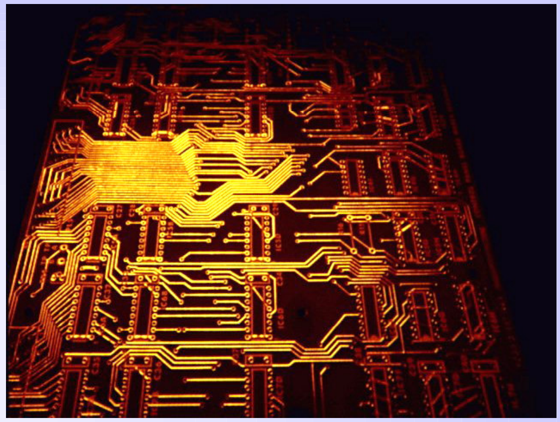

Seeing the Invisible

Computational Intelligence in Threat Assessment

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Imagine you are sitting at you desk reading this article one bright Tuesday morning. During the two seconds it has taken most of you to read the first worlds of this sentence, several trillion neutrinos – mostly produced in the sun's nuclear furnace – have sliced through your body, through the earth, and sped on their way into the cosmos. An uncountable number of photons, also from the sun and the cosmic background glow, have rained down on you. Your lungs have filed with vast quantities of atmospheric gas mixed with automobile exhaust fumes, dust, airborne bacteria, parasitic mites, fungus spores, as well as dried skin and hair (from our fellow humans, their livestock, and pets). A small number of C^{14} atoms in your food have decayed emitting a minute amount of radiation. The space around you is filled with modulated electromagnetic radiation – thousands of cell phone conversations, hundreds of AM and FM radio broadcasts, hundreds of satellite transmissions, and dozens of Television signals.

Yet we are oblivious, indifferent, and unaware of all these interactions. They take place in the world of the invisible. This world permeates the universe – in fact, most of the cosmos is invisible. We live among a narrow spectrum of things that reflect just the right wavelength of light, have just the right size, are close enough, and move at just the right speed to be visible to our senses. Yet invisibility is not limited to the microscopic or the large or the very close. Invisibility is a property of the many. In a field of flowers, the individual flower is lost. In a crowd, the individual person is lost. This is the goal of the terrorist, to become invisible among the many -- to pass without notice through checkpoints, through the government bureaucracies, through the grocery stores, shopping malls, state parks, movie theaters, and local taverns.

It is this protective sense of anonymity shared by all members of society that creates the greatest challenge to the intelligence community in recognizing anomalous behaviors. In this article we will discuss the use of fuzzy logic and associated artificial intelligence methods to probe this pervasive kind of invisibility. This advanced form of computational intelligence provides the intelligence analyst with the same kind of tools scientists use when probing the invisible. In fact, it is the exploration of the invisible that has challenged mankind since the first glimmer of awareness drove early man to wonder about the composition of the heavens. In the seventeenth century Anton Van Leeuwenhoek (1632-1723) turned his newly invented microscope on a drop of water an discovered an entirely unknown universe of microscope life, Wilson cloud chambers reveal the tracks of subatomic particles, telescopes show the structure of remote galaxies, radar illuminates distant aircraft or the surface features of Venus and sonar shows us the shape and properties of submarines sliding through the lightless oceans. Today, systems scientists, information technologists, and knowledge engineers are creating their own set of tools that will reveal the invisible just as certainly as a cloud chamber makes visible the tracks of ionized particles.

Fuzzy Logic - Making Visible the Invisible

The events of September 11th have raised many new and complex issues within the intelligence community, not the least of which is the nature of intelligence itself. When faced with a clear and definite threat, as we were during the Cold War, intelligence gathering could focus rather easily on the interception of signals, the exploitation of human agents, and the knowledge that governments operated as visible, cohesive entities. The collapse of the Soviet Union, the rise of nationalism and religious fundamentalism (which is a pernicious form of endemic nationalism), and the evolution of the modern world into globally connected city-states have rapidly and radically changed the playing field. Into this mix of fragmented cultures with fragmented eleventh century tribal mindsets, and a rising distrust of technology we now have internationally distributed terrorists collectively using the technological framework of the west to destroy us with our own sword. The fact that agents of this terrorist sub-culture are living, working, and planning their operations within the United States has put the intelligence community in a short term, defensive posture. Our open society with its disdain for government oversight, its concern for personal privacy, and its high degree of autonomous mobility makes tracking individuals not only extremely difficult but cost prohibitive. The individual becomes an invisible part of the mass. Individual behaviors blend with the ordinary behavior of a diverse and culturally rich society, obscuring in statistical fluctuations important behavior patterns.

