Techniques for Diagnosing Software Faults

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1 Introduction

This technical report is meant to report our findings and ideas with respect to spectrum-based fault localization and model-based diagnosis. In the following we want to introduce and compare model-based diagnosis (MBD), spectrum-based fault localization (SFL) and our contributions using 3-inverters as a running example (which is simple, yet sufficiently interesting).

The remainder of this paper is organized as follows. The concepts and definitions used in this paper are given in the next section. The combination of model-based diagnosis and Bayesian reasoning, as it is normally applied to, e.g., digital circuits, is discussed in Section 3. Spectrum-based fault localization, including the system transformation for instrumentation to collect data to reason about failures is discussed in Section 4.1. In Section 4.2 we investigate several novel approaches for applying model-based diagnosis, and notably Bayesian reasoning to systems that have been prepared for spectrum-based fault localization.

2 Preliminaries

Definition 1 By a system under observation, or system we mean a tuple \( (C, V, S) \), where

- \( C \) is a finite, non-empty set of components \( \{c_1, \ldots, c_n\} \).
- \( V \) is a finite, non-empty sequence \( x_1, \ldots, x_k \) of observable variables, with respective domains \( D_1, \ldots, D_k \).
- \( S \in D_1 \times \ldots \times D_k \) represents the specified behavior.

Further, by an observation we mean a tuple \( \langle v_1, \ldots, v_k \rangle \in D_1 \times \ldots \times D_k \). An observation \( \emptyset \notin S \) is called a failure.

With each component \( c_m \in COMPS \) we associate a health variable \( h_m \) which denotes component health. The health states of a component are healthy (true) and faulty (false), but this concept can easily be generalized to any finite domain [?].

Definition 2 An h-literal is \( h_m \) or \( \neg h_m \) for \( c_m \in COMPS \).

Definition 3 An h-clause is a disjunction of h-literals containing no complementary pair of h-literals.

Definition 4 Let \( S_N \) and \( S_P \) be two disjoint sets of healthy and faulty components, respectively, such that \( C = \{m \mid m \in S_N \cup S_P\} \) and \( S_N \cap S_P = \emptyset \). A diagnosis candidate is \( d_k(S_N, S_P) \)

\[
( \bigwedge_{c_m \in S_N} \neg h_m ) \land ( \bigwedge_{c_m \in S_P} h_m )
\]

Definition 5 A diagnosis \( D = \{d_1, \ldots, d_k, \ldots, d_K\} \) is an ordered set of all \( K \) diagnosis candidates.
For simplicity, we refer to \( d \) in terms of a set of the negations literals only.

The purpose of diagnosis is to identify the component, or combination of components that causes observed system failures, and the starting point of such an analysis is a system \( \langle C, V, S \rangle \), and a sequence of observations \( obs_1, \ldots, obs_m \) that contains at least one failure. Note that in our definition of a system under observation the components in \( C \) are not related to the observations, and without further information we cannot exclude any diagnosis candidate from the powerset of \( C \) except the empty diagnosis candidate, which indicates that all components function correctly.

In this report we will describe and compare several techniques that help make meaningful selections of diagnosis candidates in one or both of the following ways:

- by reducing the number of diagnosis candidates, and
- by ranking diagnosis candidates with respect to the likelihood that they explain the observations.

Figure 1 illustrates the combinations of techniques that we will consider.

The primary technique for reducing the number of diagnosis candidates is model-based diagnosis (MBD). It entails that the system description \( \langle C, V, S \rangle \) is complemented with a model, on the basis of which we can exclude diagnosis candidates that do not logically explain all observations. The number of remaining diagnosis candidates is typically large, and Bayesian reasoning (BR) is normally applied as a companion to model-based diagnosis, to rank the remaining diagnosis candidate with respect to the probability that they reflect reality in presence of the observed behavior. In addition to providing the ranking, the calculated probabilities can also play a role in determining the quality of a diagnosis, and to guide the search for valid diagnosis candidates, but these applications are outside the scope of this paper.

As a second technique for ranking diagnosis candidates, we will consider spectrum-based fault localization (SFL). In this case, the observations relate to the activity of the components, and the diagnosis candidates are ranked according to the extent to which this activity coincides with the occurrence of failures. The measurements required for SFL are achieved through instrumentation, and we model this by a transformation of a system into a variant of that system that provides the necessary observations.

Traditionally, MBD+BR and SFL are applied to hardware and software, respectively. Some approaches to model-based software diagnosis exist, but a major problem with these approaches is that in general, neither the software models used in the development cycle, nor the models that can be derived from existing code, allow for a significant reduction of the number of diagnosis candidates. In this paper we investigate a different approach, where Bayesian reasoning is applied to calculate the probability that diagnosis candidates are supported by observations in the context of the instrumented system, which we also use for SFL. In addition, model-based diagnosis based on a simple, automatically generated causal model (\( SD_C \) in Figure 1) is used to counter the computational complexity.

2.1 Model-based Diagnosis

Without loss of generality, in this section we consider digital systems, which we define to be systems whose variable domains \( D_1, \ldots, D_k \) equal the set \{true, false\}. 
Definition 6 A system description for a digital system \( \langle C, V, S \rangle \) is a propositional formula \( M \) that involves at least the following propositional variables:

- the observable variables of the system, \( x_1, \ldots, x_k \),
- \( h_1, \ldots, h_n \), where \( n \) is the number of components in \( C \). These are the so-called health variables, where \( h_i \) represents the proposition that component \( c_i \) is healthy (functioning correctly).

Furthermore we require that

\[
\begin{align*}
    h_1 \land \ldots \land h_n \land x_{obs}^+ \land x_{obs}^- \land M \nmid \bot & \iff \text{obs} \in S,
\end{align*}
\]

where for \( \text{obs} := \langle v_1, \ldots, v_k \rangle \), \( x_{obs}^+ \) denotes the conjunction of literals \( x_i \) for which \( v_i = \text{true} \), and \( x_{obs}^- \) denotes the conjunction of literals \( \neg x_i \) for which \( v_i = \text{false} \).

Now a diagnosis candidate \( d \) is called a diagnosis candidate for the combination of a system \( \langle C, V, S \rangle \), a description of that system, and a single observation \( \text{obs} \) iff

\[
\begin{align*}
    h_{d^+} \land h_{d^-} \land x_{obs}^+ \land x_{obs}^- \land SD \nmid \bot,
\end{align*}
\]

where \( h_{d^+} \) denotes the conjunction of literals \( h_i \) for which \( c_i \in d \), and where \( h_{d^-} \) denotes the conjunction of literals \( \neg h_i \) for which \( c_i \notin d \), and where \( x_{obs}^+ \) and \( x_{obs}^- \) are as in Definition 6. The notion of a diagnosis for a single observation is extended to the notion of a diagnosis for a sequence of observations by requiring that the above condition holds for all observations in the sequence.

2.2 Observation-based Fault Localization

Given a system \( \langle C, V, S \rangle \) and a sequence of observations \( obs_1, \ldots, obs_m \), we define \( \langle C, V', S' \rangle \) and \( obs'_1, \ldots, obs'_m \) to be as follows.

- \( V' := a_1, \ldots, a_n, e \), i.e., the number of variables in the modified system is equal to the number of components, plus one. All variables of \( V' \) have domain \{true, false\}.
- For \( obs'_j := \langle a_1, \ldots, a_n, e \rangle \) we have
  - \( a_j \) indicates whether or not component \( c_j \) was involved in the computation that resulted in observation \( obs_j \),
  - \( e \) indicates whether \( obs_j \) is a failure or not, i.e., \( e \) is equal to the truth value of the condition \( obs_j \in S \).
- We define \( S' \) to contain those observations \( obs'_j := \langle a_1, \ldots, a_n, e \rangle \) having \( e = \text{false} \).

