apologizing, and I felt hot. I realized that it was not the room that had gotten warm, but my body. Catharsis in this case does not involve the acting out of anger, the mistake of the systematic studies of anger "catharsis." It is rather an internal process: heat seems to metabolize the adrenaline for bodily preparation to fight. Body heat signals the internal orgasm of anger.

These comments on catharsis were brief. For further discussion, see my book (1979), article, Catharsis and Other Heresies (2007), or my video on emotions, backed up by two Swedish rock stars (Scheff 2009).

Cross-References

- ► Aristotle (384 BC–322 BC)
- ► Aristotle on Pleasure and Learning
- ► Dewey, John
- ► Psychodynamics of Team Learning

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Causal Attribution

► Attribution Theory of Motivation

Causal Induction

► Causal Learning

Causal Inference

► Causal Learning
► Human Causal Learning

Causal Learning

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Synonyms

Causal induction; Causal inference; Causal reasoning; Contingency learning

Definition

Learning the cause–effect relationships or determining the causal status among a set of two or more events. Learning causal relationships can be characterized as a bottom-up process whereby events that share contingencies become causally related, and/or a top-down process whereby cause–effect relationships may be inferred from observation and empirically tested for its accuracy.

Theoretical Background

Causal learning has its roots in philosophy. Aristotle proposed four causes: material (what something is made of), formal (i.e., structural, how something is made, its structure and form), efficient (or moving; necessary for the effect's existence), and final (i.e., functional, the purpose, an egg is the cause of a chicken). The British Empiricists (Hume, Lock, J. S. Mill, et al.) suggested that cause–effect relationships cannot be observed, but are merely inferred through statistical regularities between events, often captured in associative properties (see e.g., Hume 1739). Nativists, such as Kant (1781), argued that the human mind has a priori knowledge of the construct of causality. The concept of causation is applied to our knowledge (both a priori and acquired through experience) to allow us to label events as causal when they appear so to us.

Investigation of causal learning in psychology follows from these philosophical roots. Treatment of concepts involving causal learning and induction fall into three groups: Perception, Associative learning, and Reasoning.

Belgian psychologist Albert Michotte argued that causality is determined directly through perception. He demonstrated this by describing our perception of causality in how billiard balls move and interact on a billiard table. When one billiard ball strikes a second, the first ball transfers its motion to the second. Michotte (1963) referred to this perception of transfer of movement from one colliding object to the next as "ampliation of the movement," what is now generically referred to as the "launching effect." This gestalt approach treats causal knowledge as being derived directly from perception rather than acquired through experience of contingency relations between causally connected events. Thus, Michotte's framework – which still dominates the field of causal perception – shares more with Kant's nativist framework than with Hume's empiricism.

The associative learning approach to causal learning is a direct descendent of the associationist philosophy of David Hume. Proponents of an associative learning approach to causal learning and induction argue that the laws of associative learning, such as contiguity, contingency, and temporal priority, provide a sufficient account for how humans and other animals acquire understanding of cause–effect relationships. Pavlovian conditioning involves pairing an antecedent event (called a conditioned stimulus or CS) with a subsequent, usually motivating, event (called the unconditioned stimulus or US), thereby establishing a CS–US association. The CS–US association may be represented causally, with the CS as the cause of the US. Instrumental learning, in which changes in behavior are driven by their consequences, may also serve as a model of causal learning. This case is particularly strong for goal-directed learned behavior in which the action is made as if to produce the goal (for appetitive or desirable outcomes) or prevent the goal from happening (for aversive or undesirable outcomes) (Dickinson 2001). In this framework, instrumental actions are suggested to be mediated by causal knowledge. Much of the work to support this framework comes from research investigating the parallels between associative learning phenomena in nonhuman animals and similar phenomena in human contingency learning experiments. The degree to which effects in human contingency learning mirror those found in animal conditioning experiments establishes the latter as a model for the former. This approach has been largely successful in establishing a connection between these two research paradigms, and few would dispute that this similarity is meaningful. Where the debate centers is on the interpretation of this similarity between animal conditioning experiments and human contingency learning experiments. Proponents of the associationist approach argue that the similarity reflects the role of the simple, algorithmic-level learning mechanisms of Pavlovian and instrumental conditioning in causal learning in both nonhuman animals and humans. An alternative perspective is that the similarities between these two research paradigms reflect the operations of rational top-down psychological principles of causal reasoning and induction at least in humans and perhaps in nonhuman animals as well.

An alternative theoretical approach to causal learning and reasoning involves the application of rational statistical models (also called normative or functional models) to human causality. This approach has also been extended to work with nonhuman animals in recent years (Penn and Povinelli 2007). According to the normative approach, causal knowledge is acquired by computing the covariation between candidate causes and effects. The delta-p model is one popular generic form of the computation rule for the contingency between cause and effect (see Fig. 1; after Allan 1980). The indicated conditional probabilities can be pieced together into a causal model. A causal model is a representation containing both a structural framework consisting of links between causes and effects, and the strength of the relationship of each link, also referred to as causal power (Cheng 1997). Rational models typically focus on delineating the rules that govern causal structure learning or how causal power is computed. An implicit assumption in these models is that causal relationships reflect either a force that

