



Formal Methods vs Machine Learning

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Luigia Petre,

Åbo Akademi University, Turku, Finland



Some background

- MSc in Computer Science, University of Bucharest 1997
- PhD in Computer Science, Åbo Akademi University, 2005
- Senior lecturer at Åbo Akademi University
 - Adjunct professor
- Research in formal methods
 - Modeling based on math to analyze software systems
- Teaching in data science, since 2018
- CA17137 – gravitational waves with machine learning
 - Awesome physics (hard!)



Formal methods

- What is a formal method?
 - Set of techniques for analysing software-based systems
 - Has
 - Language with semantics
 - Methods of formulating + evaluating properties
 - Method/s of comparing different versions of the same system
- Examples
 - Z, B, Event-B, ASM, Alloy, VDM, TLA
 - CSP, CCS, pi-calculus, Ambient Calculus



Event-B: **state**-based formal method

- States and transitions
 - States
 - Variables
 - Constants
 - Transitions (Events)
 - Guards: necessary conditions
 - Actions: some variables change
- Certain abstraction level

Semantics

Kind	Assignment	Before-after Predicate
deterministic	$x := E(t, v)$	$x' = E(t, v) \wedge y' = y$
empty	skip	$v' = v$
non-deterministic	$x : P(t, v, x')$	$P(t, v, x') \wedge y' = y$

- denote the relationship holding between the state variables of the machine just before (denoted by v) and after (denoted by v') “applying” an assignment
- if x are variables of the machine, then x' are their values just after applying an assignment
- y denotes the set of variables drawn from v which are distinct from those in x



Formal Reasoning

- **Invariant**

- Condition on the state variables that **must hold permanently**
- We *prove* that, under the invariant in question and under the guard of each event, the invariant still holds after the variables have been modified according to the transition associated with that event

- **Reachability**

- Condition that **does not hold permanently**
- We *prove* that, an event whose guard is not necessarily true now will nevertheless certainly occur within a finite number of iterations

Invariant preservation

axioms invariant guard Before-after predicate

$$P(s, c) \wedge I(s, c, v) \wedge G(s, c, v) \wedge R(s, c, v, v') \Rightarrow I(s, c, v') \quad \text{INV}$$

invariant

Where:

s sets, c constants, v variables, v' variables after action takes place

\forall -quantified over all carrier sets, constants, and variables occurring free in the proof obligation

Refinement as spatial extension

- Reality is the same
- Our view of the refined reality is more accurate
- Previously invisible details of the reality are now revealed
- More powerful microscope reveals even more details



A refined model is spatially larger than its previous abstractions

Spatial extension has corresponding **temporal extension**

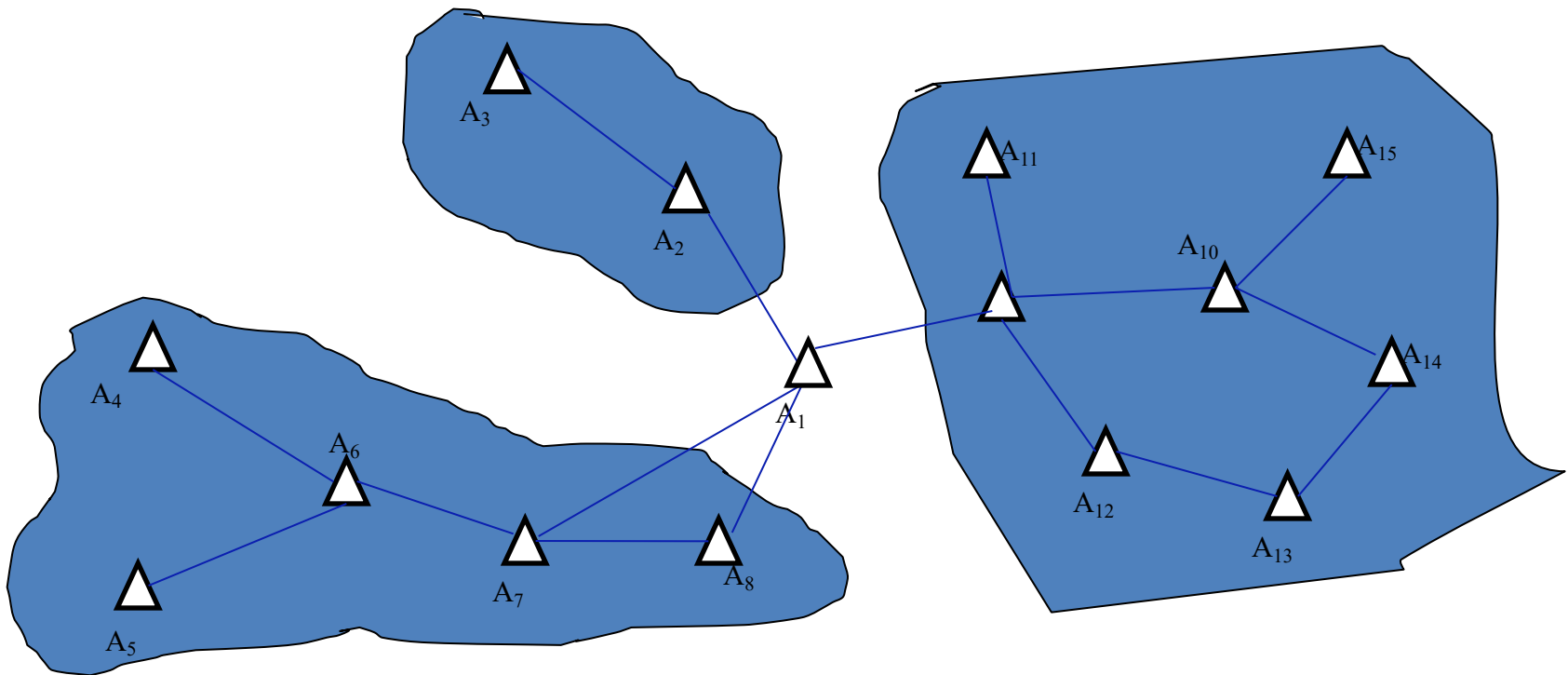
- The new variables can be modified by new transitions
 - Could not have been present in previous abstractions: the concerned variables did not exist in them
 - *New events* involve the new variables only
 - They refine some implicit events doing “nothing” in the abstraction
- Refinement will thus result in a discrete observation of reality, which is now performed using a *finer time granularity*.

