



Troubleshooting with actions

A Troubleshooting model consists of

- A set of faults \mathcal{F} ($f_i \in \mathcal{F}$) that is potentially causing the problem.
- A set of *actions* \mathcal{A} ($A_i \in \mathcal{A}$) that can fix the problem.
- A dynamic set of *evidence* $\varepsilon = \{A \in \mathcal{A} \mid A \text{ failed to fix the problem (written } A = \neg a) \}$.
- A cost $C_A(\varepsilon)$ for each action A, possibly depending on evidence ε .
- A *Bayesian Network* that provides $P(A | \varepsilon)$, $P(A | f, \varepsilon)$ and $P(f | \varepsilon)$.



Figure 1: Left: a simple model for a troubleshooting scenario with dependent actions. The dotted lines indicate that the faults f_1 to f_4 are states in a single fault node F. A₁, A₂ and A₃ represent actions, and parents of an action node A are faults which may be fixed by A. Right: the quantitative part of the model.

Definition 1. The *expected cost of repair* (ECR) of a troubleshooting sequence $s = \langle A_1, \ldots, A_n \rangle$ with costs C_{A_i} is the mean of the costs until an action succeeds or all actions have been performed:

ECR (s) =
$$\sum_{i=1}^{n} C_{A_i}(\boldsymbol{\varepsilon}^{i-1}) \cdot P(\boldsymbol{\varepsilon}^{i-1})$$
.

The goal is to determine a sequence with the lowest ECR.

Example (ECR calculation)

Consider a sequence for the model in Figure 1:

$$\begin{aligned} \text{ECR}\left(\langle A_2, A_3, A_1 \rangle\right) &= C_{A_2} + P(\neg a_2) \cdot C_{A_3} + P(\neg a_2, \neg a_3) \cdot C_{A_1} \\ &= C_{A_2} + P(\neg a_2) \cdot C_{A_3} + P(\neg a_2) \cdot P(\neg a_3 | \neg a_2) \\ &= 1 + \frac{7}{20} \cdot 1 + \frac{7}{20} \cdot \frac{4}{7} \cdot 1 = 1.55 . \end{aligned}$$

The set of faults that can be repaired by an action A is denoted fa(A). For example, in Figure 1 we have $fa(A_2) = \{f_2, f_3\}$. In models where actions can have $P(a | \varepsilon) = 1$, $fa(\cdot)$ is a dynamic entity which we indicate by writing $fa(\cdot | \varepsilon)$.

Definition 2. The *efficiency* of an action A given evidence ε is the probability that the actions solves the problem divided by its cost, that is

$$ef(A | \boldsymbol{\varepsilon}) = \frac{P(A = a)}{C_A(\boldsymbol{\varepsilon})}$$

A* Wars: The Fight for Improving A* Search for Troubleshooting with Dependent Actions

Thorsten J. Ottosen and Finn Verner Jensen Department of Computer Science, Aalborg University, Denmark

A^{*} and monotonicity of the function \underline{ECR}

A* is a best-first search algorithm that works by continuously expanding a frontier node n for which the value of the *evaluation function*

$$f(n) = g(n) + h(n),$$

is minimal until finally a goal node t is expanded (Hart et al., 1968). If node mis reachable from node n, c(n,m) is the cost from n to m. Then g(n) = c(s,n)where s is the start node, and h(n) is the *heuristic function* that guides (or misguides) the search by estimating the cost c(n, t). For Troubleshooting we have

 $f(n) = \text{ECR}(\boldsymbol{\varepsilon}^n) + \text{ECR}(\boldsymbol{\varepsilon}^n)$

where ECR (ϵ^{n}) is the ECR of the sequence defined by the path from s to n.

Definition 3 (Vomlelová and Vomlel, 2003). Let \mathcal{E} denote the set containing all possible evidence. The function $\underline{\mathrm{ECR}} : \mathcal{E} \mapsto \mathcal{R}^+$ is defined for each $\varepsilon^n \in \mathcal{E}$ as

 $\underline{\mathrm{ECR}}(\boldsymbol{\varepsilon}^n) = \mathrm{P}(\boldsymbol{\varepsilon}^n) \cdot \sum \mathrm{P}(\mathrm{f} \,|\, \boldsymbol{\varepsilon}^n) \cdot \mathrm{ECR}^*(\boldsymbol{\varepsilon}^n \cup \mathrm{f}) \;.$

where $ECR^*(e^n \cup f)$ is the optimal cost when a fault f is known.

