Causal and Plausible Reasoning in Expert Systems

Gerald Shao-Hung Liu†

Advanced Products, VHSIC Test Systems, Sentry/Schlumberger
1725 Technology Dr., San Jose, CA 95115

ABSTRACT

This study sets out to establish a unified framework for causal and plausible reasoning. We identify a primitive set of causal roles which a condition may play in the inference. We also extend Dempster-Shafer theory to compose the belief in conclusion by the belief in rules and the belief in conditions. The combined framework permits us to express and propagate a scale of belief certainties in the context of individual roles. Both the causation aspect and the certainty aspect of an inference are now accounted for in a coherent way.

I INTRODUCTION

Inference rules, as a primitive for reasoning in expert systems, contain two orthogonal components: the *inference nature* (i.e. *what* merits the conclusion and *how* is it warranted?) and the *inference strength* (i.e. *how much* is the conclusion supported - almost for certain, or weakly so?). The two inference components have largely received separate attention. To account for inference strengths some researchers resort exclusively to various 'likelihood calculi*' without causal provisions. Others, aiming to explain the inference nature, endorse symbolic rules without any likelihood mechanism (e.g. [Cohen 83]). There are also some other researchers who employ a hybrid approach (see [Szolovits 78]).

The problems with these rule representations are as follows: symbolic rules without likelihood cannot represent inference strength; likelihood rules without a causal account cannot distinguish inference nature; and hybrid representations to date are either piecewise (using separately one of the two methods in each rule) or ad hoc (lacking a sound theoretical ground for the likelihood calculus). In brief, the non-numerical approach errs on the weak side, whereas an exclusive likelihood calculus suffers from superficiality.

The goal of this research is therefore to combine causal and plausible reasoning in a coherent way. There are two aspects to this goal: identifying a primitive set of causal categories named *roles*, and extending plausible reasoning under these qualitatively different roles.

II RELATED WORK

A. Non-likelihood Symbolic Approaches

Endorsements are the explicit construction of records that a particular kind of inference has taken place (e.g. the *imprecisely* defined *supportive* condition *may be too specific* for the conclusion [Cohen 83, p133]). There are many different kinds of endorsement, corresponding to different kinds of evidence for and against a proposition. However, elaborate heuristics do not overcome the general problem with pure symbolic reasoning: they err on the weak side after all.

Categorical inferences are "ones made without significant reservations" [Szolovits 78, p116]: *IF <condition> THEN commit <decision>*. A strong causal inference, in our term, is just a categorical one with an explicit causal account: e.g. *<condition> IS-SUFFICIENT-FOR <decision>*, *<condition> IS-NECESSARY-FOR <decision>*, *<condition> EXCLUDES <decision>*, etc. Being simple to make, such categorical decisions usually depend on relatively few facts [ibid., p117]. Unfortunately, for reasons all too obvious, reasoning *exclusively* by (strong causal) categories finds limited applications only.

B. Numerical Likelihood Approaches

The *Certainty Factor (CF)* model [Shortliffe 76] attaches to each inference rule a *CF* representing the *change* in belief about the concluding hypothesis given the premised evidence. The actual formulae in the *CF* model are immaterial to our discussion, for they share the same following problems: these formulae derive from no where, and the *CF* model in itself does not deal with partial evidence bearing on multiple hypotheses.

Bayes networks (a term used in [Pearl 85]) refer to directed acyclic graphs in which the nodes signify propositions (or variables), and the strengths on the linking arcs represent the (Bayesian) conditional probabilities. Bayes networks include the "inference network" in *PROSPECTOR* [Duda, Hart, et al 76] as an important variation. These networks largely employ (variations of) Bayes' rule as the inference mechanism, therefore those usual issues in Bayesian theories [Charniak 83] are raised: the excessive number of conditional probabilities, the assumption of pairwise conditional independence as a device to escape from the preceding problem, and how to deal with partial evidence bearing on multiple hypotheses.

1. Dempster-Shafer Theory

There are two distinguishing advantages of Dempster-Shafer theory as a 'likelihood calculus' over Certainty Factors and Bayes Networks: it is able to model the narrowing of the hypothesis set with the accumulation of evidence; it permits us to reserve part of our belief to the 'don't-know' choice (a degree of ignorance).

Suppose probability judgements are required for possible answers to a particular question. These possible answers form a set named *frame of discernment.* To provide supporting evidence, a 'related' question may be asked so that the established probabilities of the answers to this related question will shed light on those to the original. The set of answers to the related question forms a *background frame of discernment*; correspondingly the original frame may be referred to as the *foreground frame.* The 'inter-relatedness' between the two questions is manifested by that not every answer in the background frame is *compatible* (i.e. logically consistent) with all the answers in the foreground frame. Furthermore, commitment of belief to an answer in the foreground frame can be counted as *reason to believe* it by the sum of probabilities of all the compatible answers in the background frame.

