and robustness.

In conclusion, the evaluation for XRL can be divided into subjective and objective types based on the source of data for evaluation. These two types are complementary and can be implemented as a combination to get a more precise and comprehensive measurement. Although we have built an evaluation framework for XRL approaches, there is still a lack of specific measurement methods (especially quantitative methods) for different XRL frameworks which need much further research focus on it.

4 EXPLAINABILITY IN RL

Fig. 2. Diagrams of different types of explainable reinforcement learning frameworks. These diagrams illustrate how different types of XRL framework makes different parts of the reinforcement learning model produce explanation and help experts get an insight into the reinforcement learning process. Note that these diagrams are just abstractions of the approaches that we will talk about and the more detailed learning process of the agent is not included in these diagrams. $o_\pi$ and $o_g$ denote two aspects of explanations: inner logic inference of agent and goal influence in action-taking. $a_t, r_t, s_t$ refer to the action, reward, and states at time $t$; The red parts in these diagrams are the explainable parts. (a) trains the agent to be explainable by having an understandable logical operation in its inner structure. (b) reconstructs reward function towards an explainable one $r'_t$ and makes it possible to see how the goal influences the agent. (c) adds an attention-based submodule to quantify the influences of state features on decision-making as $w(s_t')$ at different timestep $t'$. (d) gets an architectural level explainability in complex environments by multilevel agents, the high-level agent schedule low-level agents by the subgoal signal $g_t$ which could be utilized for explanations.
Current explainable RL works try to explain the action of RL agents while not focusing on the whole RL process since it is too intractable. Therefore they turn to make part of the process of RL understandable to human while keeping the performance. The model for RL task can be divided into several parts: state, action, reward, model, and task. In our work, we categorize current XRL work according to these partitions and show the taxonomy in Figure 2. We also do more specific categorization while providing a table for each sub-section to list specific works.

4.1 Model-explaining

Classical RL frameworks train the agent to enhance decision-making towards better results ability and do not focus on the inner decision-making logic of it. However, model-explaining XRL methods can not only obtain agents with high performance but also extract the inner logic to generate explanations. Based on the explanation logic type, we divide current model-explaining XRL methods into self-explainable and explanation-generating parts. The former tries to generate explanation by extracting the implicit explanation logic while the latter gives explanation with a fixed explanation logic.

Table 1. Self-explainable models in XRL approaches

| Type             | Description                                                                 | Model                          | Algorithm                  | Environments                        |
|------------------|------------------------------------------------------------------------------|-------------------------------|----------------------------|-------------------------------------|
| Value-based      | Learning while representing Q-value in an understandable way using different models | Decision Tree                 | Linear model U-tree [118]  | Flappy bird, MountainCar, Cartpole  |
|                  | Formula Expression                                                          | Depth-limited search [126]   | Multi-armed bandits        |                                     |
|                  | Genetic programming [70, 71]                                                |                                | MountainCar, Cartpole,     | Industrial control benchmark       |
|                  | Programmatic Policy                                                         | Programmatic interpretable RL [207] | TO RCS car racing         |                                     |
|                  | Neurosymbolic transformers [82]                                            | Imitation-projected programmatic RL [206] | TO RCS car racing         |                                     |
|                  | Learn program embedding space [201]                                         | Neural symbolic transformers   | Formation task, Unsabeled goals task |                                 |
|                  | Symbolic Policy                                                             | Deep symbolic policy generator [104] | MountainCar, Pendulum, Hopper, InvDoublePend, InvPendSswingup, LunarLander, BipedalWalker |
| Policy-based     | Learning while representing policy in an understandable way using different models | Fuzzy Controller              | Policy gradient [5]        | Hopper, BipedalWalker              |
|                  |                                                                                | Fuzzy particle swarm RL [69]  | MountainCar, Cartpole      |                                     |
|                  | Logic Rule                                                                  | Neural logic RL [87]          | Block manipulation, Cliff-walking |                                 |
|                  | Genetic programming RL [151, 152]                                           | Verifiability via iterative policy extraction [13] | Cartpole, Pong            |                                     |
|                  |                                                                                | Multi-agent verifiability via iterative policy extraction [130] | Cooperative navigation, Predator-presy, Physical deception |                                 |
|                  |                                                                                | Iterative bounding MDP [199]  | CartPole, PreeqWorld, PotholeWorld |                                 |
|                  |                                                                                | Abstraction policy graph [209] | PreeqWorld                 |                                     |
|                  |                                                                                | Q-value pruning [168]         | Super tax kar, Super mario hros |                                 |
|                  |                                                                                | Conservaive Q-improvement [170] | Robot navigation          |                                     |

4.1.1 Self-explainable. A model is self-explainable if it is constructed to be inherently interpretable or self-explanatory at the time of training by restricting the complexity of the model [36, 158]. This kind of model is also called intrinsic model [158] and can be viewed as a transparent paradigm that people can easily understand. The explanation logic is implicit since it is within the agent model. Our work summarizes the current self-explainable model and categorized it into two types based on the target of explainable model structure: value and policy. We summarize these types of methods in Table 1.
i): Value-based. Q-value in RL represents the subsequent expected discount sum of the reward of taking state and action pair \((s, a)\), which could be also utilized to build deterministic or energy-based policy. Since Q-value is the direct influence factor of the agent policy, many value-based XRL frameworks focus on Q-value. Linear Model U-tree (LMUT) [118] leverages the idea of imitation Learning (IL) [77]. The LMUT is an advanced model over continuous U-tree (CUT) [202] (an essential regression tree for value function). As a variant of decision tree, the internal node store the feature of dataset \(f_1, f_2, f_3, \ldots, f_n\) while the leaf node can be viewed as a partition of the input space. Each LMUT leaf node contains a linear model on input state feature to approximate Q-value rather than a simple constant in CUT and can furthermore record the average reward and average transfer probability to the next leaf node. The approximation of Q-value \(Q_{LMUT}^U\) is from the single linear model of the LMUT leaf node, and it can be viewed as an explanation of quantifying the effect of different features in LMUT. The researchers build the first mimic learning framework for the Q function and introduce LMUT to approximate classical neural network prediction. The authors also provide way to train such a LMUT, which can be described as two steps: data gathering phase that counts all the transition \(T\) on the LMUT and modifies the Q value, average reward as well as average transfer probability; node splitting phase does stochastic gradient descent (SGD). Once SGD gets insufficient improvement on some leaf nodes, the framework will split this leaf node to untangle the mixed feature. The experiments show that LMUT achieves the same performance as the neural network-based baselines in different environments.

LMUT uses a linear combination of features to approximate Q-value at leaf nodes of U-trees. Based on this approximating idea, formula expression becomes an effective way to directly represent Q-value. Maes et al. [126] proposed a search algorithm over the simple closed-form formulas space. The variables in the expression are the abstraction of the components of states and actions, and the operations over these variables are unary and binary mathematical operations. The policy is a greedy deterministic policy over the Q value which always tends to select the action with the maximum Q-value. The explainability is ensured by the different operations since they illustrate different effects of variables on Q-value. However the method cannot prevent combinatorial explosion, so the total number of variables, constants, and operations is limited to a small number of 6. There are also some advanced methods based on formula expression [70, 71], and they use formula expression to represent the policy. These methods will be talked about in the next section.

ii): Policy-based. Policy representation is a more direct way compared to Q-value since policy immediately guides the action-selecting of agents. In the MDP model, the policy is a probability distribution function \(\pi(s, a)\) with only a real number, so we need a more explainable model to represent it. Some representative approaches of this type are illustrated in Figure 3.

Programmatic RL (PRL) is about using a program to represent the policy. The logic rule within the program can give global explainability. Current PRL methods can be divided into two stages in Figure 3a: programmatic policy generator and programmatic policy evaluator. The former update the current programmatic policy vector in a fixed programmatic space and generate a programmatic policy by decoding the vector, while the latter simulates the generated programmatic policy to make one-step optimization for the current policy. Now the main challenge of PRL is how to select such an interpretable programmatic policy space. Verma et al. [207] present a framework called Programmatically Interpretable Reinforcement Learning (PIRL). PIRL constructs the policy over a high-level domain-specific programming language. All the operations of such a programming language are based on historical data utilization. Different from the formula mentioned above, the operations are fitted for data from the past like \(map(f, [e_1, \ldots, e_k]) := [f(e_1), \ldots, f(e_k)]\), \(fold(f, [e_1, \ldots, e_k], e) := f(e_k, f(e_{k-1}, \ldots f(e_1, e)))\) where \(e_i\) is the history data. This kind of expression can help humans fastly know the influence of history interaction towards the target policy.
A Survey on Explainable Reinforcement Learning: Concepts, Algorithms, Challenges

Fig. 3. Some examples of self-explainable policy-based methods. (a) illustrates current Programmatic Reinforcement Learning (PRL) approaches that are divided into two alternating phases. Programmatic policy generator is executed based on a fixed interpretable programmatic policy space obtained by pre-training [82, 201] or pre-given templates [206, 207]. At each step, we update the current policy vector $\phi(\pi_p)$ in such policy space with one-step optimization $\epsilon$ from the policy optimizer. Then the new policy vector $\phi(\pi_p)$ can be decoded into a programmatic policy $\pi_p$ for the next step. The programmatic policy evaluator utilizes the programmatic policy to sample batches of trajectories $\tau_i$, which is then fed to the policy optimizer to output one-step optimization $\epsilon$ for an update. (b) describes current two Decision Tree (DT) policy approaches. DT policy transform methods [13, 130] first train a DNN-based optimal policy $\pi^*$ by DRL methods. Then, DT policy is extracted with decision tree training or transformation rules $f$ based on $\pi^*$. DT policy training methods [118, 170] directly train DT policy by interaction with environment. For each interaction, they maintain the Q-value $Q(L, \cdot)$ and weight $w(L)$ of the corresponding DT leaf node $L$. And select node to perform leaf node split according to $g$ for better performance. The function $g$ considers the performance improvement of splitting leaf node based on the Q-value improvement $\Delta Q$ and the weight $w$. which lead to the benefits of being more easily explained than neural network. To get such a programmatic policy with the maximal reward in a non-smooth optimization space, they proposed a search method called neurally directed program search (NDPS). NDPS first uses DRL to find a neural policy which is an approximation of the target policy, then iteratively updates the policy by enumerating the program template and using bayesian optimization [187] or satisfiability modulo theory to get better parameters. Verma et al. [206] later claim that the above method is highly suboptimal and they propose a new framework to search for such policy by mirror descent-based meta-algorithm: perform deep policy gradient on policy space that mixes neural and programmatic representations, then do program synthesis via imitation learning in the project step. This framework significantly outperforms other PRL work. For multi-agent communication, Inala et al. [82] synthesis programmatic policy by the generated communications graph of agents. Trivedi et al. [201] first learn latent program embedding space and then the program policy searching will become more efficient. Meanwhile, the learned latent program embedding can be transferred and reused on other tasks.

As for formula expressions, they can be utilized to directly represent policy instead of the value function. This kind of policy is called symbolic policy, which is composed of simple short symbolic operations. It can get explainability from concise mathematical expressions. However, searching the whole symbolic space to fit a dataset is generally believed to be a NP-hard problem [122]. Several works [70, 71] combine genetic programming with model-based batch RL and propose genetic programming for reinforcement learning (GPRCL) to get a such policy. The genetic programming
method maintains the population, which is composed of symbolic expression individuals. And the evolutionary operations contain crossover, selection, mutation, and so on. Neural network (nn)-based algorithms have been widely leveraged for symbolic regression problem [104, 139, 153] with neural-guided search. Extending the symbolic regression problem to RL, Landajuela et al. [104] propose deep symbolic policy. By using a recurrent neural network-based symbolic policy generator and nn-based anchor policy, they can evaluate the policy by stimulation and obtain the fully symbolic policy without any nn-based dimension.

Fuzzy controller [3, 49, 69] can also be used to represent policy. These methods share the same idea that the agent policy can be viewed as the sum of policies on the cluster centers with different weights, while the weights have a negative correlation with the distance between the current state and cluster centers. That is, \( \pi(a|s) \) is a gaussian distribution \( N(a|K\varphi(s), \Sigma) \), where \( K \) is a matrix stacking actions corresponding to cluster centers, \( \varphi(s) \) is a membership function which returns a weight vector according to the distance with each cluster center, and \( \Sigma \) is a state-independent full variance matrix. Glanois et al. [49] summarize this paradigm to be the form of "IF fuzzy condition(state) DO action". By measuring the distance with the cluster centers, the action guided by the policy can be easily tracked to see the influence that comes from different cluster centers. The policy gradient method is used to train such a policy with a non-explainable critic value [3]. Fuzzy particle swarm RL (FPSRL) [69] has been utilized to construct fuzzy RL policies by training parameters on the world model. These two methods both control the number of clusters automatically and the results of them both show that they obtain the interpretable policy with high performance.

First-order logic (FOL) [12] is a formal language that describes the entities of the world and their relationships. Neural logic RL (NLRL) [87, 151, 152] represents the policies in RL by first-order logic formula. NLRL is based on policy gradient and differentiable inductive logic programming Zimmer et al. [241]. Basic work [87] shows that the NLRL describing the policy by logic rule is much more understandable by human So they allocate each logic rule weight (need to be training) indicating the importance of the action-taking while the rule itself can explain the reason for action-choosing. More work [151, 152] extends the basic work as they give weight, not for each rule but for the atoms in the rule. They utilize genetic programming reinforcement learning (GPRL) to learn policy formulas from the history of state-action interaction data and add more operations on the formula than the value-based formula method [126]. Therefore, NLRL can learn almost the best policy with better explainability and generalizability.

