Designing Accountable Systems

Severin Kacianka
severin.kacianka@tum.de
Technical University of Munich
Garching, Germany

Alexander Pretschner
alexander.pretschner@tum.de
Technical University of Munich
Garching, Germany

ABSTRACT
Accountability is often called for property of technical systems. It is a requirement for algorithmic decision systems, autonomous cyber-physical systems, and for software systems in general. As a concept, accountability goes back to the early history of Liberalism and is suggested as a tool to limit the use of power. This long history has also given us many often slightly differing, definitions of accountability. The problem that software developers now face is to understand what accountability means for their systems and how to reflect it in a system’s design. To enable the rigorous study of accountability in a system, we need models that are suitable for capturing such a varied concept. In this paper, we present a method to express and compare different definitions of accountability using Structural Causal Models. We show how these models can be used to evaluate a system’s design and present a small use case based on an autonomous car.

CCS CONCEPTS
- Software and its engineering → Designing software; • Computer systems organization → Architectures.

KEYWORDS
Accountability, Structural Causal Models, Socio-Technical Systems

1 INTRODUCTION
Accountability differs from many other system properties because it is notoriously hard to define and its benefits are elusive to name. A property like performance can often be measured with hard numbers and has the very clear benefit that more performance means more or faster operations. Security and privacy are hard to measure, but have the well understood meaning of keeping the bad guys out and keep data from unauthorized eyes. In a recent systematic literature review, Wieringa has written that many organizations are “advocating for more algorithmic accountability, yet a thorough and systematic definition of the term lacks, and it has not been systematically embedded within the existing body of work on accountability” [55][p. 2]. This finding now begs the question of what exactly these organizations are advocating if there is not even a definition of the concept. This feeling of ambiguity is reinforced when looking at the concrete examples given in the appendix of [55]. The first is an automatic system that checks if people repay their debt, the second one is a system that automatically anonymizes permits, the third and fourth systems check for fraudulent social benefit claims. All examples do something that some people cannot know or understand and might find objectionable. Accountability is now supposed to fix this. Similarly, [27] surveyed implementations of accountability in computer science and found that systems will often implement something and then just call it accountability, without trying to ground that in any definition or understanding of the term. In complex systems, accountability is often deflected and hard to pinpoint, which leads to blame being assigned to humans [12]. As an example, a “pilot error” often is not just an error of the pilots, but a complex interplay of the humans and the technical systems.

Currently, the literature does not offer any method to model the accountability of a system, especially across system boundaries. It offers no way to quantify or qualify the accountability of a system, nor even a precise language to reason about it or compare implementations. The current state of the art does not go beyond giving differing definitions of what accountability might mean and proposing implementations of accountability in specific contexts. In this paper, we show how to leverage one commonality among all definitions of accountability, namely causality, to express accountability definitions and identify them in the causal model of a system. This allows us to describe patterns in the design of a system that are necessary to fulfill a specific notion of accountability. Moreover, this knowledge helps us to reason about what data needs to be logged and, conversely, what data can be omitted, without compromising the system’s adherence to the chosen definition of accountability. We propose to use Structural Causal Models (SCMs) as the mathematical foundation. They are flexible enough to model even the most complex systems and offer a toolbox of mathematical methods to analyze them.

2 BACKGROUND
Accountability is a concept rooted in Liberalism and was first introduced by political philosophers like John Locke and Adam Smith, who used it in the 17th and 18th century to describe the fact that official representatives will have to justify their action to someone, ultimately their sovereign.1 This core idea was then picked up and refined by other political and, later, social scientists. In a survey, Lindberg gives the central idea as “when decision-making power is transferred from a principal (e.g. the citizens) to an agent (e.g. government), there must be a mechanism in place for holding the agent accountable for their decisions and tools for sanction” [33, p. 203]. Bovens writes that “[t]he most concise description of accountability would be: ‘the obligation to explain and justify conduct’, “ while also warning that “[a]s a concept, however, ‘accountability’ is rather elusive. It has become a hurrah-word, like ‘learning’, ‘responsibility’, or ‘solidarity’, to which no one can object” [6, p. 7].

This core idea is, with some variations, deeply embedded into the fabric of liberal democracies. From the idea that voters will hold politicians accountable for their performance, to companies that are accountable to their shareholders, to the legal system, where wrongdoing is discouraged by the possibility of being held accountable for one’s actions. As such, accountability rose to prominence

1See [11], [6], or [33] for a more detailed history.
in computer science together with the tight integration of computers into our societies and their increasing effect on daily life, for example by managing medical records or controlling vehicles.

This long history of the term has led to many different definitions and meanings of accountability. Lindberg, for example identified twelve different subtypes of accountability and has also cautioned us that “[i]t cannot be assumed that findings in the area of one subtype of accountability are relevant for another” [33, p. 204]. For example, if we find an implementation of accountability that works well in a societal setting, it is not a given that it will also work in a legal setting. [27] have found a tendency in computer science to not worry much about the underlying definitions of accountability. Even recent works, for example [55], usually pick some definitions and declare it as typical. This, in our opinion, wrong. Computer science should not try to pick winners, and push one theory over another. When talking about accountability, it is important to be precise about the exact meaning. As Lindberg puts it, “everything is not accountability: it is but one of many possible ways to constrain the (mis-)use of power” [33, p. 202]. Other means of limiting power are the “devolution of power, violence, economic pressure, public shaming, and anarchy” [33, p. 205]. However, since accountability is a very old concept, it has multiple meanings that often have subtle differences. This is why, when talking about accountability or making systems accountable, we should always first try to define what we actually mean. For example, in some definitions sanctioning an actor for their action is considered part of accountability, while in others a principal can only sanction an agent if they do not provide an account. Such differences have a huge impact on the underlying system design and should thus be made explicit, and not left ambiguous by just using the term accountability. In our view, all definitions of accountability have some merit in a specific context, and computer science should strive to offer ways to implement any definition. It is the purview of fields like sociology or the political sciences to debate the intricacies of the definitions themselves. They have accumulated experience in debating these finer points and computer science should rely on their insights and offer ways to realize the theories developed there. Here we will now present some approaches to accountability as an example of their wide variety and show how to formalize them later in Section 4.

2.1 Lindberg
Staffen Lindberg [33] surveyed the literature in the social sciences and distilled the following definition of accountability:

(1) An agent or institution who is to give an account (A for agent);
(2) An area, responsibilities, or domain subject to accountability (D for domain);
(3) An agent or institution to whom A is to give account (P for principal);
(4) The right of P to require A to inform and explain/justify decisions with regard to D; and
(5) The right of P to sanction A if A fails to inform and/or explain/justify decisions with regard to D [33, p. 209].

2Causes and accountability are also an important topic in law. Since causality has only been formalized very recently, relevant literature can be found under the term statistics, e.g., [9].

The first two points mean that there is an agent that has some power in a certain domain and knows that they need to give an account for their actions. The third and the fourth condition imply that there is a third party that has the right to require A to explain and justify their decisions. The last condition requires that P can sanction A. Lindberg adds an important restriction, often lost in other definitions: he distinguishes between the right of P to sanction A for not providing the information and the right to sanction A for the content of effect of an action. Another important implication is that there needs to be “standard or measurable expectations” [33, p. 211] to have accountability. Without a clear idea of what is acceptable and unacceptable behavior, it cannot be evaluated and sanctioned. As such, we always need some form of evidence.

