Learn to Capture Causality: from Concrete Representation to Abstract Learning

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Abstract

Humans learn to capture causality everywhere and everytime. As humans, sometimes we learn to model causality by concrete observations of scenes and states, and others we capture causality by learning abstract concepts. Inspired by this, we propose a possible way of designing a computational model that can capture the causal relation and structure, with a combination of concrete representation and abstract learning. We will further introduce four aspects of capture learning with detailed examples. Through these examples, we will have an insight of the necessity of these different aspects.

1 Introduction

Causality [14] is widely used to depict the relation of cause and effects, and has been developed as a scientific research topic. Ever since infancy, humans have learned to capture causality [6]. Suppose it was 6 p.m. and our parents were walking out of the kitchen with dishes of food, then we would know that there would be a delicious meal and could hardly wait to have dinner. In this example, 6 p.m. indicates the time (at dusk), which helps us to infer the next thing that would happen. The two events "parents walking out of the kitchen with dishes" and "dinner starting" usually happen in succession, indicating that they have some certain relationship to some extent. This can be an simplest form of causality, which contains two events as well as the relation in between.

In the classical area of causality, one of the most widely circulated theories is the counterfactual theory [9]. In this theory, causality are explained on the basis of counterfactual conditionals, and can be traced back to David Hume's definition of the causal relation [4]:

> Where, if the first object had not been, the second never had existed.

Ever since then, much more theories have been developed and have taken effect in a great many fields, including psychology, statistics, *etc*.

How do we as humans recognize causality? In this essay, we will discuss four fundamental aspects and methods that humans usually use, on the basis of which we will further propose the corresponding ways to design a computational model to capture causality. Both concrete representation of observations and the learned abstract concepts will be included.

2 Capture Causality from Concrete Representation

2.1 Representation of Vision

In the following, we will focus on a **static** image as vision observation. What we see through the image can construct our understanding of causality to some extent. Since causality is more about the relationship between cause and effect rather than themselves, we should pay attention to the relation among objects as a whole, instead of simply detecting the objects themselves.

One possible way of representing an image with complex relations is to use parse graph [3]. Parse graphs use a view of tree-like representation, which is suitable to handle relations with hierarchy. In the example figure 1, the man was sitting at the table near a food stand. By parsing this combination into "man at the table" and "table near the food stand", we can indicate that the man was sitting there for eating. From the perspective of causality, the man might be going to the food stand and sitting **because** he wanted to eat something. Similarly, we have "wanting to buy some food **led to** the boy walking towards the food stand".

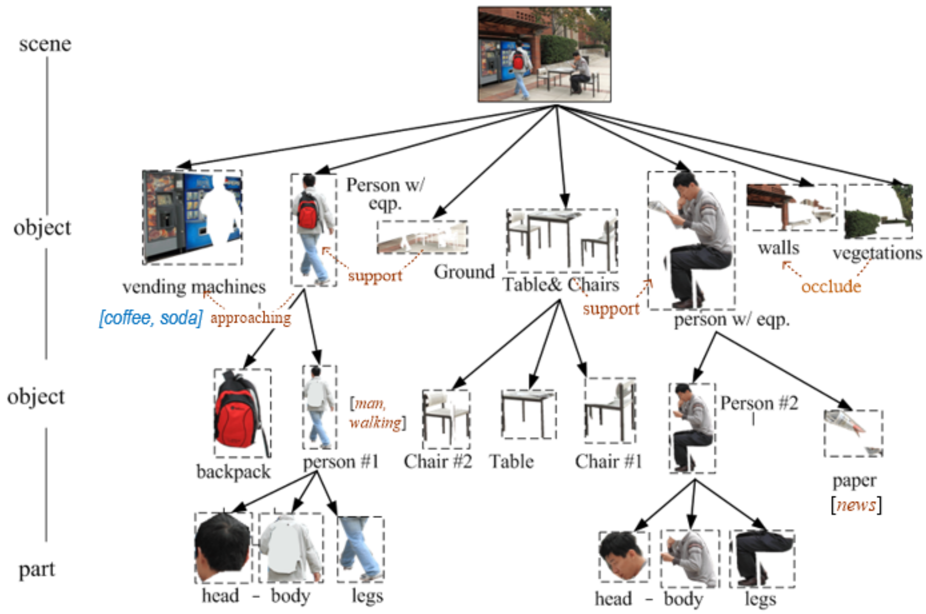

Figure 1: An example of parse graph [17]. A scene of image may be parsed hierarchically in terms of relations, intents, beliefs, *etc*.

Using representations such as parse graph is an effective way to combine the information on the surface with deeper semantic relations. Therefore, such concrete representations of static observations can serve as resources for the computational model to analyze and reason. In a word, causality lies in the parse graph!