The secret to making the invisible behavior patterns visible is the fusion of fuzzy logic with rule-based knowledge discovery. This combination allows the intelligence analyst to look deeply into conflicting pieces of evidence and find even weak patterns that are emerging from noisy data. By extracting the intelligence analyst's knowledge into rules that incorporate imprecision, degrees of evidence, and the semantics of the problem, fuzzy logic provides a powerful tool in the arsenal against terrorism. It is the microscope that allows behavior scientists to discover the individuals in the swarm.

The Nature of a Fuzzy System

In what way is the fuzzy system representation different from conventional expert systems? Fuzzy models use rules and fuzzy sets to encode knowledge, but, instead of storing all the knowledge in a set of rules that are run serially by the inference engine, a fuzzy system deals with two knowledge structures: fuzzy sets that describe the semantics of the model's data and high-level, set-theoretic rules that are run in parallel. Figure 1 illustrates, schematically, the process of running a fuzzy expert system.

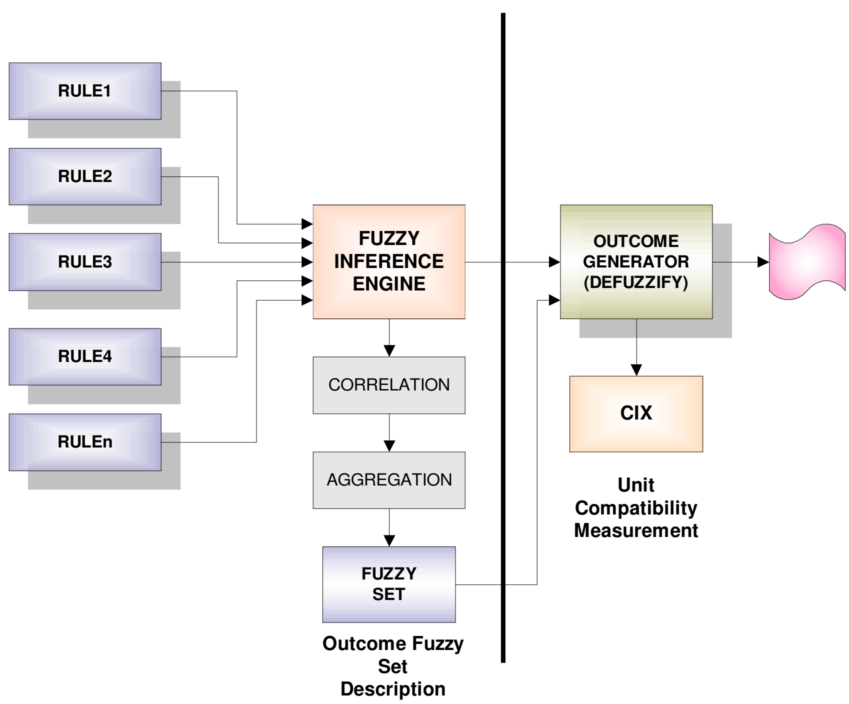

Figure 1. The Fuzzy Inference Engine

The Inference engine executes the rules but correlating the amount of evidence in a rule's premise with the degree of strength in the rule's outcome fuzzy set. These correlated fuzzy sets are then aggregated using special rules for combining fuzzy knowledge. This aggregation produces a single outcome fuzzy set for each solution variable. Finally, when all the rules have been executed, the outcome set is used to produce a final result. Along with the outcome is a measure of how much evidence exists to support the conclusion. This measure is called the unit compatibility.

It is the parallel processing – the merging of knowledge, scaled by evidence, among many rules – that allows a fuzzy system to handle conflicting evidence, build consensus, and look deeply into the problem space. Figure 2 illustrates how sets of rules are processed to create a single, composite outcome.