Example 1. (Originated from [Zadeh 84, p81]) Suppose Country *X* believes that a submarine, S, belonging to Country *Y* is hiding in *X*'s territorial waters. The Ministry of Defense of *X* wants to evaluate the possible loca-

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* 'Likelihood' in this context refers in general to such formalisms as Certainty Factors, Probability, and Belief Functions (Plausible Reasoning).

tions of S. A group of Navy experts, $E_1,..., E_M$, are summoned; each of them indicates an area which he believes S is in. Let $A_1,..., A_I$ denote the areas indicated by the experts $E_1,..., E_M$ individually ($I \le M$). Assume that there are also certain experts who, being ignorant in this case, cannot indicate any specific area. Now suppose the Ministry of Defense aggregates the experts opinion by averaging: the vote of E_m is multiplied by a number w_m, $0 \le w_m \le 1$, such that $w_1 + \cdots + w_M = 1$. Then the *reason to believe* in an area A_i is counted by a so-called basic probability assignment (bpa) to A_i: $m(A_i) = \sum_{E_m:\rightarrow A_i} w_m$, where $E_m:\rightarrow A_i$ denotes that the expert E_m votes for the area A_i. Similarly the *amount of ignorance* is measured by a *bpa* to the entire territorial waters $\bigcup_{i=1}^{I} A_i$: $m\left[\bigcup_{i=1}^{I} A_i\right] = \sum_{E_m:\rightarrow \bigcup_{i=1}^{I} A_i} w_m$.

Stated formally, let Θ_b and Θ_f be the background and the foreground frame of discernment respectively. Between Θ_b and Θ_f, the element-subset compatibility relation is denoted by ':→'. More specifically, $b:\rightarrow F$ denotes that b is compatible with all the elements in F, and there is no other superset of F being such, where $b \in \Theta_b$ is an item of supporting evidence in the background and $F \subseteq \Theta_f$ is the 'maximum supported subset' in the foreground. Such an F is called a focal element. Then the commitment of belief to F, namely a basic probability assignment (*bpa*) to F, is counted (as reason to believe) by

$$m(F) = \sum_{b:\rightarrow F} P(b) \quad (1)$$

where $P(b)$ is the background probability judgement over $b \in \Theta_b$. It is easy to see that (1) $m(\varnothing) = 0$, and (2) $\sum_{F \subseteq \Theta_f} m(F) = 1$. In addition, $m(\Theta_f) > 0$ represents the degree of partial ignorance. When all the focal elements (as supported subsets) are singletons, the basic probability assignment m reduces to a Bayesian probability.

III BELIEF CERTAINTY IN FACTS AND RULES

This section discusses how to represent belief certainty in the knowledge base. The knowledge base is first divided into (unconditional) facts and (inference) rules. They will be attached with basic probability assignments as commitment of beliefs. The role system, to be introduced later, can then be viewed as additional causal structures imposed on generic inference rules.

A. Factual Certainty

To begin with, we represent an unconditional fact by its *canonical form: X is F*. For instance, *Carol has a young daughter* is represented by *AGE(DAUGHTER(Carol)) is YOUNG*. The belief in "*X is F*" can usually be represented by an interval $[v_1,v_2]$. v_1 expresses the extent to which we confirm "*X is F*" by the available evidence, whereas v_2 express the extent to which we disconfirm it.

There are two advantages of using an interval rather than a single qualifier. First, information incompleteness (or partial ignorance, measured by $1-(v_1+v_2)$) is separated from uncertainty (expressed by v_1 or v_2 alone). Second, information absence (indicated by [0, 0]) is represented differently than negation (expressed by [0, 1]).

If several pieces of facts are related by mutual exclusion, a frame of discernment can be formed. Then the degree of confirmation in each proposition is simply its basic probability assignment. In view of this frame of discernment, any independent proposition and its negation are included in a frame by themselves. Such frames are called dichotomous frames. Then the belief interval amounts to a concise representation for the (default) dichotomous frame.

B. Rule Certainty

A central issue in evidential reasoning is how to represent uncertain rules. Bayesian probability expresses uncertain rules by the conditional probability $Prob(h|e)$, then concludes the hypothesis from uncertain evidence: $P(h|E')=\sum_i P(h|e_i)P(e_i|E')$. In the original Dempster-Shafer theory, however, the counterpart procedure is missing (in spite of the "conditional belief function" $Bel(h|e)$ defined in [Shafer 76]).

