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DOG DISEASE EXPERT SYSTEM

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Abstract: *This paper concerns our approach to expert system deliberation mechanism. Below, we present our domain, approach, and results. Finally, we conclude with future work.*
Key words: *Expert system, artificial intelligence, reasoning*

1. INTRODUCTION

Expert systems (ES) are programs for solving problems that require previous praxis or knowledge (Iglesias, 2006). Our work aims to develop simplified dog disease detection ES. Below, we present our reasoning mechanism (Section 2), suggest future work (Section 3), and conclude (Section 4).

2. DOG DISEASE DETECTION EXPERT SYSTEM

Our ES extends a general spoken dialogue manager (Fig. 1) (Nestorovič & Matoušek, 2006), however, the ES-human communication is done through a graphical user interface (GUI), bypassing the underlying manager speech user interface.

Each *problem-oriented* ES run cycle consists of two phases (Giarratano & Riley, 1998): 1) first, question posing or final hypothesis determination (*backward chaining algorithm*), and 2) knowledge inference (*forward chaining algorithm*). Both algorithms are passed *facts* about the problem:

FACT(*name*, *value*, *certainty*, *completeness*) (1)

Each fact has a symbolic *name* and holds a *value*. The *certainity* value carries information about how the system is sure about the fact (the value equals user's confidence). Finally, the *completeness* expresses level of inference entirety. Each fact provided by a human is considered as complete (= 1.0), while for each inferred fact, the completeness depends on how complete was the original set of facts (e.g., given the rule "X & Y → Z" and the X fact *only*, i.e. half of the number of input facts, the Z fact can be inferred with completeness = 0.5).

Thus, a fact may be *incomplete* and *uncertain*. A collection of these facts constitutes an *inference net* (IN) that makes use of logical operands and numeric functions. A fragment of our domain model network can be seen in Fig. 2.

The *inference mechanism* is closest to a mixture of probability models (Bayes reasoning (Müller, 2002)) with fuzzy-like logic (fuzzy reasoning (Giarratano & Riley, 1998)). The motivation was to catch the soft notion of dog disease symptoms – while some are specific for certain diseases (e.g. *quinsy*), the other are observed with a lot of other diseases (e.g. *higher temperature*). The feature of putting less stress on particular symptoms is accommodated using *relevance factors.* Hence, each fact inference is governed by three parameters – completeness, certainty, and relevance. The process accounts for a mathematical framework that uses descending shaped functions (e.g., $f(x) = 1/x^a$, where $a > 1$ and $x \in \langle A; B \rangle$ where $A, B \in \Re$). The certainty and completeness of an inferred fact are computed according to the following equations (*cert* = certainty, *rel* = relevance, *comp* = completness).

(2)

(3)

(4)

(5)

(6)

Consider *logical disjunction operator*. The implementation of the framework follows these steps.

1. Order operands according to their certainty descending, i.e. the most certain facts come first, while the facts with low or no confidence come last.
2. Split the domain $\langle A;B \rangle$ of the $f(x)$ function proportionally to operands relevances. Let the O operand be defined in the interval $\langle A_O; B_O \rangle$, where $A_O, B_O \in \Re$.
3. Compute operands weights as a definite integrals of $f(x)$. Proceed to computing the certainty and completness.

Fig. 3 demonstrates the algorithm. Facts R through V denote operands, of which T and V are totally incomplete. The

