Probability and Contiguity Trade-Offs in Causal Induction

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Abstract

Two experiments investigated the roles of contingency and temporal contiguity in causal reasoning, and the trade-off between them. Participants observed an ongoing, continuous stream of events, which was not segmented into discrete learning trials. Four potential candidate causes competed for explanatory strength with respect to a single dichotomous effect. The effect was contingent on two of these causes, with one of these (A) having a higher probability of producing the effect compared to the other (B), while B was more contiguous to the effect than A. When asked to identify the strongest cause of the effect, participants consistently and reliably selected A, as long as it was not separated from the effect by more than 2.5s. The extent of preference diminished, however, as the contiguity gradient between A and B increased. Beyond 2.5s, the high-probability, but low-contiguity cause A was seen as equally strong as the low-probability, but high-contiguity cause B, and both reliably stood out compared to the remaining two non-contingent distracter items. This apparent trade-off between contingency and contiguity, rooted in contrasting two of David Hume's (1739/1888) fundamental cues to causality, has important implications for psychological and statistical models of causal discovery, learning theory, and artificial intelligence.

KEYWORDS: Causality, Probability, Contiguity, Learning, Human Experimentation, Causal Inference.

Introduction

How do humans and other intelligent systems learn that one thing causes another? The contemporary cognitive science approach to this problem of induction can be traced back to David Hume (1739/1888), who famously argued that our sensory system is not equipped to directly perceive causality. Instead, he argued, reasoners have to interpret sensory experiences to create a mental representation of causality. Hume identified three principles underlying the formation of causal impressions: i) temporal priority of the cause *c* before the effect *e*, ii) temporal and spatial contiguity between *c* and *e*, and iii) constant conjunction between *c* and *e*. Only the latter two principles are of relevance to cognitive scientists, as the need for temporal priority of *c* over *e* is usually not debated (Reichenbach, 1956; but see also Savastano & Miller, 1998; and Tanimoto *et al.*, 2004 for discussion of bi-directional associations).

Computational approaches of causal induction have almost exclusively focused on the third Humean principle, which is commonly referred to as cause-effect *contingency*. Just how exactly contingency gives rise to causal impressions is still subject of a hot debate in the field. Suggestions range from using contingency (ΔP) - calculated by the difference between the two conditional probabilities: $P(e|c)-P(e|\neg c)$ – as a direct measure of causal strength (Allan & Jenkins, 1980; Jenkins & Ward, 1965) to more sophisticated judgment rules (e.g. Anderson & Sheu, 1995; Mandel & Lehman, 1998; White, 2003). An alternative suggestion (Shanks & Dickinson, 1987) is that causal learning may be no different from associative learning as exemplified by Rescorla & Wagner's (1972) model of Pavlovian conditioning. More recently, however, Cheng (1997) showed that all the above approaches fall short of representing causality as an unbound variable (Holyoak & Hummel, 2000), and suggested a computational causal power approach. A related approach (Buehner & Cheng, 2005) has been to model causal induction as Bayesian inference (e.g. Steyvers *et al.*, 2003; Tenenbaum & Griffiths, 2001).

In the midst of the vigorous debate over the computational details of covariation assessment, the second Humean cue – contiguity - got largely overlooked (but see Young, 1997). The majority of recent experimental studies have investigated how variations in contingency influence causal assessment; contiguity was never manipulated in these studies, and was usually kept at an immediate level.

Earlier work on causal reasoning, however, often focused on contiguity. Michotte (1946/1963) observed that even very short delays render an illusion of causal launching non-causal. In a completely different domain, Shanks, Pearson & Dickinson (1989) reported that people fail to distinguish causal from non-causal actions in an instrumental learning task when the action-outcome delay exceeded two seconds. The importance of Hume's second principle was acknowledged in early, non-computational psychological theories of causal induction (Einhorn & Hogarth, 1986; Young, 1995).

