A Fuzzy Logic-Based Computational Recognition-Primed Decision Model

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Abstract

The recognition-primed decision (RPD) model is a primary naturalistic decision-making approach which seeks to explicitly recognize how human decision makers handle complex tasks and environment based on their experience. Motivated by the need for quantitative computer modeling and simulation of human decision process as well as computerized assistance to enhance this process, we have developed a general-purpose computational RPD model using fuzzy systems technology. Fuzzy sets, fuzzy rules, fuzzy logic, and fuzzy reasoning are used to represent, interpret, and compute imprecise and subjective information that is commonly encountered in real-world applications. A heterogeneous similarity measure is introduced to acquire prior experiences by evaluating the extent of matching between the current situation and a past experience. Furthermore, an action evaluation strategy is developed, where fuzzy logic plays an important role. Through a simplified yet practical example of detecting adverse drug reaction, we demonstrate how the proposed computational model can be utilized to quantitatively describe and facilitate the decision process. Importantly, as a general-purpose technique, its application is beyond the medicine domain.

Keywords: Recognition-primed decision, Fuzzy logic, Similarity measure.

1 Introduction

Classical or traditional decision-making strategies largely use various axiomatic models where the optimal choice is based on a specific criterion or evaluative standard, usually the maximization of expected utility [8]. There is an increasing awareness that these normative models cannot adequately capture real-world decision-making [11]. Thus, some researchers turn to naturalistic decision-making techniques. Klein and his colleagues studied how fire commanders made decisions and proposed a recognition-primed decision (RPD) model [7] to characterize the decisions in naturalistic settings. The RPD model, as shown in Figure 1, describes the cognitive processes of decision makers. It includes two processes: assessing the current situation to recognize which course of action makes sense and evaluating the course of action by imagining it. Four by-products are generated in the first process: expectancies, relevant cues, plausible goals, and course of actions which will be singly evaluated in the second process by imagining how a particular action will evolve. The decision maker may either modify the course of action, or reject it and look for another option.

The RPD model represents a naturalistic decision making theory that employs a decision strategy called satisfying. Instead of trying to find the best solution, the RPD identifies the first workable option based on previous decision experiences [7]. This model is more qualitative, efficient, and suitable for experts. After studying hundreds of experienced decision makers, Klein found that about 50% to 80% of all decisions were made in this way [6]. Another study shows that the RPD was followed for 95% of all decisions made by naval officers on a cruiser [5].
Motivated by the need for quantitative computer modeling and simulation of human decision process as well as computerized assistance to enhance this process, researchers recently made progress in implementing the computational RPD model. By computational RPD, we mean a quantitative and computable RPD model that is readily implantable by computer. For instance, a long-term memory structure was proposed to represent an experience in [13]. This study headed for a “decision-specific” architecture in which other aspects of cognition such as cue abstraction, action evaluation, etc. were ignored. Liang et al. also studied the simple match of RPD, but they employed a neural network to formalize an experience [9]. Fuzzy logic is used in [12] to incorporate a fuzzy interpretation of the cue values. The use of fuzzy techniques in this work is limited since imprecise cues and environmental variables were still represented as crisp values, and the fuzziness in the process of cue abstraction and feature matching could not be captured. There are also several studies in which the RPD model was integrated with agent technologies. Norling et al. employed the RPD in Belief-Desire-Intention agent framework as a more realistic way for simulating human societies [10]. More recently, Yen et al. extended the RPD model with a team-oriented agent architecture in order to support the human-agent collaboration within a team [3, 14].

In this paper, we develop, in a systematic manner, a fuzzy logic-based general-purpose computational RPD model. Fuzzy sets are employed to formalize the representation of imprecise cues, and fuzzy reasoning is used to abstract higher level cues from lower level elementary data. A heterogeneous similarity measure is introduced to evaluate the degree of matching between the current situation and a prior experience. This similarity measure can handle different types of cues including nominal, linear and fuzzy. In addition, a more practical action evaluation strategy is developed to examine whether a course of actions is workable, where fuzzy logic is used to capture subjective information.

