KRR7: Diagnosis

Yannick Pencolé
Yannick.Pencole@anu.edu.au

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Outline

1. Types of reasonings
2. Diagnosis: an introduction
3. Model-based diagnosis
   - Knowledge representation
   - Diagnosis: an intuition

Deduction, Abduction, Learning

Example

Famous syllogism of Aristotle:

"Socrates is a man"

"Every man is mortal"

SO "Socrates is mortal"

Deduction principle (entailment, prediction, anticipation, planning...)

Elementary! My Dear Watson!

Example

Crime scene: Sherlock came and saw Socrates dead:
"Socrates is mortal"

Sherlock knew one crucial information:
"Every man is mortal"

Watson said: "what are your conclusions?"

Sherlock answered:
"Elementary! My Dear Watson! Socrates is a man, that's the reason why he had to die one day"

Is it right? Is it deduction? NO
This is abduction. Main reasoning for diagnosis. Sherlock is a master of abduction (and not deduction)...
We cannot deduce that Socrates is a man. Maybe he's a rat, a flower... This is just an hypothesis.

What about learning?

Example

A machine knows that “Socrates is a man” and sees that “Socrates is mortal”.

so it can learn a generic rule:

- “Every man is mortal”
- or “Every mortal is a man”
- or “The concept of man has a relationship with the concept of mortality”

Outline

Diagnosis problem

Definition

Given:

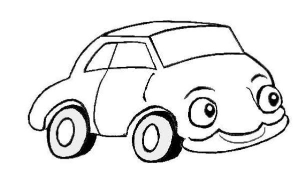
1. a system
2. a set of observations

How to:

1. determine the failures of the system
2. repair the system

Diagnosis problem: example

Example

System: 

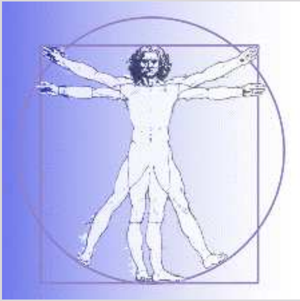
Observation: The car does not start

Possible diagnoses: The battery does not work, the starter is broken, no petrol...

Repair: test plan to discriminate among the diagnoses (check the battery, ...)

Diagnosis problem: another example

Example

System: 
Observation: Flu (40 degrees), headache
Possible diagnoses: Cold, Migraine
Repair: Take three pills per day

Diagnosis: history

History

- 70's: heuristic approaches (expert systems)
    - knowledge base = set of abductive rules (need expertises)
    - inference
- 80's: model-based diagnosis (static systems)
- 90's: model-based diagnosis (dynamic systems)

Outline

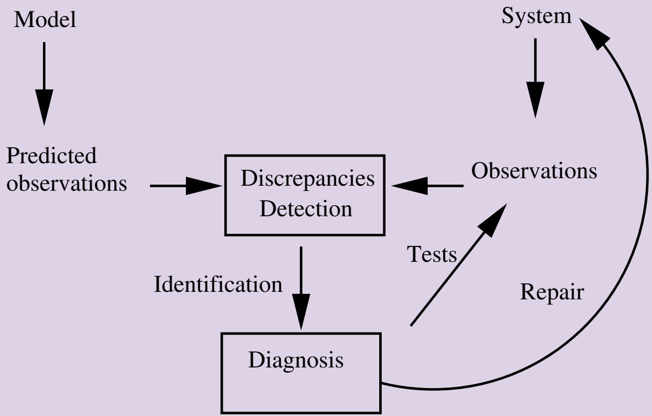
1. Types of reasonings

2. Diagnosis: an introduction

3. Model-based diagnosis
   - Knowledge representation
   - Diagnosis: an intuition

Model-based diagnosis: the idea

Model-based diagnosis



Knowledge representation

Definition

A system is a couple $(SD, COMP)$:

- $COMP$ is a finite set of constants, one constant = one component
- SD is a set of FOL sentences describing the behaviour of the system
  - Behavioral model (how a component works)
  - Structural model (how components interact)