2.2 Bovens
Mark Boven’s definition [6] became popular recently in computer science because it was used as the definition in the systematic literature review conducted by [55]. Bovens finds that accountability is hardly defined and he tries to counteract this vagueness and make it “more amendable to empirical analysis” [6, p. 7] He focuses on public accountability and gives a short definition, “the obligation to explain and justify conduct” [6, p. 9], before giving the more detailed one, as follows:

(1) There is a relationship between an actor and a forum
(2) in which the actor is obliged (4) to conduct,
(5) the forum can pose questions,
(6) pass judgement,
(7) and the actor may face consequences [6, p. 12].

Following his definition, actors can be individuals or organizations, and a forum can also be a specific person, an organization, or even the general public. The relationship between actor and forum will often, but not always, be a principal-agent relation in which the forum delegates power to the agent, who is then held to account. The obligation of the actor might be formal or informal. The act of giving an account consists of three stages. First, “the actor is obliged to inform the forum about his conduct, by providing various sorts of data about the performance of tasks, about outcomes, or about procedures” [6, p. 10]. Second, “there needs to be a possibility for the forum to interrogate the actor and to question the adequacy of the information or the legitimacy of the conduct” [6, p. 10]. Finally, “the forum may pass judgement on the conduct of the actor” [6, p. 10]. Additionally, he also requires the possibility of consequences for the actor if they do not comply with the requests of the forum.

One fundamental difference between the definitions of Lindberg and Bovens is that Bovens requires the actor to regularly update the forum, whereas Lindberg suggest that the principal can demand an account from the agent at any time.

2.3 Hall
Hall et al. [18] look at accountability from the perspective of psychology. As such they focus on what it means for an individual to feel accountable. Their exact field of study is felt accountability. In their overview, they find that at the core of accountability is the expectation that one’s actions will be evaluated. They emphasize
that it is not necessary that this evaluation does occur, but that the possibility that an evaluation occurs must be present. Furthermore, the actor needs to believe that an account-giving (i.e., an explanation) might be required. This account is then given to a salient audience that might reward or sanction the agent’s behavior.

In their review of models of accountability, they find that accounts are often used by agents to protect their self-image and develop their social identity. This underscores the important role accountability has in a society and supports the assumption that complex societies and social order necessarily need accountability to augment the reduced level of personal trust between individuals. In their survey, they describe four essential features of accountability. First, the accountability source describes to whom one feels accountable. Second, the accountability focus captures how things get done and how they relate to the results. Third, accountability salience expresses how important the task is for which an agent might be held accountable; the idea is that agents will be more careful if their action is more significant. Fourth, and finally, accountability intensity captures for how many things an agent is accountable; here it is thought that being responsible for multiple things increases stress.

2.4 RACI

The organizational sciences have developed several practical frameworks to understand accountability in an organization. Here, we present the Responsible-Accountable-Consult-Inform (RACI) framework [46, 49]. Such frameworks, sometimes called tools, are used in practical settings to explicate accountability relationships in teams and organizations. While these tools do not build on a sophisticated body of scientific literature, they are nonetheless important in practical settings because they allow people to express their understanding and perception of accountability in a given setting. We assume that such practical approaches will often be the basis for accountability expectations of systems, and thus need to be considered in any attempt to formalize accountability for them.

RACI, specifically, tries to explicate the roles of people in an organization and helps to reconcile the conception of a role, i.e., what a person thinks they are doing, with the expectation of a role, i.e., what others think the person is doing, and with the behavior of a role, i.e., what the person actually does. Following [49], having a RACI matrix helps to align these three aspects. However, they also point out that this is an ongoing process that needs to constantly realign those three aspects, whenever they drift apart. They list a few typical signs, such as “Questions over who does what” or “Concern over who makes decisions” [49, p. 4], that arise regularly during the design of systems. Among other things, one major difference of this definition from the others is the aspect of consultation, once again underlining our finding in the introduction that definitions are manifold and different. [49] define the following four aspects in the RACI framework:

- **Responsible:** The individual who completes a task. Responsibility can be shared.
- **Accountable:** The person who answers for an action or decision. There can be only one such person.
- **Consult:** Persons who are consulted prior to a decision. Communication must be bidirectional.
- **Inform:** Persons who are informed after a decision or action is taken. This is unidirectional communication.

2.5 Computer Science

A landmark publication on accountability in computer science was published by Weitzner et al. [54]. They provided a definition for Information Accountability, as an improvement on classic preventive data control measures. Classically, systems ensure a user’s privacy by ensuring that data cannot be accessed by unauthorized personnel and thus prevent data leaks. Weitzner et al. changed this premise and, drawing parallels to law enforcement, suggested to build systems in such a way that it is easy to trace data leaks and then leverage the existing legal system to punish misbehavior. This idea was later refined and formalized by Feigenbaum et al. [13, 14], albeit with a focus on security and not privacy. Coinciding with the discussion on e-voting systems, Kusters et al. [31] formalized accountability in relation to verifiability. Here, the main question is how to design an e-voting system such that the results can be trusted and any attempts to falsify the vote count or the votes will be detected and the perpetrator held to account. The A4cloud project [15], coinciding with the spread of cloud services into society and questions about data protection, has done extensive work on accountability in cloud environments, with a focus on data protection and privacy. They offer a reference architecture, tools to complete certifications, and risk assessment. Looking at their website, they defer the exact definition of accountability to contracts or service level agreements.

Furthermore, Kacianka et al. [27] conducted a systematic mapping study to understand how accountability is understood and implemented in research tools. In this study, they identified a steady rise in publications on the subject and found that most research was either a solution proposal or an evaluation of an approach. Analyzing the prominent application domains, they found that cloud computing was clearly dominant, followed by distributed data sharing and web applications. The most prominent use cases were privacy focused, in line with [54], and the most popular techniques were cryptographic and network protocols, with some dedicated accountability protocols as well. Obviously, the focus on information accountability makes related definitions different from those discussed before.

2.6 Algorithmic Accountability

The term algorithmic accountability first gained prominence with the paper by Nicholas Diakopoulos [10] where he discussed how journalists might investigate algorithms that started to make decisions that affected human lives. In this vein, the literature on the subject usually focused on the understanding of machine learning algorithms. Examples include algorithms used in court decisions [3], policing [30], and similar settings where human lives are directly affected by opaque computer systems. Most of the literature is highly critical of these systems, using terms like Weapons of Math Destruction [41] or Algorithms of Oppression [39]. The general approach to
counter the power of algorithms is to make the decisions of algorithms transparent and explainable. Recently, Maranke Wieringa surveyed the literature on algorithmic accountability and found that “[w]hat is denoted with algorithmic accountability is this kind of accountability relationship where the topic of explanation and/or justification is an algorithmic system” [55, p. 2]. Her survey also finds that typically algorithmic accountability follows the definition of Mark Bovens [6] given above.

In earlier works, transparency was often seen as a solution, but Ananny and Crawford [1] have shown that transparency alone is not sufficient for accountability. Amongst other reasons, a main point is that we also need someone to understand the output of such a transparency mechanism. To alleviate this problem, Wachter et al. [53], and later Tim Miller [35] as well as Mittelstadt et al. [36], have proposed using contrastive explanations to make decisions understandable for humans. Miller gives the example of a machine learning classifier that categorized an insect as a spider or a beetle. An explanation it would give is that the result is categorizes as a spider because it has eight legs instead of six. In contrast to the weights in a neural net or the layout of a decision tree, such an explanation would be useful and understandable for a human.

