

## **A Typology for Constructing Decisions<sup>1</sup>**

**Adele Howe**

**Paul Cohen**

**Experimental Knowledge Systems Laboratory  
Department of Computer and Information  
University of Massachusetts, Amherst 01003  
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### **Abstract**

We present a typology of decision-making situations. Some lead immediately to a decision, others must be transformed by the addition of evidence. The states in our typology are associated with appropriate transformations. By classifying decision-making situations, one can find actions to effect the transformation of an intractable decision-making situation into a tractable one. This opens the possibility of sophisticated control for knowledge systems by table lookup.

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## 1. Introduction

Decision making involves identifying, comparing, and ultimately selecting from among a set of alternatives. When the alternatives are not known in advance, or when the set of alternatives is large, decision making becomes a constructive, action-oriented process. The alternatives and their features, implicit in the description of a decision problem, must be compared and so must be made explicit as the problem is solved. As these comparisons are made, preferences among alternatives on features are also made explicit. We present a typology of decision-making situations that tells how to construct a decision, that is, when to add an alternative, a feature, or a preference to a developing decision.

The emphasis of this work is constructive decision making for AI programs. We focus first on problems where alternatives are supported by conflicting evidence. The many variants of this type of problem are organized into a typology of decision-making situations. Some situations permit an immediate choice between alternatives. Others require actions to further construct the decision. The typology associates appropriate actions with decision-making situations.

The typology shows how to solve “apples and oranges” problems and generalizes this result to provide a view of sophisticated control for decision-making AI programs as table lookup.

**Comparing the Incomparable.** Decision alternatives are compared on their salient features. Often, the values of these features cannot be easily combined. We call this the *apples and oranges problem*: When you compare apples and oranges in a grocery store you may find one fruit preferred on the basis of flavor and the other on the basis of quality. If you can combine the features to compare the alternatives on a single, composite feature, then the choice is clear. But if, as in this case, flavor and quality cannot be combined, then the choice between apples and oranges is problematic. Traditionally, the apples and oranges problem has been solved by mapping the values of features such as flavor and quality onto a uniform utility scale. The approach described here keeps the features distinct. The inevitable problem of conflicting features is solved by constructively adding features and preferences to a decision.

Closer inspection shows that the apples and oranges problem is not one, but a family of decision problems with different solutions. In this paper, we derive the space of decision problems and show how actions associated with difficult decision problems can be taken to reformulate them as easier ones.

## 2. Decision Typology

We begin with a basic decision problem in which two alternatives are compared on two features, then show how the typology of two-alternative, two-feature problems guides the construction of more complex decisions. Alternatives are referred to as  $p$  and  $q$ , features as  $F_i$  and  $F_j$ , and values of features for specific alternatives as  $F_i[p]$ . The symbol  $\tilde{>}$  indicates preference between two values. Although we will be using some mathematical symbols, none of the *values* need be numbers; for example, we can say  $flavor(\text{apples}) \tilde{>} flavor(\text{oranges})$  without quantifying quality.

**Characteristics of a Decision** Two-alternative, two-feature decision problems can be characterized along five binary and ternary dimensions:

$Sd[F_i]$ . A *significant difference* on feature  $F_i$  indicates that the values of the two alternatives are distinct. If a decision between alternatives  $p$  and  $q$  can be based on the values  $F_i[p]$  and  $F_i[q]$ , then the values are distinct.

$$Sd[F_i] = \begin{cases} 1 & \text{if } F_i[p] \text{ and } F_i[q] \text{ are distinct} \\ 0 & \text{otherwise} \end{cases}$$

*Otherwise* indicates no significant difference or that we lack evidence to tell whether there is a significant difference.

$Sd[F_j]$  Like  $Sd[F_i]$ , but for  $F_j$ .