The set of observations are stored in a so-called observation matrix, which is defined as follows

**Definition 7** Let \( M \) be the number of components, and \( N \) the number of execution runs. Let \( O \) denote the \( N \times (M+1) \) observation matrix. For \( j \leq M \), the element \( o_{ij} \) is equal to 1 (true) if component \( j \) was observed to be involved in the execution of run \( i \), and 0 (false) otherwise. The element \( o_{i0, M+1} \) is equal to 1 (true) if run \( i \) failed, and 0 (false) otherwise. The rightmost column of \( O \) is also denoted as \( e \) (the error vector).

From \( O \) it is also possible to derive the probability \( r \) that a component is actually executed in a run (expressing code coverage), and the probability \( g \) that a faulty component is actually exhibiting good behavior (expressing fault coverage, also known as the “goodness” parameter \( g \) from MBD [2]).

2.3 Bayes’ Rule

Throughout this paper, components are assumed to fail independently. Therefore, in absence of any observation the probability a particular diagnosis \( d(\Delta, C - \Delta) \) is correct is:

\[
\Pr(d) = \prod_{c_m \in \Delta} \Pr(\neg h_m) \cdot \prod_{c_m \notin C - \Delta} (1 - \Pr(\neg h_m))
\]
where $\Pr(\neg h_n)$ is the given probability that component $c_m$ is faulted (not healthy). The probability for diagnosis $d$ being correct after an observation $obs$ is given by Bayes’ rule:

$$\Pr(d|SD \land obs) = \frac{\Pr(SD \land obs|d) \cdot \Pr(d)}{\Pr(SD \land obs)}$$

The denominator $\Pr(SD \land obs)$ is a normalizing term that is identical for all $d$ and thus needs not to be computed directly. Thus,

$$\Pr(d|SD \land obs) = \alpha \cdot \Pr(SD \land obs|d) \cdot \Pr(d)$$

$\Pr(SD \land obs|d)$ is defined as

$$\Pr(SD \land obs|d) = \begin{cases} 0 & \text{if } d \text{ and } SD \land obs \text{ are inconsistent} \\ 1 & \text{if } d \text{ logically follows from } SD \land obs \\ \epsilon & \text{if neither holds} \end{cases}$$

where various policies $\epsilon$ are possible [1]: different values for $\epsilon$ will be considered in the subsequent sections of this paper.

For multiple observations, Bayes’ rule can be applied in sequence. Thus, after a set of $m$ observations $SO = \{obs_1, \ldots, obs_n\}$ the probability a particular diagnosis $d$ is correct given by applying recursively the Bayes’ rule, yielding

$$\Pr(d|SD \land SO) = \alpha \cdot \Pr(SD \land obs_1|d) \cdot \ldots \cdot \Pr(SD \land obs_n|d) \cdot \Pr(d)$$

As $SD$ does not change, we use $\Pr(d|obs)$ instead of $\Pr(d|SD \land obs)$ for simplicity.

### 2.4 3-inv

The circuit in Figure 2 will be the running example throughout this paper.

![3-inverters example](image)

Figure 2. 3-inverters example

### 3 Model-Based Diagnosis

A weak model of an inverter component $c$ is given by

$$h \Rightarrow y = \neg x$$

Consequently, the circuit is modeled by

$$h_1 \Rightarrow w = \neg x$$
$$h_2 \Rightarrow y_1 = \neg w$$
$$h_3 \Rightarrow y_2 = \neg w$$

Consider the observation $obs = ((x, y_1, y_2) = (1, 1, 0))$. It follows

$$h_1 \Rightarrow \neg w$$
$$h_2 \Rightarrow \neg w$$
$$h_3 \Rightarrow w$$
which equals

\[
(-h_1 \lor -w) \\
(-h_2 \lor -w) \\
(-h_3 \lor w)
\]

Resolution yields

\[
(-h_1 \lor -h_3) \land (-h_2 \lor -h_3)
\]

also known as conflicts [4], meaning that (1) at least \(c_1\) or \(c_3\) is at fault, and (2) at least \(c_2\) or \(c_3\) is at fault.

The minimal diagnoses are the minimal hitting set [7], given by

\[
\neg h_3 \lor (-h_1 \land \neg h_2)
\]

Thus either \(c_3\) is at fault (single fault), or \(c_1\) and \(c_2\) are at fault (double fault). Given the weak model, any other fault combination that is subsumed by the above, two minimal diagnoses, is a valid diagnosis.

Assuming all inverters have equal a priori fault probability, clearly, the single fault has higher probability, i.e., should rank higher than the double fault candidate. The posterior probability of the diagnoses, given the observations, is computed using Bayes’ rule, updating the prior probability according to the extent the observation is explained by the candidate diagnosis as explained in Section 2.3. Thus,

\[
\Pr(-h_3|\text{obs}) = \alpha \cdot \Pr(\text{obs}|-h_3) \cdot \Pr(-h_3) \\
\Pr(-h_1 \land -h_2|\text{obs}) = \alpha \cdot \Pr(\text{obs}|-h_1 \land -h_2) \cdot \Pr(-h_1 \land -h_2)
\]

Let \(\Pr(-h_3) = p\) and assume components fail independently, the prior probabilities are given by

\[
\Pr(-h_3) = p \\
\Pr(-h_1 \land -h_2) = p^2
\]

If \(\epsilon\) is defined to be one divided by the number of observations that can be explained by a given diagnosis, and since there are 4 possible observations that can be explained by \(-h_3\), and 8 possible observations that can be explained by \(-h_1 \land -h_2\) it follows that

\[
\Pr(\text{obs}|-h_3) = \frac{1}{4} \\
\Pr(\text{obs}|-h_1 \land -h_2) = \frac{1}{8}
\]

Consequently,

\[
\Pr(-h_3|\text{obs}) = \alpha \cdot \frac{1}{4} \cdot p \\
\Pr(-h_1 \land -h_2|\text{obs}) = \alpha \cdot \frac{1}{8} \cdot p^2
\]

As the two minimal diagnoses are independent (weak fault model), both must sum up to 1, determining \(\alpha\).

For \(p = 0.01\) it follows

\[
\Pr(-h_3|\text{obs}) \approx 0.995 \\
\Pr(-h_1 \land -h_2|\text{obs}) \approx 0.005
\]

Instead of accounting for the scaling constant \(\alpha\) such that the posterior probabilities sum up to 1, we can also explicitly compute \(\Pr(\text{obs})\). By definition, as explained in Section 2.3, the conditional probability is calculated as follows

\[
\Pr(-h_3|SD \land obs) = \frac{\Pr((-h_3 \land (SD \land obs)))}{\Pr(SD \land obs)} \\
\Pr(-h_1 \land -h_2|SD \land obs) = \frac{\Pr((-h_1 \land -h_2) \land (SD \land obs)))}{\Pr(SD \land obs)}
\]

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For \( \text{obs} = ((x, y_1, y_2) = (1, 1, 0)) \), the solution \( \varsigma = SD \wedge \text{obs} = \neg h_3 \vee (\neg h_1 \wedge \neg h_2) \) holds,

\[
\begin{align*}
\Pr(\neg h_3 | \varsigma) &= \frac{\Pr(\neg h_3)}{\Pr(\neg h_3) + \Pr(\neg h_1) \cdot \Pr(\neg h_2) - \Pr(\neg h_1) \cdot \Pr(\neg h_2) \cdot \Pr(\neg h_3)} \\
\Pr(\neg h_1 \wedge \neg h_2 | \varsigma) &= \frac{\Pr(\neg h_1 \wedge \neg h_2)}{\Pr(\neg h_3) + \Pr(\neg h_1) \cdot \Pr(\neg h_2) - \Pr(\neg h_1) \cdot \Pr(\neg h_2) \cdot \Pr(\neg h_3)}
\end{align*}
\]

Thus, for \( p = 0.01 \)

\[
\begin{align*}
\Pr(\neg h_3 | \varsigma) &= \frac{p}{p + p^2 - p^3} = 0.99 \\
\Pr(\neg h_1 \wedge \neg h_2 | \varsigma) &= \frac{p^2}{p + p^2 - p^3} = 0.01
\end{align*}
\]