Example 1

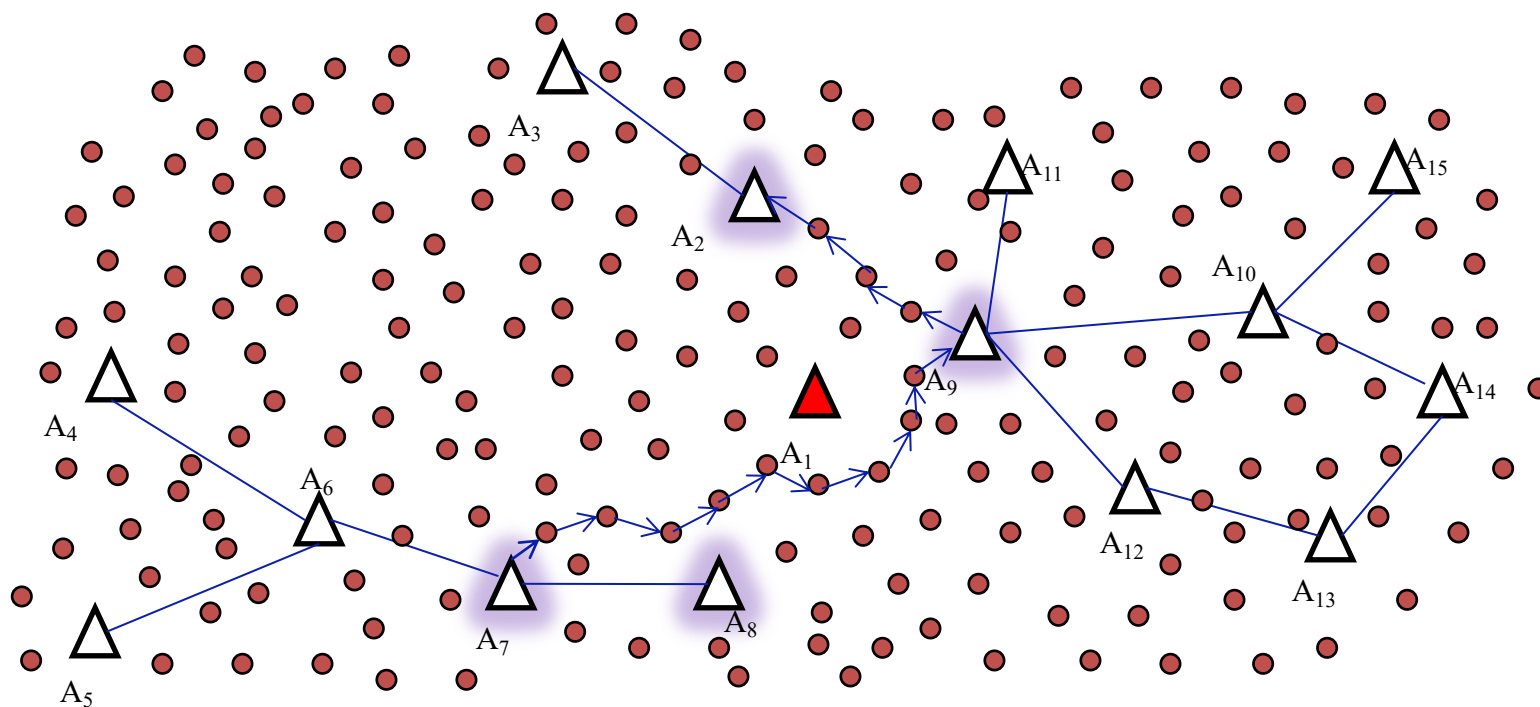
Wireless sensor-actor networks *Partitions and recovery*

