
GUEST EDITORIAL

Special Issue: Machine learning in design

ALEX H.B. DUFFY,¹ DAVID C. BROWN,² AND MARY LOU MAHER³

¹ CAD Centre, University of Strathclyde, 75 Montrose Street, Glasgow G1 1XJ, Scotland, U.K.

² AI Research Group, Computer Science Department, Worcester Polytechnic Institute, Worcester, MA 01609, U.S.A.

³ Key Centre of Design Computing, Department of Architectural and Design Science, University of Sydney, Sydney, NSW 2006, Australia

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

The purpose of the 1994 workshop was to explore issues and requirements of learning in design, to critically evaluate the current and required support from machine learning techniques, and to identify key areas for future research. As a result of the accepted position papers the workshop itself focused upon five key issues:

1. *Using Machine Learning for producing new knowledge:*
Which kinds of knowledge should we use Machine Learning to try to produce? Where are the greatest gains? Can we use Machine Learning to get anything “really new”?
2. *Learning and the process of design evaluation:*
How to learn from, and learn to do, design evaluation?
3. *Applying Machine Learning techniques versus discovering Machine Learning techniques:*
Does design provide a special environment in which there are opportunities to discover new learning methods or should we work on applying current Machine Learning techniques? How can techniques be mixed in new ways?
4. *Machine Learning for innovative design:*
How can Machine Learning provide support for the development of design systems that generate innovative design solutions?

5. *How to evaluate the results of Machine Learning when applied to design:*

How do we evaluate the changes in a design system after Machine Learning has been used? What can change? What are the metrics?

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.

Design is a complex activity embracing many different aspects such as the “actors” involved, the artefact being designed, and the design process itself. Each aspect is closely related to the others in a complex and ill-defined way.

The full papers in this special issue address each of these particular aspects of design. In addition, a collection of short papers gives an overview of the current work being carried out in the field of Machine Learning in Design (MLinD).

Two basic types of “actors” are humans and tools. Each can accomplish particular tasks and objectives, and have different roles to play during the design process. They require different types, forms, and sources of knowledge to fulfill their roles. Both create complexity as well as help to manage it. They interact in complex ways but can be an effective team in design problem-solving.

The paper by Duffy and Duffy addresses the problem of supporting learning by the designer and the Intelligent Computer Aided Design (IntCAD) system while they are carrying out a design problem-solving activity. Its focus is on enhancing the complementary roles of the human and computer tool. The paper introduces the concept of Shared Learning as a basis to develop more useful learning capabilities in IntCAD systems and “Controlled” computational learning as a means whereby Shared Learning can be realized. Controlled computational learning is proposed as a means for a designer to explore a domain

Reprint requests to: Alex H.B. Duffy, CAD Centre, University of Strathclyde, 75 Montrose Street, Glasgow G1 1XJ, Scotland, U.K. Phone: +44(0)141 552 4400 x3005; Fax: +44(0)141 552 3148; E-mail: alex@cad.strath.ac.uk

driven by particular design requirements or by their own individual needs or desires. “Domain Exploration” is discussed in the paper as a key element in design problem-solving. It occurs when a designer explores the domain of past designs to learn from the domain and apply that learned knowledge to a new problem. Thus, the system’s learning capabilities are used to support a designer’s own learning and problem-solving requirements. Consequently, the system’s learned knowledge can be used to support domain exploration or directly in design problem-solving. For example, generalized knowledge can be used by the designer to understand trends or particular relations within a domain or to configure a new design solution to meet particular design requirements.

The paper by Murdoch and Ball is concerned with configuration. Configuring a design artefact is a complex design activity involving selecting appropriate components to satisfy functional design requirements and connecting those components in such a way as to determine the best overall design solution. Consequently, numerous design configurations are often generated and evaluated to ascertain the best solution, given the particular stage of design. Each configuration will have particular strengths and weaknesses in respect to its desired functionality, quality, cost, and any other evaluation criteria.

Optimizing the configuration of the design artefact is the focus of Murdoch and Ball’s paper. They use a “Technical Merit” measure to rank past design configurations to identify prevalent characteristics that contributed to their success (high technical merit). Component parameters of past design solutions are clustered into archetypes using a neural network approach, the Kohonen Feature Map. These archetypes are then compared using “duty, reliability and cost” as criteria to identify the main characteristics that contribute to either a high or low technical merit. Thus, the approach provides a basis upon which to support a designer in the creation of new design configurations that will have potentially high technical merit, and provides guidance in component and feature selection.

Britt and Glagowski’s paper is concerned with inferring the design process from a design. As Configuration is just one of the activities in the design process that involves multiple decisions, choices, calculations, etc., the design process that produced a design can be very complex.

The capture of the decisions and their effect on the evolution of the design solution is often referred to as a design plan (or design history). Thus, the design plan represents, to some degree, the rules used to carry out the design process and to decompose the design artefact to produce an acceptable solution.

Design plans can be saved for particular designs (e.g., circuits) as part of the design procedure and then replayed under the right circumstances to help solve all or part of a new design problem. That is, the “rules” in the design plan are replayed and used to help construct a new, or partial, design solution to meet new requirements.

A limitation of this approach is that it requires existing design plans to have been saved during a previous design session. But what if this was not the case? Britt and Glagowski present a new approach, termed Reconstructive Derivational Analogy, that creates a design plan from an existing past design solution that had no previously saved plan. That is, an existing design solution is used to automatically construct a design plan (history) of a possible decision route that may have led to the creation of that solution. The “reconstructed” plan can then be replayed for new requirements and used to help create a new design solution.

The complexity of design is further illustrated by the diversity of work being carried out within the field of Machine Learning in Design. The set of short papers that represents the state of Machine Learning in Design Research gives a basic overview of the problems, issues and approaches of utilizing and developing machine learning techniques to support design.

The articles address a wide range of MLinD issues covering general knowledge acquisition and learning techniques (Arciszewski; Leo, Sleeman, and Tsinakos), the roles and use of machine learning within design (Faltings; Reich; Duffy and Duffy), multiagent design problem-solving (Grecu and Brown; Prasad, Lander, and Lesser), design knowledge compilation (Brown), formulating the design problem and supporting its evolution with the design solution (Gero; Maher), and learning from past designs to support synthesis and analysis activities (Bhatta and Goel; Prabhakar and Goel; Schnier and Gero; Schwabacher, Ellman and Hirsh; Reddy).

Although the coverage of the work is formidable, its variety is encouraging. We are sure that the authors will agree that there are many challenges that lie ahead. This compilation of short papers gives a good overview of the current activity, as well as a small insight into the variety and scope of the problems for the MLinD research community.

The editors are truly grateful for the effort and input of all the authors in this special issue. We particularly thank Professors T. Arciszewski, I. Bratko, A. Goel, Y. Reich, and D. Sleeman for their effort and comments as reviewers for the workshop and journal papers. They helped to make this special issue a reality. We consider the articles to make a significant contribution to the development of Machine Learning in Design and hope the readers find them as beneficial as we did.

REFERENCES

- 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.
- Maher, M.L., Brown, D.C., & Duffy, A. (1994). Guest editorial. *AI EDAM* 8(2), 81–82.