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# Decision-Making of BDI Agents, a Fuzzy Approach

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## Abstract

*This paper introduces and proposes Agent Fuzzy Decision-Making (AFDM), as an extension to the classical Belief-Desire-Intention (BDI) model. AFDM addresses the limitations of present formalisms within BDI models by making decisions based on quantified fuzzy judgment. The AFDM matrix model enables quantitative calculation and thus provides a more practical solution to BDI models. In addition, more flexible and controllable solutions to BDI persistence can be expected with the introduction of AFDM.*

## 1. Introduction

BDI (Belief-Desire-Intention) model represents an abstraction of human deliberation based on a theory of rational actions in the human cognition process. It is a theory of practical reasoning proposed by Bratman et al. in 1987 [1]. In a typical BDI architecture, the states of agents are represented through 3 types of component: Desires, Beliefs and Intentions.

If a goal has successfully passed through a weighing function and is chosen by an agent as an intention, we say that the agent has made a commitment to that goal. Intention is subsequently planned and executed. A deliberation selects a goal from a set of possible goals that may all meet a specific desire.

Although the BDI model has become almost a norm in the area of Multi-Agent Systems (MAS) during the last 15 years, several problems still remain. One of the key problems is intention persistence. Since the BDI model is intention-oriented, intentions play a critical role in the model. Commitment implies the temporal persistence of intentions. It means that once an intention is adopted, it should not be immediately dropped. How long should an intention persist? The problem arises when we recognize that an agent is a resource-bounded entity. How committed should an agent be to its intentions? Bratman [2] designed 3 kinds of commitments, those of blind commitment, single-minded commitment, and open-minded commitment. The selection of commitment degree is difficult since it is hard to predict how long deliberation will last. In another paper, Kinny and Georgeff [7]

adopted the concept of *degree of boldness* to express the frequency of reconsideration.

An additional problem is the gap that exists between theory and practice. The BDI model is not efficiently computable. It can be considered as a top-level model. In order to maximize the power of BDI, it is necessary to decompose goals, beliefs, desires, and intentions into even smaller components. From this point of view, it is necessary to further develop BDI into a more effective model to deal with the atomic components.

Rao & Georgeff [8], Woodridge [17] and Singh [9] have developed logic theories involving multiple worlds and logical formalisms. In their definitions, each world is viewed as a combination of time and state expressions. The logic theories greatly strengthen the usability of BDI and are recognized as critical compositions in the BDI family.

However strict, logic expression is neither effective enough nor sufficiently intuitive when applied to more complicated applications where many competing goals and many aspects of goals need to be weighed. Trying to apply logic theory to a fuzzy process is the major cause of inefficiency. Furthermore, the study of modal logics fails to bring full axiomatization and it is not easily applicable to certain application practice.

Contrasting approaches to the BDI model have been applied within the research literature. Case-Based Reasoning (CBR) is an experience-based approach in stark contrast to BDI [11][12]. The reasoning of CBR is based on the reuse of past experiences or cases. Cases in CBR are represented by a triple of *problem*, *solution of the problem*, and *outcome*. *Outcome* is the resulting state of the world when the solution is carried out and will be reused as a basis for future problems that present a certain similarity, as the basic principle of CBR defines.

Qualitative Decision Theory (QDT) [13] [14] [16], on the other hand, provides another decision theoretic solution different from traditional BDI logic. QDT is a multi-level qualitative approach developed to reason about uncertainties, which are typically represented by a plausibility function. The key to QDT application is,

however, how to remove the uncertainties or to calculate the possibilities in a broad sense, and in what way we can integrate experience with agent model.

The agent deliberation process can be viewed as an inherently fuzzy decision-making process. By using the word *fuzzy* we mean when we try to think out a solution, we usually select several goals and decide by weighing them on certain aspects we care about, such as cost, time, quality and accessibility etc, together with our preference. E.g., while we want to select a place to travel from a group of candidates, we think about cost, the time needed, how easy it is to get there (transportation), and expected enjoyment (quality of the result) etc; while we prepare our career to be an academic, we need to think about how much money to pay, how many years to spend on studying, how easy to become an academic, and expected career when successfully becoming an academic etc. On most occasions, it is more effective to weigh corresponding aspects quantitatively, if the experience values are at hand.