We present our computational RPD model along with a medical example to show the use of the model. We stress that the proposed model is general and useful for many application domains, including medicine. Despite its distinctive features that make it especially attractive and advantageous for medical decision making, to the best of our knowledge, there is no report in the literature on medial application of the RPD model, let alone a computational RPD model.

2 Proposed Computational RPD Model

To illustrate our computation RPD model, we will utilize some of the cognitive processes that a physician would employ when making decisions under uncertainty regarding suspected adverse drug reactions (ADRs). For this discussion, an ADR will refer to the unanticipated drug-associated adverse incident(s) that follow the administration of a drug when it is used properly and at an appropriate dosage [2]. ADRs represent a significant public health problem. Also, the concept of an adverse reaction following drug administration does not require extensive knowledge and expertise in order to understand the significance for decision making. The description and formalization of this example do not, and cannot, cover all aspects decision making related to the ADR problem. Our intention here is to demonstrate the applicability of the proposed computational RPD model in the medical domain without providing a comprehensive assessment of the entire problem.

2.1 Situation Awareness

In the phase of situation awareness, external environmental variables are abstracted or synthesized into a pattern of higher level cues.
for a decision task. Feature-matching is then used to diagnose the current situation.

2.1.1 Cue Types

Cue is a key concept in the RPD model since both the situation awareness and action evaluation processes are centered on cues. Cues are usually abstracted or fused from elementary data and their types could be linear, nominal or fuzzy. A linear cue refers to a variable whose values are described by or related to a straight line. For example, the blood pressure of a patient is a linear cue. A nominal (or symbolic) cue is a discrete cue whose values are not necessarily in any linear order. For example, a variable representing the gender of a patient has a value such as male, female, or unknown. A fuzzy cue is inspired by the need of representing information that is imprecise in nature. The fuzzy set theory provides a breakthrough, relatively new information processing technology for describing such imprecision, uncertainty, and subjectivity - which are common issues for more real-world applications, especially those in medicine.

Table 1. Cues for causality assessment.

<table>
<thead>
<tr>
<th>Cues</th>
<th>Cue type</th>
<th>Examples of cue values</th>
<th>Abstraction method</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temporal association</td>
<td>Fuzzy</td>
<td>Plausible, reasonable, unlikely</td>
<td>Fuzzy reasoning</td>
<td>1</td>
</tr>
<tr>
<td>Other explanations</td>
<td>Nominal</td>
<td>Yes, unlikely, no</td>
<td>Provided by experts</td>
<td>0.9</td>
</tr>
<tr>
<td>Dechallenge</td>
<td>Fuzzy</td>
<td>Plausible, reasonable, unlikely</td>
<td>Fuzzy reasoning</td>
<td>0.7</td>
</tr>
<tr>
<td>Rechallenge</td>
<td>Fuzzy</td>
<td>Plausible, reasonable, unlikely</td>
<td>Fuzzy reasoning</td>
<td>0.5</td>
</tr>
</tbody>
</table>

In the case of ADR assessment, the cues employed to evaluate the causality are abstracted from the description in [2] and summarized in Table 1. Note that detecting an unknown ADR is a complex process which includes spontaneous ADR reporting, expert clinical review, epidemiological studies, and so forth. To simplify our example, we only consider how a physician assesses the evidence for causality between a drug and an adverse event in an individual case, which may result in filing a report and trigger further investigation.

Among these four cues, temporal association refers to the temporal relationship between taking the drug and occurrence of the adverse event. Other explanations denote alternative explanations by concurrent disease or other drugs. Dechallenge is defined as the relationship between withdrawal of the drug and abatement of the adverse effect. Rechallenge describes the relationship between re-introduction of the drug and recurrence of the adverse event. Cues temporal association, dechallenge and rechallenge are all fuzzy variables which can be represented by fuzzy sets and achieved through fuzzy reasoning. The weights for these cues are assigned by an experienced physician.

2.1.2 Cue Abstraction

Fuzzy rules and fuzzy reasoning theories offer a systematic strategy to comprehend observable environmental variables and abstract or synthesize higher level cues. In what follows, we shall briefly present how to computationally represent fuzzy rules and fuzzy reasoning, and then explain how to use them in cue abstraction.

