Improved software engineering decision support through automatic argument reduction tools

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Abstract

Some of the most influential decisions about a software system are made in the early phases of the software development life cycle. Those decisions about requirements and design are generally made by teams of software engineers and domain experts who must weigh the complex interactions among requirements and the associated developmental and operational risks of those requirements. Some of these early life cycle decisions are more influential, or perhaps fateful, to subsequent software design and development than are others.

When debating about complex systems with a large number of options, humans can often be slower than an AI system at identifying the clusters of key decisions *that give the most leverage. By focusing a group of human domain experts or software engineers on these key decision clusters, more time can be devoted to these pivotal decisions and less time is wasted on irrelevancies.*

1 Introduction

In early phases of a system development, many crucial decisions about software are taken. In the process of requirements elicitation and analysis, it is common for clients to request much more than can be afforded - either because of budgetary constraints, time limitations, or other issues like safety concerns. That is, there are risks associated with requirements. (In this context, we take a broad definition of risk - anything that gets in the way of satisfying a Requirement.)

There are often things that can be done to lower the risk, and thus increase the chances of meeting requirements. In fact any verification or validation activity can be considered to be a risk reducer. In a typical system development, it is common for the number of requirements and associated risks, and therefore the number of possible mitigating activities to be quite large. Each of these mitigating actions has a cost associated with it. The Defect Detection and Prevention (DDP) tool provides an ontology for representing these requirements, risks, and mitigations, and for reasoning about them. DDP is a decision support tool to be used in the early part of the life cycle of system development. In this paper, we describe several ways that we are automating this decision support.

1.1 Imagine the Scene ...

A team of NASA's top experts are debating options on some complex deep space mission. The mission is in its early planning stages so few of the details are fixed. The

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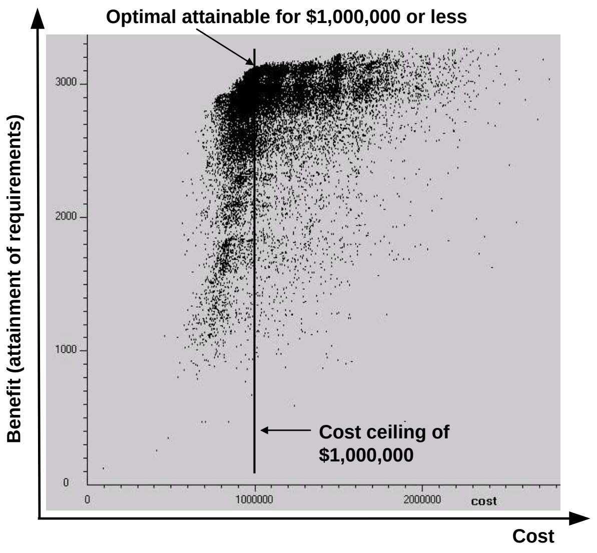


science team wants to add a new instrument package to the mission. But the propulsion experts are already worried about the payload mass and any addition worries them. Also, the electronics team members are worried about the added stress to power consumption and heat production on the on-board systems. A spirited discussion follows in which each team tries to explain the costs and benefits of their various proposals.

In the midst of this heated debated, a screen flickers. The AI system monitoring the debate produces a visual display of the several clusters of alternate decisions, each of which meets cost restrictions and satisfies requirements to an acceptable level. The visualization of these clusters helps the team to realize that some sets of decisions, although feasible, do not fit their development organization. Simultaneously, the automated monitoring system has just realized that of the dozens issues remaining, a resolution on (e.g.) four matters makes debates about most of the other issues redundant. The AI system presents to the team a decision cluster- a set of useful alternative decisions. The team finds that it has consensus on two of those decisions, so those are quickly adopted. These two decisions greatly reduce the space of remaining discussions and the group finishes their debates in time for lunch.