3 CAUSALITY

The study of causality is of a specific interest to the study of accountability, our main subject matter, because causality is a prerequisite for accountability. In understanding how causal effects work, we can improve the design of our systems to make sure that effects of causes are clearly understood and then in turn ensure that the causes of effects are easy to identify. The first notion is prospective and the second one retrospective. Both are deeply intertwined, but often only studied separately. In this paper, we combine the study of both and build on the assumption that a good prospective causal model is also a good retrospective causal model. For prospective models, we can find structures and patterns that allow us to show that some variables are not relevant to certain outcomes and once a specific outcome comes to pass, we can use retrospective reasoning to identify the concrete cause, relative to the given context.

Historically, causality and causal relationships are tightly connected to statistics. However, as laid out by [42], whereas statistical relations are epistemic and describe what we know or believe about the world, causal relationships are ontological, meaning that they describe objective constraints on the world. This means that causal relationships are much more stable and should not change if the environment changes. Still, causality is tightly linked to statistics as many “causal statements are uncertain” [44] and are thus often only true with some probability. As such, many prospective causal models will answer questions with a certain probability. For accountability, we often need exact and retrospective answers. The question Did Alice cause the crash? should have a clear retrospective answer. For this we use Actual Causality [20]. It allows us to use a (prospective) causal model and reason about it in a specific context. For example, we might have a prospective model that shows that texting while driving causes accidents (with a certain probability). Then we might have the specific context of an accident in which we know that Alice was distracted because she was texting. We can then set the context for this accident and use actual causality reasoning to find the cause of the accident; in this case Alice caused the accident by being distracted. In the literature, [8] as well [7] already suggested using actual causality as a building block for accountability, and [29] show how causality can be useful to model accountability.

3.1 Type Causality

Investigations of causality usually start with the identification of a correlation between two variables. In Figure 1a, for example, we notice a correlation between texting while driving and the number of accidents. A correlation has no direction, and many correlations will turn out to be spurious, so caused by some unknown third variable, often called a confounder. The goal of scientific investigations is now to find which correlations are the result of genuine causal mechanisms in the real world. In the end, such an investigation will yield a causal model. In our example, Figure 1b expresses the understanding that texting while driving causes accidents. Maybe just with a certain probability and under certain assumptions, but we clearly state that one is the cause of the other. This is the modeler’s understanding of a mechanism in the world. The advantage of stating it as a causal model is that all assumptions must be made explicit and that it can be tested against actual data. It might also be refined over time; Figure 1c shows a causal model that assumes that texting does not directly cause accidents, but that it does so via a mediator, namely distraction. Such details are often very important, as they improve our understanding of the problem and allow us to develop ways to affect, and often prevent, specific outcomes by targeting the mediators directly.

Such causal relations can be formalized in so-called Structural Causal Models (SCMs) [44]. They are derived from structural equation models (SEMs) (e.g., [34]), but their relations have a direction. Following Pearl [44], an SCM consists of two sets of variables,
\( \mathcal{U} \) and \( \mathcal{V} \) and a set of functions, \( \mathcal{F} \), that assigns each variable in \( \mathcal{V} \) a value based on the value of the other variables in the model. Formally,

**Definition 3.1 (Structural Causal Model).** A structural causal model \( M \) is a tuple \( M = (\mathcal{U}, \mathcal{V}, \mathcal{F}) \), where

- \( \mathcal{U} \) is a set of exogenous variables,
- \( \mathcal{V} \) is a set of endogenous variables,
- \( \mathcal{F} \) associates with each variable \( X \in \mathcal{V} \) a function that determines the value of \( X \) given the values of all other variables.

Every SCM is associated with a graphical causal model called the graphical model or the graph. Nodes are the variables; edges represent a causal relationship between them. While the graph does not include the details of \( \mathcal{F} \), its structure alone is enough to identify patterns and causes. In an SCM, exogenous variables, denoted by \( \mathcal{U} \), are external to the model, meaning that we chose not to explain how they are caused. They are the root nodes of the causal graph and are not a descendant of any other variable. Endogenous variables, denoted by \( \mathcal{V} \), are descendants of at least one exogenous variable and model components of our system and the world for which we want to explain causes. \( \mathcal{F} \) describes the relationships between all those variables. If we knew the value of every exogenous variable, we could use \( \mathcal{F} \) to determine the value of every endogenous variable. In a graphical model every node represents an endogenous variable and arrows represent functions from \( \mathcal{F} \) between those variables.

### 3.2 Actual Causality

Type causal models make predictions on how events will unfold. This is useful because we want to build systems in a way that they will probably be accountable. To achieve this, we try to make sure that the causal effects within a system are clearly understood and that the structure ensures that as many components as possible are causally independent. However, what if an unwanted event has already happened? In this case we do not care about the probabilities of events; we know they happened, but we want to find out why exactly they did happen. For this we need the concept of actual causality [20]. It is backward-looking and stands in contrast to type causality which is forward-looking.5

To illustrate actual causality, Figure 2 depicts an accident between two cars. Imagine two drivers, Alice and Bob, breaking the law at an intersection. Alice is texting and thus distracted while Bob accidentally runs over a red light. This example is designed to show that the simple but-for test1 is not adequate to attribute causality. Here, intuitively both Alice and Bob are necessary for the accident to happen. However, had Alice not been texting, Bob would still have run the red light and caused the accident. So the accident would have happened, no matter what Alice did, suggesting her behavior is not a cause, which goes against our understanding of causality. The goal of the Halpern-Pearl definition (see Appendix A for its formalization) of causality is to find a precise mathematical definition to enable algorithmic reasoning over such examples so that the result conforms with our human understanding of causality.

![Figure 2: Two cars causing an accident.](image)

### 3.3 Causality and Accountability

It is now important to note that SCMs can describe purely technical systems. They do not require a principal or any human at all. For a system to be accountable, however, we require a natural or legal person that is not just a cause for an effect, but is accountable for that effect. In other words, causality is necessary for accountability, but by itself it is not sufficient for accountability. The additional requirements are given by accountability definitions such as the ones introduced in Section 2. In our work with SCMs, we found the following differentiation of terms useful:

- **A cause** is the actual cause in an SCM as determined by the Halpern-Pearl definition of actual causality. Similarly, to **cause** means that an endogenous variable in an SCM is the actual cause of another endogenous variable. Causes are purely technical, without any notion of intent or other social attributions.12

- **Responsibility** is the commitment of an entity to act a certain way and the ability to affect or change an outcome.13 This entity is **responsible** for a certain outcome. As such we have explicit notions of normality that are used to determine responsibility. This entity is then responsible for an outcome when, had it acted normally, the outcome would not have happened.

- **Blame** is a social process in which an agent has a specific notion of normality and will find fault with some entity for the fact that this normality is violated. This agent **blames** that entity for some outcome, even if that entity is not aware of this notion of normality and thus might not be responsible for the outcome.

- A **transparent** system will have an SCM available and log enough data to set the context of the causal model after some event. **Transparency** indicates that an SCM is available, although it makes no statement about the quality of the SCM.

