Shorter Reasoning About Larger RE Models

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***Abstract*—Requirements models support communication and decision-making. However, when requirements models get too complex, it becomes difficult for stakeholders to understand all their nuances. Empirical and theoretical results show that automatically reasoning about complex RE models using standard methods takes exponential time that cripples the ability of these models to support decision making for large models.**

One resolution to this problem comes from AI where researchers report that many models have "keys". These are model elements—decisions, in RE models—with the property that once values are assigned to the keys, it becomes very fast to reason over the remaining decisions. Using a toolkit we call SHORT, this paper seeks, and finds, such keys in eight large RE models. The number of keys were typically only 12% of all decisions. Using those keys, when optimizing to achieve the most goals at least cost, SHORT ran 100 to 1000 times faster than standard methods.

Our conclusion is that that there is much value in hunting for "keys" in RE models. Finding those keys is not complex: SHORT runs in low order polynomial time and terminates in just a few minutes (even for our largest models). Also, when found, model-based RE can be greatly simplified by focusing stakeholder discussion on just the key decisions.

***Index Terms*—Requirements engineering, softgoals, search-based software engineering.**

I. Introduction

When reasoning about complex requirements, it can be useful to build a model that documents the beliefs of all the stakeholders. The process of building and analyzing such a model can help stakeholders better understand the ramifications of their decisions. That said, the effort associated with reasoning about models can sometimes overwhelm stakeholders. For example, consider a committee reviewing the goal model shown in Fig. 1 that describes the information needs of a computer science department [1]. Such a committee may have trouble with manually reasoning about all the conflicting relationships in this model. Further, automatic methods for reasoning about these models are hard to scale up: as discussed in the next section, reasoning about these models is an NP-hard task.

But are models like Fig. 1 as complex as they appear? That graph is somewhat of a tangle—if we straightened out all the dependencies, would we find that much of this model depends on just a few *key* decisions? As discussed in our *Related Work* section, such keys have been reported in other domains [2, 3, 4, 5]. The importance of key decisions is that, once their values are assigned, it becomes very simple to reason over the remaining decisions.

This paper tests if keys are (a) present and (b) useful for RE models. The next section discusses the computational cost of reasoning about RE models that contain contradictions. This is followed by notes on the syntax and semantics of the RE models used in this study. We then introduce SHORT: toolkit for finding and exploiting keys. For the small RE model shown in Fig. 2, we show that SHORT finds a very small number of key decisions that dictate what is achievable in that model. The rest of the paper then tests the generality of that initial result. SHORT is applied to eight large RE models from the i* community [6]. When translated into a node-arc format (see goo.gl/0GrGnS), the models have the sizes shown in Table I.

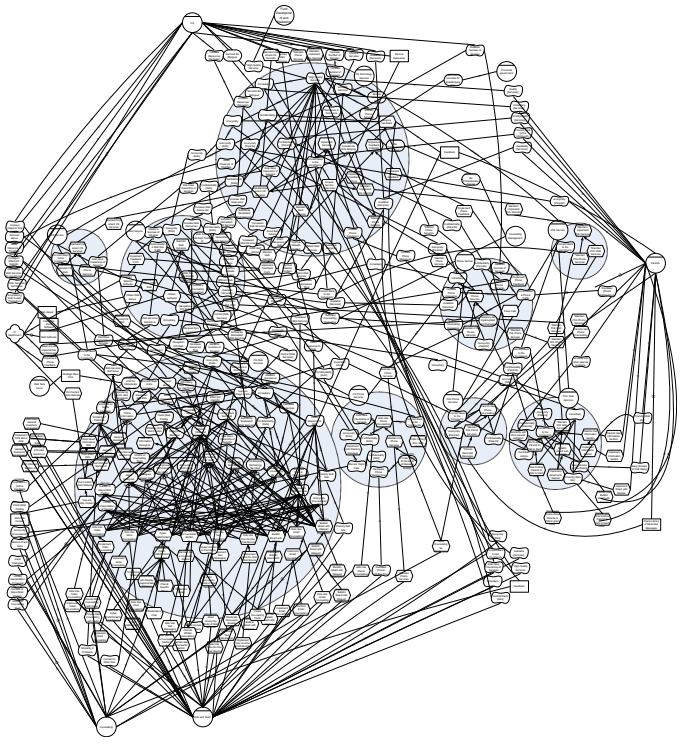


Fig. 1. A goal model presenting choices for services within a computer science department. Gray circles denote issues relating to particular stakeholders.