Two Cues Towards Causality: Contingency vs. Contiguity

Developmental psychologists attempted to determine which of the two cues, contiguity or contingency, is more important (Siegler & Liebert, 1974; Mendelson & Shultz, 1976; Shultz, 1982). These efforts were somewhat inconclusive, as they were closely entangled with another important principle of causal induction: understanding or knowledge of *mechanism* (Bullock *et al.*, 1982; Ahn *et al.*, 1995). Mendelson & Shultz, for instance, reported that whether a non-contiguous but contingent cause was preferred over a contiguous but non-contingent cause depended on variations in the physical make-up of the apparatus (i.e. mechanism), and whether such variations were commensurate with the experienced delay.

The role of causal mechanisms. Considerations of mechanism (and concomitant expectations of timeframes) have been suggested to interact with contiguity (Einhorn &

Hogarth, 1986): if reasoners assume that the mechanism linking cause and effect operates instantly, they should only consider immediate cause-effect pairings as evidence supporting a causal link; if the mechanism is thought to involve a delay, only delayed pairings ought to give rise to causal attributions. Buehner and May (2002, 2003, 2004) found partial empirical support for this *knowledge mediation hypothesis*: Delays were no longer detrimental in a causal judgment task modeled after Shanks et al. (1989), if participants expected a delayed relation. However, immediate cause-effect pairings were consistently rated as highly causal, irrespective of time-frame expectations.

These results suggest that knowledge of mechanism bridges temporal gaps; at the same time, however, experienced contiguity seems to override considerations of mechanism. Schlottmann (1999), for instance found that young children and adults readily learnt about two causal mechanisms with different timeframes. They could a) successfully predict the correct cause-effect timing for slow and fast mechanisms, and b) correctly infer (based on the experienced timeframe of the observed causal relation) which of the mechanisms (fast vs. slow) was hidden in a "mystery box". However, when contiguity and mechanism were directly pitted against each other in a forced choice task involving a contiguous and a delayed cause, young children consistently preferred the contiguous cause, even when this choice openly conflicted with well-established knowledge of a delayed mechanism. Experienced contiguity as a cue to causality thus seems to operate on a more fundamental level than higher-level considerations of mechanism.

Note that these studies did not vary the contingencies associated with each cause. While they illuminated the role of contiguity in causal induction, and how it interacts with knowledge of mechanism, they did not address the questions raised by developmental psychologists in the 1970s: Whether the two empirical cues to causality -- contingency and contiguity -- are equally important for causal induction.

A Computational Perspective. From a computational, perspective, one would expect that contingency is more fundamental than contiguity. After all, the ability to control and predict our environment – the goal of causal induction (Cheng, 1997) – is based on making use of regularity information. On the other hand, it is also evident that contiguity is vital for causal assessment. Time-lagged regularities are harder to detect, because event information needs to be kept in memory for longer; as the cause-effect interval increases, the number of potentially intervening (alternative) causes that need to be taken into account increases. In short, identification of causal relation becomes increasingly difficult as contiguity decreases.

Nonetheless, there is no causality without regularity (Cheng, 1993), and given sufficient computational resources, contingency should be the essential cue. In realistic, real-time situations, however, where computational resources are limited, one may well observe a tradeoff between the two cues.

Experiment 1

We developed a new experimental methodology aimed at studying the trade-off between contingency and contiguity in causal induction. We adopted Mendelson & Shultz's (1976) idea to pitch two causes, each with a high value on one, but a low value on the other dimension against each other. More specifically, one cause (A) had a higher contingency with respect to the effect than the other (B), but at the same time A was less contiguous with the effect than B. Unlike in Mendelson & Shultz' study, however, A and B were fully independent of each other and there was no interactive causal influence (Novick & Cheng, 2004) beyond the individual causal strengths. Furthermore, it was important to couch the task in a novel context so that participants would not have any pre-conceived notions of mechanism or expectations of time-frames. This allowed us to rule out any top-down influences and study contingency-contiguity trade-offs in a purely bottom-up manner.

To this end, we created a "Stargate" scenario: Participants were told they would observe a group of UFOs orbiting around a stargate; each UFO would attempt to open the gate. Because each UFO would use a unique signaling technique, some would be more successful than others at opening the gate, and some could open the gate faster (if successful) than others. Participants' task was to determine which UFO was most successful at opening the gate.

