

# Toward Computing Conflict-based Diagnoses in Probabilistic Logic Programming

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# Introduction

Many human-created artifacts: most knowledge is about *normal* structure and behavior.

- Little or no knowledge is available about abnormalities.
- New systems.

**Consistency-based diagnosis (CBD):** malfunctioning is diagnosed mostly based on normal behavior.

- This differs from abductive diagnosis.
- SD (System Description) specifies normal behavior via logical formulas:

$$\neg \text{Ab}(c) \rightarrow \text{Behavior}(c)$$

- E.g. an OR-gate could behave as:

$$\neg \text{Ab}(O) \rightarrow (\text{In}_1(O, \text{true}) \rightarrow \text{Out}(O, \text{true}))$$

# Introduction

## Consistency-based diagnosis (CBD):

- We are also given: observations OBS about inputs and outputs.
- We compute a **diagnosis**  $\Delta$ : an assignment to each  $Ab(c)$  being *true* or *false*.
- **Our aim in CB diagnosis:** find  $\Delta$  such that

$$SD \cup OBS \cup \Delta \not\models \perp$$

$\Delta$  should include the (subset-)minimal number of abnormalities.

However, there can be several candidate diagnoses.

- Probability theory has been used to *rank* diagnoses.
- **Bayesian diagnostic system** by Flesch & Lucas (2007): translated the notion of *data conflict* in Bayesian networks to probabilistic MBD.

# Overview

- We generalize Bayesian diagnostic problems to probabilistic logic programs
  - enables combination of logics and probabilities for model-based diagnosis
  - allows better modeling of the structure of the diagnostic problem
- ProbLog is used to model the diagnostic problems.
- Properties of probabilistic-based diagnosis in this context are studied

# Outline

- 1 Introduction
- 2 Bayesian diagnostic system
- 3 Diagnoses in PLP
- 4 Diagnoses with incomplete observations
- 5 Conclusions

# Setting

From logical approach to probabilistic approach:

- All atoms are modeled as random variables
- We observe random variables  $\Omega = \{\text{inputs and outputs}\}$ .
- **Probabilistic model-based diagnosis**: we assign a probability to diagnosis candidate  $\Delta$ :

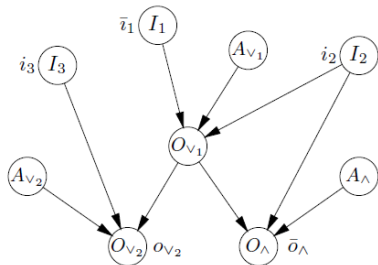
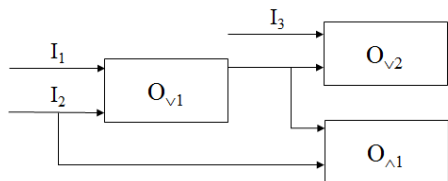
$$P(\Omega \mid \Delta)$$

- $P(\Omega \mid \Delta)$ : how likely is to obtain the observations if  $\Delta$  is assumed.

**Bayesian diagnostic system** - Flesch & Lucas (2007)

- Bayesian network represents the SD (system description).
- Implications are modeled by direct relationships in the network
- Outputs depend on inputs and abnormality variables

## Example - Bayesian diagnostic system



### General assumptions

- Assumption 1: component has *deterministic* behavior if it is **not abnormal**.
- Assumption 2: component has *probabilistic* behavior if it is **abnormal**. The output does not depend on the inputs anymore.

# Conflict measure in diagnosis

Logical consistency and conflict-based consistency

- If diagnosis  $\Delta$  is logically consistent, we know that it is also  $P$ -consistent

$$P(\Omega \mid \Delta) \neq 0 \text{ iff } SD \cup OBS \cup \Delta \not\models \perp$$

- Can we say more about  $P(\Omega \mid \Delta)$  in these cases?

Flesch & Lucas (2007) proposed the notion of **conflict-based diagnosis**.

- Intuition: measure how much related are  $I$  and  $O$  under  $\Delta$ .

$$conf_{\Delta}(\Omega) = \log \frac{P(I \mid \Delta)P(O \mid \Delta)}{P(I, O \mid \Delta)}$$

- If  $conf_{\Delta} > 0$ :  $I$  and  $O$  are “conflicting”.
- If  $conf_{\Delta} \leq 0$ :  $\Delta$  is called conflict-based diagnosis.



# Modeling in ProbLog

We represent a Bayesian diagnostic system as a ProbLog program.

