BPM-meets-IoT: A Research Perspective on Smart Spaces and Smart Manufacturing

PhD Course on Smart Environments: Technologies, state of the art and research challenges

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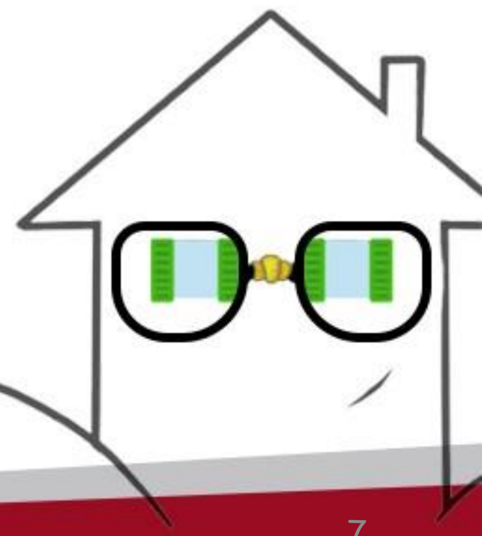
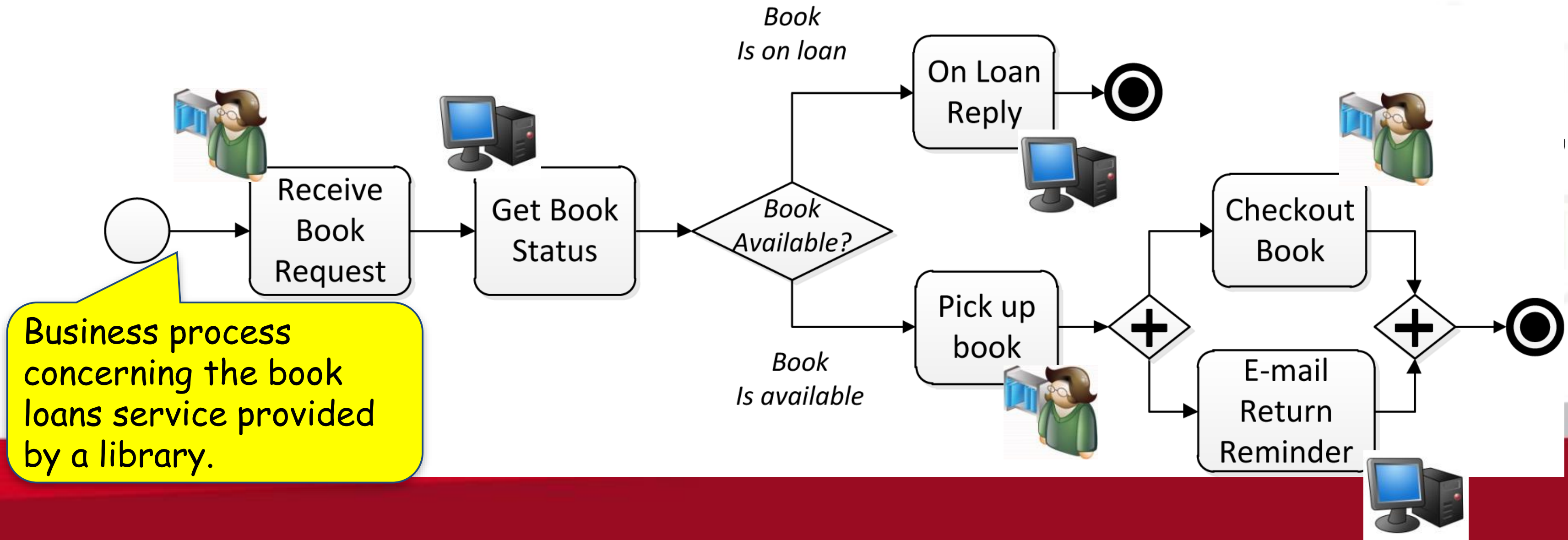


Thanks to prof. Andrea Marrella and ing. David Ghedalia for slides on SmartPM, to prof. Andrea Marrella and prof. Massimo Mecella for slides on BPM and Process Mining

Business Processes

A business process consists of a set of activities that are performed in coordination in an organizational and technical environment. These activities jointly realize a business goal

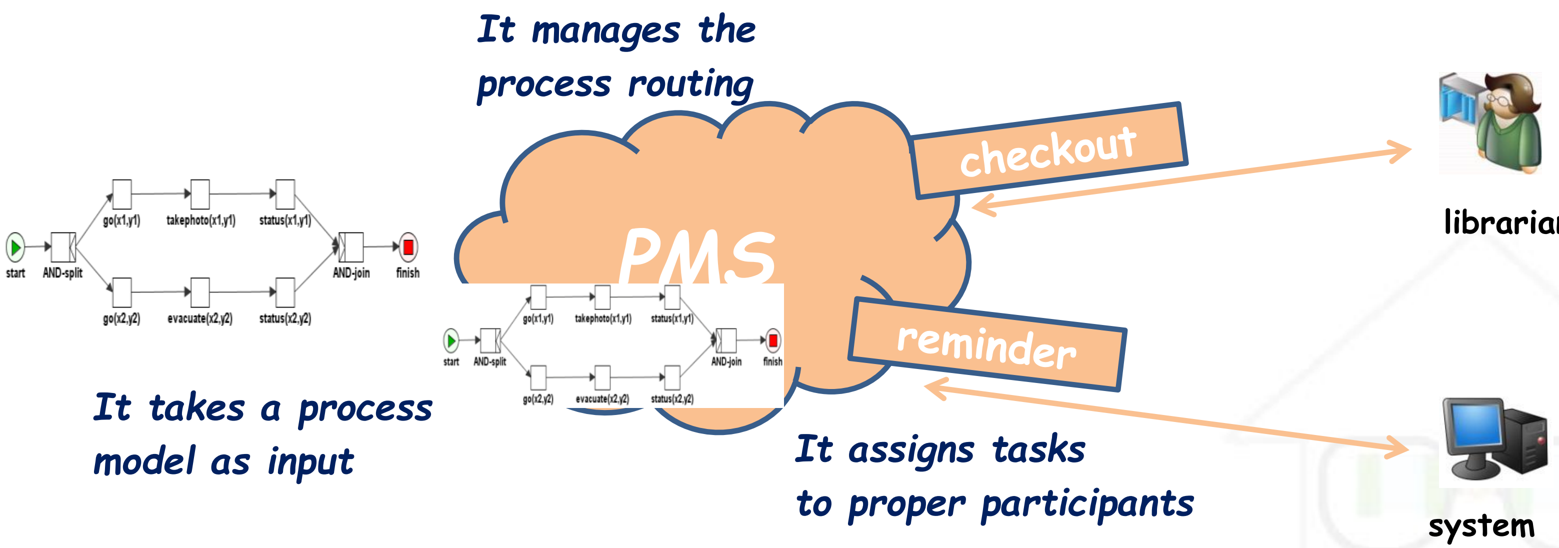


Business Processes and Information Systems

- Currently, business processes are the core of most information systems
  - production line of a car manufacturer
  - procedures for buying tickets on-line
- This requires that organizations specify their **flow of work** (their business processes) for the **orchestration** of participants, information and technology for the realization of products and services
- An information system that supports a business process is called ***Process Management System*** (or ***Process Aware Information System***)

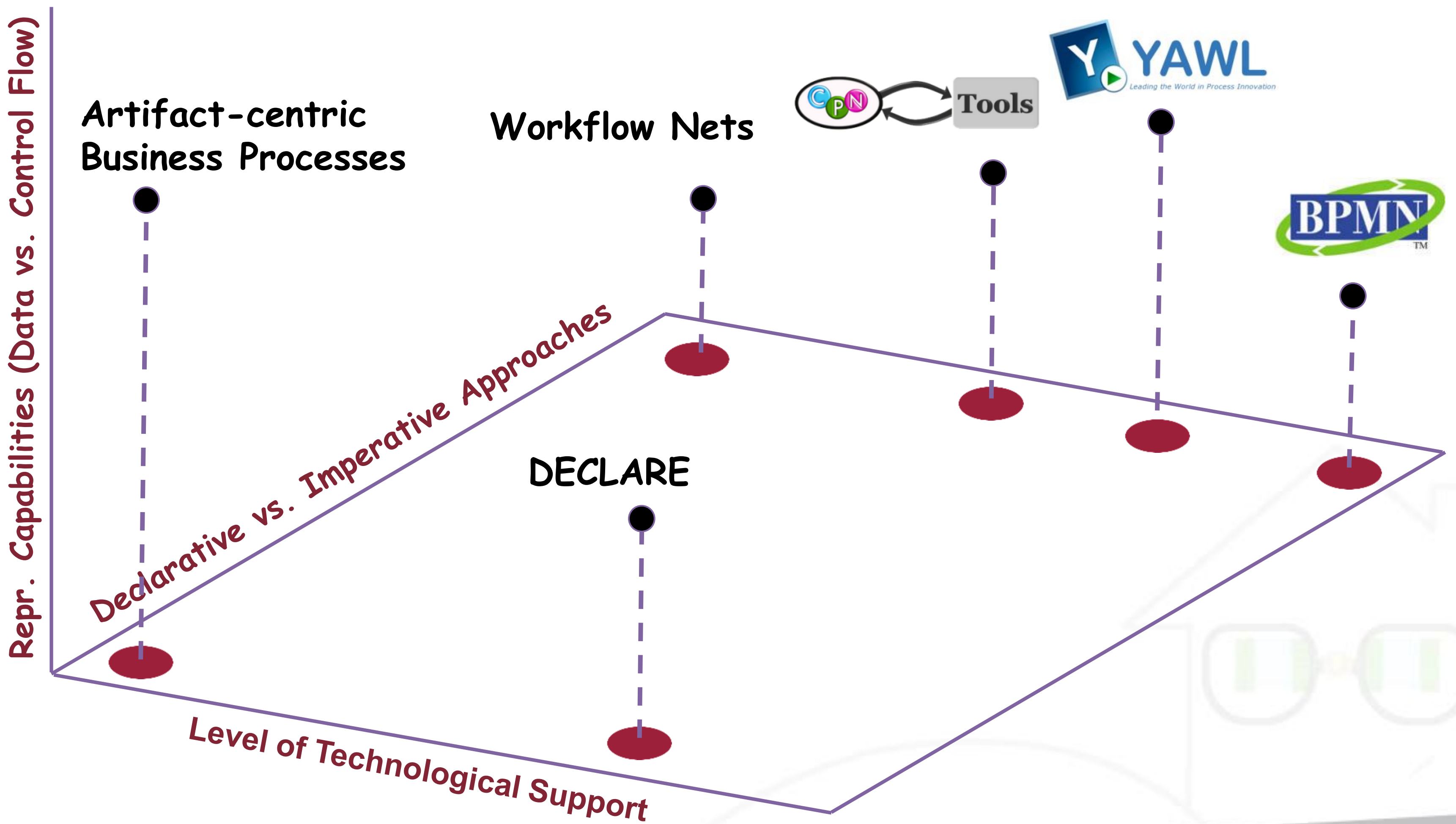
Process Management Systems

A **Process Management System (PMS)** *is a generic software system that is driven by explicit process representations to coordinate the enactment of business processes*



- A PMS is driven by a specific business process model…

Modeling Languages for Business Processes



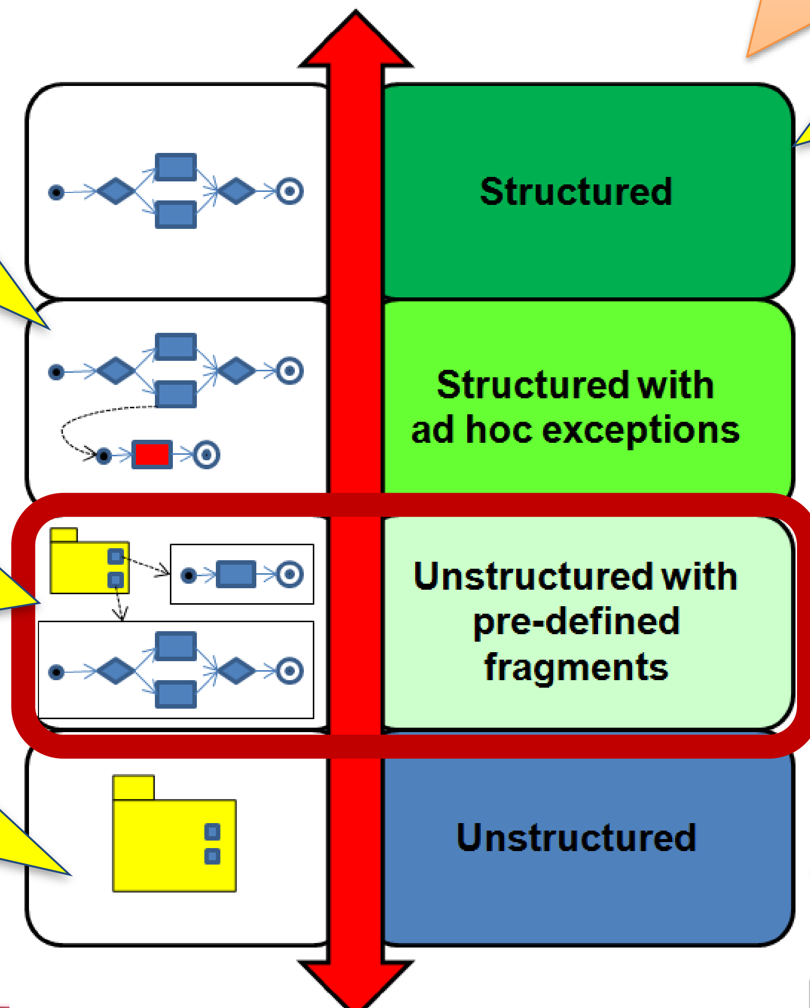
Classifying Business

S. Kemsley. *The changing nature of work: From structured to unstructured, from controlled to social.* BPM, 2011

Such processes require to be **adapted** according to **changing circumstances during the execution.**

Class of processes where **process modeling could not be completed before the execution.**

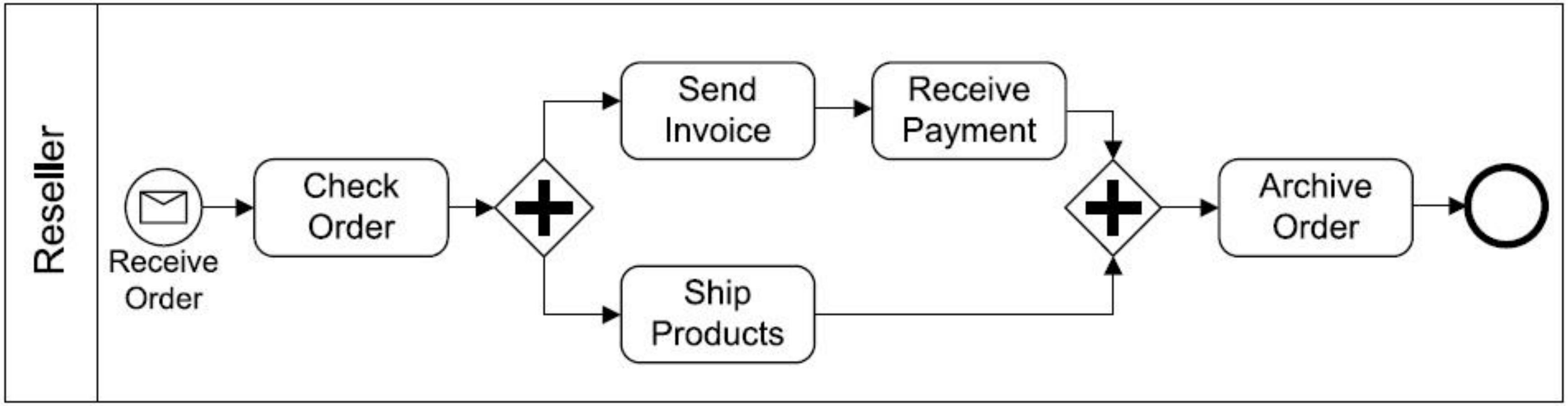
It is **impossible to define a priori the exact steps to be taken** in order to complete an assignement



These processes are **completely predictable** and all possible paths are **well-understood.**

Process Models

- A **process model** is a **process representation** that consists of a set of activities and execution constraints between them, criteria to indicate the start and termination of the process, and information about participants, associated IT applications and data, etc.
- Process models focus on the **process structure** rather than on technical aspects of their realization.
- Here a BPMN (imperative) process model



Process mining .. a bit of history

- The term “Process Mining” emerged in the 1998 in the software engineering field with Cook and Wolf, specifically in the work: “*Discovering models of software processes from event-based data*”.
- Applying process mining to workflows has been proposed for the first time in the work of Agrawal and Leymann: “*Mining Process Models from Workflow Logs*” (1998).
- However, its roots date back about half a century….
  - For example, in 1958, Anil Nerode presented an approach to synthesize finite-state machines from example traces, in the research work: “*Linear Automaton Transformations*”.
- The first survey of process mining was published in 2003 by van der Aalst et al.
  - After that, the progresses of process mining have been spectacular….