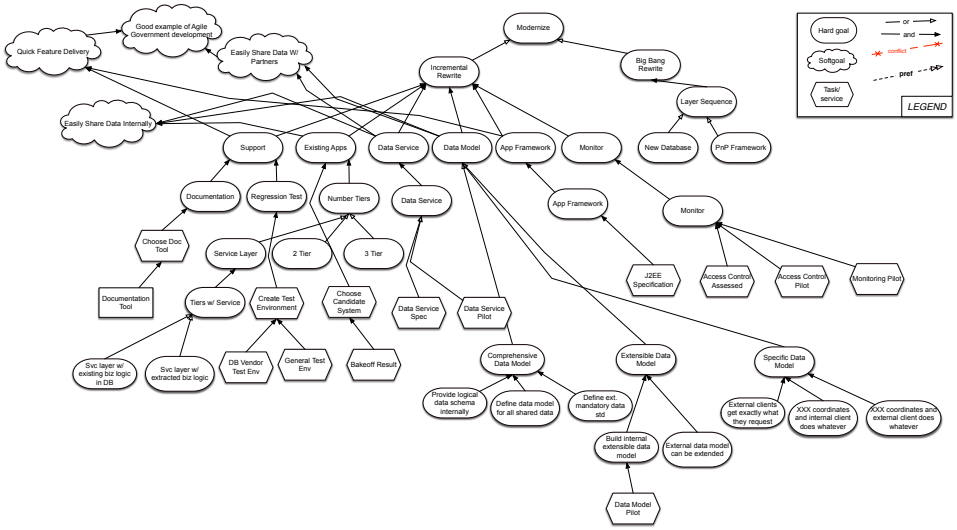


Fig. 2. A goal model for IT System modernization. Used at the Software Engineering Institute to guide discussions. Examples of modernization include the Y2K problem (moving from 2 digit to 4 digit years); end-of-life decisions on operating systems and database COTS products; and improving architectural support for new capabilities (e.g. support for mobile devices). This model comments on the refactoring, re-architecting, and redesign of existing systems to improve satisfaction of business goals. Note that the model has dozens of decisions and three top-level goals: "Good Example ...", "Easily Share Data Internally", "Modernize".

Model	Nodes	Edges	
CSServices	351	510	(see Fig. 1)
CSCounselling	350	470	
CSFD&Marketing	326	422	
CounsellingMgmt	206	239	
CSSAProgram	114	168	
CSITDepartment	126	162	
KidsAndYouth	81	81	
IT Modernization	53	57	(see Fig. 2)

TABLE I
GOAL MODELS USED IN THIS STUDY, SORTED BY NUMBER OF EDGES.

Our results show that:

- Checking for the presence of keys *is not a complex task*, even for models containing potential inconsistencies. SHORT runs in low-order polynomial time and terminates in just a few minutes (even for our largest model). This is a significant result since all our prior attempts at this kind of reasoning suffered from crippling runtimes that prevented scale up [7, 8].
- Using those keys, SHORT can find decisions that lead to *most* goals at *least* costs *100s to 1000s of times faster than standard methods*. The decisions found by SHORT are competitive, and sometimes even better than those found by standard optimizers.
- The number of keys per models is small: typically 12% of all decisions. That is, for models with keys, RE can be greatly simplified by *focusing stakeholder discussion just on the key decisions*.

While it is insightful to explore the models of Table I, we take care not to over-generalize our results. Specifically, our results *do not* show that all requirements models contain a small number of key decisions. However, our results do suggest that it can be beneficial to look for keys since if they exist, we achieve "shorter" reasoning about large RE models, where "shorter" is measured as follows:

- Large models can be processed in a very short time;
- Runtimes for automatic reasoning about RE models is shorter so stakeholders can get faster feedback from their models;
- The time required for manual reasoning about models is shorter since stakeholders need only debate a small percent of the issues (just the key decisions).

II. Background

A. Complexity and Simplicity

Given multiple stakeholders writing assertions into a requirements model, it is likely that those stakeholders will generate models that can contain contradictions. In formal logic, if some set of assertions generates a contradiction then all the assertions are discarded as inconsistent. But in requirements models, when inconsistencies are detected, it is standard practice to focus on zones of agreement and avoid the parts of the model leading to the inconsistencies. Nuseibeh lists several strategies for this approach [9]:

- *Ignore:* Skip over edges that lead to contradictions;
- *Circumventing:* "Slip around" inconsistencies; i.e. if inference is blocked due to inconsistency, the inference can explore other avenues.
- *Ameliorating:* When conflicts cannot be avoided, it is prudent to try reduce the total number of conflicts.

The problem with these tactics is that they can be very slow. Formally, the study of models with contradictions is the called "abductive reasoning". Poole's THEORIST system [10] offers a clean logical framework of such reasoning.

In that framework, a goal graph is a *theory* that contains a small number of upper-most *goals*. When we reason about that theory, we make *assumptions* about either (a) initial facts or (b) how to resolve contradictory decisions. In the general case, only some subset of the theory can be used to achieve some of the goals using some of the assumptions without leading to contradictions (denoted $\bot$). That is:

$$\begin{array}{l} T \subseteq \mathit{theory},\ A \subseteq \mathit{assumptions},\ G \subseteq \mathit{goals} \\ T \wedge A \vdash G \\ T \wedge A \nvdash \bot \end{array} \quad (1)$$

A *world of belief* is a solution that satisfies these invariants. For many years we have tried to find such worlds using a variety of methods. For example Menzies' HT4 system [7] combined forward and backward chaining to generate worlds while Ernst et al. [8] used DeKleer's ATMS (assumption-based truth-maintenance system) [11].

The bad news is that those implementations suffered from cripplingly slow runtimes that scaled very poorly to larger models. Such slow runtimes are not merely a quirk of those implementations—rather they are fundamental to the process of exploring models with many contradictions. It is easy to see why: exploring all the the subsets in Equation 1 is a very slow process. Bylander et al. [12] and Abdelbar *et al.* [13] both confirm that abduction is NP-hard; i.e. when exploring all options within a requirements goal model, we should expect very slow runtimes.

The good news is that just because an inference task is NP-hard, that does not necessarily mean that that task will always exhibit exponential runtimes. Numerous AI researchers studying supposedly NP-hard tasks report the existence of a small number *key* variables that determine the behavior of the rest of the model. When such keys are present, then the problem of controlling an entire model simplifies to just the problem of controlling the keys.

Keys have been discovered in AI many times and called many things: *variable subset selection, narrows, master variables*, and *backdoors*. In the 1960s, Amarel observed that search problems contain *narrows*; i.e. tiny sets of variable settings that must be used in any solution [3]. Amarel's work defined macros that encode paths between the narrows in the search space, effectively permitting a search engine to leap quickly from narrows to narrows.

