Causal Emergence of "Soft" Events

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Abstract

Some events, like moods or qualitative evaluations, are not grounded in any particular observations or actions but can emerge as the result of internal or external interactions. "Opinion" rules extracted from diverse sources such as blogs, newspaper articles, chat rooms, etc. can be synthesized together into a fuzzy cognitive map linking event nodes together. We explore in this paper how to learn fuzzy cognitive maps with dynamic programming techniques.

Introduction

How can we predict "soft" events that have more to do with our subjective interpretation of events than the rigorous observations of facts? Events in this category include complex political events (Axelrod, Nozicka, & Shapiro 1976; Kosko 1992), such as the eruption of war or the instability of a government, and also simple real-world events for which we get a "hunch" (e.g. whether a marriage will last or someone will get hired (Gladwell 2005)). A cognitive map is a representation that loosely links events together through rules of thumb and association rules. A cognitive map is also a decision-making tool when actions underlie certain events. The recent explosion of user-generated content such as blogs provides new sources of data for mining "opinion" rules characterized by the positive or negative association of events casually expressed as pros and cons. Those "opinion" rules can then be synthesized into cognitive maps which can be further learned using dynamic programming techniques. What is learned is the strength of a node at equilibrium that can be used to predict the emergence of "soft" events and to detect the causal relationships of desired events in what-if simulations. This position paper explores this technique, which can substitute for the extraction of micro-behavior rules in population-based methods, to predict emergent events from multi-agent interactions.

This paper is organized as follows. Learning cognitive maps is first introduced. Then we present the relevant dynamic programming (DP) techniques to evaluate the emergence of events in a cognitive map. We then illustrate this methodology with an example and present some conclusions.

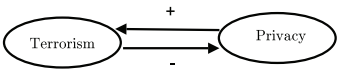

Figure 1: Simple cognitive map describing the opinion that terrorism dilutes privacy but that increased privacy facilitates terrorism.

Learning Cognitive Maps

Simple cognitive maps are a graphical representation tool of the cause-and-effect relationship between concepts, events, actions, etc. expressed as directed edges between nodes (Fig. 1). They differ from other graphical representations for problem solving, such as Bayesian belief nets and influence diagrams, mainly because feedback loops, i.e cycles, are allowed. Fuzzy cognitive maps further expand this representation by assigning a value to the edges in the fuzzy causal range $[-1, 1]$ and a value A at the nodes as an adaptive function f of the sum of all incoming edges W times the value of the causal nodes as follows:

$$A_i(t+1) \leftarrow f(A_i(t) + \sum_{j=1, j\neq i}^{n} W_{ji} A_j(t)) \qquad (1)$$

If the function is a sigmoid function, this value is bounded within $[0, 1]$ and can be evaluated comparatively with other value nodes. Fuzzy cognitive maps have been learned successfully as an associative neural network (Kosko 1992). Few other learning paradigms have been applied to cognitive maps (E.I. Papageorgiou & Vrahatis 2004). Several expert opinions can be combined in a single cognitive map.

Dynamic Programming Techniques

Dynamic programming has been used extensively to solve shortest-path optimization problems and Markov decision processes involving sequential decision-making. It works by reinforcing an estimate from component estimates until convergence according to the principle of optimality (Atallah 1999). In the case of cognitive maps, the components are the nodes specified in the adjacency matrix of causal relationships. Given a problem decomposition into subproblems in a recurrence relation, a DP algorithm computes the node values based on the value of their components in a bottom-up

fashion. Dynamic programming is a brute-force approach since it needs to compute all node values and not just the relevant ones in order to arrive at an exact solution and the challenge is to scale up through approximate solutions. For example, the DP equation to compute the largest set of subtrees through node i with children $C(i)$ is as follows:

$$L(i) \leftarrow \max_{i' \subset C(i)} (1 + \sum L(i')) \tag{2}$$

In stochastic dynamic programming, the transition between nodes is uncertain, reflecting the confidence of an associative "opinion" rule that one event A implies another event B computed as the conditional probability of event B given event A, that is $\frac{\#texts\, relating\, A \cap B}{\#texts\, relating\, A}$ in a text mining context. The cognitive map equation (Eq. 1) is a stochastic DP equation given P_{ij}^W the probabilities from node i to node j in the opinion set W where r_{ij} reflects whether A_i is favorable to $A_j(\pm 1)$.