A fuzzy if-then rule “if x is A then y is B” can be defined as a binary fuzzy relation \( R \), where both A and B are often fuzzy values that are defined by fuzzy sets. Upon a fuzzy if-then rule, fuzzy reasoning offers human-like inference that can be formalized as follows [4]:

$$
\mu_{y}(y) \geq r\left[ \mu_{x}(x) \land \mu_{y}(x, y) \right]
$$

(1)

where \( \mu_{x}(x) \), \( \mu_{y}(x,y) \) and \( \mu_{o}(y) \) are the membership functions of the fuzzy sets that define the given fact \( x \), the fuzzy relation \( R \) and the conclusion \( y \). If the algebraic product is chosen as the T-norm operator, \( \mu_{x}(x, y) \) equals to \( u_{x}(x) \cdot u_{y}(y) \). Then equation (1) can be simplified as

$$
\mu_{y}(y) \geq r\left[ \mu_{x}(x) \land \mu_{y}(x, y) \right] \cdot \mu_{o}(y)
$$

(2)

where \( r \) equals the maximum of \( \mu_{x}(x) \land \mu_{y}(x, y) \). Actually, \( r \) represents a measure of the degree of fulfillment for the antecedent part of a rule.

Equation (2) presents the simplest case of fuzzy reasoning: single rule with single antecedent. If \( x \) is crisp (e.g. \( x' = x_{o} \)), then \( r \) equals \( \mu_{x}(x_{o}) \). If we use the algebraic product operator for conjunction, then

$$
\mu_{y}(y) = \mu_{x}(x_{o}) \cdot \mu_{y}(y)
$$

(3)
Formulas (2) and (3) can be extended to the case of multiple rules. For instance, if there are two rules, the problem is expressed as:

premise 1 (fact): \( x \) is \( A' \)

premise 2 (rule 1): if \( x \) is \( A_1 \) then \( y \) is \( B_1 \)

premise 3 (rule 2): if \( x \) is \( A_2 \) then \( y \) is \( B_2 \)

consequence (conclusion): \( y \) is \( B' \)

In this case, we need to unite the fuzzy inference results for both rules. If we take algebraic sum as the T-conorm operator, then

\[
\mu_a(y) = \mu_{a_1}(y) + \mu_{a_2}(y) - \mu_{a_1}(y)\mu_{a_2}(y)
\]

\[
= \mu_a(x_0)\mu_{a_1}(y) + \mu_a(x_0)\mu_{a_2}(y) - \mu_a(x_0)\mu_{a_1}(y)\mu_{a_2}(y)
\]

(4)

where \( \mu_{a_1}(y) \) and \( \mu_{a_2}(y) \) are the inferred fuzzy sets for rules 1 and 2, respectively. The inference procedure can be easily extended to the case of multiple antecedents in a fuzzy rule.

The abovementioned formulas form a computational process of fuzzy reasoning which can be utilized to abstract high-level cues from elementary data. For the listed cues in Table 1, we chose temporal association as an example to show how fuzzy reasoning is employed to achieve this process. The cue value of temporal association can be inferred from the time duration \((t_d)\) between taking the drug and appearance of an adverse effect. We define the following fuzzy reasoning rules linking cause (drug) and effect (ADR):

- If \( t_d \) is short, then temporal association is plausible;
- If \( t_d \) is medium, then temporal association is reasonable;
- If \( t_d \) is long, then temporal association is unlikely;

Both \( t_d \) and temporal association are fuzzy variables and characterized by triangular fuzzy sets (Figure 2).

![Fuzzy sets for time duration](image)

Figure 2a. Fuzzy sets for time duration

Figure 2b. Fuzzy sets for temporal association.

For a particular ADR, if the time duration is 1 day (i.e., \( t_d = 1 \)) then only the first two rules are activated. According to equations (3) and (4), we can get the fuzzy set for the corresponding temporal association:

\[
\mu_{a_0}(x) = \begin{cases} 
\frac{2}{5}x, & 0 \leq x \leq 0.5 \\
\frac{1}{25} \left(16x^2 + 6x - 2\right), & 0.5 < x \leq 1 
\end{cases}
\]

(5)

This membership function represents the actual fuzzy cue value abstracted from time duration through fuzzy reasoning. This fuzzy cue value will be compared with the corresponding cue value stored in a prior experience. It should be noted that not all cue values are abstracted in this way. Depending on applications, some cue values may be just physicians’ observation, and some others may need direct computation instead of reasoning.

