Chapter6
Computational models of tacit knowledge

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Abstract: When an expert designer uses a term such as “interference fit" or “H7-r6", they effortlessly invoke a rich set of associations across a wide range of experience. While at one level, the meaning of a termsuch as H7 is formally specified, many of these associations are implicitand hard to characterize formally. The explicit concepts build on layersof implicit abstraction; e.g. the concept of _t would be difficult toachieve without the commonsense notion of “tight", discriminated byhuman infants from five month onwards. We propose that such ubiquitousexpertise may be acquired as functionally relevant low-dimensionalchunks in an experiential space, which are then stabilized through language.The technical terms of design build on these everyday conceptsby mechanisms such as extension or narrowing of their semantics. Wesuggest a two-stage computational analog of this process: a) the babydesigner stage learns elementary concepts as tacit patterns on an inputspace; and b) the novice designer stage relates these early conceptsto explicitly defined design terms to arrive at a grounded semantics forthe new symbols. We illustrate the process through the development ofconcepts such as interference fit.

Now we see tacit knowledge opposed to explicit knowledge; but these twoare not sharply divided. While tacit knowledge can be possessed by itself, explicit knowledge must rely on being tacitly understood and applied.Hence all knowledge is either tacit or rooted in tacit knowledge. A whollyexplicit knowledge is unthinkable. - Michael Polanyi [1]

6.1 Design concepts build on everyday experiences

Consider a designers' understanding of the terms “running fit" and “interference fit" in mechanical assemblies. A running fit, where an object slides smoothly with very little clearance, may have a tolerance of H7-g6 (e.g. in a bush bearing) [2]. On the other hand an interference fit that can transmit force (e.g. a gear on a shaft), may have a tolerance of H7-r6. Terms such as “H7” are formally defined as a band of tolerance for the hole, and “g6” or “r6”, as a tolerance range on the shaft. A formal inference process can then combine these two definitions to de-

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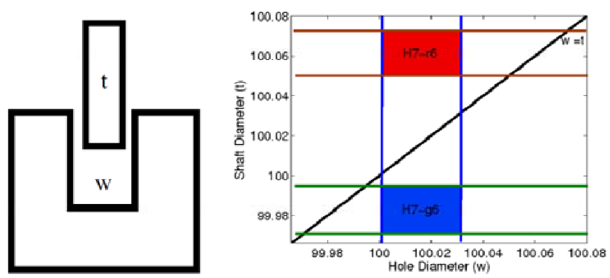
termine that the combination “H7-g6" indicates an intersection of these two constraints, corresponding to a rectangular region in the space of hole and shaft diameters (Fig. 6.1).

However, for the experienced mechanical engineer, the meaning of these terms extends far beyond this formal definition - it includes a wide set of associated concepts and constraints - how they resist force or permit motions, the feel of trying to rotate a shaft in different fits and that the difficulty increases with tighter fits, the differing sounds a shaft makes when the fit changes due to component wear, and so on. Even if one could give a name for every sound and every sensory feel, it would not be possible to write down all rules related to all associations; thus much of this knowledge is tacit. Here, we use the term “tacit knowledge” knowledge of this kind, which we cannot explicate.

It has been suggested that tacit knowledge works together with the explicit, and may be difficult to separate out cleanly [1]. As one gains experience of a domain, one learns the stable patterns that lead to functional distinctions – these have been called chunks [3]. The structure of these chunks may be hidden even from one who knows it; it can be difficult to model. A novice relies on explicit knowledge-alone, and is unable to handle the high-dimensionality of the sensory data, and works falteringly. For an expert the scene resolves itself in a small number of chunks, each of which may encode patterns of considerable complexity. Thus, the dimensionality of the decision space is significantly reduced.



