Compiling Experience into Knowledge

Rainer Knauf
Faculty of Computer Science and Automation
Technical University Ilmenau
PO Box 100565, 98684 Ilmenau, Germany

Abstract

Typical application fields of Knowledge Based Systems are a usually characterized by having human expertise as the only one source to specify their desired behavior. Their design, evaluation and refinement has to make effective use of this valuable source. After sketching the concept of collecting validation experience in a Validation Knowledge Base (VKB), the paper introduces an estimation of the significance of the cases collected in the VKB. A high significance signalizes that a VKB should not longer serve as a case-based source of external knowledge, but compiled into the Knowledge Base instead. A technology to compile well-selected cases into the Knowledge Base of the system under evaluation is shown.

Introduction

AI systems' design and maintenance heavily depends on the quality of the human expertise and effectiveness of its involvement. For their validation and refinement, a case based technology (Knauf, Gonzalez, and Abel 2002) was introduced. To make validation results less dependent on the experts' opinions and to decrease the workload of the experts, a concept to collect case oriented experience in a Validation Knowledge Base (VKB) was developed (Knauf et al. 2004). To estimate the usefulness of these concepts and to reveal their weaknesses, a prototype test was performed (Knauf, Tsuruta, and Gonzalez 2005).

The VKB concept so far utilizes external knowledge in a VKB as an additional source of knowledge for system validation. However, at some point a VKB should not longer serve as a case-based source of external knowledge, but compiled into the Knowledge Base instead. A technology to do so is introduced here.

Collecting experience: VKB so far

The VKB is s set of previous (historical) test cases and their best rated solutions (Knauf, Tsuruta, and Gonzalez 2005), i.e. a database of test cases and their associated solutions that received an optimal rating in previous validation sessions. These solutions are considered an additional (external) source of expertise that did not explicitly appear in the solving session, but it is a subject of the rating session.

The usefulness of the VKB approach could be proven by an experiment with human experts. Starting with an initial rule base, validation sessions as described in (Knauf, Gonzalez, and Abel 2002) have been performed and a VKB has been built. (Knauf, Tsuruta, and Gonzalez 2005) could show the VKB's contribution to the validation knowledge in this experimental case study.

Evaluating experience: A metrics

In case the VKB contains cases with an optimal solution that is different from the system's solution and a certain significance that the optimal solution in VKB is correct, a system refinement based on the VKB's content is indicated. Depending on the application, a minimum number n^{min} of entries for a test case input t_j and a minimum significance level $0 \ll sig^{min} \leq 1$ needs to be determined. Indications for the correctness of an optimal solution sol_{Kj}^{opt} to a case input t_j in VKB are high values of the following metrics

- approval rate $app = \dfrac{\#\text{ of positive ratings } r_{ijk} = 1}{\text{total } \#\text{ of ratings to } t_j}$
- persistence rate $per = \dfrac{\#\text{ of entries for } t_j \text{ with } sol_{Kj}^{opt}}{\text{total } \#\text{ of entries to } t_j}$
- agreement rate $agr = \dfrac{\#\text{ of experts providing } r_{ijk} = 1}{\text{total } \#\text{ of experts providing a } r_{ijk}}$

In case the minimum number n^{min} of entries for a test case input t_j is reached and all three of the above rates exceed the minimum significance level sig^{min}, the pair $[t_j, sol_{Kj}^{opt}]$ is worth to be compiled into the Knowledge Base.

Utilizing experience: Compiling VKB

The refinement procedure looks for rule chains of cases in the VKB, which have a different solution in VKB than the rule chain ends up with. It starts with the last rule in this chain and analyses *all* VKB cases using this rule. It systematically constructs new rules as a substitute of it, which map the the cases that have a different solution to this different solution and keeps the mapping of all other cases (at all, not only those in VKB) as it was before the refinement. So it is pretty "conservative", because it changes the I/O behavior of the rule as few as possible, i.e. exclusively for cases that are shown to be solved wrong by the rule base. The technique is applicable to rule bases as introduced in (Knauf, Gonzalez, and Abel 2002) and consists of the following steps.

