Causal Reinforcement Learning: A Survey

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Abstract

Reinforcement learning is an essential paradigm for solving sequential decision problems under uncertainty. Despite many remarkable achievements in recent decades, applying reinforcement learning methods in the real world remains challenging. One of the main obstacles is that reinforcement learning agents lack a fundamental understanding of the world and must therefore learn from scratch through numerous trial-and-error interactions. They may also face challenges in providing explanations for their decisions and generalizing the acquired knowledge. Causality, however, offers a notable advantage as it can formalize knowledge in a systematic manner and leverage invariance for effective knowledge transfer. This has led to the emergence of causal reinforcement learning, a subfield of reinforcement learning that seeks to enhance existing algorithms by incorporating causal relationships into the learning process. In this survey, we comprehensively review the literature on causal reinforcement learning. We first introduce the basic concepts of causality and reinforcement learning, and then explain how causality can address core challenges in non-causal reinforcement learning. We categorize and systematically review existing causal reinforcement learning approaches based on their target problems and methodologies. Finally, we outline open issues and future directions in this emerging field.

1 Introduction

"All reasonings concerning matter of fact seem to be founded on the relation of cause and effect. By means of that relation alone we can go beyond the evidence of our memory and senses."

—*David Hume, An Enquiry Concerning Human Understanding.*

Humans possess an inherent capacity to grasp the concept of causality from a young age (Wellman, 1992; Inagaki & Hatano, 1993; Koslowski & Masnick, 2002; Sobel & Sommerville, 2010). This innate understanding empowers us to recognize that altering specific factors can lead to corresponding outcomes, enabling us to actively manipulate our surroundings to accomplish desired objectives and acquire fresh insights. A deep understanding of cause and effect enables us to explain behaviors (Schult & Wellman, 1997), predict future outcomes (Shultz, 1982), and use counterfactual reasoning to dissect past events (Harris et al., 1996). These abilities are intrinsic to the development of human intelligence, forming the basis for modern society and civilization, as well as propelling advancements in science and technology (Glymour, 1998).

For example, consider the story of humans battling scurvy (Pearl & Mackenzie, 2018), depicted in Figure 1. Scurvy once plagued human exploration of the world, claiming the lives of approximately 2 million sailors. After an arduous journey, humans discovered that consuming citrus fruits could prevent this dreadful disease. Today, we understand that scurvy stems from a deficiency of vitamin C, but back in the 19th century, this causal relationship was unclear. Initially, people believed acidity could cure the disease, but heating the juice for purification destroyed the vitamin C content, rendering it ineffective against scurvy. Subsequently, acidity was dismissed as a mere placebo and the blame shifted to rotten meat. This misjudgment took a heavy toll on Scott's Antarctica expedition. It was only when the true cause of scurvy was comprehended that effective strategies to combat this disease emerge. This example highlights the importance of understanding causality in real-world decision-making and the perilous consequences that can arise from drawing conclusions based on unreliable correlations.

Figure 1: Unraveling the mystery of scurvy: the cruciality of causal understanding in decision-making.

Understanding causality has been a fundamental challenge in machine learning. While pure data-driven methods [1] excel at capturing correlations among variables, they often fall short in interpreting causal relationships (Pearl & Mackenzie, 2018). This challenge is evident in the context of scurvy prediction, where a strong correlation between consuming rotten meat and getting scurvy does not establish causation. The true cause lies in a deficiency of Vitamin C in the diet. To grasp causality, it becomes crucial to formulate and test assumptions about the data generation process. As a solution, causal inference has emerged as a powerful tool, offering a mathematical framework for reasoning about causality in the learning process (Schölkopf et al., 2021; Kaddour et al., 2022). In machine learning, causal inference has been applied in various fields, including computer vision (Lopez-Paz et al., 2017; Shen et al., 2018; Tang et al., 2020; Wang et al., 2020b), natural language processing (Wu et al., 2021; Jin et al., 2021; Feder et al., 2022), and recommender systems (Zheng et al., 2021; Zhang et al., 2021b; Gao et al., 2022). These results have demonstrated that causality can significantly improve the robustness and interpretability of machine learning models and enable more effective knowledge transfer across domains.

Reinforcement learning (RL (Sutton & Barto, 2018) is a popular machine learning paradigm for decision-making problems. It involves actively intervening in the environment to learn from the outcome of certain behaviors. This property makes RL naturally connected to causality, as agents can actively make and test assumptions during the learning process. However, in most RL studies, agents are only allowed to intervene in action variables, making it challenging to fully understand the causal relationships that drive the underlying data generation process. This difficulty is further compounded in off-policy and offline settings due to the gap between the (possibly unknown) behavior policy and the target policy, and the unobserved confounders that influence both action and outcome (Zhang et al., 2020b).

Causal RL is an emerging subfield of RL that harnesses the power of causal inference. It is an umbrella term for RL approaches that incorporate assumptions or knowledge about the underlying causality in the data to inform decision-making. To illustrate the distinction between causal and traditional RL, consider the following example. Picture yourself as a 19th-century captain embarking on your maiden voyage, seeking an effective policy to prevent scurvy. Using traditional RL methods often involves extensive trial-and-error exploration, which can be both costly and dangerous. In contrast, with causal RL, you would begin by analyzing the causal relationships and making informed assumptions. Armed with the prior knowledge that food intake causally influences the disease, you can bypass many meaningless and superstitious attempts such as relying on lucky charms or rituals, thereby increasing efficiency and safety. Moreover, by leveraging techniques from causal inference, you can establish that consuming rotten meat has no causal effect on developing scurvy, avoiding erroneous conclusions that lack generalizability. To further elaborate on the distinctive capabilities of causal RL in addressing the challenges faced by traditional RL, we will delve into a more detailed discussion spanning sections 3 to 6.

As causality inherently shapes human thought and reasoning (Sloman, 2005; Sloman & Lagnado, 2015; Pearl, 2009b; Pearl & Mackenzie, 2018), it is reasonable to expect that causal RL will transcend the limitations of traditional methods and tackle new challenges in increasingly complex application scenarios. Nevertheless, a significant obstacle lies in the lack of a clear and unified conceptualization of causal assumptions and knowledge, as they have been encoded in diverse forms across prior research, tailored to specific problems and

[1] Pure data-driven methods refer to approaches that focus exclusively on summarizing or mining data, without considering the underlying mechanisms that govern the data generation process.

objectives. The use of disparate terminologies and techniques makes it challenging to understand the essence, implications, and opportunities of causal RL, particularly for those new to the realms of causal inference and RL. In light of this, this paper aims to provide a comprehensive survey of causal RL, consolidating the diverse advancements and contributions within this field, thereby establishing meaningful connections and fostering a cohesive understanding.

Our main contributions to the field are as follows.

- We provide a comprehensive survey of causal RL, contextualizing existing research within the framework of structural causal models (Pearl, 2009a;b). We investigate fundamental questions, including the definition and motivations of causal RL, and how it improves traditional RL approaches. Additionally, we present a clear and concise overview of the foundational concepts in causality research and RL. To the best of our knowledge, this is the first comprehensive survey of causal RL in the existing RL literature [2].
- We identify the key challenges in RL that can be effectively addressed or improved by explicitly considering causality. To facilitate a deeper understanding of the benefits of incorporating causality-aware techniques, we further propose a problem-oriented taxonomy. Furthermore, we conduct a comparative analysis of existing causal reinforcement learning approaches, examining their methodologies and limitations.
- We shed light on major unresolved issues and promising research directions in causal RL. These include advancing theoretical analyses, establishing benchmarks, and tackling specific learning problems. As these research topics gain momentum, they will propel the application of RL in real-world scenarios. Hence, establishing a common ground for discussing these valuable ideas in this burgeoning field is crucial and will foster its continuous development and success.

2 Background

To better understand causal RL, an emerging field that combines the strengths of causality research and RL, we start by introducing the fundamentals of and some common concepts relevant to the two research areas.

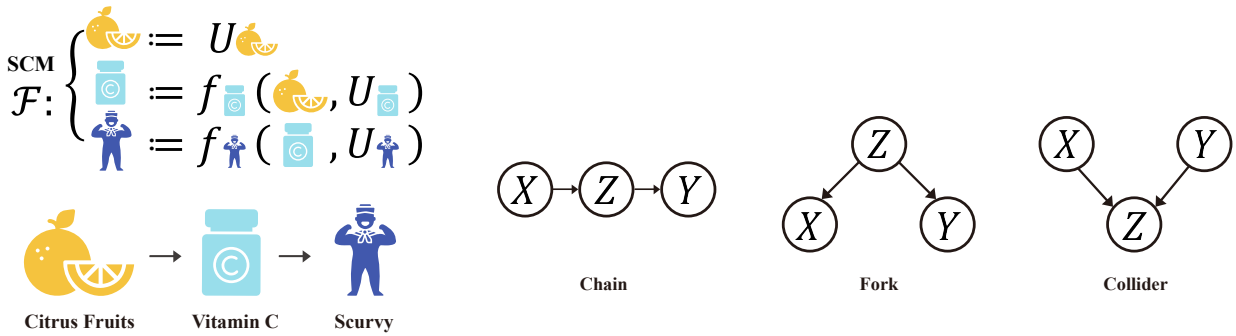
2.1 A Brief Introduction to Causality

We first discuss how to use mathematical language to describe and study causality. In general, there are two primary frameworks that researchers use to formalize causality: SCMs (structural causal models) Pearl (2009a); Glymour et al. (2016) and PO (potential outcome) (Rubin, 1974; Imbens & Rubin, 2015). We focus on the former in this paper because it provides a graphical methodology that can help researchers abstract and better understand the data generation process. It is noteworthy that these two frameworks are logically equivalent, and most assumptions are interchangeable.

Definition 2.1 (Structural Causal Model)**.** An SCM is represented by a quadruple $(\mathcal{V}, \mathcal{U}, \mathcal{F}, P(\mathbf{U}))$, where

- $\mathcal{V} = \{V_1, V_2, \cdots, V_m\}$ is a set of endogenous variables that are of interest in a research problem,
- $\mathcal{U} = \{U_1, U_2, \cdots, U_n\}$ is a set of exogenous variables that represent the source of stochasticity in the model and are determined by external factors that are generally unobservable,
- $\mathcal{F} = \{f_1, f_2, \cdots, f_m\}$ is a set of structural equations that assign values to each of the variables in $\mathcal{V}$ such that f_i maps $\mathbf{PA}(V_i) \cup U_i$ to V_i, where $\mathbf{PA}(V_i) \subseteq \mathcal{V} \backslash V_i$ and $U_i \subseteq \mathcal{U}$,
- $P(\mathbf{U})$ is the joint probability distribution of the exogenous variables in $\mathcal{U}$.

[2] We note that Schölkopf et al. (2021) and Kaddour et al. (2022) discussed causal RL alongside many other research subjects in their papers. The former mainly studied the causal representation learning problem, and the latter comprehensively investigated the field of causal machine learning. The present study, however, focuses on examining the literature on causal RL and provides a systematic review of the field.



(a) (b)

Figure 2: (a) A simplified version of the SCM and causal graph for the scurvy prediction problem. It includes three binary endogenous variables - consumption of citrus fruits, intake of vitamin C, and occurrence of scurvy - along with the relevant exogenous variables. (b) The three basic building blocks of causal graphs.

Structural causal model. SCM, as stated in definitionn 2.1, provides a rigorous framework for examining how relevant features of the world interact. Each structural equation $f_i \in \mathcal{F}$ specifies the value of an endogenous variable V_i based on its direct causes $\mathbf{PA}(V_i) \cup U_i$. By defining these equations, we can establish the causal links between variables and mathematically characterize the underlying mechanisms of the data generation process. To generate samples from the joint distribution $P(\mathbf{V})$, we first sample the exogenous variables from $P(\mathbf{U})$, which represent the source of stochasticity in the model, and then evaluate the endogenous variables sequentially using the structural equations in $\mathcal{F}$. Once the values of the exogenous variables $\mathbf{U}$ are set, all endogenous variables $V_i \in \mathcal{V}$ are determined with perfect certainty. In particular, we primarily deal with Markovian models for which the exogenous variables are mutually independent [3].

Causal graph. Each SCM is associated with a causal graph $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}$, where nodes $\mathcal{V}$ represent endogenous variables and edges $\mathcal{E}$ represent causal relationships determined by the structural equations. Specifically, an edge $e_{ij} \in \mathcal{E}$ from node V_j to node V_i exists if the random variable $V_j \in \mathbf{PA}(V_i)$. In certain cases, when the parent set $\mathbf{PA}(V_i)$is too small and the omitted variables influence multiple variables in $\mathcal{V}$, the model is no longer Markovian. These omitted variables are known as unobserved confounders. To deal with these variables, we can represent each of them using a dashed arc with bidirectional arrows, which signifies the two variables linked by the arrows are influenced by the same confounder. By acknowledging the presence of these latent variables, we restore the Markov property. Figure 2a illustrates the SCM of the scurvy problem (a simplified version) and the corresponding causal graph. Figure 2b introduces the three fundamental building blocks of the causal graph: chain, fork, and collider. These simple structures can be combined to create more complex data generation processes. In situations where the exact forms of structural equations remain unknown, we can still leverage causal graphs to encode our prior understanding of causality in terms of conditional independence. Such structured knowledge plays a vital role in causal analysis, providing valuable insights and guidance.

Product decomposition.The causal Markov condition (Pearl, 2009b) establishes a connection between causation and probabilities. It states that for every Markovian causal model with a causal graph $\mathcal{G}$, the induced joint distribution $P(\mathbf{V})$ is Markov relative to $\mathcal{G}$. Specifically, a variable $V_i \in \mathcal{V}$ is independent of any variables that are not its direct causes or effects, given the set of all its direct causes $\mathrm{PA}(V_i)$ in $\mathcal{G}$. This property enables a structured decomposition along causal directions, which is referred to as the causal factorization (or the disentangled factorization) (Schölkopf et al., 2021):

$$P(\mathbf{V}) = \prod_{i=1}^{n} P(V_i|\mathrm{PA}(V_i)), \tag{1}$$

where the (conditional) probability distributions of the form $P(V_i|\mathrm{PA}(V_i))$ are commonly referred to as causal mechanisms (Schölkopf et al., 2021). Remark that equation 1 is not the only way to decompose a joint distri-

[3]The Markovian assumption is generally considered as a convention in causal inference (Pearl, 2009b).

