Heterogeneous Neuron Models based on Similarity

Lluís A. Belanche Muñoz

Dept. de Llenguatges i Sistemes Informàtics
Universitat Politècnica de Catalunya
c/Jordi Girona Salgado, 1-3
08034 Barcelona, Spain.

belanche@lsi.upc.es

In this research, artificial neural models are extended to handle missing and non-real data and weights, and made to compute an explicit similarity relation. Artificial Neural Networks (ANN) constitute a class of models amenable to learn non-trivial tasks from representative samples. When exposed to a supervised training process, they build an internal representation of the underlying target function by combining a number of parameterized base functions (PBF). The network relies in the representation capacity of the PBF (that is, of the neuron model) as the cornerstone for a good approximation. This is true at least for the most widespread PBF: that used in the MultiLayer Perceptron –basically a scalar product between the input and weight vectors plus an offset, followed by a squashing function– and that used in Radial Basis Function networks –a distance metric followed by a localized response function. The task of the hidden layer(s) is to find a new, more convenient representation for the problem *given* the data representation chosen, a crucial factor for a successful learning process that can have a great impact on generalization ability (Bishop 1995, p. 296).

Additionally, in theory ANN design should follow the principle: *Similar patterns should yield similar outputs* (Rumelhart et al 1993). However, what "similar patterns" means is problem-dependent, and only in counted occasions will coincide with the fixed interpretation of similarity that a network is going to perform. In this respect, a marked shortcoming of the neuron models existent in the literature is the difficulty of adding prior knowledge to the model, either of the data or of the problem to be solved. Furthermore, in classical neuron models, inputs are continuous real-valued quantities. However, in many important domains from the real world, objects are described by a mixture of continuous and discrete variables, where some values may be lacking, and usually characterized by some source of uncertainty.

This work deals with the development of general classes of neuron models, accepting heterogeneous inputs by aggregation of continuous (crisp or fuzzy) numbers, linguistic information, and discrete (either ordinal or nominal) quantities, with provision also for missing information. The internal stimulation of these neural models is based on an explicit *similarity relation* between the input and the weight tuples (which are also heterogeneous). The framework is very comprehensive and several particular models can be derived as instances thereof –in particular, the two mentioned standard models are shown to compute a specific similarity function provided all inputs are real-valued and complete. A family of models defined as a composition of a Gower-based similarity function (Gower 1971) with a sigmoid squashing function is shown to be a useful brick for constructing layered architectures (Heterogeneous Neural Networks or HNN) (Belanche 2000), trained by means of Evolutionary Algorithms.

These networks –limited thus far to feed-forward structures– are capable to learn from non-trivial data sets with an effectiveness comparable, and often better, than that of classical networks, specially exhibiting a remarkable robustness when information degrades due to the growing presence of missing data. There is also an increase in flexibility by accepting training processes using imprecise or vague data, both in the input *and* the weights. The rationale behind the approach is that, by respecting the nature of the data, and endowing the neuron models with the properties of an explicit and *ad hoc* similarity measure, it is expected that the resulting neural structures are able to learn from datasets in a satisfactory way, both from the point of view of generalization performance and readability of results.

This hypothesis has been validated by experimentation in classification and regression problem domains, coming either from standard benchmarks or from real-world problems (e.g. Valdés, Belanche and Alquézar 2000) with encouraging results. Work is in progress towards proving the universal approximation property of these networks.

References

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