

One possible role for machine learning in collaborative design (a few preliminary thoughts)

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1 Introduction and Motivation

As the name implies, collaborative design is a process performed by many designers. Each designer makes a subset of the decisions comprising a design and must modify his or her decisions when they adversely influence some aspect of the design. To complicate the task, each designer is equipped with his or her specific schema or world-view that makes communication between them difficult. Definitions of commonly used objects can serve as examples of this difficulty. Movable partitions may be seen as "walls" by space planners but would not fit into that category from the viewpoint of structural designers. Others may think of the word "wall" as associated with amounts and color of paint while a computer graphics specialist may be more concerned with the "two sidedness" of the "wall" object for manipulation purposes. The attribute of two sides has external and internal implications when related to fire codes, insulation, or covering.

During the collaborative design process, the individual designers make decisions about the design based on a set of objectives that are important from their perspective and for which they are prepared to design and evaluate their designs. Many of these decisions may have several alternatives from which the designer can select and that have different influences on design decisions already made, and yet to be made, by other designers with other objectives. However, oftentimes the designer making a decision is unaware of, or unable to determine, how his or her decision will impact these other design objectives.

One approach to addressing this problem is to provide the designers with "design advisors" that observe what the designer is doing and attempt to predict what influences, if any, the current decisions being made will have on other designers and design objectives. Design advisors have been introduced, although somewhat vaguely, in the framework of concurrent design in several places [Finger 92, Pohl 92]. In this paper we define design advisors as agents capable of supporting decision making process pro-actively, rather than reactively as design critics. For example, if a designer had a design advisor that could support the decision making process with respect to the ease or difficulty of disassembly of components forming a design, that design advisor would be able to give advice about which decisions among the multiplicity of alternatives would lead to a good design product with respect to product disassembly and recycling. Hence, design advisors merely provide advice to designers or, equivalently, design agents who, in turn, are solely responsible for the decision making process.

Development of these design advisors in a nonautomatic manner using manual knowledge acquisition and modeling methods may be prohibitively expensive. However, using machine learning, it should be possible to acquire these influences from past design experience and to use this knowledge to determine the adverse influences that a current set of design decisions may have on some set of important aspects of the product, either not familiar to the designer or seen in a different schema. This paper will discuss the role that machine learning can play in developing these design advisors and will outline a connectionist approach to acquiring and representing this knowledge.

2 A Methodology: Adaptive Design Advisors for Collaborative Design

In this section we propose a methodology to develop an adaptive design advisor framework for collaborative design. The following are the assumptions on which the methodology is based:

- *Early stages in design are critical decision making stages.* The early design stages need to account for downstream considerations of design, manufacturing, construction, maintenance, and disassembly of the design product.

- *Early design decisions are abstracted information about the design process.* Design decisions that are made in the early design stages together with their downstream influences need to be represented in an abstract way to allow for learning and reasoning about the design objectives.
- *The design process encompasses multiple perspectives.* In each design stage, different objectives for, and perspectives of, a design product offer a natural “clustering” of design decisions. Decisions within a cluster have relatively scarce interaction with decisions in other clusters, compared to the decisions within the cluster. However, these “inter-cluster” interactions are of fundamental importance for the quality of design product. There are one or more design agents that are responsible for the decision making process delegated to each such cluster.
- *The dependency structure in the decision making process is identifiable.* The dependencies between different design decisions can be established through the cooperative process of identification, dialog, and negotiation among intelligent agents.
- *Different perspectives require different representations of design decisions.* Design decisions that are made by different agents contain information which are selectively used by other agents.
- *Evaluative knowledge exists and is usable to guide the synthesis process.* This is the key assumption for enabling a machine learning approach employed in the proposed collaborative framework. This assumption leads to a requirement that the machine learning approach must be capable of capturing the “inverse” of the evaluative knowledge. In other words, the learning approach must construct mappings from the desired functionality to the form of the artifact that satisfies this desired functionality by observing results of past design processes. The connectionist approach reported in [Ivezic 92] meets this requirement.

A methodology for building an adaptive design advisor environment is given and illustrated by an example from [Pohl, 1992]. The following are the steps involved in the methodology:

- *Identification of multiple design perspectives.* Different design perspectives are usually easily identified. These perspectives have associated a group of decisions that are tightly interrelated among each other.

A relatively large number of perspectives are identifiable in the architectural building design domain. Some of these perspectives are noise isolation, construction, space adjacency, thermal, and structural. Even within these globally identifiable perspectives, there are views that observe different parts of the domain. For example, structural considerations that are concerned with seismic reliability of a residential building are concerned with horizontal slabs only to the extent to which they provide sufficient stiffness to ignore the differential horizontal deflections between vertical elements.

- *Identification of design decisions and their dependencies.* Each design advisor deals with a multiplicity of design decisions that together represent a complete solution of the design product from this advisor’s perspective. For each design decision there need to be identified dependent design decisions both within the domain of the advisor and outside the domain.

Consider two perspectives of an architectural design of residential buildings: structural and thermal perspectives. Structural consideration includes selection of the roof system for the building. Thermal consideration includes the management of the temperature fluctuations in the interior of the building. Given the large diurnal temperature spans, thermal analysts may require large structural mass in order to keep the temperature fluctuations low. This requirement is not typically considered by the structural designer and it will interfere with the decisions to select a light roof system.