In later work, data mining researchers in the 1990s explored examined what happens when a data miner deliberately ignores some of the variables in the training data. Kohavi and John report trials of data sets where up to 80% of the variables can be ignored without degrading classification accuracy [5]. Note the similarity with Amarel's work: it is more important to reason about a small set of important variables than about all the variables.

At the same time, researchers in constraint satisfaction found "random search with retries" was a surprisingly effective strategy. Crawford and Baker reported that such a search took less time than a complete search to find more solutions using just a small number of retries [4]. Their ISSAMP "iterative sampling" algorithm makes random choices within a model until it gets "stuck"; i.e. till further choices do not satisfy expectations. When "stuck", ISSAMP does not waste time fiddling with current choices (as done by older chronological backtracking algorithms). Instead, ISSAMP logs what decisions were made before getting "stuck". It then performs a "retry"; i.e. resets and starts again, this time making other random choices to explore. Crawford and Baker explain the success of this strange approach by assuming models contain a small set of *master variables* that set the remaining variables (and this paper calls such master variables the *key decisions*). Rigorously searching through all variable settings is not recommended when master variables are present, since only a small number of those settings actually matter. Further, when the master variables are spread thinly over the entire model, it makes no sense to carefully explore all parts of the model since much time will be wasted "walking" between the far-flung master variables. For such models, if the reasoning gets stuck in one region, then the best thing to do is to leap at random to some distant part of the model.

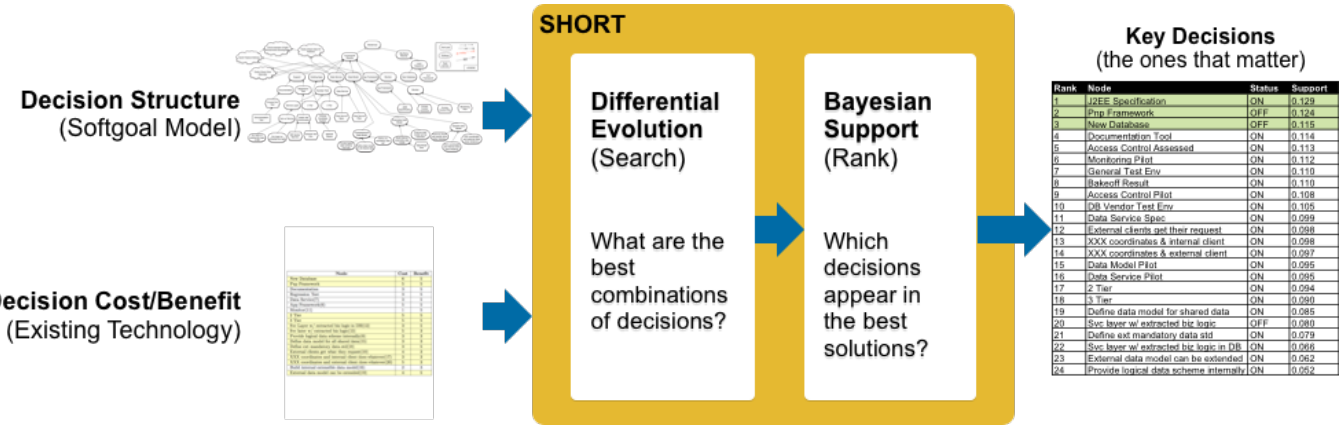
A similar conclusion comes from the work of Williams et al. [2]. They found that if a randomized search is repeated many times, that a small number of variable settings were shared by all solutions. They also found that if they set those variables before conducting the rest of the search, then formerly exponentially runtimes collapsed to low-order polynomial time. They called these shared variables the *backdoor* to reducing computational complexity.

Combining the above, we propose the following strategy for faster reasoning about RE models:

1) Use random search with retries to find the backdoors (which we call the "key" decisions) in RE models;
2) Debate, then decide, about the keys before exploring anything else;
3) To avoid trivially small solutions, our random search should strive to cover as much of the model.
4) Accordingly, we implement this strategy within a multi-objective optimizer that seeks to maximize goal coverage, while at the same time minimizing the number of conflicts and minimizing the sum of the costs of the decisions made within that model.

1. **Nodes:** Nodes in a goal model can be of type *leaf*, *com*bine, or *con*tribute (*com* nodes have sub-types *and, or*). *Leaf* nodes are different to the rest since they have no children. On the other hand, when dealing with *and,or* nodes, it is expected to meet *all,one* (respectively) of the requirements in the child nodes. *Con* nodes divide into *softgoals*, which users are willing to surrender if need be, and *hardgoals* which users are more eager to achieve.
2. **Labels:** Nodes N_i have labels $\{1, ½, 0, -½, -1\}$ for "satisfied, partially satisfied, undefined, denied, partially denied".
3. **Edges:** *Con* nodes connect to their other nodes via one four edges types "makes, helps, hurts, breaks" with weights $E_j \in \{1, ½, -½, -1\}$, respectively.

Fig. 3. Syntax of goal models.



Rank	Node	Status	Support
1	J2EE Specification	ON	0.129
2	Pnp Framework	OFF	0.124
3	New Database	OFF	0.115
4	Documentation Tool	ON	0.114
5	Access Control Assessed	ON	0.113
6	Monitoring Pilot	ON	0.112
7	General Test Env	ON	0.110
8	Bakeoff Result	ON	0.110
9	Access Control Pilot	ON	0.108
10	DB Vendor Test Env	ON	0.105
11	Data Service Spec	ON	0.099
12	External clients get their request	ON	0.098
13	XXX coordinates & internal client	ON	0.098
14	XXX coordinates & external client	ON	0.097
15	Data Model Pilot	ON	0.095
16	Data Service Pilot	ON	0.095
17	2 Tier	ON	0.094
18	3 Tier	ON	0.090
19	Define data model for shared data	ON	0.085
20	Svc layer w/ extracted biz logic	OFF	0.080
21	Define ext mandatory data std	ON	0.079
22	Svc layer w/ extracted biz logic in DB	ON	0.066
23	External data model can be extended	ON	0.062
24	Provide logical data scheme internally	ON	0.052

Fig. 4. Finding solutions with SHORT. Costs and benefits are inputs are domain-specific constructs that, in our work, we develop with users as part the model elicitation process.