Now suppose that there is a second observation \( \text{obs}' = ((x, y_1, y_2) = (1, 1, 1)) \), which does not reveal any faulty behavior. Using the same reasoning as for the first \( \text{obs} \), all possible diagnoses explain \( \text{obs}' \)

\[
\begin{align*}
d_1 &= (h_1 \wedge h_2 \wedge h_3) \\
d_2 &= (h_1 \wedge h_2 \wedge \neg h_3) \\
&\vdots \\
d_7 &= (\neg h_1 \wedge \neg h_2 \wedge h_3) \\
d_8 &= (\neg h_1 \wedge \neg h_2 \wedge \neg h_3)
\end{align*}
\]

As mentioned before, probabilities are updated as follows

\[
\Pr(d_k | \{\text{obs}, \text{obs}'\}) = \alpha \cdot \Pr(\text{obs}' | d_k) \cdot \Pr(\text{obs} | d_k) \cdot \Pr(d_k)
\]

Due to the first observation, we only consider the two minimal diagnoses \( d_2 \) and \( d_7 \). Thus

\[
\begin{align*}
\Pr(\neg h_3 | \{\text{obs}, \text{obs}'\}) &= \alpha \cdot \Pr(\text{obs}' | \neg h_3) \cdot \Pr(\text{obs} | \neg h_3).p \\
\Pr(\neg h_1 \wedge \neg h_2 | \{\text{obs}, \text{obs}'\}) &= \alpha \cdot \Pr(\text{obs}' | \neg h_1 \wedge \neg h_2) \cdot \Pr(\text{obs} | \neg h_1 \wedge \neg h_2).p^2
\end{align*}
\]

Similarly to the previous observation, it follows that

\[
\begin{align*}
\Pr(\text{obs}' | \neg h_3) &= \frac{1}{4} \\
\Pr(\text{obs}' | \neg h_1 \wedge \neg h_2) &= \frac{1}{8}
\end{align*}
\]

Consequently

\[
\begin{align*}
\Pr(\neg h_3 | \{\text{obs}, \text{obs}'\}) &= \alpha \cdot \frac{1}{4} \cdot \frac{1}{4} \cdot p = \alpha \cdot \frac{1}{16} \cdot p \\
\Pr(\neg h_1 \wedge \neg h_2 | \{\text{obs}, \text{obs}'\}) &= \alpha \cdot \frac{1}{8} \cdot \frac{1}{8} \cdot p^2 = \alpha \cdot \frac{1}{64} \cdot p^2
\end{align*}
\]

### 4 Observation-based Diagnosis

In the following we assume that we cannot apply model-based techniques to derive diagnoses. Consider the same circuit. However, now we necessarily abstract from system structure and component behavior. Observations are associated with pass or fail information. Hence, the following observation matrix \( O \) is obtained:

\[
\begin{array}{ccc|c}
0 & 1 & 1 & 1 \\
1 & 0 & 1 & 1 \\
\end{array}
\]

\( obs_1 \) (c1 and c2 are involved, leading to \( y_1 = 1 \), i.e., a pass)

\( obs_2 \) (c1 and c3 are involved, leading to \( y_2 = 0 \), i.e., a fail)

There are generally two approaches towards diagnosing the above problem. The first approach, SFL, is popular in software. The second approach is based on logic reasoning, similar to MBD, but without the knowledge that comes from modeling component behavior and interconnection structure.
4.1 SFL

Returning to the example presented in the previous section, suppose we have the following $O$

\[
\begin{array}{ccc}
1 & 1 & 0 \\
1 & 0 & 1
\end{array}
\]

The data in $O$ can be compactly represented using four counters for each diagnosis. Let $d$ be a diagnosis, $S_F$ be the set of indices of non healthy components in $d$, $e$ be the index of the error detection information:

- $a_{11}(d) = \sum_{n=1..N} \big[ (\bigvee_{c_m \in S_F} o_{nm}) \land e_n \big]$  
- $a_{10}(d) = \sum_{n=1..N} \big[ (\bigvee_{c_m \in S_F} o_{nm}) \land \neg e_n \big]$  
- $a_{01}(d) = \sum_{n=1..N} \big[ (\bigwedge_{c_m \in S_F} \neg o_{nm}) \land e_n \big]$  
- $a_{00}(d) = \sum_{n=1..N} \big[ (\bigwedge_{c_m \in S_F} \neg o_{nm}) \land \neg e_n \big]$

where $[\cdot]$ is the Iverson’s operator [5].

Diagnosis in SFL consists in identifying the diagnoses that are more probable explanations for the errors. This is done by means of similarity coefficients taken from data clustering techniques [6], which are defined using the four counters just defined. As an example, the Ochiai similarity coefficient is defined as follows

\[
s(j) = \frac{a_{11}(j)}{\sqrt{(a_{11}(j) + a_{01}(j)) \ast (a_{11}(j) + a_{10}(j))}}
\]  

(1)

For the three single faults it follows

<table>
<thead>
<tr>
<th></th>
<th>$a_{01}$</th>
<th>$a_{10}$</th>
<th>$a_{11}$</th>
<th>$s$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\neg h_1$</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0.7</td>
</tr>
<tr>
<td>$\neg h_2$</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$\neg h_3$</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Compared to MBD, the second conflict is missing. Including this information would yield (3rd row)

\[
\begin{array}{ccc}
1 & 1 & 0 \\
1 & 0 & 1
\end{array}
\]

\begin{array}{ccc}
0 & 1 & 1
\end{array}

$obs_3$ ($c_2$ and $c_3$ are involved, leading to a fail)

For the three single faults it would follow

<table>
<thead>
<tr>
<th></th>
<th>$a_{01}$</th>
<th>$a_{10}$</th>
<th>$a_{11}$</th>
<th>$s$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\neg h_1$</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0.5</td>
</tr>
<tr>
<td>$\neg h_2$</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0.5</td>
</tr>
<tr>
<td>$\neg h_3$</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>1</td>
</tr>
</tbody>
</table>

For double faults it follows

<table>
<thead>
<tr>
<th></th>
<th>$a_{01}$</th>
<th>$a_{10}$</th>
<th>$a_{11}$</th>
<th>$s$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\neg h_1 \land \neg h_2$</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>0.82</td>
</tr>
<tr>
<td>$\neg h_2 \land \neg h_3$</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>0.82</td>
</tr>
<tr>
<td>$\neg h_1 \land \neg h_3$</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>0.82</td>
</tr>
</tbody>
</table>

Note that this way of counting multiple diagnoses start converging to a value that is merely dependent on the pass/fail ratio of the matrix as typically all component combinations will be involved in any computation (the triple fault $\neg h_1 \land \neg h_2 \land \neg h_3$ is involved in all - for the example above $s(\neg h_1 \land \neg h_2 \land \neg h_3) = 0.82$. Here, SFL does not provide a sound basis for multiple fault diagnosis.
4.2 Logic Reasoning

In this section we describe the logic reasoning (LR) method to compute diagnoses and present several approaches to compute the associated probabilities.

4.2.1 Compute Diagnoses

Unlike the MBD approach mentioned earlier, which statically deduces information from the program source, \( O \) is the only, dynamic source of information, from which both a model, and the input-output observations are derived. Apart from exploiting dynamic information, this approach only requires a generic component model, avoiding the need for detailed functional modeling or relying, e.g., on invariants or pragmas for model information. Note, however, that this default model can easily be extended when more detailed information is available.

Abstracting from particular component behavior, each component \( c_j \) is modeled by the weak model

\[
h_j \Rightarrow (x_j \Rightarrow y_j)
\]

where \( h_j \) models the health state of \( c_j \) and \( x_j, y_j \) model its input and output variable value correctness (i.e., we abstract from actual variable values, in contrast to the earlier example). This weak model implies that a healthy component \( c_j \) translates a correct input \( x_j \) to a correct output \( y_j \). However, a faulty component or input may lead to an erroneous output.