Definition

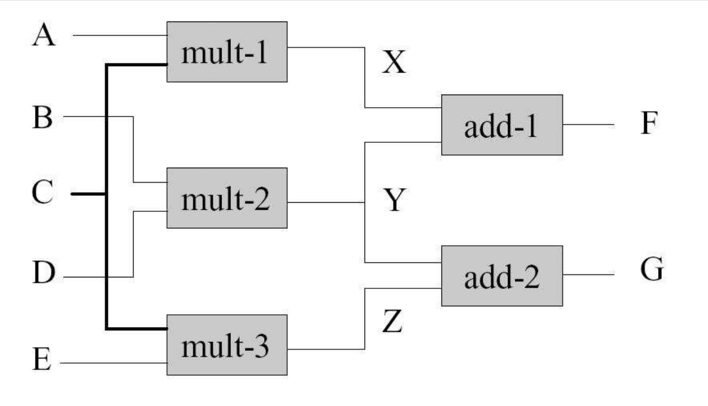
A observed system is a system $(SD, COMP)$ with some observations OBS:

- OBS is a set of atomic sentences.
- Each atomic sentence represents an observation

Knowledge representation: example

Example

Davis circuit



Knowledge representation: symbols

Example

$COMP = \{a1, a2, m1, m3, m3\}$

SD **predicates**:

- *Add* additioner
- *Mult* multiplier
- *In*1 input 1
- *In*2 input 2
- *Out* output
- *Ab* abnormal
- *Sum* sum
- *Prod* product

Knowledge representation: behavioural model

Example

Note: all the variables are universally quantified.

Behavior of an additioner

- $Add(x) \wedge \neg Ab(x) \wedge In1(x,u) \wedge In2(x,v) \wedge Sum(u,v,w) \Rightarrow Out(x,w)$
- $Add(x) \wedge \neg Ab(x) \wedge In1(x,u) \wedge Out(x,w) \wedge Sum(u,v,w) \Rightarrow In2(x,v)$
- $Add(x) \wedge \neg Ab(x) \wedge Out(x,w) \wedge In1(x,u) \wedge Sum(u,v,w) \Rightarrow In1(x,u)$

Behavior of a multiplier

- $Mult(x) \wedge \neg Ab(x) \wedge In1(x,u) \wedge In2(x,v) \wedge Prod(u,v,w) \Rightarrow Out(x,w)$
- $Mult(x) \wedge \neg Ab(x) \wedge In1(x,u) \wedge Out(x,w) \wedge Prod(u,v,w) \Rightarrow In2(x,v)$
- $Mult(x) \wedge \neg Ab(x) \wedge Out(x,w) \wedge In1(x,u) \wedge Prod(u,v,w) \Rightarrow In1(x,u)$

Knowledge representation: structural model

Example

Topology, structural model:

$COMP = \{a1, a2, m1, m3, m3\}$

$Add(a1); Add(a2); Mult(m1); Mult(m2); Mult(m3)$

Connections: use of the equality

- $Out(m1, u) \wedge In1(a1, v) \Rightarrow u = v$
- $Out(m2, u) \wedge In2(a1, v) \Rightarrow u = v$
- $Out(m2, u) \wedge In1(a1, v) \Rightarrow u = v$
- $Out(m3, u) \wedge In1(a2, v) \Rightarrow u = v$
- $In2(m1, u) \wedge In1(m3, v) \Rightarrow u = v$

Knowledge representation: observations

Example

Only the inputs and the output of the circuit are observable.

- $In1(m1, 3)$: “The input 1 of the multiplier 1 is 3”
- $In2(m1, 2)$ ....
- $In1(m2, 2)$
- $In2(m2, 3)$
- $In1(m3, 2)$
- $In2(m3, 3)$
- $Out(a1, 10)$
- $Out(a2, 12)$

Main idea

Definition

A State of the system $SD, COMP$ is a sentence Φ_Δ with $\Delta \subseteq COMP$ like:

$$\bigwedge_{c \in \Delta} Ab(c) \wedge \bigwedge_{c \notin \Delta} \neg Ab(c)$$

The component of Δ are abnormal.

