Rule based logic has been used to capture human expertise in classification, assessment, diagnostic and planning tasks. Probability has traditionally been used to capture decision making under uncertain conditions. For example, consider the rule:

**IF Symptom-A is present THEN diagnosis is illness-X**

There will be situations in which we are uncertain about the presence of Symptom-A. In such cases we can enter the probability of Symptom-A being present which will result in a confidence factor in our diagnosis of illness-X. A number of methods have been used to propagate probabilities during rule based inference. Many of these techniques are based on the probabilistic inference techniques used in Mycin and Prospector. The weakness of such techniques is that they do not reflect the way human experts reason under uncertainty. XpertRule Knowledge Builder allows an alternative methodology to the probabilistic reasoning approach. This involves defining Symptom-A and illness-X as logical attribute with values likely, unsure, unlikely. This allows the expert to dictate the relationship between the symptoms and diagnosis, instead of relying on the mathematical propagation of probabilities.

Many people confuse the above example of uncertain reasoning with fuzzy reasoning. Probabilistic reasoning is concerned with the uncertain reasoning about well defined events or concepts such as Symptom-A and Illness-X. On the other hand, Fuzzy Logic is concerned with the reasoning about 'Fuzzy' events or concepts. Examples of fuzzy concepts are 'temperature is high' and 'person is tall'. When is a person tall, at 170 cm, 180 cm or 190 cm? If we define the threshold of tallness at 180 cm, then the implication is that a person of 179.9 cm is not tall. When humans reason with terms such as 'tall' they do not normally have a fixed threshold in mind, but a smooth fuzzy definition. Humans can reason very effectively with such fuzzy definitions, therefore, in order to capture human fuzzy reasoning we need fuzzy logic. An example of a fuzzy rule which involves a fuzzy condition and a fuzzy conclusion is:

**IF salary is high THEN credit risk is low**

**Fuzzy reasoning involves three steps:**

1. Fuzzification of the terms that appear in the conditions of rules.
2. Inference from fuzzy rules.
3. Defuzzification of the fuzzy terms that appear in the conclusions of rules.

**Fuzzification**

Lotfi Zadeh pioneered a method of modelling human imprecise reasoning using fuzzy sets. Using this technique, the concept 'tall' is related to the underlying objective term which it is attempting to describe; namely the actual height in centimetres. The transformation of an objective term into a fuzzy concept is called fuzzification. As an example, the term 'tall' can be represented in this graph:
It shows the degree of membership with which a person belongs to the category (set) 'tall'. Full membership of the class 'tall' is represented by a value of 1, while no membership is represented by a value of 0. At 150 cm and below, a person does not belong to the class 'tall'. At 210 cm and above, a person fully belongs to the class 'tall'. Between 150 cm and 210 cm the membership increases linearly between 0 and 1. The degree of belonging to the set 'tall' is called the confidence factor or the membership value. The shape of the membership function curve can be non-linear.

The purpose of the fuzzification process is to allow a fuzzy condition in a rule to be interpreted. For example the condition 'person = tall' in a rule can be true for all values of 'height', however, the confidence factor or membership value of this condition can be derived from the above graph. A person who is 180 cm in height is 'tall' with a confidence factor of 0.5 (membership value of the club 'tall'). It is the gradual change of the membership value of the condition 'tall' with height that gives fuzzy logic its strength.

Normally fuzzy concepts have a number of values to describe the various ranges of values of the objective term which they describe. For example, the fuzzy concept 'tallness' may have the values 'Tall', 'Medium height' and 'Short'. Typically, the membership functions of these values are as shown in the graph below:

![Membership Function](image)

Typically, fuzzy concepts have an odd number of values; 3, 5 or 7. We can extend the above values by adding very short and very tall. The real power of fuzzy logic systems, compared to crisp logic systems, lies in the ability to represent a concept using a small number of fuzzy values. This therefore reduces the number of rules required to capture the knowledge relating to that concept. To achieve the same accuracy with crisp logic, a large number of logical values would be required resulting in a large rule base.

**Fuzzy Inference**

Inference from a set of fuzzy rules involves fuzzification of the conditions of the rules, then propagating the confidence factors (membership values) of the conditions to the conclusions (outcomes) of the rules. Consider the following rule:

**IF (applicant is young) AND (income is low) THEN credit limit is low**

Inference from this above rule involves (using fuzzification) looking up the membership value (MV) of the condition 'applicant is young' given the applicant's age, and the MV of 'income is low' given the applicant's salary. The method proposed by Lotfi Zadeh is to take the minimum MV of all the conditions and to assign it to the outcome 'credit limit is low'. An enhancement of this method involves having a weight for each rule between 0 and 1 which multiplies the MV assigned to the outcome of the rule. This weight can be edited on the Pattern rules view, or assigned at run time. By default each rule weight is set to 1.0.

In a fuzzy rule base a number of rules with the outcome 'credit limit is low' will be fired. The inference engine will assign the outcome 'credit limit is low', the maximum MV from all the fired rules.

**In summary fuzzy inference involves:**
Defuzzification

If the conclusion of the fuzzy rule set involves fuzzy concepts, then these concepts will have to be translated back into objective terms before they can be used in practice. For a rules set including the credit limit rule described in the previous section, fuzzy inference will result in the terms 'credit limit is low', 'credit limit is medium' and 'credit limit is high' being assigned membership values. However, in practice, to use the conclusions from such a rule base we need to defuzzify the conclusions into a crisp credit limit figure. To do this we need to define the membership functions for the credit limit outcomes as shown in this diagram:

One method of defuzzification is to place the confidence factors (MV) generated by inference for each fuzzy outcome at the point where the membership function has its highest value. The required defuzzified value can then be calculated as the centre of gravity of the three MV vectors. This is illustrated in the example below, assuming that fuzzy inference results in MV of 0.3, 0.5 and 0.7 for the low, medium and high credit limit outcomes respectively.