Main purpose of the algorithm:

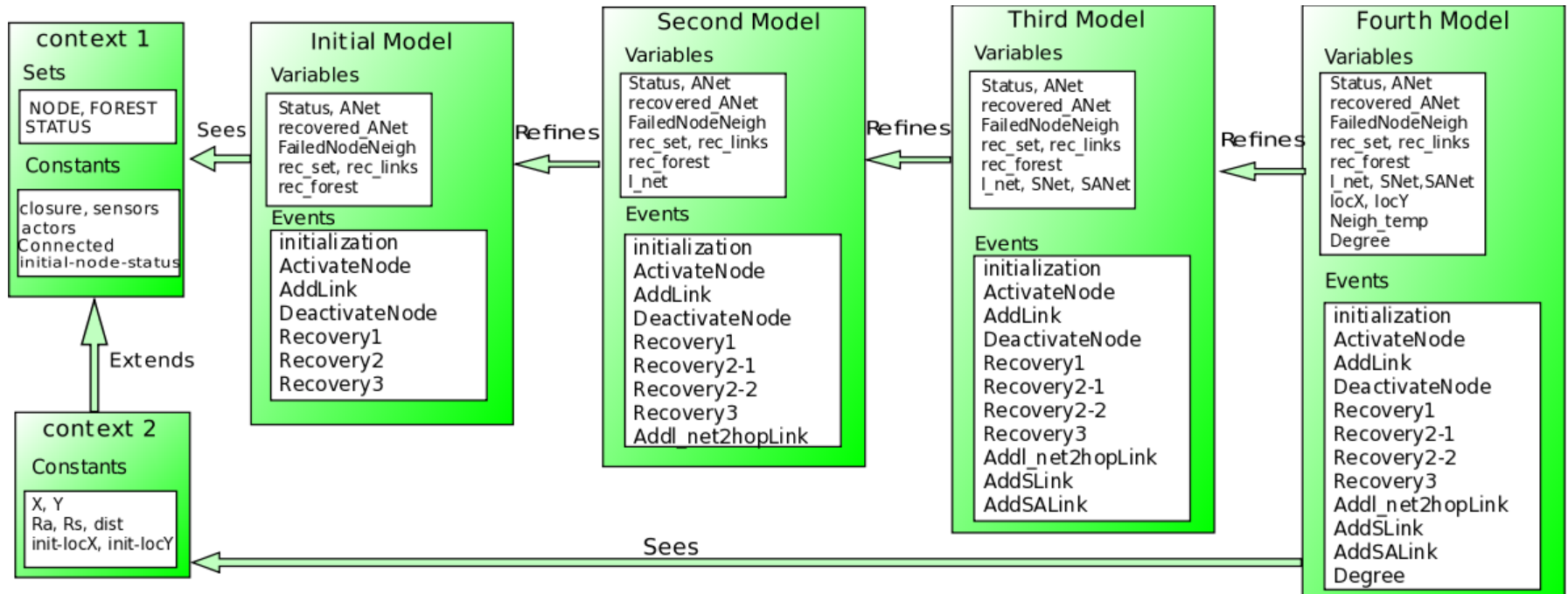
→ Re-establish connections among partitions formed by an actor failure



Result for Example 1



Refinement overview



We show that recovery is possible when the sensors are in a transitive closure relation.