Example

1. $\Delta = \{a1, m2\}$;
   $\Phi_\Delta = Ab(a1) \wedge Ab(m2) \wedge \neg Ab(a2) \wedge \neg Ab(m1) \wedge \neg Ab(m3)$
2. $\Delta = \emptyset$; $\Phi_\Delta = \neg Ab(a1) \wedge \neg Ab(a2) \wedge \neg Ab(m1) \wedge \neg Ab(m2) \wedge \neg Ab(m3)$: state where every component has a normal behaviour
3. $\Delta = \{a1, a2, m1, m2, m3\}$;
   $\Phi_\Delta = Ab(a1) \wedge Ab(a2) \wedge Ab(m1) \wedge Ab(m2) \wedge Ab(m3)$: where every component has an abnormal behaviour

Main idea

Definition

A Diagnosis of the system $SD, COMP$ is a state Φ_Δ such that:

$$SD, OBS, \Phi_\Delta \text{ is satisfiable}$$

The state is possible according to SD, OBS (consistency-based).

Definition

A diagnosis exists iff:

$$SD, OBS \text{ is satisfiable}$$

If not, the model is not well-designed or incomplete.

Detection of abnormalities

Definition

Normal behaviour of the system:

$$SD, \Phi_{\emptyset}$$

where $\Phi_{\emptyset} = \bigwedge_{c \in COMP} \neg Ab(c)$.

Definition

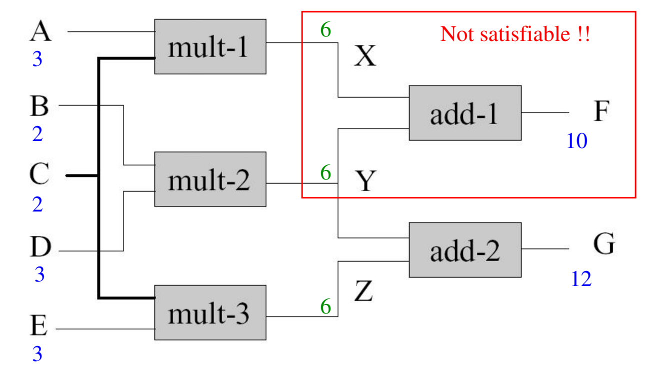
How to detect abnormal observations OBS?
Check the satisfiability of:

$$SD, \Phi_{\emptyset}, OBS$$

Detection of abnormalities: example

Example

In the presented example, $SD, OBS, \Phi_\emptyset$ is unsatisfiable so *OBS* is an abnormal observations.



Identification of abnormalities

Definition

If we have detected that the observations are abnormal, we need to identify which components are faulty. We need satisfiability back!!

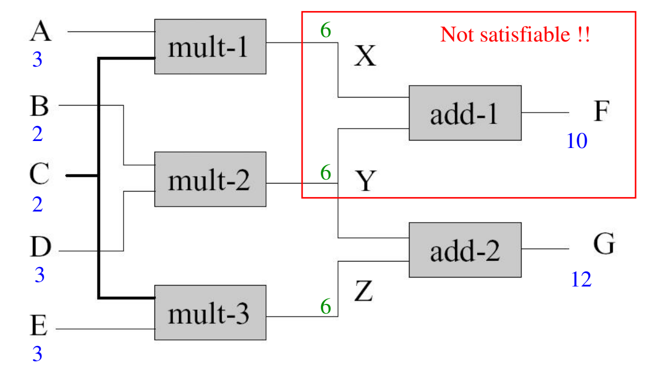
$$SD, OBS \models Ab(?) \vee ... \vee Ab(?)$$

- Which abnormalities are entailed by SD, OBS?
- Use of inference algorithms to solve that problem.

Identification of abnormalities: example

Example

$SD, OBS \models Ab(a1) \vee Ab(m1) \vee (Ab(m2) \wedge Ab(a2)) \vee (Ab(m2) \wedge Ab(m3))$



Identification of abnormalities: example

Example

$SD, OBS \models Ab(a1) \vee Ab(m1) \vee (Ab(m2) \wedge Ab(a2)) \vee (Ab(m2) \wedge Ab(m3))$

From that, we guess the following set of states are diagnoses:

1. $Ab(a1) \wedge \neg Ab(a2) \wedge Ab(m1) \wedge \neg Ab(m2) \wedge \neg Ab(m3)$
   - only a1 and m1 are faulty
2. $\neg Ab(a1) \wedge Ab(a2) \wedge \neg Ab(m1) \wedge \neg Ab(m2) \wedge \neg Ab(m3)$
   - only a2 is faulty
3. $Ab(a1) \wedge Ab(a2) \wedge Ab(m1) \wedge \neg Ab(m2) \wedge \neg Ab(m3)$
   - a1, a2, and m1 are faulty
4. $Ab(a1) \wedge Ab(a2) \wedge Ab(m1) \wedge Ab(m2) \wedge Ab(m3)$
   - everything can be faulty!!!
5. ...