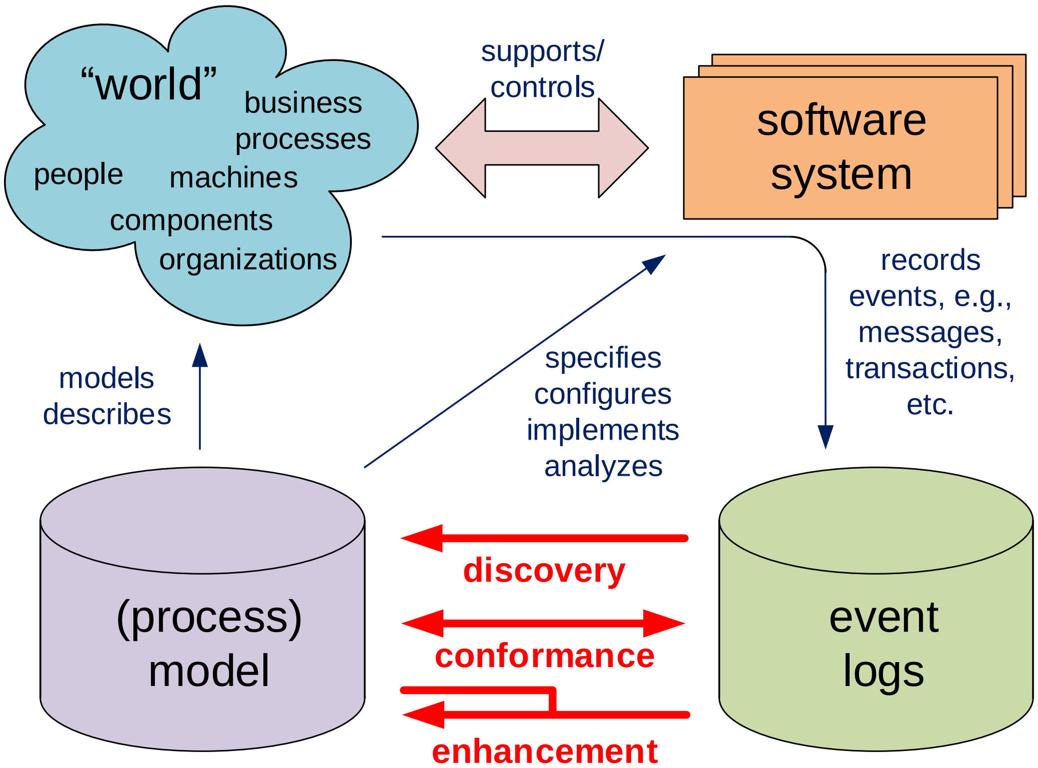
Great Idea in ICT?

- Over the last decade, event data started to become **readily available** and process mining algorithms have been implemented in various academic and commercial systems.
- Today, there is an active group of researchers working on process mining, and it has become one of the **hot topics** in ICT research.
  - **ICPM 2019** - 1st International Conference on Process Mining
- Moreover, there is a rapidly growing **interest from industry** in process mining. More and more software vendors started adding process mining functionality to their tools.

Great Idea?

W.M.P. van der Aalst received in 2017 an Alexander von Humboldt Professorship, the highest German award for academics, with a value of **five million euros** for opening a research center in data science and process mining!

Process mining techniques

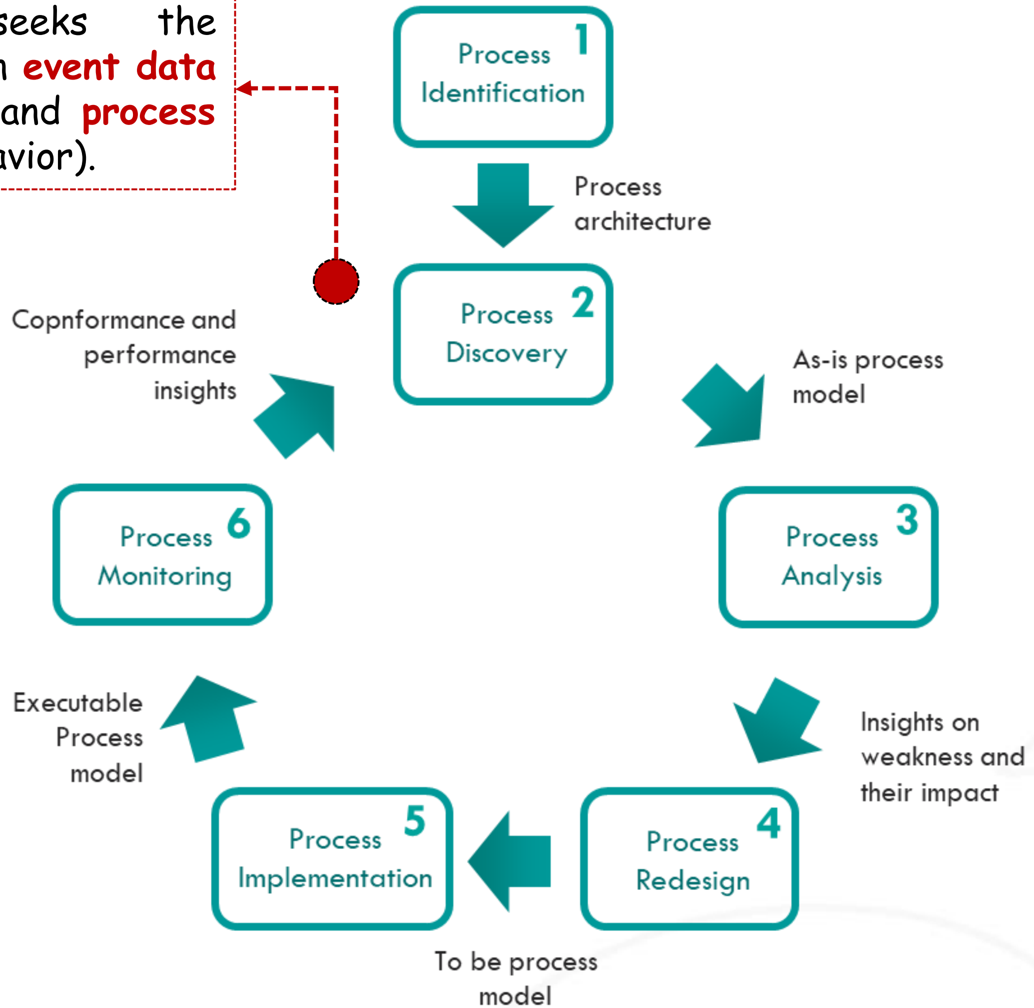


- **Process discovery**
  - "What is really happening?"
- **Conformance checking:**
  - "Do we do what was agreed upon?"
- **Other techniques:**
  - **Performance analysis:**
    - "Where are the bottlenecks?"
  - **Process prediction:**
    - "Will this process instance be late?"
  - **Process enhancement:**
    - "How to redesign and refine this process?"

❖ **Process mining techniques have become mature over the years and are nowadays supported by various academic/commercial tools.**

Process Mining in the BPM life cycle

Process Mining seeks the **confrontation** between **event data** (observed behaviour) and **process models** (expected behavior).



Process Mining tools

- ProM
- Apromore
- Disco (Fluxicon)
- Perceptive Process Mining
- Celonis Discovery
- ARIS Process Performance Manager
- QPR ProcessAnalyzer
- Interstage Process Discovery (Fujitsu)
- Discovery Analyst (StereoLOGIC)
- XMAnalyzer (XMPro)
- …

ProM: Academic Process Mining Tool

- Download and install **ProM 6.9** from http://www.promtools.org/

ProM
process mining workbench

600+ plug-ins available covering the whole process mining spectrum

(Rough) structure of an Event Log

- A single execution of a process is recorded into a **trace** (or a **case**).
- A trace consists of **events** such that each event relates to one trace.
- Events within a case are ordered (through timestamps) and can have **attributes**.
  - Examples of typical attribute names are activity, time, costs, and resource.
- **Minimal requirement**: ordered events referring to:
  - an activity name
  - a case id

case id	event id	properties				
		timestamp	activity	resource	cost	...
1	35654423	30-12-2010:11.02	register request	Pete	50	...
	35654424	31-12-2010:10.06	examine thoroughly	Sue	400	...
	35654425	05-01-2011:15.12	check ticket	Mike	100	...
	35654426	06-01-2011:11.18	decide	Sara	200	...
	35654427	07-01-2011:14.24	reject request	Pete	200	...
2	35654483	30-12-2010:11.32	register request	Mike	50	...
	35654485	30-12-2010:12.12	check ticket	Mike	100	...
	35654487	30-12-2010:14.16	examine casually	Pete	400	...
	35654488	05-01-2011:11.22	decide	Sara	200	...
	35654489	08-01-2011:12.05	pay compensation	Ellen	200	...
3	35654521	30-12-2010:14.32	register request	Pete	50	...
	35654522	30-12-2010:15.06	examine casually	Mike	400	...
	35654524	30-12-2010:16.34	check ticket	Ellen	100	...
	35654525	06-01-2011:09.18	decide	Sara	200	...
	35654526	06-01-2011:12.18	reinitiate request	Sara	200	...
	35654527	06-01-2011:13.06	examine thoroughly	Sean	400	...
	35654530	08-01-2011:11.43	check ticket	Pete	100	...
	35654531	09-01-2011:09.55	decide	Sara	200	...
	35654533	15-01-2011:10.45	pay compensation	Ellen	200	...
4	35654641	06-01-2011:15.02	register request	Pete	50	...
	35654643	07-01-2011:12.06	check ticket	Mike	100	...
	35654644	08-01-2011:14.43	examine thoroughly	Sean	400	...
	35654645	09-01-2011:12.02	decide	Sara	200	...
	35654647	12-01-2011:15.44	reject request	Ellen	200	...

Event logs as multi-set of traces

- An event log can be seen as a multi-set of traces.

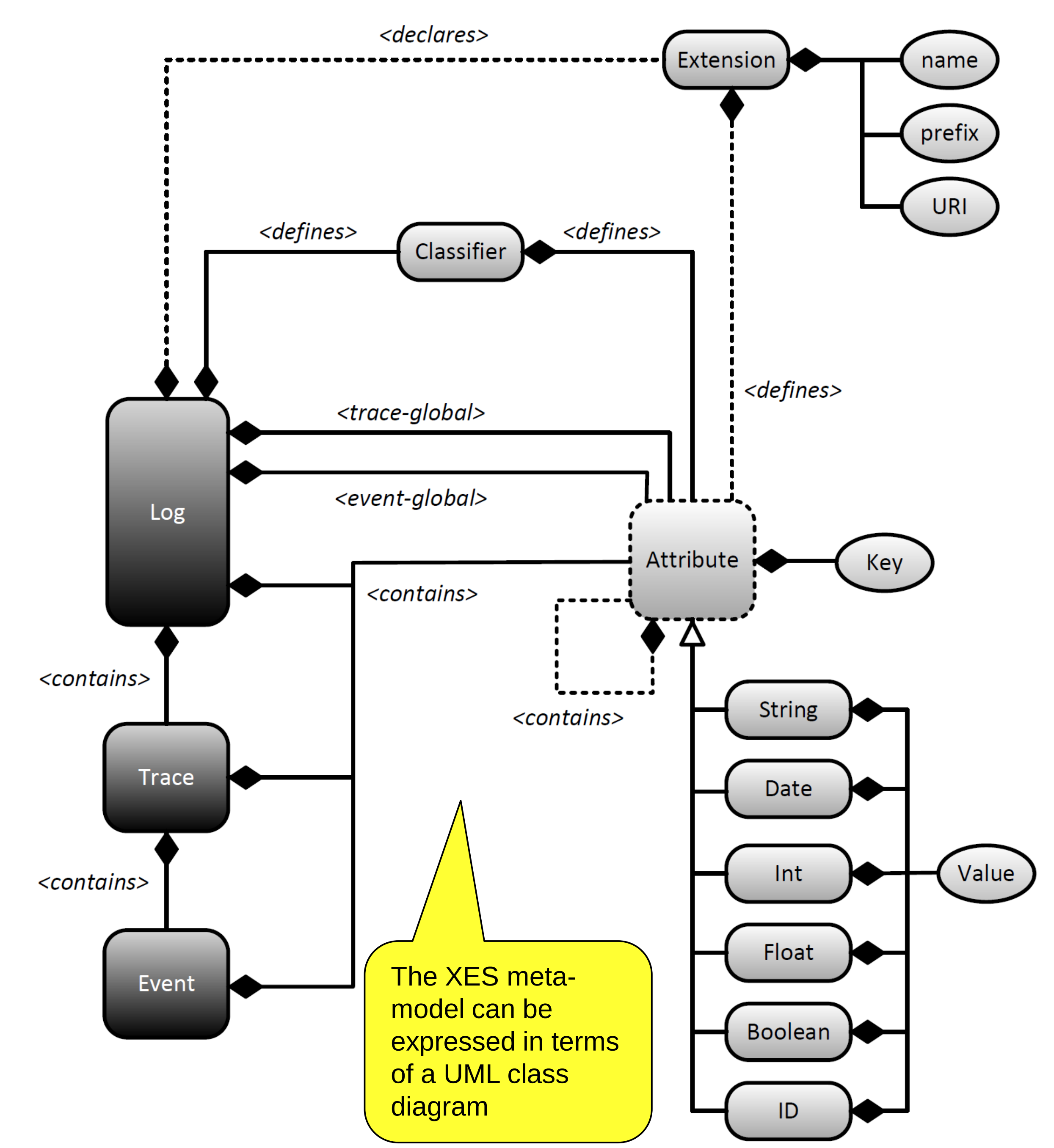
$$L_1 = [\langle a,b,c,d\rangle^3, \langle a,c,b,d\rangle^2, \langle a,e,d\rangle]$$

  - Three traces <a,b,c,d>
  - Two traces <a,c,b,d>
  - One trace <a,e,d>

XES (eXtensible Event Stream)

- De-facto standard for storing, representing and exchanging event logs.
- See www.xes-standard.org.
- Adopted by the IEEE Task Force on Process Mining.
- Predecessor: MXML (2010).
- The format is supported by the majority of process mining tools.