Table 1: Reduction rules to construct substitutes for an invalid rule

$R1$	$pos \in Pos$, s_{pos} has a value set with no $\leq$ relation, $\{s_{pos}^1, \ldots, s_{pos}^m\}$ are the values of s_{pos} occurring in T_l^s		
	$[T_l^s, Pos, \{p_1, \ldots, p_n\}]$	$\hookrightarrow$	**1.** $[T_l^{s,1} \setminus \{[t_j, sol_s] \in T_l^s : s_{pos} \neq s_{pos}^1\}, Pos \setminus \{pos\}, \bigcup_{i=1}^n p_i \cup \{(s_{pos} = s_{pos}^1)\}]$ … **m.** $[T_l^{s,m} \setminus \{[t_j, sol_s] \in T_l^s : s_{pos} \neq s_{pos}^m\}, Pos \setminus \{pos\}, \bigcup_{i=1}^n p_i \cup \{(s_{pos} = s_{pos}^m)\}]$
	Continue with each $T_l^{s,i}$ $(1 \leq i \leq m)$ separately.		
$R2$	$pos \in Pos$, s_{pos} has a value set with a $\leq$-relation, s_{pos}^{min} / s_{pos}^{max} are the smallest / largest value of s_{pos} within T_l^s		
	$[T_l^s, Pos, \{p_1, \ldots, p_n\}]$	$\hookrightarrow$	$[T_l^s, Pos \setminus \{pos\}, \bigcup_{i=1}^n p_i \cup \{(s_{pos} \geq s_{pos}^{min}), (s_{pos} \leq s_{pos}^{max})\} \cup S_{excl}]$
	S_{excl} is the set of excluded values for s_{pos}, which have to be mapped to a solution different from sol_s because of belonging to some other T_u^v with $v \neq s$: $S_{excl} = \{(s_{pos} \neq s_{pos}^j) : \exists [t_j, sol_s] \in T_l^s \exists [t_m, sol_v] \in T_u^v (v \neq s)$ with $\forall p \neq pos : s_p^j = s_p^m, s_{pos}^{min} < s_{pos}^m < s_{pos}^{max}\}$		

Identifying "Guilty Rules" If the last rule r_l in the rule trace for a case input $t_j \in \Pi_{inp}(T)$ infers a solution different from $sol_{Kj}^{opt} \in \Pi_{outp}(T)$, this rule r_l is "guilty" and therefore, subject of the following refinement technology. Let $T_l \subseteq T$ be the set of cases that have r_l as their last rule in the rule traces for the cases in T.

Simple Refinement by Conclusion Replacement If all cases $t_j \in T_l$ have the same solution sol_{Kj}^{opt}, in rule r_l the conclusion part is substituted by sol_{Kj}^{opt}.

Reconstructing the Remaining Guilty Rules The remaining guilty rules are used by a set of cases T_l, which have different optimal solutions. The subsets with the same optimal solution are considered separately:

1. T_l of the rule r_l is split into subsets T_l^s $(1 \leq s \leq n)$ according to the n different solutions $sol_{Kj}^{opt,1}, \ldots, sol_{Kj}^{opt,n}$ for the cases $t_j \in T_l$.
   The if–part(s) of the new rule(s) that substitute r_l are expressions $e_i \in E$ of a set of p new alternative rules $\{r_l^1, r_l^2, \ldots, r_l^p\}$ for each T_l^s and will be noted as a set of sets $P_l^s = \{\{e_1^1, \ldots, e_{p_1}^1\}, \ldots, \{e_1^p, \ldots, e_{p_p}^p\}\}$. The corresponding rule set of P_l^s is
   $$r_l^1 : \bigwedge_{i=1}^{p_1} e_i^1 \rightarrow sol_s \qquad \cdots \qquad r_l^p : \bigwedge_{i=1}^{p_p} e_i^p \rightarrow sol_s$$
2. Pos is the set of Positions (dimensions of the input space), at which the input data $t_j \in \Pi_{inp}(T_l^s)$ of the test cases $t_j \in T_l^s$ are <u>not</u> identical.
   The generation of the p different if–parts in P_l^s is managed by a formal *reduction system*, which is applied to triples $[T_l^s, Pos, P_l^s]$ until Pos becomes the empty set $\emptyset$.
3. The initial situation is $[T_l^s, Pos, P_l^s]$ with $P_l^s = \{\{(s_1 = s_1^{ident}), \ldots, (s_q = s_q^{ident})\}\}$
   $s_1, \ldots, s_q$ are those positions, at which all test data $t_j \in \Pi_{inp}(T_l^s)$ have the same value s_i^{ident}. Initially, P_l^s stands for just one rule:
   $$r_l^1 : \bigwedge_{i=1}^{q} (s_i = s_i^{ident}) \rightarrow sol_{Kj}^{opt,s}$$
4. The reduction terminates with the situation $[T_l^s, \emptyset, P_l^s]$.

Table 1 shows the reduction rules applied to the triples. In (Knauf, Gonzalez, and Abel 2002) it is shown, that the reduction system is terminating, complete, and correct.

Recompiling the constructed rules The new rules generated so far are "one–shot–rules", i.e. they infer directly from a system's input to a system's output. These rules might be difficult to read, because they may have very long if–parts, and difficult to interpret by subject matter experts. This problem can be defused by introducing the intermediate hypotheses into the computed new rules.

Summary

The formerly developed concept of a Validation Knowledge Base (VKB) was intended to model collective best experience of several human experts. The VKB is constructed and maintained across various validation exercises. If the knowledge gained in a VKB turns out to be well accepted by the expert community over a long period of time, this knowledge is worth to be complied into the system's Knowledge Base. This way, the knowledge dedicated to evaluate a system shifts to knowledge used to improve the system. Therefore, the paper introduced a technology to compile the case based knowledge of a VKB into the rule based knowledge of the system's Knowledge Base.

References

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