

"Diagnosis" Chair

Louise Travé-Massuyès



SCIENTIFIC DIRECTOR : NICHOLAS ASHER COORDINATING INSTITUTION : UNIVERSITÉ FÉDÉRALE TOULOUSE MIDI-PYRÉNÉES



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Synergistic transformations in model based and data based diagnosis



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Chair and co-chairs

Ontinental





Louise Travé-Massuyès

CNRS Research Director LAAS-CNRS, University of Toulouse

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Diagnosis theories, Model-Based Diagnosis, Data-Based Diagnosis, Machine Learning, Monitoring and Health Management, Diagnosability, Sensor placement, Diagnosis architectures, Qualitative models and qualitative reasoning formalisms



(LAAS-CNRS)

Nathalie Barbosa Roa

Data scientist and Big Data engineer Continental Automotive France SAS https://www.linkedin.com/in/nathaliebarbosaroa/ Fault detection, data-based, time series, manufacturing, machine learning





LAAS

CNRS

Xavier Pucel

Research engineer ONERA / DTIS, University of Toulouse <u>https://sites.google.com/view/xavier-pucel/accueil</u> *Autonomous robots, diagnosis, decision, verification and validation, planning and scheduling*



Elodie Chanthery

Assistant Professor LAAS-CNRS, INSA, University of Toulouse <u>https://homepages.laas.fr/echanthe/</u> Diagnosis, prognosis, hybrid systems, autonomous systems, distributed systems





Diagnosis

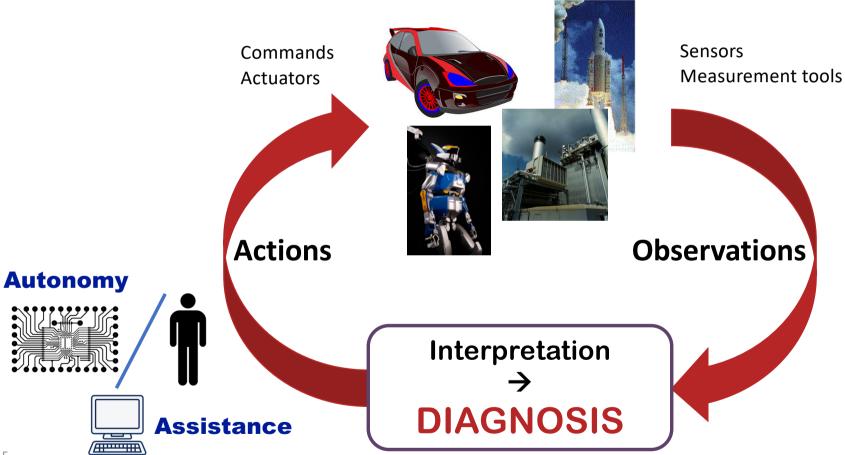


The process of identifying or determining the nature and root cause of a failure, problem, or disease from the symptoms resulting from selected measurements, checks or tests.