	Effect	No Effect
Cause	a	b
No Cause	c	d

$\Delta p = p(\text{effect/cause}) - p(\text{effect/no cause})$

Causal Learning. Fig. 1 2×2 contingency table showing relationships between Cause (present = cells a and b; or absent = cells c and d) and Effect (present = cells a and c; or absent = cells b and d). At the bottom of the figure is the equation for calculating delta p, the change in judged contingency between cause and effect. This equation takes into account the difference between the probability of the effect given the presence of the cause (cells a and b) and the probability of the effect given the absence of the cause (cells c and d)

allows a cause to generate or prevent its effects, or a physical mechanism that ties effects to their causes – though these forces or mechanisms are rarely specified in descriptions or parameters of the models. While there has been a tension in the literature on whether associative or rational models provide better theoretical tools to investigate causal learning, a consensus view has recently emerged that the two classes of models are more complementary than exclusionary and they reside at different levels of analysis as characterized by Marr (1982). Associative models are thought to operate at the algorithmic level of explanation (though most associative models, such as the Rescorla-Wagner, 1972, model are presented in computational form), while rational models reside at the computational level of analysis.

There has been a recent extension of rational models that focuses on the role of agency in causal learning and judgments. The basic premise is that an agent can manipulate, or observe another's manipulation of, an outcome. This manipulation is termed an intervention and can directly affect that event's causal status. If intervening on the event results in changes in other events (e.g., watering the lawn results in green grass), then the manipulated event is deemed a cause of the other, resulting events. Manipulations can include turning a dichotomous event on or off (e.g., flicking a light switch), increasing or decreasing a continuous event's value (e.g., turning up or down a thermostat setting), or increasing or decreasing the likelihood of a probabilistic event (e.g., smiling or frowning when asking someone for a date). Knowledge derived from interventions, often characterized as a top-down process, can be contrasted with the bottom-up processes of deriving knowledge from observations in the absence of intervention (e.g., via associative learning). Evidence suggests that causal induction from interventions develops early in human development, and may be lacking in nonhuman species, though the comparative question is only beginning to receive attention. Interventions may be effective in judging causal relationships because they permit the generation of many cell b and cell d events (see Fig. 1).

Important Scientific Research and Open Questions

While a consensus is starting to emerge regarding the complementary roles of bottom-up (e.g., associative) and top-down (e.g., rational) models of causal learning and induction, this is by no means a ubiquitous view (Shanks et al. 1996). One or the other approach may yet win out favor over the other. In fact, rational (propositional) processes have recently been proposed as an alternative account for bottom-up associative processes. Nevertheless, the nature of the relationship between associative and rational accounts is still an open question. Another important area of future inquiry concerns brain–behavior relationships in causal learning and inference. Imaging methods are starting to identify neural structures active during causal inference in humans. But more experimental approaches that dissect the contribution of neural systems to causal processes are still needed to move beyond hypothesis generation and into establishing the brains mechanistic role in causal learning and inference.

Cross-References

► Animal Learning and Intelligence
► Associative Learning
► Bottom-up- and Top-down Learning
► Bounded Rationality and Learning
► Contingency in Learning
► Human Causal Learning

► Human Contingency Learning
► Inductive Reasoning
► Inferential Learning and Reasoning
► Normative Reasoning and Learning
► Pavlovian Conditioning
► Psychology of Learning (Overview Entry)
► Role of Prior Knowledge in Learning Processes

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Causal Learning and Illusions of Control

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Synonyms

Contingency learning; Illusions of causality; Superstitious behavior

Definition

► Causal learning is the process by which people and animals gradually learn to predict the most probable effect for a given cause and to attribute the most probable cause for the events in their environment. Learning causal relationships between the events in our environment and between our own behavior and those events is critical for survival. From learning what causes fire (so that we could either produce or prevent the occurrence of fire at will) to learning what causes rain, what causes cancer, or what caused that particular silly accident that we had with the car a few days ago, both the history of humankind and our individual history are full of examples in which causal learning is crucial. But, as can be said for other forms of learning as well, causal learning is not free of errors. Systematic biases and errors are known to occur under certain conditions. One of such common biases is the illusion of control. *The illusion of control can be defined as the belief that one's behavior is the cause of a desired event that is actually independent of it.* Illusions of control are an important factor in the development of superstitions. For instance, the superstitious belief that by dancing one can produce rain, is normally accompanied by the illusion of controlling rain.

Theoretical Background

The origins of research on causal learning can be traced back to the Greek philosopher Aristotle and it has ever since interested philosophers, experimental psychologists, cognitive scientists and, in general, all scientists interested in how humans learn and acquire knowledge. Nowadays, causal learning is generally studied in the experimental psychology tradition and is normally considered to be a central aspect of cognition. However, as it is the confluence of causal learning and the illusion of control research what we are addressing in this entry, it is interesting to note that this general cognitive perspective has not been applied to the study of the illusion of control until very recently. The illusion of control has traditionally been regarded as one of those cases in which the cognitive system fails to work in an adaptive manner. As such, the study of the illusion of control has been more often linked to Clinical, Health, and Social Psychology than to the Cognitive and Learning Sciences. Today, however, the study of the illusion of control is recovering its place as part of the Learning Sciences and is being regarded as the normal consequence of the way the learning system works.

In a typical laboratory experiment on the illusion of control, a given outcome (e.g., getting points in