To remedy the problem, this study follows [Ginsberg 84], [Baldwin 85] and [Yen 85] to extend the original Dempster-Shafer theory, but a different approach is taken. In practice, our approach differs from [Ginsberg 84] and [Baldwin 85] in that it takes into account those frames of discerment more general than the dichotomous ones (those which include only two propositions); our approach differs from [Yen 85] in that it is based on associational strengths more general than the 'partition-based conditional probabilities'. Additionally, in methodology our approach differs from all previous ones in that it relates to the fundamental compatibility relation with the background frames. As a result, we can *derive*, not define, the extension theory. Examples comparing these approaches are given below.

The following two paragraphs define the terms needed for the extension. Their mathematical relations are then expressed below.

An inference rule of the form $A_i \rightarrow C_j$ in general may have either the antecedent A_i or the consequent C_j as sets (rather than singletons) of some elements. •This is especially true for hierarchical narrowing of the hypothesis set, e.g. *evidence* $\xrightarrow{0.6}$ *{DISEASE is HEPATITIS, DISEASE is CIRRHOSIS}*. Therefore we assume in general $A_i=\{a_k | a_k \in A_i\} \subseteq \Theta_a$ and $C_j=\{c_l | c_l \in C_j\} \subseteq \Theta_c$. Θ_a is the antecedent frame of discerment containing all possible a_k's, and Θ_c is the consequent frame of discerment containing all possible c_l's. In addition, there is a conditional frame of discernment $\Theta_{c|A}$ containing all possible pairs of c_l *given* A_i's. An inference rule $A_i \rightarrow C_j$ can then be viewed as a subset, $\{c_l \text{ given } A_i | c_l \in C_j\}$, of $\Theta_{c|A}$.

To provide a basis for the basic probability assignments over Θ_a, Θ_c, and $\Theta_{c|A}$, certain background frames as the supporting evidence have to be assumed. Let $\Theta'_a=\{a'_m\}$ be the background of $\Theta_a=\{a_k\}$, $\Theta'_c=\{c'_n\}$ be the background of $\Theta_c=\{c_l\}$, and $\Theta'_{c|A}=\{c'_n \text{ given } A_i\}$ be the background of $\Theta_{c|A}=\{c_l \text{ given } A_i\}$. To prevent confusion, Θ'_a is called the background antecedent frame, and Θ_a the foreground antecedent frame. Similarly Θ'_c is referred to as the background consequent frame; Θ_c the foreground consequent frame. And $\Theta'_{c|A}$ and $\Theta_{c|A}$ the background conditional and the foreground conditional frames respectively.

According to (1), a basic probability assignment to the foreground antecedent A_i measures the 'reason to believe' A_i by compatible evidence in the background:

$$m(A_i|E') = \sum_{a'_m:\rightarrow A_i} P(a'_m|E') \qquad \textit{where } A_i \subseteq \Theta_a, \text{ and } a'_m \in \Theta'_a \quad (3)$$

where E' denotes the source of observation. In analogy, a conditional bpa can be defined to measure the 'reason to believe' the conditional proposition C_j *given* A_i (corresponding to an inference $A_i \rightarrow C_j$):

$$m(C_j|A_i) \triangleq m(\{c_l\}|A_i) \triangleq m(\{c_l \text{ given } A_i\}) \quad (4)$$

$$= \sum_{c'_n:\rightarrow C_j=\{c_l\}} P(c'_n|A_i) \qquad \textit{where } c'_n \in \Theta'_c,\ c_l \in C_j \subseteq \Theta_c,\ A_i \subseteq \Theta_a$$

Actually, background probabilities $P(c'_n|E')$'s can also determine directly the *bpa* to a foreground consequent C_j:

$$m(C_j|E') = \sum_{c'_n \leftrightarrow C_j} P(c'_n|E') \qquad \textit{where } C_j \subseteq \Theta_c, \text{ and } c'_n \in \Theta'_c \quad (5)$$

But the goal is to express $m(C_j|E')$ in terms of $m(C_j|A_i)$ and $m(A_i|E')$. The rationale is similar to the Bayesian conditioning procedure $P(h|E')=\sum_i P(h|e_i)P(e_i|E')$. That is, there may not be direct probabilities available for the conclusion.

Example 2 *(Continued from Example 1)*: Suppose the Ministry of Defense of Country X attempts to conjecture the intention of S based on its locations.