Decision tree (DT) [159], which can be categorized into classification tree and regression tree for different tasks, used to have little application in classical RL for they cannot be updated online with stochastic gradient descent. However, in XRL region, DT has derived policy-based and value-based methods. The linear model U-tree mentioned above in the value-based explainable method is a typical variant of DT. From the aspect of policy-based methods, DT policy can be regarded as performing responding actions according to different features of DT. These features generated by training is explainable for human to know the understanding of agents toward the whole RL tasks. As for comparison of value-based and policy-based decision tree RL, Silva et al. [182] prove that the policy-based DT method is more beneficial than the value-based DT method theoretically. Current frameworks of policy-based DT methods are summarized in Figure 3b. Since with existing DRL methods we can obtain efficient DNN-based policy, one possible method is to transform DNN-based policy into DT policy with similar performance. As for DT policy extraction, the DNN-based optimal policy can be utilized to provide training data for DT policy. A typical DT policy transform method is Verifiability via Iterative Policy Extraction (VIPER) [13]. VIPER is a kind of policy extraction algorithm. The idea comes from leveraging model compression (distillation) [76] to transform a pre-trained DNN policy into a DT policy. VIPER utilizes the unexplainable optimal policy to

J. ACM, Vol. 1, No. 1, Article 1. Publication date: January 2022.
generate trajectories for DT training, and the resampling technique is leveraged to focus on states that are significant for agent interaction. Ross et al. [168] do an improvement over the imitation learning algorithm DAGGER and propose Q-DAGGER which uses Q-value for the oracle. Then VIPER is applied to learn a much smaller DT policy. Milani et al. [130] extend VIPER into Multi-Agent RL (MARL) and propose MAVIPER, which grows the tree of each agent by predicting other agents’ behaviors. It is also feasible to use transformation rules to achieve policy extraction. Topin et al. [199] define a novel MDP called Iterative Bounding MDP (IBMDP) that considers the features and its value ranges in the tasks. They give the value update rules to transform the DNN-based policy in IBMDP into DT policy in the base MDP. Therefore this method can be combined with the current non-interpretable RL algorithm to get an explainable DT policy. Topin and Veloso [200] similarly propose an interface performing policy summarization to build an abstraction policy graph, which can extract state-specific explanations for whole-policy explainability. The other kind of DT method is directly training a DT policy. By maintaining the Q-value as well as weight information at the leaf node of DT and performing leaf node split at a specific stage, the DT policy can be obtained with high performance. [170] utilizes the lazy updating idea and enlarges the tree size only when the approximation of future discount reward gets larger in a specific amount, which is called Conservative Q-Improvement (CQI).

Table 2. Explanation-generating models in XRL approaches

| Description | Explanation Type | Algorithm | Environments |
|-------------|-----------------|-----------|--------------|
| Counterfact | Generative deep learning [147] | Q*bert, Seaquest, Crazy Climber, Space Invaders |
|             | Gradient information-based generation [190] | Guided Maze, University Buildings |
|             | Action influence model [125] | Cartpole, MountainCar, Taxi, LunarLander, BipedalWalker, Starcraft |
| Human explanation | Automated rational generation [38] | Frogger |
|             | Clustering [46] | LunarLander |
|             | Neural network-based [45] | LunarLander |
|             | Summarization from query template [66] | GridWorld, Cartpole, Part inspection task |
|             | Policy abstraction and summarization [21] | Level-based foraging, Multi-robot warehouse, Multi-robot search and rescue |
| Verify | Verify basing on Marabou verification [93] | Adaptive video streaming task, Internet congestion control task |
|             | Mirror descent [5] | Pendulum, Acc, Car-racing, MountainCar, Road, Obstacle |
|             | Verification toolchain [240] | Pendulum, Cartpole, Self-driving |
|             | Verification-in-the-loop [89] | B1, B2, Tora, MountainCar, Pendulum, Cartpole |

4.1.2 Explanation-generating. This type of explainable model may not be inherently explainable or have an understandable structure. Instead, they can utilize an auxiliary explicit explanation logic to generate explanations automatically while training. Usually, the explicit explanation logic is learned from how humans understand a specific task or human habits of thinking to understand new things. The explanation can be in various types. Here we list some classical works to describe these kinds of explainability and show them in Table 2.

To capture the counterfactual explanations for policy, Olson et al. [147] obtain local explainability by generating counterfact state \( s' \) that minimally differs from current state \( s \) but leads the agent to perform a different action. Inputting the current state \( s' \), they utilize deep generative model to generate such counterfact states that are realistic images. Stein [190] leverages a similar idea to
generate explanations, he first computes Q-value difference of counterfactual action pair, which is composed of actions from the agent’s selection and human query at the current state. Then the framework performs gradient descent to find the decision boundary and transforms it into natural language form. He also trains the agent by the explanation, therefore, the planning performance can be used to evaluate the quality of generated explanation. Instead of the method of generating, Madumal et al. [125] model the counterfact in the task by causal model. The basis of this method is the structural causal model (SCM) [61], which represents the world with large amounts of variables divided into exogenous (external) and endogenous (internal) parts as well as many potential relations between the random variables. Action influence model (AIM) [125] towards XRL is a typical work drawn from SCM. More concretely, AIM is a directed acyclic graph, which offers not only the fact but also the counterfact. That is, it can provide explanation for both the "why" question and the "why not" question. This model generates the explanation by the counterfact: to explain "why perform X", we just need to simulate Y (the counterfact of X), and explain "why not perform Y". The simulating process is guided by structural equations. Since it is intractable to discover the whole internal relations of the real environment variables, the multivariate regression model can be leveraged to approximate the structural equations at the training of RL agents. Then with a NLP template method, the explanation is eventually received. The method is evaluated in Starcraft with different structural equation approximation ideas. And a human study has been done to confirm its explainable goodness and accuracy of prediction. The drawback of the causal model is that it must be pre-given, which will limit its generalizability.

A more straightforward idea for generating explanation is to learn the implicit explanation logic from reasonable explanations of humans. Ehsan et al. [38] proposed a specific conception: rationale—the explanation of an action based on the way humans think. They generate rationale in two steps. First, collect a corpus of the user explanation of the action, then train an encoder-decoder network with the corpus. Given the environments state \( S = x_1, x_2, ..., x_n \), the network is able to output the word sequence (rationale) \( O = o_1, o_2, ..., o_m \) (\( o_i \) is the word). The combined input image and the natural language explanation in the corpus are used for training. The authors categorize the parameters in the network into focused-view configuration (focus on local information and short-term factors) and complete-view configuration (focus on the whole environment and long term factors). After training, the model can generate explanation with the same semantics as human explanation.

Instruction-based behavior explanation (IBE) [45, 46] is based on interactive RL. Interactive RL accelerates the training by human experts inputting instructions to the agent. Basic IBE [46] makes the agent gain the ability to reuse the instruction explaining the decision-making. It first predicts the action target and then utilizes human instructions to construct a mapping from the action target to an understandable expression. The target of action in time \( t \) started at state \( s_n \) is defined as \( \Delta s = s_{n+t} - s_n \). By simulating with the policy \( \pi(s, a) \) in \( t \) times iteration, we can estimate the state \( s_{n+t} \) and get the prediction of \( \Delta s \). To get the mapping function, they select the top \( x \) total reward history and do clustering on \( \Delta s \) to get a classifier. Then for each cluster, calculate the normalized expected value of instruction as the explanation. The explainability is confirmed while keeping the performance. The clustering method can only be applied to simple environments. When dealing with environments that are more challenging and have no verification approach, it is impossible for agents to dynamically update the policy. Therefore, IBE is advanced immediately by them [45], they construct the mapping function by neural network model and make it applicable for changing policy.

In real life, we sometimes perceive the environment by asking questions and building the model in our mind, which means that the explanation of answering the query is another possible way. Hayes and Shah [66] introduce this kind of method. To obtain explanation of a specific query, the
author first maps the query into a decision-making query statement drawn from the pre-defined
template, then uses a graph-search algorithm to find the states that are relevant to the question.
In the end, the framework counts the attributes among the founded states to build the summary
in a natural language form. This query-based explanation is combined with another idea called
code annotation which marks the variables and actions in the state space. The generated policy
explanation fits experts’ expectations, but unfortunately, it does not demonstrate the reliability
of explanation in more complex tasks. Boggess et al. [21] expand this work into Multi-Agent
RL (MARL). For the policy in MARL that grows exponentially with the number of agent and state
variables, they first translate the learned policy into a multi-agent MDP (MMDP) based on a set
of specified feature predicates. They proposed methods for answering "When, Why not, What" questions in MARL with more restricted relevancy filters selecting relevant features and action sets
of queried actions. Additionally, by converting MMDP into a directed weighted graph with edge
weight relating to transition probability in MMDP, Dijkstra’s algorithm [34] can find the shortest
as well as the most representative path, which can be utilized to generate the policy abstraction
and summarization based on feature predicates set.

Formal verification techniques can enhance the safety and trustworthiness of RL paradigms.
Verily [93] is a typical one. Verily considers the space of all possible states in the environment, while
formal verification is leveraged to distinguish the unexpected state sequences in the state space.
The formal verification is mainly focused on the safety and liveness properties, which have been
defined as the query for logic operations. To achieve this kind of verification, Verily uses Marabou
verification method [91] which comes from the satisfiability modulo theories (SMT) verification
engine for DNN. If the answer is not, Verily can generate a counterexample by the logic verification
to explain it. The counterexample can also guide the updates of DNN architecture. Anderson et al.
[5] share the same mirror descent idea with Verma et al. [206] while they perform updating and
projecting steps between neurosymbolic class and restricted symbolic policy class to allow efficient
verification. Zhu et al. [240] propose a verification toolchain to maintain the safety of learning neural
network policy. With such constraints, they additionally design a counterexample-guided inductive
synthesis framework to find out a deterministic policy that is much more verifiable and simple to
approximate the neural network policy. Similarly, Jin et al. [89] propose a verification-in-the-loop
training framework to train and iteratively refine the abstracted state space from counterexample
if verification fails.

4.2 Reward-explaining

Another significant part of RL tasks is the reward function, which is the main factor to estimate
an action in short term or policy in long term. Each RL algorithm needs to receive reward signal
from the environment and update the agent to maximize the total expected reward. Meanwhile,
starting from the perspective of environments, a good reward function can help people achieve the
precise target while a bad one can cause many wrong decisions according to reward hacking [? ].
Tracking the weight of considered aspects in the reward function and finding a reasonable reward
function weight can give an explanation for the RL agents’ process. Based on this idea we divide
the current reward-based XRL work into two types: reward shaping and reward decomposition.
And the approaches are listed in Table 3.

4.2.1 Reward Decomposition. As for explaining the reward function, explanation at the reward level
focus on the reward itself. However, the reward function is just a real number value that is produced
by lots of implicit factors. It is intractable if we only focus on the output value. Decomposing the
reward function and seeing the influence of aspects in the reward towards the decision-making
Table 3. Reward-explaining methods in XRL approaches

| Explanation Type       | Description                                                                 | Algorithm                                                                 | Environments                                      |
|------------------------|-----------------------------------------------------------------------------|----------------------------------------------------------------------------|--------------------------------------------------|
| Reward Decomposition   | Decomposing the reward function and see the influence of components towards the decision-making process and the correspondence between each other | Reward and Q-value decomposition [90]                                     | GirdWorld game, LunarLander                       |
|                        |                                                                           | Counterfactual multi-agent policy gradient [42]                           | Starcraft                                         |
|                        |                                                                           | Shapley Q-value [211]                                                     | Cooperative navigation, Prey-and-predator, Traffic junction |
|                        |                                                                           | Counterfactual-based Shapley value [108]                                 | Starcraft                                         |
| Reward Shaping         | Finding an understandable reward function directly                         | Termination and relevance classifiers [132]                              | Maze                                             |
|                        |                                                                           | Intrinsic and extrinsic reward [124]                                    | GridWorld                                        |
|                        |                                                                           | Planning with action models [88]                                          | Office World, Montezuma’s revenge                 |
|                        |                                                                           | Tree-structured policy-based progressive RL [222]                        | Temporally language grounding in untrimmed videos |
|                        |                                                                           | Self-supervised attention-aware RL [221]                                | Assault, Frostbite, Berzerk, Carnival, Freeway, WizardOfWar, Kangaroo, Asteroids, Ms Pacman |

process as well as the correspondence between each other is a feasible idea. Here we introduce several reward decomposition methods.

Horizontal reward decomposition [90] is for reward explaining at the horizontal level. The authors first decompose the reward function in MDP $\mathbb{R} : S \times A \rightarrow \mathbb{R}^{|C|}$, where $C$ is the reward components number. The target is still optimize the total reward: $R(s,a) = \sum_{c \in C} R_c(s,a)$. Additionally, the Q-value is decomposed too: $Q^\pi(s,a) = \sum_{c \in C} Q^\pi_c(s,a)$. And they give the way to train such a decomposed Q-value based on neural network. To explain the decomposition, they focus on comparing pairwise actions. A simple way is to directly compare $\tilde{Q}(s,a_1)$ and $\tilde{Q}(s,a_2)$. If there is some component $c_i$ such that $Q_{c_i}(s,a_1) > Q_{c_i}(s,a_2)$ and choose the action $a_1$, than these components are the advantage over $a_2$. This way is described as reward difference explanation (RDX) in the form of $\Delta(s,a_1,a_2) = \tilde{Q}(s,a_1) - \tilde{Q}(s,a_2)$. RDX only tells experts which components may be the advantage over the other factors and does not point out which component is the most important one. If the factor number is gained large enough, RDX can just provide a little explanation. So they provide another explanation: minimal sufficient explanation (MSX). MSX is a two-tuple $(MSX^+, MSX^-)$ corresponding to the positive and negative factors. MSX$^+$ select the minimal set of components that the total $\Delta(s,a_1,a_2)$ is large than a dynamic threshold, while MSX$^-$ checks the sum of $-\Delta(s,a_1,a_2)$ with the other threshold. The approach is only tested in environments having a finite small action space which is easy to enumerate.

For multi-agent tasks, the most popular method is Centralized Training with Decentralized Execution (CTDE), which let the agents train with the local view while the central critic estimates the joint value function. The main challenge of CTDE is how to assign each agent credit, and current methods can be divided into explicit and implicit methods according to the training process of the central critic and local agent. Instead of implicit methods treating the structure as an entirety, the explicit methods train the central critic and local agent separately. Therefore the allocated credits are explainable for humans. For how to get the credit for each local agent, Shapley value [169] can be an effective tool. Shapley value is the average of influence of a feature (or multi-agent RL, the entity is a single agent) in different situations. To calculate it, we can measure the change in the output on whether consider the target feature or agent. One of the main challenges is that the computing costs grow exponentially with the number of agents, which means we have no idea how to approximate it in complex environments. Starting from the idea of calculating Shapley
value, the basic method called counterfactual multi-agent (COMA) policy gradient \cite{42} utilizes a counterfactual advantage function to perform local agent training. However, this method ignores the correlation and interaction between local agents, which leads to failure on more complex tasks. Wang et al. \cite{211} combine the Shapley value with the Q value and perform reward decomposition at a higher level in multi-agent tasks to guide the policy gradient process. With this kind of Q-value, they run DDPG \cite{111} to make a reasonable planning of global reward: the greater contribution of the individual agent, the more reward it will get. Compared with the traditional shared reward approach (which is inefficient because of assigning rewards to agents with lower contribution values), it assigns credit to each agent which can explain how global reward is divided during training and how much each agent contributes. The drawback of this network-based method is that it over-relied on the assumption that local agents take actions sequentially. Li et al. \cite{108} instead use counterfactual-based methods to quantify the contribution of each agent, which is more stable and effective.