In designing the task, it was essential to avoid a discretely marked trial structure. Trial structures either confound contingency with contiguity (see Buehner & May, 2003) or remove the event-parsing aspect of causal learning (Allan *et al.*, 2003), resulting in an artificial judgment task that bears little resemblance with causal discovery. We used Macromedia Director to present participants with continuous event streams that were not divided into individual learning trials. Although the event stream was controlled by an underlying trial structure, the appearance to the participant was one of a continuous sequence of events. We strongly encourage readers to watch sample stimuli provided at
http://www.cardiff.ac.uk/psych/home/buehnerm/Stimuli

Method

Participants. Ninety-nine undergraduate students from Cardiff University participated to fulfill part of a course requirement.

Apparatus and Procedure. Event sequences were programmed using Macromedia Director, and displayed on a computer screen. The displays represented a 'stargate' in the middle of the screen, which was either open or closed, and four static UFOs, arranged near each corner of the gate. Each UFO had a unique color scheme for its two windows. A 'signalling' UFO was displayed with an overlay of colored stripes, with the color pattern matching the color scheme of the windows. By default, the stargate was closed, and UFOs were inactive. Activity (open gate, active UFO) was scheduled by the program and lasted 500ms. Figure 1 displays sample stimulus materials.

Figure 1. Stimulus Materials. The top right UFO is "active" in this screenshot, and the gate is closed.

Each participant worked on four conditions presented in random order, each consisting of a sequence of trials, presented in random order. The appearance to the participant was one of a continuous stream of events; trial delineation was not made explicit to the participant, and trials were not marked.

In each condition, activity of two UFOs (A&B) was probabilistically linked to the opening of the gate, with A always having a higher probability of opening the gate than B as specified in the Design section. The other two UFOs (C&D) were programmed to activate on 25% of the trials, at a random time throughout each trial; activity in these UFOs was unrelated to the gate opening. The base-rate of the gate opening was zero, i.e. it only opened conditional on activity in A or B. The locations and color schemes of each of the four UFOs were randomized for each condition.

The event-structure was organized as follows: If A or B were scheduled to be active on a given trial, they would emit a signal at a random point during the first 5 seconds of that trial. If the signaling was successful, the gate opened for 500ms after the relevant delay. Activity in A and B was independent of each other, so that on some trials both A and B would signal; on such trials, A and B would both produce the effect according to their respective probability and delay. In other words, A and B were truly independent of each other and did not interact to produce the effect (Novick & Cheng, 2004).

Participants observed the event streams for each condition, and then had to indicate which UFO was most successful in opening the gate. To this end, they were told to imagine they could "zap" one of the UFOs to emit a signal, and were asked to decide which UFO they would zap in order to open the gate. The experiment lasted about 30 minutes.

Design. The two variables of interest, Contingency and Contiguity, were controlled as follows. A always opened the gate with a higher probability than B. The extent of the probability gradient between A and B was manipulated between participants in five conditions: a) 75% vs. 25%; b) 75% vs. 50%; c) 100% vs. 25%; d) 100% vs. 50%; and e) 100% vs. 75%. Participants were randomly allocated to one of these pairs of probabilities.

The cause-effect contiguity of the low-probability cause (B) was always set to 500ms. The contiguity of the high-probability cause (A) varied within participants across four conditions, and took values of 500ms, 1000ms, 1500ms, and 2000ms.

Results

For sake of brevity, analyses are only reported for data collapsed across the five probability gradients.[1] All statistical analyses are based on an alpha-level of .05 with Bonferroni-corrections for multiple tests, where applicable.

