

# Abductive model-based diagnosis

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## ABSTRACT

This paper analyses general process for abductive model-based diagnosis in practice and discusses different assessment methods to create propositional Horn clause abduction problem (PHCAP), as presented in [1]. The paper starts with a brief introduction explaining motivation and basics of abduction as well as describing a formalism for PHCAP. Afterwards it describes the adoption of abductive model-based diagnosis in practice. Furthermore, it is shown how the knowledge of several different failure assessment methods can be used to support a propositional Horn clause theory. In the end discussion is provided and conclusions are drawn.

## 1. INTRODUCTION

Trying to find an explanation is a natural reaction after an unexpected event that results in a loss, damage or injury. It can serve various purposes, such as diminishing uncertainty, assigning responsibility (or blame) or taking action to prevent something from going wrong in the future. It is reasonable to think of events that are part of the same situation as if they progress step-by-step, where one event follows another. For example, when we press the computer power button, the computer will turn on. The same way goes backwards, meaning that when something happens (an effect), we believe something has happened shortly before (a cause). This is called linear thinking and it proposes a cause-effect relationship between two consecutive events.

Over the years, many fault diagnosis methods have been developed to improve safety and reliability of complex technical systems. Accurate identification of failure sources has become very important. Model-based diagnosis presents a way to determine root causes based on observed anomalies (effects). There exists a type of diagnosis, that generates explanations for given observations using knowledge of failures and their effects, called *abductive* model-based diagnosis.

Abduction is a term used in the field of Artificial Intelligence, representing a generation of explanations for a set of events from given domain theory. The basic rule for generating explanations can be formulated as  $\alpha \rightarrow \beta$ , where  $\alpha$  is derived as an explanation of  $\beta$  [2]. Formally, this rule can also be written as  $\psi \models \phi$ , where  $\psi$  represents a set of explanations

or causes and  $\phi$  denotes a set of observations. Therefore, in order to apply abductive model-based diagnosis reasoning, we first need a formalisation of failures and their discoverable effects. Then we can deduce diagnoses from observed symptoms.

Since abduction is in general intractable, we need a formalism in the framework of mathematical logic for describing the behaviour of a system that allows computing explanations rather efficiently. In this research, a propositional Horn clause abduction problem (PHCAP) is considered. In order to find a solution to a PHCAP, we first need:

- **Knowledge base:** a tuple  $(A, Hyp, Th)$ , where  $A$  represents the set of propositional variables within the Horn theory,  $Hyp$  a subset of these propositional variables that constitute the hypotheses, and  $Th$  the Horn theory or set of Horn clauses that describe knowledge;
- **Observations:** observed symptoms that abduction derives explanations for.

The solution  $\Delta$  can then be found by satisfying two conditions as follows:

1.  $\Delta \cup Th$  is consistent
2.  $\Delta \cup Th \models Obs$ :  $Obs$  is a logical consequence of  $\Delta \cup Th$ .

## 2. ABDUCTIVE MODEL-BASED DIAGNOSIS IN PRACTICE

Application of abductive model-based diagnosis in practice faces two challenges: the computational complexity and the initial domain modelling effort required. This research focuses on latter, discussing different failure assessments used in practice and how they can serve as a basis for abductive diagnosis. The process comprises following steps:

1. **Model development:** failure assessments need to contain information of failures and their symptoms to form a Knowledge base (described in previous Section) and enable an abductive diagnosis;

2. **Fault detection:** in order to start the diagnosis process, a symptom has to be observed by, for example, a condition monitoring system.
3. **Fault identification:** in this step, a solution to PHCAP is computed. There exist various approaches of deriving abductive explanations [3].

### 3. ABDUCTIVE MODEL GENERATION WITH FAILURE ASSESSMENTS

In this Section we discuss various common failure assessments in regard to constituting the basis of an abductive knowledge base using translation into a propositional Horn theory.

#### 3.1 Failure Mode Effect Analysis (FMEA)

Records in FMEA represent connections between single faults and a conjunction of effects, formally written as a set of tuples  $(C, M, E)$ , where  $C$  is a component,  $M$  a failure mode and  $E$  a set of failure effects. The conversion to a propositional Knowledge base is therefore straightforward. Hypotheses  $Hyp$  are all component-failure mode pairs. The set  $A$  is the union over all hypotheses and propositional variables representing effects. The Horn theory  $Th$  consists of Horn clauses where a single hypothesis implies one of its effects.

#### 3.2 Fault Tree Analysis (FTA)

Fault tree represents logical paths of cause-effect relationships. In this research we focus on trees with two most common logical gates, AND and OR. The set  $A$  consist of all events in fault tree. Hypotheses  $Hyp$  can be narrowed down to only events that represent the initial root causes, so only propositional variables corresponding to primary events are included. Horn clauses are created as follows: in case of an AND gate, a conjunction of variables from inputs to the output event from  $A$  is created; and in case of an OR gate, for each input into the gate a Horn clause is created.

#### 3.3 Physics of Failure (PoF)

The Physics of Failure approach uses knowledge of physics to analyse root causes of failures, namely knowledge on failure mechanisms and potential degradation with life cycle stress information. Gray et al. [4] present a Failure Mode Assessment (FMA) based on diagnostic and prognostic techniques. The method decomposes a system into its subcomponents and each part is then analysed regarding potential failure modes and damage driving physics. Aggravating boundary conditions are also stated. The final analysis therefore comprises the fault mode, the component, the conditions promoting the damage and effects such as automatically retrieved state indicators and manual part inspections.

To create PHCAP model, an FMA is declared as a set of tuples  $(C, M, \phi)$ , where  $C$  is a component,  $M$  a fault mode and  $\phi$  a Boolean expression relating effects to one another. As the effects are connected by disjunctions, but Horn clauses

require conjunctions, first, the disjunctions need to be converted to conjunctions using laws of Boolean algebra, namely writing the expression in disjunctive normal form. The composition of  $Hyp$  and  $A$  is then similar to one in the FMEA.

### 4. DISCUSSION

Resulting models have different structure and expressiveness. The most straightforward and simple translation into a propositional Horn theory is achieved using FMEA, as each clause describes a cause-effect relationship between a single failure and a single effect. However, the model is rather strict with all its conjunctions, so observation data have to be preprocessed to remove noise or any inaccurate measurements. Additional improvements to the diagnosis can be made using other information FMEA brings, such as a severity rating.

FTA-based models can express a wider range of situations than FMEA, however, at a cost of combining fault trees for each possible observation to create a Knowledge base. If FTA is quantitative, cause likelihoods can be calculated using probabilities of basic events corresponding to hypotheses.

In the last approach presented, namely FMA-based models, effects are presented as an expression that contains disjunctions, causing an additional conversion step to conjunctions before the Horn theory can be created. This can result in an exponentially larger model than the original one. The disadvantages are also that resulting diagnoses have to be mapped back to the initial causes and additional final subset checks are needed to ensure minimal explanations. The main advantage is therefore in integration of knowledge of failure mechanisms and life cycle stress.

### 5. CONCLUSION

Even though applications of model-based diagnosis have been developed for various domains, there is still a need to construct a suitable model. This paper proposed a way to create a formalisation for abductive model-based diagnosis exploiting existing failure assessments used in practice.

The paper started with a short introduction of abduction and PHCAP. Afterwards, three failure assessment methods were presented, namely FMEA, FTA and FMA. Each was described with respect to its capabilities to form a basis for an abductive diagnosis.

Resulting models differ in structure and expressiveness. Additional information that analyses methods provide can be used to further improve results of the initial diagnosis.

### 6. REFERENCES

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