As each row in \( O \) specifies which components were involved, we interpret a row as a “run-time” model of the program as far as it was considered in that particular run. Consequently, \( O \) is interpreted as a sequence of typically different models of the program, each with its particular observation of input/output correctness. The overall diagnosis can be viewed as a sequential diagnosis approach that incrementally takes into account new structural program (and pass/fail) evidence with increasing \( N \).

A single row \( O_n, \ast \) corresponds to the (sub)model

\[
h_m \Rightarrow (x_m \Rightarrow y_m), \text{ for } m \in I_n
\]

\[
x_{s_i} = y_{s_i-1}, \text{ for } i \geq 2
\]

\[
x_1 = \text{true}
\]

\[
y_{s'} = \lnot e_n
\]

where \( I_n = \{m \in \{1, \ldots, M\} \mid o_{nm} = 1\} \) denotes the well-ordered set of component indices involved in computation \( n \), \( s_i \) denotes the \( i \)th element in this ordering, (i.e., for \( i \leq j, s_i \leq s_j \)), \( s' \) denotes its last element. The resulting component chain logically reduces to

\[
\bigwedge_{m \in S_n} h_m \Rightarrow \lnot e_n
\]

For example, consider the row \((M = 5)\)

<table>
<thead>
<tr>
<th>c1</th>
<th>c2</th>
<th>c3</th>
<th>c4</th>
<th>c5</th>
<th>e</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

This corresponds to a model where components \( c_1, c_4 \) are involved. As the order of the component invocation is not given (and with respect to our above weak component model is irrelevant), we derive the model

\[
h_1 \Rightarrow (x_1 \Rightarrow y_1)
\]

\[
h_4 \Rightarrow (x_4 \Rightarrow y_4)
\]

\[
x_4 = y_1
\]

\[
x_1 = \text{true}
\]

\[
y_4 = \lnot e_n
\]

In this chain the first component \( c_1 \) is assumed to have correct input \((x_1 = \text{true})\), typical of a proper test, its output feeds to the input of the next component \( c_4 (x_4 = y_1) \), whose output is measured in terms of \( e_n (y_4 = \lnot e_n) \). This chain logically reduces to

\[
h_1 \land h_4 \Rightarrow \text{false}
\]
If this were a passing computation \((h_1 \land h_4 \Rightarrow \text{true})\) we could not infer anything (apart from the exoneration when it comes to probabilistically rank the diagnosis candidates as explained in next section). However, as this run failed this yields

\[-h_1 \lor -h_4\]

which, in fact, is a conflict. In summary, each failing run in \( O \) generates a conflict according to

\[\bigvee_{m \in S_n} -h_m\]

As in the former MBD approach, the conflicts are then subject to a hitting set algorithm that generates the diagnostic candidates.

To illustrate this concept, again consider the example program. For the purpose of the spectral approach we assume the program to be run two times where the first time we consider the correctness of \(y_1\) and the second time \(y_2\). This yields the observation matrix \( O \) below

<table>
<thead>
<tr>
<th>(c_1)</th>
<th>(c_2)</th>
<th>(c_3)</th>
<th>(e)</th>
<th>(\text{obs})</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>(\text{obs}_1)</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>(\text{obs}_2)</td>
</tr>
</tbody>
</table>

From \(\text{obs}_2\), it follows

\[-h_1 \lor -h_3\]

which equals the first conflict from the earlier MBD approach, and the diagnosis trivially comprises the two single faults \(\{1\} (-h_1)\) and \(\{3\} (-h_3)\). Compared to the earlier MBD approach, the second conflict \((-h_2 \lor -h_3)\) is missing due to the fact that no additional knowledge is available on component behavior and component interconnection. Although this would suggest that the dynamic approach yields lower diagnostic performance than the earlier MBD approach, note that the example program is ideally suited to static analysis, whereas real programs feature extensive control flow, rendering the previous approach extremely difficult. However, if, for some reason, we were able to capture the second conflict in terms of the execution trace according to

<table>
<thead>
<tr>
<th>(c_1)</th>
<th>(c_2)</th>
<th>(c_3)</th>
<th>(e)</th>
<th>(\text{obs})</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>(\text{obs}_3)</td>
</tr>
</tbody>
</table>

then our observation-based approach would yield exactly the same set of minimal diagnoses.

### 4.2.2 Classical Model for Computing Probabilities

Computing probabilities is done in much the same way as in MBD. For every diagnosis candidate, we update the posteriors by the extent that the observation is explained by the candidate diagnosis. In contrast to the MBD case, an observation is not an input or output value, but pass or fail information \(e_m\) (as the input and outputs are already taken into account by \(e\)).

Suppose the following two observations

<table>
<thead>
<tr>
<th>(c_1)</th>
<th>(c_2)</th>
<th>(c_3)</th>
<th>(e)</th>
<th>(\text{obs})</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>(\text{obs}_1)</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>(\text{obs}_2)</td>
</tr>
</tbody>
</table>

After \(\text{obs}_1\), all diagnoses are still possible (8 in total)

\[d_1 = (h_1 \land h_2 \land h_3)\]
\[d_2 = (h_1 \land h_2 \land \neg h_3)\]
\[\ldots\]
\[d_7 = (\neg h_1 \land \neg h_2 \land h_3)\]
\[d_8 = (\neg h_1 \land \neg h_2 \land \neg h_3)\]

and their probabilities are updated according to Bayes’ rule

\[\Pr(d_i|\text{obs}_1) = \alpha \cdot \Pr(\text{obs}_1|d_i) \cdot \Pr(d_i)\]
where \( \epsilon \) is defined as follows
\[
\epsilon = \begin{cases} 
\frac{E_P}{E_P + E_F} & \text{if run passed} \\
\frac{E_F}{E_P + E_F} & \text{if run failed} 
\end{cases}
\]  
(2)

where \( E_P = 2^M \) and \( E_F = (2^l - 1) \cdot 2^{M-l} \) are the number of passed and failed observations that can be explained by diagnosis \( d_k \), respectively, and \( l = |S_N| \) is the number of faulty components in the diagnosis. Although this observation does not help much in pinpointing the fault (all diagnoses are still valid), its update makes single faults more probable than multiple faults.

As mentioned before, when considering \( obs_2 \), the minimal set of diagnoses is \( \neg h_1 \) or \( \neg h_3 \), and their probabilities are updated by
\[
\begin{align*}
\Pr(\neg h_1|\{obs_1, obs_2\}) &= \alpha \cdot \Pr(\neg h_1|\neg h_3) \cdot \Pr(\neg h_1|\neg h_2) \\
\Pr(\neg h_3|\{obs_1, obs_2\}) &= \alpha \cdot \Pr(\neg h_3|\neg h_3) \cdot \Pr(\neg h_3|\neg h_2)
\end{align*}
\]
yielding
\[\Pr(\neg h_1|\{obs_1, obs_2\}) = \alpha \cdot \frac{4}{12} \cdot \frac{8}{12} \cdot p = 0.5\]
\[\Pr(\neg h_3|\{obs_1, obs_2\}) = \alpha \cdot \frac{4}{12} \cdot \frac{8}{12} \cdot p = 0.5\]

However, if we assume \( O \) also includes the second MBD conflict, i.e., \( obs_3 \), then the set of consistent diagnoses is the same as for MBD, i.e., \( \neg h_3 \) and \( \neg h_1 \land \neg h_2 \).
\[
\begin{align*}
\Pr(\neg h_3|O) &= \alpha \cdot \Pr(\neg h_3|\neg h_3) \cdot \Pr(\neg h_3|\neg h_3) \cdot \Pr(\neg h_3|\neg h_3) \cdot \Pr(\neg h_3|\neg h_3) \cdot \Pr(\neg h_3|\neg h_3) \cdot \Pr(\neg h_3|\neg h_3) \\
\Pr(\neg h_1 \land \neg h_2|obs_3) &= \alpha \cdot \Pr(\neg h_1 \land \neg h_2|\neg h_3) \cdot \Pr(\neg h_1 \land \neg h_2|\neg h_3) \cdot \Pr(\neg h_1 \land \neg h_2|\neg h_3) \cdot \Pr(\neg h_1 \land \neg h_2|\neg h_3) \cdot \Pr(\neg h_1 \land \neg h_2|\neg h_3) \cdot \Pr(\neg h_1 \land \neg h_2|\neg h_3)
\end{align*}
\]
Consequently
\[
\begin{align*}
\Pr(\neg h_3|O) &= \alpha \cdot \frac{4}{12} \cdot \frac{4}{12} \cdot \frac{8}{12} \cdot p \\
\Pr(\neg h_1 \land \neg h_2|O) &= \alpha \cdot \frac{6}{14} \cdot \frac{6}{14} \cdot \frac{8}{14} \cdot p^2
\end{align*}
\]
Note that when the two failed observations are available, the minimal diagnosis \( \neg h_1 \) is no longer a valid explanation.