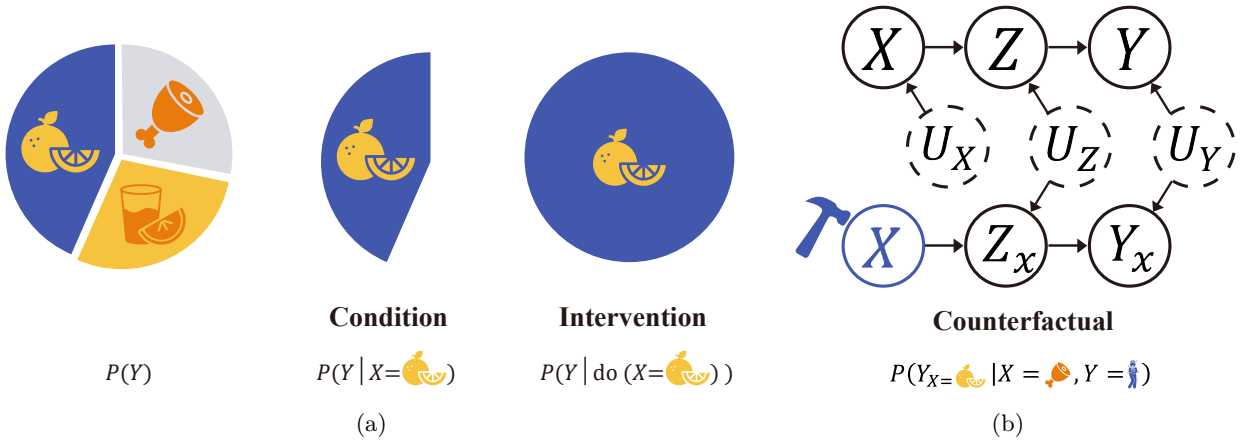


Figure 3: (a) An illustration of the difference between condition and intervention, in which X is a discrete variable with three possible values: fresh citrus fruit, heated juice, or rotten meat. Marginal probabilities study all subgroups within a population, while conditional probabilities focus on a specific subgroup, like sailors who have consumed fresh citrus fruits. Intervention, on the other hand, examines the probability of scurvy by mandating that all sailors consume fresh citrus fruits. (b) An illustration of the counterfactual probability. Counterfactual probability explores events that occur in the imaginary world (the bottom network), such as asking whether sailors would be protected from scurvy if they had consumed enough citrus fruit, given that they consumed meat in the factual world (the upper network).

bution $P(\mathbf{V})$. By utilizing the chain rule, we can also alternatively derive $P(\mathbf{V}) = \prod_{i=1}^{n} P(V_i|V_1, \cdots, V_{i-1})$. However, equation 1 is the only approach that decomposes $P(\mathbf{V})$ as the product of causal mechanisms. To illustrate, let us consider Figure 2a, which depicts the data generation process of the scurvy prediction problem with a chain structure. We use the variables, X, Z, and Y to represent citrus fruit consumption, vitamin C intake, and healthiness, respectively. The joint distribution $P(X, Y, Z)$ can be decomposed as $P(X)P(Z|X)P(Y|Z)$ or $P(Y)P(Z|Y)P(X|Y, Z)$. The former decomposition conforms to the causal graph of the given example, whereas the latter does not.

Intervention. Intervention represents an active approach to engage in the data generation process, as opposed to passive observation. There are two types of interventions: hard interventions, which involve directly setting variables to constant values, and soft interventions, which modify the probability distribution of a variable while retaining some of its original dependencies. Many research questions involve predicting the effects of interventions. For example, finding a way to prevent scurvy is essentially about identifying effective interventions (through food or medicine) that lower the probability of getting scurvy. To differentiate from conditional probability, researchers introduced the do-operator, using $P(Y|\mathrm{do}(X) = x)$ to denote the intervention probability, meaning the probability distribution of the outcome variable Y when variable X is fixed to x. Figure 3a illustrates the difference between conditional and intervention probabilities. Furthermore, an important distinction between statistical models and causal models lies in the fact that the former specifies a single probability distribution, while the latter represents a collection of distributions. Different interventions on a causal model can yield diverse joint distributions, hence learning from interventions helps improve the agents' robustness to certain distributional shifts (Schölkopf et al., 2021; Thams, 2022).

Counterfactual. Counterfactual thinking revolves around posing the hypothetical "what if ...?" questions, such as "What if the scurvy patient had eaten enough citrus fruit? Would their health have been maintained?". This cognitive process allows us to retrospectively analyze past events and consider alternative outcomes if certain factors had been altered. By engaging in counterfactual thinking, we gain insights from experiences and identify opportunities for further improvements.

In the context of SCMs, counterfactual variables are often denoted with a subscript, such as $Y_{X=x}$ (or Y_x when there is no ambiguity) where X and Y are two sets of variables in $\mathcal{V}$. This notation helps researchers differentiate the counterfactual variables from the original variable Y. The key difference between Y and Y_x

is that the latter is generated by a modified SCM with structural equations $\mathcal{F}_x = \{f_i : V_i \notin X\} \cup \{X = x\}$. Counterfactual reasoning, building on this formalism, aims to estimate probabilities such as $P(Y_{X=1}|X = 0, Y = 1)$. We can consider counterfactual reasoning as creating an imaginary world different from the factual one, whereas intervention only studies the factual one. See Figure 3b for a visual representation of counterfactual reasoning using the twin network method (Pearl, 2009b). The two networks represent the factual and counterfactual (imaginary) world respectively. They are connected by the exogenous variables, sharing the same structure and variables of interest, except the counterfactual one removes arrows pointing to the intervened variables. In particular, counterfactuals are assumed to satisfy consistency constraints such as $X = x \Rightarrow Y_x = Y$, meaning the counterfactual outcome matches its factual counterpart if the intervened variable is set to its actual value (Pearl, 2009b).

Mediation analysis. Mediation is a causal concept that closely relates to counterfactuals. The goal of mediation analysis is to examine the direct or indirect effects of a treatment variable X on an outcome variable Y, mediated by a third variable M (referred to as the mediator). To illustrate, let's consider the direct effect of different food consumption on the prevention of scurvy. In a counterfactual world, if we prevent changes in the mediator variable M (e.g., vitamin C intake), then whatever changes the outcome variable Y (e.g., whether a sailor gets scurvy) can only be attributed to changes in the treatment variable X (e.g., the food consumed), allowing us to establish the observed effect as a direct effect of X on Y. It is worth noting that, in cases like this, the statistical language can only provide the conditioning operator, which merely shifts our attention to groups with equal values of M. On the other hand, the do-operator precisely captures the concept of keeping the mediator M unchanged. These two operations lead to fundamentally different results, and conflating them can yield opposite conclusions. In summary, such analyses are crucial for understanding the potential causal mechanisms and paths in complex systems, with applications spanning various fields including psychology, sociology, and epidemiology (Pearl & Mackenzie, 2018).

Causal discovery and causal reasoning. In the field of causal inference, there are two primary areas of focus: causal discovery and causal reasoning. Causal discovery involves inferring the causal relationships between variables of interest (in other words, identifying the causal graph of the data generation process). Traditional approaches use conditional independence tests to infer causal relationships, and recently some studies have been conducted based on large datasets using deep learning techniques. Glymour et al. (2019) and Vowels et al. (2022) comprehensively survey the field of causal discovery.

As opposed to causal discovery, causal reasoning investigates how to estimate causal effects, such as intervention probability, given the causal model. Interventions involve actively manipulating the system or environment, which can be costly and potentially dangerous (e.g., testing a new drug in medical experiments). Therefore, a core challenge of causal reasoning is how to translate causal effects into estimands that can be estimated from observational data using statistical methods. Given the causal graph, the identifiability of causal effects can be determined systematically through the use of do-calculus (Pearl, 1995).

2.2 A Brief Introduction to Reinforcement Learning

Reinforcement learning studies sequential decision problems. Mathematically, we can formalize these problems as Markov decision processes.

Definition 2.2 (Markov decision process)**.** An MDP $\mathcal{M}$ is specified by a tuple $\{\mathcal{S}, \mathcal{A}, P, R, \mu_0, \gamma\}$, where

- $\mathcal{S}$ denotes the state space and $\mathcal{A}$ denotes the action space,
- $P : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \to [0, 1]$ is the transition probability function that yields the probability of transitioning into the next states s_{t+1} after taking an action a_t at the current state s_t,
- $R : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$ is the reward function that assigns the immediate reward for taking an action a_t at state s_t,
- $\mu_0 : \mathcal{S} \to [0, 1]$ is the probability distribution that specifies the generation of the initial state, and
- $\gamma \in [0, 1]$ denotes the discount factor that accounts for how much future events lose their value as time passes.

Markov decision processes. In definition 2.2, the decision process starts by sampling an initial state s_0 with μ_0. An agent takes responsive action using its policy π (a function that maps a state to an action) and receives a reward from the environment assigned by R. The environment evolves to a new state following P; then, the agent senses the new state and repeats interacting with the environment. The goal of an RL agent is to search for the optimal policy π^* that maximizes the return (cumulative reward) G_0. In particular, at any timestep t, the return G_t is defined as the sum of discounted future rewards, i.e., $G_t = \sum_{i=0}^{\infty} \gamma^i R_{t+i}$. A multi-armed bandit (MAB) is a special type of MDP that focuses on single-step decision-making problems. On the other hand, a partially observable Markov decision process (POMDP), generalizes the scope of MDPs by considering partial observability. In a POMDP, the system still operates based on an MDP, but the agent can only access limited information about the system state when making decisions. For example, in a video game, a player may need to deduce the motion of a dynamic object based on the visual cues displayed on the current screen.

Value functions. The return G_t evaluates how good an action sequence is. However, in stochastic environments, the same action sequence can lead to diverse trajectories and consequently, different returns. Moreover, a stochastic policy π outputs a probability distribution over the action space. Considering these stochastic factors, the return G_t associated with a policy π becomes a random variable. In order to evaluate policies under uncertainty, RL introduces the concept of value functions. There are two types of value functions: $V^\pi(s)$ denotes the expected return obtained by following the policy π from state s; $Q^\pi(s,a)$ denotes the expected return obtained by performing action a at state s and following the policy π thereafter. The optimal value functions correspond to the optimal policy π^* are denoted by $V^*(s)$ and $Q^*(s,a)$.

Bellman equations. By definition, $V^\pi(s) = \mathbb{E}_\pi[G_t|S_t = s]$ and $Q^\pi(s,a) = \mathbb{E}_\pi[G_t|S_t = s, A_t = a]$. These two types of value functions can be expressed in terms of one another. By expanding the return G_t, we can rewrite value functions in a recursive manner:

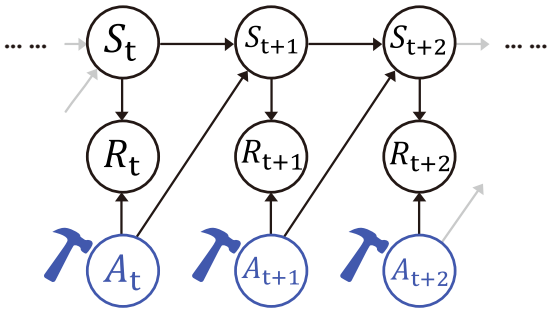
$$\begin{aligned} V^\pi(s) &= \sum_{a\in\mathcal{A}} \pi(a|s) \left(R(s,a) + \gamma \sum_{s'\in\mathcal{S}} P(s'|s,a) V^\pi(s') \right) \\ Q^\pi(s,a) &= R(s,a) + \gamma \sum_{s'\in\mathcal{S}} \sum_{a'\in\mathcal{A}} \pi(a'|s') Q^\pi(s',a'). \end{aligned} \tag{2}$$

When the timestep t is not specified, s and s' are often used to refer to the states of two adjacent steps. The above equations are known as the Bellman expectation equations, which establish the connection between two adjacent steps. Similarly, the Bellman optimally equations relate the optimal value functions:

$$\begin{aligned} V^*(s) &= \max_{a\in\mathcal{A}} \left(R(s,a) + \gamma \sum_{s'\in\mathcal{S}} P(s'|s,a) V^*(s') \right) \\ Q^*(s,a) &= R(s,a) + \gamma \sum_{s'\in\mathcal{S}} P(s'|s,a) \max_{a'\in\mathcal{A}} Q^*(s',a'). \end{aligned} \tag{3}$$

When the environment (also referred to as the dynamic model or, simply, the model) is known, the learning problem simplifies into a planning problem that can be solved using dynamic programming techniques based on the Bellman equations. However, in the realm of RL, the main focus is on unknown environments. In other words, agents do not possess complete knowledge of the transition function $P(s'|s,a)$ and the reward function $R(s,a)$. This characteristic brings RL closer to decision-making problems in real-world scenarios.

Categorizing reinforcement learning methods. There are several ways to categorize RL methods. One approach is based on the agent's components. Policy-based methods generally focus on optimizing an explicitly parameterized policy to maximize the return, while value-based methods use collected data to fit a value function and derive the policy implicitly from it. Actor-critic methods combine both of them, equipping an agent with both a value function and a policy. Another classification criterion is whether Rl methods use an environmental model. Model-based reinforcement learning (MBRL) methods typically employ a well-defined environmental model (such as AlphaGo (Silver et al., 2017)) or construct one using the collected data. The model assists the agent in planning or generating additional training data, thereby enhancing the learning process. Furthermore, RL can also be divided into on-policy, off-policy, and offline



MDP

Initial State: $S_0 = U_{S_0}$

Transition: $S_{t+1} = f_{S_{t+1}}(S_t, A_t, U_{S_{t+1}})$, for $t = 0, \cdots, \infty$

Reward: $R_t = f_{R_t}(S_t, A_t, U_{R_t})$, for $t = 0, \cdots, \infty$

Policy: $A_t = \mathrm{do}(a \sim \pi(\cdot \mid S_t))$, for $t = 0, \cdots, \infty$

POMDP

Observation: $O_t = f_{O_t}(S_t, U_{O_t})$, for $t = 0, \cdots, \infty$

Figure 4: An illustrative example of casting an MDP or a POMDP problem into SCM. Actions are marked with hammers in the causal graph because they are intervened variables controlled by policies.

approaches based on data collection. On-policy RL only utilizes data from the current policy, while off-policy RL involves data collected by other policies. Offline RL disallows data collection, restricting the agent to learn from a fixed dataset.

2.3 Causal Reinforcement Learning

Before formally defining causal RL, let us cast an RL problem into SCM. To do this, we consider the state, action, and reward at each step to be endogenous variables. The state transition and reward functions are then described as deterministic functions with independent exogenous variables, represented by the structural equations $\mathcal{F}$ in the SCM. The initial state can be considered an exogenous variable such that $S_0 \in \mathcal{U}$. This transformation is always possible using autoregressive uniformization (Buesing et al., 2019), without imposing any extra constraints. It allows us to formally discuss causality in RL, including dealing with counterfactual queries that cannot be explained by non-causal methods. Figure 4 presents an illustrative example of this transformation. In practice, states and actions may have high dimensionality, and the granularity of the causal model can be adjusted based on our prior knowledge. While the SCM representation allows us to reason about causality in decision-making problems and organize causal knowledge in a clear and reusable way, it does not constitute causal RL on its own. In this paper, we define causal RL as follows.

Definition 2.3 (Causal reinforcement learning)**.** Causal RL is an umbrella term for RL approaches that incorporate additional assumptions or prior knowledge to analyze and understand the causal mechanisms underlying actions and their consequences, enabling agents to make more informed and effective decisions.

This definition emphasizes two fundamental aspects that distinguish causal RL from non-causal RL. 1) It emphasizes a focus on causality, seeking to advance beyond superficial associations or data patterns. To meet this goal, 2) it necessitates the incorporation of additional assumptions or knowledge that accounts for the causal relationships inherent in decision-making problems.