2 The DDP Tool

The above scene is not science fiction- some of the technology has already been developed and applied to Jet Propulsion Laboratory (JPL) missions. At JPL, the DDP tool [2] is in use to organize interactive knowledge acquisition and decision making sessions with spacecraft experts . The DDP tool and process works as follows:

DDP assertions are either:

- *Requirements* (free text) describing the objectives and constraints of the mission and its development process;
- *Weights* (numbers) associated with requirements, reflecting their relative importance;
- *Risks* (free text) describing events that can damage requirements;
- *Mitigations*: (free text) describing actions that can reduce risks;
- *Costs*: (numbers) effort associated with mitigations, and repair costs for correcting Risks detected by Mitigations;
- *Mappings*: directed edges between requirements, mitigations, and risks.
- *Part-of relations* structure the collections of requirements, risks and mitigations;

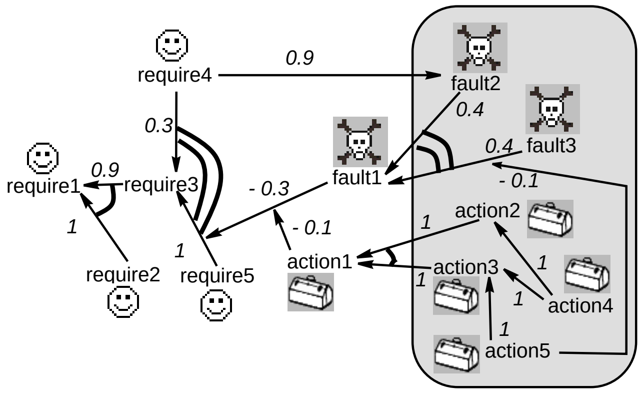
Figure 1. DDP's ontology

- 6 to 20 experts are gathered together for short, intensive knowledge acquisition sessions (typically, 3 to 4 half-day sessions). These sessions *must* be short since it is hard to gather together these experts for more than a very short period of time.
- The DDP tool supports a graphical interface for the rapid entry of the assertions. Such rapid entry is essential, lest using the tool slows up the debate.
- Assertions from the experts are expressed in using an ultra-lightweight decision ontology (e.g. see Figure 1). The ontology *must* be ultra-lightweight since:
  - Only brief assertions can be collected in short knowledge acquisition sessions.
  - If the assertions get more elaborate, then experts may be unable to understand technical arguments from outside their own field of expertise.

The result of these sessions is a network of influences connecting project requirements to risks to possible mitigations. A (highly) stylized version of that network is shown in Figure 2.

The ontology of Figure 1 may appear too weak for useful reasoning. However, in repeated sessions with DDP, it has been seen that the ontology is rich enough to structure and simplify debates between NASA experts. For example, DDP has been applied to over a dozen applications to study advanced technologies such as

- a computer memory device;
- gyroscope design;
- software code generation;
- a low temperature experiment's apparatus;



Faces denote requirements;

Toolboxes denote mitigations;

Skulls denote risks;

Conjunctions are marked with one arc; e.g. *require1* if *require2* and *require3*.

Disjunctions are marked with two arcs; e.g. *fault1* if *fault2* or *fault3*.

Numbers denote weights; e.g. *action5* reduces the contribution of *fault3* to *fault1*, *fault1* reduces the impact of *require5*, and *action1* reduces the negative impact of *fault1*.

Oval denotes structures that are expressible in the latest version of the JPL semantic net editor (under construction).

Figure 2. A semantic net of the type used at JPL [3].

- an imaging device;
- circuit board like fabrication;
- micro electromechanical devices;
- a sun sensor;
- a motor controller;
- photonics; and
- interferometry.

In those studies, DDP sessions has found cost savings exceeding \$1 million in at least two of these studies, and lesser amounts (exceeding \$100,000) in the other studies. The DDP meetings have also generated numerous design improvements such as savings power or mass and shifting of risks from uncertain architectural to better understood design. Further, at these meetings, some non-obvious significant risks have been identified and mitigated. Lastly, DDP can be used to document resolutions to those debates. Hence, DDP is in use at JPL:

- not only as a group decision support tool (as it was designed to do);

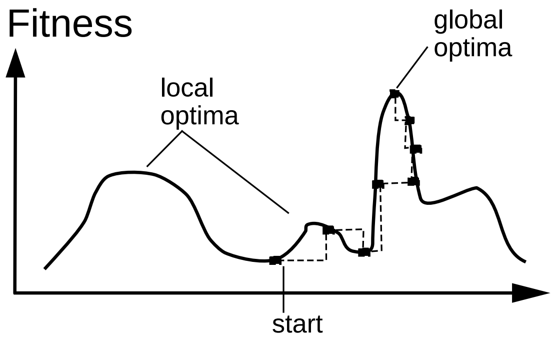


Figure 3. Simulated annealing, an example.