4.2.2 Reward Shaping. Trying to obtain an explainable reward function is also an achievable approach. There are some works \cite{88, 124, 132, 196, 221, 222} skip the process of finding ways to explain the reward function and seek for understandable reward function directly.

Based on the interactions between the agent and human, Mirchandani et al. \cite{132} propose a reward-shaping method to shape the sparse reward to be associated with human instruction goal and current state by termination and relevance classifiers. Tabrez and Hayes \cite{196} also propose a framework called Reward Augmentation and Repair through Explanation (RARE). It utilizes partially observable MDP (POMDP) to approximate the understanding of collaborators towards the joint tasks. The authors accomplish this goal by modifying and correcting the reward function constantly. If a more plausible reward function is founded, it will be evaluated to see whether the advantage of taking it is larger than abandoning it or not. And if so, a repairing representation will be generated.

For more complex tasks, defining multi-level rewards is a reasonable way to explainability. It is different from task decomposition since the decomposed reward is the real reward received from the environment. While defining reward with multi-level means that the reward we take into consideration not only concentrates on the extrinsic reward received from the environment but also the intrinsic reward which is for better understanding and explanation. Lyu et al. \cite{124} define the reward with two levels of intrinsic and extrinsic reward. Extrinsic reward is for the sub-tasks reward in formal, which comes from the basic RL environment, while the intrinsic reward is received when constructing a plan (a series of learned sub-tasks). The intrinsic reward is evaluated based on the generated plan. DRL approaches are applied at the sub-tasks level, trying to optimize the extrinsic total reward and get the best policy for the low-level agent. And the authors use the symbolic planning (SP) method to schedule the sub-tasks at a higher level and get the optimal plan. While Lyu et al. \cite{124} pre-define the action models, Jin et al. \cite{88} extend their work to automatically learn the action model and let one option model correspond to several action models rather than just one in Lyu et al. \cite{124}. Therefore, it will converge much faster than the basic work. For temporally language bounding in untrimmed videos task, Wu et al. \cite{222} propose tree-structured policy-based progressive reinforcement learning. While the leaf policy receives the extrinsic reward from the external environment, the root policy, which does not directly interact with the external environment, measures the reward from both selections of high-level semantic branch intrinsically and how selected semantic branch action influence the external environment extrinsically. Therefore this process provides explainable credit within the tree-structured policy. For the problem that defining intrinsic reward cannot get performance as good as defining extrinsic reward, Wu et al. \cite{221} propose intrinsic mega-reward to encourage
the agent to gain more individual control ability which can be divided as direct and latent control. A relational transition model is designed to obtain such control ability. This framework achieves excellent results over most of the existing intrinsic reward approaches.

### 4.3 State-explaining

State-explaining is a kind of local explainability. Since observation of the current environment is the direct information that guides decision-making at the start of each timestep, state-explaining methods update the classical RL algorithm with an introspection part to simultaneously analyze input observation while performing the decision-making process. The analysis processes proposed by most of the existing frameworks are attention-based methods. Attention-based methods answer questions about which states or components of states are doing a great influence on the training results by defining a quantitative evaluation method of the important factor and trying to visualize it. We present a categorization that arranges these frameworks by the time of target explainable states and lists them in Table 4. We briefly review the related work giving the state-level explainability in this section.

| Explanation Type       | Description                                                                 | Algorithm                                      | Environments                      |
|------------------------|-----------------------------------------------------------------------------|-----------------------------------------------|-----------------------------------|
| Historical Trajectory  | Quantify the influence of each historical observations towards the decision making of agent | Sparse Bayesian RL [238]                      | GridWorld, Vehicle routing        |
|                        |                                                                             | Visual sparse Bayesian RL [133]                | Navigation                        |
|                        |                                                                             | Introspection [178]                           | Frogger                           |
|                        |                                                                             | Monte Carlo sampling [75]                     | Harvest, Predator-Prey            |
|                        |                                                                             | Neural network-based Shapley Value [234]      | Power system                      |
|                        |                                                                             | Deep Gaussian process [59]                    | MsPacman, Pong                    |
|                        |                                                                             | Super-pixel [118]                             | Flappy bird, MountainCar, Cartpole |
|                        |                                                                             | Social attention model [107]                  | Highway                           |
|                        |                                                                             | Attention neuron [197]                        | Cartpole, Ant, Pong, CarRacing    |
|                        |                                                                             | Interpretable DQN [6]                         | MsPacman                          |
|                        |                                                                             | Neural evolution [198]                        | CarRacing, DoomTakeCover          |
|                        |                                                                             | Region Sensitive Rainbow [228]                | Taxi drivers’ passenger-seeking   |
|                        |                                                                             | Stacked hierarchical attention [224]          | Inhuman, Reverbo Zork, Ztu        |
|                        |                                                                             | Random value mask-based importance [154]      | Pointing game                     |
|                        |                                                                             | Explainable generative adversarial imitation learning [148] | Taxi drivers’ passenger-seeking   |
|                        |                                                                             | Perturbation-based saliency [54]              | Breakout, Pong, SpaceInvaders     |
|                        |                                                                             | Partial features with convolution neural network [289] | Connect four                    |
|                        |                                                                             | Machine versus human attention [58]          | Freeway, Seaquest, Breakout, MonteZuma's revenge |
|                        |                                                                             | Object saliency map [83]                      | MsPacman                          |
|                        |                                                                             | Unsupervised video object segmentation [50]   | BeamRider, Breakout, Pong, Q* bert, Seaquest, Space Invaders |
|                        |                                                                             | DQNViz [210]                                  | Breakout                          |
| Future Prediction       | Make prediction of the future interaction and check it in the future         | Forward simulations [203]                     | GridWorld navigation              |
|                        |                                                                             | Discounted expected of future state visitations [229] | Blackjack, Cartpole, Taxi        |
|                        |                                                                             | Task space disentangling for multi-goal RL [105] | Push, Pushlight, Pickup, PickupColors |
|                        |                                                                             | Semantic Predictive Control [149]             | CARLA, GTA, Flappy bird, TORCS car racing |
|                        |                                                                             | MC Dropout and Bootstrapping-based LSTM [125] | Obstacle detecting task           |

4.3.1 **Historical Trajectory.** Target explainable state spaces at different times is the main divider of the state-explaining methods. Starting from the trace of historical decisions, we want to know the

J. ACM, Vol. 1, No. 1, Article 1. Publication date: January 2022.
influence of each history observation on the decision-making process of the agents. Some works give approaches to estimating the influence of historical observation.

The main factor of these approaches is how to quantify the influence of historical interaction. It is intuitive to extract the interaction that affects most to later decision-making. Sparse Bayesian Reinforcement Learning (SBRL) [238] records past experiences while training the agent, which is for knowledge transferring and continuous action search. It provides an understandable way to explain how historical data samples influence the learning process. Visual SBRL (V-SBRL) [133] stores the significant past experiences as images and the images can tell humans how a decision is made by the previous memorized experiences. V-SBRL uses a sparse filter to maintain the most important image and discard the trivial images to keep the image set sparse. V-SBRL contains three parts: a state image encoder to encode high-dimensional image data; the SBRL framework to calculate Q values, and a relevance vector machine to capture the relevance sample as candidates for the target image set; the snapshot storage selects the most important state-action pair from the candidates.

Sequeira and Gervasio [178] try to extract interestingness elements from historical observation. Interestingness element stands for historical interactions that have a great contribution to decision-making. They make the RL agent more explainable by introspective analysis. The interestingness elements obtained from historical data are found through a three-level introspection analysis. First, environment-analysis does certainty analysis on transition function and finds reward outliers in historical interaction. The second interaction-analysis does frequency analysis et al. to help characterize the environment dynamics. In the end, Meta-analysis combines the historical interaction data and analyzing results at different levels to identify more complex aspects of the interactions. The interestingness elements are outputted in the form of video.

While SBRL and interestingness elements methods measure the importance of interactions, Shapley value can be an effective way to calculate and visualize the contribution of each feature in previous trajectories. A main problem is that the naive computing Shapley value method has an intolerant $O(2^n)$ complexity. To approximate the Shapley value, Heuillet et al. [75] use Monte Carlo sampling, while Zhang et al. [234] utilize a deep model to calculate the gradient of features and combine them as a Shapley value. With a module that separates time and space, they are able to build a 3D feature-time-SHAP value map to visualize the importance of each timestep.

To combine the importance of timestep in vertical and episode relationship in horizontal, Guo et al. [59] capture this kind of sequential dependency by deep Gaussian Process (GP), which receives inputs of timestep embedding containing state-action pairs from RNN and episode embedding from MLP. The GP with deep recurrent kernels outputs both the correlation between timesteps and the joint effect across episodes. Additionally, this kind of output can be utilized to predict the total reward of the episode by linear regression, whose regression coefficient can identify the important timestep, which also enhances the explainability.

4.3.2 Current Observation. Many papers are trying to find the significant feature of decision-making at the current state, especially in the video and image environment. This type of approach provides post-hoc explanations based on analyzing how input states influence output policy. Some methods of this type are illustrated in Figure 4.

The linear model U-tree (LMUT) method [118] that is mentioned above also proposed an evaluation of the features. The corresponding influence of a LMUT node is evaluated with the product of two functions corresponding to the certainty of the Q-value and square weight of features respectively. The paper applies it to some video games and gets some pixels that with relatively high influence. They call such pixels super-pixels that have a high influence on current decision-making.
There are many works based on self-attention [6, 54, 83, 107, 197, 198, 224, 228]. Self-attention proposes a way to calculate an attention score matrix $X$ stands for the relations between every two features in the input based on the Key, Query, and Value matrices. For some environments where the agent needs to interact with other entities like self-driving [106], the self-attention DNN [107] considering each entity will perform better than normal DNN for the network structure is more fitted for the tasks. What’s more, the attention matrix can be considered a kind of explanation for current observation and decision-making. Many other works leverage the same idea from attention-based DNN to generate explanation: Tang and Ha [197] propose attention neuron to successfully focus on subparts of unordered observation, Annasamy and Sycara [6] utilize the attention-embedded DNN to build auto-encoder to reconstruct input states. Self-attention-based Neuroevolution [198] selects spatial patches of pixels instead of individual pixels from visual input. The neuroevolution framework is designed to only focus on the relevant regions and ignore the irrelevant regions in the input images. These spatial patches will be sent to the self-attention framework to get the importance. By neuroevolution, the agent can focus on the regions that are significant to the task and relatively give out the irrelevant regions, which enhances the effectiveness and explainability. Region Sensitive Rainbow (RS-Rainbow) [228] is proposed to find the important regions in the input images. RS-rainbow gives the claim that the important regions in the input images are all dynamic. So in the RS-rainbow framework, the DNN is followed by a region-sensitive module to detect the dynamic important regions. The authors proposed three methods to visualize the regions: weights-overlay, soft saliency mask and binary saliency mask. The RS-rainbow framework trains an interpretable agent embedded into classical RL models like A3C [134] and PPO [177] framework. Text-based game is much more challenging for RL to obtain reasoning capabilities. Xu et al. [224] propose a hierarchical attention model for explainability in a text-based game task. For the text-based game is a POMDP model, they add the Knowledge Graph (KG) into observation to represent game history. The hierarchical attention is a two-level framework: In high-level attention the query vector is composed of score and KG to compute groups of attention value on textual observations. In low-level attention, the high-level output is viewed as the query to compute attention on KG sub-graphs. Therefore, the multi-modal inputs can be transformed into explainable forms.
Another traditional model is the saliency map. There is a slight difference between saliency and attention. Attention is a general concept covering all aspects that influence selection mechanisms while saliency intuitively describes some part of the scene, possibly an object or a region. The saliency map tells us the impact of pixels on the image classification results. It can be constructed by calculating the gradient of the normalized scores in the correct classification corresponding to the image pixels. Many works \cite{54, 58, 83, 148, 154, 209, 212} extend this idea to RL agent to enhance explainability. Petsiuk et al. \cite{154} measure pixel importance by multiplying a random value mask between \([0, 1]\) and then observing how it affects the decision, this work is extended by Pan et al. \cite{148} to be applicable for geographic regions. At the same time, Greydanus et al. \cite{54} propose a framework with the same idea called perturbation-based saliency, which directly imposes a small perturbation on the certainty of specific features to observe the changes as the influence of the strategy. This framework is utilized by Guo et al. \cite{58} to compare human and RL agent attention, while their work shows how RL becomes more human-like in training. Since the pixel saliency map is inconvenient for users to understand, Wäldchen et al. \cite{209} extend it to partial features with convolution neural network. Object saliency map \cite{83} also performs an improvement on the pixel saliency map into object saliency map with an additional template matching step. Template matching is utilized to assign each detected object a channel as the input to the neural network. The object saliency map can be constructed by pixel saliency map plus object detection, which is understandable for human.

Instead of local spatial information, Goel et al. \cite{50} first learn to capture and segment the moving object in the video sequence by flow information. With the representation of the learned objects, the policy can focus on moving objects in a more explainable way.

Wang et al. \cite{210} propose a special input visualize framework for RL. They directly visualize the process of DQN \cite{135} with a visualization tool. The visualization of the entire DQN process contains what each stage is doing and the activation level of each layer in the convolutional neural network.

\subsection*{4.3.3 Future Prediction.} The two sub-type we introduced above are giving explanations for already existing states, but this future prediction type makes predictions of the future as explanations based on the trained model.

A simple way to get the prediction of the future is repeating forward simulations from the current state \cite{203}. However, the forward simulation result may not match the classical Q-value for the stochastic environment, systematic biases in training \cite{64} and so on. Therefore, Yau et al. \cite{229} weight the events by the importance that the agent puts when performing Q-Learning. They additionally define parameterized \(H(s, a)\) as the discounted expected of future state visitations starting with state-action pair \((s, a)\), and give the loss function with DQN style to approximate such a map function (the iteration of \(H\) is aligned with Q-learning update). After training such a framework, the "belief" map can be obtained and visualized by \(H\), which is consistent with Q-function. This framework is consistent with current value-based unexplainable RL frameworks. Lee et al. \cite{105} directly combine future prediction with multi-goal RL. To be explainable, they constrain the goal space to those that are semantically meaningful and explainable by using weak supervision to automatically disentangle task space and ignore irrelevant features. After training, the goals over the explainable latent space will have much more representative semantical meaning, which can generate trustworthy predictions for the current agent.