In RL, the primary objective is to determine the policy π that yields the highest expected return, rather than inferring the causal effect of a specific intervention. The policy π can be seen as a soft intervention that preserves the dependence of the action on the state, i.e., $\mathrm{do}(a \sim \pi(\cdot|s))$. Different policies result in varying trajectory distributions. On-policy RL directly learns the causal effects of actions from interventional data, while off-policy and offline RL involve passively observing and learning from data collected by behavior policies, which makes them susceptible to spurious correlations (Zhang et al., 2020b; Deng et al., 2021).

We note that there is a lack of clarity and coherence in the existing literature on causal RL, primarily because causal modeling is more of a mindset than a specific solution. Various forms of causal modeling have been explored in previous work, depending on prior knowledge and research purpose. Ideally, we would have a perfect understanding of the data generation process and access to the true causal model (e.g., the SCM), enabling us to answer any correlation, intervention, and counterfactual queries. However, given the complexity of the real world, the true causal model is generally inaccessible. Fortunately, by leveraging structural knowledge (e.g., the causal graph) and observational data, we can identify the causal effect of interest through certain causal reasoning techniques (Pearl & Mackenzie, 2018). If multiple domains are

available, it is often beneficial to examine the invariant factors across them, such as causal representation (the causal variables involved in the data generation process), causal structure (causal graph), and causal mechanisms. In cases where prior knowledge about these factors is lacking, we can introduce certain inductive biases to obtain reasonable estimates, such as sparsity, independent causal mechanisms, and sparse mechanism shifts Schölkopf et al. (2021); Sontakke et al. (2021); Huang et al. (2022a;b).

With a solid understanding of the foundational concepts and definitions, we are now well-equipped to explore the realm of causal reinforcement learning. The upcoming sections delve into four crucial challenges where causal RL demonstrates its potential: sample efficiency, generalizability and knowledge transfer, spurious correlations, and considerations beyond return. In each of these sections, we first briefly overview the specific challenge, followed by a high-level explanation of why causality may provide valuable insights and solutions. We then review existing methods and techniques, shedding light on the advancements and potential limitations of causal RL.

3 Enhancing Sample Efficiency through Causal Reinforcement Learning

3.1 The Issue of Sample Efficiency in Reinforcement Learning

In RL, training data is typically not provided before interacting with the environment. Unlike supervised and unsupervised learning methods that directly learn from a fixed dataset, an RL agent needs to actively gather data to optimize its policy towards achieving the highest return. An effective RL algorithm should be able to master the optimal policy with as few experiences as possible (in other words, it must be sample-efficient). Current methods often require collecting millions of samples to succeed in even simple tasks, let alone more complicated environments and reward mechanisms. For example, AlphaGo Zero was trained over roughly 3×10^7 games of self-play (Silver et al., 2017); OpenAI's Rubik's Cube robot took nearly 10^4 years of simulation experience (OpenAI et al., 2019). This inefficiency entails a high training cost and prevents the use of RL techniques for solving real-world decision-making problems. Therefore, the sample efficiency issue is a core challenge in RL, necessitating the development of RL algorithms that can save time and computational resources.

3.2 Why Causality Helps Improve Sample Efficiency?

Sample efficiency has been extensively explored in RL literature (Kakade, 2003; Osband et al., 2013; Grande et al., 2014; Yu, 2018). Several factors influence sample efficiency, and one significant factor is abstraction. A well-abstracted problem eliminates unnecessary difficulties, facilitating an efficient learning process. Some non-causal approaches (Jong & Stone, 2005; Zhang et al., 2022) achieve abstraction by aggregating states that yield the same reward sequence. While these approaches help reduce the complexity, they still suffer from redundant dependencies and are vulnerable to spurious correlations. In contrast, causal relationships in the real world are typically stable and sparse (Pearl, 2009b; Huang et al., 2022a), which leads to more effective abstraction. See Figure 5 for a comparison between these two types of abstraction. By accurately identifying the relevant features and necessary dependencies in the data generation process, causal modeling significantly reduces the complexity of the learning problem, thus improving sample efficiency.

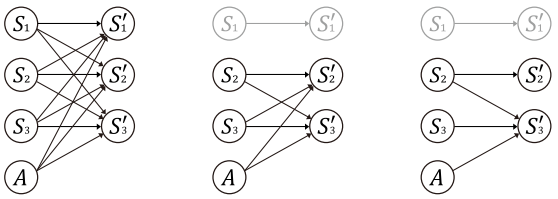


Figure 5: An illustration of a state transition between adjacent time steps. (Left) No abstraction. All variables are fully connected. (Middle) An irrelevant covariate S_1 is removed but the rest are still fully connected. (Right) Only the causal edges are preserved.

Designing effective exploration methods is another way to improve sample efficiency (Yang et al., 2022b). Some research has drawn inspiration from developmental psychology (Ryan & Deci, 2000; Barto, 2013) and used intrinsic motivation to motivate agents to explore unknown environments efficiently (Pathak et al., 2017; Burda et al., 2022). These approaches encourage agents to prioritize the exploration of regions of high

Table 1: Selected methods utilizing causality to optimize sample efficiency.

Category	Paper	Technique	Environments or Tasks	Source
Representation Learning	Sontakke et al. (2021)	Causal representation learning	Manipulation (CausalWorld)	ICML
	Lee et al. (2021)	Intervention Domain randomization	Manipulation (Isaac Gym)	ICRA
	Huang et al. (2022b)	Causal dynamics learning	Car Racing (OpenAI Gym) VizDoom	ICML
	Wang et al. (2022)	Causal dynamics learning	Chemical Manipulation (robosuite)	ICML
Directed Exploration	Seitzer et al. (2021)	Intervention	Manipulation (OpenAI)	NeurIPS
Data Augmentation	Buesing et al. (2019)	Counterfactual reasoning	Sokoban	ICLR
	Lu et al. (2020)	Counterfactual reasoning	Cart Pole (OpenAI Gym) MIMIC-III	NeurIPS Workshop
	Pitis et al. (2020)	Counterfactual reasoning	Spriteworld Pong (Roboschool) Manipulation (OpenAI)	NeurIPS
	Zhu et al. (2021)	Counterfactual reasoning	Manipulation (CausalWorld)	OpenReview

epistemic uncertainty. They implicitly assume regions of equal uncertainty are equally important, which rarely holds in reality. Consider a robotic manipulation problem in which the agent needs to move an object to a target location. The state space (including information about the object and the robot arm) is vast, but most regions have limited information about the task, even if they show high uncertainty. Only the regions where the agent can causally influence the object (have a causal effect on the outcome, e.g., changing its momentum) are of interest. In scenarios like this, non-causal methods often demonstrate lower efficiency compared to causal RL methods, which harness the power of causal inference to estimate causal influence (Seitzer et al., 2021), leading to better exploration.

Model-based reinforcement learning (MBRL) (Wang et al., 2019; Luo et al., 2022) also helps improve sample efficiency. However, synthesizing trajectories de novo is highly challenging, especially for complex environmental dynamics. Compared to non-causal models built on correlations, causal models are more robust and enable counterfactual reasoning, which allows for generating samples based on real data. By explicitly considering the posterior distribution of exogenous variables, rather than relying on a fixed prior distribution like the Gaussian distribution, causal RL enables generating higher-quality training data compared to non-causal approaches (Buesing et al., 2019).

3.3 Causal Reinforcement Learning for Addressing Sample Inefficienty

As outlined in the previous section, causality offers some valuable principles for designing sample-efficient RL algorithms. We can organize existing research into three lines according to these principles: representation learning, directed exploration, and data augmentation. The representative works are shown in Table 1.

3.3.1 Representation Learning for Sample Efficiency

A good representation of the environment can be beneficial for sample-efficient RL. By providing a compact and informative representation of the environment, an RL agent can learn more effectively with fewer samples. This is because a good representation can help the agent identify important features of the environment and abstract away unnecessary details, allowing the agent to learn more generalizable policies and make better use of its experiences.

The research of Sontakke et al. (2021) involved clustering the trajectories generated from various environments with different physical properties and using the clustering outcomes as a causal representation to capture crucial information such as mass, size, and shape. With the state augmented by the causal representation, the learn policies exhibit outstanding zero-shot generalization ability and require only a small number of training samples to converge in new environments. Causality also facilitates state abstraction. Lee et al. (2021) assumed the availability of an environmental model and used causal reasoning to identify relevant context variables. Specifically, the proposed method conducts interventions to alter one context variable at a time and observes the causal influence on the outcome. This approach effectively reduces the

dimensionality of the state space and simplifies the learning problem. However, in many scenarios, direct intervention on states may not be feasible. In such cases, an alternative approach to achieve causality-based state abstraction is to learn the causal dynamics model using collected data. Huang et al. (2022b) introduced a method to learn action-sufficient state representations from data collected by a random policy. These representations consist of a minimal set of state variables that contain sufficient information for decision-making. Wang et al. (2022), on the other hand, studied task-independent state abstraction which only omits action-irrelevant variables that neither change with actions nor influence actions' results, identified through conditional independence tests based on conditional mutual information. Their approach includes variables that are potentially useful for future tasks rather than being restricted to a particular training task.

3.3.2 Directed Exploration for Sample Efficiency

While a good representation of the environment is beneficial, it is not necessarily sufficient for sample efficient RL (Du et al., 2020). To improve sample efficiency, researchers have been studying directed exploration, strategies that guide agents to explore specific regions of the state space, which are deemed more informative or likely to yield high rewards. This can be done by giving bonuses to exploratory behaviors that discover novel or uncertain states. However, from a causal perspective, it is important to note that not all regions of high uncertainty are equally important. Only those regions that establish a causal relationship with the task's success are worth exploring. Seitzer et al. (2021) studied the problem of directed exploration in robotic manipulation tasks, where the agent must physically interact with the target object to generate valuable data before acquiring complex manipulation skills such as object relocation. The authors proposed a method to quantify the causal influence of actions on the object and incorporated it into the exploration process to guide the agent. Experimental results demonstrate that the proposed method significantly improves the sample efficiency across various robotic manipulation tasks. On the other hand, Sontakke et al. (2021) introduced a method to learn self-supervised experiments based on the principle of independent causal mechanisms. This method utilizes the concept of One-Factor-at-A-Time (OFAT), wherein good experimental behavior should examine one factor at a time while keeping others constant. The rationale behind this approach is that altering only one causal factor should yield less information compared to changing multiple factors simultaneously. Consequently, the learning problem of experimental behavior can be reformulated as minimizing the amount of information contained in the generated data (also referred to as maximizing "causal curiosity" in the paper). Empirical results show that RL agents pre-trained with causal curiosity exhibit improved efficiency in solving new tasks.

3.3.3 Data Augmentation for Sample Efficiency

Data augmentation is a common machine learning technique that aims to improve the performance of algorithms by generating additional training data. Counterfactual data augmentation is a causality-based approach that uses a causal model to imitate the environment and generate data that is unobserved in the real world. This is particularly useful for RL problems because collecting large amounts of real-world data is often difficult or expensive. By simulating different counterfactual scenarios, RL agents can determine the effects of different actions without interacting with the environment, leading to more sample-efficient learning.

The implementation of counterfactual data augmentation follows a counterfactual reasoning procedure that consists of three steps (Pearl, 2009a), as demonstrated in Figure 6:

1. **Abduction** is about using observed data to infer the values of the exogenous variables $\mathcal{U}$;
2. **Action** involves modifying the structural equations of the variables of interest in the SCM; and
3. **Prediction** uses the modified SCM to generate counterfactual data by plugging the exogenous variables back into the equations for computation.

While MBRL methods can generate samples as well by fitting a probabilistic density model, they lack the capability to effectively model exogenous variables. This limitation can lead to under-fitting when dealing with complex distributions of exogenous variables (Buesing et al., 2019). In contrast, counterfactual

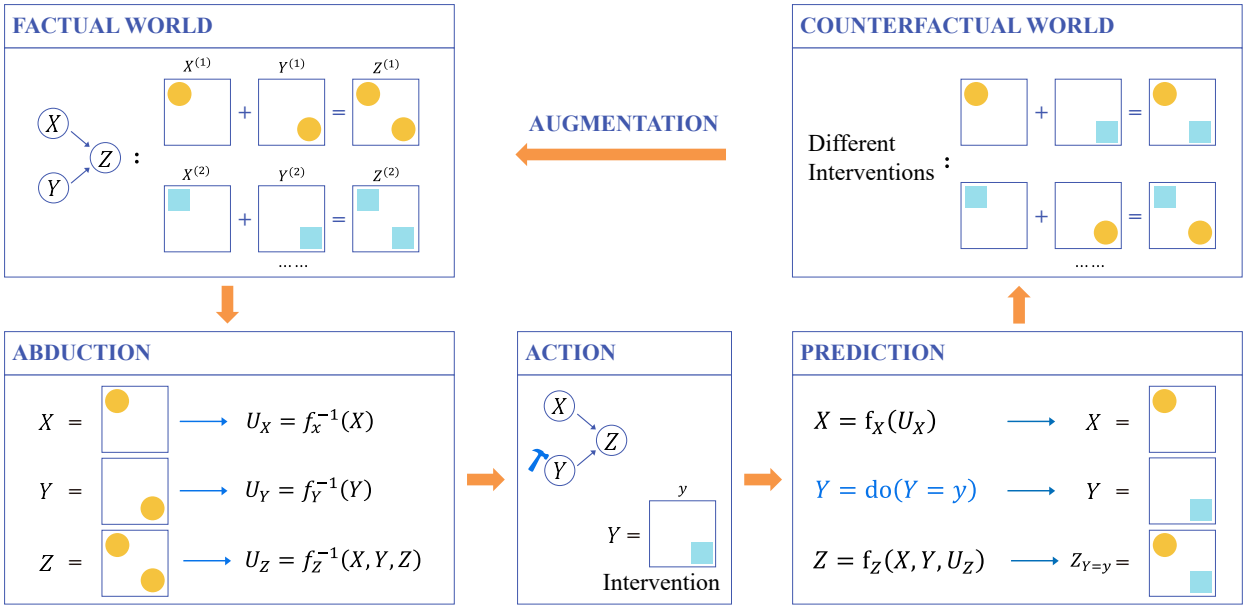


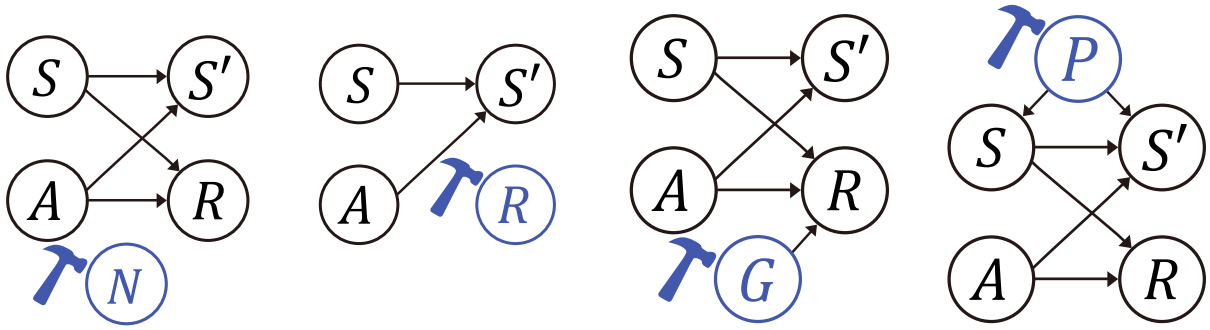
Figure 6: An example of counterfactual data augmentation following the counterfactual reasoning procedure: abduction, action, and prediction. The outcome of this procedure is then used to augment the training data observed in the factual world.

data augmentation explicitly incorporates exogenous variables using the SCM framework. From a Bayesian perspective, traditional MBRL approaches implicitly rely on a fixed prior, such as the Gaussian distribution, for exogenous variables, whereas counterfactual data augmentation leverages additional information from the collected data to estimate the posterior distribution of exogenous variables. Consequently, counterfactual data generation produces high-quality training data, leading to improved policy evaluation and optimization.

