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Commonsense Knowledge Representation and Reasoning with Fuzzy Neural Networks

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Abstract— **This paper highlights the theory of commonsense knowledge in terms of representation and reasoning. A connectionist model is proposed for commonsense knowledge representation and reasoning. A generic fuzzy neuron is employed as a basic element for the connectionist model. The representation and reasoning ability of the model is described through examples.**

I. Introduction

The knowledge which is possessed by humans about the world is called *commonsense knowledge* and the method for making inferences from this knowledge is called *commonsense reasoning* [5]. The computational framework which is provided by fuzzy logic has been employed by Zadeh [11]-[15] to establish the preliminary basis for commonsense knowledge representation and reasoning. Zadeh defines commonsense knowledge as a collection of *dispositions* - propositions with implied fuzzy quantifiers [12]. He introduces a fuzzy-set-based meaning-representation system named *test-score semantics* [14] that provides a base for representing the meaning of complex propositions. Propositions containing fuzzy predicates, fuzzy quantifiers, modifiers, and qualifiers, can be represented by the test-score semantics. *Syllogistic reasoning* in fuzzy logic is proposed as a systematic basis for inference from commonsense knowledge [12], [13], [15]. A set of rules is derived for combining evidence through conjunction, disjunction, and chaining.

There are several methods for implementing knowledge-based systems [2]; a key factor that must be considered, is computational constraints. Connectionist models have a good potential in areas where many hypotheses are pursued in parallel and high computation rates are required. There are a number of connectionist models of knowledge base representation and reasoning [1], [3], [6]-[10]. However, they are unable to model the commonsense knowledge defined by Zadeh.

In this paper, a connectionist model of commonsense knowledge representation and reasoning is proposed. Fuzzy neurons are used to form the structure of a fuzzy neural network. Section II reviews the theory of commonsense knowledge. A fuzzy neural network implementation of commonsense knowledge is introduced in Section III.

II. Commonsense Knowledge Representation and Reasoning

Zadeh's approach to the semantics of natural languages has two principal components. The first component, which is called *test-score semantics*, is a translation system for representing the meaning of propositions [14]. The second component, known as *syllogistic reasoning* [13], is an inferential system for arriving at an answer to a question which relates to the information resident in a knowledge base.

A. Representation

In Zadeh's approach, a disposition is converted into a proposition with explicit fuzzy quantifiers. For instance, *Frenchmen are not very tall* is viewed as *Most Frenchmen are not very tall.* A proposition p is regarded as a collection of elastic constraints, $C_1, C_2, \ldots, C_k$, which restrict the values of a vector X. *Canonical form* [14] is used to represent the meaning of p. When p represents a fact, its canonical form is expressed as

$$p \rightarrow X \; is \; A$$

and when p is a conditional proposition, its canonical form is expressed as

$$p \rightarrow \text{if } X \; is \; A \text{ then } Y \; is \; B$$

where X and Y are constrained variables defined in U and V, respectively. A and B are fuzzy subsets of U and V.

Four rules are defined to facilitate the representation of the meaning of a proposition:

1. Modification rule

A proposition of the form $p \triangleq N \; is \; F$, is represented by

$$p \triangleq N \; is \; F \rightarrow \prod_X = F$$

where $\prod_X = F$ is a possibility assignment equation [11]. The modified proposition $p^+ \triangleq N \; is m F$, where m is a modifier given by

$$N \; is \; mF \rightarrow \prod_X = F^+$$

where F^+ is the modification of F induced by m. In particular:

(a) If $m \triangleq$ *not* then $F^+ \triangleq$ *complement* F.

(b) If $m \triangleq$ *very* then $F^+ \triangleq F^2$.

(c) If $m \triangleq$ *more or less* then $F^+ \triangleq F^{1/2}$.