Semantic Predictive Control (SPC) \cite{149} is a semantic-based framework. SPC dynamically learns the environment and aggregates the multi-scale feature maps to predict future semantic segmentation. By adopting deep layer aggregation to extract multi-scale feature representations and after
being processed by a multi-scale prediction module, the predicted feature maps are aggregated to estimate not only the future events but also the future semantic segmentation.

Lütjens et al. [123] train an ensemble of LSTM networks using Monte Carlo Dropout and bootstrapping. It can get a policy that can measure the novelty (uncertainty) of the observation. Drawn from the uncertainty measurement, the framework can explain what the model knows and what the model does not know. The LSTM [78] can estimate the probability of future events and predict the uncertainty of new observations.

4.4 Task-explaining

Hierarchical reinforcement learning (HRL) [11] can deal with the situation that the decision-making becomes much more complex in RL tasks. Generally, HRL has the main idea that constructs an high-level controller choosing option (macro-action) and some low-level controllers choosing primitive actions, and the option outputted by the high-level controller can be viewed as a sub-goal that the low-level controllers need to achieve. The division work of HRL on RL tasks and options made by high-level controller give higher architectural explainability over the mentioned above XRL works for seeing how high-level agent schedules the low-level tasks. Here we dive deeply into HRL and categorize the HRL work into two parts: whole top-down structure and simple task decomposition. The approaches we talked about are listed in Table 5.

| Type                                | Description                                                                 | Algorithm                                      | Environments       |
|-------------------------------------|-----------------------------------------------------------------------------|------------------------------------------------|--------------------|
| Whole Top-to-Down structure         | Strictly dividing the real task sets into multi-level. Low-level task sets are the subset of high-level task set while the high-level task sets have its own task elements that lower task sets do not have. | Hierarchical policy [180]                      | Minecraft          |
|                                     |                                                                             | Boolean formula tasks dividing [140]           | GridWorld          |
| Simple Task Decomposition           | Just dividing the tasks into 2 levels. Usually low level tasks are the sub-tasks that decomposed from the real task while high level task is scheduling the sub-tasks. | Multi-task RL with context-based representations [188] | Meta-World         |
|                                     |                                                                             | Language instructions for hierarchical deep RL [86] | Mujoco, CLEVR      |
|                                     |                                                                             | Symbolic planner [124]                         | GridWorld          |
|                                     |                                                                             | Environment dynamics learning [18]             | Robotic manipulation task |
|                                     |                                                                             | Model primitives [220]                         | Maze, Pickup-Place  |

4.4.1 Whole Top-to-Down Structure. For hierarchical tasks with this structure, the real task sets are divided into multi-level. Low-level task sets are the subset of high-level task sets, while the high-level task set has its own task elements that lower task sets do not have. This rigorous and clear structure produces explainability for it is consistent with human life experiences and could see how high-level agent schedules low-level tasks.

A typical work [180] gives an approach to train in the environment with multi-tasks to get a hierarchical policy. For the task division sets: $G_1, G_2, ..., G_k$, we have $G_1 \subset G_2 \subset ... \subset G_k$. The task at each level has a policy $\pi_k$ which is composed of four parts: base tasks set policy $\pi_{k-1}$, an instruction policy $\pi_{k}^{\text{inst}}$ to give instruction $g$ telling $\pi_{k-1}$ to execute which base task, an augment flat policy $\pi_{k}^{\text{Aug}}$ for $\pi_k$ directly chooses its own action instead of choosing from base tasks, a switch policy $\pi_{k}^{\text{sw}}$ gives a signal $e$ to decide to select an action from whether the base task or the augment flat. By representing the state by the pair $(e_t, g_t)$, the state based on time sequence can be viewed as a finite state Markov chain paradigm, and it can also give the relation between each state. To train such a hierarchical policy, they give an approach of two steps. First, learning the basic skills from $G_{k-1}$ to ensure that the previously learned policy can be utilized by giving instructions to the
base policy. That is to say, this stage is building the connection between the instruction policy and
the base policy. Then sampling from $G_k$ to learn the new skill and switch policy. Both two steps are
based on the classical actor-critic RL algorithm. The ability that reuses the previous skills while
learning new skills as well as the explainability are verified in Minecraft games.

Another idea is about the logic combination of base tasks in bool algebra form [140]. For task
expression, the boolean operation is available like disjunction, conjunction, and negation. It is
possible to combine the base tasks with the bool operation. The framework they proposed is for
lifelong learning which needs to utilize previously learned skills to solve new tasks. So the tasks
$G_i$ also has the sequential relation $G_1 \subset G_2 \ldots \subset G_{t-1} \subset G_t$. In the paper, the framework first
learns goal-oriented approximation of value function for each base task and then combines these
approximations in a specific way. This framework can not only learn skills of new tasks without
further learning but also successfully represent the optimal policy for the current RL task which is
represented by bool algebra.

4.4.2 Simple Task Division. Different from the strict whole top-down structure, the simply divided
sub-tasks have the same status and do not have priority over each other. From multi-task RL’s
perspective, we need to find an efficient approach for knowledge transfer between tasks. Thus,
the metadata, which informs relations across multiple tasks, can be leveraged as an effective tool
for capturing task structures. Sohani et al. [188] utilize metadata to learn explainable contextual
representations across a family of tasks. However, these sub-tasks are corresponding to a final goal
that restricts the problem to a higher level. Therefore we can divide the task into 2 levels. Usually,
the low-level task is the sub-tasks that are decomposed from the real task and with the same status
while the high-level task is to schedule the sub-tasks.

Many methods explicitly divide the task and construct the high-level agent as a scheduler for low-
level agents. Jiang et al. [86] train the high-level agent to produce language instructions for low-level
agents. The low-level agents perform condition-RL algorithm while training high-level agents with
language model-based RL algorithm. The language instructions yielded by high-level agents are all
human-explainable. The symbolic planning-RL method [124] we talk about in Section 4.2 applies
the idea of doing simple task division. It uses a planner-controller-meta-controller framework
to solve hierarchical tasks. The planner works at a high level using symbolic knowledge to get
long-term scheduling of the sub-tasks and get the intrinsic reward. The controller that works at the
low level uses traditional DRL methods to solve sub-tasks for extrinsic reward. The meta-controller
learns the extrinsic reward with the input of both planner and controller while giving a new intrinsic
reward target for the planner at the same time. In Dot-to-Dot (D2D) [18] framework, the high-level
agent constructs the dynamic changes of the environment as well as the states and gives direction
to the low-level agents. And the low-level agent receives guidance from the high-level agent and
solves the decomposed simpler sub-tasks. After this process, the high-level agent can learn an
explainable representation of the decision-making process while the low-level agent learned the
larger state and action space effectively.

Wu et al. [220] do not directly divide the task like the two approaches we mentioned above. They
use the primitive model, which may be not so individually effective to learn to decompose the
mixed tasks. First, the primitive model is used to approximate piecewise functional decomposition
while these primitive models are specialized in their own region which means the sub-policy is
specialized in these regions too. The sub-policies are then transferred to compose the tasks that
we really want to solve. With the combination of such sub-policies, this framework can maintain
architectural explainability. The explainability is verified on high-dimensional continuous tasks
both on lifelong learning and single-task learning.

J. ACM, Vol. 1, No. 1, Article 1. Publication date: January 2022.
5 HUMAN KNOWLEDGE FOR RL PARADIGM

The mainstream XRL frameworks we categorized and talked about above pay little attention to human influence in seeking explainability. However, the result of several works of this type has shown the benefits of human participation in XRL [28, 53, 57, 96, 110, 235]. To emphasize the kind of human knowledge-based approaches and encourage future research of it, we put it in this separate section for discussion. The pre-given human prior knowledge about the tasks can be utilized as criteria to evaluate and guide the agent, while this kind of supervision can also produce post-hoc explanations for specific input. Additionally, compared with classical RL and normal XRL training that do not require human participation, human knowledge-embedded RL framework [128, 161, 162] does show improvement in performance, explainability as well as safety. As for the content of human knowledge, although it may not be completely compatible with the task, the agent will make attempts to implement it properly on the task during the training process. This optimization process fits the natural human learning process that most time the guidance and knowledge from the experts is vague and not so specific, but we can still utilize it for more efficient learning as well as more precise understanding. Considering the efficiency of human knowledge-based RL and the lack of it in current XRL community, we try to emphasize the importance of human knowledge-based RL by introducing existing small amount of work in this section. Here we discuss them based on our taxonomy work on XRL.

5.1 Fuzzy controller representing human knowledge

We have talked about approaches that use fuzzy controllers to represent policy in Section 4.1.1. Meanwhile, fuzzy logic can also be leveraged to represent human knowledge. Model-explaining approaches in XRL use self-explainable models to approximate Q-value or policy in RL framework. As for leveraging human knowledge, the main challenge is to decide how to represent human knowledge in an explainable way that the agent can easily understand since human knowledge is imprecise as well as vague in most of the new tasks, and sometimes it only covers a small part of the state space. To represent such an approximate rather than accurate model, classical approaches like bivalent logic rules are not fitted for they are deterministic. Fuzzy logic can give us an effective paradigm to represent human knowledge in an uncertain and imprecise form which is the same as the environment. Typical work on fuzzy logic is made by Zhang et al. [235]. They propose a policy network called KoGuN which is composed of two main parts: knowledge controller and refine module. The knowledge controller is given a set of fuzzy rules made by humans. Each rule corresponds to one action and all the human knowledge represented by fuzzy rules is fitted for the task. To mitigate this knowledge mismatch problem, they add trainable weight $\beta_i$ for each rule $l_i$ to learn to adapt the current new task and optimize the knowledge controllers like a neural network. The controller output an action preference vector $p = [p_1, p_2, ..., p_n]$ where $p_i$ is the result of rule $l_i$. The refine module takes $p$ as input and outputs the refined $p^*$ which could be viewed as a correction of the rough-based policy. A dynamically weighted sum of $p$ and $p^*$ is used as the final result: $w_1 p + w_2 p^*$ where $w_1 + w_2 = 1$. $p$ provided by fuzzy controller takes a larger position at the start of training and the proportion of refining model result $p^*$ is gradually increasing while the proportion of $p$ is correspondingly decreasing during the training process.

5.2 Dense Reward on human language

The sparse reward is widely set by most RL tasks since it is simple and easy to define: just need to give the reward when the agent achieves a sub-goal or the final goal otherwise the reward is zero. It is easy to be seen that learning with sparse reward is slow and challenging, thus we try to define a dense reward function that gives a reward signal as well as an action is done.
The dense reward function must be set sufficiently delicate to evaluate each action of the agent and to keep the optimal policy unchanged. Many work [9, 23, 63, 120, 141] have been conducted to provide an additional reasonable dense reward function. A creative work proposed by Goyal et al. [53] gives dense reward based on natural language annotation from humans. They first define MDP(+L) as a variant of MDP. MDP(+L) is defined by \( \langle S, A, P, R, \gamma, l \rangle \) where \( l \) is a language command describing the agent behavior and the other are the same with components in MDP. The initial \( R \) in MDP is denoted as \( R_{ex} \) while the dense reward determined by the language \( l \) is denoted as \( R_{lan} \). The authors add a Language-Action Reward Network (LEARN) to estimate whether the agent is following the language command \( l \) which is obtained from human annotators. This framework extract the sequence of past action \( (a_1, a_2, ..., a_{t-1}) \) and turn it into an action-frequency vector \( a_t \). Then LEARN takes \( a \) and natural language commands \( l \) as its input and outputs the probability distribution on whether the action-frequency vector is related to the natural language command. The distribution is over two classes: related and unrelated while the probability of these two classes is denoted as \( p_R(a_t) \) and \( p_U(a_t) \). To measure the relevance between \( a \) and \( l \), potential function is defined as \( \phi(a) = p_R(a_t) - p_U(a_t) \), then the language reward at time \( t \) can be defined as \( R_{lan}(a_t) = \gamma \phi(a_t) - \phi(a_{t-1}) \). The target optimal policy can be generated based on new reward function \( R_{ext} + R_{lan} \) which is also optimal based on the original reward function \( R_{ext} \) based on reward shaping theorem [141].

### 5.3 Gaze Position-based attention

We have talked about the agent using the attention-based idea to learn the important feature in the input vector of image or video in Section 4.3. For imitation learning framework, it has corresponding ways to get attention by imitation. Zhang et al. [237] summarize these methods as learning attention from humans while the human trainers provide the attention map to the learning agent. Human participation can implicitly show their attention through expression and gaze position. If the model can capture this attention information paralleled with demonstration, this kind of information can be utilized as an additional source of evaluative feedback. Here we introduce some works that are based on gaze position [57, 96, 110]. Guan et al. [57] augment the human attention data perturbing irrelevant regions. Kim et al. [96] leverage a visual attention model to train a mapping from images to vehicle control signals, it can also generate textual explanations for the action of agent. The textual explanation training data are given by humans, while attention alignment is leveraged to build the connection between the controller and explanation (both weekly and strongly). Li et al. [110] view gaze as probabilistic variables which can be predicated utilizing stochastic units embedded in DNN. Based on this idea, they implement the gaze framework by selecting important features and estimating the uncertainty of human gaze supervisory signals.

### 5.4 Automatic Task Decomposition

For complex tasks or multi-task problems with sparse rewards, it is hard to train an efficient agent directly. Therefore hierarchical RL (HRL) paradigm is proposed to deal with it. Based on decomposing complex tasks, HRL reuses and shares lots of low-level policies while the high-level policies do the scheduling work. To accelerate the task decomposing process, Chen et al. [28] utilize human instruction and demonstration to train a high-level language generator and use the generator to guide the low-level policies. Imitation learning is used to train the generator which is composed of multilayer LSTM networks. The generator takes the encoded state (containing explicit information like environment and goal) as input and outputs the natural language instruction. After that, the low-level policies get the input from the concatenation of the last hidden state of the input instruction and the encoded state. By passing through fully connected layers, the network can
obtain the action. This natural language instruction utilizing framework can not only decompose
the complex task successfully, but also have high generalizability on the new task.