Buesing et al. (2019) proposed the counterfactually-guided policy search (CF-GPS) algorithm, designed to search for the optimal policies in POMDPs. They framed model-based POMDP problems using SCMs. The proposed algorithm evaluates the outcome of counterfactual actions based on real experience, thereby improving the utilization of experience data. In a similar vein, Lu et al. (2020) proposed a sample-efficient RL algorithm based on the SCM framework. Their objective was to address issues related to mechanism heterogeneity and data scarcity. Their approach empowers agents to evaluate the potential consequences of counterfactual actions, thereby circumventing the need for actual exploration and alleviating biases arising from limited experience. Pitis et al. (2020) presented a novel framework that leverages a locally factored dynamics model to generate counterfactual transitions for RL agents. Specifically, the term "locally factored" indicates that the state-action space can be partitioned into a disjoint union of local subsets, each has its own causal structure. This locally factored approach allows for an exponential reduction in the sample complexity of training a dynamics model and enables reliable generalization to unseen states and actions. More recently, Zhu et al. (2021) proposed a novel approach to overcome the limitations of existing MBRL methods in the context of robotic manipulation tasks. These tasks are particularly challenging due to the diversity of object properties and the risk of robot damage. The proposed method uses SCMs to capture the underlying dynamics and generate counterfactual episodes involving rarely seen or unseen objects. Experimental results demonstrate superior sample efficiency, requiring fewer environment steps to converge compared to existing MBRL algorithms.

3.4 Limitations

Despite the advancements in improving sample efficiency through causal RL methods, it is crucial to acknowledge their limitations. One common limitation is learning causal representation from high-dimensional observations, such as image data. On the one hand, the presence of unobserved confounders complicates



(a) Generalize to noise or irrelevant variables.

(b) Generalize to different reward assignments.

(c) Generalize to different goals.

(d) Generalize to different physical properties.

Figure 7: Different types of generalization problems in reinforcement learning represented by causal graphs. In these graphs, S and S' represent states in adjacent time steps, A represents actions, R represents rewards, N represents irrelevant variables (e.g., background color), G represents goals (e.g., target position), and P represents physical properties (e.g., mass).

the learning process. On the other hand, learning a causal model in a latent space is generally infeasible without domain knowledge. Effectively extracting causal representations thus relies on making certain assumptions (Schölkopf et al., 2021), introducing a second limitation: sensitivity to model misspecification or inaccurate causal assumptions, which can result in suboptimal performance. Additionally, scaling causal RL to complex environments presents a significant challenge due to increased computational costs and model complexity. For instance, the algorithm proposed by Sontakke et al. (2021) exhibits exponential growth in complexity. Moreover, the counterfactual reasoning procedure in Buesing et al. (2019) assumes access to the true transition function, observation function, and reward function, limiting its practical applicability. In addition, learning a causally correct model with limited prior knowledge poses a significant challenge. In certain scenarios, acquiring a causal model can be more daunting than directly learning policies, often requiring a substantial amount of interventional data, which may counteract the sample efficiency gains.

4 Advancing Generalizability and Knowledge Transfer through Causal Reinforcement Learning

4.1 The Issue of Generalizability in Reinforcement Learning

Generalizability poses another major challenge in the deployment of RL algorithms in real-world applications. It refers to the ability of a trained policy to perform effectively in new and unseen situations (Kirk et al., 2022). The issue of training and testing in the same environment has long been a critique faced by the RL community (Irpan, 2018). While people often expect RL to work reliably in different (but similar) environments or tasks, traditional RL algorithms are typically designed for solving a single MDP. They can easily overfit the environment, failing to adapt to minor changes. Even in the same environment, RL algorithms may produce widely varying results with different random seeds (Zhang et al., 2018a;b), indicating instability and overfitting. Lanctot et al. (2017) presented an example of overfitting in multi-agent scenarios in which a well-trained RL agent struggles to adapt when the adversary changes its strategy. A similar phenomenon was observed by Raghu et al. (2018). Furthermore, considering the non-stationarity and constant evolution of the real world (Hamadanian et al., 2022), there is a pressing need for robust RL algorithms that can effectively handle changes. Agents should possess the capability to transfer their acquired skills across varying situations rather than relearning from scratch.

4.2 Why Causality Helps Improve Generalization and Facilitate Knowledge Transfer?

Some previous studies have shown that data augmentation improves generalization (Lee et al., 2020; Wang et al., 2020a; Yarats et al., 2021), particularly for vision-based control. This process involves generating new

data by randomly shifting, mixing, or perturbing observations, which makes the learned policy more resistant to irrelevant changes. Another common practice is domain randomization. In sim-to-real reinforcement learning, researchers randomized the parameters of simulators to facilitate adaptation to reality (Tobin et al., 2017; Peng et al., 2018). Additionally, some approaches have attempted to incorporate inductive bias by designing special network structures to improve generalization performance (Kansky et al., 2017; Higgins et al., 2017; Zambaldi et al., 2019; Raileanu & Fergus, 2021).

While these works have demonstrated empirical success, explaining why certain techniques outperform others remains challenging. This knowledge gap hinders our understanding of the underlying factors that drive successful generalization and the design of algorithms that reliably generalize in real-world scenarios. To tackle this challenge, it is essential to identify the factors that drive changes. Kirk et al. (2022) proposed using contextual MDP (CMDP) (Hallak et al., 2015) to formalize generalization problems in RL. A CMDP resembles a standard MDP but explicitly captures the variability across a set of environments or tasks, which is determined by contextual variables such as goals, colors, shapes, mass, or the difficulty of game levels. From a causal perspective, these variabilities can be interpreted as different types of external interventions in the data generation process (Schölkopf et al., 2021; Thams, 2022). Figure 7 illustrates some examples of the generalization problems corresponding to different interventions. Previous methods simulate these interventions during the training phase by augmenting original data or randomizing certain attributes, allowing the model to learn from various domains. By carefully scrutinizing the causal relationships behind the data, we can gain a better understanding of the sources of generalization ability and provide a more logical explanation.

More importantly, by making explicit assumptions on what changes and what remains invariant, we can derive principled methods for effective knowledge transfer and adaptation (Zhang et al., 2015; Gong et al., 2016). To illustrate this point, let us recall the example discussed in Figure 2a, where we can use X, Y, and Z to represent citrus fruit consumption, vitamin C intake, and the occurrence of scurvy, respectively. Consider an intervention on fruit consumption (the variable X), one would have to retrain all modules in a non-causal factorization such as $P(X, Y, Z) = P(Y)P(Z|Y)P(X|Y, Z)$ due to the change in $P(X)$. In contrast, with the causal factorization $P(X, Y, Z) = P(X)P(Z|X)P(Y|Z)$, only $P(X)$ needs to be adjusted to fit the new domain. The intuition behind this example is quite straightforward: altering fruit consumption ($P(X)$) does not impact the vitamin C content in specific fruits ($P(Z|X = x)$) or the likelihood of developing scurvy conditioned on the amount of vitamin C intake ($P(Y|Z = z)$). This property is referred to as *independent causal mechanisms* (Schölkopf et al., 2021), indicating that the causal generation process comprises stable and autonomous modules (causal mechanisms) (Pearl, 2009b) such that changing one does not affect the others. Building on this concept, the sparse mechanism shift hypothesis (Schölkopf et al., 2021; Perry et al., 2022) suggests that small changes in the data distribution generally correspond to changes in only a subset of causal mechanisms. These assumptions provide a basis for designing efficient algorithms and models for knowledge transfer.

4.3 Causal Reinforcement Learning for Improving Generalizability

Generalization involves various settings. Zero-shot generalization entails the agent solely acquiring knowledge in training environments and then being evaluated in unseen scenarios. While this setting is appealing, it is often impractical in real-world scenarios. Alternatively, we may allow agents to receive additional training in target domains, categorized as transfer RL (Zhu et al., 2020), multitask RL (Vithayathil Varghese & Mahmoud, 2020), lifelong RL (Khetarpal et al., 2022), among others. To comprehend the essential capabilities required for generalization and the expected outcomes of learning algorithms, causal RL explicitly considers the factors that govern changes in distribution. This section, therefore, categorizes existing causal RL approaches for generalization based on specific factors of change. The representative works are shown in Table 2.

[4]The term "toy" refers to simple, synthetically constructed datasets or simulation environments that are used to experimentally verify findings. It is not a concrete environment or task. We use this term consistently throughout the paper.

[5]When the causal effect is unidentifiable, we can resort to set identification (partial identification), deriving its upper and lower bounds, which allows us to assess the robustness of our estimates against unobserved confounding.

Table 2: Selected methods utilizing causality to improve generalizability.

Category	Paper	Technique	Environments or Tasks	Source
Irrelevant variables	Zhang et al. (2020a)	Causal representation learning	Toy [4] Cart-pole (dm_control) Cheetah (dm_control)	ICML
	Bica et al. (2021b)	Causal representation learning	OpenAI Gym MIMIC III	NeurIPS
	Wang et al. (2022)	Causal dynamics learning	Chemical Manipulation (robosuite)	ICML
	Saengkyongam et al. (2022)	Causal representation learning	Toy	ICML Workshop
	Ding et al. (2022)	Causal discovery	Manipulation (Not accessible) Unlock (Minigrid) Crash (highway-env)	NeurIPS
Dynamics	Sontakke et al. (2021)	Causal representation learning	Manipulation (CausalWolrd)	ICML
	Lee et al. (2021)	Intervention Domain randomization	Manipulation (Isaac Gym)	ICRA
	Zhu et al. (2021)	Counterfactual reasoning	Manipulation (CausalWolrd)	OpenReview
	Guo et al. (2022)	Mediation analysis	Pendulum (OpenAI Gym) Locomotion (OpenAI Gym)	ICLR
Tasks	Eghbal-zadeh et al. (2021)	Causal representation learning	Contextual-Gridworld	ICLR Workshop
	Pitis et al. (2022)	Counterfactual reasoning	Spriteworld Pong (Roboschool) Manipulation (OpenAI)	ICML Workshop
Mixed	Zhang & Bareinboim (2017)	Causal bound [5]	Toy	IJCAI
	Dasgupta et al. (2018)	Meta learning	Toy	ICLR Workshop
	Nair et al. (2019)	Causal induction	Light	arXiv
	Huang et al. (2022a)	Causal dynamics learning	Cart Pole (OpenAI Gym) Pong (OpenAI Gym)	ICLR
Others	Zhu et al. (2022b)	Causal discovery Causal dynamics learning	Toy Inverted Pendulum (OpenAI Gym)	arXiv

4.3.1 Generalize to Different Environments

First, we consider how to generalize to different environments. From a causal perspective, different environments share most of the causal mechanisms but differ in certain modules, resulting from different interventions in the state or observation variables. Building on the causal relationships within these variables, we can categorize existing approaches into two main groups: generalization to irrelevant variables and generalization to varying dynamics.

To enhance the ability to generalize to irrelevant factors, RL agents must examine the causality to identify the invariance in the data generation process. Zhang et al. (2020a) investigated the problem of generalizing to diverse observation spaces within the block MDP framework, such as robots equipped with different types of cameras and sensors, which is a common scenario in reality. In the block MDP framework, the observation space may be infinite, but we can uniquely determine the state (finite but unobservable) given the observation. The authors proposed using invariant prediction to learn the causal representation that generalizes to unseen observations. Similarly, Bica et al. (2021b) introduced invariant causal imitation learning, which learns the imitation policy based on invariant causal representation across multiple environments. Wang et al. (2022) studied the causal dynamics learning problem, which attempts to eliminate irrelevant variables and unnecessary dependencies so that policy learning will not be affected by these nuisance factors. Saengkyongam et al. (2022) focused on the offline contextual bandit problems. Their proposed approach involves iteratively assessing the invariance condition for various subsets of variables to learn an optimal invariant policy. The algorithm begins by generating a sample dataset using an initial policy and then tests the invariance of each subset across different environments. If a subset is found to be invariant, an optimal policy within that subset is learned through off-policy optimization. The experimental results suggest that invariance is crucial for obtaining distributionally robust policies, particularly in the presence of unobserved confounders. Ding et al. (2022) proposed an approach to address the generalization problem in goal-conditioned reinforcement learning (GCRL). Their method involves treating the causal graph as a latent variable and optimizing it using a variational likelihood maximization procedure. This method trains

agents to discover causal relationships and learn a causality-aware policy that is robust against changes in irrelevant variables.

Generalizing to new dynamics is a complex issue that involves different types of variations. These variations may include changes in physical properties (e.g., gravitational acceleration), disparities between the simulation environment and reality, and alternations in the range of attribute values, etc. Sontakke et al. (2021) proposed training RL agents to infer and categorize causal factors in the environment with experimental behavior learned in a self-supervised manner. These behaviors can help the agent to extract discrete causal representations from collected trajectories, which can be applicable to unseen environments, empowering the agent to effectively generalize to unseen contexts. Lee et al. (2021) proposed an approach that conducts interventions to identify relevant state variables for successful robotic manipulation, i.e., the features that causally influence the outcome. The robot exhibited excellent sim-to-real generalizability after training with domain randomization on the identified features. Zhu et al. (2021) developed an algorithm to improve the ability of agents to generalize to rarely seen or unseen object properties. This algorithm models the environmental dynamics with SCMs, allowing the agent to generate counterfactual trajectories about objects with different attribute values, which leads to improved generalizability. Guo et al. (2022) investigated the unsupervised dynamics generalization problem, which allows the learned model to generalize to new environments. The authors approached this challenge by leveraging the intuition that data originating from the same trajectory or similar environments should have similar properties (hidden variables encoded from trajectory segments) that lead to similar causal effects. To measure similarity, they employed conditional direct effects in mediation analysis. The experimental results show that the learned model performs well in new environmental dynamics.

4.3.2 Generalize to Different Tasks

Another important topic is how to generalize to different tasks. In the SCM framework, different tasks are created by altering the structural equation of the reward variable or its parent nodes on the causal graph. These tasks have the same underlying environmental dynamics, but the rewards are assigned differently.

Eghbal-zadeh et al. (2021) introduced causal contextual RL, where agents aim to learn adaptive policies that can effectively adapt to new tasks defined by contextual variables. The authors proposed a contextual attention module that enables agents to incorporate disentangled features as contextual factors, leading to improved generalization compared to non-causal agents. In order to make RL more effective in complex, multi-object environments, Pitis et al. (2022) suggested factorizing the state-action space into separate local subsets. This approach allows for learning the causal dynamic model as well as generating counterfactual transitions in a more efficient manner. By training agents on counterfactual data, the proposed algorithm exhibits improved generalization to out-of-distribution tasks.