$C[F_i, F_j]$ . A *conflict* exists when  $F_i$  and  $F_j$  support different alternatives.

$$C[F_i, F_j] = \begin{cases} 1 & \text{if } F_i[p] \succ F_i[q] \text{ and } F_j[q] \prec F_j[p] \text{ or} \\ & \text{if } F_i[p] \prec F_i[q] \text{ and } F_j[q] \succ F_j[p] \\ 0 & \text{otherwise} \end{cases}$$

$O[F_i, F_j]$ . One feature is often *more important* than another. This means that one feature is preferred to another (e.g., quality is preferred to flavor), or that there is a greater difference between the two alternatives on one feature than the other.

$$O[F_i, F_j] = \begin{cases} 0 & \text{if importance}(F_i) = \text{importance}(F_j) \\ ? & \text{if relative importance unknown} \\ 1 & \text{if importance}(F_i) > \text{importance}(F_j) \\ & \text{or importance}(F_i) < \text{importance}(F_j) \end{cases}$$

$\tilde{\succ}[F_i, F_j]$ . Assuming that  $O[F_i, F_j] = 1$ , we need to know which feature is preferred.

$$\tilde{\succ}[F_i, F_j] = \begin{cases} 0 & \text{or importance}(F_i) < \text{importance}(F_j) \\ 1 & \text{if importance}(F_i) > \text{importance}(F_j) \end{cases}$$

We illustrate these dimensions in the context of the problem of selecting fruit:  $F_i$  is *quality* and  $F_j$  is *flavor*. If the quality of apples is “good” and the quality of oranges is “poor,” then  $Sd[F_i] = 1$  because good and poor are distinct values. Similarly, if one prefers the flavor of oranges to that of apples then  $Sd[F_j] = 1$ . Since apples have better quality but oranges taste better,  $C[F_i, F_j] = 1$ . Finally, if quality is preferred to taste  $O[F_i, F_j] = 1$  and  $\tilde{\succ}[F_i, F_j] = 1$ .

The space of types characterized by these dimensions can be arranged in a table. The problem we just described is case 23 in this table, illustrated in Figure 1. In English, case 23 says “the quality of evidence for  $F_i[p]$  and  $F_i[q]$  is sufficient to claim that the difference supports a choice between  $p$  and  $q$ ; the quality of evidence for  $F_j[p]$  and  $F_j[q]$  is sufficient to claim that the difference supports a choice between  $p$  and  $q$ ; there is a conflict between  $p$  and  $q$  on  $F_i$  and  $F_j$ , and the feature  $F_i$  is more important than  $F_j$ .”

Case #	0	1	2	3	4	5	6	7	8	9	10	11
$Sd[F_i]$	0	1	1	0	1	1	0	0	1	0	1	1
$Sd[F_j]$	0	0	1	0	0	1	0	1	1	0	0	1
$C[F_i, F_j]$	0	0	0	1	1	1	0	0	0	1	1	1
$O[F_i, F_j]$	?	?	?	?	?	?	0	0	0	0	0	0
$\tilde{>}[F_i, F_j]$	*	*	*	*	*	*	*	*	*	*	*	*

Case #	12	13	14	15	16	17	18	19	20	21	22	23
$Sd[F_i]$	0	1	0	1	0	1	0	1	0	1	0	1
$Sd[F_j]$	0	0	1	1	0	0	1	1	0	1	0	1
$C[F_i, F_j]$	0	0	0	0	1	1	1	1	0	0	1	1
$O[F_i, F_j]$	1	1	1	1	1	1	1	1	1	1	1	1
$\tilde{>}[F_i, F_j]$	0	0	0	0	0	0	0	0	1	1	1	1

Figure 1: Typology of Decisions

**Collapsing the Table** Figure 1 does not represent all 40 combinations of the possible values of  $Sd[F_i]$ ,  $Sd[F_j]$ ,  $C[F_i, F_j]$ ,  $O[F_i, F_j]$ , and  $\tilde{>}[F_i, F_j]$ . From the perspective of how a decision-maker acts, the 40 decision types contain some redundancies. Consider these cases:

**Case 18a:**  $S[F_i] = 1$ ,  $S[F_j] = 0$ ,  $C[F_i, F_j] = 1$ ,  $F_i \tilde{>} F_j$

**Case 18:**  $S[F_i] = 0$ ,  $S[F_j] = 1$ ,  $C[F_i, F_j] = 1$ ,  $F_j \tilde{>} F_i$

In English, the dimension for which your evidence supports a decision is the most important dimension. The cases are identical in the sense that a decision-maker would not act differently in response to them. Consequently, the two cases are represented only by case 18 in the table.

**Decision Actions** The point of characterizing decisions is to select appropriate actions. In our approach there are three basic actions: *decision*, *transformation*, and *stuck*. *Decision* means choosing an alternative based on available evidence; for example, in case 8 (Fig. 1) there are significant differences between the alternatives on both features and their evidence does not conflict. The decision is straightforward.