Assume that these conjectures are made in the form of inference rules: $A_i \to C_j$, signifying that S cruising in Area A_i suggests Conspiracy C_j of Country Y. Suppose the Ministry relies on those Navy experts as in Example 1 to evaluate the possible locations of S, but calls the Intelligence Agency for a confirming history of activities, $c'_1, ..., $ or c'_N, in each of the areas $A_1, ..., A_I$. Assume furthermore that each of these local history reports, c'_n *within* A_i, is weighted by v_{ni} such that $\sum_n v_{ni} = 1$ for each i.

Then the *bpa* to a foreground antecedent, $m(A_i | E')$, is $\sum_{E_m :\to A_i} w_m$ as in Example 1, whereas a *conditional bpa*, $m(C_j | A_i)$, is determined by $m(C_j | A_i) = \sum_{c'_n :\to C_j} v_{ni}$. In above, the weight v_{ni} approximates the conditional probability $P(c'_n | A_i)$, and $c'_n :\to C_j$ signifies that the activity history c'_n confirms the conjecture C_j.

Recall that the goal of the Ministry was to evaluate the reason to believe each conspiracy C_j, which is measured by $m(C_j | E') = \sum_{c'_n :\to C_j} P(c'_n | E')$.

However, short of a direct history on $P(c'_n | E')$'s, the Ministry seeks to express $m(C_j | E')$ in terms of $m(C_j | A_i)$ and $m(A_i | E')$. To this end Theorem 1 provides an answer below. Two lemmas are first established.

Lemma 1. For each $a'_m \in \Theta'_a$ and $A_i \subseteq \Theta_a$ such that $a'_m :\to A_i$, the following property holds:

$$P(A_i | a'_m E') = 1$$

Lemma 2. For each $a'_m \in \Theta'_a$ and $A_i \subseteq \Theta_a$ such that $a'_m :\to A_i$, if $P(c'_n | A_i) = P(c'_n | A_i a'_m E')$ for certain $c'_n \in \Theta'_c$, then the following property holds:

$$P(c'_n | A_i) = P(c'_n | a'_m E')$$

Theorem 1. *(Propagation of Beliefs)* In an inference rule $A_i \to C_j$, if for each background antecedent a'_m that supports A_i, and each background consequent c'_n that supports C_j, the equality $P(c'_n | A_i) = P(c'_n | A_i a'_m E')$ holds, then $m(C_j | E') = \sum_{A_i \subseteq \Theta_a} m(C_j | A_i) m(A_i | E')$.

Proof: the theorem follows from (3), (4), (5), and Lemmas 1 and 2.

It should be noted (1) that this theorem was implicitly assumed in [Ginsberg 84, p126] and [Baldwin 85, p12]; (2) that not only can beliefs in consequents be composed of beliefs in antecedents and the rules, but also the *consequent ignorance* (i.e. $m(\Theta_c | E')$) can be composed of *antecedent ignorance* (i.e. $m(\Theta_a | E')$) and *rule ignorance* (i.e. $m(\Theta_c | A_i)$). This is expressed in the following corollary:

Corollary 1. *(Increasing Propagation of Ignorance)* If $m(\Theta_c | \Theta_a) = 1$ (that is, without knowing the foreground antecedent, we cannot conclude any foreground consequent except for the frame itself), then $m(\Theta_c | E') = \sum_{\Theta_a \neq A_i \subseteq \Theta_a} m(\Theta_c | A_i) m(A_i | E') + m(\Theta_a | E') \geq m(\Theta_a | E')$.

Example 3 *(Correspondence to Bayesian Beliefs):* If there is no partial ignorance involved whatsoever, and if all the antecedents and the consequents are singletons (that is, if the beliefs are all classical Bayesian probabilities [Shafer 76, p45]), then Theorem 1 $m(C_j | E') = \sum_{A_i \subseteq \Theta_a} m(C_j | A_i) m(A_i | E')$ reduces to the posterior probability: $P(h | E') = \sum_{e_i \in \Theta_a} P(h | e_i) P(e_i | E')$. In this case, a foreground frame becomes identical to its background counterpart.

Example 4 *(Correspondence to Partition-Based Probabilities [Yen 85, p8]):* If there is no partial ignorance involved whatsoever, and if both the antecedents and the consequents (as focal elements) form a *partition* in the respective foreground frames, then Theorem 1 becomes Yen's extension using 'partition-based conditional probabilities':

$$P(C_j | E') = \sum_{A_i \in \Pi_{\Theta_a}} P(C_j | A_i) P(A_i | E') \qquad (6)$$

for each $C_j \in \Pi_{\Theta_c}$, where Π_{Θ_c} and Π_{Θ_a} are partitions of Θ_c and Θ_a respectively.