- **Accountability**, finally, means that we have a natural or legal person, called an agent, that is **responsible** for some outcome. This **responsibility** is made **transparent** with an SCM, and thus allows a dedicated principal to ask this agent for his, her, or their account and **blame** this agent for an unwanted outcome. So we can actively question the agent and understand him, her, or them. This means that our attribution of blame is no longer purely subjective, but derived from objective facts. An **accountable system** is a socio-technical system in which the responsibility for every outcome is linked to an agent, so a natural or legal person. It has an **accountability**

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5Note that actual causality can also deal with probabilities for retrospective events; see [20, Ch. 2.5].

10This is based on the classic Suzy–Billy rock throwing example [20, Example 2.3.3].

11The but-for test is a simple understanding of causality that reads “A is a cause of B if, but for A, B would not have happened” [20]. It is often used in the legal context, called by its Latin name *sine qua non* test. In this domain, several improvements were developed such as the INUS (an Insufficient but Necessary element of an Unnecessary but Sufficient set) or the NESS (Necessary Element of a Sufficient Set) test. For a detailed overview, see [37].

12However, it is important to note that causes are always relative to a causal model. The causal model might be biased and thus social attributions can leak into the model.

13When this commitment is derived from moral reasons, the term “duty” will often be used.
mechanism which is an extension of the system that helps the principal to keep the agent accountable. Lastly, an accountability definition describes the necessary structures in the SCM.

We do not claim that our definitions fit all situations and it is not our intention to obfuscate the long history of these terms. Yet, we believe that it is helpful to clearly state our understanding so that it can be compared, discussed, and contrasted to others.

4 ACCOUNTABILITY STRUCTURES IN CAUSAL MODELS

With SCMs as the means to formalize causal models, we can now revisit the accountability definitions given in Section 2 and look at them through a causal lens. Unfortunately there is no automatic, deterministic way of translating them into SCMs. Causal models express the modeler’s understanding of the subject matter and their advantage is that they are unambiguous. Here, we do not argue that our translations to SCMs are perfect. Our point is that they are easy to understand, precise in their meaning, and thus enable a discussion and review of a given definition of accountability.

SCMs are useful because they may exhibit patterns, such as chains (see Appendix B.1), and specific structures, such as the Front- and Backdoor Criterion (see Appendix B.2) that allow us to show that some nodes will have no causal influence on a specific event. To leverage this, first, the models need to contain actions taken by humans, and as our purpose is the design of accountable systems, also actions taken by machines. This requires us to express the accountability relation as a set of variables that causally influence each other. On the level of accountability definitions, we do not care about the exact nature of this influence, so we do not need to specify \( \mathcal{F} \). The reason for this is that if there is a causal influence, accountability might be necessary and our system should provide data to ensure it. It is only after something unwanted has happened that we need \( \mathcal{F} \) to understand the cause and answer questions of accountability. Conversely, if we can show that a specific variable, representing the actions of an agent, cannot contribute to a specific outcome, this agent cannot be accountable for that outcome.

4.1 Lindberg, Bovens, and Hall

Lindberg’s definition of accountability requires an agent, \( A \), that should give an account for some effect, \( E \), caused by \( A \). Translated to an SCM, this means we need to have at least the relation \( A \rightarrow E \) in the model. \( A \) is a representation of the action taken by the agent and the result of that action, \( E \), will depend on some value \( A \) takes. To allow for the fact that effects are often not caused directly, but indirectly via a mediator \( M \), we would make the possible use of a mediator explicit by adding the relation \( A \rightarrow M \rightarrow E \). An example for a mediator is a power steering wheel that amplifies and translates the movements of the driver (\( A \)) into the actual angle of the wheels (\( E \)). Next, Lindberg requires a domain that is subject to accountability. This, conveniently, is captured very precisely by the model itself. It reflects the context in which \( A \) is embedded, as well as the effect \( A \) might cause. Finally, the definition contains a principal, \( P \), that transferred power to \( A \) and thus has the right to demand information from \( A \) and, should \( A \) not comply, sanction \( A \).

Figure 3 now depicts the structure of the Lindberg pattern. \( P \) will be causally affected by \( A \) and also might be affected by \( M \) and \( E \).

In Lindberg’s view, the principal is not directly involved in the course of events. Moreover, typical actions by a principal, such as helping in the design of the system or investigating an accident, are beyond the scope of the technical system and part of the society the system is embedded in. To reflect this, the models shows no arrows originating from \( P \). Any action taken by \( P \) goes beyond the limits of the technical system. In other words, it is necessary for a system to exhibit the pattern in Figure 3, but it requires additional facilities in the social world around the system to be accountable.

One interesting property of this pattern is that it seems to be at the core of several other definitions. Despite the differences in the details such as the timing, Bovens (see Section 2.2) shares the same causal model. Where Lindberg calls for an agent giving an account to a principal, Bovens considers an actor that explains his conduct to a forum. Both the principal and the forum might sanction or judge the agent or actor. This similarity of definitions suggests to us that the causal models should also be similar. One pronounced difference is that Bovens requires the actor to regularly inform the principal about changes, whereas Lindberg sees the principal as asking for accountability. In contrast to both, at the core of Hall’s definition (see Section 2.3) is an agent’s expectation that their action will potentially be evaluated by a third party. As such it also suggests the \( A \rightarrow P \) relation, but with the added twist that \( A \) only needs to believe this relation to exist. It does not matter if it exists in reality. Here, the technical system does not have to provide any logging or data, so long as \( A \) does not know this. Examples are systems that promise to randomly audit certain transactions, such as tax agencies or anti-cheat tools in online games. While in a concrete instance there might be no technical means to evaluate \( A \), the system will deter \( A \) from misbehaving by introducing the fear of an evaluation.

4.2 RACI

RACI (see Section 2.4) in contrast does not so much look at the individual, but at an organization as a whole. Similar to Lindberg above, it features agents that cause some effect, and thus also exhibits the familiar causal chain \( A \rightarrow M \rightarrow E \). It specifically extends the pattern with an accountable agent, \( AA \), that instructs \( A \) to do a specific task. To reflect that in the model, we need to extend it with an edge \( AA \rightarrow A \). Furthermore, RACI requires any consulted agents, \( C \), to be reflected in the model. We would model this by adding a dedicated node, \( C \), to the SCM to capture the outcomes of these discussions. Lastly, RACI considers dedicated agents, \( I \), that are informed of the effects. In contrast to the others, RACI requires no dedicated principal. Figure 4 shows the complete model.

4.3 Designing an Accountable System

The question now is, how can we use these accountability structures in the development of a system? Here, we assume that we have
Getting the SCM is not easy; however, parts of it can be automated by using models of a system such as fault and attack trees [22] or models of human behavior [28].

15 However, we have not proven these steps to be the best approach. They are merely distilled from our experience; other, possibly better approaches probably exist.

16 In our experience, the following steps make for a useful guideline to map accountability definitions onto causal models of systems:

1. Identify the event for which accountability is desired.
2. Identify valid agents.
3. Choose the desired definition of accountability.
4. For the given definition of accountability, check if the pattern is fulfilled for the desired agents.
   (a) If the pattern is fulfilled, stop here.
   (b) If not, change the model to fulfill the desired pattern.

5 EXAMPLE

We now use the 2018 deadly crash of an Uber car as an example for the design decision in a system [12, 40]. Here, we will look at three different design choices for the control of the system and reason about their accountability implications. In this accident, an autonomous vehicle developed by Uber crashed into a pedestrian. Elaine Herzberg, crossing a road and is regarded as the first accident in which a pedestrian was killed by an autonomous vehicle. Ms. Herzberg was pushing a bicycle while crossing a dimly lit road and the software of the car repeatedly misclassified her, ultimately hitting and killing her. The safety driver on board the vehicle was distracted and did not brake in time.