2. Composition rule

Consider the propositions $p \triangleq M \; is \; F \rightarrow \prod_X = F$ and $q \triangleq N \; is \; G \rightarrow \prod_Y = G$. Then

(a) $M \; is \; F$ and $N \; is \; G \rightarrow \prod_{(X,Y)} = F \times G$.

(b) $M \; is \; F$ or $N \; is \; G \rightarrow \prod_{(X,Y)} = \bar{F} + \bar{G}$.

(c) If $M \; is \; F$ then $N \; is \; G \rightarrow \prod_{(X,Y)} = \bar{F}' \oplus \bar{G}$.

(d) If $M \; is \; F$ then $N \; is \; G else N \; is \; H \rightarrow \prod_{(X,Y)} = (\bar{F}' \oplus \bar{G}) \cap (\bar{F} \oplus \bar{H})$.

In the above definitions, if F and G are fuzzy subsets of U and V, respectively, then $F' \triangleq$ complement F, $\bar{F} \triangleq F \times V \triangleq$ cylindrical extension of F, $F \times G \triangleq$ cartesian product of F and G, $+ \triangleq$ union, and $\oplus \triangleq$ bounded-sum.

3. Quantification rule

The meaning of the proposition $p \triangleq Q\ N\ are\ F$, containing the fuzzy quantifier Q, is represented by

$$Q\ N\ are\ F\ \rightarrow\ \prod_{\sum Count(F/N)} = Q$$

in which the *relative sigma-count* that denotes the proportion of F in N is defined as

$$\sum Count(F/N) \triangleq \frac{\sum_i \mu_F(u_i)\ min\ \mu_N(u_i)}{\sum_i \mu_N(u_i)}.$$

4. Qualification rule

A qualified proposition is written in the form of $q \triangleq p\ is\ \gamma$, where γ may be a truth value, a probability value, or a possibility value.

(a) Truth qualification

Let q be a truth-qualified proposition of the form $q \triangleq N\ is\ F\ is\ \tau$, in which τ is a linguistic truth-value such as *very true*. Then,

$$N\ is\ F\ is\ \tau\ \rightarrow\ N\ is\ G$$

where F, G, and τ are related by

$$\tau\ =\ \mu_F(G),\ \text{i.e.,}\ \mu_G(u)\ =\ \mu_\tau(\mu_F(u)).$$

(b) Probability qualification

Let q be a probability-qualified proposition given by $q \triangleq N\ is\ F\ is\ \lambda$, where λ is a linguistic probability-value such as *very likely*. Then,

$$N\ is\ F\ is\ \lambda\ \rightarrow\ \prod_{\sum Count(F)}\ =\ \lambda.$$

(c) Possibility qualification

Let q be a possibility-qualified proposition of the form $q \triangleq N\ is\ F\ is\ \omega$, in which ω is a linguistic possibility-value such as *quite possible*. A fuzzy subset G is required such that

$$N\ is\ F\ is\ \omega\ \rightarrow\ N\ is\ G.$$

Then, if $\omega \triangleq \alpha - possible$ (i.e. $\mu_\omega(v) = \alpha$ for $v = 1$ and $\mu_\omega(v) = 0$ for $v \varepsilon [0, 1)$), G, which is a fuzzy set of *type 2* [11], is given by

$$\mu_G(u)\ =\ [\alpha \wedge \mu_G(u), \alpha \oplus (1 - \mu_F(u))],\ u\varepsilon U.$$

B. Reasoning

Syllogistic reasoning in fuzzy logic can be employed in reasoning with dispositions. A fuzzy syllogism is expressed in the general form

$$\begin{array}{c} p(Q_1) \\ \underline{q(Q_2)} \\ r(Q) \end{array}$$

in which the major premise, $p(Q_1)$, is a proposition containing a fuzzy quantifier Q_1; the minor premise, $q(Q_2)$, is a proposition containing a fuzzy quantifier Q_2; and conclusion, $r(Q)$, is a proposition containing a fuzzy quantifier Q. Several syllogisms have been developed for reasoning with dispositions. Intersection/product, consequent/conjunction, and antecedent/conjunction are the basic syllogisms.