It is worth noting that such static representations also include multiple methods, including And-Or Graph [2] for logic, *etc*. Diverse methods of representing diverse contents provide multiple choices for our designed model.

2.2 Representation of Temporal Process

Empirically, we model causality of multiple events based on the sequential order most of the time, which is a **dynamic** way. Studies on voting among a large population [11] have shown that temporal order can have great significance to people's decisions due to causality. Researches on infants [8] indicate that 5-year-old children can already form a habit to infer causality according to the time order of events. Reuter *et al*. [15] investigated the role of moral and temporal factors in causal selection, and connected their findings with probabilistic models of temporal location.

Temporal order plays an important part in modeling the causality. Take Michotte's study on perception causality [10] as an example (figure 2). In sub-figure (a), (b) and (f), people tend to consider that it is ball A's striking that **leads to** ball B's moving forward. However, when it comes to sub-figure (c), (d) and (e), the result can be less explicit. This phenomenon indicates that when the temporal condition is disrupted, people's judgement of causality will change accordingly.

Consequently, it is easier for a computational model to capture causality if representations of temporal processes are given. With these sequential meanings of information, the model can make possible (but not determined) interpretations and predictions of cause and effect, and combine both to learn causality.

Figure 2: Examples of Michotte's study on perception causality. In the following we will denote the red ball as ball A, and the green one as ball B. (a) A strike B and B move forward; (b) A strike B and carry along B to move together; (c) Launching with a temporal gap, where B leaves apart from A after a while when A struck B; (d) B seems to leave farther as soon as A strikes it, as if B had consciousness and would move automatically; (e) Launching with a spatial gap, where B move forward even before A strikes it; (f) The tool effect, in which a chain reaction happens and the grey ball can be referred as a tool.

3 Capture Causality from Abstract Learning

3.1 Learning from Common Sense

Common sense has been considered as one of the unique human abilities for quite long, while many of existing AI techniques show little in it. Common sense provides the fundamental knowledge for humans' physically survival and socially living.

On the one hand, physical common sense can help the designed model to interpret the physical causality. For example, knowing the basic theories of collision will make the model instantly realize that the former ball is the reason of the latter's moving where there is a collision. Understanding why a cup drops from the edge of the table requires the common knowledge of gravity. Such physical sense may be enhanced through databases [16] or knowledge graphs [13], collecting a great deal of relevant information onto a single understanding of causality.

On the other hand, social common sense is of great significance as well. Gestures are one kind of the most commonly used social knowledge [7]. Knowing the basic gestures let us understand why a man pointing at his mouth is usually interpreted that he feels hungry. Other examples include conventional customs and habits, sympathy and empathy, laws and regulations, *etc*. These can be much useful for us to behave properly and connect with other individuals, which can help us live a better life. It is the same with respect to intelligent agents. Modern AI techniques ought to be equipped with social common sense, with which they can make causal interpretations and reasoning when encountering the similar circumstances.

On the whole, the present situation is that many existing AI techniques, such as Large Language Models (LLMs), are relatively (but not absolutely) better in physical common sense, and are terribly short in social knowledge [1]. Hence, we attach great significance to equipping intelligent agents with broader physical and social common sense. Only with enough knowledge can our designed model learn to capture causality properly.

3.2 Learning to Reason

Compared to learning from common sense which is a static process, learning to reason [5] can be a dynamic one. Reasoning is always a successor of common sense or graph representation of an image, and can bring out more predicted information. Note that the reasoning part might not be necessarily consistent with the ground truth, but it can actually help with capturing the causality.

We have seen examples of reasoning. When the young man was walking towards the food stand in figure 1, we can infer that he might want to buy something to eat. Seeing a man pointing at his mouth, we may conjecture that he was hungry. In addition, we should pay extra attention to a kind of reasoning called induction [12], which plays an important part in capturing causality. For instance, if it seems that a certain event is on a regular basis, then the next time of the event can be inferred, where the regularity comes from induction. Based on induction, more relationships between causes and effects can be established, which will form new causalities.

To conclude, reasoning is an effective way of modeling causality between abstract concepts. Therefore, learning to reason will be an essential part in building a computational model that can capture the causality.

4 Conclusion

Constructing computational models that can capture causality well fits the need of next-generation modern AI systems and the ever-increasing demand of Artificial General Intelligence (AGI). In this essay, we propose four different aspects of making a model understand, analyze and reason from causality, and discuss the feasibility based on concrete representations as well as abstract learning. We hope that our discussion will inspire the subsequent researches in this field, and can be a small step towards advanced intelligence in causality.

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