Transformations of one decision type into another are appropriate when a decision cannot be made *given the available evidence*. In case 0 (Fig. 1), the values of the alternatives on features  $F_i$  and  $F_j$  do not distinguish the alternatives, nor do we know whether one feature is preferred. A decision in this case cannot be made with confidence, but several transformations of case 0 are possible: If further evidence about  $F_i$  potentially shows that the alternatives *can* be distinguished on  $F_i$ , then obtaining the evidence transforms case 0 into case 1 (i.e., the 0 in row  $Sd[F_i]$  is replaced by a 1). Obtaining evidence of this kind for *both* features transforms case 0 into case 2. From case 2, one may confidently make a decision. Similarly, if evidence exists that  $F_i$  is preferred to  $F_j$ , then obtaining the evidence transforms case 0 into case 20. Alternatively, evidence may show that neither feature is preferred; obtaining this evidence transforms case 0 into case 6. The idea of transformations is to change one decision type into another, hopefully

more facilitative, type. Transformation is an appropriate action for any decision type with 0 in either of its first three rows or ? in its fourth.

The most obvious way to effect a transformation is to seek more evidence. The table in Figure 1 allows us to plan actions to obtain evidence, thus it guides the process of constructing a decision. However, the planned transformation may not be possible; the actual transformation depends on the evidence obtained. For example, we may gather evidence about  $F_i$  with the intention of transforming case 7 to case 8. But if the evidence, when obtained, indicates that  $F_i$  and  $F_j$  actually support different alternatives, then we end up in case 11 instead of case 8.

In case 11, we are *stuck*: all available evidence about the features has been acquired, but it supports conflicting alternatives, and neither feature is preferred. From case 11, no further transformation is possible, no action is apparent. In fact, there *are* actions appropriate for the stuck case, but they expand the decision beyond the two-alternative, two-feature case under discussion. If a decision cannot be made on the basis of evidence about the current features, then the appropriate action is to further distinguish the alternatives with additional features. Because we view decision making as a constructive process in which alternatives and features emerge only as needed, we imagine a decision-maker adding features when stuck, that is, in case 11.

Each of the 24 decision types has at least one appropriate action. Some suggest two (see Fig. 2). These are situations in which a decision can be made, but without complete confidence. For example, in case 9 there is significant evidence for  $F_i$ , but not  $F_j$ , they don't contradict given the available evidence, and neither feature is preferred. A decision could be based on  $F_i$ , but not without some uncertainty that  $F_j$  actually supports a different alternative than  $F_i$ . Multiple actions permit different strategies for selecting specific actions. For example, a conservative strategy that tries to minimize uncertainty in decisions encourages transformations.

### 3. Extensions to a Multifeature Model

The decision tables described so far allow comparison of two alternatives on two of their features. Sometimes, as noted above, a decision cannot be based solely on these features. These situations arise in three ways. First, evidence such as the preference for features may be missing. Second, complete evidence may not support a decision; for example, the values of the alternatives on the features may be accurately known, but not significantly different to support one alternative. Third, these values may be accurately known, and significantly different, but support different alternatives. In the first situation, it is fairly obvious that we should seek the missing evidence. In the last two, it is necessary to add another feature. Psychological evidence suggests that humans in these situations add features and alternatives conservatively, what [Svenson 79] calls "choice by feedback processing." Our model emulates this iterative, constructive behavior.

**Adding Features** Features may be added by substituting one for another or by combining a new feature with an old one. In either case, the typology of Figure 2 suffices to represent two-alternative, multi-feature decisions. In *substitution*, one of the two features currently under consideration is discarded and a new feature is substituted. This is appropriate when we know

Case	0	1	2	3	4	5	6	7
$Sd[F_i]$	0	1	1	0	1	1	0	0
$Sd[F_j]$	0	0	1	0	0	1	0	1
$C[F_i, F_j]$	0	0	0	1	1	1	0	0
$O[F_i, F_j]$	?	?	?	?	?	?	0	0
$\tilde{>}[F_i, F_j]$	*	*	*	*	*	*	*	*
Action	D/T	D/T	D	T	D/T	S/T	D/T	D/T