Examples 3 and 4 have different meanings. The partitioning approach by Yen allows hierarchical narrowing of the hypothesis set, although it doesn't account for ignorances, whereas the classical Bayesian approach requires a probability assignment to *every single element* in the beginning.

Example 5 *(Correspondence to Dichotomous Frames* [Ginsberg 84, p126], [Baldwin 85, p12]) Denote by $A \xrightarrow{[a,b]} C$ an inference rule with dichotomous consequents. a is the extent to which we believe C given A is true, and b is the extent we believe $\bar{C}$ given the same A. Then Ginsberg's and Baldwin's work - which really dealt with singleton C's only - can be summarized by

$$\frac{E' \xrightarrow{[c,d]} A \qquad A \xrightarrow{[a,b]} C}{E' \xrightarrow{[ca,cb]} C}$$

Additionally the consequent ignorance, $1-(ca+cb)$ in their calculation, can be identically obtained by $m(\Theta_c | E')$ in Corollary 1.

IV THE ROLE SYSTEM

In an inference rule, the relations between the condition and the conclusion are multi-dimensional. They can be causal, or more often they are associational. In some cases the condition-conclusion relationship would be affected by other auxiliary conditions. These relationships are all qualitatively different; they need to be treated accordingly. Therefore a primitive causal category, namely the *role system* [Liu 85], is established to account for these distinct relations. The role system divides the condition into six possible *roles* (which the condition may play in the inference): *associational, supportive, adverse, sufficient, necessary,* and *contrary* roles.

A. Associational Role

A great deal of the surface-level empirical knowledge belongs to the associational role. Such an inference rule in general takes the form of

$$A \underset{ASSOC}{\to} C_1[m_1], C_2[m_2], \cdots \Theta_c[m_{\Theta_c}]. \qquad (7)$$

where Θ_c is the consequent frame of discernment, C_i's $\subseteq \Theta_c$ are focal elements as the alternative consequents, and m_i's are corresponding conditional *bpa*'s given that A is true. That is, $m_i = m(C_i | A)$ as defined in (4). Most Often the consequent frame is dichotomized so that $C_2 = \bar{C_1}$ is the only focal element other than C_1 and Θ_c itself. In this case (7) may be abbreviated as in Example 5: $A \overset{[m_1, m_2]}{\underset{ASSOC}{\to}} C_1$ where m_1 and m_2 are the extent to which we believe C and $\bar{C}$ when A is true.

The inference making with an uncertain antecedent in (7) is a straightforward application of Theorem 1. Examples will be given along with the following supportive roles.

B. Supportive and Adverse Roles

Supportive and adverse roles may take place with an associational role. However, they are of secondary importance in the inference rule. That is, when a supportive (or adverse) condition is confirmed *in addition to* the primary associational role, the conclusion will be better (or worse) warranted - but the supportive or adverse role by themselves do not make a meaningful rule.

Example 6 (*Supportive Role* from [Rich 83, p349])
'Close to half' (40%) of the animals use camouflage as the defense mechanism. But those animals with *colors similar to the environment* are 'much more liable' (e.g. 80% of them) to defend themselves by camouflage.

Example 7 (Continued from Example 6. An *Adverse Role*)

Those animals with *colors different from the environment* tend not to (e.g. only 10% of them will) defend themselves by camouflage.

1. General Form

The general form of an inference rule with a supportive role is

$$A \underset{ASSOC}{\rightarrow} C_1[m_1], C_2[m_2], \cdots \Theta_c[m_{\Theta_c}] \quad where\ m_i = m(C_i \mid A) \tag{8}$$

Supported by:

$$A'_1 \underset{SUPP}{\rightarrow} C_1[m'_{11}], C_2[m'_{21}], \cdots \Theta_c[m_{\Theta,1}] \quad where\ m'_{i1} = m(C_i \mid AA'_1)$$

$$A'_m \underset{SUPP}{\rightarrow} C_1[m'_{1m}], C_2[m'_{2m}], \cdots \Theta_c[m_{\Theta,m}] \quad where\ m'_{im} = m(C_i \mid AA'_m)$$

where A'_j's are alternative focal elements over the supportive frame of discernment $\Theta_{a'}$.