(a) Peg-in-hole assembly (b) Tolerance intervals

Fig. 6.1 H7 is a tolerance interval on the hole diameter w, and g6/r6 on the shaft diameter t. [H7-g6] represents a running fit (w - t > 0) and [H7-r6] is an interference fit (w - t < 0)

Despite the increasing awareness of the tacit component of design knowledge [4, 5], most design theory formulations rely on quasi-logical systems that define one symbol only in terms of other symbols. But where does this process end, where can we relate the rules to an actual design? In practical implementations, this last link to real data is not defined formally, but is left to the implementation. This is why a common but frustrating experience in working with large symbolic design systems is that they seem to be working well for a suite of test problems, but suddenly fail on an unexpected situation. In the symbolic reasoning literature, the difficulty in specifying all possible contingencies is called the frame problem

[6]. A more general view of this process is in terms of Kripke-Wittgenstein's "paradox of rules", which suggests that rules regress from one to the other, and in the end, fail to lead to action [7].

From tacit to explicit

We highlight the importance of tacit knowledge by considering an engineering student who somehow has not experienced assemblies, and is unable to distinguish tight from loose fits. Now, the professor, when encountering such a student, may feel that it would be very difficult for her to ever learn the concepts of "fit" competently.Many such prerequisites are assumed to be present even in the most novice apprentice; these are part of what has been called *ubiquitous expertise* [8] - a large set of concepts known to all members of a society.

Concepts relating to containment, such as the constraint that a large object cannot enter a small hole, are attested in human infants by the age of 3 months, and the tight-loose distinction by 5 months [9]. The tacit knowledge underlying such distinctions form the core of the eventual design concepts of fits and tolerances.

The importance of tacit knowledge in design has been widely acknowledged [10, 4]. However, it has not been clear how such knowledge can be captured and related to the design process. Constructive approaches based on tacit knowledge have been criticized for being vague and not operationalizable [5]. It is our intention here to suggest a computational process for capturing tacit knowledge, which would then provide a mechanism for operationalizing this process. The approach extends our earlier notion of a *baby designer* to one that is able to deal with design symbols, whom we call a *novice designer*:

1. *baby designer:* discovers that certain patterns in its decision space result in consequences that have functional relevance (e.g. will an object enter the mouth or not?) This initial concept is coded as a low-dimensional chunk in this input space. Later it is associated with a linguistic label, and this helps align the concept to those prevailing in the society at large. This concept-label pair is the initial symbol.
2. *novice designer:* novice designer: is explicitly told the semantics of terms such as "interference fit". By associating these with existing symbols such as ([TIGHT]), forms an initial model of the concept.

Beyond the novice is the *expert designer*, who applies the concept in a wide-range of applications, and learns various associations for it. This is beyond thescope of the present work. Here we limit ourselves to the mechanisms for learning the initial symbol, and how it is used to derive the meaning for additional design terminology. The process of defining a derivative symbol may involve two processes, both operating on its semantic space:

1. Narrowing or Broadening: Where the concept is either a specialization or ageneralization of an earlier concept [11]. The space in which the concept is being defined remains the same.

2. Extension or Lateral transfer: Where the concept is an extension of a concept into a range of parameters or situations not available in the early models [12].

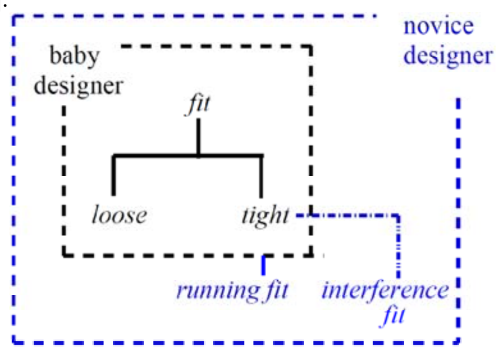


Fig. 6.2 Two-stage concept construction. First, the baby designer learns the initialconcept-label pairs ([TIGHT]) and ([LOOSE]). The novice designer extends these to arriveat the semantics of design terms like [RUNNING FIT] or [INTERFERENCE]. Forthe expert designer, this semantics is further refined through a wide range of functionalassociations.

Here the space may have new linkages added to the original space. Thus, an initial concept such as tight may be narrowed (specialized), resulting in the more precise notion of running fit and even further refined into even more specific notions such as [H7-g6], etc. On the other hand, extending the initial concept into the previously forbidden zone where a peg is larger than its hole requires linkages with concepts such as expansion (either by thermal or mechanical stress), and enables the learning of concepts such as interference fit (Fig.6.2). This is the process being elaborated in this paper, via the stage of symbol learning that we refer to as the *novice designer*.