### 4.2.3 Intermittency Model for Computing Probabilities

A disadvantage of the classical probability model is that components involved in passed runs are not exonerated, and there is not a way to distinguish between diagnoses with the same cardinality. An approach to account for the fact that, similar to SPL, components involved in passed computations should be exonerated, by extending the component model with an intermittent failure model, as introduced in MBD [2].

We include statistical information on the probability that a faulty component \( c \) will exhibit correct behavior (i.e., produce correct output). Let \( g(c) \) denote this probability. In the following we will distinguish three different Bayesian update schemes \( (\epsilon) \), which we refer to as Method 1, Method 2, and Method 3.

#### 4.2.4 Method 1

In this method, the observations made during passed runs are also taken into account by extending the \( \epsilon \) definition as follows
\[
\Pr(\text{obs}|D) = \begin{cases} 
0 & \text{if } d \text{ and obs are inconsistent} \\
1 & \text{if } d \text{ logically follows from obs} \\
1 & \text{if neither holds, run passed, and } a_{10}(d) = 0 \\
g(d) & \text{if none of the above and run passed} \\
1 - g(d) & \text{if none of the above and run failed}
\end{cases}
\]

where \( g(d) = \frac{a_{10}(d)}{a_{10}(d) + a_{11}(d)} \) (i.e., the fraction of involvement of the faulty component(s) that did not lead to a failure).

Again, considering the following two observations...
The hitting set for the weak model is equal to $\neg h_1 \lor \neg h_3$. After $obs_1$, the probabilities of $\neg h_1$ and $\neg h_3$ are updated as follows

$$
\Pr(\neg h_1|obs_1) = \alpha \cdot \Pr(obs_1|\neg h_1) \cdot p \\
\Pr(\neg h_3|obs_1) = \alpha \cdot \Pr(obs_1|\neg h_3) \cdot p
$$

where, from the definition, $\Pr(obs_1|\neg h_1) = g(\neg h_1)$ and $\Pr(obs_1|\neg h_3) = 1$. Thus

$$
\Pr(\neg h_1|obs_1) = \alpha \cdot g(\neg h_1) \cdot p \\
\Pr(\neg h_3|obs_1) = \alpha \cdot 1 \cdot p
$$

Similarly, after $obs_2$ the probabilities are updated as follows

$$
\Pr(\neg h_1|\{obs_1, obs_2\}) = \alpha \cdot \Pr(obs_2|\neg h_1) \cdot \Pr(obs_1|\neg h_1) \cdot p \\
\Pr(\neg h_3|\{obs_1, obs_2\}) = \alpha \cdot \Pr(obs_2|\neg h_3) \cdot \Pr(obs_1|\neg h_3) \cdot p^2
$$

where, from the definition, $\Pr(obs_2|D) = 1 - g(d)$, and $\Pr(obs_2|D) = 1 - g(d)$ is as previously defined. Consequently

$$
\Pr(\neg h_1|\{obs_1, obs_2\}) = \alpha \cdot (1 - g(\neg h_1)) \cdot g(\neg h_1) \cdot p \\
\Pr(\neg h_3|\{obs_1, obs_2\}) = \alpha \cdot (1 - g(\neg h_3)) \cdot 1 \cdot p
$$

Since $g(\neg h_1) = 0.5$ and $g(\neg h_3) = 0$

$$
\Pr(\neg h_1|\{obs_1, obs_2\}) = 0.2 \\
\Pr(\neg h_3|\{obs_1, obs_2\}) = 0.8
$$

which means that $\neg h_3$ is more probable to be the diagnostic explanation as $\neg h_1$ is partially exonerated. Compared to LR without intermittency, this method distinguishes between the two diagnoses, whereas in the previous method $\neg h_3$ and $\neg h_1$ were considered equally likely equal for explaining the fault.

Again, when compared to MBD approach the second conflict ($\neg h_2 \lor \neg h_3$) is missing. However, as explained in the previous section, if $obs_3$ were available, this approach would result in the same diagnostic performance as MBD

$$
\neg h_3 \lor (\neg h_1 \land \neg h_2)
$$

The probabilities are calculated according to

$$
\Pr(\neg h_3|O) = \alpha \cdot \Pr(obs_3|\neg h_3) \cdot \Pr(obs_2|\neg h_3) \cdot \Pr(obs_1|\neg h_3) \cdot p \\
\Pr(\neg h_1 \land \neg h_2|O) = \alpha \cdot \Pr(obs_3|\neg h_1 \land \neg h_2) \cdot \Pr(obs_2|\neg h_1 \land \neg h_2) \cdot \Pr(obs_1|\neg h_1 \land \neg h_2) \cdot p^2
$$

(Note that the diagnosis $\neg h_1 \land \neg h_2$ was previously discarded because it was not a minimal diagnosis. However, have we not discarded non-minimal diagnoses, its probability would be updated as follows $\Pr(\neg h_1 \land \neg h_2|\{obs_1, obs_2\}) = \alpha \cdot (1 - g(\neg h_1 \land \neg h_2)) \cdot g(\neg h_1 \land \neg h_2) \cdot p^2$). From the definition, it follows

$$
\Pr(obs_1|\neg h_3) = 1 \\
\Pr(obs_1|\neg h_1 \land \neg h_2) = g(\neg h_1 \land \neg h_2) \\
\Pr(obs_3|\neg h_3) = \Pr(obs_2|\neg h_3) = 1 - g(\neg h_3) \\
\Pr(obs_3|\neg h_1 \land \neg h_2) = \Pr(obs_2|\neg h_1 \land \neg h_2) = 1 - g(\neg h_1 \land \neg h_2)
$$
Hence,
\[
\Pr(\neg h_3 | O) = \alpha \cdot (1 - g(\neg h_3)) \cdot (1 - g(\neg h_3)) \cdot 1 \cdot p
\]
\[
\Pr(\neg h_1 \land \neg h_2 | O) = \alpha \cdot (1 - g(\neg h_1 \land \neg h_2)) \cdot (1 - g(\neg h_1 \land \neg h_2)) \cdot g(\neg h_1 \land \neg h_2) \cdot 1 \cdot p^2
\]
yielding
\[
\Pr(\neg h_3 | O) = \alpha \cdot 1^2 \cdot p
\]
\[
\Pr(\neg h_1 \land \neg h_2 | O) = \alpha \cdot (1 - 0.33)^2 \cdot 0.33 \cdot p^2
\]
thus,
\[
\Pr(\neg h_3 | O) = \alpha \cdot p
\]
\[
\Pr(\neg h_1 \land \neg h_2 | O) = \alpha \cdot 0.15 \cdot p^2
\]
Meaning that the \(\neg h_3\) is more probable than \(\neg h_1 \land \neg h_2\).