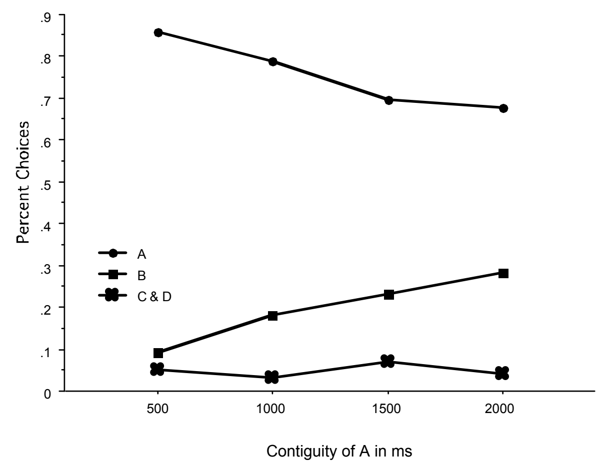

Figure 2. Experiment 1: Percentage of Participants (N=99) choosing Causes A or B or one of the two unrelated events (C&D).

Inspection of Figure 2 suggests that participants consistently selected the high-probability cause A, even when its contiguity with respect to the effect was degraded. However, the degree of preference of A over B seems to diminish as the contiguity of A decreased. Choices for the unrelated distracter causes (C&D) were below 10% in all conditions, and thus well below the chance level of 50%, (all *p*s <.001 on a Binomial test).

We constructed three separate and mutually exclusive dichotomous choice variables for causes A and B, and the two unrelated events (C&D). The proportion of choices for A was significantly higher than that for B across all four levels of contiguity (all *p*s<.001 by sign test). Cochran's Q tests with corrected alpha-level (*p*=.017) were conducted to assess the influence of contiguity on choice patterns.

[1] Preliminary analyses revealed no effects or interactions associated with probability gradient, suggesting that participants distinguished equally well between high (A) and low (B) contingencies in all five conditions.

Choices for A significantly decreased as A's contiguity with respect to the effect decreased, $Q(3,99)=13.541$, while choices for B significantly increased, $Q(3,99)=14.415$. Choices for the two unrelated causes were not affected by variations in A's contiguity, $Q(3,99) = 2.561$.

Discussion

Participants were clearly able to extract contingency information from a continuous stream of events that contained no observable trial boundaries. They reliably and consistently identified the cause that was followed by the effect with the highest probability among a choice of four. Moreover, this preference for a high-probability cause was maintained in the face of degraded contiguity: although B was highly contiguous with the effect (500ms), A was consistently preferred as the stronger and more effective cause due to its higher probability, even when A was separated from the effect by as much as 2s. The extent of this overall preference decreased, however, as the contiguity contrast between A and B increased. Experiment 1 thus suggests that people put more importance on contingency than on contiguity as reliable cues towards causality; at the same time, there seems to be some trade-off between the two, with participants shifting more weight on contiguity, as the contiguity contrast increases.

Experiment 2

Shanks et al. (1989) reported that participants failed to distinguish causal from non-causal actions when the action-outcome interval exceeded two seconds (but see Buehner & May, 2003). Perhaps the contiguity gradient in Experiment 1 was not steep enough to observe a shift from contingency to contiguity. Experiment 2 thus replicated Experiment 1, but employed a larger contiguity contrast between causes A and B: while B was still associated with a 500ms delay, A's delay could take on values of 2500ms, 3250ms, and 4000ms.

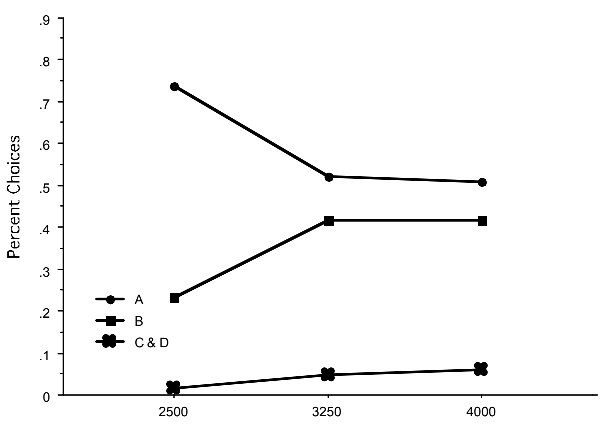

Figure 3. Experiment 2: Percentage of Participants (N=65) choosing Causes A or B or one of the two unrelated events (C & D).

Method

Participants. Sixty-five undergraduate students from Cardiff University participated to fulfill part of a course requirement.