	8	9	10	11	12	13	14	15
$Sd[F_i]$	1	0	1	1	0	1	0	1
$Sd[F_j]$	1	0	0	1	0	0	1	1
$C[F_i, F_j]$	0	1	1	1	0	0	0	0
$O[F_i, F_j]$	0	0	0	0	1	1	1	1
$\tilde{>}[F_i, F_j]$	*	*	*	*	0	0	0	0
Action	D	T	D/T	S	D/T	T/D	D/T	D

	16	17	18	19	20	21	22	23
$Sd[F_i]$	0	1	0	1	0	1	0	1
$Sd[F_j]$	0	0	1	1	0	1	0	1
$C[F_i, F_j]$	1	1	1	1	0	0	1	1
$O[F_i, F_j]$	1	1	1	1	1	1	1	1
$\tilde{>}[F_i, F_j]$	0	0	0	0	1	1	1	1
Action	D/T	D/T	D/T	D/S	D/T	D	D/T	D/S

Figure 2: Decision Actions

that two alternatives are not differentiated on an feature ( $Sd[F_i] = 0$ ). The feature does not provide a basis for a choice. It should be replaced by another, more informative, feature.

The second method for adding features is *combination*: the evidence provided by the new feature is combined with evidence accrued from previous comparisons. This is appropriate when the previous features favor different alternatives. For example, when we add another feature  $F_{new}$  to case 11, [1110\*], we hope to move to column 19, [11110], or 23, [11111]. Unlike case 11, cases 19 and 23 indicate a preference between features. Assuming that the alternatives are distinguished on  $F_{new}$  (otherwise adding it would gain nothing), and assuming that a combination of two significant features are preferred to one,  $F_{new}$  introduces a preference order when combined with the old feature it corroborates, resulting in case 19 or 23. Thus, the typology of Figure 2 suffices for a two-alternative, three-feature decision and, by induction, for two-alternative, multi-feature decisions. Since case 11 involves a conflict between features,  $F_{new}$  must corroborate either  $F_i$  or  $F_j$ . Thus, new evidence can be clustered to support one of two alternatives. This additional support contributes to an ordering over clusters of features, represented by values in the fourth (order) and fifth (preference) rows.

Clustering is the key to extending the two-alternative, two-feature situations to two-alternative, N-feature cases, and finally to N-alternative, N-feature problems, because it permits complex decision situations to be constructed iteratively within the framework of our decision typology.

**Revised Set of Decision Actions** With the ability to cluster evidence, we can determine what to do even in very difficult decision situations. The initial set of actions, *decision*, *transformation*, and *stuck* can be augmented. The new set is *decision*, *transformation by feature*, *transformation by order*, *substitution*, and *combination*. In transformation by feature (*Tf*), we acquire additional evidence about whether a feature distinguishes alternatives. This can change  $Sd[F_i] = 0$  to  $Sd[F_i] = 1$ . Transformation by order (*To*) is the corresponding action for gathering order preference information. It can transform  $O[F_i, F_j] = ?$  to  $O[F_i, F_j] = 0$  or  $O[F_i, F_j] = 1$ . If complete knowledge of the alternatives is available, but a decision still cannot be made, a state can be transformed by adding a new feature, either by substitution (*Su*) or combination (*Co*).

Figure 3 contains the decision states with their appropriate actions. The actions are divided into two rows. The first row shows the actions for states with complete evidence. The second describes actions to be performed when some of the state information is missing. The transformations are listed with numbers that indicate the set of possible states you might end up in. Note it is not possible to say exactly which of these states will arise.

The actions presented in Figure 3 are somewhat subjective. In general, combination can be done in any state. It isn't listed because other actions are often more appropriate; for example, substitution is more appropriate when one feature is insignificant. Decision could be made in cases other than those listed, but they would be precarious decisions.

### 3.1 Changes to Decision State

Adding a new feature potentially affects every cell in a decision state, that is, each value  $Sd[F_i]$ ,  $Sd[F_j]$ ,  $C[F_i, F_j]$ ,  $O[F_i, F_j]$ , and  $\tilde{>}[F_i, F_j]$ . In combination with a new feature, a previously insignificant one may become significant (e.g.,  $Sd[F_i] = 0$  but  $Sd[F_i \& F_{new}] = 1$ ).