B. About Goal Models

In order to test the value of the strategy mentioned above, we need case study material. The largest RE models we could access were goal models generated by Jennifer Horkorff and Steve Easterbrook (see goo.gl/K7N6PE). For an example of a (small) goal model, see Fig. 2.

Internally, goal models have the structure shown in Fig. 3. Nodes have labels. Initially, all labels are *undefined* and are then relabelled *satisfied* or *denied* by the STEP labeling procedure of Fig. 5 (aside: during labelling, nodes may be temporarily labeled *partially satisfied/denied*).

Decisions are label assignments. The output of an instance of model reasoning is a set of labels for nodes (some of which are undefined). Our objective is find label assignments to satisfy high-level goals and softgoals with respect to some objectives (e.g. minimal cost).

III. Goal Inference with SHORT

Fig. 4 gives a high-level overview of our approach.

Recall from our introduction that this paper explores these goals via a process called SHORT:

SH. Sample Heuristically the possible labellings.

O. Optimize the label assignments in order to cover more goals or reduce the sum of the cost of the decisions in the model. To implement the *retry* step recommended recommended by Crawford and Baker's ISSAMP [4]., we sample many times, each time resetting all the labels back to *undefined* before asking an optimizer how to make an improved sample next time.

R. Rank all decisions according to how well they performed during the optimization process.

T. Test how much conclusions are determined by the decisions that occur very early in that ranking.

SH = Sample Heuristically: The SAMPLE procedure of Fig. 6 finds one possible set of consistent labels within a goal. The procedure calls the STEP procedure (Fig. 5) over all the decisions in the model, labeling as many nodes as possible. This procedure executes in a random order since

1. When considering an edge E_j from N_i to a child N_k then:
   - If $N_i \in \{1, -1\}$ then expect $N_k = E_j * N_i$ else
   - If $E_j > 0$ then expect $N_k = N_i$ else
   - If $E_j < 0$ then expect $N_k = -N_i$.

Goal model inference does not use a fuzzy set or probabilistic approach to reasoning about conflicting influences. Rather, goal edges are either used or *ignored*. Hence:

2. If N_k is *undefined*, then it is labelled with the above expectations and we call STEP recursively over all edges to N_k's children. Children are explored in a random order. After recursion, for and-nodes, labels get set back to *undefined* if any fail's N_k's expectations (as defined by point 1).

3. Otherwise, if its label does not meet the above expectations, then we *ignore* the edge E_j.

Fig. 5. Procedure STEP: labels neighboring nodes; may *ignore* some edges. Called by the SAMPLE procedure of Fig. 6.

1. SAMPLE inputs (a) a goal model and (b) a set of *prior* decisions made by any previous run of SAMPLE (so initially, this set is empty).

2. As it initializes, SAMPLE sets all nodes to *undefined* then all *prior* nodes to *satisfied*;

3. While there are *undefined* nodes, SAMPLE (1) "picks" one *undefined* decision as *satisfied* then (2) "reflects" over its edges using the STEP procedure of Fig. 5. SAMPLE is stochastic since "picks" and "reflects" return nodes and edges in a random order.

4. SAMPLE outputs a *solution* listing all *satisfied nodes*.

Important note: if *prior* is changed, then SAMPLE will return different solutions. That is, the results from SAMPLE can be carefully tuned and improved by the OPTIMIZE procedure of Fig. 7 that carefully selects useful *prior*s.

Fig. 6. Procedure SAMPLE: tries to labels many nodes. Called by the OPTIMIZE procedure of Fig. 7.

(a) this emulates the idiosyncrasies of human discussions; (b) as mentioned above, Crawford and Baker found this to be a useful strategy for reducing computational complexity.

In the RE literature, alternate methods for sampling consistent labels within goal models include the forwards and backwards analysis proposed by Horkoff and Yu [1].

1. Given a model with n decisions, OPTIMIZE calls SAMPLE $N = 10 * n$ times. Each call generates one member of the population $pop_{i \in N}$.
2. OPTIMIZE scores each pop_i according to various objective scores o. In the case of our goal models, the objectives are o_1 the sum of the cost of its decisions, o_2 the number of ignore edges, and the number of o_3 satisfied goals and o_4 softgoals.
3. OPTIMIZE tries to each replace pop_i with a mutant q built by extrapolating between three other members of population a, b, c. At probability p_1, for each decision $a_k \in a$, then $m_k = a_k \vee (p_1 < rand() \wedge (b_k \vee c_k))$.
4. Each mutant m is assessed by calling SAMPLE(*model,prior=m*); i.e. by seeing what can be achieved within a goal after first assuming that $prior = m$.
5. To test if the mutant m is preferred to pop_i, OPTIMIZE uses Zitler's continuous domination *cdom* predicate [14]. This predicate compares two sets of objectives from sets x and y. In that comparison, x is better than another y if x "losses" least. In the following, "n'' is the number of objectives and $w_j \in \{-1, 1\}$ shows if we seek to maximize o_j.

$$\begin{aligned} x \succ y &= loss(y,x) > loss(x,y) \\ loss(x,y) &= \textstyle\sum_j^n -e^{\Delta(j,x,y,n)}/n \\ \Delta(j,x,y,n) &= w_j(o_{j,x} - o_{j,y})/n \end{aligned}$$

5. OPTIMIZE repeatedly loops over the population, trying to replace items with mutants, until new better mutants stop being found.
6. Return the population.

