Fuzzy Preferences for Multi-Criteria Negotiation

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The Negotiation Problem

We are interested in how cooperation can arise in types of environments, such as open systems, where little or nothing is known about the other agents. We view the negotiation problem as a strategic and communication rich process between different local preference/decision models. This contrasts with the classical cooperative game theoretic (axiomatic) view of negotiation process as a centralized and linear optimization problem. Although unconcerned with the processes of negotiation, such axiomatic models of negotiation (in particular those of mechanism design tradition) has assumed optimality can be achieved through design of normative rules of interactions that incents agents to act rationally (Neumann & Morgernstern 1944),(Rosenschein & Zlotkin 1994),(Binmore 1990),(Shehory & Kraus 1995),(Sandholm 1999). Likewise, in operation research the focus is the design of optimal solution *algorithms* based on mathematical programming techniques (Kraus 1997),(Ehtamo, Ketteunen, & Hamalainen 2001),(Heiskanen 1999),(Teich *et al.* 1996). In both cases optimality is achieved because: a) the geometry of the solution set is assumed to be described by a closed and convex set (therefore there is a bounded number of solution points), b) the objective functions of the individuals (the utility function) are concave and differentiable and c) some global information (such as the actual utility of the agents or the utility gradient increase vector (Ehtamo, Ketteunen, & Hamalainen 2001)) is stored by a (hypothetical) centralized mediator that (incents) acts to direct problem solvers towards pareto-optimality. However, although analytically elegant, such optimality can not be guaranteed in decentralized autonomous agent systems operating in open environments where information is sparse. Indeed, lack of information or knowledge often leads to inefficiencies and sub-optimality in the negotiated outcome.

A classic solution for handling such uncertainties is to assume agents have means to compute conditional probabilities and formulate subjective expected utilities. However this approach is problematic. Firstly, assigning prior probabilities is practically impossible. Even if assigning prior probabilities was practically achievable for interactions that are repeated (hence permitting the use of probability update mechanisms such as Bayes rule (Raiffa 1968)), the same is not true for encounters in open systems. In such environments the prior probabilities may simply be wrong, a fact that is exacerbated by the one-off nature of encounters which prevents the update of prior distributions. Secondly, the formulation of decisions based on subjective expected utility introduces the silent out-guessing problem (Young 1975)—the agent designer's choice of probabilities is based on guesses about the probable choices of others, whose choice in turn is dependent on the guesses about the probable choices of the first, and so on.

One solution to this problem is the design of mechanisms that model degrees of beliefs an agent can hold. We have previously motivated and shown how a fuzzy model is well suited for this class of problems (Faratin, Sierra, & Jennings 2000). Below we describe a new fuzzy model of choice applied to the context of buyer seller negotiation that is normatively specified by a Request For Quote (RFQ) protocol. We claim that in the absence of precise information/preferences such models can be usefully executed by agents to make choices.

A New Fuzzy Multi-Criteria Methodology

The key components of the fuzzy choice model can perhaps best be explained by means of the following illustrative negotiation situation. Assume that one agent (the 'seller') negotiates with several other agents (the 'buyers') to sell a particular product or service. The seller's RFQ is described in terms of several criteria, and several quotes have been received containing the various buyers' values on these criteria. Upon evaluating these counteroffers on the various criteria involved in the RFQ, the seller will very likely express different preferences with respect to these quotes.

Assuming that these preferences are on a [0,1]-scale, with the limit values 0 and 1 expressing no or strict preference respectively, the seller's preferences can be summarized by means of a fuzzy preference relation P (for a more fundamental discussion of fuzzy preference relations and their role in fuzzy preference structures, see (Van de Walle & Kerre 1998)). In the matrix representation of P, the i-th row of P contains preferences of the form $P_{ij} = P(o_j, co^i_j) \in [0,1]$, i.e., the degree of preference a seller has for his or her offer o compared to a counter-offer co^i made by buyer B_i, evaluated on criterion c_j, with $j \in \{1, ..., n\}$. We refer to the i-th row of P as the 'preference profile' for buyer B_i, denoted as B_iP, the P-afterset of buyer B_i.