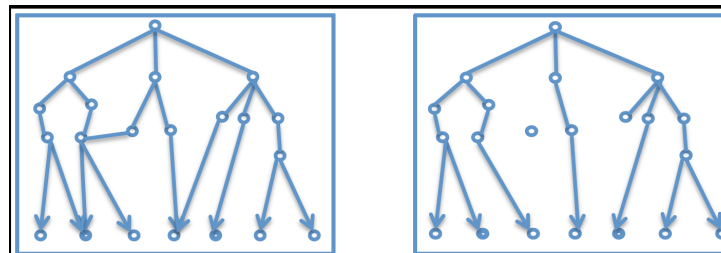
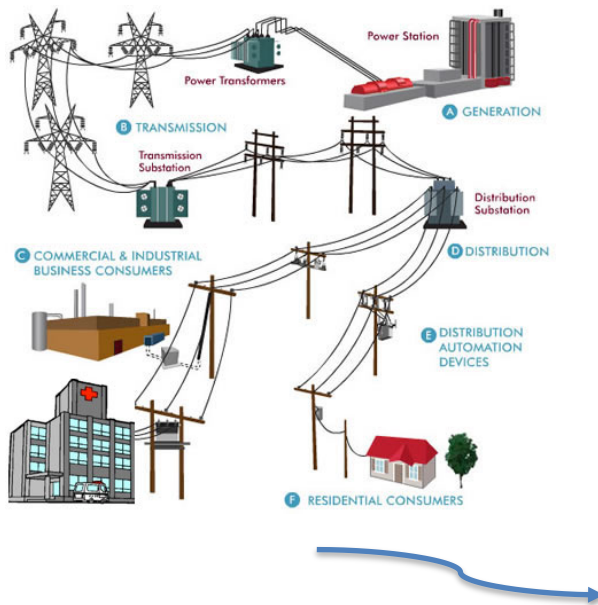