Our primitive desire is to build up a quantitative or qualitative decision-making mechanism based on a kind of fuzzy thinking mode (by deliberating on multiple aspects of goals). Such a model will, to some extent, address the limitations of the present BDI model. This flexible platform can integrate with other experience-based techniques within an Agent Fuzzy Decision-Making (AFDM) interpreter. Furthermore, by adopting a one-level matrix calculation, we wish to provide a better persistence solution.

This paper begins with definitions and a model of fuzzy decision-making, and then examines the measurement of deliberation cost within AFDM together with the concept of persistence control, followed by a simulation through a simple example scenario and conclusions.

## 2. Modeling

### 2.1 Definitions

The BDI model serves as a first-order prototype that leaves much to be further developed. Here are some basic definitions that we commission within our model.

#### Definition 1. Naming rules

We adopt capital letter followed by capital elements in brackets, e.g.  $W^G(M,M)$ ,  $G(N)$ , to express matrixes and vectors, capital letter followed by capital subscripts e.g.  $T_{M,M}$ ,  $G_M$  is used to express elements of matrixes or vectors. One-dimensional matrixes are adopted to

denote either a column of one-dimensional sub-matrix (if the matrix is 2-dimensional) or a column of elements (if the matrix is 1-dimensional); while 2-dimensional matrixes are adopted to denote values on each column of each row. For example,  $G(M)$  is used to denote a group of  $M$  goals, each of which is a  $1 \times N$  matrix; while  $G(M,N)$  denotes a matrix of  $M(\text{goals}) \times N(\text{aspects})$ , each element  $G_{M,N}$  denotes the magnitudes of each aspect of each goal.

$\rightarrow$  is used to denote vectors, while superscripts are adopted to denote the function domain. Within this paper,  $^D$  and  $^G$  denote desire domain and goal domain respectively. For example,  $W^G(M,M)$  and  $W^D(N,N)$  are weight matrixes on goal and desire;  $\overrightarrow{G^D(M)}$  is the mapping of goals in desire space. Goals are denoted as vector ( $\rightarrow$ ) only when they are mapped onto desire space.

Furthermore, we define  $M$  as the number of goals derived from planning library, and  $N$  as the number of measurable aspects or items, or number of desire aspects. In terms of the example shown in Table 1,  $M=5$ ,  $N=3$ .

#### Definition 2. Weight matrixes

$W^G(M,M)$  and  $W^D(N,N)$  are diagonal weighing matrixes adopted to impose the weighing coefficients onto different goals and different aspects correspondingly, standing for the relative importance of goals and aspects or dynamic preferences. They are sometimes also used to mask weighing of certain aspects or goals.

Diagonal matrix  $W^D(N,N)$  weighs the importance of each aspect of desire.  $W^D_{1,1}$ ,  $W^D_{2,2}$ , ...,  $W^D_{N,N}$  are experienced coefficients and can be decided either through an experience-based dynamic learning process or by human preset. Normally they are dynamically improved by agent itself. We omit the derivation of experienced values here in this paper and concentrate on the fuzzy platform itself.

$W^G(M,M)$  functions similar to  $W^D(M,M)$  except that  $W^G(M,M)$  provides weight coefficients to options rather than to aspects. If there is no preference, then  $W^G_{I,I}=1$ , where  $I \in \{1,M\}$ .

#### Definition 3. Desire

Desires denote states that agent wish to bring. More specifically here in this paper, desire has two functions during the deliberation process. First, desire descriptors  $\check{D}$  associate with beliefs and plan descriptors in option

library (Definition 6) to decide goal group; second, each desire  $D$  corresponds to some concerned aspects of current goals. The number of aspects depends on the decomposition of desire. So desire space can be considered as a multi-axis reference frame in which the axes are usually independent to each other and each axis represents an aspect of human wish, as shown in Figure 1.

