

FORMALISING SITUATED LEARNING IN COMPUTER-AIDED DESIGN

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Abstract. In this paper, we propose and begin to formalise an approach to machine learning in design called situated learning with the purpose of providing a foundation to developing better design tools in an agent-based framework. Situated learning theory postulates that the situations that an expert is exposed to forms the developmental conditions of expertise. We extend and adapt that theory for computer-aided design with the primary objective of learning the use of existing knowledge, rather than simply the knowledge itself. The idea behind situated learning is to learn situations and associate them with some knowledge with the intention of using the knowledge in similar situations.

1. Motivation

Machine learning for design has largely been concerned with acquiring design knowledge from examples. An implicit assumption behind such work has been that the knowledge is always applicable. However, the situation within which the knowledge is learned plays a role in its future applicability. Thus, in addition to learning design knowledge it is important also to learn the situation so that a basis exists for the reuse of that knowledge. One way to achieve this is to represent situations and contexts explicitly. However, current machine learning design tools do not represent situations and contexts and therefore are situation and context free. We propose a situated learning paradigm applicable in designing. In this approach, we borrow and adapt a theory from educational instruction called “situated learning” which states that situations which one experiences as a novice form the developmental conditions of an expert (Ingold 1995, Brown et al. 1989). Our primary concern is with the use of knowledge rather than the knowledge itself. Our first aim is therefore to make a design tool learn situations which existed when some knowledge was learnt, with the intention that when similar situations exist in the future it could apply the knowledge. A secondary goal of this approach is to emerge high level structure-behaviour relationships that serve as a means of improving on existing knowledge, and consequently improve the performance of the design tool especially in the conceptual design stages. In this paper we discuss the foundations of such a design tool based on agents and begin to provide a formalisation of the key concepts of situated learning in an agent-based framework.

2. Agent-Based Design

Design is essentially a collaborative and distributed activity requiring heterogeneous and multiple knowledge sources and often different kinds of problem solving (Rosenman and Gero, 1996). This often conveniently and intuitively maps onto specialists in design and computationally to computer programs that are assigned to perform various functional tasks or coordinating various subdisciplines in design. For each of these specialist agents it is neither possible nor needed to map the world in its full complexity and richness. Each agent thus has its own useful view of the world that allows it to make suitable problem representations. For example a structural engineer conceives a building in terms of structural components, while an architect sees the same building in terms of spaces. Researchers in machine learning in design (Reich 1996) also acknowledge the need for addressing the “perspectives” problem, which we believe can be addressed by the agent-based framework. In our system, each agent maps the world in its own useful way which we will call the “relevance field” of the agent.

3. What are Situations in Design

Many authors who refer to situations in computational design as well as in artificial intelligence implicitly use it as a synonym for a state as in AI and problem solving or equivalently as a snapshot of the world. Some researchers like Oki and Lloyd-Smith (1991) and Muller and Pasman (1996) state the importance of situations in terms of applicability of knowledge. In our view, a situation is a partial state composed of a set of facts that is relative to an agent. Thus two agents may at the same time be sensing the same world but the situations sensed will be different. What is the situation and what is not the situation is determined by the focus of the agent. This focus of the agent analogically maps onto the figure-ground hypothesis in Gestalt psychology, Figure 1, which state that focus forms a foreground while the rest is the background. This focus also results in interchangeability of the figure and the ground with the restriction that both cannot be focused at the same time. Situations, analogically, are also that part of the relevance field of the agent that is not in focus (background). A situation is also like a pattern that is a mechanism for indexing other knowledge or defining the applicability condition of the foreground.



(a)



(b)

Figure 1. Figure-ground hypothesis of Gestalt psychology: (a) M. C. Escher's "Circle Limit IV", and (b) E. Rubin's Vase and facial profile (Bruce and Green 1990).

3. What, When and How does our System Learn?

Since the focus in this paper is on the applicability of knowledge, we aim to learn something like “If situation S then apply knowledge K with some variable bindings” and finally arrive at a generalisation-specialisation hierarchy of S . We also want to build heuristics from detailed design analysis procedures that extend the capability of the design tool to early design phases. A learning algorithm will be executed only if there exists “interesting” facts in the world with respect to an agent. What is interesting, depends on which of the facts in the world can be used to build new concepts utilising existing highly believed concepts..

4. Beliefs as a Mechanism in Learning

We define belief as a numerical utility measure of a situation-knowledge pair. This should not be confused with belief as in classical philosophy¹. Beliefs can be generated and propagated as per existing theories of probabilistic or inexact reasoning as in artificial intelligence. Beliefs serve the purpose of assigning credits or blames to situation-knowledge pairs. At first a high value of belief would be assigned to all learnt situation-knowledge pairs. If that pair is utilised in the subsequent design iterations, then credits will be assigned that will reinforce the belief based on a normalised value of the number of times that that situation-knowledge pair has been used. If it is not used, the belief will slowly decay according to a decay function and thereafter “die”.