XES
Extensible Event Stream

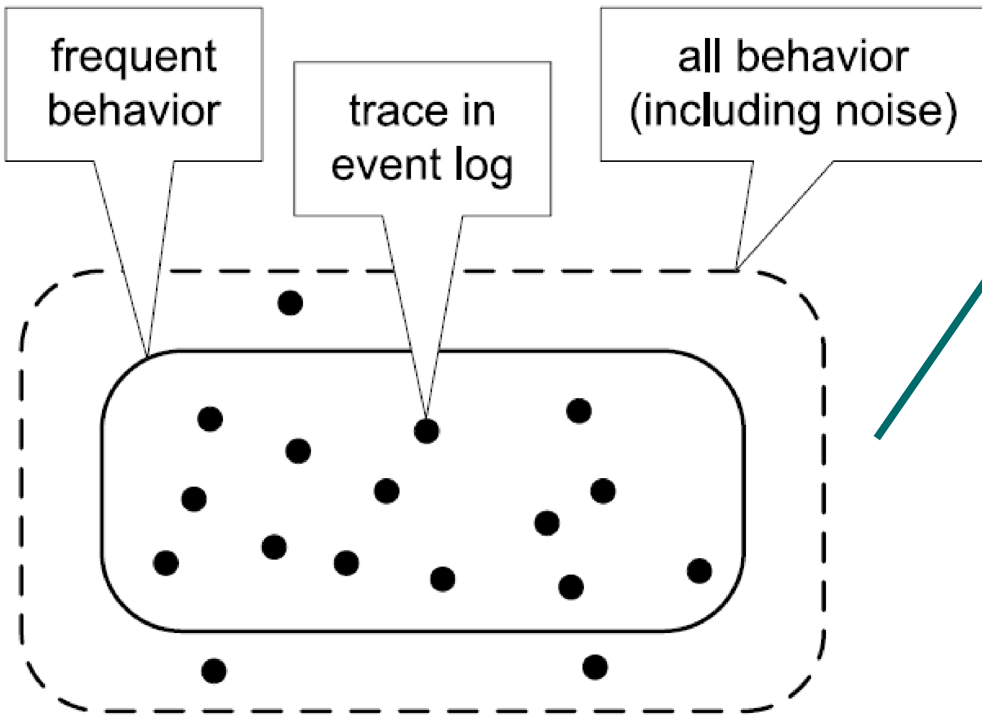


- A log contains traces and each trace contains events.
- Logs, traces, and events have attributes.
- Extensions may define new attributes and a log should declare the extensions used in it.
- Global attributes are attributes that are declared to be mandatory. Such attributes reside at the trace or event level.
- Attributes may be nested.
- Event classifiers are defined for the log and assign a “label” (e.g., activity name) to each event. There may be multiple classifiers

Noise and Incompleteness

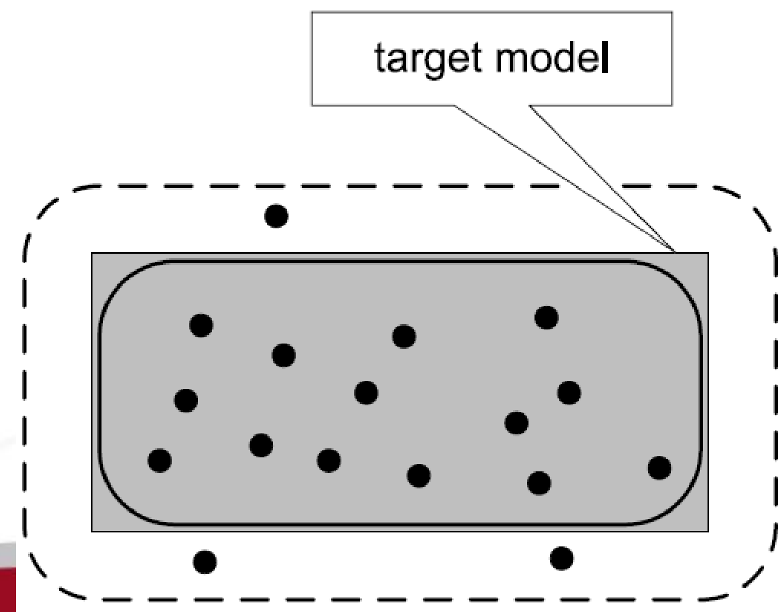
- An event log typically contains **only a fraction** of the possible process behavior.
- To successfully apply process mining in practice, one needs to deal with **noise** and **incompleteness**.
  - **Noise**: the event log contains *rare and exceptional behavior* not representative for the typical behavior of the process.
    - One is typically interested in frequent behavior and not in all possible ones.
  - **Incompleteness**: the event log contains *too few events* to be able to discover some of the underlying control-flow structures.
    - Many discovery algorithms make the *strong completeness* assumption (assuming that the log contains all possible behaviors).

Noise and Incompleteness



The **ideal process model** allows for the behavior coinciding with the frequent behavior seen when the process would be observed ad infinitum while being in steady state.

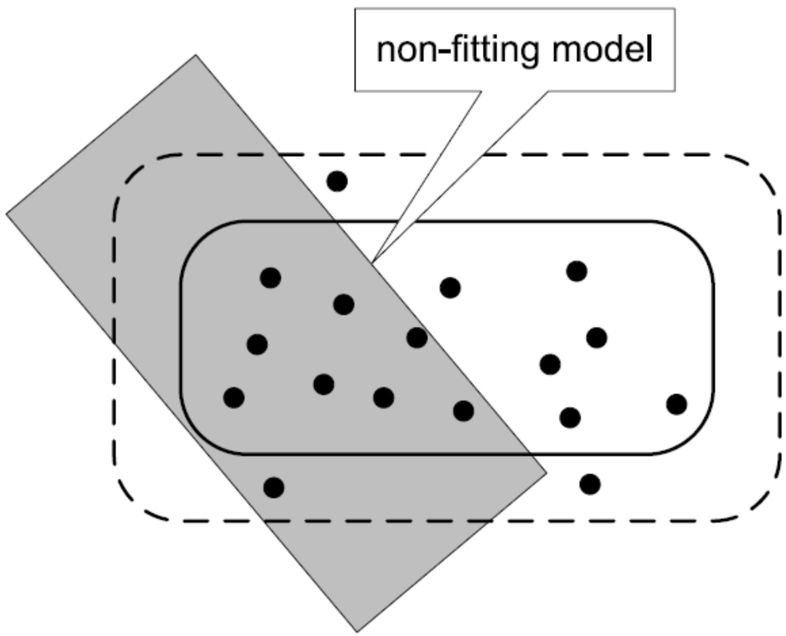
Mature process mining algorithms allow to **abstract** from infrequent behavior.



Four competing quality criteria

In general, the quality of a process mining result refers to four quality dimensions:

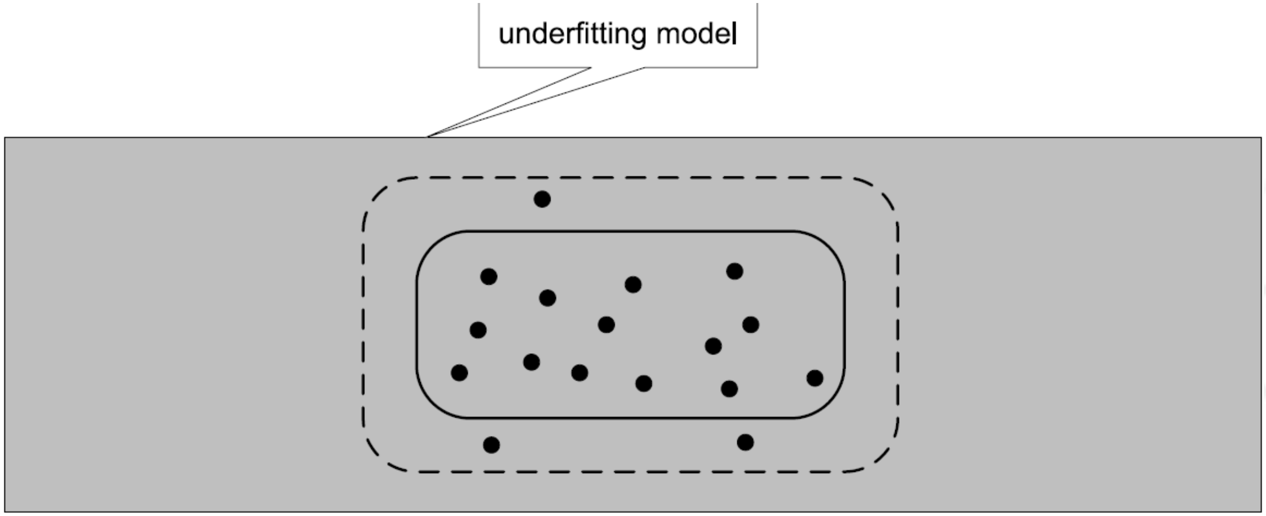
1. **Fitness**: the discovered model should allow for the behavior seen in the event log.
   - A model has a *perfect fitness* if all traces in the log can be replayed from the beginning to the end.



Four competing quality criteria

In general, the quality of a process mining result refers to four quality dimensions:

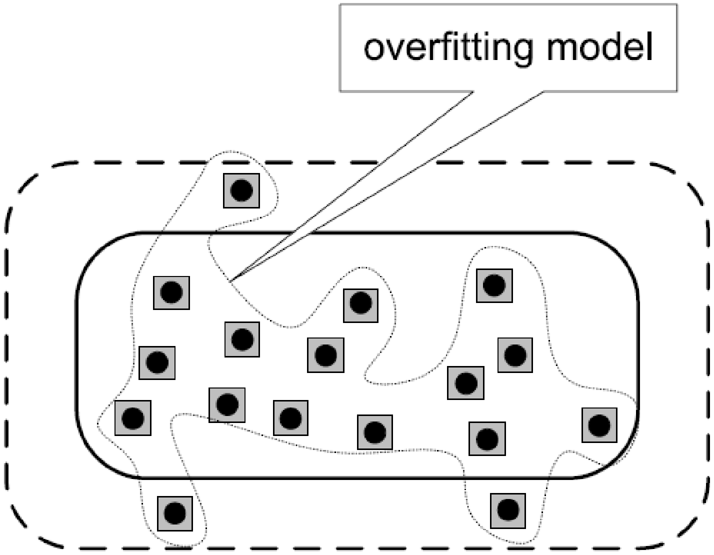
1. **Fitness**
2. **Precision** (*avoid underfitting*): the discovered model should not allow for behavior completely unrelated to what was seen in the event log.



Four competing quality criteria

In general, the quality of a process mining result refers to four quality dimensions:

1. **Fitness**:
2. **Precision** (avoid underfitting)
3. **Generalization** (avoid overfitting): the discovered model should generalize the example behavior seen in the event log.



Four competing quality criteria

In general, the quality of a process mining result refers to four quality dimensions:

1. **Fitness**
2. **Precision** (avoid underfitting)
3. **Generalization** (avoid overfitting)
4. **Simplicity**: the discovered model should be as simple as possible.

- Occam's Razor: The simplest model that can explain the behavior seen in the log is the best model.
- Metrics to quantify the **complexity** and **understandability** of a process model:
  - size of the model (e.g., the number of nodes and/or arcs),
  - "structuredness" or "homogeneity" of the model.

BP-Meets-IoT Manifesto

https://arxiv.org/abs/1709.03628

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The Internet-of-Things Meets Business Process Management: Mutual Benefits and Challenges

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Abstract
The Internet of Things (IoT) refers to a network of connected devices collecting and exchanging data over the Internet. These things can be artificial or natural, and interact as autonomous agents forming a complex system of interactions. Business Process Management (BPM) was established to identify, discover, analyze, design, implement, and monitor collaborative business processes within a single and across multiple organizations. Whereas the IoT and BPM have been so far regarded as separate topics in research and practice, we argue that there are multiple links to be explored. In this paper, we pose the question to what extent these two paradigms can be combined and we detail the challenges of the mutual combination. As a conclusion, this paper suggests areas for future research.

Keywords
IoT (Internet-of-Things) — BPM (Business Process Management) — Challenges — Manifesto

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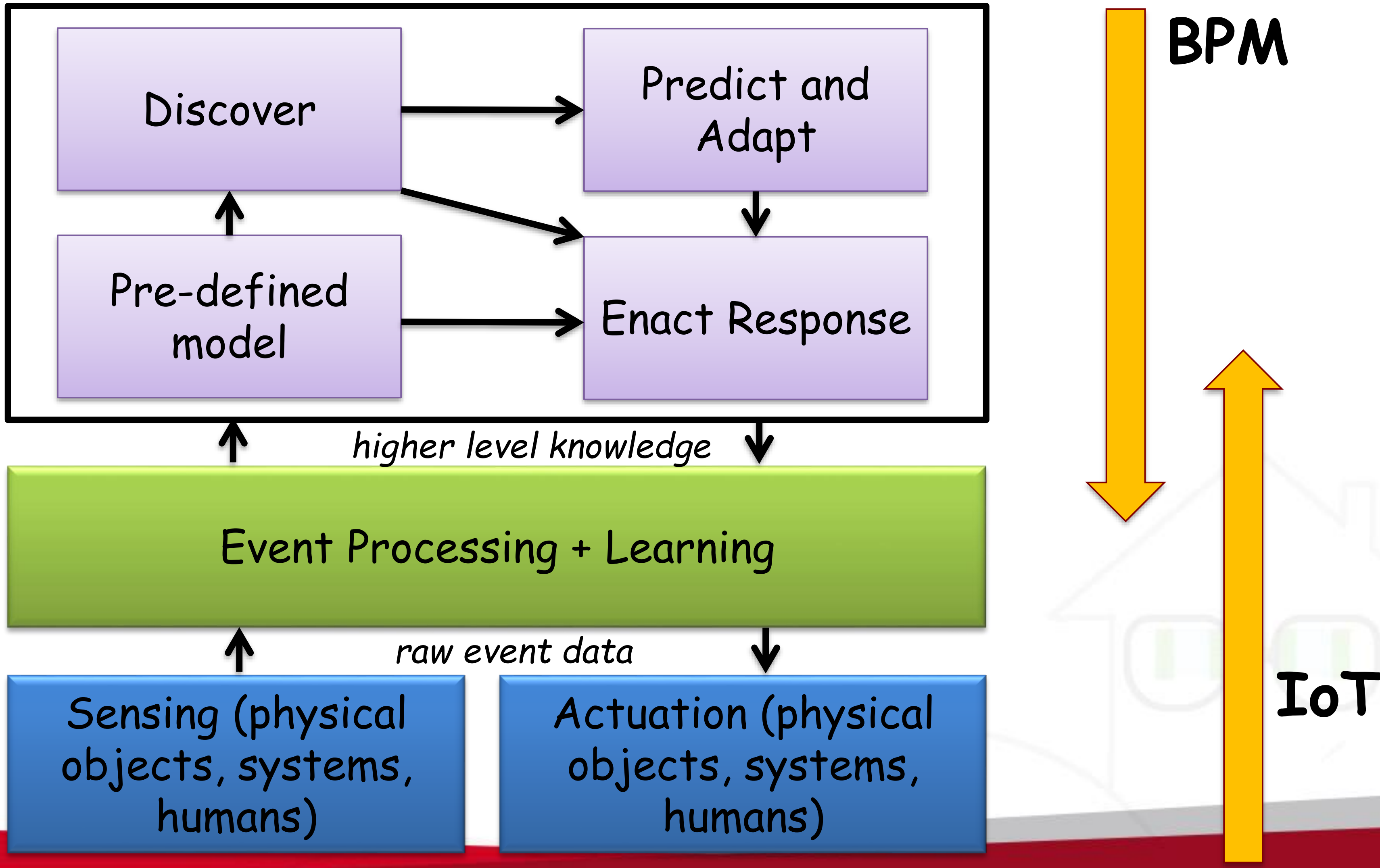
Interaction between BPM and IoT



APPLYING BPM TO SMART HOMES

Modeling Human Habits

- Idea: using modeling formalisms from Business Process Management to model human habits inside smart spaces
  - Human readable
  - Several mining techniques available in literature (process mining)
- A process model is a process representation that consists of a set of actions and execution constraints between them
- Challenges:
  - **What is a process anyway in smart spaces?**
  - **Obtaining datasets**
  - Clear gap between the granularity of sensor logs and the traces used for process mining
    - **How to aggregate sensor measurements to recognize actions?**
  - Is a human habit like a "spaghetti" process?
    - **If yes, which formalism to use?**
  - Process requires the event log explicitly segmented into traces (process instances)
    - **How to automatically segment the log?**

Leotta, Mecella, Mendling. "Applying process mining to smart spaces: Perspectives and research challenges". *In Proc. of RWBPMS Workshop CAISE 2015* (pp. 298-304)

An Idea: BPM?

- Business Process Management - BPM can be helpful at modeling human habits and activities
  - **Due to the different application contexts, challenges must be addressed**
- Few approaches using workflows already proposed but they do not leverage the strong and recent research in process mining
- Great benefits from the point of view of visual analysis
- Grounded in logics, potentially a trade-off between specification-based and learning-based approaches

Aztiria, A.; Izaguirre, A.; Basagoiti, R.; Augusto, J.C.; Cook, D. Automatic modeling of frequent user behaviours in intelligent environments. In Proc. Intelligent Environments 2010.

Processes in Smart Spaces

- Terminology of Smart Spaces
  - **Context:** the state of the environment including the human inhabitants
  - **Action:** atomic interaction with the environment or a part of it (e.g., a device)
    - Some techniques in literature focuses only on actions
    - Other techniques skip actions while recognizing activities
  - **Activity:** a sequence of actions (one in the extreme case) or sensor measurements/events with a final goal
    - Activities can be collaborative
  - **Habit:** a set of interleaving of activities that happen in specific contextual conditions
    - e.g., what a user does each morning between 08:00 and 10:00am
- **Activity and Habits can be considered the equivalent of processes in the smart space field**

Dealing with Granularity

- Clear gap between the granularity of sensor logs and the traces used for process mining [Baier2013]
- No one-to-one correspondence between sensor measurements and performed actions (tasks)
  - A single user action may trigger many sensor measurements
  - A single sensor measurement may be related to several actions
- **Required approach:**
  1. ***Aggregate sensor measurements to recognize actions***
  2. **Apply process mining**
- The kind of available sensors strongly influences the granularity and confidence of recognized actions

Baier, T., Mendling, J.: Bridging abstraction layers in process mining by automated matching of events and activities. In BPM 2013.