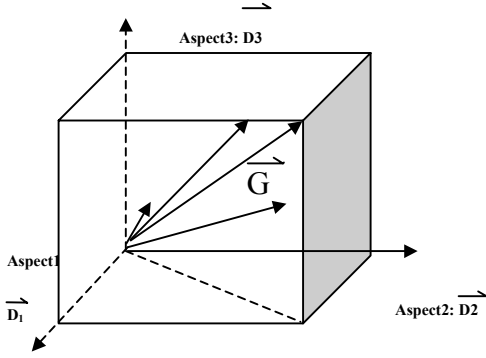


Figure 1 Desire frame example

The way of expressing goals with a set of aspects comes from human cognition mode. We usually weigh different goals by comparing different aspects that we care most. For certain kinds of decision-making, the concerned group of aspects can be concluded onto several indexes that human beings commonly care about most. The world of desire is serial, Euclidean, and also dynamic. Desire space can be denoted via:

$$\bar{D} = (\bar{D}_1 \bar{D}_2 \bar{D}_3 \dots \bar{D}_N)^T \quad [1]$$

The desire vector bases  $\bar{D}_1 \bar{D}_2 \bar{D}_3 \dots \bar{D}_N$  stand for aspects of desire. The decomposition of desires follows human cognition and quantification necessity. In terms of the example shown in Table 1, we have three aspects: accessibility, cost, and quality. The aspects can be further decomposed in different ways. Quality, for example, can be decomposed into *flavor* and *health*, while *health* can be further decomposed into *nutrition* and *hygiene degree*. We usually adopt the above-listed three attributes as the top-level desire aspects to assess the goals, to order them, and to decide upon commitment. These aspects can be further decomposed for weighing necessities.

#### Definition 4. Beliefs

Belief is the information an agent has about the world. The information could be about its internal state or about the environment. In terms of our model, belief is mainly the information contained in the dynamic option library.

By definition, beliefs are dynamic. So there should be a dynamic process to update beliefs all the time. This is so-

called belief revision process. It is critical since dynamic beliefs play a decisive role in deciding goal group and commitment revision as well. For example, if milk brand A is out of shelf, then we need to modify the magnitude of *accessibility* aspect of this option in the option library.

#### Definition 5. Goals (options)

Goals are the group of competing beliefs consistent with current desires. Within this paper, goals created from beliefs, desires and intentions are further mapped onto concerned desire bases.

A goal group is constituted as  $(G_1, G_2, \dots, G_M)^T$ , or if expressed by associating with a set of  $N$  aspects,  $(G_1(N), G_2(N), \dots, G_M(N))^T$ .  $G_1, G_2, \dots, G_M$  each represents a goal. The interpreter selects goals from an option library with the help of key properties associated with the desire descriptors. The  $I$ -th goal  $G_I$  (projecting in the desire space) is denoted as  $(G_{I,1} \times \bar{D}_1, G_{I,2} \times \bar{D}_2, \dots, G_{I,N} \times \bar{D}_N)^T$ , where  $G_{I,1}, G_{I,2}, \dots, G_{I,N}$  each represent the corresponding score (or ranking) on concerned aspects of  $I$ -th goal. For example,  $G_{I,J}$  stands for the score (or ranking) of  $I$ -th goal on  $J$ -th aspect.

The mechanism of decomposition can be further developed in order to obtain more precise result. Ranking or score judgment are both applicable on AFDM. Quantitative scores are more precise, but in some cases we use qualitative ranking scores rather than quantitative score or possibility or intensity because it is much more difficult to determine score or possibility or intensity of something so precisely with limited resource on most cases than to decide ranking. Practically, deliberation by getting the ranking on each selection, though not so precise, can be an effective way to simplify deliberation process.

#### Definition 6. Option library

The option library is a dynamic memory created to store goal information. Within option library, a desire descriptor  $\check{D}$ , a set of agent beliefs  $B$ , and a set of plans  $P$  are associated together in a triple  $\langle \check{D}, B, P \rangle$ , where the desire descriptor  $\check{D} = \langle \check{D}_1, \check{D}_2, \dots, \check{D}_K \rangle$ ,  $\check{D}_I \in \check{D}$ ,  $I \in \{1, 2, \dots, K\}$ , describes the  $K$  key characteristics of the desire.  $B, P$  are linked together by desire descriptor  $\check{D}$ .