Generalizing, in terms of \(a_{11}, a_{10}, a_{01}\), and \(a_{00}\), the probability of diagnosis \(d\) after \(O\) is observed equals
\[
\Pr(d | O) = \alpha \cdot g(d)^{a_{11}(d)} \cdot (1 - g(d))^{a_{10}(d)} \cdot Pr(d)
\]

4.2.5 Method 2

This method is essentially the same as Method 1, except that it also takes into account the number of faulty components involved in the observation (in contrast to Method 1) by taking
\[
\Pr(\text{obs} | D) = \begin{cases} 
0 & \text{if } d \text{ and obs are inconsistent} \\
1 & \text{if } d \text{ logically follows from obs} \\
1 & \text{if neither holds, run passed, and } a_{10}(D) = 0 \\
\frac{g(d)^{ct}}{1 - g(d)^{ct}} & \text{if none of the above and run passed} \\
\frac{g(d)^{ct}}{1 - g(d)^{ct}} & \text{if none of the above and run failed}
\end{cases}
\]
where \(ct\) is the number of faulty components involved in the observation, and \(g(d)\) is defined as in the previous section. The rationale is that if more faulty components are involved, it is more likely the run will fail.

For the two single fault diagnoses that follow from LR on observations \(\text{obs}_1\) and \(\text{obs}_2\) this method yields the same results as Method 1 (as \(ct = 1\))
\[
\Pr(\neg h_1 | \{\text{obs}_1, \text{obs}_2\}) = 0.2
\]
\[
\Pr(\neg h_3 | \{\text{obs}_1, \text{obs}_2\}) = 0.8
\]
However, for multiple fault diagnoses this method may give different results. Suppose again the following \(O\)
\[
\begin{array}{ccc}
1 & 1 & 0 \\
1 & 0 & 1 \\
0 & 1 & 1
\end{array}
\]
\[
\begin{array}{c}
\text{obs}_1 \\
\text{obs}_2 \\
\text{obs}_3
\end{array}
\]
As mentioned before, the hitting set for the weak model equals \(\neg h_3 \lor (\neg h_1 \land \neg h_3)\). It follows
\[
\Pr(\neg h_3 | O) = \alpha \cdot \Pr(\text{obs}_3 | \neg h_3) \cdot \Pr(\text{obs}_2 | \neg h_3) \cdot \Pr(\text{obs}_1 | \neg h_3) \cdot p
\]
\[
\Pr(\neg h_1 \land \neg h_2 | O) = \alpha \cdot \Pr(\text{obs}_3 | \neg h_1 \land \neg h_2) \cdot \Pr(\text{obs}_2 | \neg h_1 \land \neg h_2) \cdot \Pr(\text{obs}_1 | \neg h_1 \land \neg h_2) \cdot p^2
\]
From the definition, it follows
\[
\Pr(\text{obs}_3 | \neg h_3) = 1
\]
\[
\Pr(\text{obs}_3 | \neg h_1 \land \neg h_2) = g(\neg h_1 \land \neg h_2)^2
\]
\[
\Pr(\text{obs}_3 | \neg h_3) = \Pr(\text{obs}_2 | \neg h_3) = 1 - g(\neg h_3)^1
\]
\[
\Pr(\text{obs}_3 | \neg h_1 \land \neg h_2) = pr(\text{obs}_2 | \neg h_1 \land \neg h_2) = 1 - g(\neg h_1 \land \neg h_2)^1
\]
Hence,
\[
\Pr(\neg h_3|O) = \alpha \cdot (1 - g(\neg h_3)) \cdot (1 - g(\neg h_3)) \cdot 1 \cdot p \\
\Pr(\neg h_1 \land \neg h_2|O) = \alpha \cdot (1 - g(\neg h_1 \land \neg h_2))^1 \cdot (1 - g(\neg h_1 \land \neg h_2)^1) \cdot g(\neg h_1 \land \neg h_2)^2 \cdot p^2
\]

Thus, by evaluating \( g(d) \),
\[
\Pr(\neg h_3|O) = \alpha \cdot \cdot p \\
\Pr(\neg h_1 \land \neg h_2|O) = \alpha \cdot 0.049 \cdot p^2
\]

Similarly to Method 1, this method considers the single explanation more probable than the double fault.

Generalizing, the probability of diagnosis \( d \) after \( O \) is observed is updated according to
\[
\Pr(d|O) = \alpha \cdot \prod_{i \in \{1..|S_F|\}} (g(d)^i)^{pr(d,i)} \cdot (1 - g(d)^i)^{fr(d,i)} \cdot \Pr(d)
\]

where \( pr \) and \( fr \) count the number of passed and failed runs where it was observed that \( i \) faulty components where involved, respectively, i.e.,
\[
pr(d,i) = \sum_{m \in \{1..M\}} [|\{n|o_{mn} \land n \in S_F \land e_m\}| = i] \\
fr(d,i) = \sum_{m \in \{1..M\}} [|\{n|o_{mn} \land n \in S_F \land -e_m\}| = i]
\]

where \( S_F \) is the set of indices of faulty components in \( d \), and \([\cdot]\) is the Iverson’s operator.

4.2.6 Method 3

In this variant, the updates are computed based on [3], where \( \epsilon \) is defined as
\[
\Pr(obs|D) = \begin{cases} 
1 & \text{if } d \text{ and } obs \text{ are inconsistent} \\
0 & \text{if } d \text{ logically follows from } obs \\
\epsilon = 1 - g(d) & \text{if neither holds for passed and failed runs}
\end{cases}
\]

where \( g(d) \) is defined as in the previous methods. Therefore, in terms of \( a_{11}, a_{10}, a_{01}, \) and \( a_{00}, \epsilon \) can be re-written as follows
\[
\epsilon = \frac{a_{11}(D)}{a_{11}(D) + a_{10}(D)}
\]

Consequently for
\[
\begin{array}{ccc}
1 & 1 & 0 \\
1 & 0 & 1 \\
\end{array}
\]

we obtain
\[
\Pr(\neg h_1|\{obs_1, obs_2\}) = \alpha \cdot \Pr(\{obs_1, obs_2\}|\neg h_1) \cdot p \\
\Pr(\neg h_3|\{obs_1, obs_2\}) = \alpha \cdot \Pr(\{obs_1, obs_2\}|\neg h_3) \cdot p
\]

where
\[
\Pr(\{obs_1, obs_2\}|\neg h_1) = \left( \frac{a_{11}(\neg h_1)}{a_{11}(\neg h_1) + a_{10}(\neg h_1)} \right)^{a_{11}(\neg h_1) + a_{10}(\neg h_1)} \\
\Pr(\{obs_1, obs_2\}|\neg h_3) = \left( \frac{a_{11}(\neg h_3)}{a_{11}(\neg h_3) + a_{10}(\neg h_3)} \right)^{a_{11}(\neg h_3) + a_{10}(\neg h_3)}
\]
resulting in,
\[
\Pr(\neg h_1 | \{obs_1, obs_2\}) = \alpha \cdot 0.5^2 \cdot p = 0.20 \\
\Pr(\neg h_3 | \{obs_1, obs_2\}) = \alpha \cdot 1^2 \cdot p = 0.80
\]

If the second failed observation is considered, the approach diagnostic results equals to \(\neg h_3 \lor (\neg h_1 \land \neg h_2)\), and the probabilities are updated according to:
\[
\Pr(\neg h_3) = \alpha \cdot 0.67^3 \cdot p^2 = \alpha \cdot 0.30 \cdot p^2
\]

4.3 Summary

<table>
<thead>
<tr>
<th>( \Pr(\neg h_1) )</th>
<th>Classical</th>
<th>Method 1</th>
<th>Method 2</th>
<th>Method 3</th>
<th>( \Pr(\neg h_3) )</th>
<th>Classical</th>
<th>Method 1</th>
<th>Method 2</th>
<th>Method 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>(0.5)</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td></td>
<td>(0.98)</td>
<td>0.999</td>
<td>0.99</td>
<td>0.77</td>
<td></td>
</tr>
<tr>
<td>(0.5)</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td></td>
<td>(0.02)</td>
<td>0.01</td>
<td>0.001</td>
<td>0.23</td>
<td></td>
</tr>
</tbody>
</table>