We note that these derived symbols may be learned without direct experiential grounding but in terms of other symbols (e.g. in a classroom, or by reading).They inherit the semantics of the earlier symbols (including possible misconceptions)which is why it is crucial that they be directly experienced in terms of actual designs. In the absence of such experience, the symbols are incomplete, and may contain many errors, which is why design education more than many others, insists on direct, hands-on exposure.

In the next section we review our model for the first stage, the *baby designer*, followed by the *novice designer* stage which is the main focus of this paper.

6.2 Stage 1: Baby Designer

Here we review earlier work on the baby designer [13, 14]. The baby designer is a system that has a built-in preference for compact descriptions of patterns in data. Thus, for the containment task (Fig. 6.3), a simple perceptron model is able to categorize the class of fits into feasible (below the w = t line) and infeasible (above). We note that as its experience increases (from 10 to 50 to 200 instances), the number of mis-categorized instances go down, resulting in an increased confidence in the discriminating function. The "compact description" that the baby designer seeks can be defined in terms of the number of parameters required to describe an input, or its dimensionality. We suggest that in many situations, functions defined on high-dimensional input spaces characterize a set of "good" solutions that lie on a lower-dimensional subspace or manifold. These lead to the chunks that are mapped to the initial (pre-linguistic) image schema. This is a tacit concept, learned through direct experience. However, if it is a concept that is referred to in language, it would be possible for the agent to learn a label for it. Subsequently, language can be used to align this concept to societal conventions.

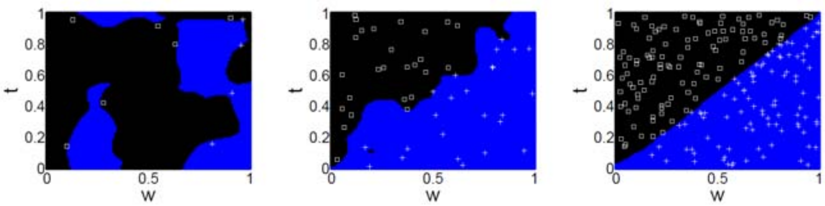


Fig. 6.3 Learning through experience that inserted-object-must-be-smaller-than-container (w > t). (a) Object of thickness t goes into a hole of width w. Feasiblesolutions in the (w; t)-space are marked "+" and failure regions as squares (□). (b) Invery early stages of exploration (10 instances explored), the learned pattern is unsureof which t can go into which w. (c) After 50 instances, the pattern w > t is beginningto emerge, and (d) is quite clear after 200 instances.

Learning the symbolTIGHT

During insertion tasks if the clearance is small, the inserted object may sometimes get stuck in the hole, when even very high insertion forces will not succeed in pushing it in (of course, a small wiggling motion or compliance may release the peg, but our Baby is yet to learn this). This type of situation is frustrating for the learner, and becomes a salient event that is attended to. The situations where this is more likely to occur may eventually get associated with the initial notion of tight. Similarly a loose clearance may involve some wiggle or play.

In the computational simulation, the learner explores many instances of tight fitand loose fit, and gradually comes to recognize the regions in the input space < w, t > corresponding to these - we call these the functionally feasible regions or FFRs (Fig. 6.4a, b, FFRs in gray). Eventually, it is realized that for the "good" instances of tight, w and t appear to vary in a related manner; they lie on a 1-dimensional manifold in the 2-D input space (Fig. 6.4(c,d)).

One may abstract further patterns by considering lower-dimensional representations for the FFRs. In this situation, we may use linear dimensionality reduction (PCA) [15]. The dominant eigenvectors converge much faster than the decision boundary - thus, the first eigenvector after 20 samples is already roughly parallel to the w = t boundary, and becomes more strongly so after a 100 samples (b,c above). This indicates that the concept of clearance lies along a 45 degree line in the w; t space (as shown in the bottom row). The invariant along either line is the quantity w – t, which becomes the learned chunk; its value eventually forms part of the semantics for the symbol [CLEARANCE].