Furthermore, in reality, generalization may involve changes in both the environmental dynamics and the task. Several studies have explored this problem from a causal viewpoint. Zhang & Bareinboim (2017) investigated knowledge transfer across bandit agents in scenarios where causal effects are unidentifiable. The proposed strategy combines two steps: deriving the upper and lower bounds of causal effects using structural knowledge and then incorporating these bounds in a dynamic allocation procedure to guide the search toward more promising actions in new bandit problems. The results indicated that this strategy dominates previously known algorithms and achieves faster convergence rates. Dasgupta et al. (2018) explored whether the ability to perform causal reasoning emerges from meta-learning on a simple domain with five variables. The experimental results suggested that the agents demonstrated the ability to conduct interventions and make sophisticated counterfactual predictions. These emergent abilities can effectively generalize to new causal structures. Nair et al. (2019) studied the causal induction problem with visual observation. They incorporated attention mechanisms into the agent to generate a causal graph based on visual observations and use it to make informed decisions. The experiments demonstrated that the agent effectively generalizes to new tasks and environments with unknown causal structures. More recently, Huang et al. (2022c) proposed AdaRL, a novel framework for adaptive RL that learns a latent representation with domain-shared and domain-specific components across multiple source domains. The latent representation is then used in policy optimization. This framework allows for efficient policy adaptation to new environments, tasks, or observations, by estimating new domain-specific parameters using a small number of samples.

4.3.3 Other Generalization Problems

In offline RL, the agent can only learn from pre-collected datasets. In this setting, agents may encounter previously unseen state-action pairs during the testing phase, leading to the distributional shift issue (Levine et al., 2020). Most existing approaches mitigate this issue through conservative or pessimistic learning (Fujimoto et al., 2019; Kumar et al., 2020; Yang et al., 2021b), rarely considering generalization to new states. Zhu et al. (2022b) proposed a solution to generalize to unseen states. They recovered the causal structure from offline data by using causal discovery techniques, and then employ an offline MBRL algorithm to learn from the causal model. The experimental results suggested that the causal world model exhibits better generalization performance than a traditional world model, and effectively facilitates offline policy learning.

4.4 Limitations

As some of the causal RL methods discussed in this section overlap with those presented earlier for sample efficiency, some of the limitations identified in the previous section are also applicable here. However, when focusing on generalizability, we observe additional limitations. It can be seen that most of the causal RL methods for generalizability utilize causal representation learning or employ counterfactual reasoning based on causal models. These approaches generally require learning from multi-domain data or allowing for explicit interventions in environmental components to simulate the generation of such data. The quality and granularity of the extracted representations closely rely on which distributional shifts, interventions or relevant signals are available (Schölkopf et al., 2021), while agents often have access to only a limited number of domains in reality.

5 Addressing Spurious Correlations through Causal Reinforcement Learning

5.1 The Issue of Spurious Correlation in Reinforcement Learning

Making reliable decisions based solely on data is inherently challenging, as correlation does not necessarily imply causation. It is important to recognize the presence of spurious correlations, which are deceptive associations between two variables that may appear causally related but are not. These spurious correlations introduce undesired bias to the learning problem, posing a significant challenge in various machine learning applications. Here are a few illustrative examples of this phenomenon.

- In recommendation systems, user behavior and preferences are often influenced by conformity, which refers to the tendency of individuals to align with larger groups or social norms. Users may feel inclined to conform to popular trends or recommendations. Ignoring the impact of conformity can lead to an overestimation of a user's preference for certain items (Gao et al., 2022);
- In image classification, when dogs frequently appear alongside grass in the training set, the classifier may incorrectly label an image of grass as a dog. This misclassification arises because the model relies on the background (the irrelevant factors) rather than focusing on the specific pixels that correspond to dogs (the actual causal) (Zhang et al., 2021a; Wang et al., 2021c).
- When determining the ranking of tweets, the use of gender icons in tweets is usually not causally related to the number of likes; their statistical correlation comes from the topic, as it influences both the choice of icon and the audience. Therefore, it is not appropriate to determine the ranking by gender icons (Feder et al., 2022).

If we want to apply RL in real-world scenarios, it is important to be mindful of spurious correlations, especially when the agent is working with biased data. For instance, when optimizing long-term user satisfaction in multiple-round recommendations, there is often a spurious correlation between exposure and clicks in adjacent timesteps. This is because they are both influenced by item popularity. From another perspective, when we observe a click, it may depend on user preference or item popularity, which creates a spurious correlation between the two factors. In both scenarios, agents may make incorrect predictions or decisions, such as only recommending popular items (a suboptimal policy for both the system and the user), and

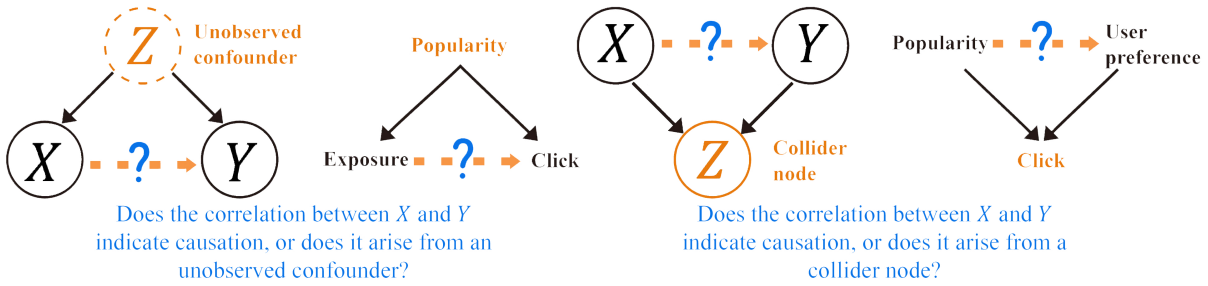


Figure 8: Causal graphs illustrating the two types of spurious correlations, with examples from real-world applications.

this can further cause filter bubbles. In a nutshell, if the agent learns a spurious correlation between two variables, it may mistakenly believe that changing one will affect the other. This misunderstanding can lead to suboptimal or even harmful behavior in real-world decision-making problems.

5.2 Why Causality Helps Address Spurious Correlations?

The non-causal approaches lack a language for systematically discussing spurious correlations. From the causal perspective, spurious correlations arise when the data generation process involves unobserved confounders (common cause) or when a collider node (common effect) serves as the condition. The former leads to confounding bias, while the latter results in selection bias. See Figure 8 for a visual interpretation of these phenomena. Causal graphs enable us to trace the source of spurious correlations by closely scrutinizing the data generation process. To eliminate the bias induced by spurious correlations, it is necessary to make decisions regarding causality instead of statistical correlations. This is where causal reasoning comes in: It provides principled tools to analyze and deal with confounding and selective bias (Pearl, 2009b; Glymour et al., 2016), helping RL agents accurately estimate the causal effects in decision-making problems.

One may assume that on-policy RL is immune to spurious correlations since it directly learns causal effects of the form $p(r|s, \text{do}(a))$ from interventional data. However, it is important to note that understanding the effect of an action on the outcome alone is insufficient for comprehending the complete data generation process. The influence of different covariates on the outcome also plays a crucial role. For example, in personalized recommendation systems, the covariates can be divided into relevant and spurious features. If the training environment consistently pairs the clicked items with specific values of spurious features (e.g., clickbait in textual features), the agent may unintentionally learn a policy based on these spurious features. When the feature distribution changes in the test environment, the agent may make erroneous decisions (Gao et al., 2022). This example demonstrates the prevalence of spurious correlations in real-world decision-making problems. Demystifying the causal relationships helps resolve such challenges.

5.3 Causal Reinforcement Learning for Addressing Spurious Correlations

Based on the underlying causal structure of the decision-making problem, spurious correlations can manifest in two distinct types: confounding bias arising from fork structures, and selective bias arising from collider structures (as depicted by Figure 8). Accordingly, we categorize existing methods into two groups. Additionally, to be self-contained, we incorporate studies on imitation learning (IL) and off-policy evaluation (OPE), given their close relevance to policy learning in RL. The representative works are shown in Table 3.

5.3.1 Addressing Confounding Bias

We start by introducing an important technique in causal inference named do-calculus (Pearl, 1995). It is an axiomatic system that enables us to replace probability formulas containing the do operator with ordinary

[6]Causal graph as a technique refers to using causal graphs to describe the data generation process, and designing graphical criteria for determining properties such as identifiability or developing algorithms based on causal graphs.

Table 3: Selected methods utilizing causality to address spurious correlations.

Category	Paper	Technique	Environments or Tasks	Source
Confounding bias - MDP: IL	Zhang et al. (2020b)	Causal graph [6]	Toy	NeurIPS
	Kumor et al. (2021)	Causal graph	Toy	NeurIPS
	Swamy et al. (2022)	Instrumental variables	Lunar Lander (OpenAI Gym) Locomotion (PyBullet Gym)	ICML
Confounding bias - MDP: OPE	Namkoong et al. (2020)	Sensitivity analysis	Toy	NeurIPS
	Bennett et al. (2021)	Proxy variables	Toy	AISTATS
Confounding bias - MDP/POMDP	Lu & Lobato (2018)	Backdoor adjustment	Pendulum (OpenAI Gym) Cart Pole (OpenAI Gym) MNIST	arXiv
	Zhang & Bareinboim (2019)	Causal bound Sensitivity analysis	Toy	NeurIPS
	Rezende et al. (2020)	Backdoor adjustment	Toy MiniPacman 3D Maze (Unity)	arXiv
	Zhang & Bareinboim (2020)	Causal graph Causal bound	Toy	ICML
	Wang et al. (2021b)	Frontdoor adjustment Backdoor adjustment	-	NeurIPS
	Liao et al. (2021)	Instrumental variables	-	arXiv
	Gasse et al. (2021)	Backdoor adjustment	Toy	arXiv
	Yang et al. (2022a)	Causal graph	Toy Cart Pole (OpenAI Gym) Lunar Lander (OpenAI Gym)	AAAI
	Zhang & Bareinboim (2022b)	Causal graph	Toy	NeurIPS
Selection bias	Bai et al. (2021)	Inverse probability weighting	Manipulation (OpenAI)	TCYB
	Deng et al. (2021)	Causal graph	D4RL	arXiv

conditional probabilities. The do-calculus includes three axiom schemas that provide graphical criteria for making certain substitutions. It has been proven to be complete for identifying causal effects (Huang & Valtorta, 2006; Shpitser & Pearl, 2006). Derived from the do-calculus, the backdoor and frontdoor adjustment are two widely used methods for eliminating confounding bias Pearl (2009b); Glymour et al. (2016). The key intuition is to block spurious correlations between the treatment and outcome variables that pass through the confounders. In situations where unobserved confounding exists, it is still possible to identify the causal effect of interest if observed proxy variables for the confounder are available (Miao et al., 2018; Ghassami et al., 2023). Another popular approach for addressing unobserved confounding is to identify and employ instrumental variables (Angrist et al., 1996; Baiocchi et al., 2014). An instrumental variable, denoted as I, must satisfy three conditions: 1) I is a cause of T (the treatment variable); 2) I affects Y (the outcome variable) only through T; and 3) The effect of I on Y is unconfounded. Since the instrumental variable I influences Y only through T, and this effect is unconfounded, we can indirectly estimate the effect of T on Y through the effect of the instrumental variable Z on Y. Furthermore, we can evaluate the robustness of the estimated causal effect against unobserved confounding by varying the strength of the confounder's effect, which is referred to as sensitivity analysis (Díaz & van der Laan, 2013; Kuang et al., 2020).

Zhang et al. (2020b) studied a single-step imitation learning problem using a combination of demonstration data and structural knowledge about the data-generating process. They proposed a graphical criterion for determining the feasibility of imitation learning in the presence of unobserved confounders and a practical procedure for estimating valid imitating policies with confounded expert data. This approach was then extended to the sequential setting in a subsequent paper (Kumor et al., 2021). Swamy et al. (2022) designed an algorithm for imitation learning with corrupted data. They proposed to use instrumental variable regression (Stock & Trebbi, 2003) to resolve the spurious correlations caused by unobserved confounding.

Several research focused on the OPE problem, which seeks to estimate the performance of policies using data generated by different policies. For example, Namkoong et al. (2020) conducted sensitivity analyses on OPE methods under unobserved confounding. They derived worst-case bounds on the performance of an evaluation policy and proposed an efficient procedure for estimating these bounds with statistical consistency, allowing for a reliable selection of policies. Bennett et al. (2021), on the other hand, proposed a new estimator

for OPE in infinite-horizon RL. The authors established the identifiability of the policy value from off-policy data by employing a latent variable model for states and actions (which can be seen as proxy variables for the unobserved confounders). The authors further presented a strategy for estimating the stationary distribution ratio using proxies, which is then utilized for policy evaluation.

Lu & Lobato (2018) introduced a novel approach called deconfounding RL, aiming to learn effective policies from historical data affected by unobserved factors. Their method begins by estimating a latent-variable model using observational data, which identifies latent confounders and assesses their impact on actions and rewards. Then these confounders are utilized in backdoor adjustment to address confounding bias, enabling the policy to be optimized based on a deconfounding model. Experimental results demonstrate the method's superiority over traditional RL approaches when applied to observational data with confounders. Liao et al. (2021) also focused on the offline setting. They found that RL practitioners often encounter unobserved confounding in medical scenarios, but there are some common sources of instrumental variables, including preferences, distance to specialty care providers, and genetic variants (Baiocchi et al., 2014). Therefore, they proposed an efficient algorithm to recover the transition dynamics from observational data using instrumental variables, and employ a planning algorithm, such as value iteration, to search for the optimal policy. Wang et al. (2021b), on the other hand, studied how confounded observational data can facilitate exploration during online learning. They proposed the deconfounded optimistic value iteration algorithm, which combines observational and interventional data to update the value function estimates. This algorithm effectively handles confounding bias by leveraging backdoor and frontdoor adjustment, achieving a smaller regret than the optimal online-only algorithm. Gasse et al. (2021) studied MBRL for POMDP problems. Specifically, They used ideas from the do-calculus framework to formulate model learning as a causal inference problem. They introduced a novel method to learn a latent-based causal transition model capable of explaining both interventional and observational regimes. By utilizing the latent variable, they were able to recover the standard transition model, which, in turn, facilitated the training of RL agents using simulated transitions. Yang et al. (2022a) proposed the causal inference Q-network algorithm to address confounding bias arising from various types of observational interferences, such as Gaussian noise and observation black-out. The authors began by analyzing the impact of these interferences on the decision-making process using causal graphs. They then devised a novel algorithm that incorporates the interference label to learn the relationship between interfered observations and Q-values in order to maximize rewards in the presence of observational interference. The model learns to infer the interference label and adjusts the policy accordingly. Experimental results demonstrate the algorithm's improved resilience and robustness against different types of interferences. Rezende et al. (2020) discussed the application of partial models in RL, a model-based approach that does not require modeling the complete (and usually high-dimensional) observation. They showed that the causal correctness of a partial model can be influenced by behavior policies, leading to an overestimation of the rewards associated with suboptimal actions. To address this issue, the authors proposed a simple yet effective solution. Since we have full control of the agent's computational graph, we can choose any node situated between the internal state and the produced action as a backdoor variable, e.g., the intended action. By applying backdoor adjustment, we can ensure the causal correctness of partial models.