III. Connectionist Model of Commonsense Knowledge

The theory described in Section II, represents the compatibility of a disposition with the data resident in an already existing explanatory database. This theory is now employed for the construction of a knowledge base as well as for reasoning. In this section, a connectionist model, which is composed of generic fuzzy neurons [4], is proposed for commonsense knowledge representation and reasoning. In the generic fuzzy neuron, the inputs and output are fuzzy sets over different universes of discourse. The connection, aggregation, and activation functions, which determine the operation of the neuron, are fuzzy relations. A number of fuzzy neurons can be defined by changing the neuron functions.

The proposed approach is explained through the following examples. Consider the propositions and their canonical forms

1. *Ed is 30 years old is true.* $\rightarrow$ *(Age(Ed) is 30) is true.*
2. *Tan is young.* $\rightarrow$ *Age(Tan) is young.*
3. *Sally is old is not possible.* $\rightarrow$ *(Age(Sally) is old) is not possible.*
4. *David is young is very likely.* $\rightarrow$ *(Age(David) is young) is very likely.*

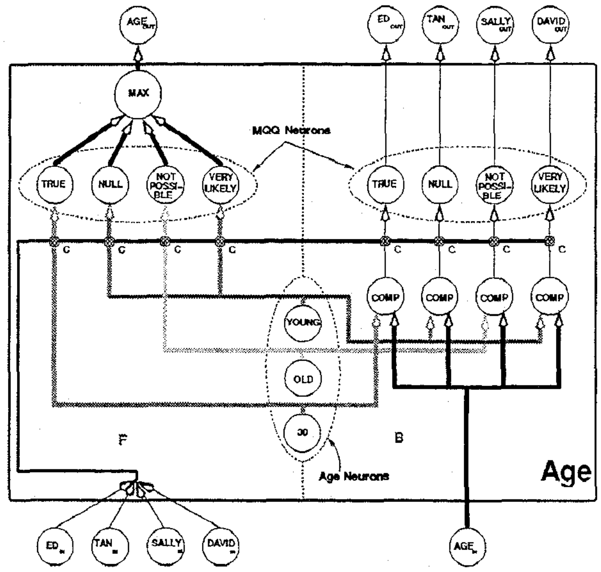

Fig. 1. Connectionist implementation of the *Age* attribute.

The constrained variables are $Age(Ed)$, $Age(Tan)$, $Age(Sally)$, and $Age(David)$. The constraints, which are fuzzy subsets of the Age domain $U = [0, 100]$, are 30, *young*, and *old*. The modifiers-quantifiers-qualifiers are *true*, *not*, *possible*, *very*, *likely*. The constraint 30 is considered a fuzzy singleton which has the value 1 for $u_i = 30$ and 0 for $u_i \varepsilon [0, 100], u_i \neq 30$. The information given in terms of the four propositions, is represented by a fuzzy neural network as illustrated in Figure 1. The network represents the Age attribute and consists of two parts: forward reasoner (Age_F) and backward reasoner (Age_B). The inputs to the forward reasoner are the values of the constrained variables. Each input is represented by a neuron. The outputs of the forward reasoner is a fuzzy subset of U.

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The Age neurons represent the constraints and are shared between the two parts of the network. The output of each neuron is a fuzzy subset of U and indicates a constraint. They have null inputs and are always active. Modifiers-Quantifiers-Qualifiers (MQQ) neurons implement the rules defined for the representation of meaning of propositions, and operate differently in each part of the network. The network inputs are distributed among the connection functions of MQQ neurons as weights. When a MQQ neuron becomes active in the forward reasoner, it maps a fuzzy subset of U into another fuzzy subset of U. The MAX neuron in the forward reasoner performs the fuzzy *max* operation.

