Knowledge acquisition for discrete event systems using machine learning

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Knowledge acquisition for an understanding of discrete event simulation systems is a difficult task. Machine Learning has been investigated to help in the knowledge acquisition process. Our approach involves consultation with a domain expert, and the use of discrete event simulation models and machine learning as tools for the intelligent analysis of simulated systems. Current methods for the analysis and interpretation of such systems are restricted to statistical techniques that say much about the reliability of an output, but little about the output inter connectivity. The objective of our work is to improve the ability to interpret the model to the level of explanation that might loosely be described as "How the simulated system works". The new interpretation techniques are based on knowledge acquisition concerning the system using machine learning tools. "How the simulated system works" is important for a decision maker's understanding of the system in terms of relationships between the various parameters, the utilisation of resources and the location of (potential) bottlenecks. This sort of understanding is important when managing queuing problems in production systems, or when planning a new system. It should be emphasised that the goal of the presented work is not a prediction nor an optimisation. The main goal here is to find interpretations of the simulation output and discovering regularities, thus helping the user to develop an intuitive understanding of the domain (see Fig. 1).

Discrete event simulation produces example situations that can be used as input data for machine learning tools. In the presented research, three simple and commonly used discrete event simulators were interpreted using different machine learning tools. The attribute based learning systems Retis and Assistant were chosen as appropriate for learning in noisy, real-world domains. The interpretation obtained by these systems was intuitive but obviously expressed in a complicated way. To enable a more powerful knowledge representation, the Inductive Logic Programming (ILP) system Markus was used. In addition to compact knowledge representation, Markus also highlighted some attribute combinations that could be useful in the attribute based learning.

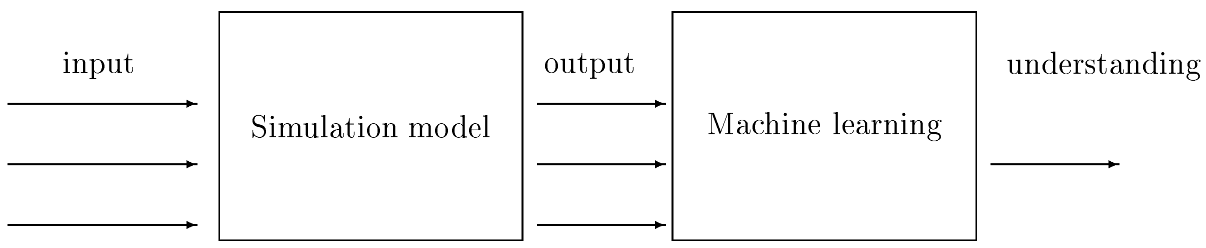

Figure 1: Using machine learning for simulation output analysis

The knowledge gained from the machine learning tools was evaluated by the domain expert, who considered that this knowledge contributed to an understanding of the system, and how it might profitably be modified. This is important because the success of the present study should not be measured in terms of prediction accuracy, but in terms of the interpretative ability of the induced descriptions.

A methodological point of interest is the combination of ILP learning with attribute-based learning, and "chaining" of classification trees. (1) The ILP system Markus, could not really cope well with the noise in the learning data, but made important contribution as a generator for new attribute combinations. These were then beneficially applied in the subsequent attribute-based learning. (2) The knowledge provided by classification trees generated for the target problem (waste in steelworks) was analysed by domain expert and decided to be helpful but not enough detailed. Thus, depending on the already generated classification tree, a new target problem was formulated and the experiments repeated. This approach enables a more flexible analysis of the simulator from different, dynamically chosen, views and was considered by domain expert to be very beneficial for the simulated system understanding.