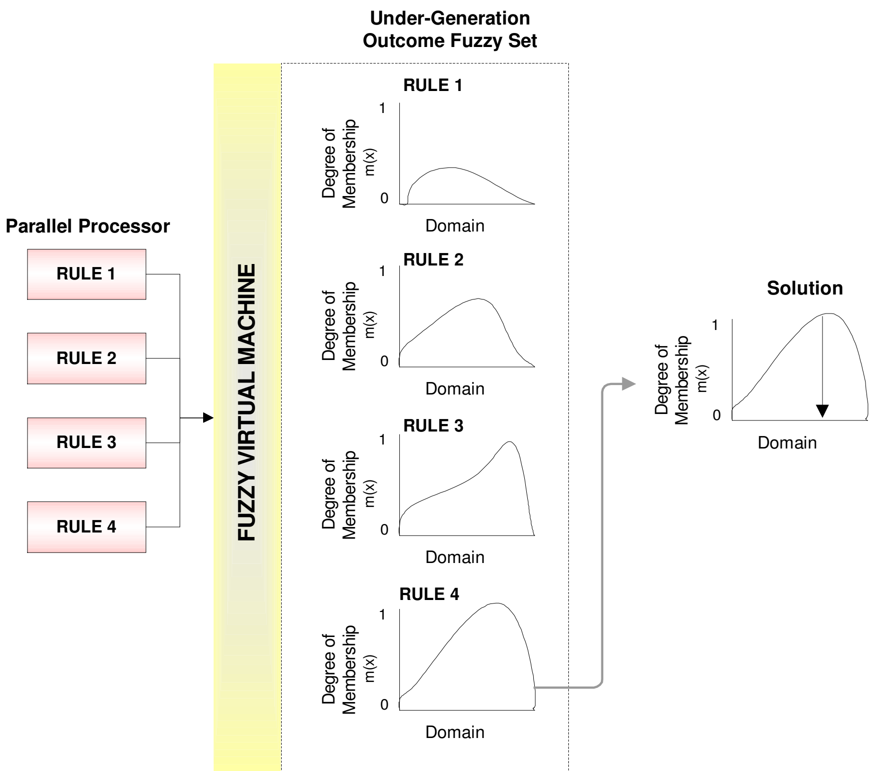

Figure 2. Fuzzy Rule Processing

Because a fuzzy model is abstracted at a very high level, its fundamental representational metaphor is semantic rather than quantitative. Fuzzy rules articulate a broad state space relationship between the antecedent and the consequent of a rule. As a result, a single rule can encapsulate a wide and dynamic range of possible states. The single rule, if height is TALL then weight is HEAVY takes the place of many, many different rules that would specify a possible weight value for a number of bracketed height values. This is very important in the intelligence analyst's quest for a deeply predictive model. As a rather simple example, the following fuzzy rule isolates behaviors that might position someone on a watch list (the fuzzy terms are shown in bold)

```
if time_since-arrival is somewhat short
    aAnd relocations are above average_relocations
    and ratio(creditcarduse,bankbalances) is high
    and count(recent_license_applications) is elevated
    then
        candidate_for_watching is Increased;
```

The degree of evidence associated with the outcome (candidate_for_watching) might very well determine its position on the watch list. And here we see the deep probing benefits of fuzzy logic.

Replacing the fuzzy components of this rule is numbers (or even intervals) destroys the robustness of the rule and hides the underlying patterns.

And fuzzy rules are suggestive not definitive. That is, a fuzzy rule accumulates evidence for or against a particular solution variable. In order to do this, a fuzzy modeling system takes a solution variable and casts it into the shape of an empty fuzzy set. Thus, a rule which says *if x is Y then z is W*, where *Y* and *W* are fuzzy sets (and **z** is a temporary fuzzy region, *Z*) can only be interpreted as: to the degree that **x** is somewhere in the fuzzy space *Y*, increase the shape of *Z* to approximate *W*. As multiple rules are executed, the fuzzy region describing **z** is modified. A final value for **z** is only found after all contributing evidence for **z**'s shape is acquired and the expected value is retrieved through the process of defuzzification. This has significant and critical implications for the capabilities of fuzzy models.

