Chapter 9: Conclusion and future scope

79-80

Conclusion and Future scope

In order to better understand the effect of different TDI values during the evolution of NN, analysis of a series of different coding schemes should be carried out. By observing how different coding schemes appear to be able (or not) to process good GA schemata, a better understanding of TDI values can be obtained. In addition, the disruptive ability of different TDI values should be compared with that of several ranges of mutation rates. By doing so, TDI values can be better understood, allowing this methodology to better assist in the design of coding schemes and the balancing between different types of evolutionary operations.

Another aspect of TDI computation to be explored relates to its effect when a population contains elements with drastically different fitness values. Although the graph shows that fitness values are starting to converge towards the 40th generation, the system seems to process the schemata of the best elements slowly. It would be important to determine if this is caused by the magnitude of the difference, or by other factors (such as evolutionary pressure, size of the population, etc.).

Finally, several question relating to the analog coding system presented in section 8 should also be explored further. In particular, the effect of using the same number of nodes, but with different coding schemes for nouns and verbs should be investigated. Furthermore, the possibility of having a GA evolve these codings should be explored.

This work has presented a mathematical methodology for predicting the effectiveness of a GA in processing NN topology. The methodology is used to predict the effectiveness of several GA coding schemes. These predictions are shown to correspond with actual results.

In addition, different ways of representing sentences at a NN output later are presented. Advantages of using non-binary representations are discussed, both from the point of view of expanding sentences that can it can process and efficiency of GA used to evolve them.

Evolution has clearly shown that having *four* independent learning rates and initial weight distributions results in far superior learning performance compared with just *one* for the whole network, and how age dependent plasticity can generate further vast improvements. However, given the complex interactions of the evolved parameters, and the extreme values some of them take, it seems unlikely that we will be able to take these observations and dispense with the evolutionary process. So, if we do require fast learning (e.g. for real time autonomous systems), evolution really *is* worth the effort. If we want to avoid evolving everything, the best we can hope for is that it will be possible to evolve some fairly robust parameter configurations that can cope well with new problems from particular identifiable classes of problems.

There exist other evolutionary strategies, whereby whole generations are tested and replaced at each stage, rather than just a few of the oldest and least fit individuals.

The study presented here is currently being extended to include those.

This section is devoted to explain the current work and further research lines that we plan to address:

• First, the representation of the examples. Which is the best way to represent the examples? Which is the best feature selection procedure?

• The second research line is the application of bootstrapping techniques to Word Sense Disambiguation in order to increase, in a simple way, the amount of training examples; alleviating the data scarceness problem. We also are interested in *on-line* learning classifiers able to adapt to new domains.

• The third line is the integration of Semantic Parsing models within Word Sense Disambiguation classifiers in order to develop a better and complementary hybrid system to deal with both tasks.