Fig. 7. Procedure OPTIMIZE: strives to find "good" priors which, when passes to SAMPLE, maximize the number of edges used while also minimizing cost, and maximizing satisfied hard goals and soft goals. OPTIMIZE is based on Storn's differential evolution optimizer [15]. OPTIMIZE is called by the RANK procedure of Fig. 8. For the reader unfamiliar with the mutation technique of step 3 and the *cdom* scoring of step 5, we note that these are standard practice in the search-based SE community [16, 17].

These are local propagation algorithms where humans interact with a SAT-solver to explore human-selected options within goals. Even with some automatic support, Horkoff and Yu report that a single manual sample of goals can take tens to hundreds of seconds (depending on the size of the model). In the same time, our automatic methods can take 1000s to 10,000s of samples. This difference in sample speed explains why our methods found keys in goal models, but prior research has not.

O = Optimize: Fig. 6 discusses how we SAMPLE one set of labels from a softgoal model. As described at the bottom of that figure, that SAMPLE-ing process can be controlled via the *prior* decisions passed to the model. The OPTIMIZE procedure of Fig. 7 is a multi-objective evolutionary algorithm that learns what *prior*s decisions lead to *better* labellings. Here, *better* means labels that result in (a) greater coverage of goals and softgoals, (b) minimization of skipped edges; (c) least cost solutions. Note: for this paper, we assume that all decision costs are equal (in future work, we will explore other distributions).

R= Rank: The RANK procedure of Fig. 8 reflects of the results of the optimizer to rank each decisions. Decisions are ranked by the odds that they are associated with the better goals. Note that the key decisions will the ones found in the first part of those decisions.

1. Run OPTIMIZE $N = 20$ times, keep all decisions d in the generated population $pop_{i \in N}$ and their objectives o.
2. For each objective $o_j \in o$, do
   - Sort and separate the top 10% o_j scores; call that "best" b and the remainder "rest".
   - For each decision $d_k \in d$, do
     - Count how many times n_1 that d_k is associated with a "best" objective score. Set $n_2 = N - n_1$
     - The value of d_k for objective o_j is the probability p times the support s that d_k appears more often in "best" than "rest". That is, $s_{j,k} = n_1 * 0.1$ and $p_{j,k} = (n_1 * 0.1)/(n_1 * 0.1 + n_2 * 0.9)$.
3. Let *ordering* be all decisions, sorted descending by the value of decision d_k across all objectives; i.e. $v_k = \sum_j s_{j,k} \times p_{j,k}$

Fig. 8. Procedure RANK: ranks all decisions according to how well they performed during the optimization process. Used by the TEST procedure of Fig. 9.

1. Run RANK to get a sorted list of decisions d. 2. For all decisions $1 \leq x \leq |d|$, do
   - Build a *prior* set using decisions $d_1..d_x$ from *ordering*;
   - 20 times, call *SAMPLE(model, prior)*
   - Record for position x the median and IQR of the objectives found in those results.

Aside: median= 50th percentile; IQR=(75th-25th) percentile.

Fig. 9. Procedure TEST: from a ranked list of decisions d, set the first few decisions, then selected the rest at random.

T = Test: The TEST procedure of Fig. 9 takes a ranked list of decisions, then tests what happens when the first few are fixed and the rest are selected at random.

A. Reporting the Results

The SHORT process described above is a large-scale "what-if"+optimization procedure. In order to succinctly describe the results of the above, we apply the following statistical summarization method.

Fig. 10 shows what is reported by TEST after studying the modernization model of Fig. 2. At each point along the x-axis, TEST samples the goal model 20 times using *prior* decisions taken from $1 \leq i \leq x$. In the solutions returned by SAMPLE, *root cost* is the sum of decision costs; *root goal/softgoals* are the sum of the number of satisfied goals/soft goals. The blue and red plots show the median and variation around the median.

In these results, after making three decisions, the variations plummet and the medians rise to a steady plateau. Fig. 10 is reporting that this model has three key decisions which, if set, make further discussion superfluous.

The decision rankings found by RANK for Fig. 2 are shown in Fig. 11. Two features of this list deserve comment:

- This list is *not* 24 decisions that could inspire $2^{24} > 16,000,000$ debates. Rather, it is an *ordering* with the property that item $x + 1$ is recommended *only* if recommendations $1..x$ are first adopted. That is, this list offers only 24 decisions to users (whether or not they which to perform actions $1..x$).

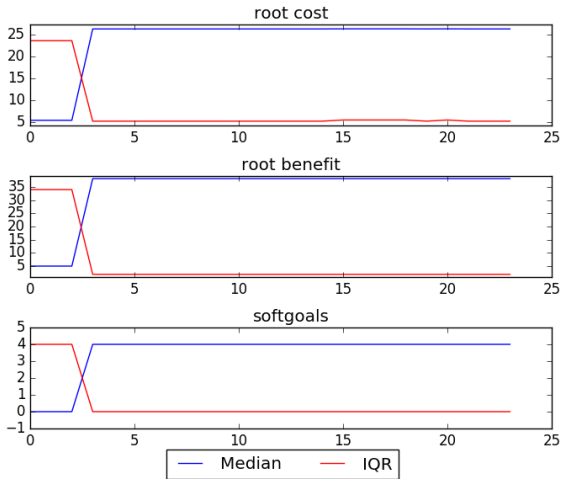


Fig. 10. The X-axis contains d decisions sorted by the RANK procedure of Fig. 8. The y-axis shows the results from the TEST procedure of Fig. 9; i.e. for $1 \leq x \leq |d|$, fix the first x decisions then, 20 times, make random choices about decisions $x+1$ to $|d|$. Results shown as median and IQR values. Median = 50% percentile and IQR=intra-quartile range= (75-25)th percentile. These results are *smoothed* such that these plots only change where this is statistically significant non-small change in the y-axis. An appendix to this paper describes our statistical smoothing procedure.

