GUEST EDITORIAL

Special Issue: Machine Learning in Design

ALEX H.B. DUFFY,[1] DAVID C. BROWN,[2] and ASHOK K. GOEL[3]

[1]CAD Centre, University of Strathclyde, 75 Montrose Street, Glasgow G1 1XJ, Scotland, UK.
[2]AI Research Group, Computer Science Department, Worcester Polytechnic Institute, Worcester, MA 01609, USA.
[3]College of Computing, Georgia Institute of Technology, Atlanta, GA 30332-0280, USA.

This issue of *AIEDAM* is based on a workshop on Machine Learning in Design held at the 1996 Conference on Artificial Intelligence in Design, AID'96 (Gero & Sudweeks, 1996), the third of such workshops, with the previous two being held at AID'92 (Gero, 1992) and at AID'94 (Gero & Sudweeks, 1994). The first two workshops also resulted in special issues of *AIEDAM* (Maher et al., 1994; Duffy et al., 1996).

The purpose of the 1996 workshop was to explore the issues in and requirements of learning in design, with a view to critically evaluating the current and needed support available from machine learning techniques. The objective was not only to identify key areas for future research, but also to stimulate synergy in the machine learning in design research community.

As a result of the accepted position papers, the workshop itself focused on developing a "taxonomy" for machine learning in design (see http://www.cs.wpi.edu/~dcb/AID/taxonomy.html). Participants were required to describe the position of their work relative to the proposed taxonomy, and to suggest how the taxonomy might be modified to make it a better, more generic reflection of the field.

The basis for a taxonomy were given as seven "dimensions" of machine learning in design, viz:

1. What can trigger learning?
2. What are the elements supporting learning?
3. What might be learned?
4. Availability of knowledge for learning.
5. Methods of learning.
6. Local versus global learning.
7. Consequences of learning.

The basic ethos of the workshop was the stimulus for this special issue. From the workshop, a subset of the papers was selected for expansion into this special issue of *AIEDAM*. The expansion was based on further development by the authors and by consideration of the workshop discussion. Particularly, authors were invited to submit papers discussing their

work in relation to the above dimensions and addressing three main elements:

a. a presentation of their machine learning in design work;
b. an attempt to categorize it in terms of the dimensions;
c. a critique of the proposed dimensions based on that attempt.

Papers also were accepted that focused only on part c.

This special issue is organized in three main parts. The first part presents the basis for the special issue. This is in the form of a revised version of the dimensions of machine learning in design presented by Grecu and Brown. Their paper discusses these dimensions in more detail and presents the need for a debate on this issue. The second part of the special issue is in the form of five papers that address all of the three elements listed above. The authors' work is presented along with a discussion and critique of the dimensions. The final part of the special issue contains two papers that specifically address critiquing the proposed dimensions.

The focus of the paper by Manfaat, Duffy, and Lee is on ways to provide a designer with usable stored design experience for problems that are dominated by spatial layout. They describe methods to turn sets of specific layout examples into generalization hierarchies and any individual design example into one or more levels of abstraction. Abstractions can be produced from different points of view, such as the function or area of the spaces in the layout. The hypothesis is that such abstractions and generalizations allow the designers to more easily be provided with (or find) appropriate stored experience that they can use for their new problem.

Gomes, Bento, and Gago describe learning in a case-based system. Each design case in their IM-RECIDE system includes causal relationships between the requirements and the design decisions. By using different degrees of matching between a new design problem and the cases, and some adaptation, they are able to produce increasingly creative designs. As some of these may be a little "too" creative, they are matched against cases representing incorrect designs (i.e., failure cases), and those that match are dis-

carded. The system stores any distinctly different correct cases it generates, as well as any produced by the user. It also stores any new failure cases from either of those sources. They show that the system's performance improves, gradually producing fewer bad designs.

Simulation normally is associated with the latter stages of the design process, where parameters are known and well defined. Ivezic and Garrett present a simulation-based decision support system that is capable of assisting with early collaborative design. Their approach uses a neural network to learn appropriate simulation knowledge and builds probabilistic behavior models from that knowledge. Monte Carlo simulation then is used to sample the trained neural network and approximate the likelihoods of parameter values. The results are integrated as a prototype simulation-based decision support system (SB-DSS) that is used as a basis to evaluate the developed techniques.

Optimization is a key problem in the middle phase of engineering design. The quality and efficiency of numerical optimization depend on the initial conditions, for example, the prototype that is selected from a prototype database for optimization and the formulation of the search space for optimization. Inductive learning potentially may enable learning of setup conditions from past episodes of design optimization. Schwabacher, Ellman, and Hirsh demonstrate that the use of standard tree-induction algorithms (such as C4.5) improves both the speed and reliability of gradient-based methods for numerical optimization. Their article also illustrates the value of detailed and careful evaluation in research on machine learning in design.

At the detailed design stages, a finite-element mesh often is used to analyze the behavior of the design under specific conditions. Dolsak, Bratko, and Jezernik's work is directed at generating an optimized mesh. They present a system, CLAUDIEN, that uses an inductive learning approach to generate rules, for the generation of a particular mesh, for a given geometric model. The approach differs from conventional mesh generation in that not only is the geometry of the model considered, but experiences of past mesh generation is encapsulated in the learned rules. The results from the system are evaluated through a series of tests to ensure the validity of the induced rules and the developed approach.

Reich's paper directly addresses the issue of discussing the dimensions proposed by Grecu and Brown. He develops an alternate set of eight dimensions based on a previously developed process of using machine learning to enhance human design practice. These dimensions then are contrasted with Grecu and Brown's, and a number of resulting research issues are highlighted and discussed. Reich's proposed dimensions are supported through discussion of a particular project example.

Sim and Duffy take a different perspective on machine learning in design than Grecu and Brown. In their paper, they analyze machine learning in design in terms of three questions: What type of knowledge is learned? How does learning occur? and When does it take place? Specification of the type of knowledge that is learned is central to this perspective, and the paper provides a productive classification of different types of knowledge transformations in machine learning in design. A particularly effective feature of this paper is its analysis and organization of a large range of operational systems around the typology of knowledge transformations.

The editors are truly grateful for the efforts of all of the authors in this special issue. We would particularly like to thank the reviewers of the workshop and journal papers. They helped to make this special issue a reality. We feel that the articles in this special issue make a significant contribution to the development of machine learning in design and hope that the readers find them as beneficial as we did.

REFERENCES

Duffy, A.H.B., Brown, D.C., & Maher, M.L. (1996). Special Issue: Machine Learning in Design. *AIEDAM*, *10(2)*.

Gero, J.S. (1992). *Artificial Intelligence in Design '92*. Kluwer Academic Publishers, The Netherlands.

Gero, J.S., & Sudweeks, F. (1994). *Artificial Intelligence in Design '94*. Kluwer Academic Publishers, The Netherlands.

Gero, J.S., & Sudweeks, F. (1996). *Artificial Intelligence in Design '96*. Kluwer Academic Publishers, The Netherlands.

Maher, M.L., Brown, D.C., & Duffy, A.H.B. (1994). Special Issue: Machine Learning in Design. *AIEDAM*, *8(2)*.