### 2.1.3 Experience Representation

To represent an experience, we take the following structure which is derived from the work of Yen et al [14]:

\[
\text{experience} \rightarrow <\text{cue, expectancy, goal, action}> \\
\quad \downarrow \quad \downarrow \quad \downarrow \quad \downarrow \\
\quad c_1 < p_1, \xi_{p_1} > < g_1, \delta_{g_1} > a_1 \\
\quad c_2 < p_2, \xi_{p_2} > < g_2, \delta_{g_2} > a_2 \\
\quad c_3 < p_m, \xi_{p_m} > < g_1, \delta_{g_1} > a_3 \\
\quad i \quad i \quad i \quad i 
\]

where an experience consists of four parts: cue, expectancy, goal and action. The cue is a collection of high-level cues that are abstracted from environment variables. The expectancy is a set of expectancies, each of which is a pair \( (p, \xi_p) \), where \( p \) is a (fuzzy) predicate, and \( \xi_p \) an adjustable numeric value that represents the significance of the corresponding expectancy \( p \). The goal has similar structures with the expectancy. The action may contain several actions, each of which is usually composed of a course of lower-level actions. For detail
We define the following distance measure to calculate the local difference between \( c_j \) and \( c_j' \):
\[
d(c_j, c_j') = \begin{cases} 
1, & \text{if } c_j \text{ or } c_j' \text{ is unknown} \\
\text{overlap}(c_j, c_j'), & \text{if cue } j \text{ is nominal} \\
\text{linear_diff}(c_j, c_j'), & \text{if cue } j \text{ is linear} \\
\text{fuzzy_dis}(c_j, c_j'), & \text{if cue } j \text{ is fuzzy value}
\end{cases}
\]

The three functions on the right side of the equation will be explained below. People often have to make decisions under the condition of incomplete information. In the above definition, unknown cue values are handled by setting a distance of 1 if either of the cue values is unknown. The function of overlap is defined as:
\[
\text{overlap}(c_j, c_j') = \begin{cases} 
0, & \text{if } c_j = c_j' \\
1, & \text{otherwise}
\end{cases}
\]

For nominal cues, the cue distance is set to 0 if the cue values are equal; otherwise it is set to 1. The function of linear_diff is defined as:
\[
\text{linear_diff}(c_j, c_j') = \frac{c_j - c_j'}{\Delta_j}
\]

The difference between the two cue values is used to represent the distance if the cue is linear. \( \Delta_j \) is employed to normalize the cue values and defined as:
\[
\Delta_j = a_j - b_j
\]

where \( a_j \) and \( b_j \) are the maximum and minimum values for cue \( j \), respectively.

Sometimes \( c_j \) and \( c_j' \) are not crisp or binary, and they should be evaluated by degree instead of hard boundary. If cues are defined in terms of fuzzy sets, then Hamming distance, one of the most commonly used distance functions, is employed to define their distance. Let cue \( j \) be defined on the universe of discourse \( X \) and \( x \) be a generic element of \( X \). If \( X \) is a collection of discrete objects, the function of fuzzy_dis is defined as:
\[
\text{fuzzy_dis}(c_j, c_j') = \frac{1}{m} \sum_{x \in X} |\mu_{c_j}(x) - \mu_{c_j'}(x)|
\]

where \( \mu_{c_j}(x) \) and \( \mu_{c_j'}(x) \) are the membership functions for the fuzzy values \( c_j \) and \( c_j' \), respectively. If \( X \) is an interval \([\alpha, \beta]\), the function is defined as:
As suggested in [1], the similarity and distance measure could use the following mapping

\[ s(c_j, c'_j) = 1 - d(c_j, c'_j) \]  

Equation (12) only defines the similarity between two values for the same cue, and thus is called local similarity measure.