In the backward reasoner, the compatibility ($COMP$) neurons compare the input with the constraints. The output of a $COMP$ neuron indicates the degree of compatibility between two fuzzy sets. The calculated compatibility degree passes through a MQQ neuron in which it is translated to a single value varying in the interval $[0, 1]$, using the membership degree of the function represented by the node.

Once a query is posed to the system, its state of activation evolves automatically and produces an answer to the query. The fuzzy neural network can respond to the queries of the form $Age(Ed, 30)$, $Age(Tan, old)$, $Age(Sally, x)$, and $Age(x, tall)$. In a query, if two arguments are specified, e.g. $Age(Tan, old)$, the inference process is carried out in both forward and backward reasoners. The forward reasoner produces a fuzzy set, whose membership degree is close to that of $YOUNG$, at its output (AGE_{OUT}) indicating that Tan is young. The backward reasoner, however, produces a value at its output (TAN_{OUT}) representing the possibility degree that Tan is old. This value would be close to 0 as the system has been told that Tan is a young person. When a constraint is not specified in a query, e.g. $AGE(Tan, x)$, the forward reasoner produces the answer. However, if the particular value of the constrained variable is not specified, e.g. $Age(x, young)$, all backward reasoner output nodes become active indicating in this example the possibility degree that the related person is $YOUNG$.

Representation and reasoning with conditional propositions is explained in this part. Let p be

$$if\ Tan\ is\ young\ then\ Tom\ is\ tall$$

in which the constrained variables are $Age(Tan)$ and $Height(Tom)$. The constraints are fuzzy sets $YOUNG$ and $TALL$. Figure 2 illustrates the connectionist implementation of p. Three blocks are displayed in the figure, Age, $Height$, and If. The Age block represents the attribute Age which was described earlier. The $Height$ block stands for the attribute $Height$ and is constructed in the same way as the Age block. It is assumed that the system has no knowledge about Tom's height in the $Height$ block. The If block implements conditional propositions. It communicates with the attribute blocks involved in the premise and conclusion parts of the *if* clause. Similar to the Age block, an If block has two reasoners and contains MQQ neurons.

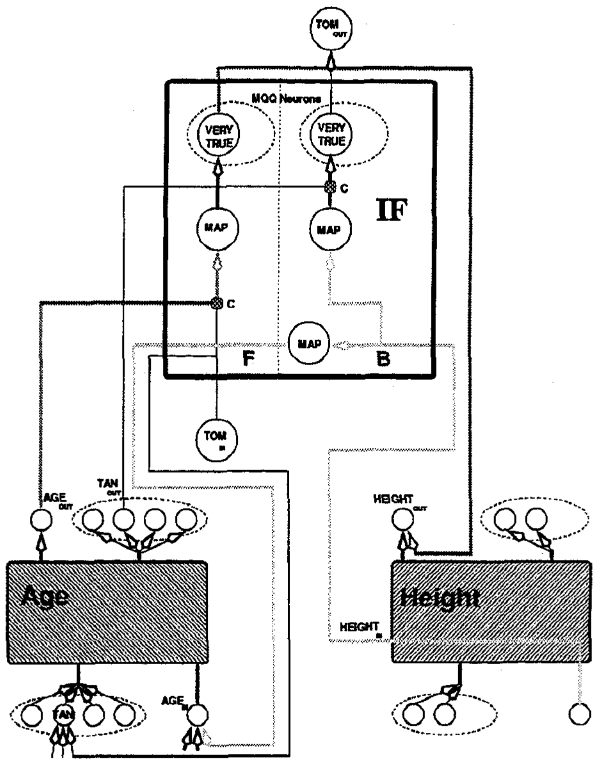

Fig. 2. Connectionist implementation of a conditional proposition.