A less familiar but highly important research topic for RL researchers is dynamic treatment regimes (DTRs) (Murphy, 2003). Closely related to the fields of biostatistics, epidemiology, and clinical medicine, this topic focuses on determining personalized treatment strategies, including dosing or treatment planning. It aims to maximize the long-term clinical outcome and can be modeled as an MDP with unobserved confounders (Wang et al., 2021b), making it highly relevant to causal RL. Zhang & Bareinboim (2019) considered a setting in which causal effect is not identifiable. They proposed an online learning algorithm to solve DTRs by combining confounded observational data. Their algorithm hinges on sensitivity analyses and incorporates causal bounds to accelerate the learning process. This online learning allows for conducting sequential, adaptive experimentation so it is getting increasingly popular. However, a challenge arises when dealing with a vast covariate and treatment space, as online learning algorithms may have unacceptable regret. To address this challenge, Zhang & Bareinboim (2020) proposed an efficient procedure that leverages the structural knowledge encoded in the causal graph to reduce the dimensionality of the candidate policy space. By exploiting the sparsity of the graph, where certain covariates are affected by only a small subset of treatments, the proposed method exponentially reduces the dimensionality of the learning problem. The experimental results consistently demonstrate that the proposed method outperforms state-of-the-art (SOTA) methods in

terms of performance. More recently, Zhang & Bareinboim (2022b) further explored the challenge of policy space with mixed scopes, i.e., the agent has to optimize over candidate policies with varying state-action spaces. This becomes particularly crucial in medical domains such as cancer, HIV, and depression, where finding the optimal combination of treatments is essential for achieving desired outcomes. To tackle this issue, the authors propose a novel method that utilizes causal graphs to identify the maximal sets of variables that are causally related to each other. These sets are then utilized to parameterize SCMs, enabling the representation of different interventional distributions using a minimal set of components, thereby enhancing the efficiency of the learning process.

5.3.2 Addressing Selection Bias

Selective bias occurs when data samples fail to represent the target population. For example, selective bias arises when researchers seek to understand the effect of a certain drug on curing a disease by investigating patients in a selected hospital. This is because those patients may differ significantly from the population regarding their residence, wealth, and social status, making them unrepresentative.

Bai et al. (2021) investigated the selective bias associated with using hindsight experience replay (HER) in goal-conditioned reinforcement learning (GCRL) problems. In particular, HER relabels the goal of each collected trajectory, allowing the agent to learn from failures (not reaching the original goal). However, there is a concern that the relabeled goal distribution may not accurately represent the original goal distribution, resulting in significant bias for agents trained with HER. To address this issue, the authors proposed to use inverse probability weighting, a technique in causal inference, to assign appropriate weights to the rewards computed for the relabeled goals. By reweighting the samples, the agent can mitigate the selection bias induced by HER and effectively learn from a balanced mixture of successful and unsuccessful outcomes, ultimately enhancing the overall performance. Deng et al. (2021) examined the offline RL problem through the lens of selective bias. In the offline setting, agents are vulnerable to the spurious correlation between uncertainty and decision-making, which can result in learning suboptimal policies. Taking a causal perspective, the empirical return is the outcome of both uncertainty and actual return. Since it is infeasible to reduce uncertainty by acquiring more data in the offline setting, a causal-unaware agent might mistakenly assume a causal relationship between uncertainty and return. As a result, it may favor policies that achieve high returns by chance (high uncertainty). To address this issue, the authors propose quantifying uncertainty and using it as a penalty term in the learning process. The results show that this method outperforms various baselines that do not consider causality in the offline setting.

5.4 Limitations

Most of the aforementioned approaches heavily rely on causal graphs, so making accurate causal assumptions is of significance. Particularly, when dealing with unobserved confounding, the use of proxy variables and instrumental variables may introduce additional risks. Inaccurate representation of the variables of interest through proxies can introduce new confounding or other forms of biases. On the other hand, meeting all three rigorous conditions in the definition of instrumental variables or establishing and validating these conditions in practical scenarios can be challenging. These limitations highlight the importance of carefully considering the underlying assumptions and potential risks associated with causal RL methods.

6 Considerations Beyond Return

In general, the primary objective of RL is to maximize returns. However, with the increasing integration of RL-based automated decision systems into our daily lives, it becomes imperative to examine the interactions between RL agents and humans, as well as their potential societal implications.

6.1 Explainability

6.1.1 Explainability in Reinforcement Learning

Explainability in RL refers to the ability to understand and interpret the decisions of an RL agent. It is important to both researchers and general users. Explanations reflect the knowledge learned by the agent, facilitate in-depth understanding, and allow researchers to participate efficiently in the design and continual optimization of an algorithm. In addition, explanations provide the internal logic of the decision-making process. When agents outperform humans, we can extract knowledge from the explanations to guide human practice in a specific domain. For general users, explanations provide a rationale behind the decision, thereby enhancing their comprehension of intelligent agents and instilling greater confidence in the agent's capabilities.

6.1.2 Leveraging Causality for Explainability

Explainable RL methods can be broadly categorized into two groups: post hoc and intrinsic approaches (Puiutta & Veith, 2020; Heuillet et al., 2021). Post hoc explanations are provided after the model execution, whereas intrinsic approaches inherently possess transparency. Post hoc explanations, such as the saliency map approach (Greydanus et al., 2018; Mott et al., 2019), often rely on correlations. However, as we mentioned earlier, conclusions drawn based on correlations may be unreliable and fail to answer causal questions. On the other hand, intrinsic explanations can be achieved using interpretable algorithms, such as linear regression or decision trees. Nevertheless, the limited modeling capacity of these algorithms may prove insufficient in explaining complex behaviors (Puiutta & Veith, 2020).

In contrast, humans possess an innate and powerful ability to explain the connections between different events through a "mental causal model (Sloman, 2005)". This cognitive ability enables us to employ causal language in our everyday interactions, using phrases such as "because," "therefore," and "if only." By harnessing causal relationships, we acquire natural and flexible explanations that do not rely on specific algorithms or models, thereby greatly facilitating efficient communication and collaboration. Drawing inspiration from human cognition, we can integrate causality into RL to provide explanations that enable agents to articulate their decisions and interpretations of the environment and tasks using causal language. Furthermore, in cases when the agent makes mistakes, we can respond with tailored solutions guided by causal insights.

6.2 Fairness

6.2.1 Fairness in Reinforcement Learning

As machine learning applications continue to permeate various aspects of our daily lives, fairness is increasingly recognized as a significant concern by business owners, general users, and policymakers. In real-world scenarios, fairness concerns often exhibit a dynamic nature (Gajane et al., 2022), involving multiple decision rounds. For example, resource allocation and college admissions can be modeled as MDPs (D'Amour et al., 2020), wherein actions have cumulative effects on the population, leading to dynamic changes in fairness. Ignoring this dynamic nature of a system may lead to unintended consequences, e.g., exacerbating the disparity between advantaged and disadvantaged groups (Liu et al., 2018; Creager et al., 2020; D'Amour et al., 2020). In decision-making problems like these, RL agents should strive to genuinely benefit humans and promote social good, avoiding any form of discrimination or harm towards specific individuals or groups.

6.2.2 Leveraging Causality for Fairness

When considering the application of reinforcement learning to solve fairness-aware decision-making problems, it is crucial to first examine the available prior knowledge. Detailed causal modeling allows us to characterize and understand the intricate interplay between decision-making and environmental dynamics (Zhang et al., 2020c; Tang et al., 2023). Specifically, we can determine what observable variables and latent factors are involved in a specific problem and how they affect (long-term) fairness. Moreover, fairness and discrimination often require counterfactual reasoning (Pearl & Mackenzie, 2018). For example, in *Carson v. Bethlehem*

Steel Corporation (1996) [7], the ruling made it clear that determining whether an individual or group would be treated differently by altering only the sensitive attribute (e.g., sex, age, and race) while holding other factors constant is at the heart of discrimination issues. As highlighted by Kusner et al. (2017) and Zhang & Bareinboim (2018), many correlation-based metrics (Zafar et al., 2015; Wen et al., 2021) disregard the causal relationships behind the data generation process, resulting in an inaccurate measurement of fairness, which may increase discrimination in certain scenarios. Through counterfactual analysis, we can explore fairness by comparing the differences in causal effects between the factual and imagined worlds. In summary, causality provides a principled approach to studying fairness in reinforcement learning.

6.3 Safety

6.3.1 Safety in Reinforcement Learning

Safety is a crucial concern in RL (Garcıa & Fernández, 2015; Gu et al., 2022). RL agents may sometimes act unexpectedly, especially when faced with unseen situations. This issue poses a significant risk in safety-critical applications, such as healthcare or autonomous vehicles, where even a single error could have severe consequences. Additionally, RL agents may prioritize higher returns over their own safety, known as the agent safety problem (Fulton & Platzer, 2018; Beard & Baheri, 2022). For instance, in domains like robotic control, agents may sacrifice their lifespan for a higher mission completion rate. Addressing these safety concerns and developing robust methods to ensure safe decision-making in RL are vital for the practical deployment of RL systems in real-world applications.

6.3.2 Leveraging Causality for Safety

Safe RL problems are typically formulated as constrained MDPs (Altman, 1995; 1999), which extend MDPs by incorporating an additional constraint set to express various safety concerns. Existing methods primarily focus on preventing constraint violations (Achiam et al., 2017; Chow et al., 2017), and seldom explicitly considering causality. By incorporating causal analysis, we can better understand the causes behind unexpected outcomes, and develop preventive solutions to avoid RL agents from repeatedly breaching safety constraints (Everitt et al., 2021). Additionally, causal world models and counterfactual policy evaluation techniques allow us to access RL policies before deployment, thereby enabling the identification of potential safety issues (Hart & Knoll, 2020). Overall, the integration of causality helps ensure RL methods and systems are used safely and responsibly, mitigating the risk of catastrophic consequences.

6.4 Beyond Return with Causal Reinforcement Learning

In this section, we explore causal RL methods that aim to address and alleviate challenges related to explainability, fairness, and safety. The representative works are shown in Table 4.

6.4.1 Explainable Reinforcement Learning with Causality

One way to generate explanations is to use the concept of counterfactuals such as exploring the minimal changes necessary to produce a different outcome. The term "counterfactual" is popular in multi-agent reinforcement learning (MARL). For example, Foerster et al. (2018) proposed a method named counterfactual multi-agent policy gradients for efficiently learning decentralized policies in cooperative multi-agent systems. More precisely, counterfactuals help resolve the challenge of multi-agent credit assignment so that agents and humans can better understand the contribution of individual behavior to the team. Some subsequent studies followed the same idea (Su et al., 2020; Zhou et al., 2022). These approaches did not perform the complete counterfactual reasoning procedure as shown in Figure 6, missing the critical step of abduction, which offers opportunities for further enhancements. More recently, Triantafyllou et al. (2022) established a connection between Dec-POMDPs and SCM, enabling them to investigate the credit assignment problem in MARL using causal language. They proposed to formalize the notion of responsibility attribution based on the actual causality, as defined by counterfactuals, which is a significant stride in developing a rigorous framework that supports accountable MARL research. Mesnard et al. (2021), on the other hand, studied

[7] https://caselaw.findlaw.com/us-7th-circuit/1304532.html

Table 4: Selected methods utilizing causality for goals beyond maximizing returns.

Category	Paper	Technique	Environments or Tasks	Source
Explainability	Foerster et al. (2018)	Counterfactual	StarCraft	AAAI
	Madumal et al. (2020)	Counterfactual reasoning	OpenAI Gym StarCraft	AAAI
	Bica et al. (2021a)	Counterfactual reasoning	Toy MIMIC-III	ICLR
	Mesnard et al. (2021)	Counterfactual reasoning	Toy Key-to-Door (Not accessible) Interleaving (Not accessible)	ICML
	Tsirtsis et al. (2021)	Counterfactual reasoning	Toy Therapy	NeurIPS
	Triantafyllou et al. (2022)	Counterfactual reasoning	Goofspiel (Not accessible)	AAAI
	Herlau & Larsen (2022)	Mediation analysis	Toy DoorKey (Not accessible)	AAAI
Fairness	Zhang & Bareinboim (2018)	Counterfactual reasoning Mediation analysis	Toy	AAAI
	Huang et al. (2022c)	Causal graph Causal reasoning	Toy	AAAI
	Balakrishnan et al. (2022)	Causal graph Counterfactual reasoning	Toy	AAAI
Safety	Hart & Knoll (2020)	Counterfactual reasoning	BARK-ML	IROC
	Everitt et al. (2021)	Causal graph	-	Synthese

the temporal credit assignment problem, i.e., measuring an action's influence on future rewards. Inspired by the concept of counterfactuals from causality theory, the authors proposed conditioning value functions on future events, which separate the influence of actions on future rewards from the effects of other sources of stochasticity. This approach not only facilitates explainable credit assignment but also reduces the variance of policy gradient estimates.

Madumal et al. (2020) used theories from cognitive science to explain how humans understand the world through causal relationships and how these relationships can help us understand and explain the behavior of RL agents. They presented an approach that integrates an SCM into reinforcement learning and used the learned model to generate explanations of behavior based on counterfactual analysis. For example, when quiring why a Starcraft II agent builds supply depots instead of barracks (a typical counterfactual query), the agent can respond by explaining that constructing supply depots is more desirable, as it helps increase the number of destroyed units and buildings. To evaluate the proposed approach, a study was conducted involving 120 participants. The results demonstrate that the causality-based explanations outperformed other explanation models in terms of understanding, explanation satisfaction, and trust. Bica et al. (2021a) proposed an innovative approach to gain insights into expert decision processes by integrating counterfactual reasoning into batch inverse reinforcement learning. Their method focuses on learning explanations of expert decisions by modeling their reward function based on preferences with respect to counterfactual outcomes. This framework is particularly helpful in real-world scenarios where active experimentation may not be feasible. Tsirtsis et al. (2021) conducted a study on the identification of optimal counterfactual explanations for a sequential decision process. They approached this problem by formulating it as a constrained search problem and devised a polynomial time algorithm based on dynamic programming to find the solution. Specifically, this problem requires the algorithm to search for another sequence of actions that differs from the observed sequence of actions by a specified number of actions. The study conducted by Herlau & Larsen (2022) explores the application of mediation analysis in RL. The proposed method focuses on training an RL agent to optimize natural indirect effects, which allows for identifying critical decision points. For instance, in the task of unlocking a door, the agent can effectively recognize the event of acquiring a key. By leveraging mediation analysis, the agent can acquire a concise and interpretable causal model, enhancing its overall performance and explanatory capabilities.