Case		0	1	2	3	4	5	6	7
$Sd[F_i]$		0	1	1	0	1	1	0	0
$Sd[F_j]$		0	0	1	0	0	1	0	1
$C[F_i, F_j]$		0	0	0	1	1	1	0	0
$O[F_i, F_j]$		?	?	?	?	?	?	0	0
$\tilde{>}[F_i, F_j]$		*	*	*	*	*	*	*	*
Actions	All Info	Co D	Su D	D		Su,Co D	Co	Co D	Su D
	Part Info	Tf 0,1,4 To 6, 12,20	Tf 1,5,8 To 7, 13,14	To 5,8 21	Tf 3,4,5 To 9, 16,22	Tf 2,4 To 10, 17,18	To 11, 19,23	Tf 6, 7,10	Tf 7, 8,11

	8	9	10	11	12	13	14	15	
$Sd[F_i]$	1	0	1	1	0	1	0	1	
$Sd[F_j]$	1	0	0	1	0	0	1	1	
$C[F_i, F_j]$	0	1	1	1	0	0	0	0	
$O[F_i, F_j]$	0	0	0	0	1	1	1	1	
$\tilde{>}[F_i, F_j]$	*	*	*	*	0	0	0	0	
Actions	All Info	Co D	Su Co	Su Co	Co	Co Su	Su D	Su Co	Co D
	Part Info		Tf 9,10,7	Tf 10,11,8		Tf 12,13, 14,17,18	Tf 13,15, 17,19	Tf 14,15, 18,19	

	16	17	18	19	20	21	22	23	
$Sd[F_i]$	0	1	0	1	0	1	0	1	
$Sd[F_j]$	0	0	1	1	0	1	0	1	
$C[F_i, F_j]$	1	1	1	1	0	0	1	1	
$O[F_i, F_j]$	1	1	1	1	1	1	1	1	
$\tilde{>}[F_i, F_j]$	0	0	0	0	1	1	1	1	
Actions	All Info	Co Su	Su Co	Su Co	Co	Co Su	Co D	Co Su	Co
	Part Info	Tf 16,17, 13,14,18	Tf 17,19, 15	Tf 18,19, 15		Tf 20,13, 14,17,18		Tf 22,13, 14,17,18	

Figure 3: Revised Multi-Feature Decision Actions



Less obviously, adding a new feature can make a previously significant one insignificant. This happens when the alternatives differ so enormously on the new feature that any differences on the old one(s) cease to be significant.  $C[F_i, F_j]$  may change if the new feature produces a conflict, and  $O[F_i, F_j]$  and  $\tilde{>}[F_i, F_j]$  change by clustering features. Within the framework of our typology, the effects of adding a new feature are:

1. to introduce a conflict where there was none
2. to take a side in a conflict
3. to join the consensus ( $C[F_i, F_j, F_k] = 0$ ) but lend it legitimacy since  $Sd[F_k] = 1$
4. to introduce an ordering where there was none (e.g.  $O[F_i, F_j] = 0$  but  $O[F_i, (F_j, F_k)] = 1$ )
5. to change an ordering (e.g.,  $\tilde{>}[F_i, F_j] = 1$  but  $\tilde{>}[F_i, (F_j, F_k)] = 0$ )
6. to produce a change in relative significance when adding radically divergent features.

Figure 4 shows all the possible actions and their effects for a single case in the typology, case 4. In this example, there is enough of a difference to support a decision on  $F_i$ , but not  $F_j$  and the evidence of the two features is contradictory. Four actions are appropriate: transformation by feature (the 0 value for  $Sd[F_j]$  may indicate insufficient evidence), transformation by order, substitution (for  $F_j$ ), and combination. Note that it is possible to return to the same state, case 4, but by different paths. Substituting  $F_j$  or combining features transforms case 4 to case 5. But note that when case 5 was reached by combining features, one of them,  $F_i$  or  $F_j$ , actually represents the evidence of two features and so supports a decision more strongly. (This difference will be represented explicitly in a more complete state table).

**The Mechanics of Combining Features** As mentioned above, combining features may produce major changes in the decision state. However, the set of possible new states can be enumerated. Figure 5 presents the set of possible states that can be reached by combining a new feature with all previous states.

The first five columns of Figure 5 have the same values as the rows in previous tables.  $Sd[F_k]$  is the significant difference value of the new feature; it is always 1, indicating that the new feature discriminates the alternatives.  $Sd[F_C]$  is the significant difference of the combined features; the values in its column are the features that have been combined along with their possible values.  $C[\text{all}]$  shows whether there is a conflict between the combined values and the single feature.  $\tilde{>}[F_N, F_x]$  describes an order between the combined feature and the single feature. The column labeled 'Transition' shows the possible transitions from that state. Finally, # indicates how many significant features had been combined to produce the  $F_C$  feature.