To continue our ADR example, recall that the cue value for temporal association has been abstracted in section 2.1.2. It is represented as a fuzzy set whose membership function is given by equation (5). For the same cue, its value stored in experience1 is “plausible” whose membership function is:

\[ \mu_\alpha(x) = \begin{cases} 0, & 0 \leq x \leq 0.5 \\ 2x - 1, & 0.5 \leq x \leq 1 \end{cases} \]  

To calculate the distance between these two cue values mentioned above, we apply equation (11) and get

\[ d(c_w, c'_w) = 0.0367 \]

where \( c_w \) and \( c'_w \) represent the cue values of temporal association in current situation and in experience1, respectively. Thus, their similarity

\[ s(c_w, c'_w) = 1 - 0.0367 = 0.9633 \]

For cues dechallenge and rechallenge, we can employ the same procedure to abstract their actual cue values and find out their similarities with corresponding cue values stored in experience1. Here, without loss of generality, we simply assume that \( s(c_d, c'_d) = 0.86 \) and \( s(c_r, c'_r) = 0.79 \). For the cue other explanations, we assume that its value is given by decision makers. If its value is “no”, we can compute \( s(c_oe, c'_oe) = 1 \) by applying (7).

After getting the local similarity of each cue, our next step is to integrate them into a scalar form. The similarity of each cue can be summed to give a total weighted similarity between two cue sets \( V \) and \( V' \):

\[ s(V, V') = \sum_{j=1}^{n} w_j s(c_j, c'_j) \]  

where \( w_j \) is the weight for cue \( j \), which represents the relative significance of that cue and is usually assigned by human experts.

The degree of similarity usually involves the possible utility/reusability of solutions. To reuse the actions in a past experience, a few important cues among all the cues are often required to be satisfied. That is, if the value of a required cue in the current situation is not similar or close to the value of the same cue in a past experience, this experience cannot be utilized to solve the current problem no matter how similar the other cues are. A potential shortcoming with formula (14) is that if the required cues are not close, the value of the similarity measure could still be high when the other cues are pretty similar and the number of cues in the set is large. We extend the above formula by assigning 0 to \( s(V, V') \) when one of the required cues is not close. In addition, the weighted similarity measure should be divided by the sum of all the weights so that the total similarity is in \([0, 1]\). Assume that the weight of a cue is between 0 and 1, and 1 is assigned to the required cue in a cue set. The new strategy for aggregation of similarities is defined as follows:

\[ S(V, V') = \begin{cases} 0, & \text{if } \exists j \in (1, n), w_j = 1 \text{ and } s(c_j, c'_j) < \delta \\ \frac{\sum_{j=1}^{n} w_j s(c_j, c'_j)}{\sum_{j=1}^{n} w_j}, & \text{otherwise} \end{cases} \]

where \( \delta \in [0, 1] \), a threshold given by human experts. Equation (15) represents the total similarity between two sets of cue values, and thus is called global similarity measure.

Using equation (15), we can get a final similarity value between the current situation and experience1 in our example:

\[ s(V, V') = \frac{0.9633 \times 1 + 0.86 \times 0.7 + 0.79 \times 0.5}{1 + 0.9 + 0.7 + 0.5} = 0.92 \]

Since 0.92 is very close to 1 and the similarities between current situation and other experiences are smaller than 0.92, the actions in experience1 can be reused to handle current problem.

### 2.1.5 Feature matching

The feature matching process can be obtained through the similarity measure presented above. We assume that there are different types of experience knowledge bases, and each knowledge base can deal with a specific decision type which could be inferred from the information associated with the decision task [14]. Once the decision type is determined, the experience knowledge base to be matched is fixed. After that, the current situation is compared with the past experiences in the
selected experience knowledge base. Suppose that \( Q \) is the set of observed cues in current situation and \( T_i \) (\( i = 1, 2, \ldots M \), where \( M \) is the number of experiences in the database) is the set of cues considered in a past experience. The matching is performed through computing the similarity between \( Q \) and \( T_i \) coordinate-wise using equation (15) in the feature space. The current situation is matched with a past experience to degree \( \epsilon \), if and only if given a small nonnegative number \( \epsilon \in [0,1] \), \( s(Q,T_i) \geq \epsilon \), where the number \( \epsilon \) is a similarity threshold given by human experts. If more than one experience is matched with the current situation, the one with the highest similarity is chosen.