The option library may be updated dynamically by other software entities or by agent itself.

#### Definition 7. Intention

Intentions are viewed as those goals that an agent has committed to achieve. They constitute triggers for corresponding plans from the plan library. Intentions, each associated with a plan with descriptors, are organized in

several tree or graphic structures managed by corresponding commitment management mechanism.

Only the goal with the maximum vector magnitude (other weighing rules can also be applied) in the deliberation process will be selected to commit, the other goals are ordered to work as substitutions. If the committed intention fails in the following planning or execution, then the option with the second highest magnitude (or score, ranking) will be selected to commit.

#### Definition 8. Knowledge base

The knowledge base is composed of a set of default rules associated with the deliberation process, such as aspect revision rules and goal weighing criteria. It also includes rules that handle exceptions, an occurrence where no similar goals stored in the option library, and rules switching function etc.

### 2.2 Formal background

Practical reasoning consists of two major activities. The first is deliberation, deciding *what* to do; the second is planning or means-end reasoning, deciding *how* to achieve the intention, as shown in Figure 2.

Generally speaking, there are limitless of desires in an agent system at the same time, some strong, some weak. Although desires are possibly inconsistent, the goals generated from beliefs and desires are required to be consistent, and achievable in our approach. More specifically in this paper, we pay our major attention to the decision-making of a group of consistent goals.

Planning is also an important part of an interpreter. Traditionally agent engineers tend to associate plans with intentions. That is, an intention will be further planned into possible actions after intention is generated. However, planning and deliberation are somewhat related to each other [16]. Separation of the two processes significantly lessens the working burden but cause theoretical bug. That is, deliberation cannot ensure best planning result even if the environment is static. In this paper, planning is simplified by associating plans with goals that are selected after fuzzy deliberation, although we sometimes still explain deliberation and planning separately for conceptual considerations.

We go on use the similar formalism of Wooldridge [17] and define Des, Bel, Int, Act, Gal correspondingly all possible desires, beliefs, intentions, actions and goals. B, D, I are the states of a BDI agent at any given moment constituting an agent state triple  $\langle B, D, I \rangle$ , where  $B \subseteq \text{Bel}$ ,  $D \subseteq \text{Des}$ , and  $I \subseteq \text{Int}$ , while goal G is a mixing state,  $G \subseteq \text{Gal}$ . We use g to denote an arbitrary element of goal matrix,  $g =$

$G_{I,J} \mid I \in \{1, N\}, J \in \{1, M\}$ . In addition, we denote S as an arbitrary set,  $\wp(S)$  is the powerset of S.

The general interpretation procedure can be described as follows. At the beginning of deliberation, the option generating function (function *Opt*) reads the desire descriptors and perceps the environment to get beliefs, returning a list of possible goals for further deliberation; then the goals are mapped onto desire space and assigned with real values from experience and beliefs by a mapping function (function *Map*); the goals are further filtered by an embedded filter function for consistence check and the best goal is selected through synthesis weighing all the surviving goals together with a plan of actions and is committed as intention (function *Wgh*). If there is an atomic action now, agent executes it (function *Act*). Otherwise, the agent will execute later on. Any external events that have occurred during the interpreting cycle are then added to the desire queue. Internal events are also added up as they occur. Next, reconsiderations follow in a loop to check if there are impossible intentions or realized intentions or if there are necessities of modifying them, and modify the corresponding status, see Figure 4.

Interpretation can be modeled with following main functions:

$$\text{Opt: } \wp(\text{Bel}) \times \wp(\text{Int}) \times \wp(\text{Des}) \rightarrow \wp(\text{Gal})$$

$$\text{Map: } \begin{array}{l} \text{Gal} \rightarrow \vec{D} \\ g \rightarrow \mathbb{R} \end{array}$$