Apparatus, Procedure, and Design. The same design and procedure as in Experiment 1 was employed, except that the contiguity of A could take on values of 2500ms, 3250ms, and 4000ms (varied within-subjects), while the contiguity of B remained at 500ms. The same five probability gradients as in Experiment 1 were varied between subjects.

Results

Results and Discussion

Inspection of Figure 3 suggests that A is no longer preferred over B when A's delay exceeds 2.5s. As in Experiment 1, choices for distracter items C&D never exceeded 10% in any of the conditions, again well below the chance level of 50% (all *p*s < .001 on a Binomial test).

The proportion of choices for A was significantly higher than choices for B in the 2500ms condition, $Z=4.032$, $p<.001$ on a Sign test; no significant difference in choice patterns was obtained in the 3250ms and 4000ms conditions, $Z=.768$ and $Z=.645$, respectively. Choices for A significantly declined as the contiguity of A decreased, $Q(2,65)=15.630$, while choices for B significantly increased, $Q(2,65)=9.600$; choices for C were not affected by variations in A's contiguity, $Q(2,65)=2.000$.

As expected, with a steeper contiguity gradient, contingency no longer dominated choice patterns. Both cues were equally important in determining choice patterns. Remarkably, B never was preferred over A, suggesting that contiguity was never more important than contingency, at least not within the parameters of this design.

General Discussion

The goal of this paper was to investigate how contiguity and contingency relate to each other in causal induction. In particular, we wanted to find out whether people selectively weigh one cue as more important than the other. Towards this end we created a novel experimental setup, which allowed us to study causal induction under ecologically valid conditions: events were presented in one continuous flow, with no discrete trial boundaries. Within this framework, event parsing becomes part of causal induction, as it does in real life. Our choice of scenario furthermore ruled out recruitment of prior knowledge of mechanism and associated timeframes. Previous experiments investigating the role of contiguity within demarcated learning trials examined contrasts between experienced and expected timeframes (e.g. Allan et al., 2003). In such studies, variations of contiguity determined whether each individual *trial* was seen as evidence for or against the causal relation in question. In our design, the absence of trials made such evaluations immaterial. Instead, participants had to consider the entire stream of events when making causal judgments.

This trial-free notion of causal learning is similar to rate-based accounts of learning (Anderson & Sheu, 1995; Gallistel & Gibbon, 2000). Anderson & Sheu, for instance, found that causal judgments followed a grating contrast based on the rates of effect occurrence conditional on the presence vs. the absence of the cause. In their instrumental learning task, Anderson & Sheu varied response-outcome intervals while keeping contingencies constant. While they reported sensitivity to both contiguity and contingency, their design did not allow systematic investigations of the interaction between the two cues (for a related argument on relative contiguity, see also Wasserman & Neunaber, 1986).

As we have argued in the introduction, degradations in causal judgment due to reductions in contingency follow readily from a computational analysis of the inductive problem; degradations due to reduced contiguity may appear non-normative (apart from mis-matches between expected and experienced time-frames), but nonetheless are to be expected under realistic circumstances involving limited memory and computational resources. What was less clear, however, was how these two cues interact to determine causal induction. Our results suggest a dominance of contingency over contiguity. This dominance is moderated by a trade-off curve, however, such that contingency gradually loses its dominance when the cause-effect delay increases.

When considering such trade-offs, it is important to separate *utility* from *causality* (Oaksford & Chater, 1998). A response may have perfect contingency with a desired outcome, but produce the outcome only after a long delay. An alternative response may produce the outcome right away, but unreliably. Depending on the cost of responding and the time available to interact with the environment, it may be more beneficial for the organism to engage in the low-contingent response. Our experiment asked participants to select the cause that is most successful in producing the effect (without any reference to time). The one-shot nature of our dependent measure clearly requested an answer based on causality, rather than utility, and our results show that people were aware of this.

We hope that our empirical results will inform and constrain modeling efforts in event parsing and statistical learning. Our current results indicate that contiguity at best is equally important as contingency, but never outweighs it. Future research will need to investigate whether this parameter ordering also holds in situations involving steeper contiguity gradients.

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