Diagnosis in the decision loop







Objectives

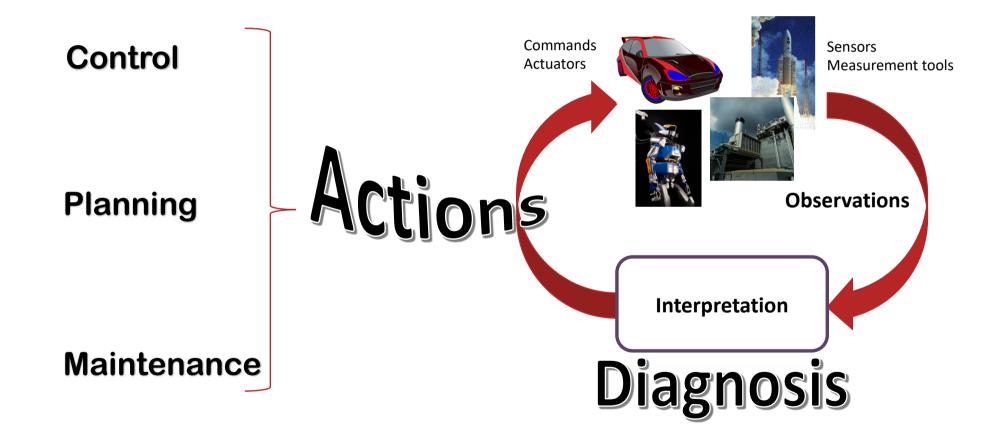


- Increased safety
 - Ability to avoid catastrophic or critical events for installations, stakeholders, and the environment
- Increased reliability
 - Ability to perform a function under given conditions for a given period of time
- Increased availability
 - Ability to perform a function at a given time under given conditions



Appropriate/optimized actions







Diagnosis





Detect inconsistencies w.r.t. a reference Detect anomalies/faults, specific situations Identify root causes Estimate the internal state of a system

Identify and recommend Determine responsabilities



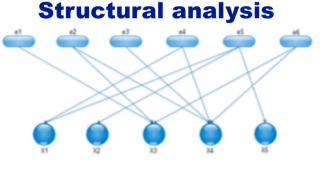
Model-based diagnosis



 Uses a model obtained from knowledge

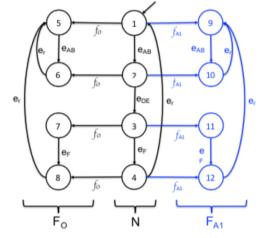
Logical theory

 $\begin{aligned} \mathsf{COMPS} &= \{\mathsf{A1}, \mathsf{A2}, \mathsf{M1}, \mathsf{M2}, \mathsf{M3}\} \\ \mathsf{SD} &= \{\mathsf{ADD}(\mathsf{x}) \land \neg \mathsf{AB}(\mathsf{x}) \Rightarrow \mathsf{Output}(\mathsf{x}) = \mathsf{Input1}(\mathsf{x}) + \mathsf{Input2}(\mathsf{x}), \\ \mathsf{MULT}(\mathsf{x}) \land \neg \mathsf{AB}(\mathsf{x}) \Rightarrow \mathsf{Output}(\mathsf{x}) = \mathsf{Input1}(\mathsf{x}) \times \mathsf{Input2}(\mathsf{x}), \\ \mathsf{ADD}(\mathsf{A1}), \mathsf{ADD}(\mathsf{A2}), \mathsf{MULT}(\mathsf{M1}), \mathsf{MULT}(\mathsf{M2}), \mathsf{MULT}(\mathsf{M3}), \\ \mathsf{Output}(\mathsf{M1}) &= \mathsf{Input1}(\mathsf{A1}), \mathsf{Output}(\mathsf{M2}) = \mathsf{Input2}(\mathsf{A1}), \ldots \end{aligned}$ $\\ \mathsf{OBS} &= \{\mathsf{Input1}(\mathsf{M1}) = 2, \mathsf{Input2}(\mathsf{M1}) = 3, \mathsf{Input1}(\mathsf{M2}) = 2, \mathsf{Input2}(\mathsf{A1}), \ldots \end{aligned}$



Estimation theory Parity space theory

 $\begin{aligned} \dot{x}(t,p) &= f(x(t,p), u(t), p), \\ y(t,p) &= h(x(t,p), p), \\ x(t_0,p) &= x_0 \in X_0, \\ p \in P \subset \mathcal{U}_{\mathcal{P}}, \ t_0 \leq t \leq T, \end{aligned}$