Example 2

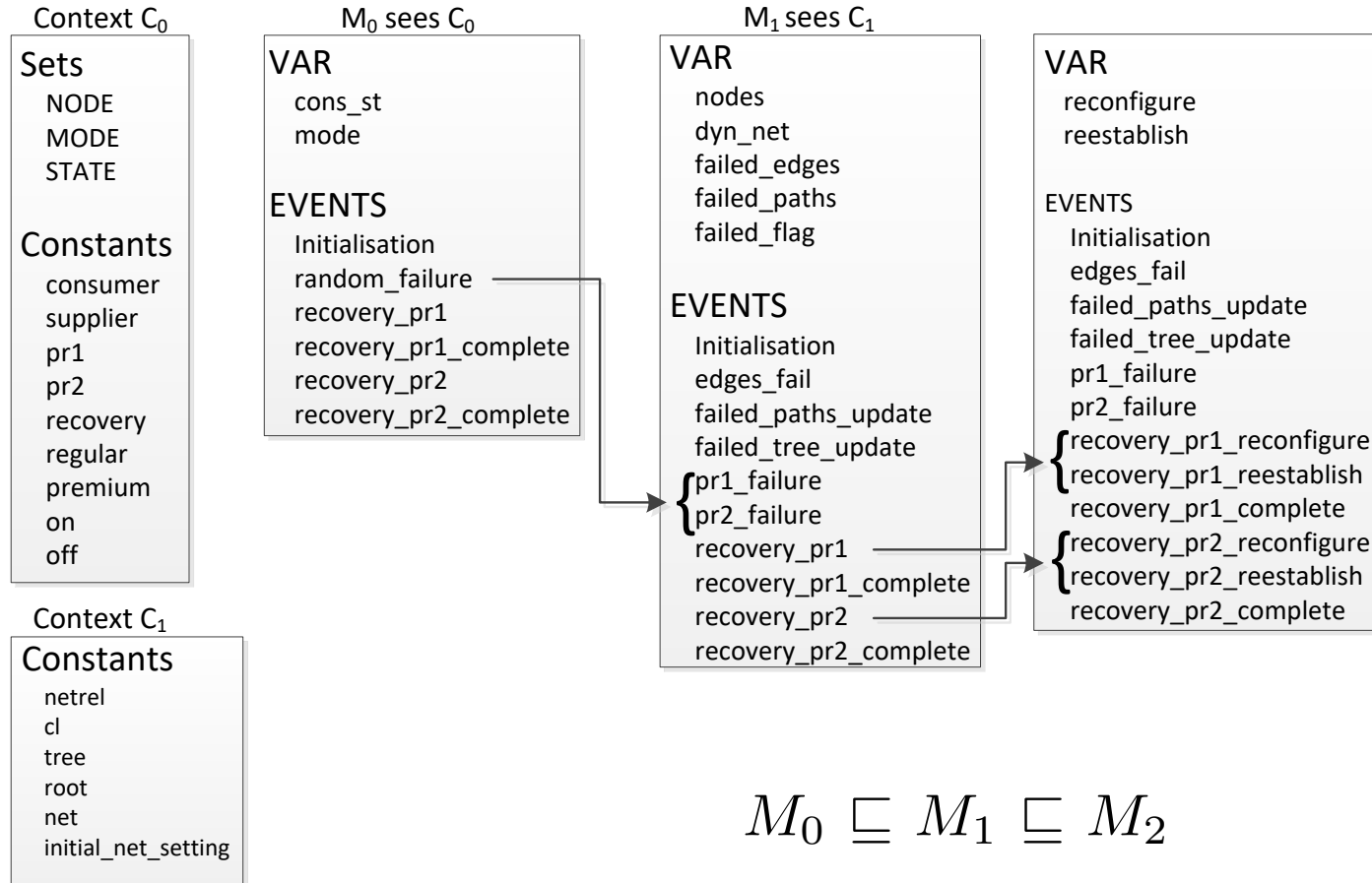
Smart electrical grids modeling

Smart grid recovery from failures

- Configurations
 - Momentary: tree
 - All possibilities: graph
- Recovery
 - Reconfiguration
 - Reestablishment
- Priorities
 - Hospitals/street lighting



Refinement overview



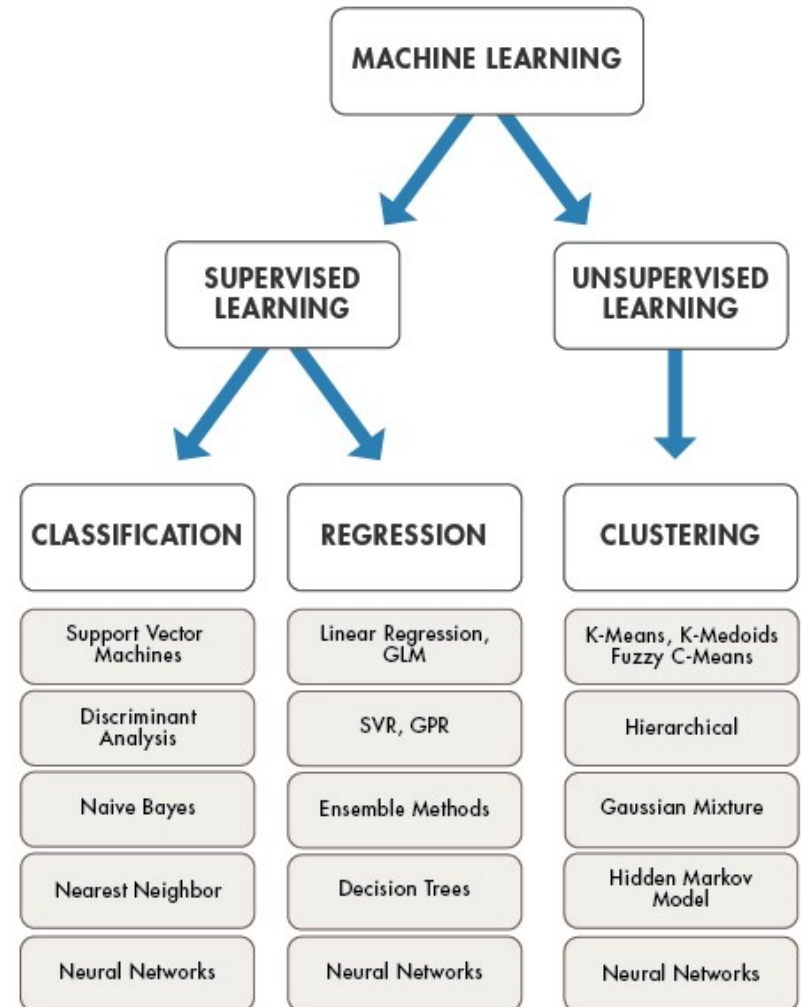
Summing up

- The sciences do not try to explain, they hardly even try to interpret, they mainly make models.

John von Neumann

- We aim at making *correct* models
 - With respect to the requirements
 - To analyze properties
 - What about machine learning?

Machine Learning



Formal Methods vs Machine Learning

- Deductive vs inductive approach
- Max Planck Institute (Germany)
 - Can we learn invariants?
 - And then prove properties
 - Can we learn models?
 - And then invariants, and then prove
- Correctness of ML algorithms
 - Linear regression vs deep learning



What about CA13137?

- Autoencoder for GW
- GW – the anomaly?
- How about the latent space?
 - Can we learn something about the GW parameters from there?