Example (ECR* calculation)

Assume the fault f can be repaired by two actions A_1 and A_2 and that $P(a_1|f) = 0.9$ and $P(a_2|f) = 0.8$. Furthermore, let both actions have cost 1. Since instantiating the fault node renders the actions conditionally independent, $P(a | \varepsilon \cup f) = P(a | f)$ and the efficiencies of the two actions are 0.9 and 0.8, respectively. We get

$$ECR^{*}(\boldsymbol{\varepsilon} \cup f) = ECR(\langle A_{1}, A_{2} \rangle) = C_{A_{1}} + P(\neg a_{1} | f)$$

because the optimal sequence with independent actions is found by ordering the actions w.r.t. descending initial efficiency (Kadane and Simon, 1977).

Definition 4. A heuristic function $h(\cdot)$ is *monotone* if

 $h(n) \le c(n,m) + h(m),$

whenever m is a successor node of n.

For monotone heuristic functions A* is *guaranteed* to have found the optimal path to a node when the node is expanded (Hart et al., 1968).

Theorem 1. Under the assumption of no questions, constant costs, a single initial fault, and conditional independence of actions given that the fault is known, then the heuristic function $\underline{ECR}(\cdot)$ is monotone.

```
\cdot C_{A_1}
```

 $\cdot C_{A_2} = 1 + 0.1 \cdot 1 = 1.1$.

Hybrid-A* Algorithm

Definition 5. A *dependency graph* for a troubleshooting model given evidence ε is the undirected graph with a vertex for each action $A \in \mathcal{A}(\varepsilon)$ and an edge between two vertices A_1 and A_2 if $fa(A_1 | \varepsilon) \cap fa(A_2 | \varepsilon) \neq \emptyset$.

Definition 6. A *dependency set leader* for a troubleshooting model given evidence ε is the first action of an optimal sequence in a connectivity component in the dependency graph given ε (a *dependency set*).

Theorem 2 (Koca and Bilgiç, 2004). *The globally optimal sequence is given by* the following algorithm:

- I. Construct the dependency sets and retrieve the set leaders.
- **II.** Calculate $ef(\cdot)$ for all set leaders.

Hybrid-A*: We exploit Theorem 2 and avoid branching whenever the most efficient action belongs to a small dependency set (which is solved by brute-force).



Figure 2: An example of what the search tree looks like in the hybrid approach. For some nodes, the normal A* branching is avoided, and near goal nodes this branching is almost avoided for all nodes.

Experimental results



Figure 3: Comparison of normal A* (Ottosen and Jensen, 2008) with the hybrid approach. The X-axis indicates average dependency of the model (that is, the average size of $fa(\cdot)$ over all actions), and the Y-axis represents time in seconds. All models had 20 actions and 20 faults.



III. Select the set leader with the highest $ef(\cdot)$ and perform it. **IV.** If it fails, update the probabilities, and continue in step (2).

References

P. E. Hart, N. J. Nilsson, and B. Raphael. A formal basis for the heuristic determination of minimum cost paths. IEEE Trans. Systems Science and Cybernetics, SSC-4(2):100–7, 1968.

J. Kadane and H. Simon. Optimal strategies for a class of constrained sequential problems. The Annals of

Statistics, 5:237–255, 1977.

E. Koca and T. Bilgiç. A troubleshooting approach with dependent actions. In R. L. de Mántaras and L. Saitta, editors, ECAI 2004: 16th European Conference on Artificial Intelligence, pages 1043–1044. IOS Press, 2004. ISBN 1-58603-452-9.

- T. J. Ottosen and F. V. Jensen. Better safe than sorry—optimal troubleshooting through A* search with efficiency-based pruning. In *Proceedings of the Tenth Scandinavian Conference on Artificial Intelligence*, pages 92–97. IOS Press, 2008. ISBN 978-1-58603-867-0.
- *Volume 7, Number 5*, pages 357–368, 2003.

M. Vomlelová and J. Vomlel. Troubleshooting: Np-hardness and solution methods. Soft Computing Journal,