Modeling Deliberation Over Combinatorially-Structured Domains: Similarity, Attraction and Compromise Effects

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Introduction and Motivation

Recently, preference reasoning has grown into an important topic in Artificial Intelligence. Preference models are currently used in many AI applications, such as scheduling and recommendation engines.

On the other hand, in psychology, Decision Field Theory (DFT) [J.R. Busemeyer, 1993] formalizes the process of deliberation in decision making. While DFT has mainly tackled the problem of making a single decision, decision can be more complex and it can be helpful to organized them in a combinatorial structure over which decisions can be applied sequentially.

In [Martin, 2018], we introduce a model where soft constraints support a deliberation process performed through DFT and we consider a sequential approach, where deliberation is applied to each variable. Here we consider three important effects in human decision making studied in multialternative DFT, namely, the similarity, attraction and compromise effect. We show that our approach captures these phenomena where complex decisions are decomposed in a combinatorial structure.

Background

Soft Constraints Soft constraints are an AI formalism for expressing preferences over large sets of options compactly. A soft constraint [Meseguer, Rossi, and Schiex, 2005] requires a set of variables and associates each instantiation of the variables to a value from a partially or totally ordered set. In fuzzy constraints the set of preferences is interval $[0, 1]$, so for example a fuzzy constraint on variables X and Y, both with domain $\{a, b\}$, would, associate preference 0.8 to tuple $(X = a, Y = b)$, etc. A Soft Constraint Satisfaction Problem (SCSP) is a tuple $\langle V, D, C, A\rangle$ where V is a set of variables, D is the domain of the variables and C is a set of soft constraints (each one involving a subset of V) associating values from A. Given assignment to all the variables, its preference is obtained combining the preferences coming from all of the constraints with an appropriate operator. In Fuzzy CSPs (FCSPs) this is min. An optimal solution, say s, of an SCSP is then a complete assignment with an undominated preference. Optimal solutions are found using search algorithms, like branch and bound, which exploit methods for propagating preferences from one variable to another via the constraints. Unless certain restrictions are imposed, such as a tree-shaped constraint graph, finding an optimal solution is an NP-hard problem [Meseguer, Rossi, and Schiex, 2005].

Multialternative Decision Field Theory Decision Field Theory (DFT) attempts to formalize the deliberation process by assuming that a decision maker's preference for each option evolves during deliberation and by integrating a stream of comparisons of evaluations among options on attributes over time [R. Roe, 2001]. Multialternative DFT extends DFT to settings with more than two options. In DFT a valence value $v_i(t)$ is associated with a choice to be made at any moment in time t, which represents the advantage or disadvantage of some attribute of options i when compared with other options. The valence vector, $V(t) = CMW(t)$ is a product of three matrices (C, M and $W(t)$) and represents the valence of all of the options. The first matrix contains the personal evaluation of each option with respect to each attribute. The second component is a vector of attention weights, $W(t)$, allocated to each attribute at a particular moment in time. The third and final matrix C contains parameters describing how to aggregate the evaluation of an option with the evaluation the other options in order to obtain its advantage (or disadvantage). Furthermore, at any moment in time, each alternative is associated with a preference strength $P(t)$, strength for alternative i at time t, denoted $P_i(t)$ representing the integration of all the valences considered for alternative i from the start of the deliberation process up to to time t. A new preference $P(t + 1)$ is formed at each moment from the previous preference $P(t)$ and the new input valence vector, $V(t+1)$,as follows $P(t+1) = SP(r) + V(t+1)$. Here matrix S models how the preference of one option influences the preference of another option. For example, one can assume a higher (negative) interaction among options which are very similar.

Effects in Human Decision Making Certain behavior have been identified as characterizing human decision making. The similarity effect occurs when introducing a new competitive option to the choice set reduces the probability of choosing similar options. The attraction effect shows that the introduction of a new dominated option to a choice set increases the probability of choosing the dominant product. Finally, the compromise effect refers to the fact that when three options are available, the compromise option is chosen more frequently than either of the extremes.

Sequential decision making over soft constraint networks

In [Martin and Venable, 2018] we describe a sequential approach for decision making over soft constraint networks. We assume a set of correlated decisions to be made, $X = \{X_1, \ldots, X_n\}$, where each variable X_i can take different values from its domain. To represent the agent's personal evaluation we use a FCSP defined over the variables in X for each attribute. If, for example, we wanted to buy a car, variables could describe different car models, and could be brand, engine and type. Then, we would have a FCSP for each attribute, that is one describing the preferences in terms of, say, fuel efficiency and one for comfort. The preference values from the FCSPs, are used to populate DFT's matrix M. We consider tree-shaped FCSPs with topological order of the variables $O = X_1 > X_2 > ..... > X_n$. Proceeding sequentially, at each step we deliberate a value for a variable X_i via DFT and we propagate the effect of this decision to the variables yet to be assigned, using soft constraint propagation.