Figure 5 presents the single step transitions when adding features to states as represented in the two feature tables. We are currently working on a state transition diagram that will describe all the possible transitions in the construction of a decision between two alternatives.

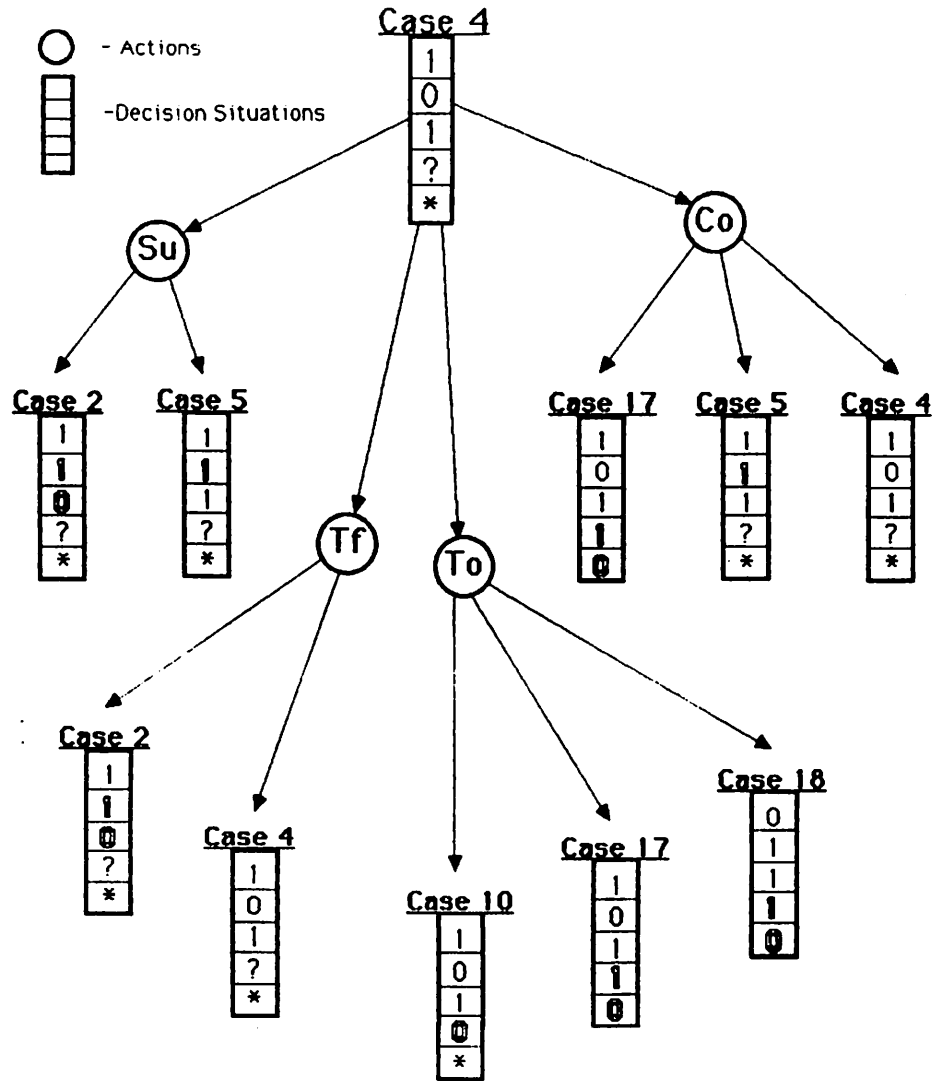


Figure 4: Single Transition with Multiple Features

Sd[F <sub>i</sub> ]	Sd[F <sub>j</sub> ]	C[F <sub>i</sub> , F <sub>j</sub> ]	O[F <sub>i</sub> , F <sub>j</sub> ]	Σ[F <sub>i</sub> , F <sub>j</sub> ]	Sd[F <sub>k</sub> ]	Sd[F <sub>C</sub> ]	C[all]	Σ[F <sub>C</sub> , F <sub>x</sub> ]	Transition	#
0	0	0	0	*	1	ij 0/1	0/1	?	0000* → 0/1 1 0/1 0/1?	0
0	0	1	0	*	1	ik 1	1	1	0010* → 1 0 1 1 0	1
1	0	0	0	*	1	ij 1	0/1	?	1000* → 1 1 0/1 0/1?	1
1	0	1	0	*	1	ik 1	1	1	1010* → 1 0 1 1 0	2
1	0	1	0	*	1	jk 1	1	1	1010* → 1 1 1 1 1	1
1	1	1	0	*	1	ik 1	0/1	?	1100* → 1 1 0/1 0/1?	2
1	1	1	0	*	1	ik 1	1	1	1110* → 1 1 1 1 0	2
0	0	0	1	0/1	1	ij 0/1	0/1	?	00010/1 → 0/1 1 0/1 0/1?	0
0	0	1	1	0	1	ik 1	1	0	00110 → 1 0 1 1 0	1
0	0	1	1	0	1	jk 1	1	?	00110 → 0 1 1 0/1?	1
0	0	1	1	1	1	ik 1	1	?	00111 → 1 0 1 0/1?	1
0	0	1	1	1	1	jk 1	1	1	00111 → 0 1 1 1 1	1
1	0	0	1	0/1	1	ij 1	0/1	?	10010 → 1 1 0/1 0/1?	1
1	0	1	1	0	1	ik 1	1	0	10110 → 1 0 1 1 0	2
1	0	1	1	0	1	jk 1	1	?	10110 → 1 1 1 0/1?	1
1	0	1	1	1	1	ik 1	1	?	10111 → 1 0 1 0/1?	2
1	0	1	1	1	1	jk 1	1	1	10111 → 1 1 1 1 1	1
1	1	0	1	0/1	1	ij 1	0/1	?	11010/1 → 1 1 0/1 0/1?	2
1	1	1	1	0	1	ik 1	1	0	11110 → 1 1 1 1 0	2
1	1	1	1	0	1	jk 1	1	?	11110 → 1 1 1 0/1?	2
1	1	1	1	1	1	ik 1	1	?	11111 → 1 1 1 0/1?	2
1	1	1	1	1	1	jk 1	1	1	11111 → 1 1 1 1 1	2

## 4. Conclusions

We have presented a model of constructive decision making. We envision a decision-maker starting with a two-alternative, two-feature problem, then acquiring information, and perhaps adding features, under the guidance of actions associated with decision types. This model raises the intriguing possibility of controlling decision making in AI programs by table lookup. Each decision situation is first classified, then modified by one of the associated actions. The model is not intended to produce optimal solutions to complex decision problems given complete information, but rather to explore methodologies for structuring decision problems, performing symbolic comparisons, and reasoning about uncertain decisions.