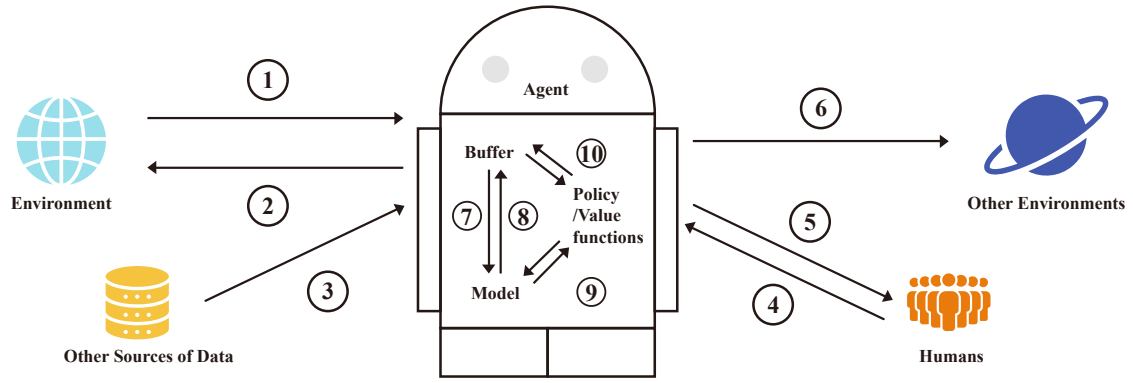


Figure 9: A schematic diagram illustrating the integration of causality into the reinforcement learning process. The numbered edges represent some key components: 1) Abstraction and extraction of causal representations from raw observations; 2) Directed exploration guided by causal knowledge; 3) Fusing (possibly confounded) data; 4) Incorporating causal assumptions or knowledge from humans. 5) Providing causality-based explanations; 6) Generalization and knowledge transfer; 7) Learning causal world models; 8) Counterfactual data generation; 9) Planning with world models; 10) Enhanced training of policies and value functions with causal reasoning.

6.4.2 Fair Reinforcement Learning with Causality

In addition to explainability, we also want RL agents to align with human values and avoid potential harm to human society, with fairness being a key consideration. Nevertheless, little work has been done to study fairness in RL. One popular idea is to quantify fairness using statistical measures, such as demographic parity, a measure that quantifies the disparity in positive outcomes across different subgroups defined by protected attributes like gender and age. Such measures are then turned into constraints (Balakrishnan et al., 2022) to enforce certain types of fairness, framing fair policy learning into a constrained optimization problem. Sometimes, our focus lies on counterfactual inquiries, such as accessing the potential impact of altering a sensitive attribute on the outcomes. Answering such queries necessitates the evaluation of counterfactual outcomes. Zhang & Bareinboim (2018) pioneered the adoption of the SCM framework to conceptualize fairness, enabling researchers to quantitatively evaluate counterfactual fairness. By leveraging counterfactual statements, researchers can systematically analyze different forms of discrimination (direct, indirect, and spurious discrimination) and their impact on decision-making processes. Huang et al. (2022c) studied fairness in recommendation scenarios, focusing on the bandit setting, in which sensitive attributes should not causally influence the rewards. Similarly, Liu et al. (2020) explored the issue of fairness in recommendation scenarios. Their research centered around finding the right balance between accuracy and fairness in multi-step interactive recommendations, which were modeled using MDPs. They employed causal graphs to formally analyze fairness and evaluated it using counterfactuals. The experimental results demonstrate that their proposed approach not only enhances fairness but also maintains good recommendation performance.

6.4.3 Safe Reinforcement Learning with Causality

Finally, safety is a fundamental challenge to making RL widely applicable in the real world. Causal inference provides some valuable tools for studying safety. As an example, Hart & Knoll (2020) investigated the safety issue relates to autonomous driving. Researchers can conduct counterfactual policy evaluations before deploying any policy to the real world by utilizing counterfactual reasoning. The experimental results show that their method demonstrated a high success rate while significantly reducing the collision rate. On the other hand, Everitt et al. (2021) studied a critical concern known as reward tampering, which refers to the potential for RL agents to manipulate their reward signals. This manipulation can lead to unintended consequences and undermine the effectiveness of the learning process, thus posing a potential safety threat. In this paper, the authors presented a set of design principles aimed at developing RL agents that are robust against reward tampering, ensuring their behavior remains aligned with the intended objectives. To establish

Table 5: The three components of causal learning.

	Available information	Targets to identify	Typical questions
Causal feature extraction	Observations	Causal variables (representation)	What factors account for the change in position?
Causal discovery	Causal variables	Causal graph	Does mass determine the change in position of an object?
Causal mechanisms learning	Causal graph	Causal mechanisms	How mass determine the change in position of an object?

these design principles, the authors developed a unified causal framework supported by causal graphs, which provide a precise and intuitive understanding of the reward tampering issue.

6.5 Limitations

Despite the promising results achieved by causal RL methods discussed in this section, it is important to acknowledge the limitations associated with their reliance on counterfactual reasoning. Obtaining accurate and reliable counterfactuals often requires strong assumptions about the underlying causal structure, as counterfactuals, by definition, cannot be directly observed. Furthermore, the computational complexity of counterfactual reasoning can be a bottleneck, especially when dealing with high-dimensional state and action spaces, hindering real-time decision-making in complex tasks, which remains an ongoing challenge.

We summarize the core ideas discussed spanning sections 3 to 6 by presenting Figure 9. This schematic diagram captures the various approaches to integrating causality into the reinforcement learning process, highlighting the key components and their interactions. As we conclude this section, we recognize that while significant progress has been made in the field of causal RL, there remain important yet underexplored avenues for future research and development. In the final section of this paper, we turn our attention to the open problems and future directions. By examining these uncharted territories, we aim to inspire future studies and contribute to the continued advancement of causal RL, paving the way for new breakthroughs and applications.

7 Open Problems and Future Directions

7.1 Causal Learning in Reinforcement Learning

In section 3.3 and section 4.3, we explained how causality dynamics learning - a class of methods closely related to MBRL - can improve sample efficiency and generalizability (Wang et al., 2022; Huang et al., 2022b). These methods focus on understanding the cause-and-effect relationships between variables and the process that generates these variables. Instead of using complex, redundant connections, to model the data generation process, these methods prefer a sparse, modular style. As a result, they are more efficient and stable than traditional model-based methods and allow RL agents to adapt quickly to unseen environments or tasks. However, we may not have perfect knowledge of the causal variables a priori in reality. Sometimes, we must deal with high-dimensional and unstructured data like visual information. In this case, RL agents need to be able to extract causal representations from raw data (Schölkopf et al., 2021). Depending on the task, causal representations can take various forms, ranging from abstract concepts like emotions and preferences to more concrete entities such as physical objects.

The complete process of learning a causal model from raw data is known as causal learning (Peters et al., 2017). It is different from causal reasoning (Imbens & Rubin, 2015; Glymour et al., 2016), which only focuses on estimating specific causal effects given the causal model. Causal learning involves extracting causal features, discovering causality, and learning causal mechanisms. Table 5 briefly summarizes their characteristics. All three of these components are significant and deserve further investigation. A great deal of research has been done on causal discovery (Spirtes et al., 2000; Pearl, 2009b; Peters et al., 2017; Vowels et al., 2022), a process of recovering the causal structure of a set of variables from data, particularly concerning conditional independence tests (Spirtes et al., 2000; Sun et al., 2007; Hoyer et al., 2008; Zhang et al., 2011).

Under certain assumptions, such as faithfulness, algorithms can identify the Markov equivalence class of the underlying causal graph from observational data. Integrating RL with causal discovery empowers an agent to actively gather interventional data from the environment. This opens up an intriguing research direction that focuses on exploring methods for leveraging interventional data, or a combination of observational and interventional data, to facilitate efficient causal discovery (Addanki et al., 2020; Jaber et al., 2020; Brouillard et al., 2020; Zhu et al., 2022a).

As for causal feature extraction, also known as causal representation learning (Schölkopf et al., 2021; Wang & Jordan, 2022; Shen et al., 2022), one possible solution is to learn latent factors from high-dimensional observations using autoencoders (Yang et al., 2021a; Eghbal-zadeh et al., 2021; Tran et al., 2022). These methods can approximatively recover causal representations and structures by virtue of carefully designed constraint terms. This idea inherently embeds an SCM into the learner, implicitly binding causal discovery and causal mechanisms learning in one solution. Additionally, in scenarios involving multiple environments or tasks, causal representations can also be derived through techniques like mining invariance (Zhang et al., 2020a; Bica et al., 2021b; Saengkyongam et al., 2022) or clustering trajectories from diverse domains (Sontakke et al., 2021). However, determining the optimal number and granularity of causal variables remains challenging, as the optimal causal representations often depend on the specific task. Overall, causal learning in RL is an underexplored problem and has the potential to advance the RL community. Conversely, RL techniques may also contribute to the field of causal learning (Zhu et al., 2022a).

7.2 Causality-aware Multitask and Meta Reinforcement Learning

Multitask reinforcement learning (Parisotto et al., 2015; Teh et al., 2017; D'Eramo et al., 2020; Vithayathil Varghese & Mahmoud, 2020) focuses on simultaneously learning multiple tasks by sharing knowledge and leveraging synergies across tasks. This scenario commonly arises in robot manipulation, where a robot needs to acquire various skills, such as reaching, grasping, and pushing. Meta-learning (Duan et al., 2016; Finn et al., 2017; Gupta et al., 2018; Xu et al., 2018), on the other hand, involves training on a task distribution to gain the ability to adapt quickly to a new task. Impressive results have been achieved without explicitly considering causality, leading to the question: Is training a high-capacity model on a diverse range of tasks sufficient to generalize to new tasks? Recent research empirically validates this hypothesis, as large pre-trained models on diverse datasets have demonstrated remarkable performance in tasks requiring few-shot learning or even zero-shot generalization ability (Brown et al., 2020; Wei et al., 2021).

As shown in Figure 7, different tasks are essentially different interventions in the data generation process (Schölkopf et al., 2021), so it is not surprising that models trained on multiple tasks can achieve excellent generalizability – they implicitly learn the causal relationships governing the data generation process of these tasks. Dasgupta et al. (2018) provide compelling evidence for this proposition. Their study demonstrates that the capability of causal inference may emerge from large-scale meta-RL. Nonetheless, testing all possible interventions and their combinations in real-world scenarios is impractical. This is where causal modeling comes into play. As discussed in the previous section, causal models enable the explicit incorporation of prior knowledge, helping agents to align their understanding of the world with human cognition. Moreover, causal relationships facilitate problem abstraction (Wang et al., 2022), thereby eliminating the need of testing irrelevant interventions. Additionally, agents that organize their knowledge using causal structures benefit from the stability of causal relationships. While non-causal agents would require finetuning the whole model for even a slightly changed task, a causality-aware agent would only need to adjust a few modules (Huang et al., 2022a), exhibiting a stronger knowledge transfer ability. These properties may also contribute to lifelong (or continual) learning (Xie & Finn, 2022; Khetarpal et al., 2022), allowing for fast adaptation to new tasks that arise in sequence.

7.3 Human-in-the-loop Learning and Reinforcement Learning from Human Feedback

Human-in-the-loop learning (HiLL) (Mosqueira-Rey et al., 2022) is a form of machine learning in which humans actively participate in the development cycle of machine learning models or algorithms. This can involve providing labels, preferences, or other types of feedback. When the data or task being learned is complex or requires high levels of cognition, HiLL often produces better results because humans can

provide valuable insights or knowledge to the model that it may be difficult for the model to learn on its own (Mosqueira-Rey et al., 2022; Zhang & Bareinboim, 2022a).

In the context of RL, HiLL typically involves incorporating human expertise into the MDP to replace the reward function that provides feedback signals. This approach allows us to train RL agents with the help of human knowledge and values, alleviating the challenges associated with defining a sophisticated reward function (Zhang & Bareinboim, 2022a). This idea is closely related to RLHF (Reinforcement Learning from Human Feedback) (Christiano et al., 2017), a concept that has gained increasing attention recently in the training of large language models (Ziegler et al., 2020; Glaese et al., 2022; Ouyang et al., 2022), where human instructors provide rewards (or penalties) to a model to encourage (or discourage) certain behaviors. From a causal perspective, humans can provide machine learning models with a strong understanding of causality based on their knowledge of the world, which can help filter out behaviors that may lead to negative outcomes. However, it is important to note that humans and machines may have different observations or perceptions of the world, and non-causal-aware RL agents may be influenced by confounding variables (Gasse et al., 2021). In addition, we often need to consider the issue of limited budgets, as our goal is to provide meaningful feedback to RL agents at the lowest possible cost. Finally, in addition to scalar feedback, we may also provide more informative feedback to agents in the form of counterfactuals (Karalus & Lindner, 2022).

7.4 Theoretical Advances in Causal Reinforcement Learning

Theoretical research in causal RL has mainly concentrated on the MAB problem. Lattimore et al. (2016) first introduced the causal bandit problem, where interventions are treated as arms, and their impact on the reward and other observable covariates is associated with a known causal graph. Unlike contextual bandits, in this setting, the observations occur after each intervention is made. Using the structural knowledge from the causal model, the agent can efficiently identify good interventions, achieving strictly better regret than algorithms that lack causal information. Sen et al. (2017) further considered incorporating prior knowledge about the strength of interventions. Since different arms (interventions) share the same causal graph, samples from one arm can inform us about the expected value of other arms. The authors demonstrated significant theoretical and practical improvements by leveraging such information leakage.

However, these works only focused on intervening in a single node on the causal graph, where causal effects propagate only to the first-order neighbors of the intervened node. Yabe et al. (2018) generalize this setting by studying an arbitrary set of interventions, allowing for causal effects to propagate throughout the causal graph. Lee & Bareinboim (2018) also investigated the scenario of pulling arms in a combinatorial manner. They showed that considering all interventable variables as one arm may lead to a suboptimal policy, and the structural information can be used to identify the minimal intervention set that is worth intervening in. Lu et al. (2021) improved the naïve bounds derived in Lattimore et al. (2016), devising algorithms for causal bandit problems with sublinear cumulative regret bounds. Nair et al. (2021) study the causal bandit problem with budget constraints. In this setting, there is a trade-off between the more economical observational arm (i.e., no interventions on the causal graph) and the high-cost interventional arms. While the observational arm is less rewarding, it offers valuable information for studying other arms at a significantly lower cost. More recently, Kroon et al. (2022) introduced the concept of "separating set" from causal discovery to causal bandit problems, which renders a target variable independent of a context variable when conditioned upon. By utilizing this separating set, the authors developed a bandit algorithm that does not rely on the assumption of prior causal knowledge. On the other hand, Bilodeau et al. (2022) studied the adaptivity issue concerning the d-separator, i.e., whether an algorithm can perform nearly as well as an algorithm with oracle knowledge of the presence or absence of a d-separator.

In comparison to the fruitful results achieved in causal bandit problems, there have been relatively few attempts in the context of MDP problems. As discussed in Section 5.3, some studies focused on DTRs (Zhang & Bareinboim, 2019; 2020), which can be modeled as an MDP with a global confounder variable. Additionally, there have been some investigations into confounded MDP (Zhang & Bareinboim, 2016; Wang et al., 2021b), which extend the concept of DTR by admitting the presence of unobserved confounders at each time step. In the theory of causal RL, aside from understanding how causal information, especially causal graphs, enhance the regret bounds, the identifiability of causal effects (Zhang et al., 2020b; Lu et al., 2022) and structure (Huang et al., 2022a) are also of great interest. While existing research provides valuable

insights into the theoretical foundations of causal RL, further theoretical advancements are necessary. In addition to helping us comprehend the reasons behind the success of existing causal RL methods, we also hope that future theoretical advances will pave the way for designing novel and effective approaches that are both interpretable and robust for real-world applications.