$$A_i(t+1) \leftarrow f(A_i(t) + \sum_{j=1, j \neq i}^{n} P_{ij}^W r_{ij} A_j(t)) \tag{3}$$

The key differences from fuzzy cognitive maps and temporal associative memories (Kosko 1992) are that (1) the links express probabilistic non-determinism in the causal relationships between nodes rather than fuzziness and (2) that Monte Carlo simulations rather than neural network "tuning" lead to the inference of future events. In a Monte Carlo simulation, $A_i(t+1)$ is approximated as a moving average based on a random sample and modulated by the learning rate α:

$$A_i(t+1) \leftarrow (1-\alpha) A_i(t) + \alpha \arg sample_j P_{ij}^W r_{ij} A_j(t) \tag{4}$$

Illustration

Figure 2 shows a cognitive map for a counter-insurgency doctrine extracted from a recent opinion article (Fick 2007) on the current situation in Afghanistan. The cycles (e.g., C4, C5, C6, C7, C4) express the paradoxes of this problem. Table 1 shows the evaluations of nodes C1 and C7 using DP (Eq. 4) with the cognitive map of Fig. 2 and successively "clamping" C8 (Infrastructure), C4 (Force Protection) and combined C8 and C4. The hyperbolic tangent function bounds node values in the [-1,1] range. The results show the paradox described in the article, namely, how insurgency increases with an increase in Force Protection without establishing legitimacy for the government. Combining Force Protection with increased Infrastructure (C4+C8) produces the best results according to this cognitive map.

Conclusions

Of course, opinions are just opinions and do not guarantee the accuracy of scientific determinism. However, in the broader sociological context, opinions can influence behavior and consequently the course of events. They can be self-fullfilling prophecies. Dynamic programming can preserve the feedback loop property of cognitive maps and their predictive power of "soft" events as well as identify the tipping points necessary to influence a course of events. This claim was illustrated with an example of a synthesized cognitive map from manually extracted opinions on recent events.

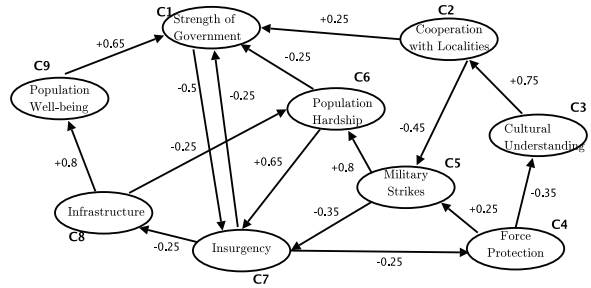

Figure 2: Counter-insurgency cognitive map and influence

Iter	C1/ C8	C7/ C8	C1/ C4	C7/ C4	C1/ C8+C4	C7/ C8+C4
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	1.0	0	0	0	0.720	-0.503
4	2.25	0	0	0	1.76	-0.0156
5	2.25	-0.0063	0	0	2.97	-0.0303
6	3.37	-0.0175	0	0	4.18	-0.047
7	3.36	-0.0265	0	0	4.17	-0.0594
8	3.36	-0.0365	-0.0125	0	4.16	-0.0676
9	4.02	-0.0432	-0.0193	0.0005	4.82	-0.0723
10	4.02	-0.0471	-0.0193	0.0005	4.81	-0.0723

Table 1: DP cognitive map evaluation (multiplied by 10^4) of Fig. 2 ($\alpha = 0.01$)

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