The preference profiles of P form the starting point of a detailed analysis that starts with the pairwise comparison of the preference profiles. Technically speaking, we compute a degree of inclusion for every pair of profiles - i.e., we determine to what degree every profile is a subset of (or included in) every other profile. This degree reflects how the seller's preferences on one counteroffer compare to the preferences on another counteroffer. Taking the transitive closure of the pairwise comparison matrix resulting from this computation, leads to a fuzzy quasi-order relation, which we can process in a standard way. The result of that process is a family of partial rankings of all counter-offers, of which every particular member is a partial rank order corresponding to a particular level of fuzziness of the fuzzy quasi-order relation. More formally, we proceed as follows.

The Dependency Relation

Based upon the seller's preference relation P, we build the dependency relation D, a binary fuzzy relation in the set of buyers $B = \{B_1, ..., B_n\}$, in the following way:

$$D(B_i, B_j) = \mathrm{SH}(B_iP, B_jP),$$

where $\mathrm{SH}(A, B)$ is the degree of subsethood of a fuzzy set A in a universe X in a fuzzy set B in X, defined by:

$$\mathrm{SH}(A, B) = \frac{1}{n} \sum_{x \in X} \min(1, 1 - A(x) + B(x)),$$

with n the cardinality of X. This subsethood measure is a weak fuzzy inclusion, i.e.,

$$A \subseteq B \Rightarrow \mathrm{SH}(A, B) = 1,$$

for any two crisp sets A and B.

The Fuzzy Quasi-Order Closure

The next step consists of calculating the fuzzy quasi-order closure Q of the dependency relation D. A binary fuzzy relation R in a universe X is called a fuzzy quasi-order relation in X if and only if it is reflexive and transitive. It is well known that any binary fuzzy relation R has a fuzzy quasi-order closure Q, i.e., a least inclusive fuzzy relation Q containing R and possessing reflexivity and transitivity properties (Bandler & Kohout 1988).

Cutting the Fuzzy Quasi-Order Relation

The following characterization of fuzzy quasi-order relations in terms of α-cuts will prove to be very important (Bandler & Kohout 1988). Consider a binary fuzzy relation R in X, then :

$$R \text{ is a fuzzy quasi-order relation in } X$$
$$\Updownarrow$$
$$(\forall \alpha \in [0,1])(R_\alpha \text{ is a quasi-order relation in } X).$$

In our buyer-seller negotiation example terminology, the α-cuts of the relation Q, representing quasi-order relations in the set of buyers B, have the following interpretation : $(B_i, B_j) \in Q_\alpha$ if and only if buyer B_i is evaluated by the seller on the criteria at most as good as buyer B_j, with degree of confidence α. To each Q_α corresponds an equivalence relation E_α defined by :

$$(B_i, B_j) \in E_\alpha \Leftrightarrow (B_i, B_j) \in Q_\alpha \wedge (B_j, B_i) \in Q_\alpha.$$

This equivalence relation partitions the set of buyers B in classes of buyers among which the seller is indifferent, i.e, who score equally well on the evaluation criteria of the seller.

The corresponding quotient set B_α is given by $B_\alpha = \{[b]_\alpha \mid b \in B\}$ with

$$[b]_\alpha = \{c \mid (b, c) \in Q_\alpha\}.$$

Finally, on the quotient set A_α we can define the order relation $\leq_\alpha$:

$$[b]_\alpha \leq_\alpha [c]_\alpha \Leftrightarrow (b, c) \in Q_\alpha.$$

Each equivalence class consists of a number of buyers that have to be considered as equally good. These equivalence classes become larger with decreasing α and merge gradually. This means that incomparability diminishes at the cost of increasing indifference. A relationship of the form $[a]_\alpha <_\alpha [b]_\alpha$ actually means that all buyers in $[b]_\alpha$ are more preferred by the seller than those in $[a]_\alpha$.

We now have obtained a family of partial rank orders that express at the various $alfa$-levels the ranking of the buyers according to the seller's preferences as expressed in P. This information will allow us to suggest to the seller which buyers to negotiate with, depending upon the degree of imprecision in that given negotiation phase.

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