Special Session on

INCREMENTAL LEARNING/ LEARNING IN NONSTATIONARY ENVIRONMENTS

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Rationale & Motivation for this Special Session

One of the fundamental goals in computational intelligence is to achieve brain like intelligence, a remarkable property of which is the ability to incrementally learn from noisy and incomplete data, and ability to adapt to changing environments. The ability of a computational model to learn under various environments have been well-researched with promising progress, but a vast majority of these efforts make two fundamental assumptions: i) there is sufficient and representative training data; and ii) such data are drawn from a fixed – albeit unknown – distribution. Alas, these assumptions often do not hold in many applications of practical importance. Recent efforts towards incremental and online learning may allow us to relax the "sufficiency" requirement by continuously updating a model to learn from small batches of data. Yet, in many incremental learning algorithms the second assumption still remains: the data that may incrementally become available are still drawn from a fixed – but yet unknown – distribution. More recently, other incremental approaches – also called *concept drift* algorithms - have attempted to remove this assumption, by allowing a stream or batches of data whose underlying distribution change over time. These early approaches, however, make other assumptions such as restricting the type of change in the distribution, are primarily of heuristic in nature with many free parameters requiring fine-tuning, and have not been evaluated on large scale real-world applications.

Considering that our ultimate goal in computational intelligence is to attain brain-like intelligence, and that the plasticity of brain-like intelligence can, and routinely does, learn incrementally and in nonstationary environments, the need for a framework for learning from – and adapting to – a nonstationary environment is very real. Combined with a growing number of real-world applications that can immediately benefit from such algorithms, it is clear that there is much work to be done for solving the incremental and/or nonstationary learning problems. We should also note that while incremental and nonstationary learning may at first appear to be different topics, learning in nonstationary environments must necessarily be incremental in nature. Therefore, incremental and nonstationary learning are two intrinsically connected pieces of a more general and increasingly important computational intelligence challenge.

While papers on these topics have appeared in recent IJCNN meetings, they have typically been far and few in between, and scattered into many different sessions. Against this background, a special session on incremental / nonstationary learning is very timely and relevant, and hence would be of great interest to the attendees of IJCNN 2009. Researchers working in any of the related areas of incremental / nonstationary learning or concept drift are encouraged to submit their contributions to this special session.

Goals of the Proposed Session:

The proposed session on incremental / nonstationary learning has three main goals:

1. Introduce the problem of incremental / nonstationary learning, and its associated issues, to the greater neural network & computational intelligence community who may not have been familiar with the topic, yet would like to familiarize themselves with the most recent approaches for solving this problem;
2. Provide a forum for researchers who have been actively working in this area to exchange new ideas with each other, as well as with the rest of the neural network & computational intelligence community.
3. Present recent approaches to incremental learning and learning in nonstationary environments from two perspectives: first, the more traditional and theoretical view of machine learning and computational intelligence; and second, from the more practical and application oriented view of using neural networks.

Scope of the Proposed Session

The scope of the proposed session includes, but not limited to

- Incremental learning / lifelong learning / cumulative learning
- Learning in non-stationary environments / concept –drift environments / dynamic environments
- Architectures / techniques / algorithms for learning in such environments
- Applications that call for incremental learning or learning in nonstationary environments
- Development of test-sets / benchmarks for evaluating algorithms learning in such environments
- Issues relevant to above mentioned or related fields