In the aftermath of the crash the accountability of the parties was hotly contested. At first the police claimed it was the pedestrian’s fault because at the site of the accident, crossing the road was illegal. Next, the car’s safety driver was blamed because she did not pay attention to the road. The manufacturer of the car’s chassis, Volvo, was quick to distance itself from any blame, arguing that its chassis had a collision avoidance system which would have prevented the crash, but it was turned off by Uber to test their own software. Velodyne, the manufacturer of the car’s LiDAR, also pointed out that their system was capable of detecting a pedestrian, but that their system does not take the decision to brake. The search for reasons went as far as criticizing Uber’s development process, the testing process of having only one driver in the car and even the car-friendly (and pedestrian-hostile) layout of the road in Arizona or the point of autonomous cars in general. At the time of writing, the safety driver is being indicted with negligent homicide [50]. All these claims have in common that they ask counterfactual questions...
of a causal model. Our goal is now to structure the causal model in such a way that accountability can clearly be attributed. We focus on a simplified model that consists of three agents, namely Uber, who built the car, Volvo, who contributed the chassis, and the safety driver, who was supervising the car. We show how different SCMs give us different possible agents and how certain structures of an SCM allow us to show that certain agents cannot be accountable for a given outcome.

5.1 Models of the System

Once we have the SCM $M$ of the socio-technical system, we can then use it to evaluate it for its accountability. To illustrate this, we look at ways to design an autonomous car (see Figure 7). This example illustrates three ways that the control of such a system can be structured. In Figure 7a, the human can take over at any point in time. Figure 7b depicts a scenario where any input by the human can be overridden by the machine, and Figure 7c shows a setup where the human cannot influence the car at all. In causal models, the lack of arrows between two variables expresses the strong assumption that there is no causal connection between these two variables. In these Figures we used rounded boxes for possible agents (i.e., natural and legal persons) and rectangular boxes for technical components. Here, we do not model any preemption. Temporal ordering and the fact that one event might preempt another has a huge influence on the model [21].

For simplicity, we assume this causal model to be binary. The meaning of the variables is as follows:

1. $\text{collide w/ Pedestrian}$, $P$, is true if a collision with a pedestrian occurs and false otherwise.
2. $\text{Trajectory set}$, $T$, is true if an evasive maneuver is conducted and false otherwise.
3. $\text{Safety Driver}$, $D$, is true if the driver tries to change $T$ and otherwise false.
4. $\text{Uber Software}$, $S$, is true if the car’s software tries to change $T$ and otherwise false.
5. $\text{Emergency Brake}$, $E$, is true if the chassis tries to change $T$ and otherwise false.
6. $\text{Volvo}$, $V$, is true if $E$ is enabled and otherwise false.
7. $\text{Uber}$, $U$, is true if Uber influences $S$ or $E$.

Here it is important to note that we have a very lax approach to levels of abstraction. Uber and Volvo are companies with unfathomable complexities, the safety driver is a single individual, the software and the emergency brake are complex technical systems, and the trajectory the outcome of multiple decisions. However, SCMs can be abstracted quite well [4] and so this mixing of layers is easy to do formally. Still, it is important to bear in mind that these variables will in reality be complex SCMs in their own right.

Formally, our model $M = (\langle U, V, R \rangle, F)$ looks like this:

$U = \{ U_U, U_V, U_D \}$ are the three exogenous variables.

$V = \{ P, T, D, S, E, V, U \}$ are the seven endogenous variables.

$\forall v \in U \cup V : R(v) \rightarrow \{ \text{true, false} \}$; since we assume a binary model, the range is $\{ \text{true, false} \}$ for all variables.

Figure 7: Three possible designs for a (semi-)autonomous car. While the SCMs show social entities, the system is not accountable as-is.

Now we need to define $F_X$, so the structural equations for every endogenous variable:

$U = U_U, V = U_V, D = U_D$, meaning that $U$, $V$, and $D$ are set by some exogenous variables.\(^{18}\)

$E = \{ \neg U \quad U = \text{true} \}
V \quad U = \text{false}$, so long as Uber is not disabling $E$, it is the value of $V$.

$S = U$ for Figure 7a and Figure 7c, says that the software will follow whatever Uber had in mind. It is trickier for Figure 7b. Here we need to decide if $U$ or $D$ can override the other and in what way. The simplest model would be a model in which the car will break if either Uber or the safety driver wants to break. In this case $S = U \lor D$ would be the correct equation. If one could preempt the other, we would need to change the model to contain such a preemption relation.

For Figure 7a $T = S \lor E \lor D$ and for the others $T = S \lor E$, if neither $S$, nor $E$, nor, as in Figure 7a, $D$ influence $T$, the car will hit the pedestrian.

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\(^{17}\)This example, is of course, highly simplified. In the real world, most causal models will not be binary.

\(^{18}\)This might seem redundant, but the point is that only endogenous variables can be identified as causes in a causal model. In real models, an endogenous variable will likely be influenced by several exogenous variables. For example, the safety driver might be influenced by blood alcohol level; other influences are the weather or the road conditions.
\[ P = \neg T, \text{ if the car is on a collision course with the pedestrian it will always } \]
\[ \text{hit her if the trajectory is not changed.} \]

5.2 Checking for Accountability

We now have three distinct versions of \( M \). These models describe the causal relations, but this alone is not sufficient for accountability. Our goal now is to give a justification of why these options are accountable and decide between the three. First, we need to decide which event(s) we are concerned about. In this example, we only care about potential collisions with pedestrians. This means that we only care about causes that affect \( P \). Next, we need to identify valid agents. Since accountability only has a meaning for natural or legal persons, we can exclude any technical components in \( M \), leaving us with three potential agents: Uber (\( U \)), Volvo (\( V \)), and the safety driver (\( D \)).

As the third step, we need to decide on a notion of accountability (\( D \)). Here we have two possibilities: Either \( D \) is prescribed by some law or standard or we want to find a \( D \) that is suitable for our socio-technical system. If we look at the pattern given by the RACI definition, it is easy to see that \( M \) cannot be accountable in that sense. It is enough to look at the structure to see that \( M \) simply does not have the necessary endogenous variables to fulfill the RACI requirements. This is not surprising, as RACI is aimed at organizations and a discussion is not something that translates well to real-time systems like cars. If we were under obligation to make that system RACI-accountable, we can see that this is impossible, given the current \( M \). We would need to look for ways to extend \( M \) with the required nodes.

Making this system accountable according to Hall’s definition would require us to convince the three agents that their behavior will potentially be evaluated and that any misbehavior will be punished. In extremis, this would mean that if we are convincing enough, we do not need to add any technical means of accountability to our system. In practice, we would need to find a trade-off between the cost of supervision and the compliance of the agents. For example, it might make sense to collect all vehicle data to create a plausible scenario of evaluation. To give an example, most people respect speed limits, despite the fact that speed traps are quite rare.

In many technical systems, the notions of Lindberg and Bovens will appeal to the developers. In contrast to RACI, they do not require many additional nodes, and in contrast to Hall, they both define a clear relationship between an agent (or actor) and a principal (or forum). To apply their notion, we first need to identify the basic structure they prescribe: \textit{Agent} \rightarrow \textit{Mediator} \rightarrow \textit{Effect}.

