**Part II: Sciences**

**CHAPTER 6 OF “TIME AND CAUSALITY ACROSS THE SCIENCES”**

**6. Unifying Intervention and Time in Causal Learning**

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**ABSTRACT**

Both interventions and temporal information have received considerable attention in psychology as cues for learning causal structure. We survey the recent literature and propose a unification. In particular, we highlight recent work on the development of the capacity to generate and learn from interventions, and on adults' use of intervention to learn locally and incrementally in complex situations with many variables. We also trace the evolution of psychological perspective on learning from events in time, from simple conditioning to recent work showing sophisticated interactions between new evidence and established causal model-based expectations. Finally, we will argue that intervention and time are difficult to separate both conceptually and experimentally and discuss some new work exploring human intervention selection and causal learning in continuous time.

Refer to: Buehner, Rottman, Lagnado, Sloman, Pacer, Davis, Bramley

**Very rough plan:**

* Time plus noise reveals (part of) causality, i.e. if X^t-1 predicts Y^t is either an effect of X or they share a parent (i.e. granger causality), a signal is passed forward
* Crucially, interventions inject bespoke ‘noise’ signals and rule out shared parents
* However, their role, and how to choose them, depends on the sophistication of one’s representation and measurements of the environment
* Now survey from CBNs upward:
* Finish by discovering real time control as the ultimate window on causality.
* Note that the natural level of human causality is the continuous variable continuous time case

Mention the Steyvers aliens as an example where the signal can be very idiosyncratic

Other end of spectrum, noisy generative binary case, the ``signa” is very weak, and we only get “successor” data (todo, read papers on this).

**We return to 2—3 working examples throughout.**

1. Classic high-level scenario (repeatable across similar individuals): Like rock music -> play in rock band -> get tinnitus (stay in school, get good job, have midlife crisis) – *these kind of generalities work ok in CBN form, interventions work across repeated general contexts (time usually muddied).* Or else, policies and other factors – buy-bust effect on drug crime; testing effect on school attainment and psychological health… *Can imagine, size or nature of intervention might be a recoverable signal (i.e. correlation between number of tests and later-life satisfaction)*.
2. Economy (many shocks, feedback etc, hard to intervene) - *discretisa­­­­tion can be problematic, but formidable complexity*
3. Heterogeneous Rube-Goldberg event sequence: Candle burns through string, laundry falls, knocks over cup, hits switch, turns on fan, blows door shut etc. – *here we use intuitive physics to predict effects, mostly order only, but time important if one path unlocks another. Probabilities relate more to subjective uncertainty about states forces etc (ground truth feels deterministic).*

(D) A cyclic system: Maybe A “drinking bird” – 1 The water evaporates from the felt on the head. 2 Evaporation lowers the temperature of the glass head ([heat of vaporization](https://en.wikipedia.org/wiki/Enthalpy_of_vaporization)). 3 The temperature decrease causes some of the dichloromethane vapor in the head to condense. 4 The lower temperature and condensation together cause the pressure to drop in the head (by the [ideal gas law](https://en.wikipedia.org/wiki/Ideal_gas_law)). 5 The higher [vapor pressure](https://en.wikipedia.org/wiki/Vapor_pressure) in the warmer base pushes the liquid up the neck. 6 As the liquid rises, the bird becomes top heavy and tips over. 7 When the bird tips over, the bottom end of the neck tube rises above the surface of the liquid. 8. A bubble of warm vapor rises up the tube through this gap, displacing liquid as it goes. 9. Liquid flows back to the bottom bulb (the toy is designed so that when it has tipped over the neck's tilt allows this). Pressure equalizes between top and bottom bulbs. 10. The weight of the liquid in the bottom bulb restores the bird to its vertical position 11. The liquid in the bottom bulb is heated by ambient air, which is at a temperature slightly higher than the temperature of the bird's head. – *here we need some intuitive physics to pick our interventions, heating the beak, adding more fluid etc… CBN doesn’t really work, need continuous vars*

1. **Interventions can be “shocks”** (aka manipulations) and/or **“blocks”** (aka controlling confounding). Their role shifts with the context, specifically the degree of timekeeping, and the type of variables. Shocks inject change/information into causal system without changing its structure. Sustained interventions also block, e.g. they absorb all incoming influences to a variable potentially revealing others.
2. **Sketch a 2 dimensional space of causal inference contexts with different degrees of knowledge of timing, and different levels of variable richness**
   1. Top left: **Classic causal Bayesian network** settings (Bramley etc, Sloman etc, Griffiths etc, Coenen etc) – Causal variables are states present/absent (could be occurrence/non occurrence of event in time window) (or n-ary) and timekeeping is very weak. We are able to observe only after performing our interventions and waiting “long enough for causality to propagate, but not so long that it dies out”. Tests are IID (i.e. we test multiple clones of the same scenario, or we wait “long enough” again for the first test/state etc to be washed away. Here interventions have a special role because they are the only reliable time signature. They are both shocks and blocks.
   2. Middle left: **Time order only** (Bramley etc, Langado etc, stepwise inference stuff from rottman) Order only. Causal variables are events (or state changes). Timekeeping is purely ordinal. But trials separated by “enough time” to reset system. Causal inference impoverished/heuristic but can be made perfect with interventions. Shocks make things happen. Blocks allow for tracing of causal path.
   3. Bottom left: **Events in real time** (Time in causal structure learning/ Pacers’ rates etc) – Question of “when” to intervene. Vanishingly unlikely that event would have occurred ­­­­