Exeprimental results

We implemented this sequential decision making approach and we test it on randomly generated problems with two attributes and three variables. Each generated instance comprises of a pair of tree-shaped FCSPs over the same set of variables. We consider variable domain sizes between 2 and 8 with increments of 2 and a number of deliberation iterations ranges between 20 and 50. In order to show that the sequential procedure does not violate the three essential experimental findings concerning multichoice situations, we replicate the corresponding scenario is our combinatorial setting. In particular, we consider both settings in which the FCSPs are constrained to have only 2/3 solutions as well as setting where the effects are observed on a subset of solutions among many others. In both cases we define the preference in the constraints so to exhibit the appropriate behavior.

In all of the experiments we introduced two solutions A and B which asymmetric preferences in the two FCSPs (i.e., A is hugely preferred in one and disliked in the other FCSP and viceversa for B). Then a third solution C was introduced with a preference defined according to the effect that we want to observe. In the similarity case C's preferences are similar to A's in both FCSPs, in the attraction effect C's preferences are slightly below A's and in the compromise effect they are in between A's and B's preferences in both FCSPs.

The behavioral effects are preserved for decision over a combinatorial domain. In Figure 1 the probabilities of A and B being chosen decrease and reverse when C is introduced. In Figure 2 the introduction of C increases the probability of choosing A over B. In Fig 3 C has a higher probability of choosing A or B.

Future Work

In the future, we plan to test our model on behavioral data of human decision making over complex domain and in data sets

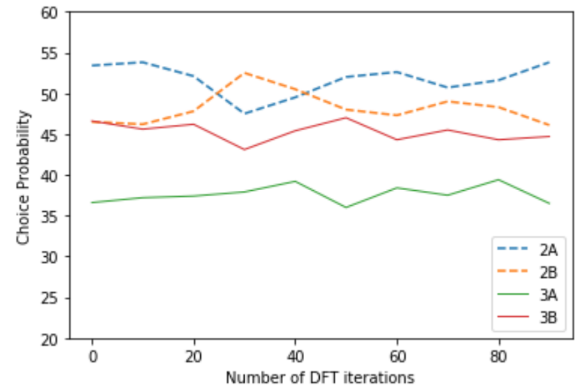

Figure 1: Similarity effect: probability of choice over 100 runs as a function of the number of deliberation iterations. 2A/2B probability of choosing option A/B without C. 3A/3B probability of choosing A/B when option C is available.

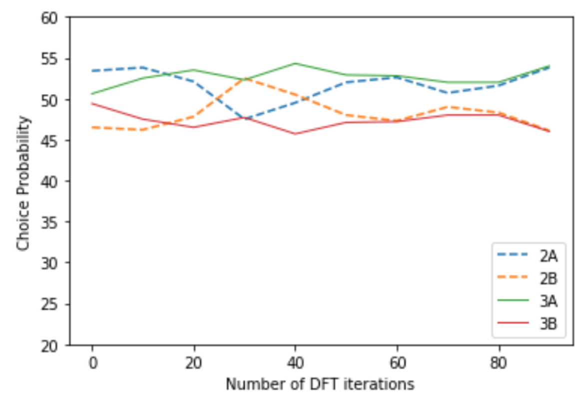

Figure 2: Attraction effect: 2A, 2B, 3A and 3B as in the caption of figure 1

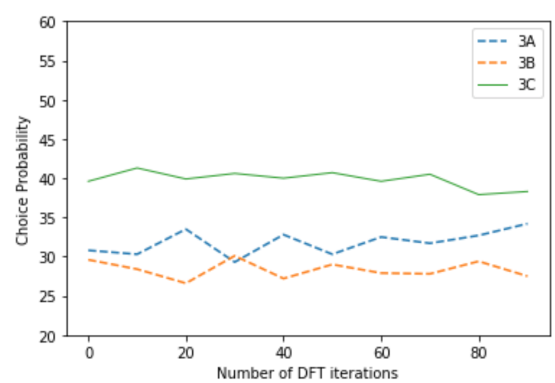

Figure 3: Compromise effect: 3A, 3B and 3C as in the caption of figure 1

in PrefLib [Mattei and Walsh, 2013]. We also intend to investigate the use of other compact preference models, such as probabilistic CP-nets [Boutilier et al., 2004] which look like a very interesting candidate to represent preferences according to attributes and their weights in the deliberation procedure.

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