DES diagnosis theory



Data-based diagnosis



- Uses "only" data
 - Learning phase
 - Recognition phase

3

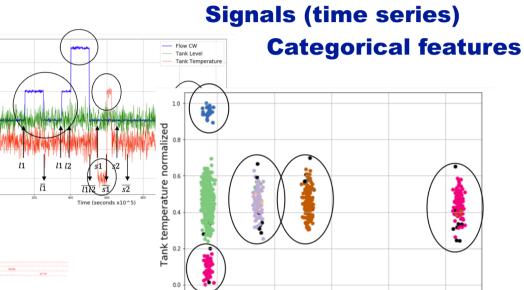
4 5

6

7

9

11 (91002,15495376



0.5

0.6

Flow CW normalized



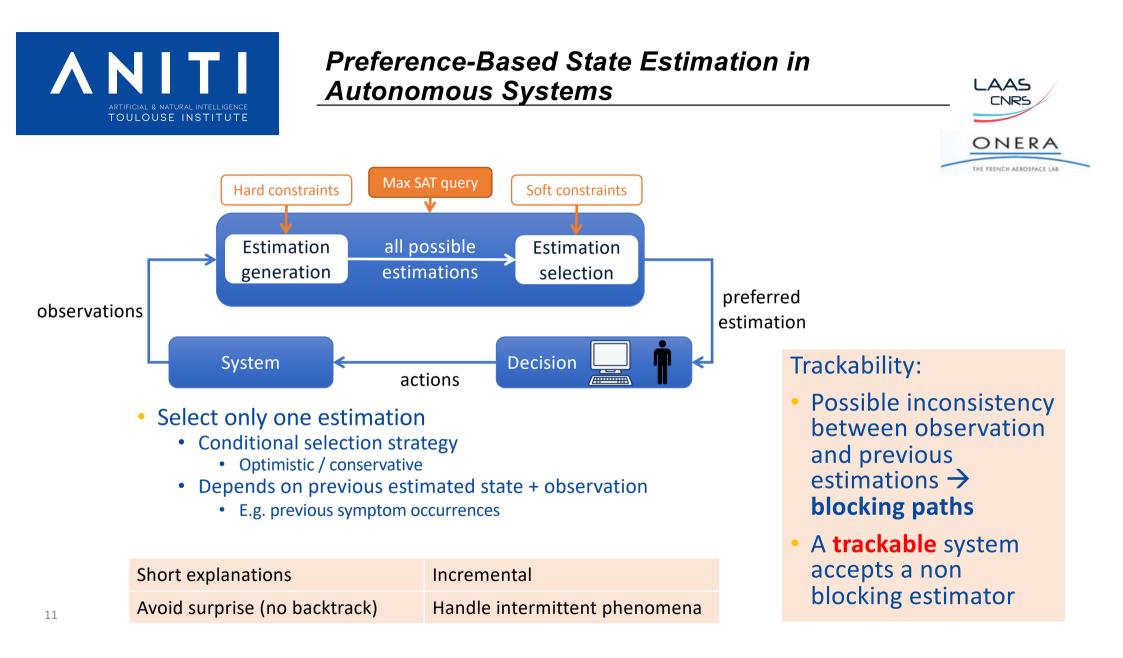
- 14 (////0/,100/9290/ 15 (300002,1550833696) 16 (91005,1550834022) 17 (91005,1550834070) 18 (91002,1550834122) 19 (450000, 1550834241) 20 (390001,1550839758) 21 (395002,1550840248) (3950022,1550840250) 22 23 (445001, 1550841568)
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 - \rightarrow Temporal patterns