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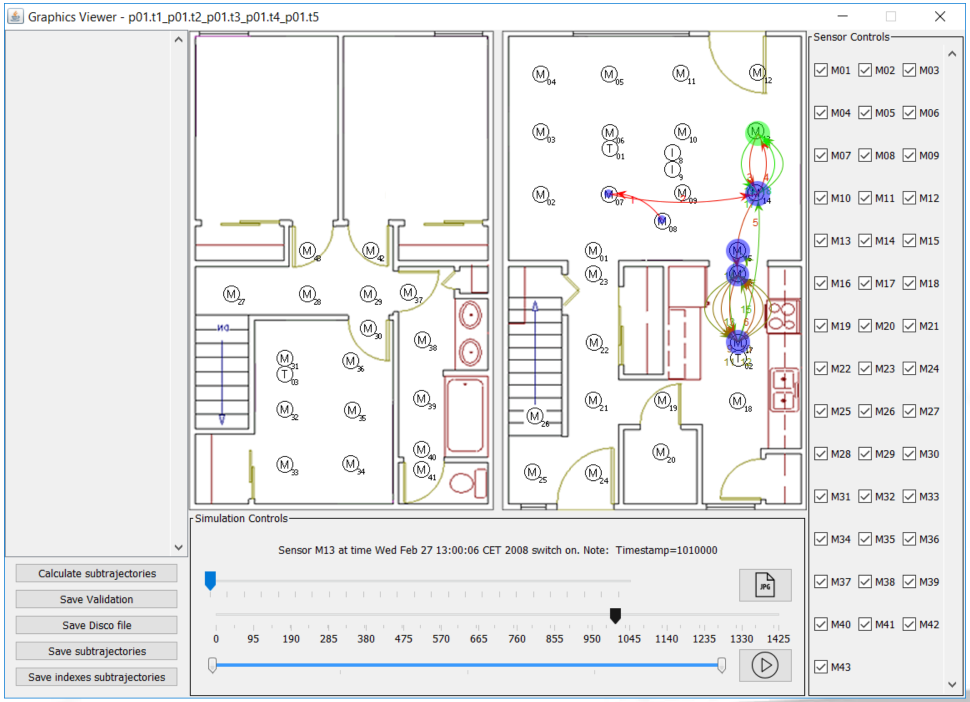
Bridging the Gap between Sensor Logs and Event Logs

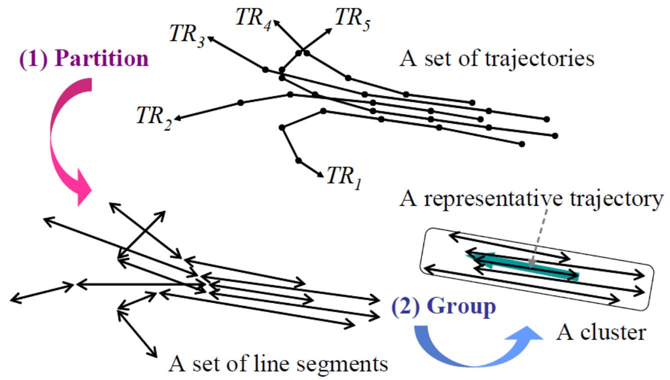
- No one-to-one correspondence between sensor measurements and actions (tasks) performed
  - A single user action may trigger many sensor measurements
  - A single sensor measurement may be related to several actions
- The classes of available sensors influence the kind of actions that can be recognized
  - We initially focused on a specific category of sensors: Presence Infrared Sensors (PIRs)



Leotta, Mecella, Sora. "Visual process maps: a visualization tool for discovering habits in smart homes." <u>*Journal of Ambient Intelligence and Humanized Computing (2019)*</u>, 1-29.

Bridging the Gap between Sensor Logs and Event Logs

- TRACLUS [Lee2007]: Trajectory clustering algorithm
  - Two phases:
    - Trajectory partitioning
    - Density-based line-segment clustering



- We can now classify each trajectory as a specific movement action: STAY, AREA, MOVEMENT

Leotta, Mecella, Sora. "Visual process maps: a visualization tool for discovering habits in smart homes." *Journal of Ambient Intelligence and Humanized Computing (2019)*, 1-29.

Bridging the Gap between Sensor Logs and Event Logs

Given a trajectory δ returned by TRACLUS

$\boldsymbol{I_m(\delta)}$ reflects how many sensors are involved in the trajectory

$$I_m(\delta) = \frac{number\ of\ distinct\ sensors}{total\ number\ of\ sensors}$$

$\boldsymbol{I_a(\delta)}$ reflects how trajectory time is distributed among sensors (Gini coefficient)

$\boldsymbol{I_s(\delta)}$ reflects how much time is spent under a single sensor

$$I_s(\delta) = \frac{time\ spent\ under\ the\ most\ frequent\ sensor}{total\ time\ of\ trajectory}$$

Leotta, Mecella, Sora. "Visual process maps: a visualization tool for discovering habits in smart homes." Journal of Ambient Intelligence and Humanized Computing (2019), 1-29.

Bridging the Gap between Sensor Logs and Event Logs

Classification Index:

$$I_{tot}(\delta) = w_m I_m(\delta) + w_a I_a(\delta) + w_s I_s(\delta)$$

With:

$$w_m + w_a + w_s = 1$$

Subtrajectory classification:

$$f(\delta) = \begin{cases} STAY, & 0 \leq I_{tot}(\delta) < T_a \\ AREA, & T_a \leq I_{tot}(\delta) < T_m \\ MOVEMENT, & T_m \leq I_{tot}(\delta) \leq 1 \end{cases}$$

Leotta, Mecella, Sora. "Visual process maps: a visualization tool for discovering habits in smart homes." Journal of Ambient Intelligence and Humanized Computing (2019), 1-29.

Log Segmentation (1/2)

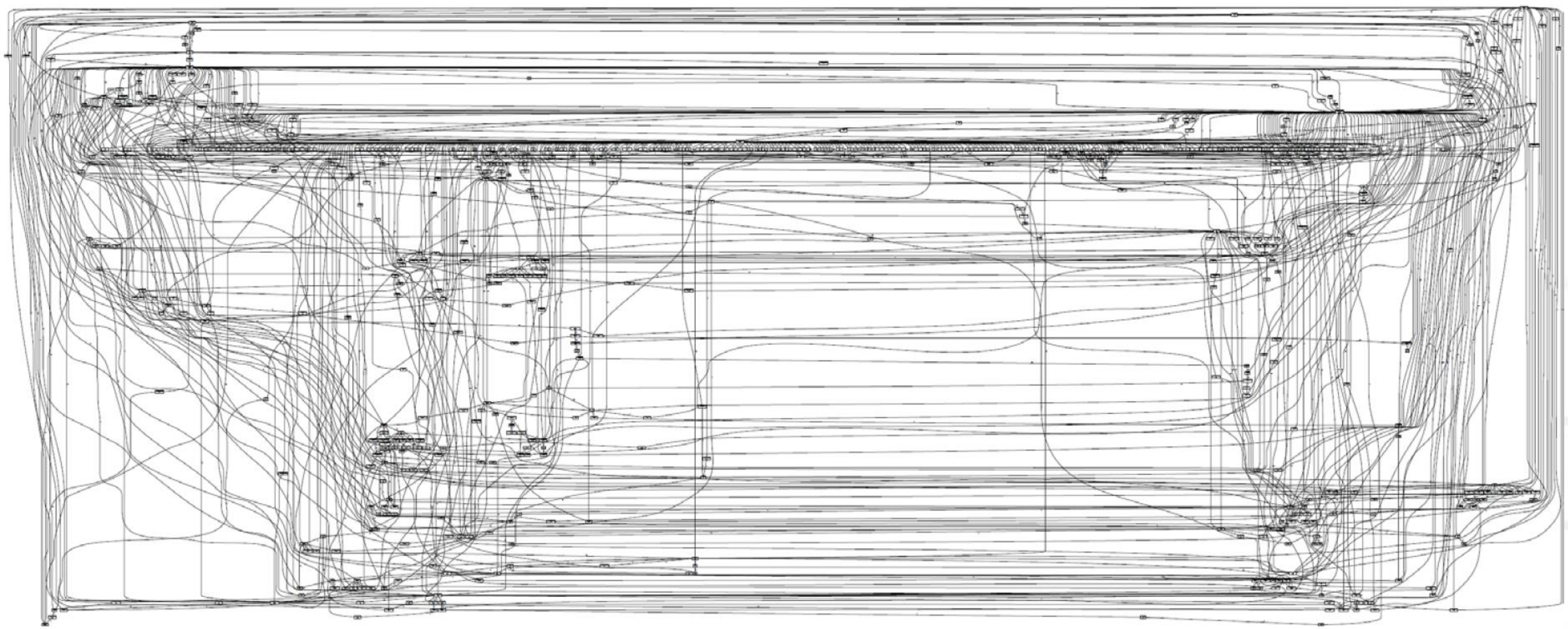
- A common prerequisite of process mining techniques is to have an event log explicitly segmented into cases (process instances)
  - Case "start" and case "end" events
  - For each event, which case it belongs to
  - **Relatively easy to instrument a process in an industrial or business environments**
- This assumption is usually not met by sensor logs, as labeling is generally an expensive task to be performed by humans
  - *Especially difficult to associate actions (derived from sensor measurements) to activities and habits in the interleaved case and in presence of multiple users*

Log Segmentation (2/2)

- How do we define habits and activities?
  - Manually defined?
  - Automatically learned and adapted?
  - **Active learning?**
- What about multiple users?
  - Usually sensor logs do not contain any information about which user(s) caused a certain sensor to trigger or to provide a specific measurement
    - The employment of body-area sensors and tags is usually perceived as invasive by the user and do not solve all the issues
  - **Mining habits in a multi-user scenario is significantly harder**
    - e.g., even though multiple users can be identified by the spatial distance between PIRs triggering close in time, when trajectories intersect
    - tracking techniques or reasoning must be employed to keep following users

Which Formalism? (1/2)

- Question: Does a human habit resemble a "spaghetti" process?
  - Approaches to deal with unstructured processes do exist as both imperative and declarative modeling formalisms
  - Human processes in smart spaces are very similar to "artful" processes (e.g., treating patients in hospitals)



Which Formalism? (2/2)

- Declarative modeling formalisms
  - Usually based on temporal logics (e.g., DECLARE [Pesic2007])
    - Already applied to smart spaces for reasoning [Magherini2013]
  - The notion of time is qualitative and not quantitative
    - **Time is a first-class property of a measurement**
    - **Attempts to support a quantitative notion of time** [Westergaard2012]
  - **Are typical constraints enough?**
- Fuzzy mining [Günther2007]
  - Borrows concepts from the world of maps and cartography
  - Zoom in and out on a process model highlighting the importance of certain tasks and connection between tasks
  - **More suitable for offline analysis than for online monitoring**

Westergaard, M., Maggi, F.M.: Looking into the future. In OTM 2012

Magherini, T., Fantechi, A., Nugent, C.D., Vicario, E.: Using temporal logic and model checking in automated recognition of human activities for ambient-assisted living. IEEE Trans. Hum. Mach. Syst. 2013

Pesic, M., Schonenberg, H., van der Aalst, W.M.P.: Declare: full support for loosely structured processes. In EDOC 2007

Günther, C.W., van der Aalst, W.M.P.: Fuzzy mining – adaptive process simplification based on multi-perspective metrics. In BPM 2007

Maps and Cartography (1/2)

- Road map of Italy
- Abstract from small cities and roads
- Big cities aggregate local roads
- Usage of color and size

Maps and Cartography (2/2)

Aggregation

Clustering of coherent, less significant structures

Abstraction

Removing isolated, less significant structures

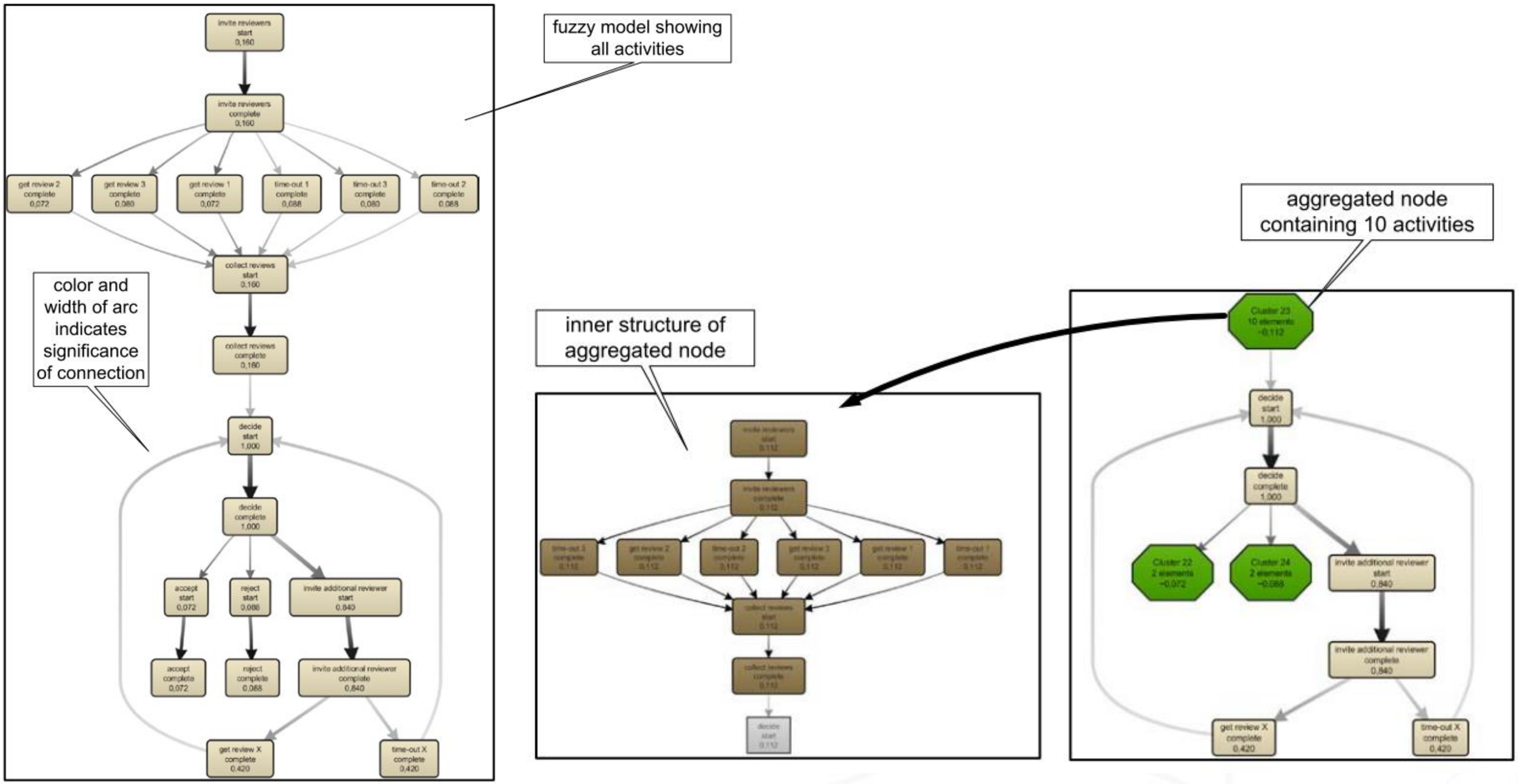
Fuzzy Mining (1/2)

- Fuzzy Mining takes as input different cases of a process and compute a graph G = <V, E> where V is a set of nodes and E is a set of directed arcs
  - An arc between two nodes v1 and v2 is present if v1 precedes (even not immediately) v2
- Significance Metrics
  - Measure the importance of an event (unary metric) or a precedence relation (binary metric)
  - Frequency in the log
- Correlation Metrics
  - Binary metrics showing how closely related two events are
  - Distance in log is taken into account
  - Deep comparison (e.g., names of the events)

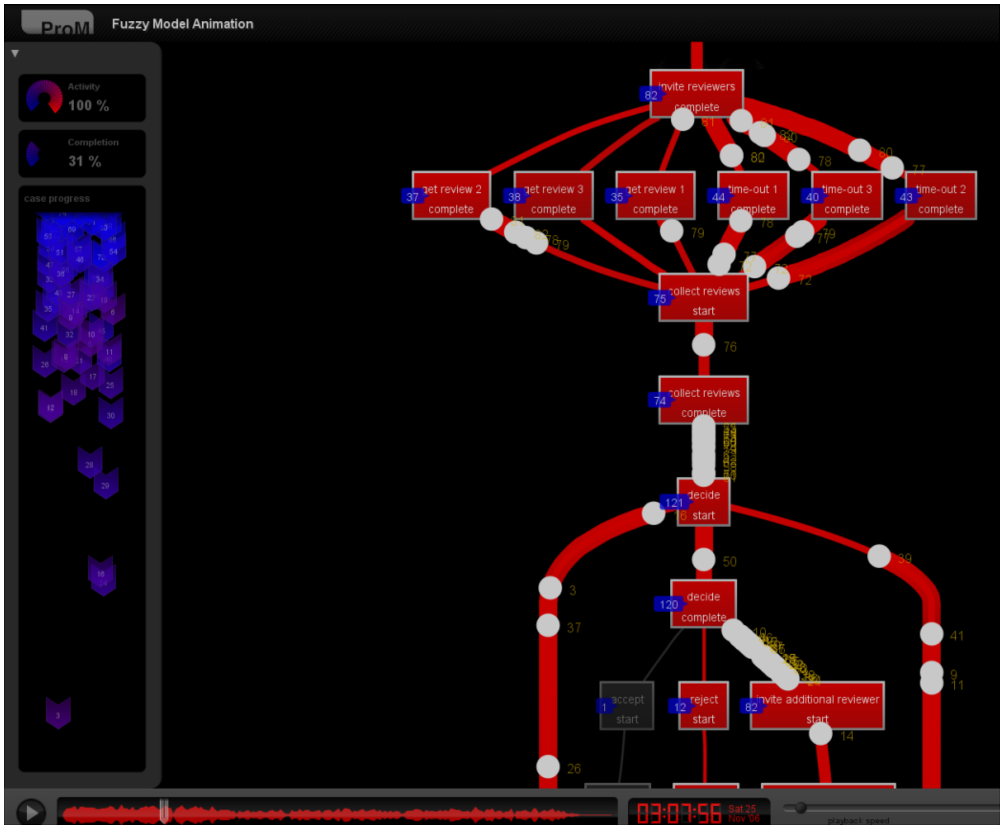
Fuzzy Mining (2/2)