- but also a design rationale tool to document decisions.

That is not to say DDP cannot be improved.

2.1 Improving DDP with Simulated Annealing

Optimizing risk mitigations means *minimizing* costs while *maximizing* benefits. That is, it is a classic *optimization problem*. A commonly-used search technique for such optimization is *simulated annealing* [6], illustrated in Figure 3. Simulated annealing is a kind of hill-climbing search for finding a good solution. A simple hill-climber simply jumps to the next best solution and can hence miss globally optimal solutions since it can't move to a near-by higher peak if, to do so, means traveling down-hill across a valley. Simulated annealing avoids this problem using a "jump" factor that is a function of a "temperature" variable. At high "temperatures", simulated annealing can sample more of the local terrain since it can jump up-hill *or* down-hill. As the search proceeds and the "temperature" cools, simulated annealing jumps less and less. Eventually, the jumping mechanism "freezes" and simulated annealing completes its search like a simple hill climber.

A simulated annealing capability is now part of the DDP tool [13]. This gives automated support for the difficult choices that project managers have to make among possible mitigations needed to reduce risk to acceptable levels. It is common in systems being developed at JPL for expert to identify 50 to 100 risks to requirements, and 50 to 100 mitigating actions that can be taken to reduce these risks to acceptable levels. Making a binary choice for each of 50 mitigations gives a search space of size 2^{50}. A simulated annealing algorithm can search this space in a few minutes to give an adequate solution, or can be run for several hours to give a near optimal solution.

In a typical JPL system development, such a search could be conducted overnight, between DDP sessions. This would provide the session participants the additional information

Figure 4. Clusters of mitigations.

that they need to finish the requirements and/or high level design.

2.2 Improving DDP with Clustering

When search a complex space of decision options, simulated annealing produces a *near-optimal* solution. That is, after a large number of steps of the simulated annealing algorithm, a set of decisions is discovered that meets the objective function, and meets it more closely than any other decision set checked. However, it should be noted that the data of this search space is generally produced by expert judgment. Although such judgments are typically quite good (and are the best measure available), they cannot be assumed to be completely accurate. Thus, other sets of decisions, that are judged to meet the objective function at a slightly lower level, may have other properties that make them more desirable.

For example, if there are 100 decisions to be made (perhaps 100 mitigating activities that the project manager may do to assure product quality), there are 2^{100} possible sets of decision that could be taken. Of these, it would not be surprising for the simulated annealing to identify 1000 that are within 2% of the optimal value of the objective function. To ask a project manager or management team to chose among these 1000 may be a daunting task. We have been experimenting with various clustering strategies to reduce the complexity of this decision. As seen in figure Figure 4, this large number of decisions may be collected into a much smaller of clusters. Each cluster has the property that all its members share 95% of the decision. With this visualization, the human experts can now choose the cluster that best fits the characteristics of their development organization. That is, if the management team is aware that their team is especially strong in formal specification, but much weaker in model checking, then they would choose a cluster that includes more formal specification activities rather than model checking activities.

3 Improving DDP with the TAR2 Tool

In a typical use of DDP, experts sketch out mappings between requirements, risks, and mitigations then search for the cheapest mitigations that most reduce risks. As discussed previously, this search can be overwhelming large. Figure 5.A shows the results of 50,000 runs with DDP for one deep space mission with 99 possible mitigations; i.e. $2^{99} \approx 10^{30}$ possibilities. This space is too large to explore

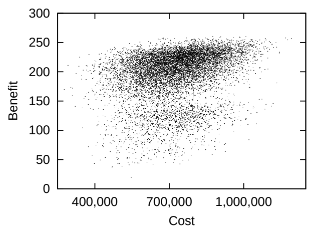


Figure 5.A: Before. Here, one dot is one project plan; i.e. one possible setting to the 99 risk mitigation options.