In Figure 7a, we can find the following causal chains leading to the crash: \( U \rightarrow S \rightarrow T \rightarrow P, U \rightarrow E \rightarrow T \rightarrow P, V \rightarrow E \rightarrow T \rightarrow P, \) and \( D \rightarrow T \rightarrow P \). Here, the structure of the chain including the safety driver is an exact match with this structure. For Uber and Volvo we have two steps in the mediator and would need to show that they can be treated as a single node. For Figure 7a and Figure 7c the argument is straightforward because \( S = U \), so these two nodes could be joined into one. In Figure 7b, we need to clarify if \( U \) or \( D \) has the final say over the matter. As the model is given here, it would not be Lindberg accountable because both \( U \) and \( D \) would be accountable for \( T \). Similarly, Volvo only has an influence on the trajectory if Uber is allowing them to do so. So they fulfill this pattern if \( U = false \).

If we now take another look at \( T \), we can see that its equation is as follows: \( T = S \vee E \vee D \). Again, we have the problem that we cannot disentangle the effects from \( U, E, \) and \( D \). However, given that \( U \) will always disable \( V \) (because \( E = \neg U, \) if \( U = true \), we can at least rule out \( V \) as an eligible agent. In Figure 7a and Figure 7b, it is unclear if the safety driver or Uber are accountable, because both have a causal effect on \( T \). This agrees with the investigations in the aftermath of the accident as there it was also unclear at first who was to be held accountable for the deadly crash. Figure 7c causality is much clearer because \( D \) has no causal influence on \( T \) at all.

Lastly, we will notice that none of the models has a principal. So we need to determine who \( A \) is accountable to. In the real world this role will be filled with the authorities, so we would need to make sure that they have all the evidence they need to understand the actions of \( A \). So far, just judging from the SCMs, we could either pick Lindberg’s or Boven’s definition. Here, we would pick Lindberg’s because is has the notion that \( P \) might inspect the behavior of \( A \) on demand. Boven’s suggests regular reports, which seem unnecessary for a car because accidents are rare. Boven’s would be more suitable if we were, for example, checking for violations of the speed limit.

Given the three possible designs for the system, which would be the easiest to make Lindberg accountable? Figure 7c, where \( D \) has no causal influence and \( V \) is inhibited by \( U \), is attractive because only \( U \) is left as an agent. There would be no confusion about accountability. However, Figure 7a or Figure 7b might be attractive in practice because keeping the human-in-the-loop allows the technical system to make wrong decisions without clear accountability of the manufacturer.

5.3 Leveraging the Structure of \( M \)

Specific structures in causal models allow us to prove that one variable cannot affect another in a specific way, even if there is a path between those two variables. Two such structures are the Front and the Back-Door Criterion (see Appendix B.2). Knowing that a specific variable has no causal influence on another is invaluable for the design of a system, because this means that we do not need to measure (or “log”) it. This is helpful from an engineering perspective, because it allows us to not store specific data and thus save the cost for storage and the development of the data logging functionality. It is also often desirable from a privacy perspective, because it allows to justify not storing specific sensitive data. So if we can, for example, show that skin color or religion have no causal influence, we can justify not logging them, without compromising a system’s accountability. To return to our example in Figure 7c, we might just be interested in the effect of \( S \) on \( T \). The question now is, what other values do we need to control for to calculate the effect of \( S \) on \( T \)?

Employing the Back-Door Criterion, we can see that we do have an open backdoor path, namely \( S \leftarrow U \rightarrow E \rightarrow T \), that will confound our estimate of the effect of \( S \) on \( T \). To deconfound this reading, we could either control for \( U, E, \) or both of them. This

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19Note that in general showing that two causal models are equivalent is not trivial and cannot be treated as a graph problem; see Appendix B.4.

20Here binary models are not the best examples. It is easier to think of \( S \) and \( E \) contributing different amounts to a real valued function.
now allows us to justify not logging one of these variables, provided we are only interested in the effect of $S$ on $T$.

5.4 Actual Causality

So far we used our models in a type causal manner, that is we looked at the future, ensuring that the accountability for a specific event was clear and easy to attribute. How would we now use this model after an accident has actually happened? For this we can employ actual causality reasoning (see Section 3.2). First, we need to ensure that we can set the context correctly. So in our real-world system, we need sensors and logs that can tell us what has actually happened. Here we can leverage the fact that a causal model is determined by its exogenous variables. Looking at Figure 7, we have three exogenous variables: $U_C$ for Uber, $V_C$ for Volvo, and $U_D$ for the safety driver. All can be either true or false.

If we measure $U_C = \text{false}, V_C = \text{false}, U_D = \text{false}$ and assume the model in Figure 7a, will a crash occur?

$$E = \text{false}$$
$$S = U = \text{false}$$
$$T = S \lor E \lor D = \text{false} \lor \text{false} \lor \text{false} = \text{false}$$
$$P = \neg T = \text{true}$$

Here we can read this as Neither Uber nor the driver, nor Volvo tried to change the trajectory, therefore the car crashed into the pedestrian. However, this sentence already includes the counterfactual assumption Had either Uber, the driver, or Volvo done something else, the crash would not have happened. We can now formally check if this is correct. Since we assumed the model to be binary, there is only one other thing the agents could have done, namely whatever makes their “measurement” true. So, we can change the value of $U$ in the model and see if the result changes.

$$E = \text{false}$$
$$S = U = \text{true}$$
$$T = S \lor E \lor D = \text{true} \lor \text{false} \lor \text{true} = \text{true}$$
$$P = \neg T = \text{false}$$

This setting can be read as Uber changed the trajectory and therefore the car did not crash into the pedestrian. So we can say that because there is a counterfactual world in which $U$ could have prevented the crash, $U$ is a cause for the crash to happen. If we now look at the causal model for Figure 7c, we see that $T = \neg S \lor \neg E$, so $D$ has no influence on $T$ (or any other variable in the model). If $D = \text{false}$, we would get the same result as above. However, if in the SCM above, we were to set $D = \text{true}$, $T$ would be true and the crash would be prevented. What would now happen in Figure 7c?

$$E = \text{false}$$
$$S = U = \text{false}$$
$$T = S \lor E = \text{false} \lor \text{false} = \text{false}$$
$$P = \neg T = \text{true}$$

Despite the fact that we set $D = \text{true}$, so the driver tried to prevent the accident in the counterfactual world, the accident still happens. This means that $D$ is not a possible cause for the accident and, since causality is a requirement for accountability, can also not be held accountable for the crash.

6 CONCLUSION

Accountability is embedded deep into the fabric of society. Algorithmic systems need to be designed in a way that conforms with these societal expectations. This means that such important design decisions cannot be hidden deep within the system. They need to be made explicit, communicated, and discussed. SCMs are uniquely suitable for that because they allow us to formalize causality, the necessary core of all definitions of accountability. In the current literature, SCMs are mainly used in scientific studies. The models there are small and communicate assumptions about mechanisms in a study. Developing SCMs for socio-technical systems is, despite some early work, still a hard problem. Similarly, no clear-cut ways of identifying principals or express definitions of accountability as SCMs exists.

Despite these open problems, we are convinced that SCMs offer the clarity that is a requirement to make meaningful design decisions. While SCMs are not sufficient to ensure accountability, a correct understanding of the underlying causal mechanisms is necessary for any notion of accountability. Expressing this as an SCM allows us to realize that we need certain structures in systems to enable accountability. Without these structures, a system cannot be accountable. Once we have identified a specific structure, we can utilize existing definitions of accountability and reuse the knowledge that comes with them; we do not need to invent our own notions of accountability. SCMs are a powerful tool to analyze systems and, if they are not accountable, provide a well-reasoned argument why this is the case, and how the system should be improved.