$$\text{Wgh: } \wp(\text{Gal}) \rightarrow \wp(\text{Int})$$

$$\text{Act: } \text{Int} \rightarrow \text{Act}$$

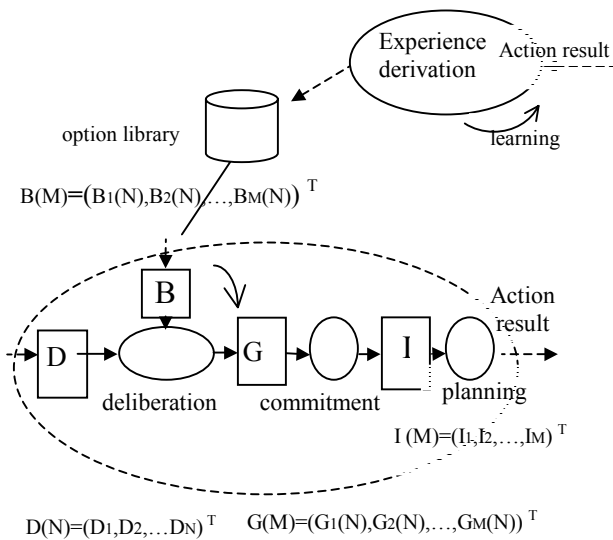
Belief revision function Brf is actually a perception function, which determines a new set of beliefs by taking perceptual inputs and the agent's current beliefs.

$$\text{Brf: } \text{Per} \times \wp(\text{Bel}) \rightarrow \wp(\text{Bel})$$

The most important and unique characteristics of our model are: a set of goals is mapped onto desire space and each element of the goals is assigned with a real value, enabling the quantitative weighing of different goals.

### 2.3 Fuzzy model

The selection of goals is based upon the matching of desires and beliefs. In terms of our case in Table 1, selection is decided by the matching of the keyword *Milk* in the current option library. Searching mechanism can be extended to synonym/conjunctive-work.

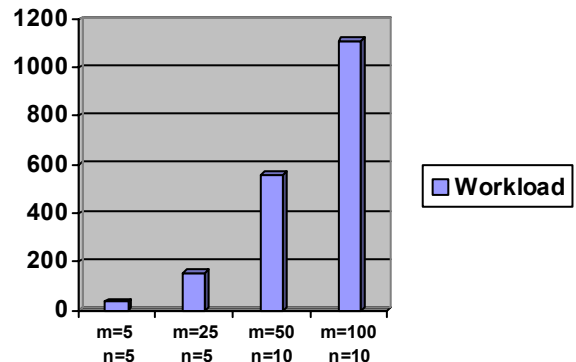
$$\begin{aligned} \overrightarrow{G^D(M)} &= G(M, N) \times \overrightarrow{D(N)} \quad [2] \\ \overrightarrow{Q^D(M)} &= W^G(M, M) \times G(M, N) \times W^D(N, N) \times \overrightarrow{D(N)} \quad [3] \end{aligned}$$
$$|\overrightarrow{Q^D_I}| = \sum_{J=1}^N [(W^G_{I,I} \times G_{I,J} \times W^D_{J,J})^2]^{1/2} \quad [4]$$


Suppose  $L$  is the 1<sup>st</sup> empty element in the intention queue and  $I_L$  is the  $L$ -th intention, then the top ranking goal  $G_I$  is committed as  $I_L$ . Formally,

The calculation of Euclidean lengths could be time-consuming when  $N$  is a big number. Alternatively on most occasions, we use Manhattan distance to measure the goals. In this case,

### 3. Cost estimation and persistence solution

Except for weighing aspects or goals. The weight matrix is sometimes also adopted to mask options or aspects. Predominantly we use incremental matrix solution to adjust the dimension of matrixes instead of spending lots of efforts to change matrix volume in real environment. That is, empty coefficients will be adopted onto certain goals or aspects when they are no longer useful in processing. The interpreter will skip the calculation on goals or aspects if the corresponding coefficients are 0. Whenever a new option or new aspect emerges, the interpreter will first search option library to check if there is empty rows or columns. If yes, then the new option or aspect will be filled into the vacancy.



On the other hand, time estimation of deliberation and planning is critical for an agent to keep the timing of the process and thus to wholly control the deliberation

process. Such *control* is achievable with the adoption of AFDM since the reasoning process deals with the calculation of matrixes that are fixed once the numbers of aspects and goals are decided. This will be another merit of AFDM interpretation. Here we assume that the time cost on fuzzy deliberation and planning is always dominant in practical control loop.