The next step is to associate the frequently occurring chunks to linguistic labels. The availability of such labels will enable different instances of situations labeled as “tight" to be related to each other and inform the semantic model (section 6.2.1).

The learning achieved upto this point is part of the ubiquitous expertise that all human adults would be expected to have. It is based on this knowledge that we expect the student to construct her learning of new symbols relating to toleranced fits (section 6.3).

6.2.1 Language label learning

At this stage, our *Baby Designer* has an implicit notion of the categories TIGHT and LOOSE, in terms of low dimensional chunks. This is based on a measure of the probability of wedging, which may vary from person to person. Once the agent has a label with which this concept may be communicated across other agents, this concept will stabilize and acquire a richer meaning adapted to the social conventions.

To learn the label, we consider that the agent has the idea that sequences of sounds may refer to concepts. Then, when it is exposed to adult speaker narratives that describe tight or loose situations, even without any knowledge of other words or grammar, we find that words like “tight" emerge as the most likely keyword for TIGHT and also that this can be done for any language [14].

Now, whenever tight and loose situations are observed, the learner may compute the probabilities of different words occurring in the two contexts. We find that even after a dozen or so exposures observes it is able to determine that the term “tight" occurs more frequently in the context of TIGHT and may form this label-meaning pair.

Once learned, the language label permits changes in the semantics. The learner observes other context where “tight” is being uttered, and modifies its own image schema to comply with the observation. If the observation matches the schema, then the learner gains confidence in the schema. If it does not match, but seems similar, the learner *extends* the semantics to include such cases. If its own usage fails to be understood, the interpretation may be *narrowed*. Other extensions, such as metaphorical extension to novel spaces etc. are not considered in this work.

Thus the language label serves as an index with which the meaning can be related to other concepts. The semantics of TIGHT, which in our simulation was initially correlated only with a range of insertion angles, can now be associated with other notions - e.g. fits have low clearances, the inserted object has less play, as w gets very near t, it may require some insertion force etc. As the learner finds that its image schema is able to cover most of the situations where the term is used, it transitions from the initial image schema TIGHT$_i$ to a mature, linguistically-informed image schema TIGHT. It is now ready to learn more advanced concepts such as those related to fits and tolerances.