Fuzzy Systems as Universal Approximators

Fuzzy researchers have proved an interesting property of fuzzy systems: they are capable of approximating <u>any</u> function. This means that, if we know the behavior of a system, we can approximate that behavior through a fuzzy system to any degree of precision. The precision depends on the granularity of the fuzzy sets and rules. To move toward fine grain approximation (that is, to represent rather than approximate, in the broadest sense) we decompose the control variable into a larger number of over-lapping fuzzy regions and write rules that specify the behavior in these new regions. This proof forms the basis for fuzzy logic's rapid rise in popularity among control engineers. It is also an important consideration in modeling complex, nonlinear problems in business, scientific analysis, and especially in the intelligence community. Intelligence analysts often understand the general behavior of a system (in this case, perhaps, population dynamics and small swarm behaviors) without having a corresponding mathematical model. In fact, it is often impossible to construct the set of differential equations that accurately represent the system. Knowing that a fuzzy system is a universal approximator means that we can be sure that the gross to fine behaviors of any linear or nonlinear system can be modeled.

Fuzzy System Benefits

Building intelligence models using fuzzy logic has many important and critical benefits. These benefits - enabling a clean and robust encoding of anomalous behavior patterns - work together to give the analyst the kind of deep insight power needed to discover the invisible.

Reduced Cognitive Dissonance. Cognitive dissonance is the difference between the way an expert visualizes or expresses a problem and its solution and the way it is coded in the expert/decision support system. A fuzzy model dramatically reduces this difference by encoding knowledge at a much higher level. The encoding, in fact, is done very close to the equivalent English language expression. Cognitive dissonance is built into conventional decision/expert systems in two ways :(1) state transitions in a model must be expressed in crisp variables so that the division is often arbitrary and not in accordance with the true semantic meaning of the state and .(2) in conventional models, complex problem states must be decomposed into many different rules that state the predicates and actions for each combination of problem states. We can see this in a simple financial analyst's statement of how profitability is related to other factors,

when price is high but demand is low and quantity-on-hand is excessive, then profitability will be correspondingly reduced.

This can be expressed in the following fuzzy rule almost exactly as stated,

```
if price is high
and demand is low
and quantity-on-hand is excessive
           then profitability is severely reduced.
```

Where *high*, *low*, *excessive* and *severely reduced* are fuzzy sets. However, in a conventional model the problem states associated with *high*, *low*, *excessive* and *reduced* must be expressed as mathematically precise expressions. Thus, one formulation of the rule might be,

```
if price > 25.00
and demand < 1200
and quantity-on-hand > 4200
then profitability=
    profitability-(QOH*unitprice)
```

Now this looks like a fairly straightforward conversion between the imprecise statement of the expert and the crisp expression in conventional systems. But appearances are deceiving. The fuzzy rule is much more expressive and powerful than the crisp rule since the value of *profitability* will be proportionally adjusted according to the various truth states of the three antecedent propositions. Unlike conventional systems, the truth of the action is related to the truth of the antecedent as a function of the fuzzy sets. In a conventional rule the antecedent is either true or false, thus the action (the value of *profitability*) is either equal to the assignment statement or no assignment is done! In the fuzzy rule, if *price* is only slightly high then profitability is only slightly reduced. This behavior is not present in the conventional rule. In fact, we would have to introduce many conventional rules to encapsulate the behavior of a single fuzzy rule. And, as we add these rules, the distance between what the expert said and what the model encodes becomes greater and greater. At some point, usually very soon, the mapping between the visualization of the expert and the logic of the model becomes disjoint and difficult to follow. The degree to which this mapping is altered determines how well the model reflects the expert's actual problem statement and solution.

Use of Multiple Conflicting, Cooperating and Collaborating Experts. A common assumption in nearly all expert systems (at least those that appear in the literature which are the ones that have actually succeeded) is that there is a single expert or the underlying experts are all in close agreement. In the real world this is hardly ever the case for anything except toy problems. Since a conventional model can only partition its solution space into true or false, this creates significant difficulties when the problem and solution states have fuzzy properties. And many, if not most, real world problems have fuzzy characteristics. This is most evident where we have conflicting experts. Conventional expert and decision support systems are unable to handle directly opposing views. As an example, consider the rules,

```
the product.price must be low
the product.price must be high
```

In all conventional systems a statement cannot be both true and false (this is Aristotle's Law of Non-Contradiction and the Law of the Excluded Middle.) The above rule is like saying,

```
product.price =  0
product.price = 36
```

Most people would say this is nonsense since the price cannot be both zero and 36 at the same time. Yet in the real world, when we are developing a new product pricing model, the marketing and sales manager may say that the price should be low to gain market share, while the finance manager might say that the price should be high to cover costs and accelerate the pay-back. This inability to be in two (or more) states at the same time is due to the Boolean nature of conventional systems. In a fuzzy model, with its partial degrees of membership, the statement: the product.price must be low has a degree of truth *x*, while the statement the product.price must be high has another degree of truth *y*.