The defuzzified value of credit limit is calculated as the centre of gravity of the three Mvs (viewed) as weights placed at 500, 1000, and 1500. The expression for the defuzzified value is:

\[
\frac{(HV_{low} \times MV_{low} + HV_{med} \times MV_{med} + HV_{high} \times MV_{high})}{(MV_{low} + MV_{med} + MV_{high})}
\]

HV_low, HV_med, HV_high are the values of credit limit that give the highest membership values for low, medium and high credit.
MV_low, MV_med, MV_high are the MV values generated by fuzzy inference for low, medium and high credit outcomes.

Applying the above formula to the above example gives a defuzzified credit limit value of UK pounds £1133.33.

Note that the defuzzification stage is not required if the outcomes are crisp concepts such as 'diagnosis is a faulty printer'. In these cases, fuzzy inference results in assigning confidence factors (or probabilities) to the various outcomes.

While the main principles of fuzzy logic are broadly agreed on, there are a number of various methods of fuzzy inference and defuzzification. The methods described above are the most widely used and are the ones implemented in XpertRule Knowledge Builder.

**Fuzzy logic implementation in XpertRule Knowledge Builder**

**Design Concepts**
The fuzzy logic implementation in Knowledge Builder was developed with three objectives in mind; to provide comprehensive features, to maintain ease of use and to integrate seamlessly with the non fuzzy (crisp) Rules in Knowledge Builder.

**Fuzzy Objects**
- An Object of type List is defined as Fuzzy by setting its isFuzzy Property to True.
- A Fuzzy Object can either be used to represent Fuzzy Knowledge (Rules), or to represent a Fuzzy Attribute used in the definition of those Rules.

**Fuzzy Attributes**
- The fuzzyValue property of a Fuzzy Object holds its numeric runtime input value. This can be assigned by using procedural commands (e.g. @Assign Pressure.fuzzyValue = 50).
- The numeric range of the fuzzyValue property is mapped to the Object Values using the Fuzzy Membership Functions. These graphical functions derive the Fuzzy Membership Value (fuzzyMV) of each of the discrete Values (Instances) for any given fuzzyValue input.

**Fuzzy Rules**
- The fuzzyValue property holds the "defuzzified" numeric output value for the Rules Object, which is derived from the fuzzyMV and Fuzzy Membership Functions of each of the Values (Instances).
- The derivation of fuzzyMV of each of the Values (Instances) is based on which Rules fire at runtime and the fuzzyMV of the Values of the individual Fuzzy Attributes used by those rules.
- The Value with the highest fuzzyMV is selected.
- A Fuzzy Rules Object can contain both Fuzzy and non-Fuzzy Attributes (where the fuzzyMV is assumed to be 1.0 for the selected Value and 0.0 for all other Values).
- Fuzzy Rules inference for an Object can be made from either Cases/Rules or a Decision Tree (depending on the setting of the knowledgeMode property)
  - More than one Rule / Tree Path may fire
  - The rule condition is considered to be True if the fuzzyMV of its Values is greater then 0.
    - For Objects where the multiSelect property is set to True, the "defuzzified" fuzzyValue is not required (and therefore no Fuzzy Membership Functions are defined). The output from such an object, which is still held in fuzzyMV for each of the Values, represent the Confidence Factors in each of the possible rule outcomes. Here all Object Values with fuzzyMV > 0 are selected.
    - A Fuzzy Rules Object can be used as an Attribute in another Fuzzy (or non-Fuzzy) Rules Object
Defining a Fuzzy Object in XpertRule Knowledge Builder

- Using the Knowledge Representation Wizard on the Object Wizards Tab, select the Fuzzy Option. Alternatively the isFuzzy Property can be set directly on the Object Control Properties Tab.
- Make sure that the "Values" of the List Object are defined on the Instance Properties Tab.
- On the Fuzzy Membership Functions Tab (this is not necessary if the Object's multiSelect Property is set to True):
  - Define the Minimum and Maximum range for the fuzzyValue (on the x-axis)
  - Select the Membership function of each Value (highlight then right-mouse-click)
  - Enter the reflex points for each function (2 for S & Z, 3 for Lambda and 4 for Pi)

XpertRule Knowledge Builder Inference from Fuzzy Logic

Inference from a set of fuzzy rules involves fuzzification of the conditions of the rules, then propagating the confidence factors (membership values) of the conditions to the conclusions (outcomes) of the rules. Consider the following rule:

IF (applicant is young) AND (income is low) THEN credit limit is low
Inference from this above rule involves (using fuzzification) looking up the membership value (MV) of the condition 'applicant is young' given the applicant's age, and the MV of 'income is low' given the applicant's salary. The method proposed by Lotfi Zadeh is to take the minimum MV of all the conditions and to assign it to the outcome 'credit limit is low'.

In a fuzzy rule base a number of rules with the outcome 'credit limit is low' will be fired. The inference engine will assign the outcome 'credit limit is low', the maximum MV from all the fired rules.

**In summary fuzzy inference involves:**

- Defuzzification of the conditions of each rule and assigning the outcome of each rule the minimum MV of its conditions multiplied by the rule weight.
- Assigning each outcome the maximum MV from its fired rules.
- Fuzzy inference will result in confidence factors (MV's) assigned to each outcome in the rule base.