5. Formalisation

In this section we present the formalisation of the concepts for situated agent-based learning in computer-aided design.

5.1. DESIGN STRUCTURE STATE

A subset of this set is sensed by agent Z and is called the sensed design structure state and is denoted by D_t^Z . Note that this set is internal to the agent while D_t is outside the agent .

$$D_t = \langle s_1, s_2, \dots, s_n \rangle \quad n \in I^+ \quad (1)$$

where D_t = design structure state defined at t , Figure 2

I^+ = set of positive integers, typically very large

n = the maximum bound of an index

¹ Although refutations exist, the most commonly accepted relation between belief and knowledge in classical philosophy is that “knowledge is justified true belief”. (Ackermann, 1972).

$s_i =$ structure variable such that $s_i = \langle O_j \rangle \langle A_k \rangle \langle V_k \rangle$: Object, attribute, value triple. i, j, k are appropriate indices.

5.2. DESIGN BEHAVIOUR STATE

A subset of the design behaviour state posted onto the world by agent Z is called the actual design behaviour state and is denoted by B_t^Z .

$$B_t = \langle b_1, b_2, \dots, b_n \rangle \quad n \in I^+ \quad (2)$$

where $B_t =$ design behaviour state defined at iteration t , Figure. 2

$b_i =$ behaviour variable such that $b_i = \langle O_j \rangle \langle A_k \rangle \langle V_k \rangle$: An object, attribute, value triple i, j, k are appropriate indices.

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Figure 2. A high level description of an agent-based framework for situated learning.

5.3 EXOGENOUS VARIABLE SET

The subset of this set, sensed by agent Z , is called the sensed exogenous set and is denoted by E_t^Z . Note that this set is internal to the agent.

$$E_t = \langle e_1, e_2, \dots, e_n \rangle \quad n \in I^+ \quad (3)$$

where $e_i =$ exogenous variable such that $e_i = \langle A_k \rangle \langle V_k \rangle$: An attribute value pair, j, k are appropriate indices

5.4 CONTEXT SET

The set of exogenous variables in the world has a subset called context where the variables and values do not change during the course of designing. That subset, C , is called the context set. The context set is defined as:

$$\forall t, \forall C : C_t \subseteq E_t \text{ and } C_t \equiv C_{t+1} \quad (4)$$

5.5 WORLD STATE

The world state is the union of all the states in the system.

$$W_t = \langle \varphi_1, \varphi_2, \dots, \varphi_n \rangle \in n \times I^+ \quad (5)$$

where $\varphi = \text{b l s l e}$

W_t = world state at iteration t defined as a n -tuple of facts, Figure 2.

5.6 RELATIONS BETWEEN DESIGN STRUCTURE STATE, EXOGENOUS VARIABLE SET AND BEHAVIOUR STATES

A relationship between these three states is :

$$W_t = D_t \cap B_t \cap E_t \quad (6)$$

The sets in W_t are also mutually exclusive which means that

$$D_t \cap B_t = \emptyset, \quad B_t \cap E_t = \emptyset, \quad D_t \cap E_t = \emptyset \quad (7)$$

Thus it follows that $D_t \cap B_t \cap E_t = \emptyset$

5.7 RELATIONS BETWEEN THE ELEMENTS SENSED

The mapping from a design structure state to a design behaviour state is called analysis in design. Exogenous variables are used in this process. Thus, for any agent Z we have the following:

$$\mathcal{A}^Z\{D_t^Z, E_t^Z\} : (D_t^Z, E_t^Z) \cap \cap B_t^Z \quad (8)$$

where \mathcal{A}^Z = analysis function specific to agent Z .

5.8 RELEVANCE FIELD AND RELEVANCE FUNCTION OF THE AGENT

The relevance field of the agent typically comprises of some structure, behaviour and exogenous variables which form a subset of the world state, Figure 2. Thus, we have:

$$R_t^Z = \langle \square_1, \square_2, \dots, \square_m \rangle \quad (9)$$

where R_t^Z = Relevance field of the agent Z such that typically $m < n$

m = a positive integer denoting the maximum bound of an index.

Also $R_t^Z \subseteq W_t$. Typically, the relevance fields of two agents Z_i and Z_j cannot be the same, ie. $R_t^{Z_i} \neq R_t^{Z_j}$.