In this way a fuzzy model can accommodate the differing points of view from many experts. These are combined to produce the over-all model recommendation. As an example the following are rules from an actual product-pricing model,

```
the product.price must be high
the product.price must be low
the product.price be around 2*mfgCosts
if the competition.price is not very high
    then the product.price
        must be near the competition.price
```

Why does this work? Because in a fuzzy model all the rules are effectively run in parallel. and fuzzy rules are not absolute. The affect of running rules in parallel is that the final result depends on the combined output from each individual rule. However, since fuzzy rules do not indicate absolutes, this final output reflects the melding of knowledge from each expert. In essence, fuzzy rules accumulate evidence. Each rule enters into evidence a set of facts with varying degrees of truth. Although the process of aggregating this evidence is not done by simple addition, the net effect is to weight clusters of evidence based on (1) the truth associated with the rule and (2) the expertise franchise or ranking of the expert.

Improved Knowledge Representation. In conventional expert and decision support systems nearly all the knowledge is encoded in the rules. These rules are executed serially. Each rule acquires more knowledge until either some goal has been determined (in Backward chaining) or no more rules can execute (in forward chaining.) In a fuzzy reasoning system, however, the knowledge is embedded in several representations: rules, fuzzy sets, hedges and the methods of implication and defuzzification.. Rules take data elements and find their memberships in fuzzy sets (a rule can also create a fuzzy set if necessary). The shape, density, and overlap of the fuzzy sets dictate the semantics of the model data spaces. Hedges intensify, dilute, and otherwise dynamically modify the shape of a fuzzy set. The distribution of knowledge across a set of inter-dependent and inter-related structures allows a designer to construct a much more flexible, powerful, and extensible model infrastructure. Models can be more finely tuned, can represent a wider variety of fundamental data types, can be in a greater number of problem states, and handle a more effective collection of goals.

Reduced Rule Set. Because fuzzy models are parallel processors, the knowledge handling activities in the rules is done at a set theoretic level. Rules combine fuzzy states to produce a composite output fuzzy state. Each rule contributes evidence to the final solution. As a result, the Cartesian Product of all the states is evaluated at once. This has the affect of drastically reducing the number of rules needed to represent a given model state. When rules are reduced, model comprehension is improved, mean-time-to-repair (referred to as MTTR) is reduced, mean-time-between-failure (referred to as MTBF) is increased, mode maintenance is improved, and model extensibility is increased with less risk in introducing new faults.

More robust models. Model robustness is tied to the corresponding engineering term. A robust model is one with predictable and stable behaviors. A value of $x+n$ as input consistently yields $y+m$ as output. As "n" changes, "m" also changes. This not necessarily a linear relationship but it is a steady and predictable relationship. Many expert and decision support systems are not robust due to the large number of rules and the rather "ad-hoc" nature of how rules are executed. In most cases, the numbers of rules in a fuzzy system are significantly and profoundly smaller than the number of rules in a conventional system for the same problem. This means that the model flow state can be more accurately predicted. We can understand its behavior in terms of the standard input-process-output model. Consequently, we can build models with predicted and stable robustness. Such robustness means that fuzzy models lend themselves to easier validation and verification. We can place much more confidence in a fuzzy model because we know its operating characteristics and can predict its long-term behavior. That is, we can assure ourselves that the model is reliable.

In Conclusion

While, in order to reach a larger audience, many financial and pricing examples have been used to illustrate fuzzy model benefits, the corresponding application to intelligence models and behavior analysis should not be minimized. Behavior models based on fuzzy logic provide a deep as well as broad capability for discovering and accurately isolating a wide variety of behavior patterns. It is this ability to easily capture the knowledge of experienced intelligence analysts, to merge opinions for collaborating and even conflicting analysts, and to measure the results based on the amount of supporting evidence that give fuzzy models a strong place among the tools in the post September 11th intelligence community.