7.5 Benchmarking Causal Reinforcement Learning

In RL, we are typically interested in the efficiency and convergence of the algorithm. Atari 2600 Games and Mujoco locomotion tasks (Brockman et al., 2016) are commonly used as benchmarks for discrete and continuous control problems. There are also experimental environments that evaluate the generalizability and robustness of RL, such as Procgen (Cobbe et al., 2020). Some benchmarks focus on multitask learning, meta-learning, and curriculum learning for reinforcement learning, such as RLBench (James et al., 2019), Meta-World (Yu et al., 2021), Alchemy (Wang et al., 2021a), and Causal-World Ahmed et al. (2022). Among them, Causal-World offers a wide range of robotic manipulation tasks that share a common attribute set and structure. In these tasks, the robot is required to construct a goal shape using the provided building blocks. One notable feature of this benchmark is its provision of interfaces that allow manual modification of object attributes such as size, mass, and color. This enables researchers to intervene in these attributes and generate a series of tasks with consistent causal structures.

Since causal RL is not limited to a particular type of problem, evaluation metrics may vary depending on the specific mission. While existing experimental environments have provided good benchmarks for evaluating algorithms with various metrics, the underlying data generation processes in these environments often remain opaque, concealed within game simulators or physics engines. This lack of transparency makes it difficult for researchers to fully understand the causal mechanisms behind the problems they are attempting to solve, hindering the development of the field. Recently, Ke et al. (2021) proposed a new set of environments focusing on causal discovery in visual-based RL, allowing researchers to specify the causal graph and customize its complexity. Nevertheless, as we demonstrated in sections 3 to 6, a large portion of the existing research still relies on toy environments to evaluate the effectiveness of algorithms. Furthermore, in addition to the previously mentioned properties, a good benchmark should consider the multiple factors comprehensively, as discussed in section 6.4. Thus, developing a comprehensive benchmark for assessing the performance of causal RL methods remains an ongoing challenge.

7.6 Real-world Causal Reinforcement Learning

Finally, it is worth noting that the practical implementation of causal RL in real-world applications remains limited. To make it more widely applicable, we must carefully examine the challenges posed by reality. Dulac-Arnold et al. (2020; 2021) identified nine critical challenges that are holding back the use of RL in the real world: limited samples; unknown and large delays; high-dimensional input; safety constraints; partial observability; multi-objective or unspecified reward functions; low latencies; offline learning; and the need for explainability.

We have discussed some of these issues throughout this paper, many of which are related to ignorance of causality. For instance, the challenge of learning from limited samples corresponds to the sample efficiency issue discussed in section 3.3. Learning from high-dimensional inputs and multiple reward functions relates to the generalization problem outlined in section 4.3. Offline learning raises concerns about spurious correlations (section 5.3), and security and explainability are covered in section 6.4.

Although causal models offer promising solutions to these real-world challenges, current experimental environments often fall short of meeting the research needs. As discussed in section 7.5, popular benchmarks are often treated as black boxes, and researchers have limited access to and understanding of the causal mechanisms by which these black boxes generate data. This lack of transparency significantly hinders the development of this research field. In order to facilitate the widespread adoption and application of causal RL, it is crucial to address these limitations and cultivate a culture of causal thinking.

8 Conclusion

In summary, causal RL is a promising method of solving complex decision-making problems under uncertainty. It is an understudied but significant research direction. By explicitly integrating assumptions or knowledge about the causal relationship underlying the data generation process, causal RL algorithms can learn optimal policies more efficiently and make more informed decisions. In this survey, we aimed to clarify the terminologies and concepts related to causal RL and to establish connections between existing work. We proposed a problem-oriented taxonomy and systematically discussed and analyzed the latest advances in causal RL, focusing on how they address the four critical challenges facing RL.

While there is still much work to be done in this field, the results to date are encouraging. They suggest that causal RL has the potential to significantly improve the performance of RL systems in a wide range of problems. Here, we summarize the key conclusions of this survey.

- Causal RL is an emerging branch of RL that emphasizes understanding and utilizing causality to make better decisions (section 2.3).
- Causal modeling can enhance sample efficiency (section 3.3) and generalization ability (section 4.3); however, there are also fundamental challenges and limitations to consider (section 3.4 and section 4.4). With limited causal information, RL agents may need to learn about causal representation and environmental dynamics from raw data (section 7.1).
- Causal effects and relationships are identifiable under certain conditions (section 2.3 and section 7.4), i.e., agents can learn them from observational data. Furthermore, multitask learning and meta-learning may help facilitate causal learning (section 7.2) In turn, harnessing causality can enhance the ability to transfer knowledge and effectively address a wide range of tasks (section 4.3).
- Correlation does not imply causation. Spurious correlations can lead to a distorted understanding of the environment and task, resulting in suboptimal policies (section 5.3). In addition to employing causal reasoning techniques, leveraging human understanding of causality can further enhance reinforcement learning (section 7.3).
- In real-world applications, performance is not the only concern. Factors such as explainability, fairness, and security, must also be considered (section 6.4). Current benchmarks call for increased transparency and a comprehensive, multi-faceted evaluation protocol for reinforcement learning (section 7.5), which has significant implications for advancing real-world applications of causal reinforcement learning (section 7.6).

We hope this survey will help establish connections between existing work in causal reinforcement learning, inspire further exploration and development, and provide a common ground and comprehensive resource for those looking to learn more about this exciting field.

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A A Brief Introduction to Environments and Tasks

In this section, we briefly introduce the environments and tasks mentioned spanning sections 3 to 6.

A.1 Autonomous Driving

BARK-ML: `https://github.com/bark-simulator/bark-ml`. BARK is an open-source behavior benchmarking environment. It covers a full variety of real-world, interactive human behaviors for traffic participants, including Highway, Merging, and Intersection (Unprotected Left Turn).

Crash (highway-env): `https://github.com/eleurent/highway-env`. The highway-env project gathers a collection of environments for autonomous driving and tactical decision-making tasks, including Highway, Merge, Roundabout, Parking, Intersection, and Racetrack. Crash is a modified version by (Ding et al., 2022) that is not publicly available.

A.2 Classical Control

Cart-pole (dm_control): `https://github.com/svikramank/dm_control`. Cart-pole is an environment belonging to the DeepMind Control Suite. It involves swinging up and balancing an unactuated pole by applying forces to a cart at its base.

Acrobot (OpenAI Gym): `https://www.gymlibrary.dev/environments/classic_control/acrobot/`. The Acrobot environment consists of two links connected linearly to form a chain, with one end of the chain fixed. The goal is to apply torques on the actuated joint to swing the free end of the linear chain above a given height while starting from the initial state of hanging downwards.

Mountain Car (OpenAI Gym): `https://www.gymlibrary.dev/environments/classic_control/mountain_car/`. The Mountain Car MDP is a deterministic MDP that consists of a car placed stochastically at the bottom of a sinusoidal valley, with the only possible actions being the accelerations that can be applied to the car in either direction. The goal of the MDP is to strategically accelerate the car to reach the goal state on top of the right hill.

Cart Pole (OpenAI Gym): `https://www.gymlibrary.dev/environments/classic_control/cart_pole/`. A pole is attached by an un-actuated joint to a cart, which moves along a frictionless track. The pendulum is placed upright on the cart and the goal is to balance the pole by applying forces in the left and right direction on the cart.

Pendulum (OpenAI Gym): `https://www.gymlibrary.dev/environments/classic_control/pendulum/`. The system consists of a pendulum attached at one end to a fixed point, and the other end being free. The pendulum starts in a random position and the goal is to apply torque on the free end to swing it into an upright position, with its center of gravity right above the fixed point.

Inverted Pendulum (OpenAI Gym): `https://www.gymlibrary.dev/environments/mujoco/inverted_pendulum/`. This environment involves a cart that can moved linearly, with a pole fixed on it at one end and having another end free. The cart can be pushed left or right, and the goal is to balance the pole on the top of the cart by applying forces on the cart.

A.3 Game

MiniPacman: `https://github.com/higgsfield/Imagination-Augmented-Agents`. MiniPacman is played in a 15×19 grid-world. Characters, the ghosts and Pacman, move through a maze.

Lunar Lander (OpenAI Gym): `https://www.gymlibrary.dev/environments/box2d/lunar_lander/`. This environment is a classic rocket trajectory optimization problem. The landing pad is always at coordinates $(0, 0)$. The coordinates are the first two numbers in the state vector. Landing outside of the landing pad is possible. Fuel is infinite, so an agent can learn to fly and then land on its first attempt.

Bipedal Walker (OpenAI Gym): https://www.gymlibrary.dev/environments/box2d/bipedal_walker/. This is a simple 4-joint walker robot environment.

Car Racing (OpenAI Gym): https://www.gymlibrary.dev/environments/box2d/car_racing/. Car Racing is a top-down racing environment. The generated track is random in every episode. Some indicators are shown at the bottom of the window along with the state RGB buffer. From left to right: true speed, four ABS sensors, steering wheel position, and gyroscope.

Beam Rider (OpenAI Gym): https://www.gymlibrary.dev/environments/atari/beam_rider/. The agent controls a space-ship that travels forward at a constant speed. The agent can only steer it sideways between discrete positions. The goal is to destroy enemy ships, avoid their attacks and dodge space debris.

Pong (OpenAI Gym): https://www.gymlibrary.dev/environments/atari/pong/. The agent controls the right paddle, competing against the left paddle controlled by the computer.

Pong (Roboschool): https://github.com/openai/roboschool. Roboschool is an open-source software for robot simulation, which is now deprecated. Pong allows for multiplayer training.

Sokoban: https://github.com/mpSchrader/gym-sokoban. This game is a transportation puzzle, where the player has to push all boxes in the room on the storage locations/ targets. The possibility of making irreversible mistakes makes these puzzles so challenging especially for RL algorithms.

SC2LE: https://github.com/deepmind/pysc2. SC2LE is a RL environment based on the StarCraft II game. It is a multi-agent problem with multiple players interacting. This domain poses a grand challenge raising from the imperfect information, large action and state space, and delayed credit assignment.

VizDoom: https://github.com/Farama-Foundation/ViZDoom. ViZDoom is based on Doom, a 1993 game. It allows developing AI bots that play Doom using only visual information.

A.4 Healthcare

MIMIC-III: https://physionet.org/content/mimiciii/1.4/. MIMIC-III is a large, freely-available database comprising deidentified health-related data associated with over forty thousand patients who stayed in critical care units of the Beth Israel Deaconess Medical Center between 2001 and 2012.

Therapy: https://github.com/Networks-Learning/counterfactual-explanations-mdp/blob/main/data/therapy/README.md. This dataset contains real data from cognitive behavioral therapy. The data were collected during a clinical trial with the patients' written consent A post-processed version of the data is available upon request from Kristina.Fuhr@med.uni-tuebingen.de.

A.5 Robotics

A.5.1 Locomotion

Cheetah (dm_control): https://github.com/svikramank/dm_control. Cheetah is an environment belonging to the DeepMind Control Suite. It is a running planar bipedal robot.

OpenAI Gym: https://www.gymlibrary.dev/environments/mujoco/. These environments are built upon the MuJoCo (Multi-Joint dynamics with Contact) engine. The goal is to make the 3D robots move in the forward direction by applying torques on the hinges connecting the links of each leg and the torso.

PyBullet Gym: https://github.com/benelot/pybullet-gym. This is an open-source implementation of OpenAI Gym MuJoCo environments using the Bullet Physics (https://github.com/bulletphysics/bullet3).

D4RL: https://github.com/Farama-Foundation/D4RL. D4RL is an open-source benchmark for offline RL. It includes several OpenAI Gym benchmark tasks, such as the Hopper, HalfCheetah, and Walker environments.

A.5.2 Manipulation

CausalWorld: `https://github.com/rr-learning/CausalWorld`. CausalWorld is an open-source simulation framework and benchmark for causal structure and transfer learning in a robotic manipulation environment where tasks range from rather simple to extremely hard. Tasks consist of constructing 3D shapes from a given set of blocks - inspired by how children learn to build complex structures.

Isaac Gym: `https://github.com/NVIDIA-Omniverse/IsaacGymEnvs`. Isaac Gym offers a high performance learning platform to train policies for wide variety of robotics tasks directly on GPU.

OpenAI: The origin version is developed by OpenAI, known as "Ingredients for robotics research" (`https://openai.com/research/ingredients-for-robotics-research`), and now is maintained by the Farama Foundation (`https://github.com/Farama-Foundation/Gymnasium-Robotics`). It contains eight simulated robotics environments.

robosuite: `https://github.com/ARISE-Initiative/robosuite`. robosuite is a simulation framework powered by the MuJoCo physics engine for robot learning. It contains seven robot models, eight gripper models, six controller modes, and nine standardized tasks. It also offers a modular design for building new environments with procedural generation.

A.6 Navigation

Unlock (Minigrid): `https://github.com/Farama-Foundation/MiniGrid`. The Minigrid library contains a collection of discrete grid-world environments to conduct research on Reinforcement Learning. Unlock is task designed by (Ding et al., 2022), which is not publicly available.

Contextual-Gridworld: `https://github.com/eghbalz/contextual-gridworld`. Agents are trained on a group of training contexts and are subsequently tested on two distinct sets of testing contexts within this environment. The objective is to assess the extent to which agents have grasped the causal variables from the training phase and can accurately deduce and extend to new (test) contexts.

3D Maze (Unity): `https://github.com/Harsha-Musunuri/Shaping-Agent-Imagination`. This environment is built on the Unity3d game development engine. It contains an agent that can move around. The environment automatically changes to a new view after every episode.

Spriteworld: `https://github.com/deepmind/spriteworld`. Spriteworld is an environment that consists of a 2D arena with simple shapes that can be moved freely. The motivation was to provide as much flexibility for procedurally generating multi-object scenes while retaining as simple an interface as possible.

Taxi: `https://www.gymlibrary.dev/environments/toy_text/taxi/`. There are four designated locations in the grid world. When the episode starts, the taxi starts off at a random square and the passenger is at a random location. The taxi drives to the passenger's location, picks up the passenger, drives to the passenger's destination (another one of the four specified locations), and then drops off the passenger. Once the passenger is dropped off, the episode ends.

A.7 Others

Chemical: `https://github.com/dido1998/CausalMBRL#chemistry-environment`. By allowing arbitrary causal graphs, this environment facilitates studying complex causal structures of the world. This is illustrated through simple chemical reactions, where changes in one element's state can cause changes in the state of another variable.

Light: `https://github.com/StanfordVL/causal_induction`. It consists of the light switch environment for studying visual causal induction, where N switches control N lights, under various causal structures. Includes common cause, common effect, and causal chain relationships.

MNIST: `http://yann.lecun.com/exdb/mnist/`. The MNIST dataset contains 70,000 images of handwritten digits.