The relevance field at any point of time completely describes the portion of the world the agent has access to. The function that generates the relevance field of the agent Z is defined as follows :

$$f_R^Z \{S^Z \subseteq B_{SK} \subseteq K^Z\} : S^Z, B_{SK}, K^Z \mapsto R_t^Z \quad (10)$$

where f_R^Z = Relevance function of agent Z

$S^Z \subseteq B_{SK} \subseteq K^Z$: A list of situations S^Z in agent Z connected to a list of knowledge K^Z with a belief B_{SK} .

5.10 FOCUS FIELD AND FOCUS FUNCTION OF THE AGENT

The focus field is a subset of the relevance field. It is the foreground or the focus of attention of the agent. The focus field is derived by a function called the focus function. Hence, we have the focus function as:

$$f_F^Z \{S^Z \subseteq B_{SK} \subseteq K^Z, R_t^Z\} : S^Z, B_{SK}, K^Z, R_t^Z \mapsto F_t^Z \quad (11)$$

where f_F^Z = focus function of agent Z

F_t^Z = focus field of agent Z

$$F_t^Z \subseteq R_t^Z \text{ and } F_t^Z = \langle \square_1, \square_2, \dots, \square_l \rangle \quad l < m \quad (12)$$

where l = a positive integer denoting the maximum bound of an index.

Once, the focus field is determined the situation is defined .

5.11 SITUATION

The situation is defined as the difference between the relevance field and the focus field for an agent:

$$S_t^Z = R_t^Z \setminus F_t^Z \quad (13)$$

ie, S_t^Z is defined as:

$$S_t^Z = \langle \square_1, \square_2, \dots, \square_p \rangle \quad p < m \quad (14)$$

where p = a positive integer denoting the maximum bound of an index.

It is obvious that $R_t^Z = S_t^Z \square F_t^Z$. Also at any instant of time:

$$S_t^Z \square F_t^Z = \square. \quad (16)$$

5.12 FOCUS-SITUATION DUALITY

A situation and focus or vice-versa has a unidirectional duality iff:

$$(S \bullet F)_{t,t+i} : \square S, F, i : (S_t \equiv F_{t+i}) \quad (17a)$$

or

$$(F \bullet S)_{t,t+i} : \square F, S, i : (F_t \equiv S_{t+i}) \quad (17b)$$

There may be a bidirectional duality $(F \oplus S)_{t,t+i}$ between situation and focus iff $(F \bullet S)_{t,t+i} \square (S \bullet F)_{t,t+i}$ is true. In this case $R_t^Z \equiv R_{t+i}^Z$.

6. Discussion

The concept of machine learning is design is extended through the introduction of the world within which learning occurs. This world is bifurcated into situation and focus, where focus maps onto potential knowledge to be learned. This extension allows for learned knowledge to be situate. The effect of this additional situation knowledge is to contextualise the learned knowledge and have a system be capable of determining when the learned knowledge could be applicable. This begins to address one of the difficult questions in machine learning: when is the learned knowledge useful.

This paper has presented an outline of the basic building blocks of the concepts involved and provided a formal representation of them.

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References

- Ackermann, R. (1972) *Belief and Knowledge*, Anchor Books, New York.
- Brown, J., Collins, A. and Duguid, S. (1989) Situated cognition and the culture of learning. *Educational Researcher*, **18**(1), 32-42.
- Bruce, V. and Green, P. (1990) *Visual Perception: Physiology, Psychology and Ecology*, 2nd. Edition, Lawrence Erlbaum, London.
- Gero, J. S. (1990) Design prototypes: A knowledge representation schema for design, *AI Magazine* 11(4), 26-36.
- Gero, J. S. (1996) Design tools that learn: a possible CAD future, in B.Kumar (ed.), *Information Processing in Civil and Structural Design*, Civil Comp, Edinburgh, 17-22.
- Ingold, T. (1995) Lecture at workshop on situated learning within post secondary education, <http://www.dur.ac.uk/~dps8zz2/Lave/TimIngold.html>.
- Oki, A. and Lloyd Smith, D. (1991) Metaknowledge reasoning in civil engineering expert systems, *Computers and Structures*, **40**(1), 7-10
- Muller, W, and Pasman, G. (1996) Typology and organisation of design knowledge, *Design Studies*, **17**(2), 111-130
- Reich, Y. (1996) Modelling engineering information with machine learning, *Artificial Intelligence in Engineering Design, Analysis and Manufacturing*, **10**(2), 171-174
- Rosenman, M. and Gero, J. S. (1996) Modelling multiple views of design objects in a collaborative CAD environment, *Computer-Aided Design*, **28**(3), 193-205.

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