Persistence of intention is one of the key difficulties of BDI models because usually deliberation takes more time than action, while the cost of time on deliberation and planning is usually unpredictable. There is a dilemma presented by Wooldridge and Parsons [10]: an agent that doesn't stop to reconsider sufficiently often may attempt to achieve its attention even after it is clearly not able to achieve; while an agent that continuously reconsiders may spend insufficient time actually work to achieve them. So, on many occasions agents don't know if it is wise to go on deliberation.

Our study on persistence shows that:

1. Reconsideration must be embedded into the control loop. In addition, reconsideration is not continuous, but rather discrete occurring at loop intervals. The maximum reconsideration frequency equals loop frequency.
2. Different reconsideration policies are necessary for different agent architectures. In a MAS domain, agents' cooperation on perception of the environment, reconsideration, and action may make persistence problems quite different from those of a single agent.
3. The solution of the problem lies in the prediction of the time cost of each component in the control loop. If the time costs are predictable, then persistence problem can be solved through *tuning* the reconsideration frequency.
4. Different world dynamics may place differing requirements upon the reconsideration and commitment strategy.

Figure 4 shows how the control loop of BDI decision-making can be controlled with AFDM. Reconsideration (including re-planning) happens in the loop symbolized by {}. Control algorithm of AFDM keeps almost the same as traditional models except that we introduce function *Trigger*(B, D,  $\Delta$ ) to decide triggering of reconsideration. Traditionally, it is hard to decide whether to keep going or to reconsider. With the adoption of AFDM, more flexible reconsideration schedules can be applied since the cost

can be estimated from the dimensions of the dynamic matrix model.

Different schedules can be integrated with function *Trigger*(B, D,  $\Delta$ ) to provide different persistence solutions. Besides the three types of commitments proposed by Bratman: blind commitment, single-minded commitment, and open-minded commitment, we also proposed 2 kinds of triggers that can be integrated into the control loop to provide more flexible reconsideration, *Trigger by time limit* and *Trigger by utility*. Thus, the control loop is more controllable than it used to be.

For the consideration of paper length, we are going to talk about the concrete persistence solutions elsewhere.

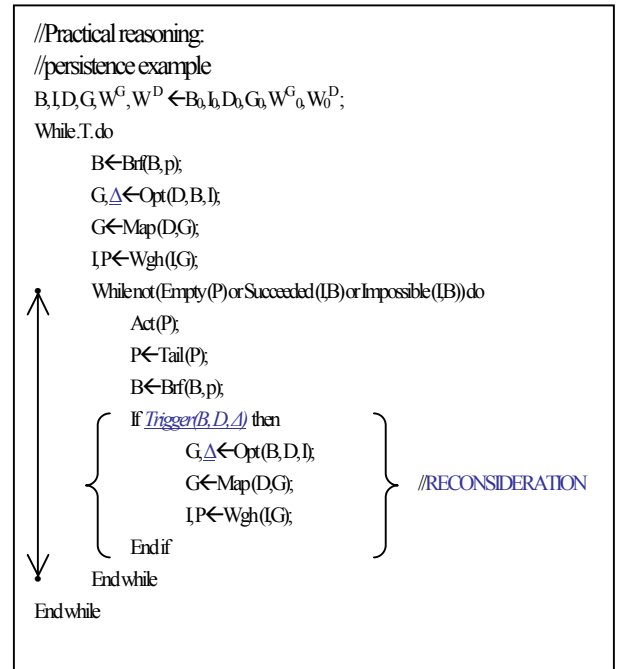


Figure 4 Practical reasoning

## 4. Example scenarios

The following simplified examples will be adopted to explain our theory: John feels thirsty and wants to drink something to quench his thirst (desire). He has 6 possible choices in brain (option library), which are: drink some water, drink a glass of juice, take some rice, drink some tea, drink a bottle of cola, or drink a bottle of beer. Deliberation process helps him decide which choice to select by evaluating following corresponding aspects: [1] The quality or the effect of the goal; [2] The accessibility, meaning how easy an agent can achieve the goals, including the time necessary for achieving the goal; [3] The economic payoff, in the form of money or other kinds

of cost. These three aspects are common indexes an agent needs to take into account on most cases. Each aspect weighs a part in decision-making. They can be further divided into more detailed aspects.