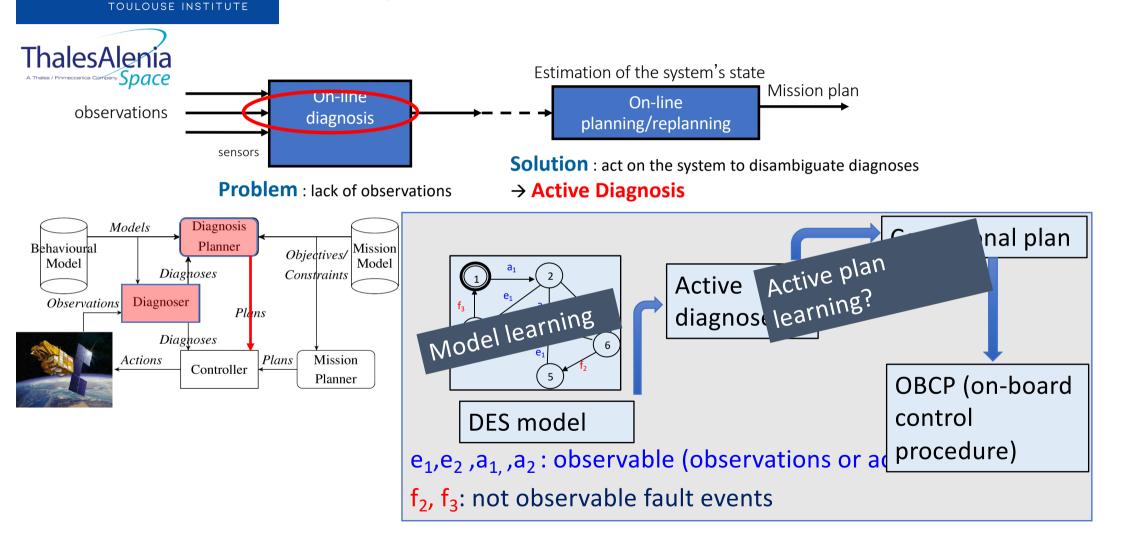
→ Classification/clustering

0.8

07



ANITIA ARTIFICAL & NATURAL INTELLIGENCE Coupling Diagnosis and Planning for active <u>diagnosis</u>





Dynamic clustering and automatic learning of discrete event models

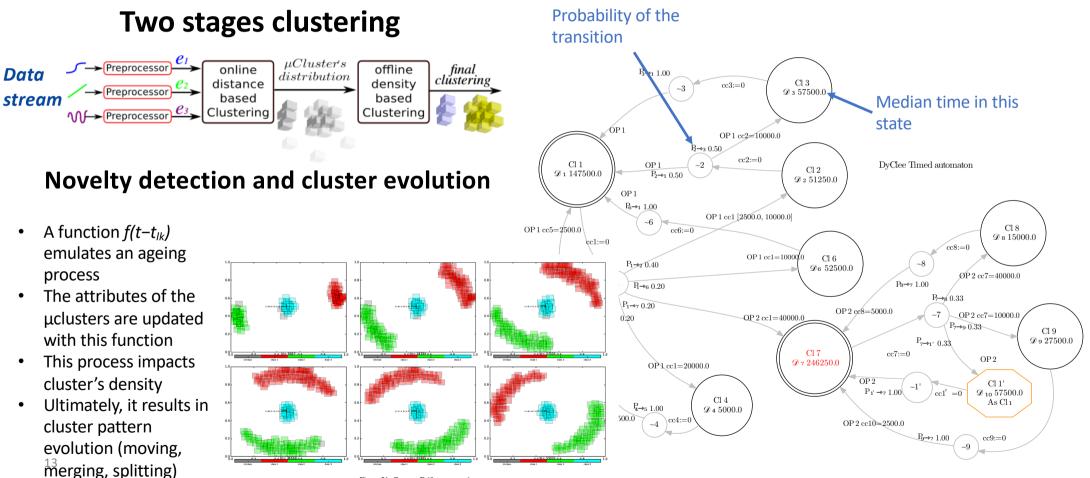


Figure 21: Concept Drift toy example



Project of the chair

- Highlight and understand the correspondences that may exist between MBD and DBD techniques, in particular for feature generation and diagnosability analysis
- Integrate knowledge based models and learning
- Learn diagnosis models : abstract up data configurations and map them to symbolic or analytical models suitable for diagnosis reasoning



Project of the chair

- Integration of knowledge based models and learned models: heterogeneous and non structured data
- Diagnosability analysis
 - Diagnosability checks: situation signature learning
 - Joint analysis based on structural models and data
- Heterogeneous feature identification (selection and/or generation) in evolving environments
 - How and when ?
- Explanations related to diagnosis
 - not only what but why and how

 \rightarrow Possible post doc topics



Possible interactions with other chairs

- Joao Marques Silva : HYBRID SUBSYMBOLIC \rightarrow SYMB.
- Leila Amgoud: HYBRID-ARGUMENT
- Jean-Michel Loubès: FAIR/ROBUST ML
- Hélène Fargier: INDUSTRIAL DESIGN with UNCERTAINTY and PREFERENCES

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