1) J2EE Specification (satisfied)
2) *Pnp Framework (denied)*
3) *New Database (denied)*
4) Documentation Tool (satisfied)
5) Access Control Assessed (satisfied)
6) Monitoring Pilot (satisfied)
7) General Test Env (satisfied)
8) Bakeoff Result (satisfied)
9) Access Control Pilot (satisfied)
10) DB Vendor Test Env (satisfied)
11) Data Service Spec (satisfied)
12) External clients get their request (satisfied)
13) Co-ordinates & internal client (satisfied)
14) Co-ordinates & external client (satisfied)
15) Data Model Pilot (satisfied)
16) Data Service Pilot (satisfied)
17) 2 Tier (satisfied)
18) 3 Tier (satisfied)
19) Define data model for shared data (satisfied)
20) *Svc layer w/ extracted biz logic (denied)*
21) Define ext mandatory data std (satisfied)
22) Svc layer w/ extracted biz logic in DB (satisfied)
23) External data model can be extended (satisfied)
24) Provide logical data scheme internally (satisfied)

Fig. 11. Results of decision ordering on Fig. 2. Read "satisfied/denied" as equivalent to ensuring that a leaf node is achieved or not achieved. Note the *denied* items at positions $x \in \{2, 3, 20\}$. These are recommendations of what *not* to do. The rest are all positive recommendations. The implication of Fig. 10 is that after following the recommendations for the first 3 decisions, the remaining decisions will have little additional impact on overall cost or satisfaction.

- If users cannot implement all these recommendations, they can easily read from Fig. 10 the effects of implementing just the first x items.

IV. Why Did it Work?

It is insightful to ask: why are three decisions so impactful on this model? The answer lies in the topology of the model. As seen in Fig. 2, the model divides at the top between a large left-hand-side sub-tree and a much smaller sub-tree.

In Fig. 11, decisions two and three are required to throw the reasoning out of the small right-hand-side tree. Also, using decision one (about using J2EE specifications) selects the *smallest* (and hence, cheapest to implement) sub-tree from the left-hand-side. The J2EE specification's parent's parent achieves the overall goal of "Modernize" while at the same leading to two softgoals ("Quick Feature Delivery" and "Good example of agile government development"). Hence, in terms of minimizing cost and maximizing goal and soft goal coverage, these three decisions are good choices.

In summary, the topology of Fig. 2 leads naturally to prioritizing the first three decisions of Fig. 11. Hence, this particular model has only a few key decisions.

This leads to one of our research questions: Just how common is this kind of topology? Will all models contain keys or are the results from the IT Modernization model just a fortuitous quirk of that model?

Evidence suggests that the results from Fig. 2 will generalize to many more models. First, similar results have been shown in other research areas (see discussion in §II-A); and our own work has shown similar findings in software-specific areas—see [18, 19, 20]. However, none of these studies looked at RE-related models. Accordingly, the rest of this paper tests for the presence of key decisions in example requirements goal models.

V. Looking for Keys in RE Models

The Fig. 2 model has 53 nodes and 57 edges. Table I shows some details on the other goal models used in this study. The largest of our sample is the *CSServices* models shown in Fig. 1. For images of all these models, see goo.gl/K7N6PE.

Fig. 12 shows SHORT's results from eight models after making the first 6,12,25,50,100% of the decisions along the ranking found by RANK. In a result consistent with Fig. 10, there is little change to goal or soft goal coverage are making just a few decisions: typically, just 12% of the decisions.

Two exception to the pattern "12% is enough" are CSCounselling and ITDepartment. Those models achieved nearly max goal coverage at 12% but did not peak until making 25% of the decisions. Even with that exception, the general conclusion is clear: with SHORT, only a minority of the decisions need to be made with care, since once those are made, the goal coverage is robust (unchanging) for the remaining decisions.

Fig. 13 shows the runtimes required to generate our results. Empirically, these runtimes fit the curve $secs =$

Model	Result	Percentage of Decisions					
		0	6	12	25	50	100
Counselling	SGs	60	60	70	80	70	60
	Goals	50	60	70	60	70	40
	Costs	0	5	10	20	28	35
Management	SGs	50	50	60	60	50	40
	Goals	50	50	50	60	60	60
	Costs	0	4	8	20	24	32
Marketing	SGs	70	70	70	60	60	30
	Goals	70	70	70	70	60	40
	Costs	0	6	8	11	12	20
ITDept	SGs	70	70	60	70	70	60
	Goals	60	50	50	80	80	70
	Costs	0	2	4	9	17	18
SAProgram	SGs	80	80	80	80	80	80
	Goals	70	70	70	60	55	60
	Costs	0	1	2	3	3	5
Services	SGs	50	50	50	50	50	50
	Goals	30	50	60	60	70	70
	Costs	0	4	7	13	19	24
Kids&Youth	SGs	50	40	50	50	40	20
	Goals	50	50	70	60	60	70
	Costs	0	0	0	4	7	10

Fig. 12. Percentages of Softgoals and Goals covered, and total Costs, with respect to their maximum values after applying top 6,12,25,50,100% of decisions found and ranked by SHORT for the goal models of Table I.