Other systems have viewed decision making as a constructive process. GODDESS, a domain independent decision support system, constructs a hierarchical goal representation of decision alternatives by selectively focusing the users attention on the most crucial issues [Pearl 82]. Users assign numeric values to probabilities and importance, and the program propagates them through the structure. ARIADNE does not address the decision formulation problem, but rather emphasizes evaluation by using linear programming algorithms to produce a dominance structure for the alternatives' probabilities and utilities and by allowing the iterative addition of alternatives [Sage 84].

Three facets of the decision typology model are particularly appealing. First, two-alternative, two-feature decisions can be characterized according to the dimensions of the decision without requiring an underlying scale of comparison. Second, the typology relates actions to decision types. Finally, the model shows how to change difficult decisions into more tractable ones using well defined transformations that explicitly identify the possible results of actions.

Before the model is fully realized, we must resolve two issues. First, the conditions and mechanisms for adding new alternatives must be specified as they were for new features. We believe that alternatives can be clustered like features, so the two-alternative, two-feature typology might serve for multiple alternatives and features. The second issue is to add continuous values to the model. The binary/ternary formalism is abstract. For most situations, this abstraction is not only acceptable, but fully indicative of the appropriate actions. However, it does not explicitly capture the effects of extreme values or context.  $Sd[F_i]$  indicates a disparity between alternatives on  $F_i$ , but not its magnitude. The difference in degree of differentiation between alternatives on features is captured in the  $O[F_i, F_j]$  dimension, which may favor the feature that produces a great disparity. This, in turn, implies that  $O[F_i, F_j]$  is *not* independent of alternatives.

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