In the forward reasoner, a MAP neuron, which contains the relation $\overline{YOUNG}' \oplus \overline{TALL}$, maps the input fuzzy set AGE_{OUT} into another fuzzy set on the the Height domain. In the backward reasoner, the $COMP$ neuron, which contains the relation $TALL$, calculates the degree of compatibility of the input fuzzy set $HEIGHT_{IN}$ with the fuzzy set $TALL$. The MAP neuron in this part, maps a fuzzy set from $Height$ domain into Age domain using the relation $\overline{YOUNG}' \oplus \overline{TALL}$. If the neuron's input is the fuzzy set $TALL$, the output becomes the fuzzy set $YOUNG$. The inference process is demonstrated with the following examples. Given the query $Height(Tom, x)$, the input TOM_{IN} activates $SALLY_{IN}$ as a result. In the Age block the inference process is carried out, producing the fuzzy set $YOUNG$ at its output AGE_{OUT} neuron. Next, the MQQ neuron in the If block receives $YOUNG$ at its input, and since the weight provided by TOM_{IN} in its connection function is 1, the neuron provides the fuzzy set $TALL$ at its output. The fuzzy set $TALL$ passes through the MQQ neuron. The result has a membership degree very close to that of fuzzy set $TALL$ because of the modified-truth-value $VERY\ TRUE$. Consequently, the result appears at the output neuron, $HEIGHT_{OUT}$. If there is no information on Tan's age, AGE_{OUT}

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remains inactive and so does $HEIGHT_{OUT}$. Correspondingly, if the query $Height(x, tall)$, is posed to the system, the backward reasoner in the *If* block, produces a possibility degree that Tom is tall. There would be a very small value at AGE_{OUT} if the system has no knowledge of Tan's age.

Often the input information possesses a hierarchical structure so that the representation and reasoning scheme must deal with it accordingly. The approach which is presented in this paper can represent this information and reason from it. To illustrate this ability, consider the following propositions

1. *Pigeon is a bird.*
2. *Canary is a bird is true.*
3. *Cat1 is a cat is likely.*
4. *Cat2 is a cat.*
5. *Most birds are not mammal.*
6. *Cats are mammal.*

in which *bird* and *cat* are subsets of *mammal*. Figure 3 shows a connectionist realization of these propositions. The left part of the figure represents the forward reasoner and the right part displays the backward reasoner. MQQ and MAX neurons are employed for construction of the network. As stated earlier, MQQ neurons operate differently in the forward and backward reasoners. Once a query is posed to the system, the state of activation evolves automatically and the system produces an answer to the query at the output nodes. Consider the query *Is Cat*1 *a mammal*? which is posed by providing the input to the $CAT1_{IN}$ neuron. The nodes $LIKELY$, MAX, and CAT neurons in C_F block become active. The output of CAT neuron will be a number in the interval $[0, 1]$ that represents the possibility degree of $CAT1$ being a CAT. A similar inference process is done in the M_F part, so that its output node $MAMMAL_{OUT}$ denotes the degree that Cat1 is a mammal. The connection functions of the MQQ nodes in M_F, B_B, and C_B perform the *max* operation on the weight and neuron input. As a result, the system will also be able to respond to queries such as *Is Cat a mammal*?.

The proposed architecture performs syllogistic reasoning as a basis for inference from commonsense knowledge. Different parts of the system can be linked together to provide multiple inheritance.

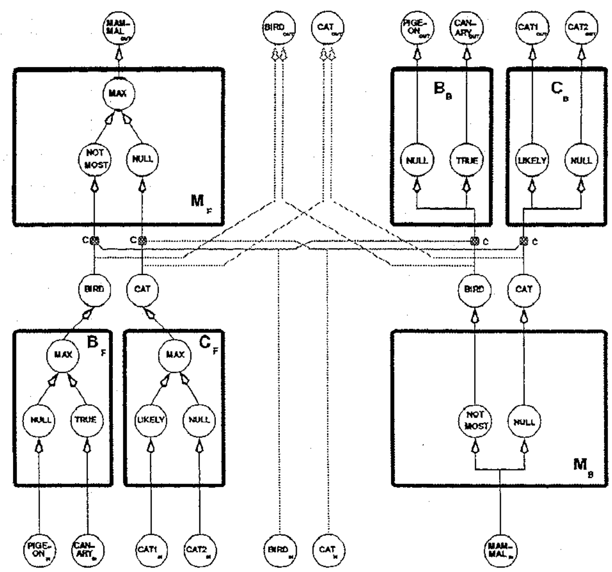

Fig. 3. Connectionist implementation of knowledge with hierarchy structure.