6 CHALLENGES AND FUTURE DIRECTIONS FOR XRL
Currently the research of XRL is still in an early stage, thus we still have doubts in aspects such
as the architecture and evaluation metrics. Based on the reviewed paper and material of XRL, we
propose some promising future directions for XRL research here.

6.1 Full explainability
These XRL approaches we mentioned above as well as our categorization work are all based on
making part of the RL framework explainable, which can be viewed as partially explainable methods
and improving partial explainability. A essential problem is that the other parts except the target
explainable part are still untransparent for experts. Some complex tasks such as self-driving have a
high requirement of explainability for the reason of safety. Therefore just one explainable part is not
enough and is still unconvincing. To solve this problem, we need full explainability on the whole
MDP process for RL agent. A direct approach is to construct an integrated approach utilizing all
parts explaining methods. For example, Huber et al. [81] combine both global and local explanation
to integrate strategy summarization with saliency maps. However, the different part-explaining
methods can have far different structures and are limited to few environments, which makes the
combination challenging work. A possible way we guess is doing abstraction on these approaches
at a higher level and then combining them.

6.2 Balance of explainability and performance
Utilizing a more explainable model or algorithm has a side effect on the performance of the
agents. One reason is that the more explainable models need correspondingly more computing
resources to generate a good enough explanation. Glanois et al. [49] believes that we need to make
a tradeoff between explainability and performance. However, Mania et al. [127], Rudin and Carlson
[172] point out that sometimes we rely too much on deep learning methods, for some specific
tasks simple models can be considered and can also receive an excellent performance without the
intransparency of deep learning models that may lose the generalizability. More further research
should be conducted to decide how to maintain the balance of explainability and performance.

6.3 Evaluation methods
Although we have talked about the current evaluation method for XRL in Section 3, there is still no
evaluation approach that can be accepted by most of the experts in DRL community. One reason is
that the XRL approaches are highly limited to the specific tasks which may be far different from
each other and the forms of explanation can be too diverse to summarize a common measurement
method. What’s more, being explainable and interpretable is much more viewed as a subjective
perception of human beings in many papers which just claims that their approaches are explainable
without mathematical formulas or rigorous derivation supporting their expression. Once a common
evaluation method for XRL is determined, we can compare different XRL approaches and decide
which one is state-of-art. Shen et al. [179] propose a software platform for self-driving to compare
different XRL agents in the same driving scenario and evaluate the precision of explanation made by
XRL agent. But for XRL measurement, not only the XRL performance and precision of explanation,
but also legal and ethical aspects should be considered in the evaluation method for applying it in
the real scene.

J. ACM, Vol. 1, No. 1, Article 1. Publication date: January 2022.
6.4 Human knowledge-based framework

Zhang et al. [237] summarize the framework combining human knowledge with RL. They illustrate that human knowledge can be in a variety of forms like human gaze attention [96, 110] or intrinsic reward from human trainer [216]. They share similar ideas within XRL such as attention-based state-explaining and reward shaping-based reward-explaining XRL methods in our taxonomy. We have already emphasized the idea that the human knowledge-based paradigm can enhance the explainability and efficiency of the model in Section 5. However, few researchers explicitly mention human knowledge-based paradigms in XRL field. Future XRL research can consider leveraging the human knowledge-based paradigm to construct new XRL frameworks obtaining high user-oriented explainability and efficiency.

7  CONCLUSION AND FUTURE WORK

Explainability of RL is of growing importance due to practical, safe, and trustworthy concerns. It provides the RL agent with the ability to act reasonably in the real world and to be responsible for humans. In order to have a detailed understanding of the architecture and goal of XRL, we review recent work in reinforcement learning related to the concern of explainability. The survey first gives an in-depth introduction to XRL model explainability and metrics for evaluating XRL approaches. To further advance explainability on RL, we proposed a new categorization of current XRL approaches: model-explaining methods building the model as a white box or generating explanations directly, reward-explaining methods which regularize the reward function to be understandable, state-explaining methods for the attention-based explanation of observation, and hierarchical task decomposition to get architectural level explainability. Among the reviewed papers, we notice that there exist some human knowledge-based XRL frameworks that can be abstracted to training based on imitation learning or human-in-the-loop RL. They can not only accelerate the training process but also give an explanation of the decision-making. We discuss this type of method separately in Section 5 and organize these works into our taxonomy structure since many other XRL works pay little attention to it. After that, we discuss the challenges and promising future directions in XRL that can be summarized as these aspects: Full explainability, the balance between explainability and performance, evaluation metrics, and human knowledge-based XRL frameworks.

We believe that our work can make people with little knowledge of RL get into the explainable reinforcement learning field and construct a general understanding of explainable reinforcement learning.

REFERENCES

[1] Julius Adebayo, Justin Gilmer, Ian Goodfellow, and Been Kim. 2018. Local explanation methods for deep neural networks lack sensitivity to parameter values. *arXiv preprint arXiv:1810.03307* (2018).
[2] Julius Adebayo, Justin Gilmer, Michael Muelly, Ian Goodfellow, Moritz Hardt, and Been Kim. 2018. Sanity checks for saliency maps. *Advances in neural information processing systems* 31 (2018).
[3] Riad Akrour, Davide Tateo, and Jan Peters. 2019. Towards Reinforcement Learning of Human Readable Policies. In *Workshop on Deep Continuous-Discrete Machine Learning*.
[4] David Alvarez-Melis and Tommi S Jaakkola. 2018. On the robustness of interpretability methods. *arXiv preprint arXiv:1806.08049* (2018).
[5] Greg Anderson, Abhinav Verma, Isil Dillig, and Swarat Chaudhuri. 2020. Neurosymbolic reinforcement learning with formally verified exploration. *Advances in neural information processing systems* 33 (2020), 6172–6183.
[6] Raghuram Mandymam Annasamy and Katia Sycara. 2019. Towards better interpretability in deep q-networks. In *Proceedings of the AAAI conference on artificial intelligence*.
[7] Alessio Ansuini, Alessandro Laio, Jakob H Macke, and Davide Zoccolan. 2019. Intrinsic dimension of data representations in deep neural networks. *Advances in Neural Information Processing Systems* 32 (2019).
[8] Ines Arous, Lilijana Dolamic, Jie Yang, Akansha Bhardwaj, Giuseppe Cuccu, and Philippe Cudré-Mauroux. 2021. Marta: Leveraging human rationales for explainable text classification. In AAAI Conference on Artificial Intelligence.

[9] Adrià Puigdomènech Badia, Bilal Piot, Steven Kapturovski, Pablo Sprechmann, Alex Vittvitskiy, Zhaoan Daniel Guo, and Charles Blundell. 2020. Agent57: Outperforming the atari human benchmark. In International Conference on Machine Learning.

[10] Gagan Bansal, Besmira Nushi, Ece Kamar, Walter S Lasecki, Daniel S Weld, and Eric Horvitz. 2019. Beyond accuracy: The role of mental models in human-AI team performance. In Proceedings of the AAAI Conference on Human Computation and Crowdsourcing.

[11] Andrew G Barto and Sridhar Mahadevan. 2003. Recent advances in hierarchical reinforcement learning. Discrete event dynamic systems 13, 1 (2003), 41–77.

[12] Jon Barwise. 1977. An introduction to first-order logic. In Studies in Logic and the Foundations of Mathematics. Vol. 90. 5–46.

[13] Osbert Bastani, Yewen Pu, and Armando Solar-Lezama. 2018. Verifiable Reinforcement Learning via Policy Extraction. In Advances in neural information processing systems.

[14] Marc G Bellemare, Will Dabney, and Rémi Munos. 2017. A distributional perspective on reinforcement learning. In International Conference on Machine Learning.

[15] Yoshua Bengio, Ian Goodfellow, and Aaron Courville. 2017. Deep learning. Vol. 1.

[16] Marc G Bellemare, Will Dabney, and Rémi Munos. 2017. A distributional perspective on reinforcement learning. In International Conference on Machine Learning.

[17] Christopher Berner, Greg Brockman, Brooke Chan, Vicki Cheung, Przemyslaw Dębik, Christy Dennison, David Farhi, Quirin Fischer, Shariq Hashme, Chris Hesse, et al. 2019. Dota 2 with large scale deep reinforcement learning. arXiv preprint arXiv:1912.06680 (2019).

[18] Benjamin Bezyet, Ali Shafti, and A Aldo Faisal. 2019. Dot-to-dot: Explainable hierarchical reinforcement learning for robotic manipulation. In IEEE/RSJ International Conference on Intelligent Robots and Systems.

[19] Mustafa Bilgic and Raymond J Mooney. 2005. Explaining recommendations: Satisfaction vs. promotion. In Beyond personalization workshop, IUI.

[20] Alexander Binder, Wojciech Samek, Grégoire Montavon, Sebastian Bach, and Klaus-Robert Müller. 2016. Analyzing and validating neural networks predictions. In Proceedings of the ICML 2016 Workshop on Visualization for Deep Learning.

[21] Kayla Boggess, Sarit Kraus, and Lu Feng. 2022. Toward Policy Explanations for Multi-Agent Reinforcement Learning. arXiv preprint arXiv:2204.12568 (2022).

[22] Christine L Borgman. 1986. The user’s mental model of an information retrieval system: An experiment on a prototype online catalog. International Journal of man-machine studies 24, 1 (1986), 47–64.

[23] Yuri Burda, Harrison Edwards, Amos Storkey, and Oleg Klimov. 2018. Exploration by random network distillation. arXiv preprint arXiv:1810.12894 (2018).

[24] Ursula Challita, Walid Saad, and Christian Bettstetter. 2019. Interference management for cellular-connected UAVs: A deep reinforcement learning approach. IEEE Transactions on Wireless Communications 18, 4 (2019), 2125–2140.

[25] Jianyu Chen, Bodi Yuan, and Masayoshi Tomizuka. 2019. Model-free deep reinforcement learning for urban autonomous driving. In 2019 IEEE intelligent transportation systems conference (ITSC).

[26] Long Chen, Xuemin Hu, Bo Tang, and Yu Cheng. 2022. Conditional DQN-Based Motion Planning With Fuzzy Logic for Autonomous Driving. IEEE transactions on intelligent transportation systems 23, 4 (2022), 2966–2977.

[27] Qingyun Chen, Wanzhong Zhao, Lin Li, Chunyan Wang, and Feng Chen. 2020. ES-DQN: A Learning Method for Autonomous Driving. IEEE transactions on vehicular technology 71, 3 (2022), 2472–2484.

[28] Valerie Chen, Abhinav Gupta, and Kenneth Marino. 2021. Ask Your Humans: Using Human Instructions to Improve Generalization in Reinforcement Learning. In International Conference on Learning Representations.

[29] YiLun Chen, Chiyu Dong, Praveen Palanisamy, Priyamunthen Madugalie, Katharina Muelling, and John M Dolan. 2019. Attention-based hierarchical deep reinforcement learning for lane change behaviors in autonomous driving. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops.

[30] Amine Chraibi, Said Ben Alla, and Abdellah Ezzati. 2021. Makespan Optimisation in Cloudlet Scheduling with Improved DQN Algorithm in Cloud Computing. Scientific Programming 2021 (2021), 7216795:1–7216795:11.

[31] Sven Coppens, Jan Van den Bergh, Kris Luyten, Karin Coninx, Iulianna Van der Lek-Ciudin, Tom Vanallemearsch, and Vincent Vandeghinste. 2018. Intellingo: An intelligible translation environment. In Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems.

[32] Suma Dawn, Utkarsh Saraogi, and Utkarsh Singh Thakur. 2020. Agent-based Learning for Auto-Navigation within the Virtual City. In 2020 International Conference on Computational Performance Evaluation (ComPE).
[33] Richard Dazeley, Peter Vamplew, and Francisco Cruz. 2021. Explainable reinforcement learning for broad-xai: A conceptual framework and survey. arXiv preprint arXiv:2108.09003 (2021).

[34] Edsger W Dijkstra et al. 1959. A note on two problems in connexion with graphs. Numerische Mathematik 1, 1 (1959), 269–271.

[35] Finale Doshi-Velez and Been Kim. 2017. A roadmap for a rigorous science of interpretability. arXiv preprint arXiv:1702.08608 (2017).

[36] Mengnan Du, Ninghao Liu, and Xia Hu. 2019. Techniques for interpretable machine learning. Commun. ACM 63, 1 (2019), 68–77.

[37] Jiajun Duan, Di Shi, Ruisheng Diao, Haifeng Li, Zhiwei Wang, Bei Zhang, Desong Bian, and Zhehan Yi. 2019. Deep-reinforcement-learning-based autonomous voltage control for power grid operations. IEEE Transactions on Power Systems 35, 1 (2019), 814–817.

[38] Upol Ehsan, Pradyumna Tambwekar, Larry Chan, Brent Harrison, and Mark O Riedl. 2019. Automated rationale generation: a technique for explainable AI and its effects on human perceptions. In Proceedings of the 24th International Conference on Intelligent User Interfaces.

[39] Abdur R Fayjie, Sabir Hossain, Doukhí Oualid, and Deok-Jin Lee. 2018. Driverless car: Autonomous driving using deep reinforcement learning in urban environment. In 2018 15th international conference on ubiquitous robots (ur).

[40] A. Feinberg. 1996. Markov Decision Processes: Discrete Stochastic Dynamic Programming (Martin L. Puterman). SIAM Rev. 38, 4 (1996), 689.

[41] Borja Fernández-Gauna, Manuel Graña, Juan-Luis Osa-Amilibia, and Xabier Larrucea. 2022. Actor-critic continuous state reinforcement learning for wind-turbine control robust optimization. Information Sciences 591 (2022), 365–380.

[42] Jakob Foerster, Gregory Farquhar, Triantafyllos Afouras, Nantas Nardelli, and Shimon Whiteson. 2018. Counterfactual multi-agent policy gradients. In Proceedings of the AAAI conference on artificial intelligence.

[43] Danilo Franco, Nicola Novarin, Michele Donini, Davide Anguita, and Luca Oneto. 2022. Deep fair models for complex data: Graphs labeling and explainable face recognition. Neurocomputing 470 (2022), 318–334.

[44] Scott Fujimoto, Herke Hoof, and David Meger. 2018. Addressing function approximation error in actor-critic methods. In International conference on machine learning.

[45] Yosuke Fukuchi, Masahiko Osawa, Hiroshi Yamakawa, and Michita Imai. 2017. Application of Instruction-Based Behavior Explanation to a Reinforcement Learning Agent with Changing Policy. In International Conference on Neural Information Processing.