- Aggregated metrics are obtained by combining significance and correlation metrics
- What kind of metrics are considered can be tuned
- During the analysis, filtering based on thresholds is employed to filter out and to aggregate events and arcs
- Fuzzy mining is supported by commercial tools (e.g., Disco by Fluxicon) and open source tools (e.g., ProM)

Fuzzy Mining: Applying filtering



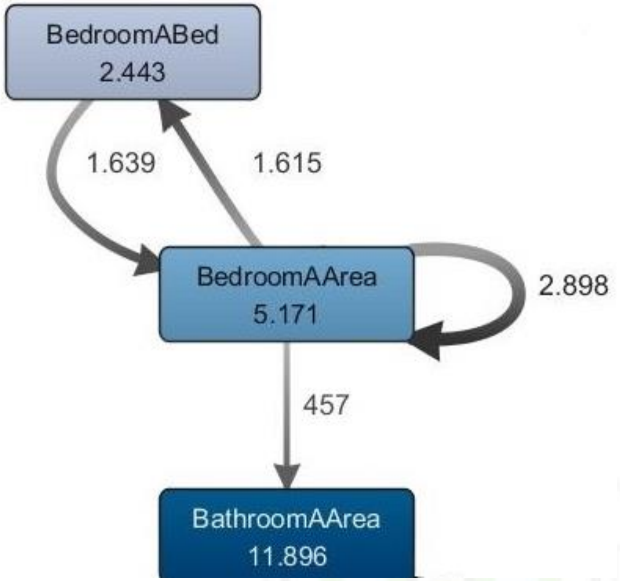
Fuzzy Mining: Replaying



- Fuzzy Mining main intent is analysis
  - No enactment
- The availability of players allows to replay logs on the models

Discovering Human Habits

- Segmentation performed for simplicity on a daily basis → **daily human habit**
- Once the sensor log is turned into a (movement) action log, we apply fuzzy mining [Günther2007]:
  - Well suited for unstructured process
  - Automated process discovery
  - Nodes representing actions
    - **In our case STAY or AREA actions**
    - ***MOVEMENT* actions ignored**
  - Connections representing precedence relations
  - Borrows concepts from the world of maps and cartography
  - Zoom in and out on a process model highlighting the importance of tasks and connections between them

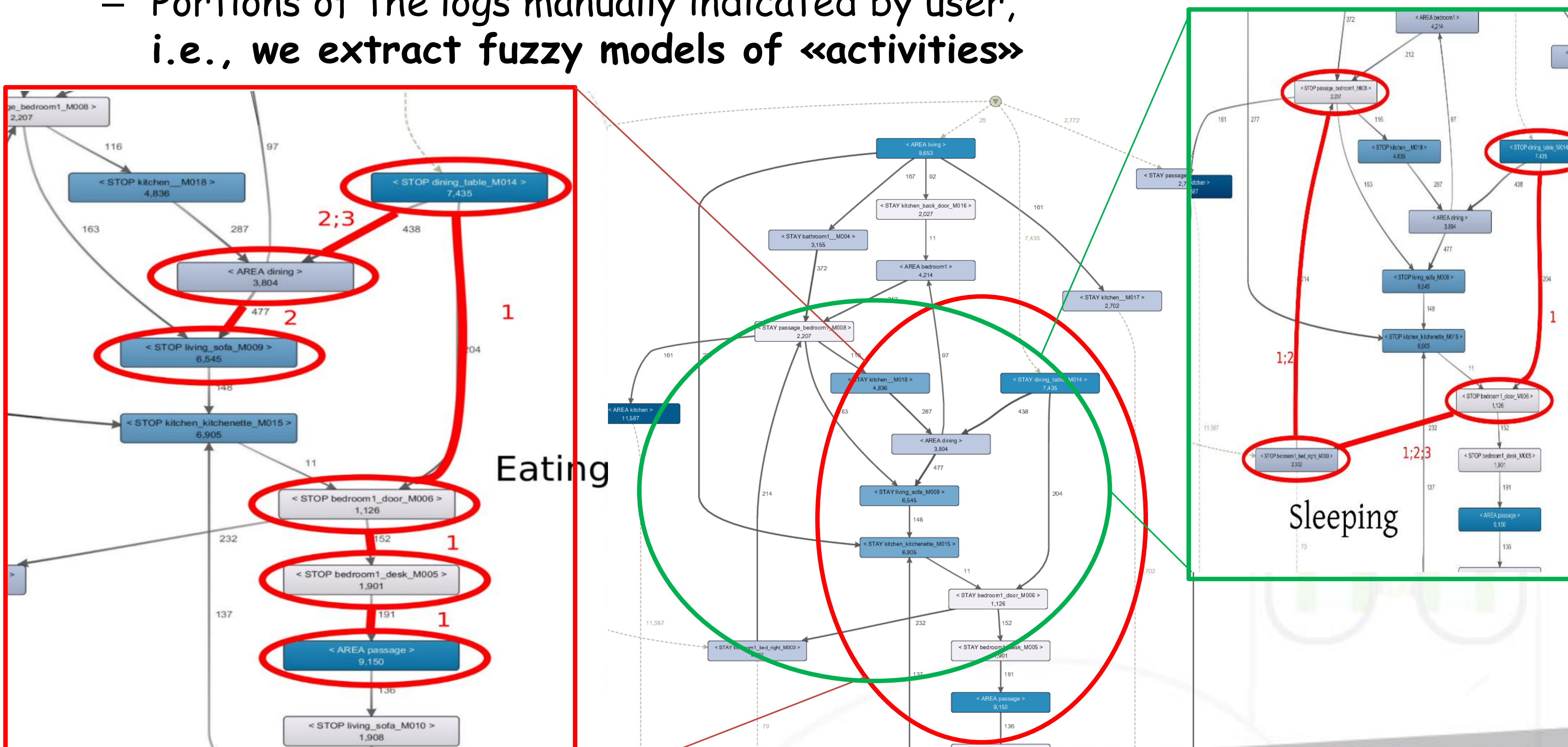


Leotta, Mecella, Sora. "Visual process maps: a visualization tool for discovering habits in smart homes." *Journal of Ambient Intelligence and Humanized Computing (2019)*, 1-29.

SAPIENZA UNIVERSITÀ DI ROMA

Discovering Human Habits

- We initially segment traces splitting on:
  - Entire days, **i.e., we extract fuzzy models of the «daily habit»**
  - Portions of the logs manually indicated by user, **i.e., we extract fuzzy models of «activities»**



Leotta, Mecella, Sora. "Visual process maps: a visualization tool for discovering habits in smart homes." <u>*Journal of Ambient Intelligence and Humanized Computing (2019)*</u>, 1-29.

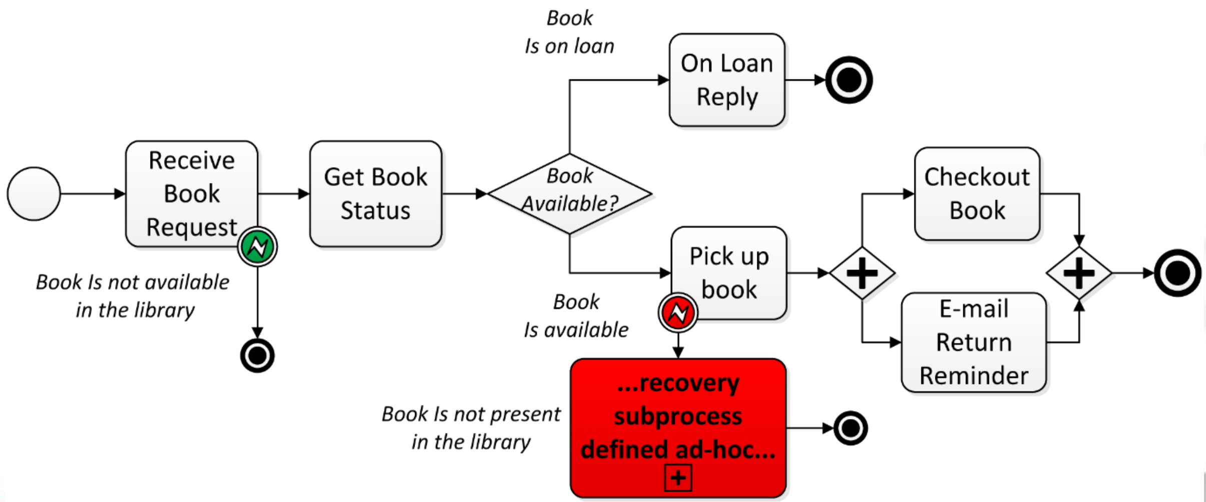
Discovering Human Habits: Current Work

- More fine-grained segmentation
  - According for example to topological consideration
- Support for multiple users
  - Employing for example tracking of sensor onsets
  - Spatial and tempolar locality
  - No markers
- Evaluation of different process modeling formalisms
- Employing models for enactment purposes

APPLYING BPM TO SMART MANUFACTURING

Process Adaptation

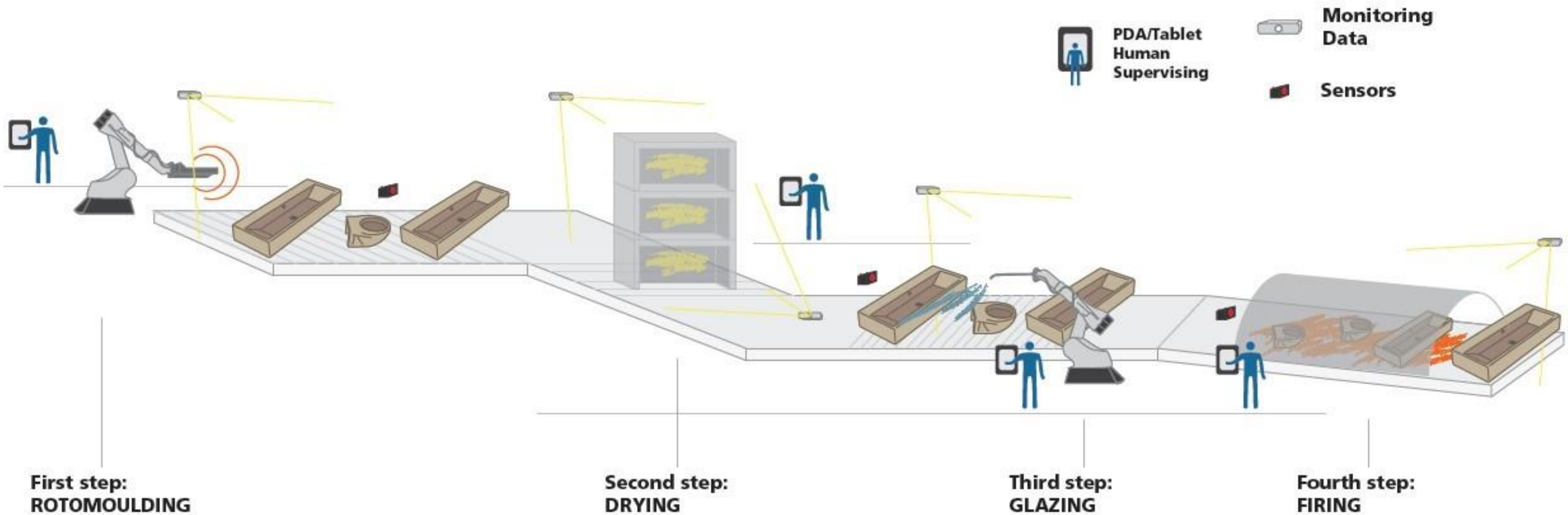
- It is the ability of a process to **cope with exceptions** and **deviate at run-time** from the execution path prescribed by the process.
- Existing BPM environments provide support for the handling of :
  - **anticipated exceptions**, captured in the process model at design-time.
  - **unanticipated exceptions**, managed manually at run-time.



Adaptation of (traditional) business processes

- Traditional business processes (e.g., administrative and financial processes) are usually easily **predictable**.
  - They reflect **routine work** with **low flexibility requirements**.
  - After being modeled, they can be **repeatedly instantiated** and **executed in a controlled way**.
  - Exception handlers can be properly **modeled at design-time**.
  - Data flows **do not play a relevant role** in process adaptation.

A Case Study

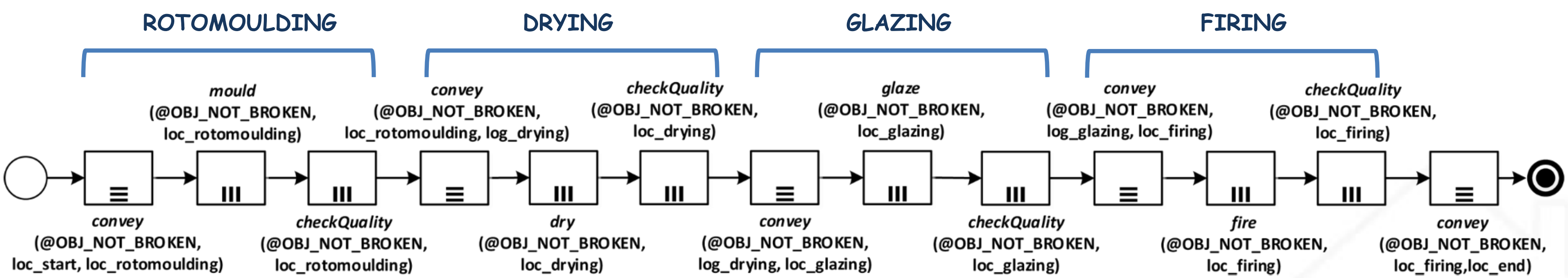

PDA/Tablet
Human
Supervising
Monitoring
Data
Sensors
First step:
ROTOMOULDING
Second step:
DRYING
Third step:
GLAZING
Fourth step:
FIRING

Cyber-Physical Process (CPP)

- In a ceramic plant, a dedicated **cyber-physical process** (CPP) coordinates the working of the robot arms and the machinery in the various steps of the production line.

Starting from a digital CAD model, an initial raw model of a ceramic product is generated.