## Example 1

```
0.1::ab(C).
0.5::in1(C,true) ; 0.5::in1(C,false).
0.5::in2(C,true) ; 0.5::in2(C,false).

0.5::out(C, true) ; 0.5::out(C,false) :- ab(C).

out(o1, true) :- \+ ab(o1), (in1(o1, true) ; in2(o1,true)).
out(o1, false) :- \+ ab(o1), in1(o1,false), in2(o1, false).

out(a1, true) :- \+ ab(a1), in1(a1, true), out(o1, true).
out(a1, false) :- \+ ab(a1), (in1(a1, false) ; out(o1,false)).
```

Advantage is specifying *local* logical structure directly (as opposed to encode this in CPTs of Bayesian networks).

# Basic properties

## Property 1

There is a conflict-based diagnosis (i.e.  $conf_{\Delta} \leq 0$ ) for any given diagnostic PLP and set of observations.

This is the trivial diagnosis: all components are assumed abnormal (thus,  $conf_{\Delta} = 0$ )

Now, let us assume **complete observations**, i.e., all inputs and outputs are known.

## Property 2 (sketch)

If  $\Delta$  is consistency-based diagnosis, then it is conflict-based.

Intuitively, this means that if  $\Delta$  is a consistency-based diagnosis, then  $P(I, O | \Delta)$  is at least  $P(I | \Delta) \times P(O | \Delta)$ .

## Basic properties (cont.)

### Property 3 (sketch)

Explanations of inputs and outputs (as given in ProbLog) directly provide consistency-based diagnoses, and therefore conflict-based diagnoses.

Hence, no probabilistic reasoning is necessary.

### Example 2

```
0.1::ab(C).
0.5::in1(C,true) ; 0.5::in1(C,false).
0.5::in2(C,true) ; 0.5::in2(C,false).
0.5::out(C, true) ; 0.5::out(C,false) :- ab(C).
```

```
out(o1, true) :- \+ ab(o1), (in1(o1, true) ; in2(o1,true)).
out(o1, false) :- \+ ab(o1), in1(o1,false), in2(o1, false).
```

Consider  $\Omega = \{\text{in1}(o1, \text{false}), \text{in2}(o1, \text{false}), \text{out}(o1, \text{true})\}$   
 $\Delta = \{\text{\+ ab}(o1)\}$  is not consistency-based, thus it cannot be conflict-based.  
 In contrast,  $\Delta' = \{\text{ab}(o1)\}$  is consistency-based and thus conflict-based.

# Incomplete observations

Here, logical consistency does **not** imply a conflict-based diagnosis.

## Example 3

Consider the OR-gate example with  $\Omega = \{\text{in}(o1, \text{false}), \text{out}(o1, \text{true})\}$ .  
 $\Delta = \{\setminus + \text{ab}(o1)\}$  is consistency-based. However,  $\Delta$  is **not** conflict-based.

$$P(I \mid \Delta) = 0.5$$

$$P(O \mid \Delta) = 0.75$$

$$P(I, O \mid \Delta) = 0.25$$

Hence,  $\text{conf}_{\Delta}(\Omega) \simeq 0.18$ .

# Incomplete observations

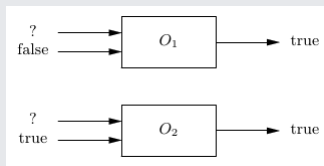
Again, explanations can be used to identify malfunctioning components

## Property 4 (sketch)

If, assuming some component is abnormal reduces the conflict (then it is not the case that the observed outputs follow from the observed input)

⇒ there is some explanation for the observed inputs and negated observed outputs in which the component is assumed to be normal.

## Example 4



- If  $\Delta = \{\setminus + \text{ab}(o1), \setminus + \text{ab}(o2)\}$ , then  $\text{conf}_{\Delta}(\Omega) \simeq 0.05$ .
- By Prop. 4, we do not need to examine  $O_2$ , as its output is completely determined by its input ( $I_2$ ).  $\Delta' = \{\setminus + \text{ab}(o1), \text{ab}(o2)\}$  lead to  $\text{conf}_{\Delta'} = 0.18$
- This is not the case for  $O_1$ . Indeed,  $\Delta'' = \{\text{ab}(o1), \setminus + \text{ab}(o2)\}$ ,  $\text{conf}_{\Delta''} = -0.12$

# Conclusions & Future work

## Conclusions:

- Preliminary exploration of conflict-based diagnosis in PLP
- Abductive machinery of PLPs seems very useful to computing conflict-based diagnoses

## Future work:

- Further studying the partial observations
- Generalizing the framework, e.g. probabilistic behavior of systems
- Consider conflict-based diagnosis with time