[46] Yosuke Fukuchi, Masahiko Osawa, Hiroshi Yamakawa, and Michita Imai. 2017. Autonomous self-explanation of behavior for interactive reinforcement learning agents. In International Conference on Human Agent Interaction.

[47] Fatih Gedikli, Dietmar Jannach, and Mouzhi Ge. 2014. How should I explain? A comparison of different explanation types for recommender systems. International Journal of Human-Computer Studies 72, 4 (2014), 367–382.

[48] Muriel Gervay, Ioannis Dimopoulos, and Sovan Lek. 2003. Review and comparison of methods to study the contribution of artificial neural network models. Ecological Modelling 160, 3 (2003), 249–264.

[49] Claire Glanois, Paul Weng, Matthieu Zimmer, Dong Li, Tianpei Yang, Jianye Hao, and Wulong Liu. 2021. A Survey on Interpretable Reinforcement Learning. arXiv preprint arXiv:2112.13112 (2021).

[50] Vikash Goel, Jameson Weng, and Pascal Poupart. 2018. Unsupervised video object segmentation for deep reinforcement learning. Advances in neural information processing systems 31 (2018).

[51] Ziv Goldfeld, Ewout van den Berg, Igor Melnyk, Nam Nguyen, Brian Kingsbury, and Yury Polyanskiy. 2018. Estimating information flow in deep neural networks. arXiv preprint arXiv:1810.05728 (2018).

[52] Xiaoyu Gong, Jiayu Yu, Shuai Lü, and Hengwei Lu. 2022. Actor-critic with familiarity-based trajectory experience replay. Information Sciences 582 (2022), 633–647.

[53] Prasoon Goyal, Scott Niekum, and Raymond J. Mooney. 2019. Using Natural Language for Reward Shaping in Reinforcement Learning. In International Joint Conference on Artificial Intelligence.

[54] Samuel Greydanus, Anurag Koul, Jonathan Dodge, and Alan Fern. 2018. Visualizing and Understanding Atari Agents. In International Conference on Machine Learning.

[55] Alex Groce, Todd Kulesza, Chaoqiang Zhang, Shalini Shamasunder, Margaret Burnett, Weng-Keen Wong, Simone Stumpf, Shubhomoy Das, Amber Shinsel, Forrest Bice, et al. 2013. You are the only possible oracle: Effective test selection for end users of interactive machine learning systems. IEEE Transactions on Software Engineering 40, 3 (2013), 307–323.

[56] Lin Guan, Mudit Verma, Sihang Guo, Ruohan Zhang, and Subbarao Kambhampati. 2020. Explanation augmented feedback in human-in-the-loop reinforcement learning. arXiv preprint arXiv:2006.14804 (2020).

[57] Lin Guan, Mudit Verma, Sina Sihang Guo, Ruohan Zhang, and Subbarao Kambhampati. 2021. Widening the pipeline in human-guided reinforcement learning with explanation and context-aware data augmentation. Advances in Neural Information Processing Systems 34 (2021), 21885–21897.

J. ACM, Vol. 1, No. 1, Article 1. Publication date: January 2022.
[58] Suna Sihang Guo, Ruohan Zhang, Bo Liu, Yifeng Zhu, Dana Ballard, Mary Hayhoe, and Peter Stone. 2021. Machine versus human attention in deep reinforcement learning tasks. *Advances in Neural Information Processing Systems* 34 (2021), 25370–25385.

[59] Wenbo Guo, Xian Wu, Usmann Khan, and Xinyu Xing. 2021. Edge: Explaining deep reinforcement learning policies. *Advances in Neural Information Processing Systems* 34 (2021), 12222–12236.

[60] Tuomas Haarnoja, Aurick Zhou, Pieter Abbeel, and Sergey Levine. 2018. Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor. In *International conference on machine learning*.

[61] Joseph Y. Halpern and Judea Pearl. 2001. Causes and Explanations: A Structural-Model Approach - Part II: Explanations. In *International Joint Conference on Artificial Intelligence*.

[62] Xiaoxu Han, Hongyao Tang, Yuan Li, Guang Kou, and Leilei Liu. 2020. Improving multi-agent reinforcement learning with imperfect human knowledge. In *International Conference on Artificial Neural Networks*.

[63] Anna Harutyunyan, Will Dabney, Thomas Mesnard, Mohammad Gheslaghi Azar, Bilal Piot, Nicolas Heess, Hado P van Hasselt, Gregory Wayne, Satinder Singh, Doina Precup, et al. 2019. Hindsight credit assignment. *Advances in neural information processing systems* 32 (2019).

[64] Hado Hasselt. 2010. Double Q-learning. *Advances in neural information processing systems* 23 (2010).

[65] Matthew Hausknecht and Peter Stone. 2015. Deep recurrent q-learning for partially observable mdps. In *2015 aaai full symposium series*.

[66] Bradley Hayes and Julie A. Shah. 2017. Improving Robot Controller Transparency Through Autonomous Policy Explanation. In *ACM/IEEE International Conference on Human-Robot Interaction*.

[67] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*.

[68] Nicolas Heess, Dhruva TB, Srinivasan Srim, Jay Lemmon, Josh Merel, Greg Wayne, Yuval Tassa, Tom Erez, Ziyu Wang, SM Eslami, et al. 2017. Emergence of locomotion behaviours in rich environments. *arXiv preprint arXiv:1707.02286* (2017).

[69] Daniel Hein, Alexander Hentschel, Thomas A. Runkler, and Steffen Udluft. 2017. Particle swarm optimization for generating interpretable fuzzy reinforcement learning policies. *Engineering Applications of Artificial Intelligence* 65 (2017), 87–98.

[70] Daniel Hein, Steffen Udluft, and Thomas A Runkler. 2018. Interpretable policies for reinforcement learning by genetic programming. *Engineering Applications of Artificial Intelligence* 76 (2018), 158–169.

[71] Daniel Hein, Steffen Udluft, and Thomas A. Runkler. 2019. Generating interpretable reinforcement learning policies using genetic programming. In *Genetic and Evolutionary Computation Conference*.

[72] Bernease Herman. 2017. The promise and peril of human evaluation for model interpretability. *arXiv preprint arXiv:1711.07414* (2017).

[73] Matteo Hessel, Joseph Modayil, Hado Van Hasselt, Tom Schaul, Georg Ostrovski, Will Dabney, Dan Horgan, Bilal Piot, Mohammad Azar, and David Silver. 2018. Rainbow: Combining improvements in deep reinforcement learning. In *AAAI conference on artificial intelligence*.

[74] Alexandre Heuillet, Fabien Couthouis, and Natalia Diaz-Rodriguez. 2021. Explainability in deep reinforcement learning. *Knowledge-Based Systems* 214 (2021), 106685.

[75] Alexandre Heuillet, Fabien Couthouis, and Natalia Diaz-Rodriguez. 2022. Collective explainable AI: Explaining cooperative strategies and agent contribution in multiagent reinforcement learning with shapley values. *IEEE Computational Intelligence Magazine* 17, 1 (2022), 59–71.

[76] Geoffrey Hinton, Oriol Vinyals, Jeff Dean, et al. 2015. Distilling the knowledge in a neural network. *arXiv preprint arXiv:1503.02531* (2015).

[77] Jonathan Ho and Stefano Ermon. 2016. Generative adversarial imitation learning. *Advances in neural information processing systems* 29.

[78] Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural computation* 9, 8 (1997), 1735–1780.

[79] Carl-Johan Hoel, Katherine Driggs-Campbell, Krister Wolff, Leo Laine, and Mykel J Kochenderfer. 2019. Combining planning and deep reinforcement learning in tactical decision making for autonomous driving. *IEEE transactions on intelligent vehicles* 5, 2 (2019), 294–305.

[80] Robert R Hoffman, Shane T Mueller, Gary Klein, and Jordan Litman. 2018. Metrics for explainable AI: Challenges and prospects. *arXiv preprint arXiv:1812.04608* (2018).

[81] Tobias Huber, Katharina Weitz, Elisabeth André, and Ofra Amir. 2021. Local and global explanations of agent behavior: Integrating strategy summaries with saliency maps. *Artificial Intelligence* 301 (2021), 103571.

[82] Jeevana Priya Inala, Yichen Yang, James Paulos, Yewen Pu, Osbert Bastani, Vijay Kumar, Martin Rinard, and Armando Solar-Lezama. 2020. Neurosymbolic transformers for multi-agent communication. *Advances in Neural Information Processing Systems* 33 (2020), 13597–13608.
A Survey on Explainable Reinforcement Learning: Concepts, Algorithms, Challenges

[83] Rahul Iyer, Yuezhang Li, Huao Li, Michael Lewis, Ramitha Sundar, and Katia P. Sycara. 2018. Transparency and Explanation in Deep Reinforcement Learning Neural Networks. In AAAI/ACM Conference on Artificial Intelligence, Ethics, and Society.

[84] Theo Jaunet, Romain Vuillemeot, and Christian Wolf. 2020. DRLViz: Understanding decisions and memory in deep reinforcement learning. In Computer Graphics Forum.

[85] Haoran Jiang and Dan Zeng. 2021. Explainable Face Recognition based on Accurate Facial Compositions. In IEEE/CVF International Conference on Computer Vision.

[86] Yiding Jiang, Shixiang Shane Gu, Kevin P Murphy, and Chelsea Finn. 2019. Language as an abstraction for hierarchical deep reinforcement learning. Advances in Neural Information Processing Systems 32 (2019).

[87] Zhengyao Jiang and Shan Luo. 2019. Neural logic reinforcement learning. In International conference on machine learning.

[88] Mu Jin, Zhihao Ma, Kebing Jin, Hankz Hankui Zhuo, Chen Chen, and Chao Yu. 2022. Creativity of AI: Automatic Symbolic Option Discovery for Facilitating Deep Reinforcement Learning. In Proceedings of the AAAI Conference on Artificial Intelligence.

[89] Peng Jin, Jiaxu Tian, Dapeng Zhi, Xuejun Wen, and Min Zhang. 2022. : A CEGAR-Driven Training and Verification Framework for Safe Deep Reinforcement Learning. In International Conference on Computer Aided Verification.

[90] Zoe Juczopaitsis, Anurag Koul, Alan Fern, Martin Erwig, and Finale Doshi-Velez. 2019. Explainable reinforcement learning via reward composition. In International Joint Conference on Artificial Intelligence.

[91] Guy Katz, Derek A Huang, Duligur Ibeling, Kyle Julian, Christopher Lazarus, Rachel Lim, Parth Shah, Shantanu Thakoor, Haoze Wu, Aleksandar Zeljic, et al. 2019. The marabou framework for verification and analysis of deep neural networks. In International Conference on Computer Aided Verification.

[92] Matthew Kay, Tara Kola, Jessica R Hullman, and Sean A Munson. 2016. When (ish) is my bus? user-centered visualizations of uncertainty in everyday, mobile predictive systems. In Proceedings of the 2016 chi conference on human factors in computing systems.

[93] Yafim Kazak, Clark W. Barrett, Guy Katz, and Michael Schapira. 2019. Verifying Deep-RL-Driven Systems. In Proceedings of the 2019 workshop on network meets AI & ML.

[94] Been Kim, Oluwasanmi Koyejo, and Rajiv Khanna. 2016. Examples are not enough, learn to criticize! Criticism for Interpretability. In Annual Conference on Neural Information Processing Systems.

[95] Been Kim, Martin Wattenberg, Justin Gilmer, Carrie Cai, James Wexler, Fernanda Viegas, et al. 2018. Interpretability beyond feature attribution: Quantitative testing with concept activation vectors (tcav). In International conference on machine learning.

[96] Jinkyu Kim, Anna Rohrbach, Trevor Darrell, John F. Canny, and Zeynep Akata. 2018. Textual Explanations for Self-Driving Vehicles. In European Conference on Computer Vision.

[97] Pieter-Jan Kindermans, Sara Hooker, Julius Adebayo, Maximilian Alber, Kristof T Schütt, Sven Dähne, Dumitru Erhan, and Been Kim. 2019. The (un)reliability of saliency methods. In Explainable AI: Interpreting, Explaining and Visualizing Deep Learning.

[98] Hedvig Kjellström, Danica Kragić, and Michael J Black. 2010. Tracking people interacting with objects. In 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. 747–754.

[99] Josua Krause, Aritra Dasgupta, Jordan Swartz, Yindalon Aphinyanaphongs, and Enrico Bertini. 2017. A workflow for visual diagnostics of binary classifiers using instance-level explanations. In 2017 IEEE Conference on Visual Analytics Science and Technology (VAST).

[100] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. 2012. Imagenet classification with deep convolutional neural networks. Advances in neural information processing systems 25 (2012).

[101] Todd Kulesza, Simone Stumpf, Margaret Burnett, Sherry Yang, Irwin Kwan, and Weng-Keen Wong. 2013. Too much, too little, or just right? Ways explanations impact end users’ mental models. In 2013 IEEE Symposium on visual languages and human centric computing.

[102] Isaac Lage, Emily Chen, Jeffrey He, Menaka Narayanan, Been Kim, Samuel J Gershman, and Finale Doshi-Velez. 2019. Human evaluation of models built for interpretability. In Proceedings of the AAAI Conference on Human Computation and Crowdsourcing.

[103] Himabindu Lakkaraju, Stephen H Bach, and Jure Leskovec. 2016. Interpretable decision sets: A joint framework for description and prediction. In Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining.

[104] Mikkel Landajuela, Brenden K Petersen, Sookyung Kim, Claudio P Santiago, Ruben Glatt, Nathan Mundhenk, Jacob F Pettit, and Daniel Faissol. 2021. Discovering symbolic policies with deep reinforcement learning. In International Conference on Machine Learning.

[105] Lisa Lee, Ben Eysenbach, Russ R Salakhutdinov, Shixiang Shane Gu, and Chelsea Finn. 2020. Weakly-supervised reinforcement learning for controllable behavior. Advances in Neural Information Processing Systems 33 (2020).
[106] Edouard Leurent. 2018. An Environment for Autonomous Driving Decision-Making. https://github.com/eleurent/highway-env.

[107] Edouard Leurent and Jean Mercat. 2019. Social attention for autonomous decision-making in dense traffic. arXiv preprint arXiv:1911.12250 (2019).

[108] Jiahui Li, Kun Kuang, Baoxiang Wang, Furui Liu, Long Chen, Fei Wu, and Jun Xiao. 2021. Shapley counterfactual credits for multi-agent reinforcement learning. In Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining.