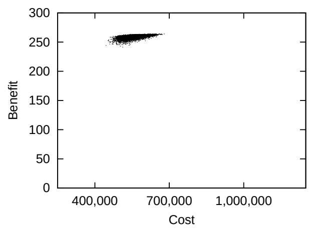


Figure 5.B: After. Results from applying the constraints learnt by the TAR2 contrast set learner.

Figure 5. An application of TAR2. X-axis= "cost" = sum of the cost of selected risk mitigations (lower is better). Y-axis= "benefit"= requirements coverage, less the effects of risk (more is better)

thoroughly. In each run, a random set of mitigations were selected each time. Note the huge range of possible costs and benefits.

10^{30} seems a dauntingly large number of options to explore. Fortunately, our TAR2 *contrast set learner* [5, 7–11] has shown that a heated discussion on most of the risk mitigations would be a *complete waste of time*. A contrast set learner finds the differences in variable settings seen in different situations. For example, an analyst could ask a contrast set leaner "what are the differences between people with Ph.D. and bachelor degrees?". TAR2 differs from other contrast set learners such as TARZAN [12] and STUCCO [1] in that it searches for the *smallest* contrast set that *most* separates preferred and undesired behavior.

TAR2 searches for a strong *select statement* that most *changes* the ratio of classes. To understand the concept of a *strong select statement*, consider the log of golf playing behavior seen in Figure 6. In that log, we only play *lots* of golf in $\frac{6}{5+3+6} = 43\%$ of the cases. To improve our game, we might search for conditions that increases our golfing frequency. Two such searches are shown in the bottom of

outlook	*temp(°F)*	*humidity*	*windy?*	*class*
sunny	*85*	*86*	*false*	*none*
sunny	*80*	*90*	*true*	*none*
sunny	*72*	*95*	*false*	*none*
rain	*65*	*70*	*true*	*none*
rain	*71*	*96*	*true*	*none*
rain	*70*	*96*	*false*	*some*
rain	*68*	*80*	*false*	*some*
rain	*75*	*80*	*false*	*some*
sunny	*69*	*70*	*false*	*lots*
sunny	*75*	*70*	*true*	*lots*
overcast	*83*	*88*	*false*	*lots*
overcast	*64*	*65*	*true*	*lots*
overcast	*72*	*90*	*true*	*lots*
overcast	*81*	*75*	*false*	*lots*

```
SELECT class
FROM original
WHERE outlook=
      'overcast'

lots
lots
lots
lots
```

```
SELECT class
FROM original
WHERE humidity >= 90

none
none
none
some
lots
```

Figure 6. Attributes that select for golf playing behavior.

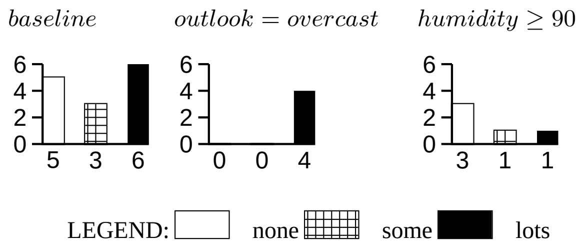


Figure 7. Changes to golf playing behavior from the baseline.

Figure 6. In the case of `outlook=overcast`, we play *lots* of golf all the time. In the case of `humidity` $\geq$ `90`, we only play *lots* of golf in 20% of the cases. The net effect of these two select statements is shown in Figure 7.