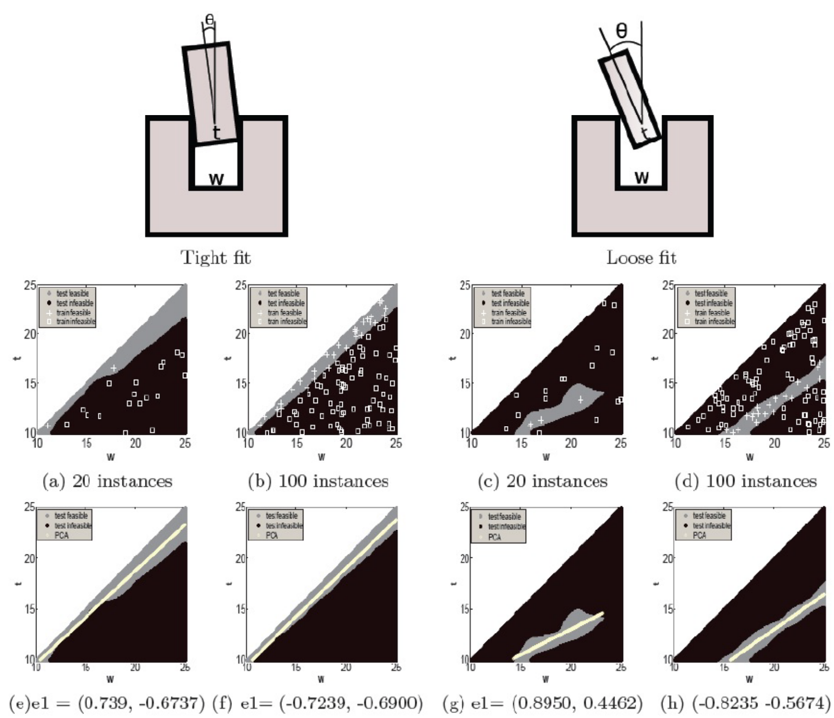


Fig. 6.4 Emergence *of chunks for fit: "tight"vs"loose":* Situations where t is close to w may cause wedging, which can occur when the insertion angle is tilted more than $\theta = \frac{w-t}{w\mu}$. Tight situations are those where wedging is more likely ($\theta$is low). Using this as a performance metric, we can learn the Functionally Feasible regions (FFRs) for both tight and loose. The FFRs (gray) learned after 20 instances (a,c), are poorer than after 100 instances (b,d). On reflective analysis, we find that these FFRs are well-approximated as lower-dimensional (1-D) linear manifolds (e,f,g,h bottom row). Using PCA, we discover the principal eigenvector to be dominant, and the number of parameters reduces from (w; t) in 2-D to an emergent 1-D chunk representing invariance in w – t . This process results in two initial chunks $\mathrm{TIGHT}_i$and LOOSE_i - but we do not know that these are called "tight" or "loose" yet.

6.3 Stage 2: Novice designer

At this point, the learner has a stabilized concept (the mature image schema tight), along with the linguistic label "tight", so it has a proper symbol [tight], with a semantics grounded in tacit knowledge. The learner can now extend this concept by being told about it, as opposed to having to encounter everything as a sensorimotor experience. Thus, the student in a design course may be told about fits and tolerances, and she can then construct these more complex concepts by building on the concept of tight. We consider the learner at this stage, when "running fit" is being introduced, where a shaft is located closely in a hole, but is free to move.

The learner recognizes this as a low-clearance situation, a special case of tight. This enables many properties associated with tight - such as low degree of wiggle to be linked with this new concept. However, RUNNING FIT is a more specific concept than tight, since it applies to a very narrow band of dimensions of shaft and hole, and is also associated with relative motion. This results in a *narrowing* of the earlier relation.

Next, the novice designer is told about "interference fit" (in a course or from a book, say). It learns that fits requiring high torque transmission may be achieved by having shaft diameter slightly greater than the hole. Now, the concept of interference fit encroaches on a region (w > t) which was considered infeasible while learning the original $TIGHT_i$relation. However, since the interference is small, it may be considered an extension of the earlier concept.

The two new concepts are thus learned as a result of narrowing and extension of the concept of tight, operating on the same design space (w; t). We shall see that while running fit may be considered a sub-category; the concept of insertion fit is more of a lateral shift Fig. 6.2.

In the problems the novice designer is asked to solve, it encounters some instances of interference fits and running fits. For example, in the interference fit situation, one may have a problem involving a gear-shaft assembly, where thefunctional criteria for interference fit may be explicitly defined in terms of thetorque τ that the assembly must transfer. This torque is linked to the contactpressure p_c through the explicit formula $\tau = 2\pi\mu r_i^2 L p_c$ where $r_i$is the nominalinside radius of the hole. The pressure $p_c = \frac{\delta_r E(r_o^2 - r_i^2)}{2rr_o^2}$, *where* $\delta_r = \delta_{rh} - {\delta_{rs}}^2$, where $\delta_r$is the degree of inter-penetration,$r_o$the outer radius of the pinion, andE the modulus of elasticity. It may emerge that a certain range of $\delta_r$would meetthe desired torque requirement while remaining within the material strengthconstraints. Now, to manufacture parts that meet this interference criterion,each part would need to meet certain tolerances. All this is explicitly told tothe novice designer, resulting in a shallow understanding of statements such as "H7-r6 is an interference fit".