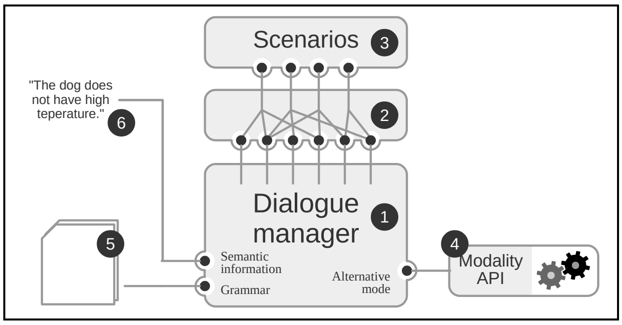

Fig. 1. Expert system overall architecture

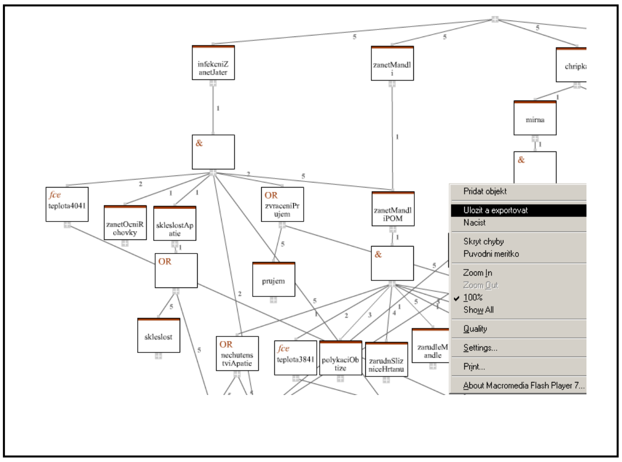

Fig. 2. Dog diseases domain knowledge model fragment

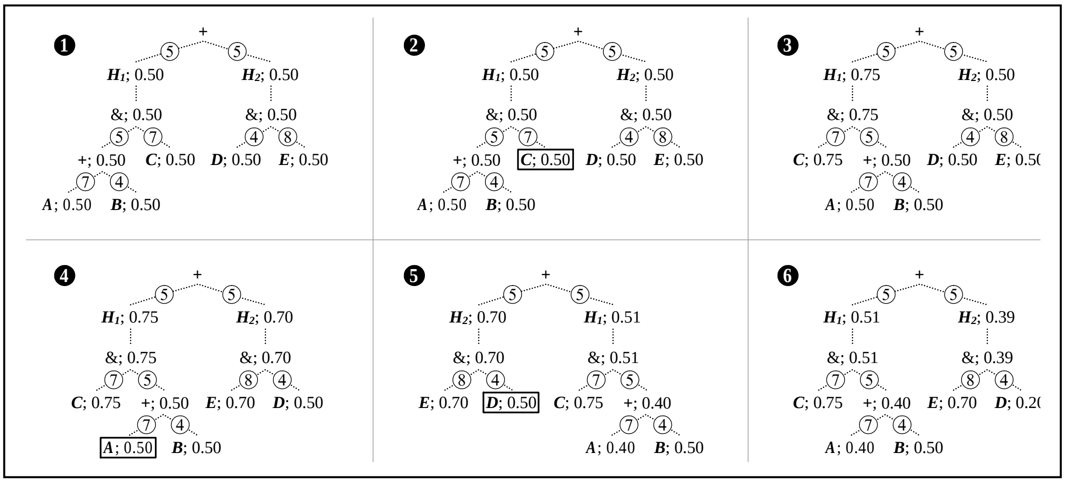

Fig. 4. Optimization example; node captions (A;0.50) express fact name and certainty respectively; circled numbers are relevances assigned to each particular operand

respective weights are denoted as w_R through w_V.

We make an optimization regarding which questions (could) fastest lead to the best hypothesis determination. The idea is based on the alpha-beta pruning algorithm (Russell & Norvig, 2009). For the conjunction-disjunction case applies: if a *disjunction* value is certain to that extent that it can not reach better position (Step 1 above) in the parent *conjunction* (thus can not reach higher weight, see Step 3), then it is worthless to elicit facts that would precise the disjunction value. A dual theorem applies for the disjunction-conjunction case.

Fig. 4 shows an optimization example. Let us consider hypotheses H_1 and H_2 (i.e. deseases) with corresponding facts *A* through *E* (i.e. symptoms) (Fig. 4, **part 1**). After starting a session, all facts are initialized with neutrality (= 0.5), resulting in both diseases to have the same probability. Resolving with the rule "first disease first," the H_1 branch is selected for searching for a missing fact to elicit from the human. Next, it is necessary to resolve the conjunction node – the *C* fact is selected since it has a higher relevance (**2**). In response, the fact is assigned the certainty of 0.75. Both conjunction and the H_1 node adopt this value (as all other facts are neutral) and get completness computed. The system restarts searching for a fact to elicit, discovering as the matter of optimization that the most optimistic case of H_2 is able to beat the most pessimistic case of H_1. Thus, H_2 branch is selected and the *E* fact picked up (**3**). The user assigns it the certainty of 0.70 (very close to the *C* fact), making H_2 stay after H_1 in the the top-level disjunction (implying H_1 better explains the underlying facts). Hence in the next cycle, the H_1 branch is selected again and the *A* fact chosen (**4**), but this time the human responds it with a low certainty of 0.40, bringing H_2 to front. Continuing, the *D* fact is chosen (**5**) and assigned the certainty of 0.20, making H_1 to be the better explanaition of the facts again. However this time, the H_2 lacks of enough potential to beat the H_1 hypothesis (**6**), resulting in the H_1 to be selected as the ES final response. Note that with optimizing the questioning process, the *B* fact was reckoned as unimportant for making a decision *in this case*.

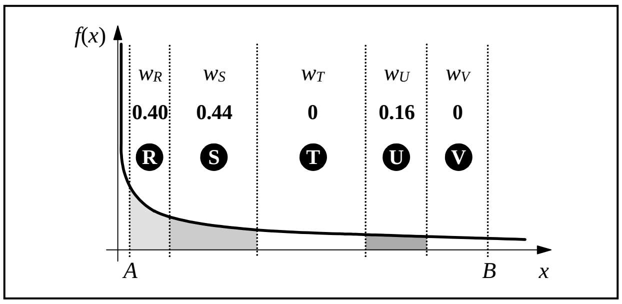

Fig. 3. Weight values computation algorithm demonstration

3. DISCUSSION AND FUTURE WORK

The ES was applied in an experimental dog disease domain with knowledge about six diseases mined from (Procházka, 1989), and tested by a professional veterinarian to prove the system correctness. However, the dog disease ES was not applied in real situations due to possible ethical aspects violation – if the ES was wrong harming a living being, would we be responsible due to supplying incorrect data during the development, or would it be the operating person due to following the ES advice? (Mařík *et al*, 1993) This is the reason why we do not intend to continue developing this application, despite it has a huge potential to be commercially applicable ("according to the American Veterinary Medical Association, the average American spends about $356 in medical expenses per dog each year" [1]). Thus, our future work conceives applying the above algorithms to create a PC hardware bugs ES – a handy application for recovering from a failure (focused group of users: amateur handymen).

4. CONCLUSION

This paper presented our approach to a reasoning mechanism with optimization. Our aim was to show the underlying ideas and present the algorithms in a comprehensive way. A simple explanaition example was provided.

5. ACKNOWLEDGEMENT

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