The Use of Fuzzy Tools for Small Scale Decision Support Systems

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Abstract

This paper discusses the use of fuzzy tools in the realm of Decision Support Systems. I have investigated the possible use of a number of different paradigms against a novel problem - that of correctly classifying the maintenance required on a concrete tiled roof, given certain input values.

1. INTRODUCTION

By setting appropriate numbers of input, output and hidden nodes, a network can be established. The number of hidden nodes can be reasonably well approximated given the expected number of rules to be generated. The number and quality of training values, number of iterations (Epochs), the learning rate and momentum will affect how well the network will learn. Training is complete when a suitable RMSE (calculated and compared at the end of each training epoch) is achieved.

The application of fuzzy systems to real-life problems is one that is not really new. Many people see such things as fuzzy lift controllers, motor vehicle gear selection and medical diagnosis as ‘high technology’, a novelty. The widespread acceptance of fuzzy classification (and hence decision support systems) will not be achieved until ‘normal’ people can access and use such tools on an everyday basis.

As a part of third year studies, we were encouraged to investigate a number of tools, using a simple classification problem as a basis. The following tools were used:

- Fuzzy CLIPS
- Fuzzy Logic Inference Engine (FLIE) Kohonen Self Organising Map (SOM) Neural Network (Multi Layered Perceptron, using the Fuzzy Cope 3 program, developed by the University of Otago)
- Fuzzy Neural Network (FuNN, using the Fuzzy Cope 3 program, developed by the University of Otago)

The problem chosen is that of determining what maintenance should take place when assessing the condition of a concrete tiled roof. This has a number of heuristics (or ‘rules of thumb’) that guide an experts’ decision when conducting a survey. By applying these heuristics I hoped a computer could determine an accurate assessment.

CLIPS and FLIE are dependent on the rules involved. The results are produced, having been interpreted by the rules (refer Fig 2).

MLP and FuNN tools use a collection of existing data with known properties to train the networks. When the network is presented with new values, the classification can be expressed. Ultimately, the network is expected to generalise, so that it can correctly categorise new values to the expected results.

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Any of the methods; best - hybrid systems

Fig 1 Solution space for AI methodology choice. This suggests that there may not be one best solution...
SOMs can `map' training data such that people can visually confirm that groupings actually exist.

The choice of tool is then a matter of considering the amount of known domain theory and suitable sample data available, the ease with which it can be associated with other applications, and the suitability of the presentation of the end result.

2. METHOD

Sample input data was reviewed then condensed to ascertain the minimum number of values upon which results depend. There are two values of consequence, being:

- Growth - determines whether a roof should be cleaned
- Wear – determines whether a roof should be replaced or resurfaced.

There is an element of overlap between these values, suggesting a fuzzy rule interpretation will be more appropriate than crisp values. This also ensures that they do, in fact, make a reasonable basis for the heuristics involved - they both have some positive correlation on the expected result.

```plaintext
if WEAR is Worn-Out then MAINTENANCE is Replace  
if WEAR is Partly-Worn and GROWTH is Heaps then MAINTENANCE is ReSurface if WEAR is Partly Worn and GROWTH is Some then MAINTENANCE is ReSurface  
if WEAR is Partly Worn and GROWTH is None then MAINTENANCE is Do Nothing  
if WEAR is Coating Damaged and GROWTH is Heaps then MAINTENANCE is ReSurface  
if WEAR is Coating Damaged and GROWTH is Some then MAINTENANCE is ReSurface  
if WEAR is Coating Damaged and GROWTH is None then MAINTENANCE is Do Nothing if WEAR is Good Condition and GROWTH is Heaps then MAINTENANCE is Clean  
if WEAR is Good Condition and GROWTH is Some then MAINTENANCE is Clean  
if WEAR is Good Condition and GROWTH is None then MAINTENANCE is Do Nothing
```

Fig 2  Rules extracted from data, used in the creation of CLIPS and FLIE systems

Sample data was generated that covered the entire spectrum of expected results and input possibilities. Rules were extracted from these values then CLIPS and FLIE programs were generated based on these values.