The `WHERE` statements within a select statement can contain conjunctions of arbitrary size. Exploring all such conjunctions manually is a tedious task. TAR2 automatically finds the strongest select statements; i.e., the statement that *most* selects for preferred behavior while *most* discouraging undesirable behavior. TAR2 calls this strongest select statement the "treatment" since it is a recommended action for improving the current situation. TAR2's configuration file lets an analyst search for the best select statement using conjunctions of size 1,2,3,4, etc. Since TAR2's search is elaborate, an analyst can automatically find the *best* and *worst* possible situation within a data set. For example, the select statements seen in Figure 7 were learnt by TAR2 and show the *best* and *worst* possible situation for playing *lots* of golf.

TAR2 processed Figure 5.A by dividing the known outputs into "preferred" and "undesired" regions (here, "preferred" means lower costs and higher benefits and "undesired" means not preferred). With knowledge of that division, TAR2 learnt a set of constraints that select for the preferred outcomes while avoiding the undesired regions. The goal of TAR2 is to *improve the mean* and *reduce the variance* in the behavior of a system.

Figure 5.A shows 50,000 runs with DDP using mitigations compatible with the constraints learnt by TAR2. Comparing Figure 5.A withFigure 5.B, we see that the variance in behavior has indeed been greatly *reduced* while *decreasing* mean costs and *increasing* mean benefits.

TAR2 generated Figure 5.B using only a small subset of the available risks mitigations. TAR2 made recommendations on only $\frac{1}{3}rd$ of the 99 mitigations available in this DDP models.

Further details on this use of TAR2 on a DDP dataset are found in reference [4].

3.1 Drawbacks with TAR2

Figure 5.B shows that it is possible to use DDP models to optimize risk mitigation actions for complex systems, using only a *small subset* of the available options. However, in two aspects, the TAR2 experiment was a failure:

- *The runtime problems:* TAR2 is too slow. The DDP model had to be executed 50,000 times to learn the constraints that generated Figure 2b. This runtime is too long to support interactive argument support. Worse still, bigger DDP models would take even longer to execute. Clearly, a faster method is required.
- *The hiding problem.* TAR2's output can hide important details. Recall from Figure 5.B that there exists a cluster of results that are the best TAR2 can find. While any point in those clusters are the best TAR2 can offer, adjacent points in the cluster may represent very different mitigations, some of which are more acceptable to the users than others.

TAR2 ran slow since it sampled a large run where mitigations were selected randomly. Perhaps some other search might be more appropriate? In the sequel, we will discuss the merits of TAR2's search vs *simulated annealing*.

As to the *hiding problem*, we believe it is best addressed as a *quantitative value* problem. A limitation of the DDP ontology is that it asks a set of experts to agree upon some numeric quantity (using a number between 0.0 and 1.0) to rate various relationships: e.g., the impact of risks on objects, the effect of mitigations on risk, etc. In our experience, these experts have been able to do this. However, it is clear that the resulting model is less robust than the numeric values may suggest.

It is our hypothesis that such experts may be more comfortable agreeing upon a probability distribution that represents the impact of a risk on an objective or the effect of a mitigation on a risk. That is, they would be given a small number of possible distributions *having previously been informed about the characteristics of each* and asked to pick among them. They would also have to pick the appropriate parameters for each – e.g. mean and standard deviation for a normal distribution.

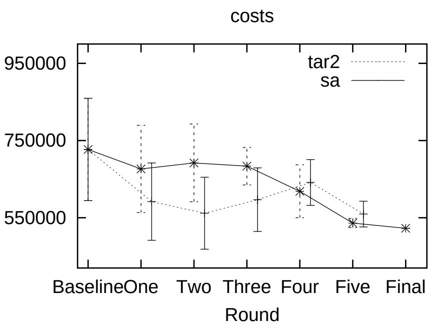
The thought is that, although this is more information for the experts to agree upon, it might get agreement faster since they would be recognizing that there is some embedded uncertainty in these values. agreeing upon a probability distribution that represents the impact of a risk on an objective or the effect of a mitigation on a risk. That is, they would be given a small number of possible distributions (having previously been informed about the characteristics of each) and asked to pick among them. They would also have to pick the appropriate parameters for each – e.g. mean and standard deviation for a normal distribution. Our thinking is that, although this is more information for the experts to agree upon, it might get agreement faster since they would be recognizing that there is some embedded uncertainty in these values.