But the following state is not a diagnosis state:

1. $\neg Ab(a1) \wedge \neg Ab(a2) \wedge \neg Ab(m1) \wedge \neg Ab(m2) \wedge Ab(m3)$
   - if m3 is faulty there must another faulty component (m2 at least)

Failure knowledge

Definition

Failure knowledge: piece of knowledge about the behaviour of components when they are faulty

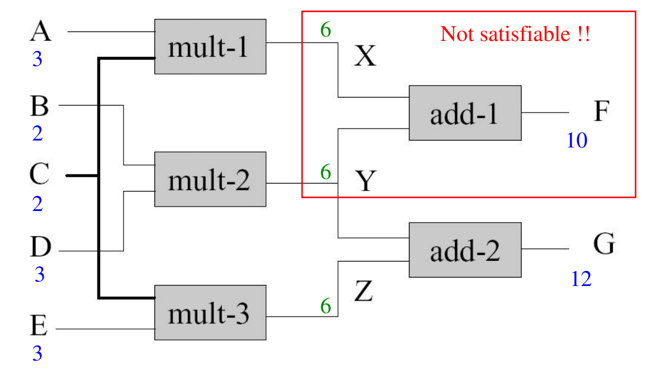
Example

- “When faulty, the output of the additioner 2 is always 0”
- $Ab(a2) \Rightarrow Out(a2, 0)$
- “Faulty additioners behave like substracters”
- $Add(x) \wedge Ab(x) \wedge In1(x, u) \wedge In2(x, v) \wedge Substract(u, v, w) \Rightarrow Out(x, w)$

Identification of abnormalities: example 2

Example

$SD, \{Ab(a2) \Rightarrow Out(a2, 0)\}, OBS \models$
$(Ab(a1) \wedge \neg Ab(a2)) \vee (\neg Ab(a2) \wedge Ab(m1)) \vee (\neg Ab(a2) \wedge Ab(m2) \wedge Ab(m3))$



Identification of abnormalities: example 2

Example

$SD, \{Ab(a2) \Rightarrow Out(a2, 0)\}, OBS \models$
$(Ab(a1) \wedge \neg Ab(a2)) \vee (\neg Ab(a2) \wedge Ab(m1)) \vee (\neg Ab(a2) \wedge Ab(m2) \wedge Ab(m3))$
From that, we guess the following set of states are diagnoses:

1. $Ab(a1) \wedge \neg Ab(a2) \wedge Ab(m1) \wedge \neg Ab(m2) \wedge \neg Ab(m3)$
   - only a1 and m1 are faulty
2. $\neg Ab(a1) \wedge \neg Ab(a2) \wedge \neg Ab(m1) \wedge Ab(m2) \wedge Ab(m3)$
   - m1 and m2 are faulty
3. $Ab(a1) \wedge \neg Ab(a2) \wedge Ab(m1) \wedge \neg Ab(m2) \wedge \neg Ab(m3)$
   - m1 and a1 are faulty
4. ...

But the following state is not a diagnosis state:

1. $\neg Ab(a1) \wedge Ab(a2) \wedge \neg Ab(m1) \wedge Ab(m2) \wedge Ab(m3)$
   - any hypothesis where a2 is faulty is not a diagnosis any more

Diagnosis representation: Partial Diagnosis

Problem

For n components, the number of potential diagnoses is 2^n. We need a clever representation.

Definition

A Partial Diagnosis is a conjunction Φ of *Ab* literals such that every state Φ' covered by Φ is a diagnosis.

