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Decision field theory: Improvements to current methodology and comparisons with standard choice modelling techniques

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A B S T R A C T

There is a growing interest in the travel behaviour modelling community in using alternative methods to capture the behavioural mechanisms that drive our transport choices. The traditional method has been Random Utility Maximisation (RUM) and recent interest has focussed on Random Regret Minimisation (RRM), but there are many other possibilities. Decision Field Theory (DFT), a dynamic model popular in mathematical psychology, has recently been put forward as a rival to RUM but has not yet been investigated in detail or compared against other competing models like RRM. This paper considers arguments in favour of using DFT, reviews how it has been used in transport literature so far and provides theoretical improvements to further the mechanisms behind DFT to better represent general decision making. In particular, we demonstrate how the probability of alternatives can be calculated after any number of timesteps in a DFT model. We then look at how to best operationalise DFT using simulated datasets, finding that it can cope with underlying preferences towards alternatives, can include socio-demographic variables and that it performs best when standard score normalisation is applied to the alternative attribute levels. We also present a detailed comparison of DFT and Multinomial Logit (MNL) models using stated preference route choice datasets and find that DFT achieves significantly better fit in estimation as well as forecasting. We also find that our theoretical improvement provides DFT with much greater flexibility and that there are numerous approaches that can be adopted to incorporate heterogeneity within a DFT model. In particular, random parameters vastly improve the model fit.

1. An introduction to decision field theory

Random Utility Maximisation (RUM) models have dominated the field of choice modelling for over 40 years (McFadden, 2000), particularly in travel behaviour research (Ben-Akiva and Bierlaire, 1999). Recently, however, there has been increasing interest in using alternative methods to make the models flexible to accommodate departures from behaviours assumed under RUM. A key example in transport research has been Random Regret Minimisation (Chorus et al., 2008; Chorus, 2010), which assumes that decision-makers seek to minimise negative emotions rather than maximising positive ones. Another example comes in the form of Bayesian Belief Networks (Parvaneh et al., 2012), which take a more heuristic approach, looking at an individual's past experiences and expectations about the different alternatives available.

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Whilst these new methods both make more of an effort to consider the underlying cognitive processes in decision making, another model, Decision Field Theory (Busemeyer and Townsend, 1992; 1993), was designed purely as a cognitive model to capture the deliberation process in decision making. Decision Field Theory (DFT) is a stochastic-dynamic model of decision-making behaviour, which was expanded to include multi-attribute (Diederich, 1997) and then multi-alternative decision-making (Roe et al., 2001), where it was renamed multi-alternative decision field theory (MDFT).[1]

Due to the psychological roots of DFT (Busemeyer and Diederich, 2002), it has predominantly been used to explain behaviour not typically studied using "traditional" choice models. DFT can theoretically explain similarity, attraction and compromise effects (Roe et al., 2001) and this has largely been the focus of DFT research with many papers looking into how well it can explain these context effects compared to other models (Tsetsos et al., 2010; Trueblood et al., 2013; Noguchi and Stewart, 2014). It is of course true that RUM models can also be used to test such effects, with notably Nested Logit being used to study the similarity effect (Guevara and Fukushi, 2016) or preference reversals (Batley and Hess, 2016). However, Decision Field Theory further differentiates from these models by being a dynamic model. This means that it can successfully be used to study risky choices or the effect of time pressure (Busemeyer and Townsend, 1993; Diederich, 1997; Dror et al., 1999). Despite the success of DFT in explaining time and context effects, it has not often been used to explain riskless choices or decision making in general.

We address this research gap in this paper by providing theoretical improvements to further the mechanisms behind DFT to better represent general decision making, incorporating potential effects of socio-demographic variables and accommodating for heterogeneity. The models are rigorously compared against RUM and RRM, both for estimation and prediction, using simulated and real datasets.

The remainder of this paper is organised as follows. The next section provides a comprehensive review of DFT: how it works, comparisons with other models and arguments in favour of using DFT. Section 3 gives our theoretical improvements for DFT. Section 4 presents the data and looks at our results from using DFT and Section 5 presents some conclusions.

2. Overview of decision field theory

Thus far, Berkowitsch et al. (2014) have provided the only comparison of DFT against mainstream choice models. As far as we are aware, DFT has never been compared to RRM or other alternative models from choice modelling, nor have the predictive capabilities of DFT been tested. We do not yet know if specific types of choices will be better explained by DFT or if certain decision-makers may be better represented by a DFT model.

In the following subsection, a summary is provided for the basic mechanisms of DFT. We then consider arguments in support of DFT and look further into how it has been used so far in transport research. We conclude by looking at how DFT has been compared to RUM thus far.

2.1. Mechanisms of decision field theory

Basic mechanism

The main idea behind Decision Field Theory is that each available alternative has a 'preference value', which updates over time. At each step, the current values are multiplied by a 'feedback matrix' before then adding on a valence vector (which can be considered as a utility at a specific moment) at that time. In its most basic form, we have:

$$P_t = S \cdot P_{t-1} + V_t, \tag{1}$$

where P_t is a column matrix containing the current preference values for each alternative at time t, and S is a feedback matrix which contains three parameters (see Section 2.1). P_{t-1} is the previous preference vector and P_0 is the initial preference vector. This is often assumed to be $[0, .., 0]'$ (Busemeyer and Diederich, 2002). Finally, V_t is the random valence vector at time t, given by:

$$V_t = C \cdot M \cdot W_t + \varepsilon_t, \tag{2}$$

where C is a contrast matrix, used to compare alternatives against each other, with $c_{i,i} = 1$ and $c_{i,j\neq i} = -1/(n-1)$, where n is the number of alternatives, and M is the attribute matrix. DFT is scale-variant (Busemeyer and Diederich, 2002) and we explore the implications of failing to ensure that the attribute matrix has been appropriately scaled in Section 4.3. At each time, t, one attribute is attended to, such that $W_t = [0..1..0]'$ with entry $j = 1$ if and only if attribute j is the attribute currently being attended to. The probability of attending to attribute j is w_j. Since these weights must sum to one, a standard uniform distribution $X \sim U(0, 1)$ can be used to select which attribute a decision-maker attends to at each timestep. It is assumed that there is no relationship between the timesteps, which means an attribute could be considered for several consecutive timesteps before the decision-maker considers a different attribute. There is also a random error vector, $\varepsilon_t = [\varepsilon..\varepsilon]'$, with $\varepsilon \sim N(0, s)$ added on to allow for flexibility in the variation of probability values that DFT predicts. The variance for the error, s, is often fixed to 1 (Trueblood et al., 2014) but can also be an estimated parameter.

[1] Some authors refer to decision field theory as DFT, others use MDFT. We shall henceforth use DFT.