(a) After \(obs_1\) and \(obs_2\)  
(b) After \(obs_1\), \(obs_2\), and \(obs_3\)

Figure 3. Probabilities updates

Let \(\Pr(\neg h_m) = 0.01\). Figure 3 lists the probabilities resulting from the various \(\epsilon\) policies for the diagnoses obtained after \(obs_1\) and \(obs_2\) only (Figure 3(a)) and after \(obs_3\) (Figure 3(b)). In the first case, the classic policy cannot distinguish between \(c_1\) and \(c_3\) while the \(g\) policies exploit the additional information provided by the exonerating observation \(obs_1\). When \(obs_3\) is included \(c_1\) is no longer a valid diagnosis by itself, and is eliminated from the (hitting) set of valid diagnosis candidates. Hence, all policies favor \(c_3\) as most likely candidate, due to (1) the lower prior probability of the double fault (all policies) and (2) the exoneration by passed runs (methods 1, 2, and 3).

5 Analytic Model

In this section we derive a simple, approximate model to assess the influence of various parameters on the wasted debugging effort \(W\). It is defined as the effort that is wasted on inspecting a component that was not faulty. In our computation of \(W\) we assume that after each inspection, the test set is rerun, possibly leading to a new ranking (without the most recently removed fault). For example, suppose a triple-fault program \((M = 6, c_1, c_2, c_3\) faulty) for which the following diagnosis \(D = \{\{1, 2, 6\}, \{3, 4, 5\}\}\) is obtained. This diagnosis induces a wasted effort of \(W = 33\%\) as \(c_0\) in the first candidate is inspected in vain, as well as, on average two out of three inspections in the second candidate (in this example we assumed that rerunning the test set didn’t change the second candidate). In contrast to related work, we measure \(W\) instead of effort so that the performance metric’s scale is independent of the number of faults in the program.

The evaluated parameters are number of components \(M\), number of test cases \(N\), testing code coverage \(r\), testing fault coverage \(g\), and fault cardinality \(C\). Consider the example \(O\) in Figure 4(a), with \(M = 5\) components of which the first \(C = 2\) components are faulty. As a faulty component can still produce correct behavior, and therefore not cause a run to fail, we use an extended encoding where ‘1’ denotes a component that is involved, whereas ‘2’ denotes a (faulty) component whose involvement actually produced a failure (and consequently a failing run).

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>C = 2 faults</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

(a) Example \(O\)

(b) \(O\) ’s failed runs only

Figure 4. Observation Matrix Example

In the following we focus on the hitting set since its constituents are primarily responsible for the asymptotic behavior of \(W\). Although their individual ranking is influenced by component activity in passed runs, the hitting set itself is exclusively determined by the failing runs. Thus, we consider the sub-matrix shown in Figure 4(b).
From Figure 4(b) it can be seen that the first 2 columns together form a hitting set of cardinality 2 (which corresponds to our choice \( C = 2 \)). This can be seen by the fact that in each row there is at least one set member involved, i.e., there is a so-called “chain” of \( c_1 \) and/or \( c_2 \) involvement that is “unbroken” from top row to bottom row.

While this chain exists by definition (given the fact that both are faulty there is always at least one of them involved in every failed run), other chains may also exist, and may cause \( W \) to increase. This occurs when those chains pertain to diagnostic candidates of equal or lower cardinality \( (B) \) than \( C \). Generally, two types of chain can be distinguished: (1) chains (of cardinality \( B < C \)) within the faulty components set, called internal chains, and (2) chains (of cardinality \( B \leq C \)) completely outside the faulty components set, called external chains. In the above example after \( N = 2 \) (so considering only the first two failed runs), there is still one internal chain (corresponding to single fault \( c_2 \)), and two external chains (corresponding to single fault \( \{3, 4\} \)), and double fault \( \{1, 2\} \). As their probability will be higher (due to the a priori probability computation) they will head the ranking. With respect to the internal fault this does not significantly influence \( W \) since this indicates a true faulty component (the real double fault \( \{1, 2\} \) being subsumed by \( \{2\} \)). Consequently, there is no wasted debugging effort. With respect to \( \{3\} \) however, this fault will induce wasted effort. After \( N = 3 \) both single faults has disappeared (both chain of \('1's have been broken during the third failing run), while the double fault \( c_3, c_4 \) is still present. From the above example it follows that (1) \( W \) is primarily impacted by external chains, and (2) the probability of a \( B \) cardinality chain still “surviving” decreases with the number of failing runs. The latter is the reason why in the limit for \( N \to \infty \) all external (and internal) chains will have disappeared, exposing the true fault as only diagnosis.

### 5.1 Number of Failing Runs

As the number of failing runs is key to the behavior of \( W \) in the following we first compute the fraction of failed runs \( f \) out of the total of \( N \) runs, given \( r \) and \( g \). Consider \( C \) faulty components. Let \( f \) denote the probability of a run failing. A run passes when note of the \( C \) components induces a failure, i.e., does not generate a ‘2’ in the matrix. Since the probability of the latter equals \( 1 - r \cdot (1 - g) \) and generating a ‘2’ requires (1) being involved (probability \( r \)) and (2) producing a failure (probability \( (1 - g) \)), the probability of not generating a ‘2’ in the matrix equals \( (1 - r \cdot (1 - g)) \). Consequently, the probability a run passes equals \((1 - r \cdot (1 - g))^C\)

\[
f = 1 - (1 - r \cdot (1 - g))^C
\]

This implies that for high \( g \) (and/or low \( r \)) a very large number of runs \( N \) is required to generate a sufficient number \( N_F = f \cdot N \) of failing runs in order to eliminate competing chains of equal of lower cardinality \( B \). As \( r \) also affects the number of external chains which, however, is not affected by \( g \), the effect of \( g \) can be seen orthogonal to \( r \) in that it only impacts the number of failed runs through \( f \). Consequently, \( g \) and \( N \) are related in that a high \( g \) is compensated by a, possible huge, increase in \( N \). In the sequel, we therefore only focus on the effect of \( r \).

### 5.2 Behavior for Small Number of Runs

While for large \( N \) the determination of \( W \) depends on the probability that competing chains will have terminated, for small \( N \) a more simple derivation can be made. Consider the case of a single failing run \( (N_F = f \cdot N = 1) \). From the first (failing) row \((k = 1)\) in the above example (Figure 4(b)) it can be seen that there are generally \( r \cdot (M - C) \) external single-fault \((B = 1)\) chains \((c_3 \text{ and } c_5)\) that induce wasted effort. As \( W \) denotes the ratio of wasted effort it follows

\[
W = \frac{r \cdot (M - C)}{M}
\]

which for large \( M \) approaches \( r \). This is confirmed by the experiments discussed later.

After the second failed run \((k = 2)\) the probability a \( B = 1 \) chain survives two failing runs equals \( r^2 \) (i.e., the probability of two ‘1’s for a particular component). Consequently, the number of \( B = 1 \) chains equals \( r^2 \cdot (M - C) \), which, in general, decreases negative-exponentially with the number of (failing) runs \((f \cdot N)\). For \( B = 2 \) the situation is less restrictive as any combination of ‘1’s of the first and second row qualifies as a double-fault chain. As on average there are \( M' = [r \cdot (M - C)]' \) ‘1’s per row there are \((M')^2\) double-faults.