Example

- $\Phi = Ab(a1) \wedge \neg Ab(a2) \wedge Ab(m1) \wedge \neg Ab(m2) \wedge \neg Ab(m3)$ is a diagnosis so it is a partial diagnosis
- $\Phi = Ab(a1) \wedge Ab(m1) \wedge \neg Ab(m2) \wedge \neg Ab(m3)$ is a partial diagnosis because it covers the two diagnoses
  - $\Phi' = Ab(a1) \wedge \neg Ab(a2) \wedge Ab(m1) \wedge \neg Ab(m2) \wedge \neg Ab(m3)$
  - $\Phi' = Ab(a1) \wedge Ab(a2) \wedge Ab(m1) \wedge \neg Ab(m2) \wedge \neg Ab(m3)$

Diagnosis representation: Kernel Diagnosis

Definition

A Kernel Diagnosis is a partial diagnosis that is covered by only itself. Kernel diagnoses provide a very economical way to implicitly represent all the diagnoses.

Example

Example 1:

- $Ab(a1)$ is a kernel diagnosis for example 1. Every conjunction covered by $Ab(a1)$ is a partial diagnosis. The empty clause $\emptyset$ is not a kernel diagnosis because it covers $\neg Ab(a1)$ which is not a partial diagnosis.
- $Ab(m1)$, $Ab(m2) \wedge Ab(a2)$, $Ab(m2) \wedge Ab(m3)$ are the other kernel diagnoses of example 1.

Example 2:

- $Ab(a1) \wedge \neg Ab(a2)$, $\neg Ab(a2) \wedge Ab(m1)$, $\neg Ab(a2) \wedge Ab(m2) \wedge Ab(m3)$

Diagnosis representation: Preferences

A diagnosis is an hypothesis (it may be true) and not a conclusion. So we may decide to prefer some of these diagnoses.

Preference criteria

- Diagnoses with a minimal number of abnormal components
- Diagnoses with a set of abnormal components that is minimal: minimal diagnoses
  - i.e. if I remove one component from this set (it becomes normal) the corresponding state is not a diagnosis anymore
- Diagnoses that “explain in the best way” the observations: explanation

Diagnosis representation: Preferences

Example

Example 1:

- **2 diagnoses with minimal cardinality**
  1. $Ab(a1) \wedge \neg Ab(a2) \wedge \neg Ab(m1) \wedge \neg Ab(m2) \wedge \neg Ab(m3)$
  2. $\neg Ab(a1) \wedge \neg Ab(a2) \wedge Ab(m1) \wedge \neg Ab(m2) \wedge \neg Ab(m3)$
- **4 minimal diagnoses**
  1. $Ab(a1) \wedge \neg Ab(a2) \wedge \neg Ab(m1) \wedge \neg Ab(m2) \wedge \neg Ab(m3)$ (same as above)
  2. $\neg Ab(a1) \wedge \neg Ab(a2) \wedge Ab(m1) \wedge \neg Ab(m2) \wedge \neg Ab(m3)$ (same as above)
  3. $\neg Ab(a1) \wedge Ab(a2) \wedge Ab(m1) \wedge Ab(m2) \wedge \neg Ab(m3)$
  4. $\neg Ab(a1) \wedge \neg Ab(a2) \wedge \neg Ab(m1) \wedge Ab(m2) \wedge Ab(m3)$

Explanation

Definition

A diagnosis Φ_Δ for an observed system $(SD, COMP, OBS)$ is an explanation for an elementary observation $o \in OBS$ iff

$$SD, \Phi_\Delta \models o$$

Preferences

1. select diagnoses that explain all the observations of OBS
2. select diagnoses that explain a biggest subset of OBS
3. select diagnoses that explain the biggest subset of OBS

Explanation: example

Example

Example 1:
All the diagnoses that cover the following sentence (which is not a partial diagnosis) are explanations of $Out(a2, 12)$

$$\neg Ab(m2) \wedge \neg Ab(m3) \wedge \neg Ab(a2)$$

for instance:

$$Ab(a1) \wedge \neg Ab(a2) \wedge \neg Ab(m1) \wedge \neg Ab(m2) \wedge \neg Ab(m3)$$

Summary

- Be careful between Deduction and Abduction
- Diagnosis reasoning is generally close to Abduction
- Model-based diagnosis for static systems
  - Description of a model with FOL (structural/behavioural model)
  - Use of Failure knowledge in the model
- Diagnosis:
  - Detection is satisfiability problem
  - Identification consists in retrieving the satisfiability
- Diagnosis representation:
  - Kernel diagnosis: an efficient way to represent all the diagnoses.
- Diagnosis preference:
  - Minimal diagnoses, Explanations