[109] Xiaoyu Li, Xueshan Han, and Ming Yang. 2022. Day-Ahead Optimal Dispatch Strategy for Active Distribution Network Based on Improved Deep Reinforcement Learning. IEEE access 10 (2022), 9357–9370.

[110] Yin Li, Miao Liu, and James M. Rehg. 2018. In the Eye of Beholder: Joint Learning of Gaze and Actions in First Person Video. In European Conference on Computer Vision.

[111] Timothy P Lillicrap, Jonathan J Hunt, Alexander Pritzel, Nicolas Heess, Tom Erez, Yuval Tassa, David Silver, and Daan Wierstra. 2015. Continuous control with deep reinforcement learning. arXiv preprint arXiv:1509.02971.

[112] Brian Y Lim and Anind K Dey. 2009. Assessing demand for intelligibility in context-aware applications. In Proceedings of the 11th international conference on Ubiquitous computing.

[113] Brian Y Lim, Anind K Dey, and Daniel Avrahami. 2009. Why and why not explanations improve the intelligibility of context-aware intelligent systems. In Proceedings of the SIGCHI conference on human factors in computing systems. 2119–2128.

[114] Kaixiang Lin, Renyu Zhao, Zhe Xu, and Jiayu Zhou. 2018. Efficient large-scale fleet management via multi-agent deep reinforcement learning. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining.

[115] Lin Lin, Xin Guan, Yu Peng, Ning Wang, Sabita Maharjan, and Tomoaki Ohtsuki. 2020. Deep reinforcement learning for economic dispatch of virtual power plant in internet of energy. IEEE Internet of Things Journal 7, 7 (2020), 6288–6301.

[116] Zachary C Lipton. 2018. The Mythos of Model Interpretability: In machine learning, the concept of interpretability is both important and slippery. Queue 16, 3 (2018), 31–57.

[117] Chang Liu, Jie Yan, Feiyue Guo, and Min Guo. 2022. Forecasting the Market with Machine Learning Algorithms: An Application of NMC-BERT-LSTM-DQN-X Algorithm in Quantitative Trading. ACM Transactions on Knowledge Discovery From Data 16, 4 (2022), 62:1–62:22.

[118] Guilin Yang, Oliver Schulte, Wang Zhu, and Qingcan Li. 2018. Toward interpretable deep reinforcement learning with linear model u-trees. In Joint European Conference on Machine Learning and Knowledge Discovery in Databases.

[119] Hui Liu, Qingyu Yin, and William Yang Wang. 2018. Towards explainable NLP: A generative explanation framework for text classification. arXiv preprint arXiv:1811.00196 (2018).

[120] Yang Liu, Yunan Luo, Yuanyi Zhong, Xi Chen, Qiang Liu, and Jian Peng. 2019. Sequence modeling of temporal credit assignment for episodic reinforcement learning. arXiv preprint arXiv:1905.13420 (2019).

[121] Zimo Liu, Jingya Wang, Shaogang Gong, Huchuan Lu, and Dacheng Tao. 2019. Deep reinforcement active learning for human-in-the-loop person re-identification. In Proceedings of the IEEE/CVF international conference on computer vision.

[122] Qiang Lu, Jun Ren, and Zhiguang Wang. 2016. Using genetic programming with prior formula knowledge to solve symbolic regression problem. Computational intelligence and neuroscience 2016 (2016).

[123] Björn Lütjens, Michael Everett, and Jonathan P How. 2019. Safe reinforcement learning with model uncertainty estimates. In 2019 International Conference on Robotics and Automation (ICRA).

[124] Daoming Lyu, Fangkai Yang, Bo Liu, and Steven Gustafson. 2019. SDRL: interpretable and data-efficient deep reinforcement learning leveraging symbolic planning. In Proceedings of the AAAI Conference on Artificial Intelligence.

[125] Prashan Madumal, Tim Miller, Liz Sonenberg, and Frank Vetere. 2020. Explainable Reinforcement Learning through a Causal Lens. In AAAI Conference on Artificial Intelligence.

[126] Francis Maes, Raphael Fonteneau, Louis Wehenkel, and Damien Ernst. 2012. Policy search in a space of simple closed-form formulas: Towards interpretability of reinforcement learning. In International Conference on Discovery Science.

[127] Horia Mania, Aurelia Giger, and Benjamin Recht. 2018. Simple random search of static linear policies is competitive for reinforcement learning. In Annual Conference on Neural Information Processing Systems.

[128] Kunal Menda, Katherine Driggs-Campbell, and Mykel J Kochenderfer. 2019. Ensembledagger: A bayesian approach to safe imitation learning. In 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS).

[129] Li Meng, Morten Goodwin, Anis Yazidi, and Paal Engelstad. 2022. Improving the Diversity of Bootstrapped DQN via Noisy Priors. arXiv preprint arXiv:2203.01004 (2022).
A Survey on Explainable Reinforcement Learning: Concepts, Algorithms, Challenges

Stephanie Milani, Zhicheng Zhang, Nicholay Topin, Zheyuan Ryan Shi, Charles Kamhoua, Evangelos E Papalexakis, and Fei Fang. 2022. MAVIPER: Learning Decision Tree Policies for Interpretable Multi-Agent Reinforcement Learning. arXiv preprint arXiv:2205.12449 (2022).

Tim Miller. 2019. Explanation in artificial intelligence: Insights from the social sciences. Artificial Intelligence 267 (2019), 1–38.

Suvir Mirchandani, Siddharth Karamcheti, and Dorsa Sadigh. 2021. Ella: Exploration through learned language abstraction. Advances in Neural Information Processing Systems 34 (2021), 29529–29540.

Indrajit Mishra, Giang Dao, and Minwoo Lee. 2018. Visual sparse Bayesian reinforcement learning: a framework for interpreting what an agent has learned. In IEEE Symposium Series on Computational Intelligence.

Volodymyr Mnih, Adria Puigdomenech Badia, Mehdi Mirza, Alex Graves, Timothy Lillicrap, Tim Harley, David Silver, and Koray Kavukcuoglu. 2016. Asynchronous methods for deep reinforcement learning. In International conference on machine learning. 1928–1937.

Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, and Martin Riedmiller. 2013. Playing atari with deep reinforcement learning. arXiv preprint arXiv:1312.5602 (2013).

Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A Rusu, Joel Veness, Marc G Bellemare, Alex Graves, Martin Riedmiller, Andreas K Fidjeland, Georg Ostrovski, et al. 2015. Human-level control through deep reinforcement learning. nature 518, 7540 (2015), 529–533.

Sina Mohseni, Nilofar Zarei, and Eric D Ragan. 2021. A multidisciplinary survey and framework for design and evaluation of explainable AI systems. ACM Transactions on Interactive Intelligent Systems 11, 3-4 (2021), 1–45.

Christoph Mohr. 2020. Interpretable machine learning.

Terrell Mundhenk, Mikel Landajuela, Ruben Glatt, Claudio P Santiago, Brenden K Petersen, et al. 2021. Symbolic Regression via Deep Reinforcement Learning Enhanced Genetic Programming Seeding. Advances in Neural Information Processing Systems 34 (2021), 24912–24923.

Geraud Nangue Tasse, Steven James, and Benjamin Rosman. 2020. A Boolean task algebra for reinforcement learning. Advances in Neural Information Processing Systems 33 (2020), 9497–9507.

Andrew Y Ng, Daishi Harada, and Stuart Russell. 1999. Policy invariance under reward transformations: Theory and application to reward shaping. In International Conference on Machine Learning.

Thu Trang Nguyen, Thach Le Nguyen, and Georgiana Ifrim. 2020. A model-agnostic approach to quantifying the informativeness of explanation methods for time series classification. In International Workshop on Advanced Analytics and Learning on Temporal Data.

Clyde E Noble. 1957. Human trial-and-error learning. Psychological Reports 3, 2 (1957), 377–398.

Florian Nothdurft, Felix Richter, and Wolfgang Minker. 2014. Probabilistic human-computer trust handling. In Proceedings of the 15th annual meeting of the special interest group on discourse and dialogue (SIGDIAL).

Besmira Nushi, Ece Kamar, and Eric Horvitz. 2018. Towards accountable ai: Hybrid human-machine analyses for characterizing system failure. In Proceedings of the AAAI Conference on Human Computation and Crowdsourcing.

Chris Olah, Arvind Satyanarayan, Ian Johnson, Shan Carter, Ludwig Schubert, Katherine Ye, and Alexander Mordvintsev. 2018. The building blocks of interpretability. Distill 3, 3 (2018), e10.

Matthew L Olson, Roli Khanna, Lawrence Neal, Fuxin Li, and Weng-Keen Wong. 2021. Counterfactual state explanations for reinforcement learning agents via generative deep learning. Artificial Intelligence 295 (2021), 103455.

Menghai Pan, Weixiao Huang, Yuhnha Li, Xin Zhou, and Jun Luo. 2020. xgail: Explainable generative adversarial imitation learning for explainable human decision analysis. In Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining.

Xinlei Pan, Xiangyu Chen, Qi-Zhi Cai, John F. Cann, and Fisher Yu. 2019. Semantic Predictive Control for Explainable and Efficient Policy Learning. In International Conference on Robotics and Automation.

Seongjin Park, Younghwan Yoo, and Chang Woo Pyo. 2022. Applying DQN solutions in fog-based vehicular networks: Scheduling, caching, and collision control. Vehicular Communications 33 (2022), 100397.

Ali Payani and Faramaz Fekri. 2019. Inductive logic programming via differentiable deep neural logic networks. arXiv preprint arXiv:1906.03523 (2019).

Ali Payani and Faramaz Fekri. 2020. Incorporating relational background knowledge into reinforcement learning via differentiable inductive logic programming. arXiv preprint arXiv:2003.10386 (2020).

Brenden K Petersen, Mikel Landajuela Larma, T Nathan Mundhenk, Claudio P Santiago, Soo K Kim, and Joanne T Kim. 2019. Deep symbolic regression: Recovering mathematical expressions from data via risk-seeking policy gradients. arXiv preprint arXiv:1912.04871 (2019).

Vitali Petsiuk, Abir Das, and Kate Saenko. 2018. Rise: Randomized input sampling for explanation of black-box models. arXiv preprint arXiv:1806.07421 (2018).

Aaron Powers and Sara Kiesler. 2006. The advisor robot: tracing people’s mental model from a robot’s physical attributes. In Proceedings of the 1st ACM SIGCHI/SIGART conference on Human-robot interaction.

J. ACM, Vol. 1, No. 1, Article 1. Publication date: January 2022.
[156] ISWB Prasetya, Maurin Voshol, Tom Tanis, Adam Smits, Bram Smit, Jacco Van Mourik, Menno Klunder, Frank Hoogmoed, Stijn Hinlopen, August Van Casteren, et al. 2020. Navigation and exploration in 3D-game automated play testing. In Proceedings of the 11th ACM SIGSOFT International Workshop on Automating TEST Case Design, Selection, and Evaluation.

[157] Pearl Pu and Li Chen. 2006. Trust building with explanation interfaces. In Proceedings of the 11th international conference on Intelligent user interfaces.

[158] Erika Puiutta and Eric Veith. 2020. Explainable reinforcement learning: A survey. In International cross-domain conference for machine learning and knowledge extraction.

[159] J. R. Quinlan. 1986. Introduction of decision trees. Machine Learning 1, 1 (1986), 81–106.

[160] Emile Rader and Rebecca Gray. 2015. Understanding user beliefs about algorithmic curation in the Facebook news feed. In Proceedings of the 33rd annual ACM conference on human factors in computing systems.

[161] Prajit T Rajendran, Huáscar Espinoza, Agnès Delaborde, and Chokri Mraidha. 2022. Human-in-the-loop Learning for Safe Exploration through Anomaly Prediction and Intervention... In SafeAI@ AAAI.

[162] Ramya Ramakrishnan, Ece Kamar, Besmira Nushi, Debadeepa Dey, Julie Shah, and Eric Horvitz. 2019. Overcoming blind spots in the real world: Leveraging complementary abilities for joint execution. In Proceedings of the AAAI Conference on Artificial Intelligence.

[163] Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. 2016. * Why should i trust you?* Explaining the predictions of any classifier. In Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining.

[164] Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. 2018. Anchors: High-precision model-agnostic explanations. In Proceedings of the AAAI conference on artificial intelligence.

[165] Brandon RichardWebster, So Yon Kwon, Christopher Clariozio, Samuel E. Anthony, and Walter J. Scheirer. 2018. Visual Psychophysics for Making Face Recognition Algorithms More Explainable. In European Conference on Computer Vision.

[166] Ariel Rosenfeld, Moshe Cohen, Matthew E Taylor, and Sarit Kraus. 2018. Leveraging human knowledge in tabular reinforcement learning: A study of human subjects. The knowledge engineering review 33 (2018).

[167] Andrew Slavin Ross, Michael C Hughes, and Finale Doshi-Velez. 2017. Right for the right reasons: Training differentiable models by constraining their explanations. arXiv preprint arXiv:1703.03717 (2017).

[168] Stéphane Ross, Geoffrey Gordon, and Drew Bagnell. 2011. A reduction of imitation learning and structured prediction to no-regret online learning. In Proceedings of the fourteenth international conference on artificial intelligence and statistics.

[169] Alvin E Roth. 1988. Introduction to the Shapley value. The Shapley value (1988), 1–27.

[170] Aaron M Roth, Nicholay Topin, Pooyan Jamshidi, and Manuela Veloso. 2019. Conservative q-improvement: Reinforcement learning for an interpretable decision-tree policy. arXiv preprint arXiv:1907.01180 (2019).

[171] Anna L Rowe and Nancy J Cooke. 1995. Measuring mental models: Choosing the right tools for the job. Human resource development quarterly 6, 3 (1995), 243–255.

[172] Cynthia Rudin and David Carlson. 2019. The secrets of machine learning: ten things you wish you had known earlier to be more effective at data analysis. (2019), 44–72.

[173] Wojciech Samek, Alexander Binder, Grégoire Montavon, Sebastian Lapuschkin, and Klaus-Robert Müller. 2016. Evaluating the visualization of what a deep neural network has learned. IEEE transactions on neural networks and learning systems 28, 11 (2016), 2660–2673.

[174] Tom Schaul, John Quan, Ioannis Antonoglou, and David Silver. 2015. Prioritized experience replay. arXiv preprint arXiv:1511.05952.