After the third failing run \((k = 3)\) the number of surviving \( B = 1 \) chains equals \( r^3 \cdot (M - C) \), whereas the number of triple faults equals \((M')^3\). As for sufficiently large \( M \) the higher-cardinality combinations outnumber the lower-cardinality combinations, \( W \) is dominated by the combinations that have the same cardinality as the fault cardinality \( C \). Consequently, assuming \( N_F \leq C \) it follows that the number of \( C \)-cardinality chains that compete with the actual \( C \)-cardinality diagnosis is approximated by \((M')^C\). However, if there are more combinations than \( M - C \) these combinations will overlap in terms of component indices. As \( W \) does not measure wasted effort on a component that was already previously inspected (and subsequently
removed from the next diagnosis), the average number of “effective” $C$-cardinality chains will never exceed $\frac{M}{C}$ (as there are $C$ indices per candidate). Hence, the number of competing $C$-cardinality chains is approximated by $\min\{\frac{M}{C}, \left(\frac{M}{C}\right)\}$.

5.3 Behavior for Large Number of Runs

For large $N_F$, the trend of $W$ can also be approximated from the probability that competing chains will still have survived after $N_F$ runs, which we derive as follows. Consider a $B$-cardinality external chain. At each row there is a probability that this chain does not survive. Similar to the derivation of $f$ we consider the probability that all $B$ components involved in the chain have a '0' entry, which would terminate that particular chain. This probability equals $(1 - r)^B$. Hence, the probability that a $B$-cardinality chain does not break per run equals $1 - (1 - r)^B$. Consequently, the probability that a chain survives $N_F$ failing runs equals

$$(1 - (1 - r)^B)^{N_F}$$

Similar to the derivation for small $N_F$, we only consider $C$-cardinality chains. The largest number of competing chains at the outset equals $\left(\frac{M'}{C}\right)$. As there always exists an $N_F$ for which this number is less than $\frac{M}{C}$ (in the asymptotic case we consider only a few chains) the number of competing chains after $N_F$ runs is given by

$$(1 - (1 - r)^C)^{N_F} \cdot \left(\frac{M'}{C}\right)$$

Consequently, $W$ is approximated by

$$W \approx \frac{(1 - (1 - r)^C)^{N_F} \cdot \left(\frac{M'}{C}\right)}{M}$$

(4)

We observe a negative-exponential (geometric) trend with $N_F$ ($N$) while $C$ postpones that decay to larger $N_F$ ($N$) as the term $1 - (1 - r)^C$ approaches unity for large $C$.

In the following we asymptotically approximate the number of failing test runs $N_F$ needed for an optimal diagnosis (i.e., $W$ approaches 0). Considering Eq. (4) a single diagnosis is approximately reached for

$$(1 - (1 - r)^C)^{N_F} \cdot \left(\frac{M'}{C}\right) = W \cdot M$$

which can be modeled as $\left(1 - (1 - r)^C\right)^{N_F} = K$. It follows $N_F = -\log K / \log 1 - (1 - r)^C$. Since for sufficiently large $C$ the term $1 - (1 - r)^C$ approaches unity, and since $\log 1 - \epsilon \approx -\epsilon$ it follows that $N_F \approx \log K / (1 - r)^C$. As $(1 - r) < 1$ it follows $N_F \approx \log K \cdot ((1 - r)^{-1})^C$ of which the second term increases exponentially with $C$. Since $K = \left(\frac{M'}{C}\right)$ for large $M$ this term also increases exponentially with $C$. However, as the term is included in a logarithm, the effect of this term is less than the previous.

6 An optimal similarity coefficient for single-faults

In this section we show how our above reasoning approach can be used to derive an optimal similarity coefficient for single-fault programs.

In the single-fault case we know that all failures relate to only one fault, which, by definition, is included in the minimal hitting set. Hence, any coefficient approach should consider the minimal hitting set only (i.e., only those $c_j$ which consistently occur in failing runs). This implies that the optimal approach is to select only the failing runs and compute the similarity coefficient. Since for these components by definition $a_{01} = 0$, one only needs to consider $a_{11}$ and $a_{10}$. This, in turn, implies that the ranking is only determined by the exonerating term $a_{10}$. Thus the ranking can be calculated as follows

$$\text{sim}(j) = \begin{cases} \text{s}(j) & \text{if } a_{01} \neq 0 \\ 0 & \text{otherwise} \end{cases}$$

In summary, once we only consider the components included in the hitting set, any of the coefficients that includes $a_{10}$ in the denominator will produce the same, optimal ranking. Experiments using this “hitting set filter” combined with a simple similarity coefficient such as Tarantula indeed confirm that this approach leads to the best performance [8].

Note that the above filter is only optimal for programs that have only 1 fault as applying this filter to any multiple-fault program would be overly restrictive. It would fail to detect faults that are not always involved in failed runs. For example,
the diagnosis for the O in the beginning of Section 4.1 when using the filtering approach would yield \( D = \{ \{1\} \} \), entirely ignoring two of the three faults. Hence, instead of considering a single-fault hitting set filter, we modify this approach in order to also allow application to multiple-fault programs. Taking the Ochiai coefficient as (best) starting point (for \( \kappa = 1 \), Eq. 5 follows from Eq. 1 by squaring, and factoring out \( a_{11}(j) \), none of which changes the ranking) and applying the above filtering approach, we derive the following similarity coefficient, coined Zoltar-S, according to

\[
s_{Z-S} = \frac{a_{11}(j)}{a_{11}(j) + a_{10}(j) + a_{01}(j) + \kappa \cdot \frac{a_{01}(j) \cdot a_{10}(j)}{a_{11}(j)}}
\]

where \( \kappa > 0 \) is a constant factor that exonerates a component \( c_j \) that was either seldom executed in failed runs or often in passed runs. We empirically verified that the higher the \( \kappa \) the more identical the diagnosis becomes with the one obtained by the hitting set filter [8]. In the context of this paper we limit \( \kappa \) to 10,000 to avoid round-off errors.

A Synthetic Results

A.1 W vs. N

Figures 5, 6, and 7 plot \( W \) vs. \( N \) for several parameters, such as number of faults \( C \), test set coverage \( r \), and failure coverage \( g \). To obtain the data, we use a simple, probabilistic model of program behavior that is directly based on \( C, N, M, r, \) and \( g \). Without loss of generality we model the first \( C \) of the \( M \) components to be at fault.

\[\text{Figure 5. } W \text{ vs. } N \text{ for } g = 0.1\]

\[\text{Figure 6. } W \text{ vs. } N \text{ for } g = 0.9\]
A.2 W vs. P

The following figures, up to Figure 24, plot W vs. P, showing that the observation-based technique (Zoltar-M using Method 2 as policy) may be of added value in order to employ several developers (P) to find the bugs. The plots were generated by fixing M = 20 and N = 100, and each point represents an average of 1,000 matrices.
A.3 Probability/Similarity Distribution

The plots in Figure 24 contain the probability/similarity distribution for the rankings obtained with the several techniques. As can be seen, the observation-based approach (coined Zoltar-M) does give extra information on the number of faults in the code, when compared with SFL techniques (Ochiai, Tarantula, Zoltar-S).
Figure 13. $W$ vs. $N$ for $M = 10$, $g = 0.9$, and $r = 0.8$

Figure 14. $W$ vs. $N$ for $M = 20$, $g = 0.1$, and $r = 0.4$

Figure 15. $W$ vs. $N$ for $M = 20$, $g = 0.1$, and $r = 0.6$

Figure 16. $W$ vs. $N$ for $M = 20$, $g = 0.1$, and $r = 0.8$

References


Figure 17. $W$ vs. $N$ for $M = 30$, $g = 0.1$, and $r = 0.4$

Figure 18. $W$ vs. $P$ for $C = 1$ and $g = 0.1$

Figure 19. $W$ vs. $P$ for $C = 2$ and $g = 0.1$


Figure 20. $W$ vs. $P$ for $C = 5$ and $g = 0.1$

Figure 21. $W$ vs. $P$ for $C = 1$ and $g = 0.9$

Figure 22. $W$ vs. $P$ for $C = 2$ and $g = 0.9$


Figure 23. $W$ vs. $P$ for $C = 5$ and $g = 0.9$

Figure 24. Probability/Similarity distribution