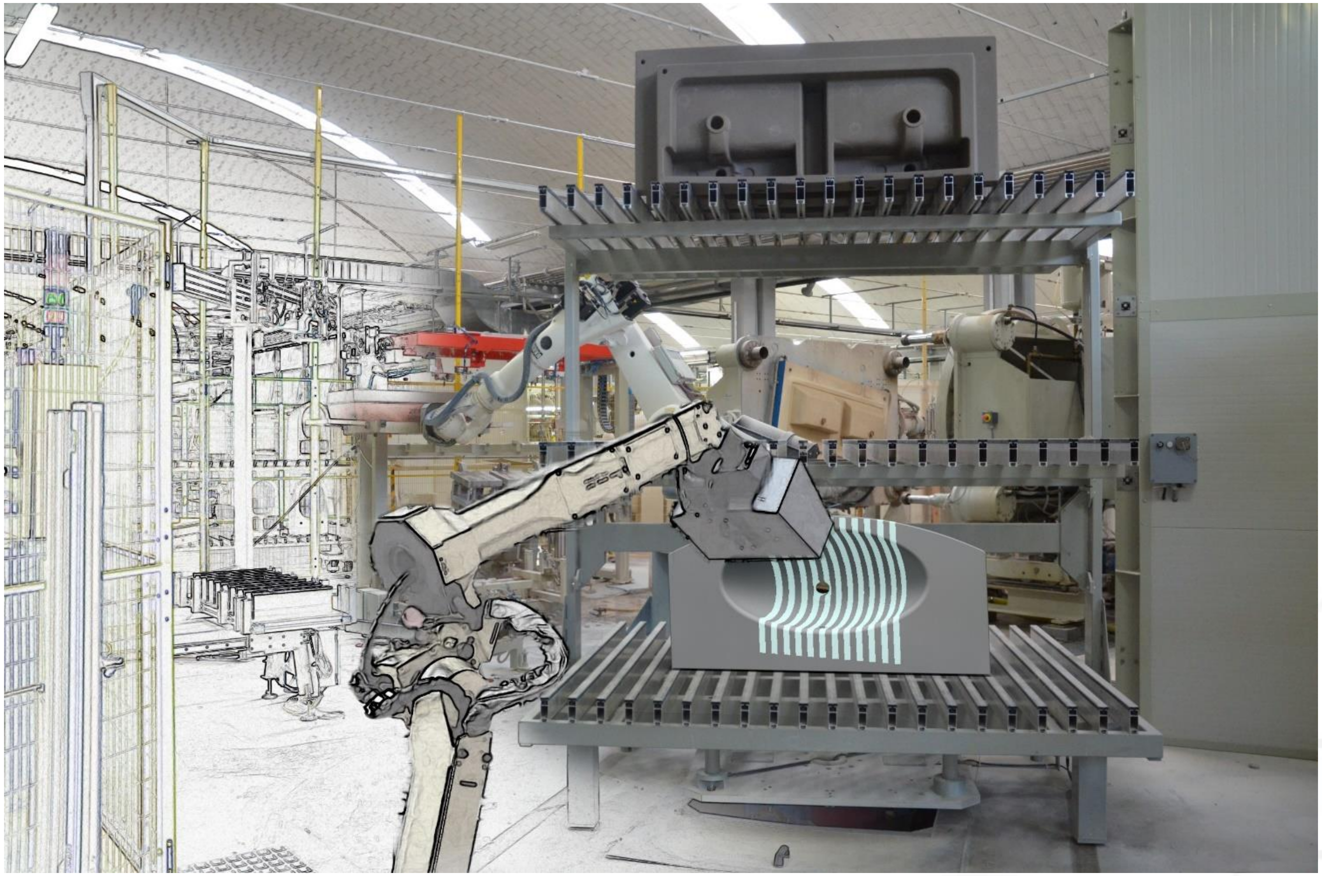
A raw model has an higher volume than the final product, since it will lose part of its volume during the next steps of the process (e.g., due to humidity, temperature, etc.)



A conveyor belt is used to move ceramic elements from a step to another. Each step is performed by a different static robotic arm or machinery located in a fixed position of the plant.

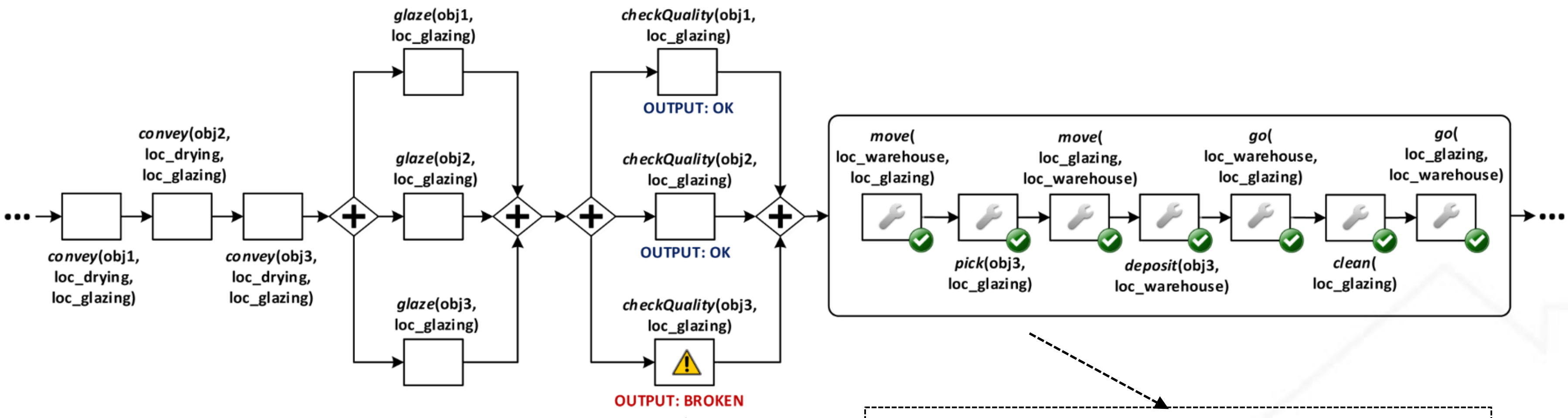
When a step completes, a quality check is performed by activating a digital 3D scanner that analyzes the surface of the ceramic elements to identify the presence of ruptures or defects.

Example of 3D scanner



Potential exceptions

- Some exceptions may be caused by the *deformation* of ceramic materials during the drying/glazing/firing steps.
  - An incorrect thermal expansion of the elements' body may cause their rupture

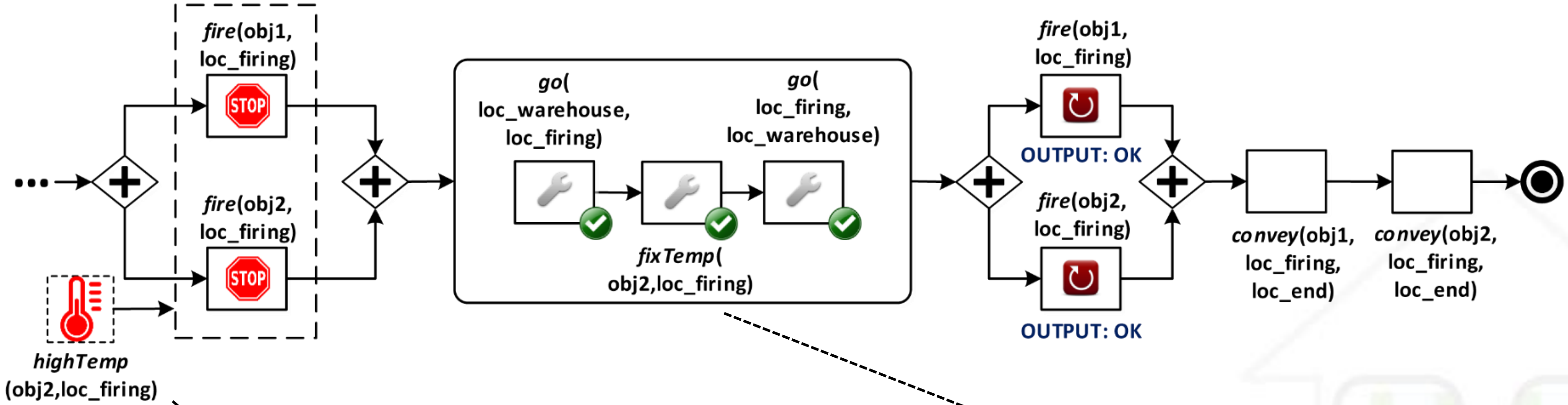


If a deformation after the glazing step is evaluated as critic and not anymore "adjustable", it is useless to proceed to the next step of the process.

Recovery procedure: A moving robot pick up and deposit the broken element in a warehouse and a technician clean the conveyor belt from debris.

Potential exceptions

- A CPP can also be jeopardized by the occurrence of exogenous events, which can asynchronously change the contextual properties of the environment.
  - An anomalous value of an environmental parameter (temperature, humidity, pressure, etc.) may affect the quality of the transformations of the ceramic material.



If during the firing step the temperature of an element reaches a dangerous value, it must be stopped before it causes defects to the ceramic materials under firing.

Recovery procedure: A technician configures the oven system to modify its temperature to a reasonable value.

Adaptation of CPPs

Key fact: recovery procedures **depend on the actual context** (e.g., the positions of actors and robots, robot's battery levels, the range of the sensors, whether a location has become dangerous to get it, etc.)

1) the **number of anticipated exceptions** to be identified at the outset (and ways to overcome them) is often **too large**;
2) many **unanticipated exceptions may arise** during process execution, and their resolution should be performed on a case-by-case basis, by exploiting information gathered at run-time.

Challenge: Build real-time **monitoring** and **automated adaptation features** during process execution, in order to:

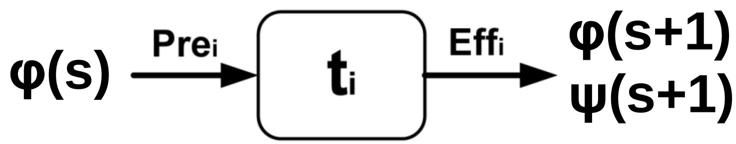
1) synthesize on-the-fly recovery procedures that **solve all exceptions** (anticipated and not anticipated) into the original process;
2) achieve the overall objectives of the original process still preserving its structure by **minimizing any human intervention**.

SmartPM Approach

Modeling approach towards a **declarative specification** of process tasks.

- Each task is described with the needed preconditions for executing it and the expected effects produced after the task execution. Data

Physical reality at situation **s** records the actual values of task outcomes.



Each task has a set of effects that turn **φ(s)** into **φ(s+1)**.

Expected reality records the desired effects of each task.

Process Adaptation: the ability to reduce the gap from the expected reality **ψ(s)** – the (idealized) model of reality used to reason – and the physical reality **φ(s)**.

Intuition:	***for each execution step***
	if **φ(s+1)** is different from **ψ(s+1)**
	then **adapt**

The aim is to find a recovery procedure that turns φ(s) (the faulty physical reality) into ψ(s) (the desired expected reality).

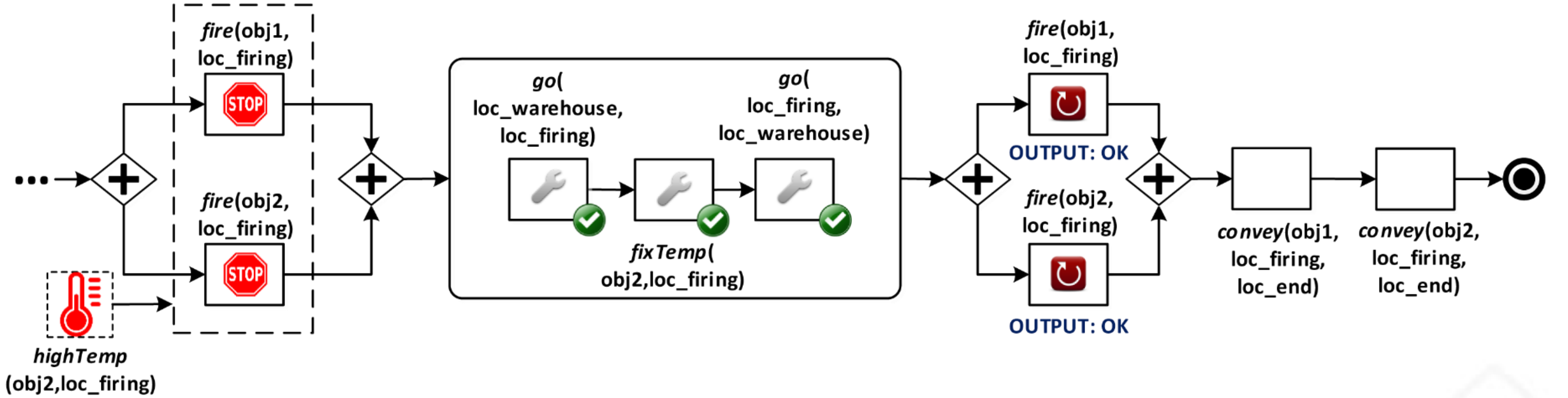
Defining data in SmartPM

- In SmartPM, contextual information is represented through a *domain theory* consisting of *discrete objects* and *variables* which may change as effects of task outcomes and exogenous events.
- For example:
  - Location: <loc_glazing, loc_firing, ...>
  - Object: <obj1, obj2, obj3, …>
  - Status(obj: Object) = [ok, high_temp, low_pressure, …]
- Physical reality can be seen as the set of all variable values in a specific state of the execution.
- Expected reality records the desired effects of each task, as defined at design-time.

Example

φ(s) = …AND ***status(obj1) = ok*** AND ***status(obj2) = ok*** …AND …

ψ(s) = …AND ***status(obj1) = ok*** AND ***status(obj2) = ok*** …AND …



The exogenous event asynchrounously changes **φ(s)**

PROCESS ADAPTATION REQUIRED!

φ(s+1) = …AND ***status(obj1) = high_temp*** AND ***status(obj2) = high_temp*** …AND …

ψ(s+1) = …AND ***status(obj1) = ok*** AND ***status(obj2) = ok*** …AND …

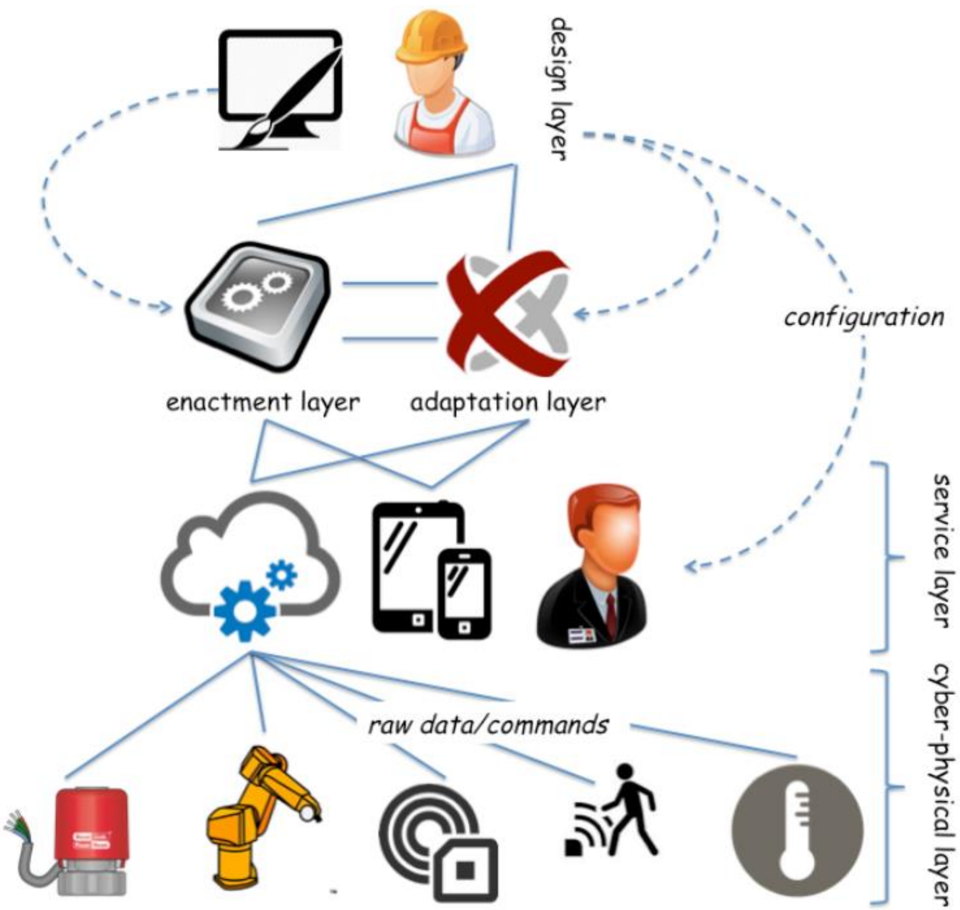
Physical-to-digital interface (where data abstraction happens)

- Sensors data are often **continuous values** over huge domains.
- To exploit automatic reasoning/verification techniques, such data must be abstracted as **discrete variables** grounded into finite domains.

Physical-to-Digital interface

- SmartPM provides some **web tools** that allow us to associate some of the data objects defined in the domain theory with the continuous data values collected from the environment.

The architecture of SmartPM



Definition of process specifications in terms of control flow, tasks precondition and effects, and formalization of the data reflecting the contextual knowledge of the cyber-physical environment under observation.