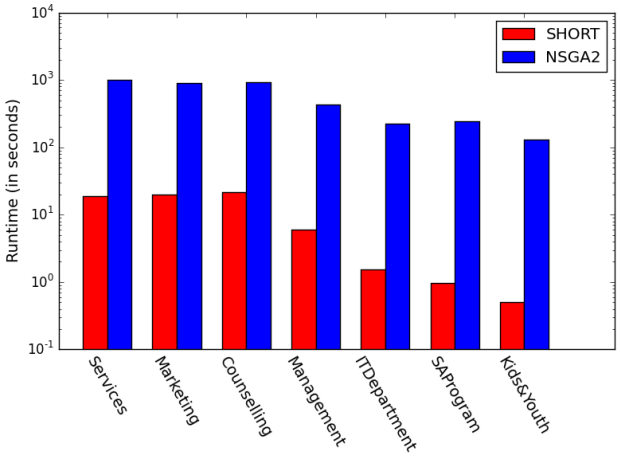


Fig. 13. Runtimes for nsga2 compared to our approach.

$nodes^2$) with an $R^2 = 0.97$; i.e. SHORT's runtimes are low-order polynomial. This is a significant result since in 1990, Bylander et al. warned that abductive search is NP-hard [12]; i.e. when exploring all options within an RE model, we should expect very slow runtimes. The pessimistic result has confirmed empirically by Menzies *et al.* [21], theoretically by Abdelbar *et al.* [13], and then again empirically by Ernst *et al.* [8].

It is insightful to compare SHORT's runtimes against the *forward* and *backwards* analysis proposed by Horkoff and Yu [1]. They report times in the range of 7 to 300 seconds (which includes human time considering various choices)—which is approximately the same as the runtimes seen in Fig. 13. The advantage of backward and forward analysis is that user involvement increases user acceptance of the conclusions. The disadvantage is that those analysis methods do not comment on the robustness of the solution. Further, a forward and backwards analysis results in one sample of the model. A SHORT-style analysis, on the other hand, includes extensive "what-if" simulations. Charts like Fig. 10 not only offer solutions but also comment on:

- The stability of the selected decisions: see the red "IQR" line in that figure;
- The trade space across multiple decisions. Users can check a display of SHORT's decision orderings (like Fig. 10) to decide for themselves when enough benefit has been obtained for enough cost.

To the best of our knowledge, forward and backward analysis has not been benchmarked against alternate techniques. Our next results compare SHORT against a state-of-the-art multi-objective optimizer called NSGA-II [22]. This is a widely used genetic algorithm that uses a novel *select* operator to find the best "parents" to make the next generation. For both NSGA-II and SHORT, the goal is to maximize the coverage of goals and soft goals, while at the same time minimizing the sum of the costs of making the decisions. Fig. 13 shows the median runtime for *one* run of NSGA-II and SHORT. Note that SHORT runs 2-3 orders of magnitude times faster.

In addition, NSGA-II returns a solution, whereas SHORT reports what happens when an increasing number of decisions are imposed on a system. In order for NSGA-II to reason like SHORT, it would have to run hundreds of 'what-if" studies. That is, NSGA-II's runtime costs would be incurred hundreds of times. The slow runtime of NSGA-II can be attributed to two major factors: a) larger exploration of solution space to obtain a greater spread of solutions; b) all pairs comparison of solutions for mutation which has a polynomial time complexity. SHORT, on the other hand, searches only around an optimum solution, reducing the search space. Finally, SHORT performs random selection of solutions for mutations.

Fig. 14 shows what objectives were reached in 20 repeated runs of NSGA-II and SHORT. Both approaches achieved remarkably similar coverage of goals—an effect that can be explained by our models having a small number of key variables which, if set the right way, control what can be achieved in the rest of the model.

VI. Threats to Validity

As with any empirical study, biases can affect the final results. Therefore, any conclusions made from this work must be considered with the following issues in mind:

Sampling bias threatens any experiment; i.e., what matters in (say) practitioner settings may not be true of our examples. The data sets used here comes from goal models taken from a repository and all but one were supplied by one individual. These were all from i* style models, and not late-stage RE models/lists.

Evaluation bias: This paper uses one measure of success, goal achievement and associated cost and benefit. Optimal

Model	NSGA2	SHORT
Services	f1: 46.77 ± 0.0 f2: 65.22 ± 0.0	f1: 46.24 ± 0.0 f2: 65.22 ± 0.0
Marketing	f1: 32.47 ± 0.0 f2: 34.38 ± 0.0	f1: 32.47 ± 0.0 f2: 34.38 ± 0.0
Counselling	f1: 54.29 ± 1.41 f2: 44.83 ± 3.45	f1: 53.59 ± 2.76 f2: 44.83 ± 3.45
Management	f1: 44.63 ± 0.82 f2: 61.11 ± 2.78	f1: 42.98 ± 1.65 f2: 61.11 ± 2.78
ITDepartment	f1: 68.42 ± 2.63 f2: 69.57 ± 0.0	f1: 68.42 ± 2.63 f2: 73.91 ± 8.69
SAProgram	f1: 78.69 ± 1.64 f2: 66.67 ± 0.0	f1: 78.69 ± 1.64 f2: 66.67 ± 0.0
Kids&Youth	f1: 22.86 ± 0.0 f2: 100.0 ± 0.0	f1: 22.86 ± 0.0 f2: 100.0 ± 0.0

Fig. 14. NSGA-II compared to our SHORT approach. Columns report Accuracy(Median ± IQR) of the objectives *f1:* Percentage of soft goals satisfied and *f2*: Percentage of goals satisfied.

solutions only consider inputs given, and may not reflect all the complexities of a given decision.

Construct Validity: The conclusions of this paper are about better processes for making *decisions* (specifically, do not waste time on all the numerous redundant issues). It would be a violation of construct validity to make another claim—that SHORT-guided decisions lead to better outcomes.