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REFERENCES

[1] Mike Ananny and Kate Crawford. 2018. Seeing without knowing: Limitations of the transparency ideal and its application to algorithmic accountability. New Media & Society 20, 3 (2018), 973–998.

[2] Steen A Andersson, David Madigan, Michael D Perlman, and others. 1997. A characterization of Markov equivalence classes for acyclic digraphs. The Annals of Statistics 25, 2 (1997), 505–541.

[3] Julia Angwin, Jeff Larson, Surya Mattu, and Lauren Kirchner. 2016. Machine Bias: There’s software used across the country to predict future criminals. And it’s biased against blacks. ProPublica (2016). 

[4] Sander Beckers and Joseph Y Halpern. 2019. Abstracting causal models. In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 33. 2678–2685.
A ACTUAL CAUSALITY

The Halpern-Pearl (HP) definition uses the following formalization of a causal model, based on Pearl’s work on type causality [19]:

**Definition A.1 (Actual Causal Model).** A causal model $M$ is a tuple $M = ((\mathcal{U}, \mathcal{V}, \mathcal{R}), \mathcal{F})$, where

- $\mathcal{U}$ is a set of exogenous variables,
- $\mathcal{V}$ is a set of endogenous variables,
- $\mathcal{R}$ associates every variable with a nonempty set $\mathcal{R}(Y)$ of possible values $Y$,
- $\mathcal{F}$ associates with each variable $X \in \mathcal{V}$ a function that determines the value of $X$ (from the set of possible values $\mathcal{R}(X)$) given the values of all other variables $F_X : (\times_{U \in \mathcal{U}} \mathcal{R}(U)) \times (\times_{V \in \mathcal{V} - \{X\}} \mathcal{R}(V)) \rightarrow \mathcal{R}(X)$.

A primitive event, given $(\mathcal{U}, \mathcal{V}, \mathcal{R})$, is a formula of the form $X = x$ for $X \in \mathcal{V}$ and $x \in \mathcal{R}(X)$. A causal formula is of the form $[Y_1 \leftarrow y_1, \ldots, Y_k \leftarrow y_k] \varphi$, where $\varphi$ is a Boolean combination of primitive events. $Y_1, \ldots, Y_k$ (abbreviated $Y$) are distinct variables in $\mathcal{V}$, and $y_i \in \mathcal{R}(Y_i)$. Intuitively, this notation says that $\varphi$ would hold if $Y_i$ were set to $y_i$ for each $i$. $(M, \mathcal{U}) \models X = x$ if the variable $X$ has value $x$ in the unique solution to the equations in $M$ in context $\mathcal{U}$ (i.e., the specific values of the variables). An intervention on a model is expressed either by setting the values of $X$ to $\overrightarrow{X}$, written as $[X_1 \leftarrow x_1, \ldots, X_k \leftarrow x_k]$, or by fixing the values of $\overrightarrow{X}$ in the model, written as $M_{\overrightarrow{X} \leftarrow x}$. So, $(M, \mathcal{U}) \models [Y \leftarrow \overrightarrow{Y}] \varphi$ is identical to $(M, \mathcal{U}) \models \varphi$.

Using this definition of a causal model, an actual cause is defined as [19]:

**Definition A.2 (Actual Cause).** $\overrightarrow{X} \models \overrightarrow{X}$ is an actual cause of $\varphi$ in $(M, \mathcal{U})$ if the following three conditions hold:

- **AC1.** $(M, \mathcal{U}) \models (\overrightarrow{X} \models \overrightarrow{X})$ and $(M, \mathcal{U}) \models \varphi$.
- **AC2.** There is a set $\overrightarrow{W}$ of variables in $\mathcal{V}$ and a setting $\overrightarrow{X}$ of the variables in $\overrightarrow{X}$ such that if $(M, \mathcal{U}) \models \overrightarrow{W} \models \overrightarrow{X}$, then $(M, \mathcal{U}) \models [\overrightarrow{X} \leftarrow \overrightarrow{X}, \overrightarrow{W} \leftarrow \overrightarrow{W}] \varphi$.
- **AC3.** $\overrightarrow{X}$ is minimal, i.e., no subset of $\overrightarrow{X}$ fulfills AC1 and AC2.

Informally, AC1 just says that a specific event $\overrightarrow{X} = \overrightarrow{X}$ actually happened, otherwise it cannot be a cause. The minimality condition AC3 ensures that only relevant events are part of a cause. In Figure 2, for example, it would remove the detail that Alice is alive from the cause. AC2 is the most complex condition and is thus traditionally explained last in any text. Here the idea is that we can show that $\varphi$ depends on $\overrightarrow{X}$ as long as we keep the variables in $\overrightarrow{W}$ fixed. This allows us to find that only the variables in $\overrightarrow{X}$ are affecting the outcome (and none of the variables in $\overrightarrow{W}$ do).

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25It is important to note that the HP definition is just one possible way to define causality. As [20, Ch. 2.2.2] puts it so eloquently after introducing all the details of the HP definition: “At this point, ideally, I would prove a theorem showing that some variant of the HP definition of actual causality is the ‘right’ definition of actual causality. But I know of no way to argue convincingly that a definition is the ‘right’ one; the best we can hope to do is to show that it is useful.”

26For an in-depth discussion of all conditions and especially AC2,[20, Ch. 2.2.2] is the most thorough resource.

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Figure 8: Three common structures in causal models. $Ux$, $Uy$, and $Uz$ denote the exogenous variables. $X$, $Y$, and $Z$ are the endogenous variables.

Coming back to the example depicted in Figure 2, we would have three endogenous variables: $\text{AT}$ for Alice texted, $\text{BR}$ for Bob runs a red light, and $\text{AH}$ for accident happens as well the exogenous variables $Ua$ and $Ub$ that set the value of the endogenous variables. For simplicity, all variables can be true or false. It is important to note that this example assumes that there are no other factors that could influence the chain of events. If there were, the model would be wrong and would need to be improved. It is thus important that each causal model is discussed and ideally peer reviewed. It is not enough to have a model: we also need a clear rational for that model. Of course this will then cause second order questions of the correctness of models, the bias of the modelers, and even who is allowed to create the models.27 Here we simply assume that a causal model is a correct and detailed enough representation of reality.

B SPECIAL STRUCTURES IN SCMS

B.1 Chains, Forks, and Colliders

In graphical causal models, some basic structures will arise repeatedly. Chains, forks, and colliders exhibit very specific rules for causal (in-)dependence [44, p. 35ff]. Figure 8 depicts these three structures. In contrast to the usual convention, we also model the exogenous variables $Ux$, $Uy$, and $Uz$ here. In most causal models, only the endogenous variables, here $X$, $Y$, and $Z$ are modeled. Exogenous variables "stand for any unknown or random effect.
that may alter the relationship between endogenous variables” [44, p. 36] and they are assumed to be independent of each other.