[175] John Schulman, Sergey Levine, Pieter Abbeel, Michael Jordan, and Philipp Moritz. 2015. Trust region policy optimization. In International conference on machine learning.

[176] John Schulman, Philipp Moritz, Sergey Levine, Michael Jordan, and Pieter Abbeel. 2015. High-dimensional continuous control using generalized advantage estimation. arXiv preprint arXiv:1506.02438.

[177] John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. 2017. Proximal policy optimization algorithms. arXiv preprint arXiv:1707.06347 (2017).

[178] Pedro Sequeira and Melinda T. Gervasio. 2020. Interestingness elements for explainable reinforcement learning: Understanding agents’ capabilities and limitations. Artificial Intelligence 288 (2020), 103367.

[179] Yuan Shen, Niviru Wijayaratne, Peter Du, Shanduqiao Jiang, and Katherine Driggs-Campbell. 2021. AutoPreview: A Framework for Autopilot Behavior Understanding. In Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems.

[180] Tianmin Shu, Caiming Xiong, and Richard Socher. 2018. Hierarchical and Interpretable Skill Acquisition in Multi-task Reinforcement Learning. In International Conference on Learning Representations.
[181] Andrew Silva and Matthew Gombolay. 2021. Encoding human domain knowledge to warm start reinforcement learning. In Proceedings of the AAAI Conference on Artificial Intelligence.

[182] Andrew Silva, Matthew Gombolay, Taylor Killian, Ivan Jimenez, and Sung-Hyun Son. 2020. Optimization methods for interpretable differentiable decision trees applied to reinforcement learning. In International conference on artificial intelligence and statistics.

[183] David Silver, Guy Lever, Nicolas Heess, Thomas Degris, Daan Wierstra, and Martin Riedmiller. 2014. Deterministic policy gradient algorithms. In International conference on machine learning.

[184] David Silver, Julian Schrittwieser, Karen Simonyan, Ioannis Antonoglou, Aja Huang, Arthur Guez, Thomas Hubert, Lucas Baker, Matthew Lai, Adrian Bolton, et al. 2017. Mastering the game of go without human knowledge. nature 550, 7676 (2017), 354–359.

[185] Karen Simonyan and Andrew Zisserman. 2014. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556 (2014).

[186] Blaž Škrlj, Matej Martinc, Nada Lavrač, and Senja Pollak. 2021. autoBOT: evolving neuro-symbolic representations for explainable low resource text classification. Machine Learning 110, 5 (2021), 989–1028.

[187] Jasper Snoek, Hugo Larochelle, and Ryan P. Adams. 2012. Practical Bayesian Optimization of Machine Learning Algorithms. In Annual Conference on Neural Information Processing Systems.

[188] Shagun Sodhani, Amy Zhang, and Joelle Pineau. 2021. Multi-task reinforcement learning with context-based representations. In International Conference on Machine Learning.

[189] William R Stauffer, Armin Lak, Shunsuke Kobayashi, and Wolfram Schultz. 2016. Components and characteristics of the dopamine reward utility signal. Journal of Comparative Neurology 524, 8 (2016), 1699–1711.

[190] Gregory Stein. 2021. Generating high-quality explanations for navigation in partially-revealed environments. Advances in Neural Information Processing Systems 34 (2021), 17493–17506.

[191] Simone Stumpf, Vidya Rajaram, Lida Li, Weng-Keen Wong, Margaret Burnett, Thomas Dietterich, Erin Sullivan, and Jonathan Herlocker. 2009. Interacting meaningfully with machine learning systems: Three experiments. International journal of human-computer studies 67, 8 (2009), 639–662.

[192] Mukund Sundararajan, Pheng-Ann Heng, and Qiqi Yan. 2017. Axiomatic attribution for deep networks. In Proceedings of the AAAI Conference on Artificial Intelligence.

[193] Richard S Sutton and Andrew G Barto. 2018. Reinforcement learning: An introduction. MIT press.

[194] Vivienne Sze, Yu-Hsin Chen, Tien-Ju Yang, and Joel S Emer. 2017. Efficient processing of deep neural networks: A tutorial and survey. Proc. IEEE 105, 12 (2017), 2295–2329.

[195] Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. 2015. Going deeper with convolutions. In Proceedings of the IEEE conference on computer vision and pattern recognition.

[196] Aaqib Tabrez and Bradley Hayes. 2019. Improving Human-Robot Interaction Through Explainable Reinforcement Learning. In ACM/IEEE International Conference on Human-Robot Interaction.

[197] Yujin Tang and David Ha. 2021. The sensory neuron as a transformer: Permutation-invariant neural networks for reinforcement learning. In Advances in Neural Information Processing Systems 34 (2021), 22574–22587.

[198] Yujin Tang, Duong Nguyen, and David Ha. 2020. Neuroevolution of self-interpretable agents. In Genetic and Evolutionary Computation Conference.

[199] Nicholay Topin, Stephanie Milani, Fei Fang, and Manuela Veloso. 2021. Iterative Bounding MDPs: Learning Interpretable Policies via Non-Interpretable Methods. In Proceedings of the AAAI Conference on Artificial Intelligence.

[200] Nicholay Topin and Manuela Veloso. 2019. Generation of policy-level explanations for reinforcement learning. In Proceedings of the AAAI Conference on Artificial Intelligence.

[201] Dweep Trivedi, Jesse Zhang, Shao-Hua Sun, and Joseph J Lim. 2021. Learning to synthesize programs as interpretable and generalizable policies. Advances in neural information processing systems 34 (2021), 25146–25163.

[202] William T. B. Uther and Manuela M. Veloso. 1998. Tree Based Discretization for Continuous State Space Reinforcement Learning. In AAAI Conference on Artificial Intelligence.

[203] Jasper van der Waa, Jurriaan van Diggelen, Karel van den Bosch, and Mark Neerincx. 2018. Contrastive explanations for reinforcement learning in terms of expected consequences. arXiv preprint arXiv:1807.08706 (2018).

[204] Abhishek Vashist, Sharan Vidash Vidya Shanmugham, Amlan Ganguly, and Sai Manoj P. D. 2022. DQN Based Exit Selection in Multi-Exit Deep Neural Networks for Applications Targeting Situation Awareness. In IEEE International Conference on Consumer Electronics.

[205] Abhinav Verma, Hoang Le, Yisong Yue, and Swarat Chaudhuri. 2019. Imitation-projected programmatic reinforcement learning. Advances in Neural Information Processing Systems 32 (2019).
[207] Abhinav Verma, Vijayaraghavan Murali, Rishabh Singh, Pushmeet Kohli, and Swarat Chaudhuri. 2018. Programmatically interpretable reinforcement learning. In International Conference on Machine Learning.

[208] George A Vouros. 2022. Explainable Deep Reinforcement Learning: State of the Art and Challenges. Comput. Surveys (2022).

[209] Stephan Wäldchen, Sebastian Pokutta, and Felix Huber. 2022. Training characteristic functions with reinforcement learning: Xai-methods play connect four. In International Conference on Machine Learning.

[210] Junpeng Wang, Liang Gou, Han-Wei Shen, and Hao Yang. 2019. DQNViz: A Visual Analytics Approach to Understand Deep Q-Networks. IEEE Transactions on Visualization And Computer Graphics 25, 1 (2019), 288–298.

[211] Jianhong Wang, Yuan Zhang, Tae-Kyun Kim, and Yunjie Gu. 2020. Shapley Q-value: A local reward approach to solve global reward games. In Proceedings of the AAAI Conference on Artificial Intelligence.

[212] Jingyuan Wang, Yang Zhang, Ke Tang, Junjie Wu, and Zhang Xiong. 2019. Alphastock: A buying-winners-and-selling-losers investment strategy using interpretable deep reinforcement attention networks. In Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining.

[213] Pin Wang and Ching-Yao Chan. 2017. Formulation of deep reinforcement learning architecture toward autonomous driving for on-ramp merge. In 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC).

[214] Sen Wang, Daoyuan Jia, and Xinshuo Weng. 2018. Deep reinforcement learning for autonomous driving. arXiv preprint arXiv:1811.11329 (2018).

[215] Ziyu Wang, Tom Schaul, Matteo Hessel, Hado Hasselt, Marc Lanctot, and Nando Freitas. 2016. Dueling network architectures for deep reinforcement learning. In International conference on machine learning.

[216] Garrett Warnell, Nicholas R. Waytowich, Vernon Lawhern, and Peter Stone. 2018. Deep TAMER: interactive agent shaping in high-dimensional state spaces. In Proceedings of the AAAI Conference on Artificial Intelligence.

[217] Lindsay Wells and Tomasz Bednarz. 2021. Explainable AI and Reinforcement Learning - A Systematic Review of Current Approaches and Trends. Frontiers in artificial intelligence 4 (2021), 550030.

[218] David M Williamson, Isaac I Bejar, and Anne S Hone. 1999. “Mental model” comparison of automated and human scoring. Journal of Educational Measurement 36, 2 (1999), 158–184.

[219] Jonathan R Williford, Brandon B May, and Jeffrey Byrne. 2020. Explainable face recognition. In European Conference on Computer Vision.

[220] Bohan Wu, Jayesh K. Gupta, and Mykel J. Kochenderfer. 2020. Model primitives for hierarchical lifelong reinforcement learning. Autonomous Agents and Multi-Agent Systems 34, 1 (2020), 28.

[221] Haiping Wu, Khimya Khetarpal, and Doina Precup. 2021. Self-supervised attention-aware reinforcement learning. In Proceedings of the AAAI Conference on Artificial Intelligence.

[222] Jie Wu, Guanbin Li, Si Liu, and Liang Lin. 2020. Tree-structured policy based progressive reinforcement learning for temporally language grounding in video. In Proceedings of the AAAI Conference on Artificial Intelligence.

[223] Xin Xin, Alexandros Karatzoglou, Ioannis Arapakis, and Joemon M. Jose. 2022. Supervised Advantage Actor-Critic for Recommender Systems. In ACM International Conference on Web Search and Data Mining.

[224] Yunqiu Xu, Meng Fang, Ling Chen, Yali Du, Joey Tianyi Zhou, and Chengqi Zhang. 2020. Deep reinforcement learning with stacked hierarchical attention for text-based games. Advances in Neural Information Processing Systems 33 (2020), 16495–16507.

[225] Roman V Yampolskiy and Joshua Fox. 2012. Artificial general intelligence and the human mental model. In Singularity hypotheses.

[226] Qiuling Yang, Gang Wang, Alireza Sadeghi, Georgios B Giannakis, and Jian Sun. 2019. Two-timescale voltage control in distribution grids using deep reinforcement learning. IEEE Transactions on Smart Grid 11, 3 (2019), 2313–2323.

[227] Ting Yang, Liyuan Zhao, Wei Li, and Albert Y Zomaya. 2021. Dynamic energy dispatch strategy for integrated energy system based on improved deep reinforcement learning. Energy 235 (2021), 121377.

[228] Zhao Yang, Song Bai, Li Zhang, and Philip HS Torr. 2018. Learn to interpret atari agents. arXiv preprint arXiv:1812.11276 (2018).

[229] Herman Yau, Chris Russell, and Simon Hadfield. 2020. What did you think would happen? explaining agent behaviour through intended outcomes. Advances in Neural Information Processing Systems 33 (2020), 18375–18386.

[230] Jason Yosinski, Jeff Clune, Yoshua Bengio, and Hod Lipson. 2014. How transferable are features in deep neural networks? Advances in neural information processing systems 27 (2014).

[231] Jason Yosinski, Jeff Clune, Anh Nguyen, Thomas Fuchs, and Hod Lipson. 2015. Understanding neural networks through deep visualization. arXiv preprint arXiv:1506.06579 (2015).

[232] Tom Zahavy, Nir Ben-Zrihem, and Shie Mannor. 2016. Graying the black box: Understanding dqns. In International conference on machine learning.

[233] Haodi Zhang, Zihang Gao, Yi Zhou, Hao Zhang, Kaishun Wu, and Fangzhen Lin. 2019. Faster and safer training by embedding high-level knowledge into deep reinforcement learning. arXiv preprint arXiv:1910.09986 (2019).
[234] Ke Zhang, Jun Zhang, Pei-Dong Xu, Tianlu Gao, and David Wenzhong Gao. 2021. Explainable ai in deep reinforcement learning models for power system emergency control. *IEEE Transactions on Computational Social Systems* 9, 2 (2021), 419–427.

[235] Peng Zhang, Jianye Hao, Weixun Wang, Hongyao Tang, Yi Ma, Yihai Duan, and Yan Zheng. 2020. KoGuN: Accelerating Deep Reinforcement Learning via Integrating Human Suboptimal Knowledge. In *International Joint Conference on Artificial Intelligence*.

[236] Ruohan Zhang, Faraz Torabi, Lin Guan, Dana H Ballard, and Peter Stone. 2019. Leveraging human guidance for deep reinforcement learning tasks. *arXiv preprint arXiv:1909.09906* (2019).

[237] Ruohan Zhang, Faraz Torabi, Lin Guan, Dana H. Ballard, and Peter Stone. 2019. Leveraging Human Guidance for Deep Reinforcement Learning Tasks. In *International Joint Conference on Artificial Intelligence*.

[238] Jiangchuan Zheng, Siyuan Liu, and Lionel M Ni. 2014. Robust bayesian inverse reinforcement learning with sparse behavior noise. In *Proceedings of the AAAI Conference on Artificial Intelligence*.

[239] Suyang Zhou, Zijian Hu, Wei Gu, Meng Jiang, Meng Chen, Qiteng Hong, and Campbell Booth. 2020. Combined heat and power system intelligent economic dispatch: A deep reinforcement learning approach. *International journal of electrical power & energy systems* 120 (2020), 106016.

[240] He Zhu, Zikang Xiong, Stephen Magill, and Suresh Jagannathan. 2019. An inductive synthesis framework for verifiable reinforcement learning. In *Proceedings of the 40th ACM SIGPLAN conference on programming language design and implementation*.

[241] Matthieu Zimmer, Xuening Feng, Claire Glanois, Zhaohui Jiang, Jianyi Zhang, Paul Weng, Li Dong, Hao Jiany, and Liu Wulong. 2021. Differentiable logic machines. *arXiv preprint arXiv:2102.11529* (2021).

[242] Luisa M Zintgraf, Taco S Cohen, Tameem Adel, and Max Welling. 2017. Visualizing deep neural network decisions: Prediction difference analysis. *arXiv preprint arXiv:1702.04595* (2017).