- *Negotiation of the interaction language between design advisors.* For each external design decision that influences its decision making process, the design advisor negotiates with the design advisor which originates the decision about the content of the information required for its own decision making process. A template for the information requested from the other advisor is established as an outcome of this negoti-

ation and both the requestor and provider of information are aware of information link. Since the dependencies are bidirectional, the two interacting advisors may each play both requestor and provider role.

In the given example, the thermal agent will initiate the negotiation about the kind of information that is needed from the structural advisor. The thermal agent may require the structural agent to make accessible the decisions about the roof system and the vertical structural system. The thermal agent may, in addition, require a particular piece of information which will closely describe the effect of the structural decisions on its own actions, for example, thickness and material of the structural walls. Conversely, the structural advisor may require information about the required structural mass from the thermal advisor to determine how to distribute the required mass among the structural elements.

- *Establishing representations for design decisions.* Design decisions shall be represented differently by different design advisors reflecting the information content important for the decision making process of each advisor. For example, while the exact width of the wall is important for the acoustic considerations, this information is irrelevant for the adjacency considerations.
- *Establishing the control strategy for the design process.* Design advisors are intended to support the decision making process by providing advice to a design agent about the consequences of its decisions with respect to other design considerations. Hence, each advisor is capable of making decisions that satisfy the global design constraints imposed on the design decisions outside of the domain of the design agent. In the case of the global conflicts between design agents, a need for an agent to resolve the conflict arises.

In our example, the control of the design process may be distributed to design agents that locally receive the advice about the good and the bad design decisions. However, when the conflict occurs between the thermal and structural agents with respect to the alternative choices for the roof system, a design agent needs to make a decision based on the global utility of the two alternatives. In this case, there exists a need for the global decision maker to resolve any conflicts according to the globally preferred solution. Still, existence of such a global decision maker doesn't restrict the remaining design agents with advice from design advisors to make decisions which do not result in a global conflict.

3 A Connectionist Approach to Adaptive Design Advisors

We propose a connectionist approach to implement these adaptive design advisors based on the methodology developed in [Ivezic 92]. The connectionist approach employs Bayesian Belief Networks [Pearl 1988] to capture the dependency structure and prior knowledge about the domain, which is then refined through the learning process. The following stages are involved in building these connectionist design advisors:

- *Elicitation of dependency structure from human experts for a given design problem.* Create a Bayesian Belief Network that reflects the elicited causal knowledge [Pearl 88]. If possible, elicit transition probabilities between the nodes and their immediate causes from the experts. This stage reflects encoding of the prior knowledge about the design problem. The causal model may be used as a mechanism for negotiation between several experts. Each expert may work on a separate part of a global model and, then, negotiate language and interactions among decisions with the other domain experts. Typically, a number of design decisions will have impact on more than one part of the global model. It is up to the experts to identify those decisions that affect their views of the design product and reconcile their views with others.
- *Definition of a collection of connectionist networks for each cluster of design decisions.* Each network addresses a design decision made within the enclosing design perspective (i.e., a cluster of design decisions made by a design agent). These connectionist networks are initialized in such a way so as to reflect the initial knowledge encoded in the causal network. They will "wrap" around the decision clusters and become advisors for the particular design agent concerned with this set of design decisions.
- *Refining of the initial design knowledge.* The original transition probabilities given in the causal network model are refined by performing connectionist learning based on existing design cases. As the design

knowledge accumulates in the form of the design cases, the initial knowledge structure will be further refined. The connectionist design advisors will observe the portions of the design descriptions which are of concern for their respective decision clusters and update their weight states and, consequently, probability distributions of the causal graph structure.

- *Synthesizing new designs by using advice from the design advisors.* For a given set of design specifications, constraints, and desired performances, the updated design advisor evaluates alternative decisions in the design process and pro-actively advises the design agent about the utility of alternative decisions.
- *Restructuring and refining design advisor knowledge.* The causal network structure is restructured upon discovery of new causal relationships. In the cases when the new design knowledge can't be encoded in the existing causal structure and connectionist networks, updating of these structures is necessary. It seems that the notion of causality [Spirtes 93] may be an important concept on which to base the restructuring process. This is a conjecture at this point of time and it will be more thoroughly investigated.

4 Issues

There are many issues that need to be addressed in this research. The principal issues are:

- *Design space representations for machine learning.* There are many examples of complex relationships that are important at some level of reasoning about an artifact. Abstractions of these relationships in order to reason about them in the early design stage, and their connectionist representations, require considerable thought and ingenuity.
- *Integration and refinement of existing domain knowledge.* In many cases, a priori qualitative knowledge about design relationships exists and it is beneficial to encode this knowledge in a learning system. Machine learning ought to refine the initial knowledge state, rather than start from the tabula rasa state.
- *Verification and explanation of the knowledge acquired through machine learning.* A comprehensive way of verifying of the knowledge acquired through learning is necessary or, at least, an explanation facility for the reasoning process ought to be provided.
- *Incremental learning and design space extension.* Facilities for incremental learning and design space extension are necessary to support "true" learning capabilities for design: as new data are available, changes need to be made to the underlying knowledge structure.
- *Complexity of design advisors.* In realistic design problems it is necessary to establish what is the complexity of interactions among the design advisors and the complexity of design advisors within a design cluster. In the case of the problems of high complexity, it may be necessary to introduce some simplifying assumptions about the importance of some of the advisor interactions.

5 References

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