IV. Conclusion

Zadeh's theory of commonsense knowledge is reviewed briefly in this paper, to establish a basis for representation of dispositions and reasoning from them. A connectionist approach is proposed for implementing commonsense knowledge and reasoning based on Zadeh's theory. The model is implemented using a fuzzy neural network, the structure of which is formed using generic fuzzy neurons. The proposed architecture performs syllogistic reasoning as a basis for inference. The examples illustrate the method of the system operation.

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References

[1] S.M. Chen, J.S. Ke, and J.F. Chang, "Knowledge representation using fuzzy petri nets," *IEEE Trans. on Knowledge and Data Engineering*, vol. 2, no. 3, pp. 311-319, 1990.

[2] J. Giarratano and G. Riley, *Expert Systems: Principles and Programming.* PWS-KENT Publishing Co., 1989.

[3] B. Kosko, "Fuzzy cognitive maps," *Int. J. Man-Machine Studies*, vol. 24, pp. 65-75, 1986.

[4] A.Z. Kouzani and A. Bouzerdoum, "A Generic Fuzzy Neuron," *Proc. of the 1995 IEEE / Nagoya University World Wisepersons Workshop on Fuzzy Logic, and Neural Networks/Evolutionary Computation*, pp. 7-12, Rubrum Ohzan, Nagoya, Japan, November 14-15, 1995.

[5] S.C. Shapiro and D. Eckroth, *Encyclopedia of Artificial Intelligence.* vol. 2, John Wiley & Sons, Inc., 1987.

[6] L. Shastri, *Semantic Networks: An Evidential Formalization and its Connectionist Realization.* Pitman Publishing, 1988.

[7] L. Shastri and V. Ajjanagadde, "From simple associations to systematic reasoning: A connectionist representation of rules, variables and dynamic bindings using temporal synchrony," *Behavioral and Brain Sciences*, vol. 16, no. 3, pp. 417-494, 1993.

[8] R. Sun, "Connectionist models of rule-based reasoning," *Proc. 13th Annual Conference of Cognitive Science Society*, pp. 437-442, Lawrence Erlbaum Associates, Hillsdale, NJ., 1991.

[9] R. Sun, "Beyond Associative Memories: Logics and variables in connectionists networks," *Information Sciences*, vol. 70, no. 1-2, pp. 49-74, 1993.

[10] R. Sun, *Integrating Rules and Connectionism for Robust Reasoning.* John Wiley & Sons, Inc., 1994.

[11] L.A. Zadeh, "PRUF-a meaning representation language for natural language," *Int. J. Man-Machine Studies*, vol. 10, pp. 395-460, 1978.

[12] L.A. Zadeh, "A theory of commonsense knowledge," *Cognitive Science Report 83-12*, University of California at Berkeley, October, 1983.

[13] L.A. Zadeh, "Syllogistic reasoning in fuzzy logic and its application to usuality and reasoning with dispositions," *IEEE Trans. on Systems, Man, and Cybernetics*, vol. SMC-15, pp. 754-763, 1985.

[14] L.A. Zadeh, "Test-score semantics as a basic for a computational approach to the representation of meaning," *Literary and Linguistic Computing*, vol. 1, pp. 24-35, 1986.

[15] L.A. Zadeh, "Fuzzy logic," *Computer*, vol. 21, no. 4, pp. 83-93, 1988.