Suppose $E \rightarrow A[m(A \mid E)]$ from previous inferences. If in addition it is known that $E' \rightarrow A'_1[m_{A'_1}], A'_2[m_{A'_2}], \cdots \Theta_{a'}[m_{\Theta_a}]$ where $m_{A'_j} = m(A'_j \mid E')$, then for each $EE' \underset{SUPP}{\rightarrow} C_i$ the *bpa* $m(C_i \mid EE')$ may be calculated from Theorem 1 and (8) as follows:

$$m(C_i \mid EE') = \sum_{A'_j \subseteq \Theta_{a'}} m(C_i \mid AA'_j) m(AA'_j \mid EE') \tag{9}$$

$$= m(C_i \mid A) m(A \mid E)[1 - \sum_{A'_j \in \{A'_1, .. A'_m\}} m(A'_j \mid E')]$$

$$+ \sum_{A'_j \in \{A'_1, .. A'_m\}} m(C_i \mid AA'_j) m(A \mid E) m(A'_j \mid E')$$

2. Examples Reformulated

Rule 1 (Reformulating Example 6):

(animal ?x) $\overset{[0.4,\,0.6]}{\underset{ASSOC}{\rightarrow}}$ (defense-by ?x camouflage)

Supported by:

(color x ?c) ∧ (habitation x ?y) ∧ (color ?y ?c') ∧ (similar ?c ?c') $\overset{[0.8,\,0.1]}{\underset{SUPP}{\rightarrow}}$

(defense-by x camouflage)

Rule 1' (Merging Examples 6 and 7):

(animal ?x) $\overset{[0.4,\,0.6]}{\underset{ASSOC}{\rightarrow}}$ (defense-by ?x camouflage)

Supported by:

(color x ?c) ∧ (habitation x ?y) ∧ (color ?y ?c') ∧ (similar ?c ?c') $\overset{[0.8,\,0.1]}{\underset{SUPP}{\rightarrow}}$

(defense-by x camouflage)

(color x ?c) ∧ (habitation x ?y) ∧ (color ?y ?c') ∧ (different ?c ?c') $\overset{[0.1,\,0.8]}{\underset{SUPP}{\rightarrow}}$

(defense-by x camouflage)

For illustration, consider the situation in which (animal x) is matched. If any of the supporting properties (color x c), (habitation x y), (color y c') or (similar c c') is unknown, then all that can be concluded is (defense-by x camouflage) with [0.4, 0.6] by virtue of the generic unsupported rule. However, if (animal x) ∧ (color x c) ∧ (habitation x y) ∧ (color y c') is known, and furthermore m(similar c c')=0.7 and m(different c c')=0.2, then more specific conclusion can be made.

According to (9), *Bel*(defense-by x camouflage) = *m*(defense-by x camouflage) in Rule 1' can be calculated by

m[(defense x camouflage)|*EE'*]

= *m*[(defense x camouflage)|(animal x)]

· (1 - *m*[(similar c c')|*E'*] - *m*[(different c c')|*E'*]) +

m[(defense x camouflage)|(animal x)..(similar c c')] · *m*[(similar c c')|*E'*] +

m[(defense x camouflage)|(animal x)..(different c c')] · *m*[(different c c')|*E'*]

$= 0.4 \cdot (1 - 0.7 - 0.2) + 0.8 \cdot 0.7 + 0.1 \cdot 0.2 = 0.62$

By the same token, *m*[(defense x camouflage)|*EE'*] in Rule 1 is $0.4 \cdot (1 - 0.7) + 0.8 \cdot 0.7 = 0.68$. Similarly *Bel*[*NOT* (defense-by x camouflage)] = *m*[*NOT* (defense-by x camouflage)] can be obtained: 0.25 in Rule 1 and 0.29 in Rule 1'.

C. Sufficient Role

A condition plays a sufficient role if the confirmation of the condition *alone* warrants the conclusion. The typical usage of such sufficient roles is to facilitate the inference process of *Modus Ponens*. In the knowledge base a sufficient role may take place at a deep causal level:

Example 8 [Patil 81, p894] Diarrhea causes the excessive loss of lower gastraintestinal fluid.

Alternatively, a sufficient role may take place on a surface, empirical basis. Consider in assessing the future market of a computer product, the executive might have this rule of thumb:

Example 9 If IBM commits itself to a five-year purchase contract totalling multi-million in revenue, then we should go for making the product.

The general form of a rule with sufficient conditions takes the form $A \overset{[m,\,0]}{\underset{SUFF}{\rightarrow}} C$ where m as the *bpa* of C conditioned on A must be *close to* 1. The inference making of such sufficient roles under uncertainty is simply a special form of Example 5 (which follows from Theorem 1):

$$\frac{A \overset{[m,\,0]}{\underset{SUFF}{\rightarrow}} C \qquad E' \overset{[c,\,d]}{\rightarrow} A}{E' \overset{[cm,\,0]}{\underset{SUFF}{\rightarrow}} C} \tag{10}$$

Note that when belief in the antecedent is severely discounted the sufficient role will effectively become a different associational role.