### 2.2 Action Evaluation

While situation awareness is to diagnose a problem, action evaluation is a process of selecting a workable course of actions to solve that problem. For human decision makers, action evaluation can be achieved by mental simulation: people scrutinize each lower-level actions to see if there exists a potential problem. For computational RPD, we assume that each course of actions has an initial state, a terminal state and several actions between them, and each action has three parts in sequence: **condition**, **execution** and **effect** (Figure 3). While an initial state is usually the trigger for a sequence of actions, the terminal state often stands for our final expectation after these actions. The **condition** of an action is a set of cues that serve as the prerequisite of **execution**. The **effect** is our expectation of the execution of an action. Usually, two actions in sequence have causal relationship, that is, the effect of one action is one of the conditions for the following action. Intuitively, the initial state is one of the conditions for the first action, and the terminal state is the effect of the last action.

![Figure 3. A course of actions.](image)

To evaluate a course of actions, we first compare the initial state (often together with a few other cues) against the **condition of action 1** using the similarity measure introduced earlier.

If they match (i.e., their similarity measure is greater than a predetermined threshold), the **effect of action 1** and other cues will be employed to compare with the **condition of action 2**. We continue this process until we reach the terminal state which is one of the effects of the last action. If we use \( s(V_1',V_1) \), \( s(V_2',V_2) \) \ldots \( s(V_n,V_n') \) to represent the similarities between the relevant cues and the **conditions of action 1** until **action n**, then the degree of our confidence with this course of actions can be defined as:

\[
CF = s(V,V') \cdot \left[ s(V_1,V_1') \cdot s(V_2,V_2') \cdots s(V_n,V_n') \right] \tag{16}
\]

where \( s(V,V') \) is the result of feature matching in the phase of situation awareness. This variable is added to the formula because it denotes the degree of appropriateness to use the chosen experience. So, the value of \( s(V,V') \) should affect our total confidence with the selected course of actions. The variable \( CF \) (confidence factor) provides a quantitative way to measure in what degree the initial state can be converted to the terminal state through a course of action. The bigger this value is, the more confident we are.

To show the action evaluation process, the action “file a report online” in experience1 is taken as an example. The action could be further divided into two lower level actions whose **conditions and effect** are shown in Table 2. To calculate the similarity between current situation and the **condition of action 1**, if we assume that the (electronic) database is accessible but other documents (e.g., detail information of the suspected drug) are not available, then using equation (7) and (15) we can get \( s(V_1,V_1') = 0.833 \). For **action 2**, if we assume that the network connection is accessible and the physician prefers to file a report online, we get 

\[ s(V_2,V_2') = 1. \]

Now we can calculate the confidence factor: 

\[ CF = 0.92 \times 0.833 \times 1 = 0.767. \]

**Table 2**. Conditions and effect of action 1.

<table>
<thead>
<tr>
<th>Action 1</th>
<th>condition</th>
<th>execution</th>
<th>effect</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>cue</strong></td>
<td><strong>value</strong></td>
<td><strong>weight</strong></td>
<td><strong>collect data</strong></td>
</tr>
<tr>
<td>causality</td>
<td>certain</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>database</td>
<td>accessible</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>other documents</td>
<td>available</td>
<td>0.4</td>
<td></td>
</tr>
</tbody>
</table>
3. Conclusion

We have developed a systematic general-purpose computational RPD model using fuzzy logic. Our approach has several distinguishing features. First, fuzzy sets and fuzzy reasoning are employed to quantitatively represent and interpret imprecise information, and handle the uncertainty in the decision-making process. Second, a heterogeneous similarity measure is created to evaluate the degree of feature matching. This similarity measure is very flexible since it not only handles different types of information (e.g., linear, nominal, fuzzy) but also incorporates various conditions including the calculation of similarity at the presence of missing information and the aggregation of similarity values in case the required information is not satisfied. Finally, we develop a more realistic action evaluation strategy which is often ignored (or simplified) in other implementations of the computational RPD model. We have provided a simplified yet practical medical example that shows the applicability of computational RPD model in decision tasks. This model can circumvent human memory limitations, and facilitate more accurate decisions.

References