Further input values were generated and these rulebased systems tested against the known or expected results.

Generated data was presented to the SOM, MLP and FuNN to train. The SOM was to generate a `map' reflecting the values submitted, showing `groupings' where they exist.

The MLP was expected to generate internal rules through the process of supervised learning and correctly classify `new' values. The FuNN would do the same, but present the resultant rules for future use or tuning.

3. RESULTS

All were successful in correctly classifying values presented to it. The MLP and FuNN were most successful in identifying areas where two result decisions may be made, giving individual weights (Certainty Factors) to each result.

4. DISCUSSION AND CONCLUSIONS

While this initial prototype works suitably given two inputs, further development is required before considering this as a commercially viable product. Many related issues have not been taken into consideration, such as:

- the type of tile and its inherent characteristics,
- the age of the roof,
- the original coating surface and its condition (if any remains),
- what maintenance has occurred in the past,
- the condition of the underlying construction,
the physical location of the roof, and
any other localised considerations.

This series of prototypes reveals that there are many ways of achieving a single, simple, goal. Through the use of several different techniques we have confirmed that these are not only possible, but can be tuned in accuracy with relatively little effort.

Future development could also meet the desire to generate a written report for the prospective client, along with expected costs for recommended work. Suitably armed, the clients can then make an informed roof maintenance decision.

![Membership functions generated with FLIE show overlaps in result and input sets](image)

**Fig 3** Membership functions generated with FLIE show overlaps in result and input sets

Other roof types could be added (through a similar process) to create a holistic tool that can be used by any technical/semi-skilled staff member.

A palmtop on the rooftop? Why not!

**FLIE Tests:**

<table>
<thead>
<tr>
<th>Crisp value:</th>
<th>Crisp Value:</th>
<th>Result: Value (0 to 100) and</th>
<th>Expected Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wear</td>
<td>Growth</td>
<td>Category produced by the DSS</td>
<td></td>
</tr>
<tr>
<td>90</td>
<td>0</td>
<td>89.93 Replace</td>
<td>Replace</td>
</tr>
<tr>
<td>90</td>
<td>100</td>
<td>89.94 Replace</td>
<td>Replace</td>
</tr>
<tr>
<td>80</td>
<td>0</td>
<td>64.54 ReSurface</td>
<td>ReSurface</td>
</tr>
<tr>
<td>80</td>
<td>100</td>
<td>79.35 ReSurface</td>
<td>ReSurface</td>
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<tr>
<td>70</td>
<td>50</td>
<td>65.72 ReSurface</td>
<td>ReSurface</td>
</tr>
<tr>
<td>60</td>
<td>50</td>
<td>65.71 ReSurface</td>
<td>ReSurface</td>
</tr>
<tr>
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<td>50</td>
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</tr>
<tr>
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<td>50</td>
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<td>ReSurface</td>
</tr>
<tr>
<td>30</td>
<td>50</td>
<td>65.7 ReSurface</td>
<td>ReSurface</td>
</tr>
<tr>
<td>20</td>
<td>50</td>
<td>65.7 ReSurface</td>
<td>ReSurface</td>
</tr>
<tr>
<td>10</td>
<td>50</td>
<td>50.05 Clean</td>
<td>Clean</td>
</tr>
<tr>
<td>10</td>
<td>0</td>
<td>10.01 Do Nothing</td>
<td>Do Nothing</td>
</tr>
</tbody>
</table>

*Table 1 Results of FLIE program given inputs listed.*

Acknowledgements
This work was carried out as part of the internal assessment portion of Third Year study at the University of Otago (Information Science Department). We were encouraged to investigate the use and application of 'Fuzzy' systems on real life classification problems, utilising new or available data sets. National Roof Refurbishers deserve mention, as they provide the inspiration for this work.

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REFERENCES