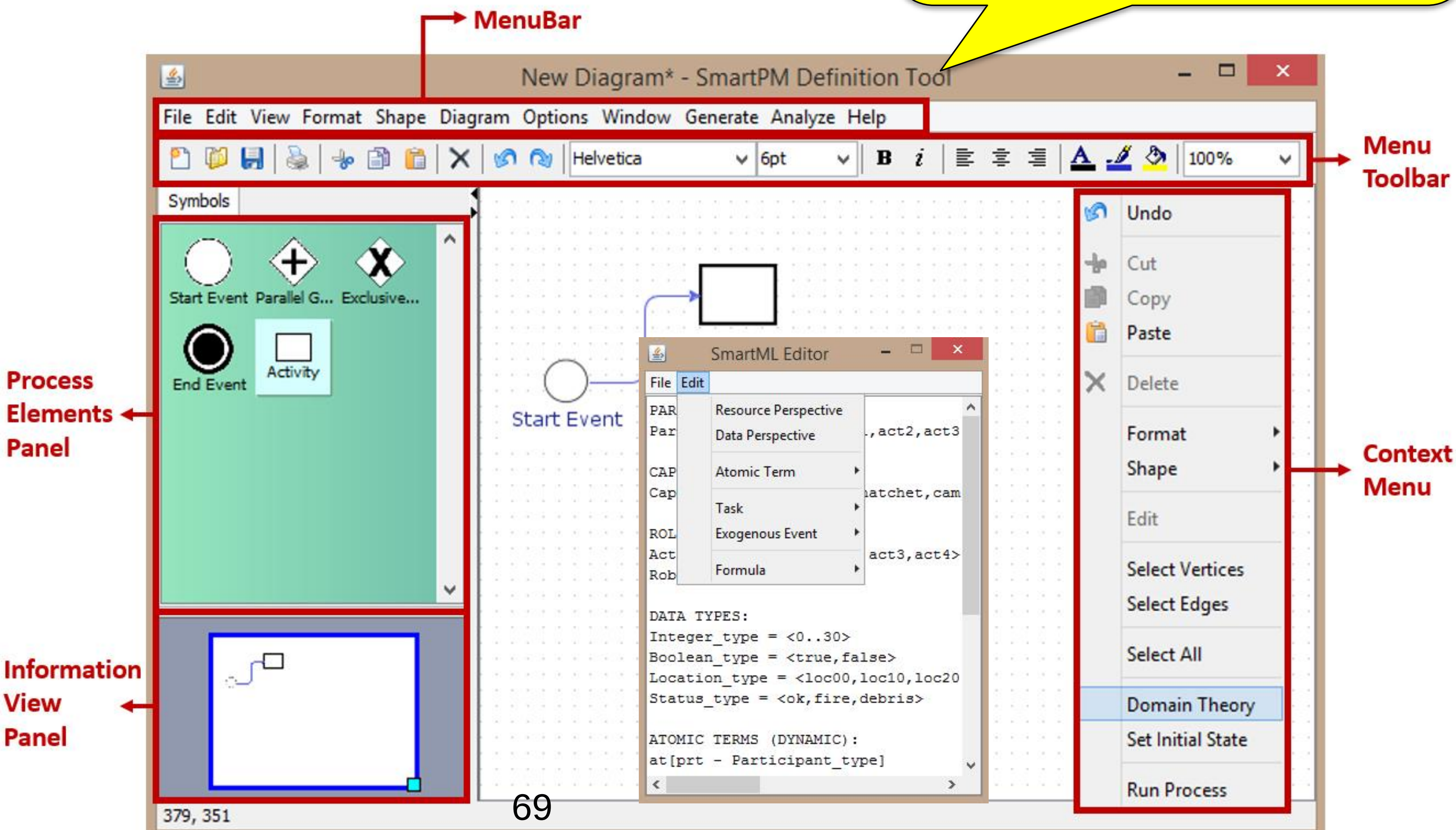
Process execution, monitoring and adaptation of running instances in case of (un)anticipated exceptions or exogenous events.

Set of services offered by the real-world entities (robots, humans, etc.) to perform specific tasks. High-level commands can be composed into complex ones.

Sensors and actuators that affect the state of the physical environment. A **physical-to-digital interface** **transforms** raw data collected by the sensors into machine-readable events, and **converts** high-level commands sent by the upper layers into raw instructions readable by the actuators.

Design Tool

Modeling canvas to define the **control flow** of the process and an **editor** to create and modify the **data**, the **resource** perspective and all the **contextual information of the scenario** in which the process will be executed.



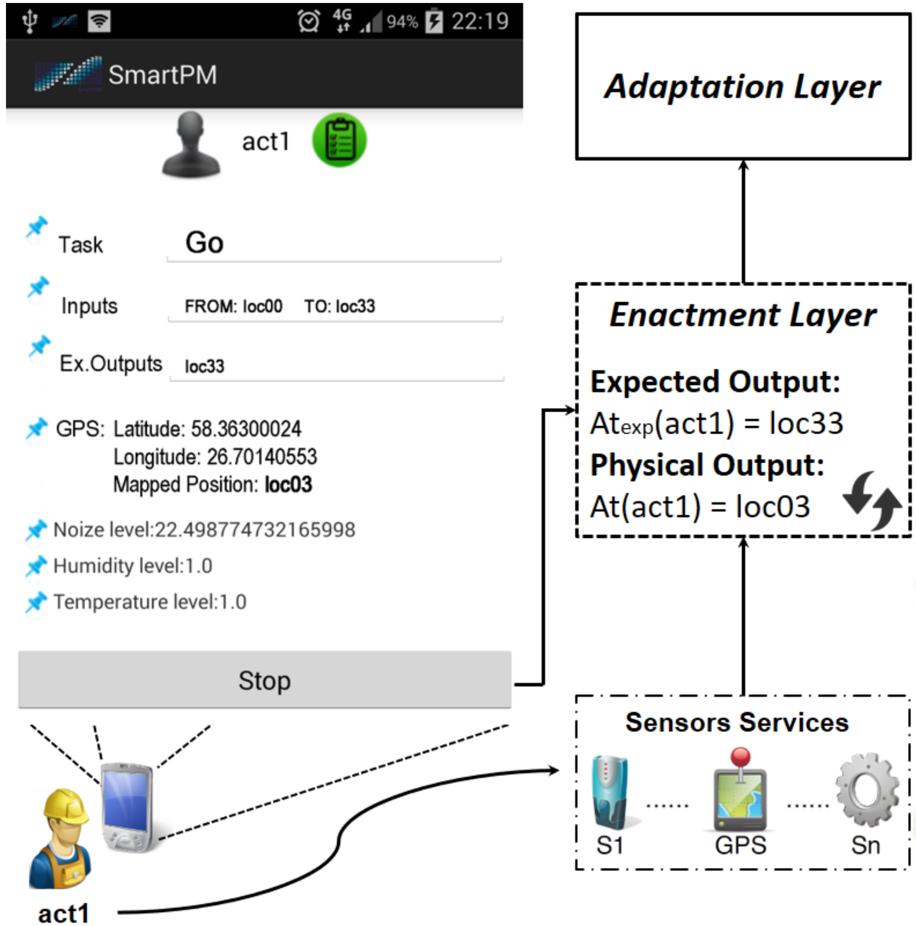
Action based languages for SmartPM

Intuition: Resorting to **action-based languages** in AI

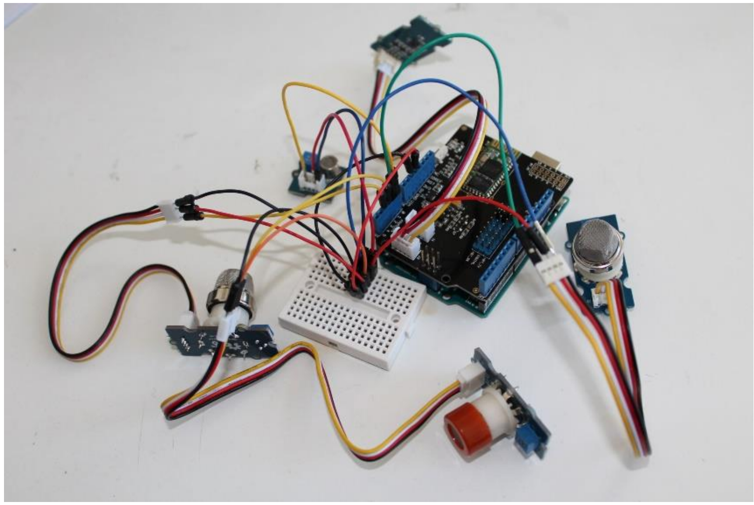
- **Situation Calculus** to model:
  - the contextual setting in which the process is meant to run
  - the support framework for managing the task life cycle
- Customization of an **IndiGolog** Interpreter to:
  - monitor the online execution of running processes
  - detect potential mismatches at run-time
  - invoke a state-of-the-art planner to synthesize a recovery procedure
- **Automated Planning** to generate a recovery plan that turns $\varphi(s)$ into $\psi(s)$
  - *Planning domain*:
    - process tasks represented as planning actions in PDDL
    - predicates to capture the contextual data describing the process domain
  - *Planning problem*: instantiation of the contextual data in a starting state (the faulty physical reality $\varphi(s)$) and in a goal state (the desired expected reality $\psi(s)$)

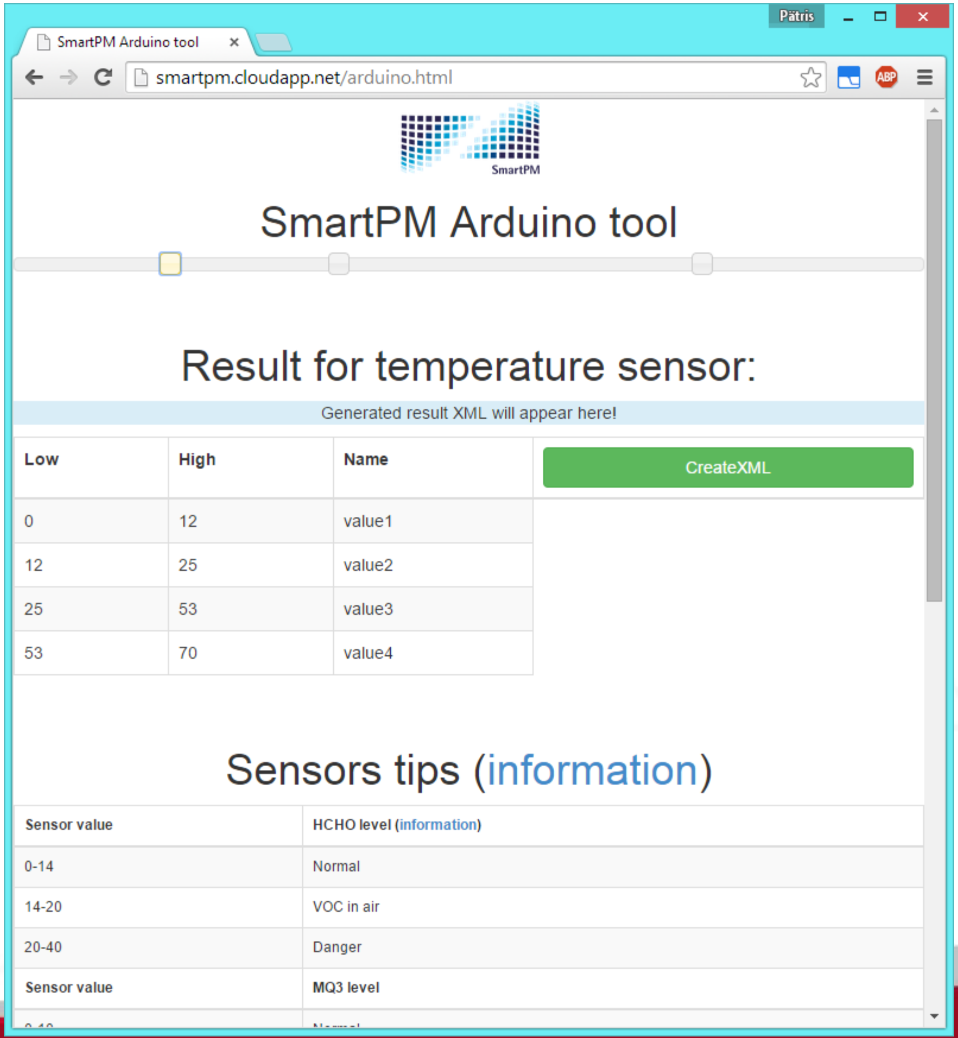
Task handler of SmartPM

The **Task Handler** is realized for Android devices. It supports the **visualization of assigned tasks** and enables **starting task execution** and **notifying of task completion** by selecting appropriate outcomes.



The SmartPM Arduino Tool





Arduino has a large variety of sensors available to measure different environmental values, for example different gas levels in the air, water quality, radiation level, etc. Arduino can be connected with Android via Bluetooth for transferring the data.

Main references on SmartPM

- *A. Marrella, M. Mecella, S. Sardina.* **Supporting Adaptiveness of Cyber-Physical Processes through Action-based Formalisms**. *AI Communications, Volume 31, Issue 1*, IOS Press, 2018

- *A. Marrella, M. Mecella, S. Sardina.* **Intelligent Process Adaptation in the SmartPM System**. *ACM Transactions on Intelligent Systems and Technology (TIST), Vol. 8(2)*, 2017

- *A. Marrella, M. Mecella.* **Adaptive Process Management in Cyber-Physical Domains**. *Book Chapter, Advances in Intelligent Process-Aware Information Systems, Intelligent Systems Reference Library, Volume 123*, Springer, 2017

AUTOMATICALLY DESIGN SMART MANUFACTURING PROCESSES

The Goal

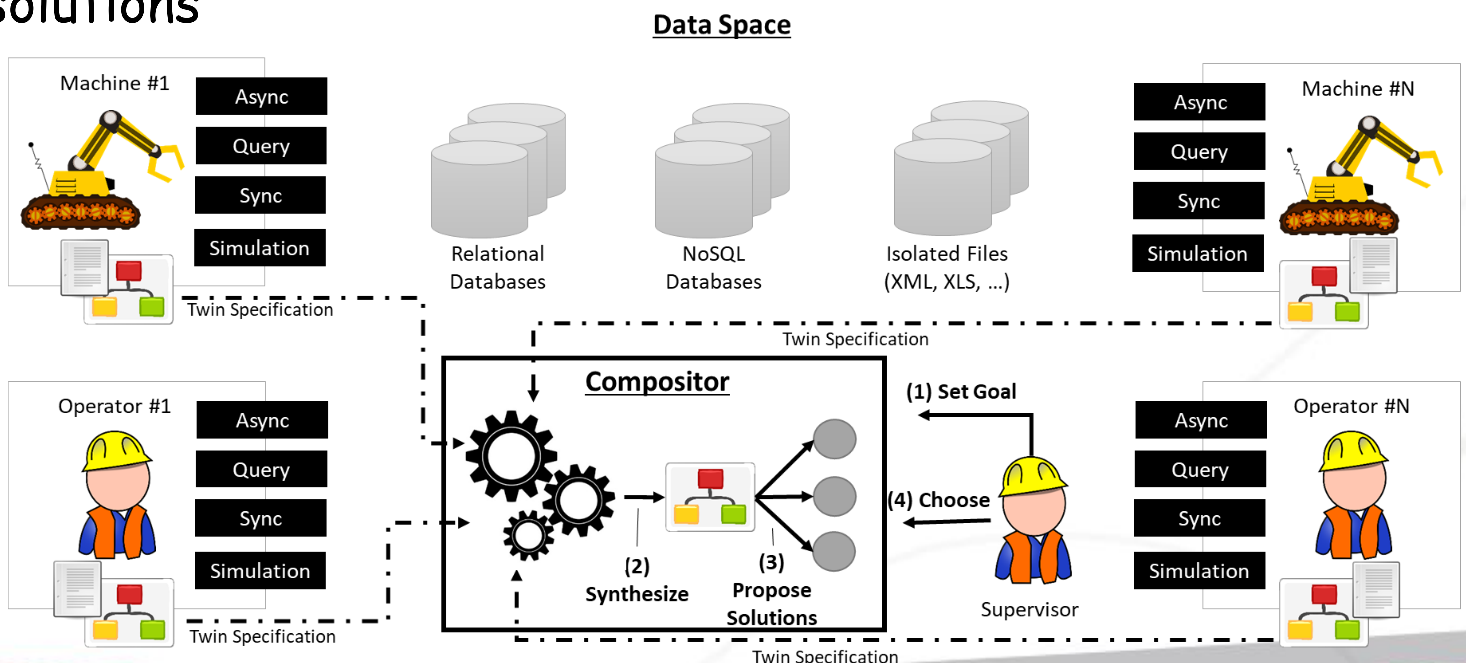
- Proposing an architecture aiming at
  - Integrating DTs and classical information systems to reach predefined goals
  - Respecting specific Key Performance Indicators – KPI regardless of sudden disruptions
  - Keeping human operators in the loop by leveraging their experience in case of uncertainty

Proposed Architecture Requirements

- The architecture must be compliant to the RAMI – Reference Architecture Model for Industry 4.0
  - It specifies logical layers for any architecture employed in Industry 4.0
- The data space can be described as a **polystore**
  - a collection of heterogeneous data sources
  - e.g., service interfaces, databases, datawarehouses
  - declarative mappings between data stores

Proposed Architecture Requirements

- A human supervisor provide goal(s)
  - A **compositor** proposes solutions satisfying the goals
  - Multiple solutions, given the current data space
- New solutions proposed at runtime for resilience and responsiveness and adaptivity
- Human responses can reduce the search space for future solutions