Imagine another example that may get common someday in the near future: a client asks a grocery agent to buy some milk for him. The agent checks his database and found 5 appropriate choices from different supermarkets. The database is connected to Internet so the corresponding aspects, cost (price, discount), accessibility (distances of shops, busy degree of shop, traffic...) and quality (healthy, flavor...) are dynamically updated. In order to simplify the example, we only demonstrate decision-making on 1<sup>st</sup> order aspects with their rankings.

Let's detail the 5 choices: milk brand A from shop U, milk brand B from shop V, milk brand D from shop W, milk brand B from shop X, and milk brand C from shop Y, see Table 1. Among them, A is the easiest to get and of highest quality, but the most expensive; while C, although cost time to get and has the lowest quality, is the cheapest choice; B and D are medium. Deliberation and planning process help the agent to decide which choice to select by weighing the 5 possible choices with corresponding coefficients and the scores (or ranking) of each choices on each evaluation aspects: accessibility, quality and cost.  $W^D(N, N)$  is first decided by empirical data and is dynamically improved with the increase of application cases. Scores (=M-ranks) are adopted to weigh to options because they are much easier to decide than quantitative values.

Table 1: Grocery agent

Ranking Scores Options	Accessibility Score (rank)	Quality Score (rank)	Cost Score (rank)
A U	5.0(1)	4.0 (1)	1.0 (4)
B V	3.0(3)	2.0 (3)	3.0 (2)
D W	2.0(4)	3.0 (2)	2.0 (3)
B X	4.0 (2)	2.0 (3)	3.0 (2)
C Y	1.0 (5)	1.0 (4)	4.0 (1)
$W^D_{J,J} \quad J=1,2,3$	30%	45%	25%

By applying fuzzy decision-making within the example shown in Table 1, we get:

$$\overrightarrow{Q^D(M)} = \begin{bmatrix} 1 & & & & \\ & 1 & & & \\ & & 1 & & \\ & & & 1 & \\ & & & & 1 \end{bmatrix} \begin{bmatrix} 5 & 4 & 1 \\ 3 & 2 & 3 \\ 2 & 3 & 2 \\ 4 & 2 & 3 \\ 1 & 1 & 4 \end{bmatrix} \begin{bmatrix} 30\% \\ 45\% \\ 25\% \end{bmatrix} \begin{bmatrix} \overrightarrow{D_1} \\ \overrightarrow{D_2} \\ \overrightarrow{D_3} \end{bmatrix}$$

Where D1, D2, D3 correspond to Accessibility, quality and cost respectively. The vector magnitudes of the five goals are calculated into the following matrix,

$$|\overrightarrow{Q^D(M)}| = (3.55, 2.55, 2.45, 2.85, 1.75)^T$$

The reasoning results are then ordered from (A|U, B|V, D|W, B|X, C|Y) into (A|U, B|X, B|V, D|W, C|Y). A|U gets the maximum score and is then selected by fuzzy reasoning as an intention. The intention is associated to the corresponding plan with plan descriptors. So intention will then trigger a plan of action combination: <go to shop U; get milk A; return>.

## 5. Conclusions

Within this paper we have proposed a fuzzy decision-making BDI interpreter. In our model, *desire* is a multi-axis reference frame in which each axis represents an aspect of human wish, and goals are weighed by mapping onto concerned desire bases. Within this model, solutions at divergent quantitative levels are achievable. Although there exists some limitation, such as experience derivation, AFDM obviates the limitations of present formalism on BDI models by a fuzzy way of decision-making. AFDM's matrix model enables BDI calculation and thus provides more flexible and controllable solutions to agent decision-making.

AFDM can be applied to a diverse range of domains where weighing of a group of goals in a quick and controllable way is in dominant need.

Our approach is merely a preliminary attempt to control BDI interpretation process in a human way of decision-making, and to embody BDI model with a quantitative or qualitative solution. Further study, including a series of applications and experiments on this platform, will be discussed in our later works.

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