Rule 2 (Examples 9 reformulated):

(has-contract-with ?target) ∧ (is ?target ibm) ∧ (contract-worth multi-million) ∧ (contract-span about-or-at-least-5-years) ∧ (contract-for ?product) $\overset{[0.9,0]}{\underset{SUFF}{\rightarrow}}$ (support ?product)

D. Necessary Role

A condition plays a necessary role if the disconfirmation (or lack of confirmation, depending on cases) of the condition enables us to refute the conclusion. In classical logic a necessary role would facilitate the inference rule of *Modus Tollens*. In semantic-rich domains, however, there are two types of necessary roles: the strong necessary role and the weak one. The strong one refers to those conditions whose lack of confirmation suffices to refute the conclusion (the condition doesn't have to be directly disproved), and the weak necessary role refers to those conditions which must be disproved in order to disprove the conclusion.

Example 10 *(Strong Necessary Role)* A suspect claiming an alibi needs to have a witness. In this case, a witness is the strong necessary condition for claiming an alibi. This is because, short of a witness taking the stand (lack of proof), the suspect cannot effectively hold his claim (the claim being refuted). Stated formally, the prosecutor has: (has-witness ?suspect) IS-STRONG-NECESSARY-FOR (has-alibi ?suspect), and he will conclude (NOT (has-alibi ?suspect)) on the basis of (NO (has-witness ?suspect)). (Note that 'NO' implies lack of evidence, whereas 'NOT' implies a negation.)

Example 11 *(Weak Necessary Role)* The employer may require its employees to demonstrate a job competence in order for them to continue to be employed. Then we have: (competent ?employee) IS-WEAK-NECESSARY-FOR (continue-to-be-employed ?employee). This is because the employer must confirm (NOT (competent ?employee)) in order to determine (NOT (continue-to-be-employed ?employee)); it is not sufficient to just have (NO (competent ?employee)).

The general form of the rule with a strong necessary condition is: $(NO\ A) \xrightarrow[SNEC]{[m,0]} \bar{C}$ whereas the weak necessary counterpart takes the form: $(NOT\ A) \xrightarrow[WNEC]{[m,0]} \bar{C}$ where m as the *bpa* of $\bar{C}$ again must be *close to* 1. In addition, to support *NO*'s and *NOT*'s as different forms of negation we define $m(NO\ A) \triangleq 1 - m(A) \geq m(NOT\ A) \triangleq m(\bar{A})$, and $m(NOT\ (NO\ A)) \triangleq m(A)$. To support uncertain inference making, we rewrite Example 5 to obtain

$$E' \xrightarrow{[c,d]} A$$

$$\frac{(NO\ A) \xrightarrow[SNEC]{[a,0]} \bar{C}}{E' \xrightarrow[SNEC]{[(1-c)a,0]} \bar{C}}$$

and

$$E' \xrightarrow{[c,d]} A$$

$$\frac{(NOT\ A) \xrightarrow[WNEC]{[a,0]} \bar{C}}{E' \xrightarrow[WNEC]{[da,0]} \bar{C}}$$

Rule 3 (Reformulating Example 10):
(NO (has-witness ?suspect)) $\xrightarrow[SNEC]{[1,0]}$ (NOT (has-alibi ?suspect))

Rule 4 (Reformulating Example 11):
(NOT (competent ?employee)) $\xrightarrow[WNEC]{[0.8,0]}$ (NOT (continued-to-be-employed ?employee))

E. Contrary Role

A contrary role is an excluding condition. In other words, the confirmation of this condition will exclude the conclusion. In many cases a contrary condition is just the complimentary view of a necessary condition. (The choice is largely a semantic one.) For instance, in Example 11 we could have established:

Rule 5 (See Rule 4):
(incompetent ?employee)) $\xrightarrow[CONTR]{[0.9,0]}$ (NOT (continued-to-be-employed ?employee))

V THE INCLUSION OF EXCEPTION ROLES

Inference rules as empirically acquired are often times *defeasible* (vulnerable) when exceptional situations present themselves. A cliche example is *birds can fly* (a defeasible rule) *but ostriches cannot* (an exception that defeats the rule). These exception conditions may be included as <u>*exception roles*</u> in the role system. Belief functions can then be used to account for <u>*plausible exceptions.*</u>

Defeasible rules have been the focal subject in 'non-monotonic reasoning,' e.g. [McDermott 80] and [Reiter 80]. However, none of the non-monotonic logics based on classical Predicate Calculus can express the rule defeasibility as a *natural matter of degree* (e.g. how likely the rule is to be valid). To remedy the problem, [Rich 83] and [Ginsberg 84] employed likelihood formalisms to express the belief tendency, but Rich's Certainty-Factor basis was ad hoc in itself, and Ginsberg seemed to have diffused the tight rule-exception association when he shielded rules from exceptions and represented the latter as retracting meta rules. Also this meta-rule approach appeared to be ad hoc at partial retraction of earlier conclusions. For example, what is precisely meant by partial retraction?