3.2 Is Simulated Annealing Better Than TAR2?

Figure 8 compares TAR2 and simulated annealing. At each round X (shown on the x-axis), simulated annealing or TAR2 was used to extract key decisions from a log of runs of a DDP model. A new log is generated, with the inputs constrained to the key decisions found between round zero and round X. Further rounds of learning continue until the observed changes on costs and benefits stabilizes.

It is insightful to compare the results from TAR2 and simulated annealing:

- As seen in Figure 8, simulated annealing and TAR2 terminate in (nearly) the same cost-benefit zone.
- Simulated annealing did so using only 40% of the data needed by TAR2; i.e. while TAR2 needed 50,000 runs of DDP, the simulated annealing method needed only 20,000.
- The bad news is that, while TAR2 proposed constraints on 33% of the mitigations, simulated annealing proposed actions on 100% of the mitigations. Such a result is consistent with the nature of simulated annealing- this search is a global search through all options. Hence, it tends to propose solutions to a large part of the model.



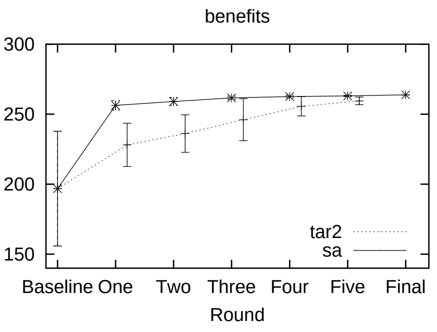


Figure 8. Comparison of TAR2 and simulated annealing.

In summary, the directed search of simulated annealing needs less data than TAR2, but in doing so, we lose the main advantage of TAR2; i.e. no drastic reduction in the space of options.

4 Conclusions and Future Work

Our current work has produced a set of tools to support decisions that need to be made by software engineers early in the software development life cycle. The DDP tool supports a model of requirements, risks (things that may cause requirements not to be attained), and mitigations (activities to reduce these risks.) This tool has been supplemented with an automated search mechanism (simulated annealing) that automates the process of finding near optimal sets of decisions in the large space of possible mitigating actions. We have also introduced some clustering abilities into DDP. This allows a visual representation of sets of decisions that are that are self-similar within each cluster, and significantly distinct between cluster. In a parallel development, we have been exploring the use of machine learning to identify those critical decisions that have an especially strong impact on cost and effectiveness.

4.1 Future Work: STAR1= simulated annealing + TAR2

In the future, we plan to explore additional ways of modeling Requirements and risk early in the lifecycle, to more completely integrate this existing set of tools, and to further test this integrated package on actual projects at JPL or other NASA laboratories. For example, the directed search of SA needs less data than TAR2, but in doing so, we lose the main advantage of TAR2; i.e. no drastic reduction in the space of options. Perhaps we can get the best of both approaches.

Our research is exploring combining the advantages of TAR2 (the selection of a small number of critical decisions) with SA (faster, directed search and an exploration of a larger space of possibilities). The "jumps" in simulated annealing are generated by mutating the best solution seen so far. In traditional SA, these mutations are selected at random. In our proposed approach, we would run a contrast set learner in parallel with the SA to build up a probability profile on settings that were most associated with worse solutions. The mutation sub-routine of the SA would then be modified to avoid mutations that include settings from the worst solutions.

Our analogy for this process is that of a rocket flying down towards some preferred solution. SA is the *gravity* that pulls the rocket down faster while the contrast set learning is the *booster* than thrusts the rocket away from undesired situations.

Specifically, our goals are:

- Implement STAR1, a combination of SA (or other AI search algorithms) and TAR2, and integrate the result with DDP
- Tune the STAR1 such that it such that it terminates in < 10 seconds (i.e. in time to interact with some active debate on some part of a DDP model).
- Augment this integrated tool (STAR1) with a decision clustering tool
- Improve the modeling of risk in DDP through probability distributions
- Test this supplemented version of DDP during live debates on system options by JPL analysts.

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