VII. Related Work

We discussed related work in the area of model "keys"/"backdoors" in §II-A. Other related work is in the area of goal model reasoning and in particular, search-based optimizations of goal models.

Horkoff and Yu, in [23], give a comprehensive overview of complete reasoning procedures for goal models. To summarize, forward reasoning begins with low-level tasks to see if higher order goals can be achieved, possibly with interactive analyst input; backward reasoning begins with a set of goals to satisfy, and attempts to find tasks that can be undertaken to satisfy the goals. The work of Sebastiani [24] was some of the first to recognize the applicability of satisfiability solving to goal models. Currently, the brute-force approach of a SAT solver, or increasingly, a Satisfiability Modulo Theory (SMT) solver, is adequate for many average-case complexity models. Most recently, Nguyen et al. [25] have proposed constrained goal models which are amenable to SMT approaches and scale to 1000s of elements. However, particularly for the backward search problem, which as we have discussed, is abductive and NP-hard, even the SAT and SMT solvers perform poorly.

In two ways, we think SHORT might be preferable to the research in the last paragraph. Firstly, SHORT is fast and scalable. The authors have been struggling to find a fast way to explore requirements models containing inconsistencies with the 1990s. As mentioned above, all our previous attempts suffered from crippling runtimes that prevented scale up [7, 8].

Secondly, one aspect where SHORT might be preferred to forward and backwards reasoning on Horkoff and Yu, is its exploration of trade spaces. Forward and backward reasoning results in one set of decisions, within some local trade-offs explored at each step. Our approach, on the other hand, offers extensive trade-off information on large sets of possible alternate decisions (e.g. Fig. 11). Harman [26] comments that understanding the neighborhood of our solutions is an open and pressing issue:

> "In some software engineering applications, solution robustness may be as important as solution functionality. For example, it may be better to locate an area of the search space that is rich in fit solutions, rather than identifying an even better solution that is surrounded by a set of far less fit solutions... [Research] has tended to focus on the production of the fittest possible results. However, many application areas require solutions in a search space that may be subject to change. This makes robustness a natural second order property to which the research community could and should turn its attention [26]."

The other related to this paper is the use of search-based techniques, such as our use of Differential Evolution, to find near-optimal solutions. Examples of this work include the Next-Release Problem studied in the search-based software engineering community, for example, in Bagnall et al. [27]. There, the problem is to determine the near-optimal set of requirements to prioritize in the next software release, given constraints such as cost and schedule. These formulations, however, tend to lack the intersectionality of the goal models we show above; dependencies rarely exist between requirements, and a simple cost metric is presumed to exist. Recently, work such as that by Tonella et al. [28] has focused on amending the straight-forward search approach with expert input, to derive a more sophisticated prioritization. We build on this work by adding in the notion of model dependencies, but use their stakeholder prioritization in our earlier steps to derive initial values for the goals (not discussed in this paper).

A possible extension here is to consider the model development as a series of steps in refining model uncertainty. Then the keys we find are areas of greater uncertainty, and more effort is needed to refine that portion of the model. This is similar to the notion of partial models expressed in Salay et al. [29].

VIII. Conclusions

We recommend SHORT since it runs very fast (in just a few minutes, even for the largest model explored here). Hence, SHORT could be useful as a decision aid to be used within a meeting. The same cannot be said for NSGA-II that can take hours to find best decisions that lead to most goals covered at least cost.

When not to use SHORT? We might recommend traditional goal model analysis (using forward and and backwards analysis) if the goal is only to increase user-acceptance of a single generated solution. However, SHORT is recommended when the objective is to

- Assert the robustness of some solution *within the space of many others* or
- To show users a "trade space" diagram (see Fig. 10) that lets then decide when enough benefit has been obtained for enough cost.

We end by repeating a comment made in the introduction: Our result do *not* show that all requirements models simplify to small number of key decisions. However:

- If keys are common in RE models, then model-based RE can be greatly simplified by focusing stakeholder debates on just the key variables (e.g., the first 12%).
- There is much evidence that many models contain keys; see [18, 19, 20], §II-A, Fig. V and Fig. 14.

Hence, we hope this work encourages others to check for keys in their models. To that end, we have made all our tools and models available on-line at https://goo.gl/gvxeaH. While some aspects of our approach are specific to goal models, the general SHORT method could be applied to a wide range of models.

Appendix: Graph Smoothing

To smooth out the charts generated in SHORT (e.g. Figure 10), we use the Scott-Knott procedure recommended by [30]. This technique recursively bi-clusters a sorted set of numbers. If any two clusters are statistically indistinguishable, Scott-Knott reports them both as one line.

Scott-Knott first looks for a break in the sequence that maximizes the expected values in the difference in the means before and after the break. More specifically, it splits l values into sub-lists m, n in order to maximize the expected value of differences in the observed performances before and after divisions. E.g. for lists l, m, n of size ls, ms, ns where $l = m \cup n$, Scott-Knott divides the sequence at the break that maximizes:

$$E(\Delta) = \frac{ms}{ls} abs(m.\mu - l.\mu)^2 + \frac{ns}{ls} abs(n.\mu - l.\mu)^2$$

Scott-Knott then applies some statistical hypothesis test H to check if m, n are significantly different. If so, Scott-Knott then recurses on each division. For this study, our hypothesis test H was a conjunction of the A12 effect size test (endorsed by [31]) and non-parametric bootstrap sampling [32]; i.e. our Scott-Knott divided the data if *both* bootstrapping and an effect size test agreed that the division was statistically significant (99% confidence) and not a "small" effect ($A12 \geq 0.6$).

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