The important advantage of causal models is that in these structures several (in)dependencies hold, regardless of the function between those variables. If we now look at Figure 8a, Z is always dependent on X. So, if we see the value of X change, we will usually also see the value of Z change. Next, Y is likely dependent on X. The reason for this is that Y depends on Z for its value and Z depends on X for its value. However, there are rare cases where changes in X will not affect Y.28 And finally, X and Y are independent, conditional on Z. The reason is that conditioning on a variable means that we fix its value. If we had a dataset consisting of three values, X, Y, and Z, we would only look at the values of X and Y, where Z has a specific value. What happens here is that Uz changes to keep Z at this specific value. So whenever X changes, Uz would compensate for that change to keep Z constant and as Y only depends on Z and not on Uz, its value is independent of the changes in X.

Figure 8b depicts a fork. Here, Y and Z both depend on X and this also means that Y and Z are likely dependent. The reason is that since both depend on X, a change in one will inform us that the other will also likely change. However, there are also cases where this is not the case. Finally, Y and Z are independent, conditional on X. Similar to the chain above, once we hold X constant, a change in either Y or Z no longer indicates a change in the other. In this structure, X is called a common cause.

The third basic structure, a collider, is depicted in Figure 8c. Here, we can see that Z is dependent on X and Y and X and Y are independent, because they are not in a parent-child relationship and their exogenous variable UX and UY are assumed to be independent. The most surprising property of a collide is that X and Y become dependent, conditional on Z. While it might be surprising that two independent variables can suddenly become dependent, it can be illustrated with a simple example [44, p. 41]: If we assume X + Y = Z and X and Y are independent, knowing that X = 3 does not tell you anything about Y. However, the moment you know that Z = 10, knowing that X = 3 lets you deduce that Y = 7.

This concept of (in-)dependency can now be generalized for all graphs with the concept of d-separation. This means that two variables are independent if every path between them is blocked. Formally [44, p. 46],

**Definition B.1 (d-separation).** A path p is blocked by a set of nodes Z if and only if

1. p contains a chain of nodes A \(\rightarrow\) B \(\rightarrow\) C, or a fork A \(\leftrightarrow\) B \(\rightarrow\) C, such that the middle node B is in Z (i.e., B is conditioned on), or
2. p contains a collider A \(\rightarrow\) B \(\leftarrow\) C such that the collision node B is not in Z, and no descendant of B is in Z.

If Z blocks every path between two nodes X and Y, then X and Y are d-separated, conditional on Z, and thus are independent conditional on Z.

**B.2 Analyzing Causal Models**

[45, p. 157] distills these properties of causal models into four rules:

1. In a chain junction, A \(\rightarrow\) B \(\rightarrow\) C, controlling for B prevents information about A from getting to C or vice versa.
2. Likewise, in a fork or confounding junction, A \(\leftarrow\) B \(\rightarrow\) C, controlling for B prevents information about A from getting to C and vice versa.
3. In a collider, A \(\rightarrow\) B \(\leftarrow\) C, exactly the opposite rules hold. The variables A and C start out independent, so that information about A tells you nothing about C. But if you control for B, then information starts flowing through the “pipe”, due to the explain-away effect.
4. Controlling for descendants (or proxies) of a variable is like “partially” controlling for the variable itself. Controlling for a descendant of a mediator partly closes the pipe; controlling for a descendant of a collider partly opens the pipe.

Even if we have a long causal path, it is enough that one junction blocks the information flow. To deconfound two variables, we need to block any noncausal path while not blocking any causal path. This leads to two prominent criteria to identify causal independence: The Back-Door and the Front-Door Criterion.29

**B.2.1 The Back-Door Criterion.**

**Definition B.2 (The Back-Door Criterion).** Given an ordered pair of variables \(X, Y\) in a directed acyclic graph G, a set of variables Z satisfies the Back-Door Criterion relative to \(X, Y\) if no node in Z is a descendant of X, and Z blocks every path between X and Y that contains an arrow into X.

Intuitively, the Back-Door Criterion [44, p. 61] ensures that (1) all spurious paths between X and Y are blocked, (2) all directed paths from X to Y are not perturbed, and (3) no new spurious paths are added.30

**B.3 The Front-Door Criterion**

**Definition B.3 (The Front-Door Criterion).** A set of variables Z is said to satisfy the Front-Door Criterion relative to an ordered pair of variables \(X, Y\) if

1. Z intercepts all directed paths from X to Y.
2. There is no unblocked path from X to Z.
3. All back-door paths from Z to Y are blocked by X.

Intuitively, the Front-Door Criterion [44, p. 69] relies on the fact that one can identify the effect of X on Z and the effect of Z on Y separately. This works because Z, so the mechanism (or mediator) by which X affects Y, is not affected by any unobserved confounders.31 Having identified the separate effect, we can then calculate the effect from X on Y.32

**B.4 Comparing an SCM to an Accountability Definition**

In our approach, we end up with two causal models. \(M = ((\mathcal{U}, \mathcal{V}, \mathcal{R}), \mathcal{F})\) is an SCM of the system that should be accountable and \(\mathcal{D} = (\mathcal{U}, \mathcal{V}, \mathcal{R})\) is an SCM of the system that should be accountable and \(\mathcal{D} = (\mathcal{U}, \mathcal{V}, \mathcal{R})\)

28All of the following examples are based on examples given by [45]; [31] provide a tool to automate the analysis.
29[17] give a detailed and in-depth explanation of the Back-Door Criterion and why it works on graphical models.
30The Front-Door Criterion will also work if Z is only weakly affected by a confounder. The results will, however, get more imprecise the bigger Z is influenced.
31See [5] for an in-depth discussion of the application of the front-door criterion.
Figure 9: Two models that are equivalent with regard to \( A \) and \( C \).

(a) \( \mathcal{F} = \{ C = A \} \)  \hspace{1cm} (b) \( \mathcal{F} = \{ C = B, B = A \} \)

Figure 10: Despite their similar structure, these two models are not equivalent.

(a) \( \mathcal{F} = \{ C = A \} \)  \hspace{1cm} (b) \( \mathcal{F} = \{ C = \neg A \} \)

\((\mathcal{U}',\mathcal{V}',\mathcal{R}'),\mathcal{F}'\) is an SCM of an accountability definition. Here it is very important to notice that in general the signatures of the two models will be different, i.e. \((\mathcal{U},\mathcal{V},\mathcal{R}) \neq (\mathcal{U}',\mathcal{V}',\mathcal{R}').\) The reason for this is that the model of a system will usually contain more nodes than those of a definition. This is in so far a problem because much of the literature on the equivalence of causal models is concerned with so called Markov Equivalence Classes\(^{33}\), which requires the signatures of the models to be identical. This, however, is not useful in comparing accountability models to system models because their signature will always be different. \( \mathcal{M} \) is supposed to be a small model focused on the important aspects of accountability, while \( \mathcal{M} \) is supposed to represent a whole system.

Figure 9 depicts two causal models. In Figure 9a, \( A \) causes \( C \) directly, whereas in Figure 9b \( A \) causes \( C \) via a mediator \( B \). The question now is if these two models are equivalent and if so what this means. If we just look at the graph structure, these two models are different. One has three endogenous variables and the other only two. However, if we look at structural equations of this model, we can see that \( B \) does not affect the influence of \( A \) on \( C \). So any useful notion of equivalence would need to find that these two models are equivalent. If it would not, this notion of equivalence would be next to useless because one can always include additional intermediate variables in any causal model. Figure 10 depicts two models that have a similar structure, but are functionally their complete opposite. Any notion of equivalence should find these two models distinct.

\(^{33}\)See for example [2, 48, 52] and [26] for recent advances.