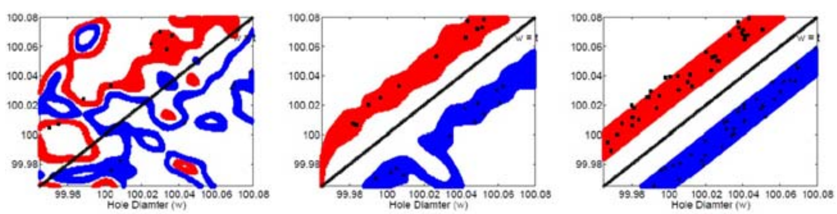
Subsequently, as she begins practice, she encounters many actual design situations. This gives substance to this understanding, by encountering instancesof the various tolerance classes and fits. Thus Fig. 6.5 shows the patterns thatemerge for H7-g6 running fits and H7-r6 interference fits.The "good" designs within this range are sampled and the patterns thatemerge after 14, 23 and 75 instances are shown in Fig.6.5. Although each instancein this data is based on explicit knowledge, the finally emergent pattern may beimplicit, especially in more complex situations. This gives the novice designersome tacit intuition for what it means to have a particular tolerance pattern.Also, once such a pattern emerges, one may become aware of it, a process knownas reification, which would result in an explicit form of knowledge.Thus, explicit and implicit are in constant interplay in the designer's life.There has been much speculation on the nature of this interaction [16] but herewe wish to provide an overview of the process.

Other parts already present in the mature tight concept are also enrichedthrough this experience. For example, the fact that insertion forces may go upas w approaches or breaches the w = t boundary was already known, but isnow reinforced along with explicit relations that relate this insertion force to thecontact pressure p_c. However, the tacit understanding of this process continues toinform the mature designer's expectation of insertion force. However, situationssuch as the process of assembly requiring thermal expansion / contraction arelearned as specific only to insertion fit and are not part of the earlier concept.

Thus, interference fit is seen by the learner as being related to tight,but also extending it in several ways. The concept is constructed as a lateralshift on tight, rather than as a subcategory.

6.4 Conclusions

Here we have argued for a very ambitious approach to modeling design knowledge. While the process is demonstrated on a toy set of symbols from a single-domain, there is reason to believe that the approach is scale-able.For one, beyond a knowledge of what constitutes an interesting functional distinction (e.g.inserting or not; wedging or non-wedging), we have used no domain knowledgeat any step of the process. While the dimensionality reduction modality usedhere is linear, a number of non-linear manifold learning approaches are todayfeasible and may be applied to data which implicitly lies on a lower-dimensionalspace. Indeed, the power of such algorithms for discovering latent relationships in design remains to be explored.



(a) 14 instances (b) 23 instances (c)75 instances

Fig. 6.5 (a) Learning the semantics for running fit H7-g6 (blue) and INTERFERENCE FIT H7-r6 (red). Though each specific instance is informed by explicit knowledge, theemergent patterns, especially in more complex situations, become part of the tacitknowledge gained by the designer through experience.

The work has two main ramifications. One is in constructing a cognitivetheory for the human design process. The concrete steps suggested in the theory overcome the obstacle of earlier suggestions of tacit knowledge that wereconsidered vague and non-operationalizable. The key observation is based onthe fact that chunks, incorporating often arise as a lower-dimensional pattern in high-dimensional design spaces is an important contribution of the present workto this literature.

Computational Tacit knowledge?

In addition to presenting an operationalizable approach to tacit knowledge learning, this work hints at a possibility of enormous potential- that computationalmo-

dels may be tuned to gain tacit knowledge, that may lead to human-like flexible behaviours. This appears to be a contradiction in terms, since it is al-most axiomatic that computers work on representations that are precise andwell-posed.
However, if we consider the patterns that the computers are learning – notthe simple linear paradigms presented in this work, but also the general regionsof a functional feasibility determination, such spaces can be quite complex. Forexample, most categorization algorithms in machine learning result in a capability to categorize (e.g. recognize objects) based on data without the programmerbeing able to articulate how exactly the algorithm is able to do the task.
This may open up a radically new approach to computational models for design knowledge, with far-reaching implications for maintaining design rationale,design repository management, and increasingly in design database exchange.However, at this point, we have a model that may be able to learn one symbolat a time. The composition of symbols often results in very different complexes,with large changes in semantics. Clearly, large scale simulations need to be runon different symbol classes to understand how their interactions may be acquired.
The methodology outlined here is a meager start in what may be a radically new-direction in design cognition.

6.5 References

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