The focus in this study will not be global issues of logic, but the local representation of defeasible rules. To this end, we propose to include an <u>*UNLESS*</u> clause as the exception role in an inference rule. Then the antecedent infers the consequent in the absence of underlying 'unless' clauses. If one of the 'unless' condition becomes satisfied (i.e. an exceptional situation takes place), the default rule is defeated and a new rule will be in place.

Rule 6: $BIRD(x) \xrightarrow[ASSOC]{[0.9,0.02]} FLY(x)$
Unless:
1. *PENGUIN(x)* **then** "see Rule 7"
2. *OSTRICH(x)* **then** "see Rule 7"
3. *OIL-COVERED(x)* **then** "see Rule 8"
4. *DEAD(x)* **then** "see Rule 8"
5. *FOWL(x)* **then** "see Rule 9"
6. "to be added as encountered"

Rule 7: $PENGUIN(x) \vee OSTRICH(x) \xrightarrow[CONTR]{[0.99,0]} NOT\ FLY(x)$
Rule 8: $OIL-COVERED(x) \vee DEAD(x) \xrightarrow[CONTR]{[1,0]} NOT\ FLY(x)$
Rule 9: $FOWL(x) \xrightarrow[ASSOC]{[0.7,0.2]} NOT\ FLY(x)$
Unless:
1. *DUCK(x)* **then** "see Rule 10"
2. "to be added as encountered"

For illustrative purpose, suppose *BIRD(Slinky)* and *EDIBLE(Slinky)*. Suppose also that it is not known directly whether *FOWL(Slinky)* or not, but the following inference can be made: $EDIBLE(x) \xrightarrow[ASSOC]{[0.5,0.2]} FOWL(x)$ Then what can be said about *FLY(Slinky)*, considering the exception predicate *FOWL*?

First, infer Slinky's liability to fly from Rule 6. Second, infer Slinky's inability to fly from Rule 9. Third, combine the previous two results and reach the overall conclusion, which is $[Bel(FLY(Slinky)),\ Bel(NOT\ FLY(Slinky))] = [0.55,\ 0.36]$. The actual calculation goes as follows:

$$Bel[FLY(Slinky) \mid E'E'']$$
$$= Bel[FLY(Slinky) \mid BIRD(Slinky) \wedge (NO\ FOWL(x))] \cdot Bel[BIRD(x) \mid E'] \cdot$$
$$Bel[NO\ FOWL(Slinky) \mid EDIBLE(Slinky)] \cdot Bel[EDIBLE(Slinky) \mid E''] +$$
$$Bel[FLY(Slinky) \mid FOWL(Slinky)]$$
$$\cdot Bel[FOWL(Slinky) \mid EDIBLE(Slinky)] \cdot Bel[EDIBLE(Slinky) \mid E']$$
$$= 0.9 \cdot 1 \cdot (1 - 0.5) \cdot 1 + 0.2 \cdot 0.5 \cdot 1 = 0.55$$

Similarly, $Bel[NOT\ FLY(Slinky) \mid E'E''] = 0.02 \cdot 1 \cdot (1 - 0.5) \cdot 1 + 0.7 \cdot 0.5 \cdot 1 = 0.36$

Although exception roles are useful for inference making, including them in the role system is more complicated than other categories of roles. This is partly because the fundamental theory is still being developed (e.g. [Moore 85]). Also the dependency-directed backtracking during conclusion retractions presents a complex efficiency issue by itself.

VI CONCLUSION

The role system manifests the qualitative difference in causations that is often overlooked in numerical likelihood representations. In particular, the auxiliary nature in supportive roles and the overruling nature in exception roles are explicitly represented now. On the other hand, with an extended Dempster-Shafer theory, the scale of belief certainties as well as ignorance can be expressed and propagated* uniformly in the context of individual roles. Study on further usage of the role information during reasoning is underway.

* The parallel combination of concluding beliefs represents a different issue, which is not covered in this paper. See [Yen 85] for alternatives to the independence assumption in the original Dempster's combining rule.

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