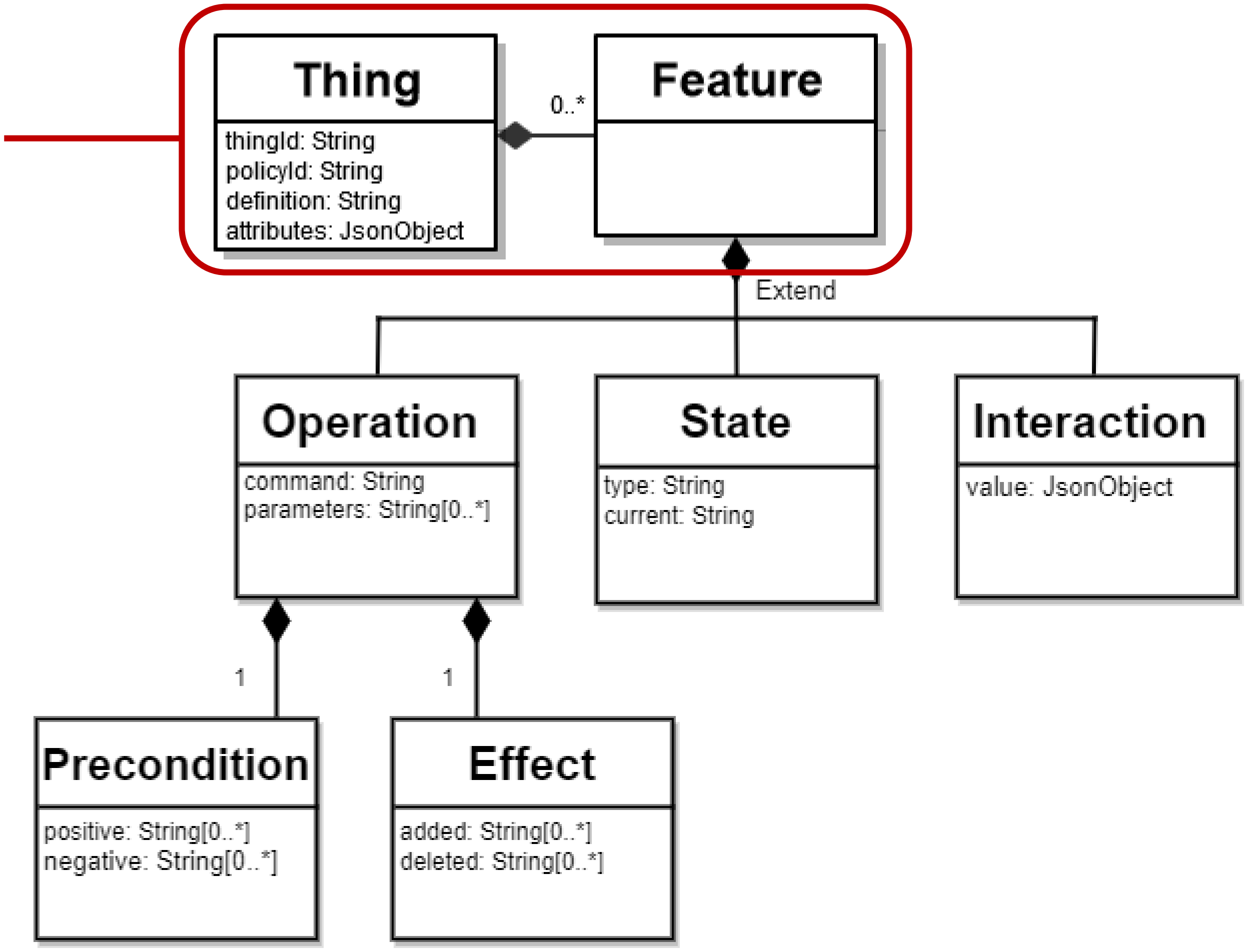


SmartPM with DT

- Use planning not only to repair an existing process → Build the entire process from scratch by imposing a final goal
- Tasks of the process are operations performed by digital twins
- Solution based on DITTO on Bosch IoT Things
- Video of the platform in action (Italian ☹):
  - https://www.youtube.com/watch?v=kFkLBXGDVLY

Modelling DTs for Planning

Built-in Entity Model in Bosch IoT Things



Digital Twin Planning Language

Interaction

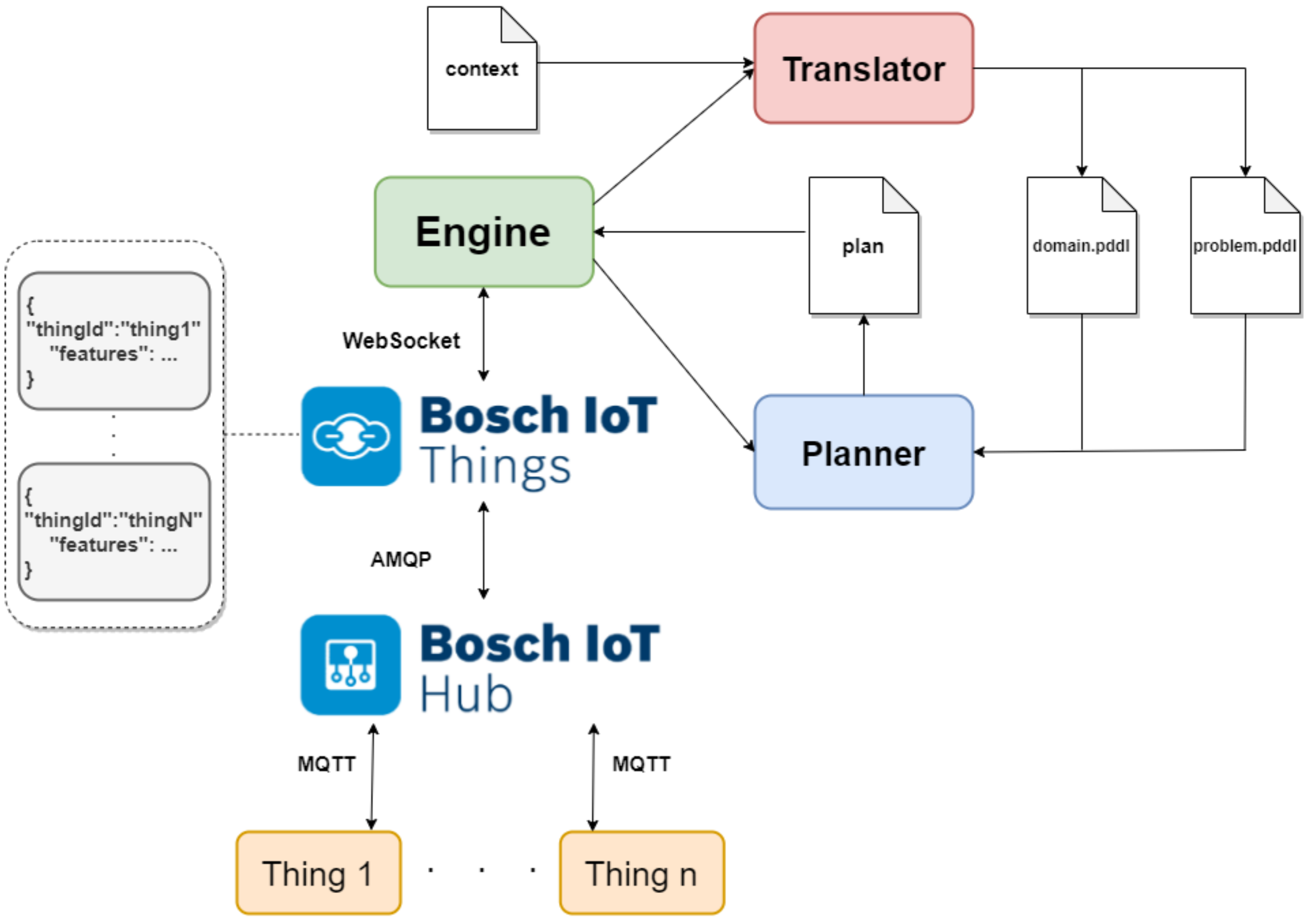
State

```
{
  "thing":{
    "thingId":"com.myThings:rb1",
    "attributes":{
      "type":"Robot"
    },
    "features":{
      "status":{
        "properties":{
          "type":"interaction",
          "value":"waiting"
        }
      },
      "at":{
        "properties":{
          "type":"state",
          "value":{
            "type":"Location",
            "current":"loc1"
          }
        }
      },
```

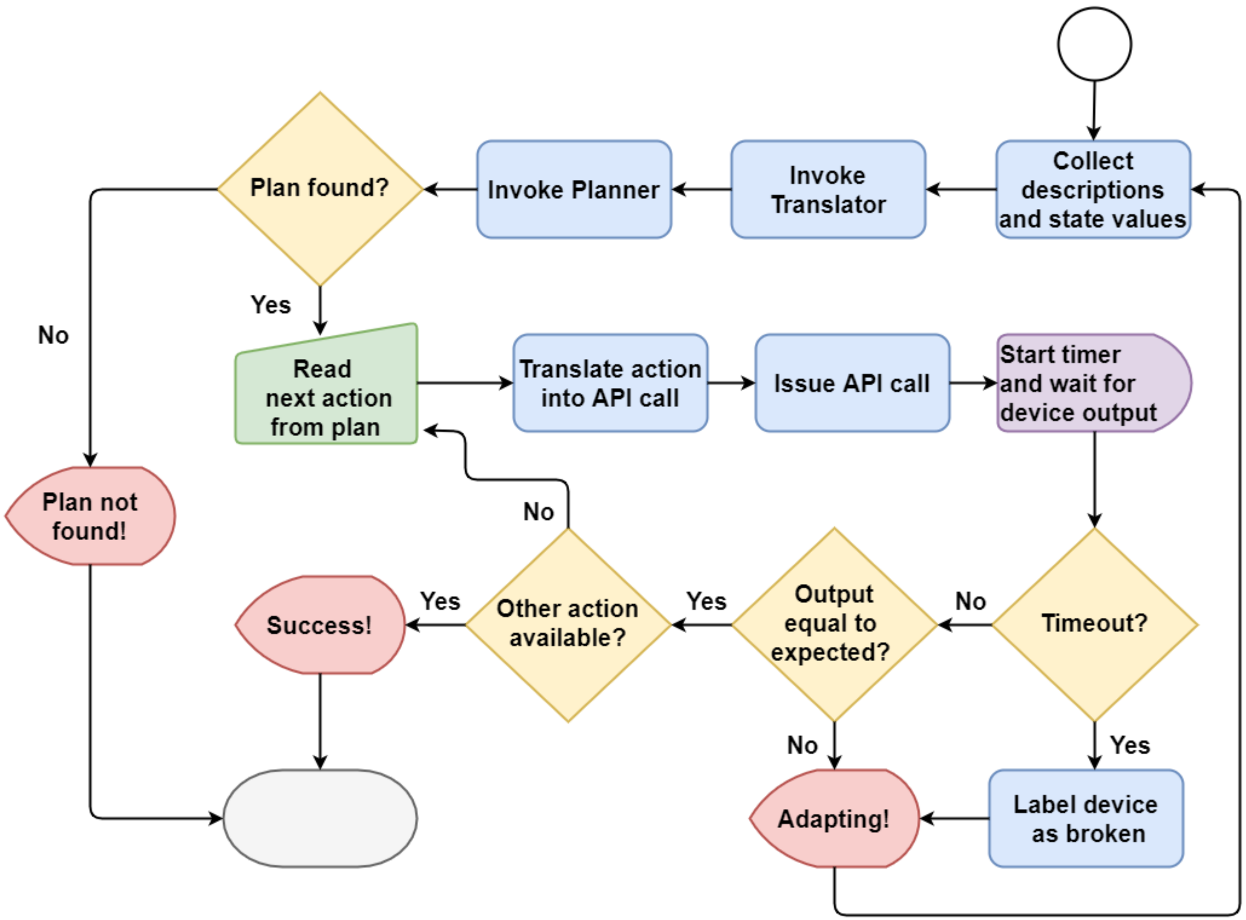
Operation

```
          "movement":{
            "properties":{
              "type":"operation",
              "command":"move",
              "parameters":[
                "Location - from",
                "Location - to"
              ],
              "requirements":{
                "positive":[
                  "at:from"
                ]
              },
              "effects":{
                "added":[
                  "at:to"
                ],
                "deleted":[
                  "at:from"
                ]
              }
            }
          }
        }
      }
    }
}
```

Proposed Architecture



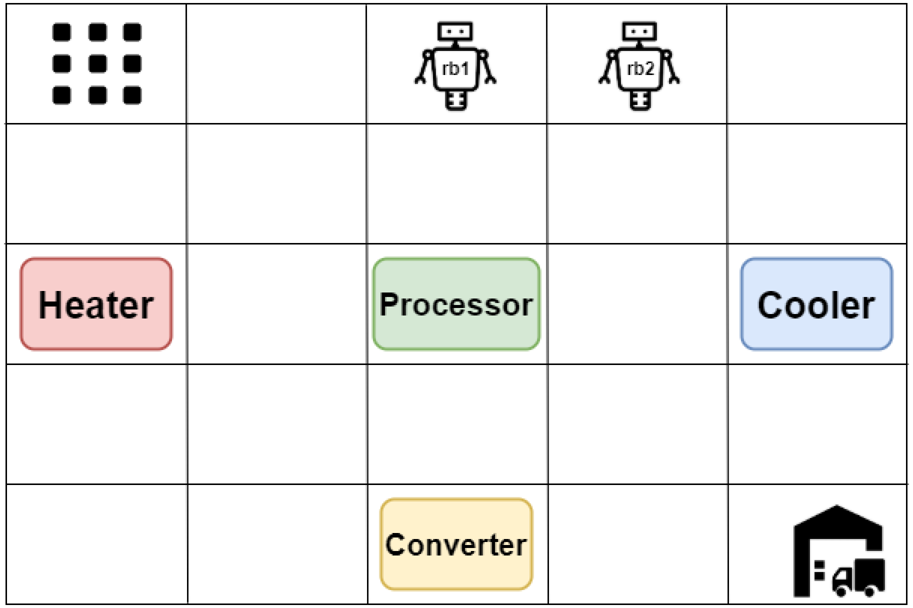
Workflow



Collect descriptions and state values
Invoke Translator
Invoke Planner
Plan found?
Yes
No
Read next action from plan
Translate action into API call
Issue API call
Start timer and wait for device output
Timeout?
No
Yes
Output equal to expected?
Yes
No
Other action available?
Yes
No
Success!
Plan not found!
Label device as broken
Adapting!

Example

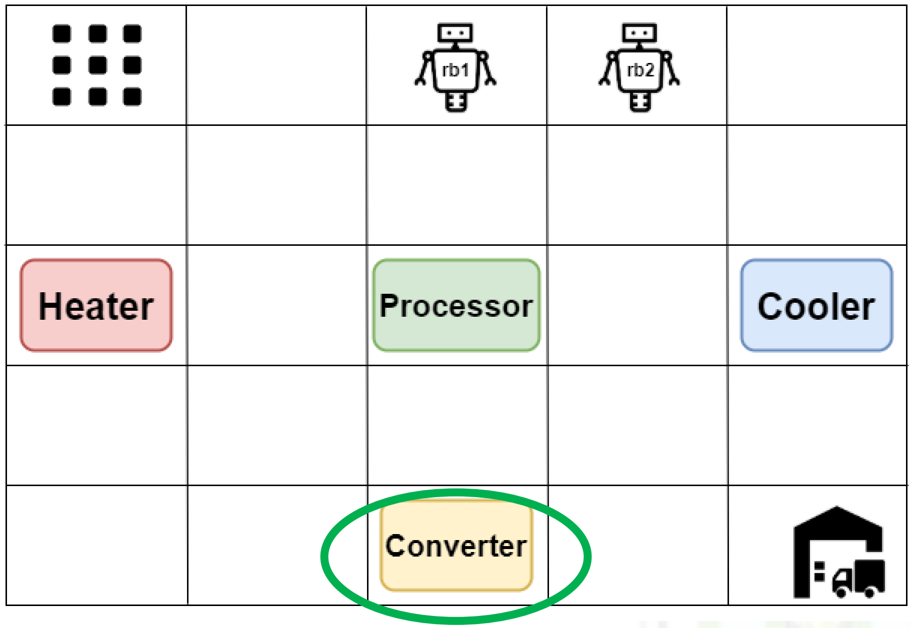
- Objects are in an initial location
- Goal: transform and place all the objects in a storage
- In order to be transformed, an object must be heated, processed and cooled
- In alternative, a converter is able to perform the three operations in one pass



- Two robotic carriers are able to move the objects in any position of the grid

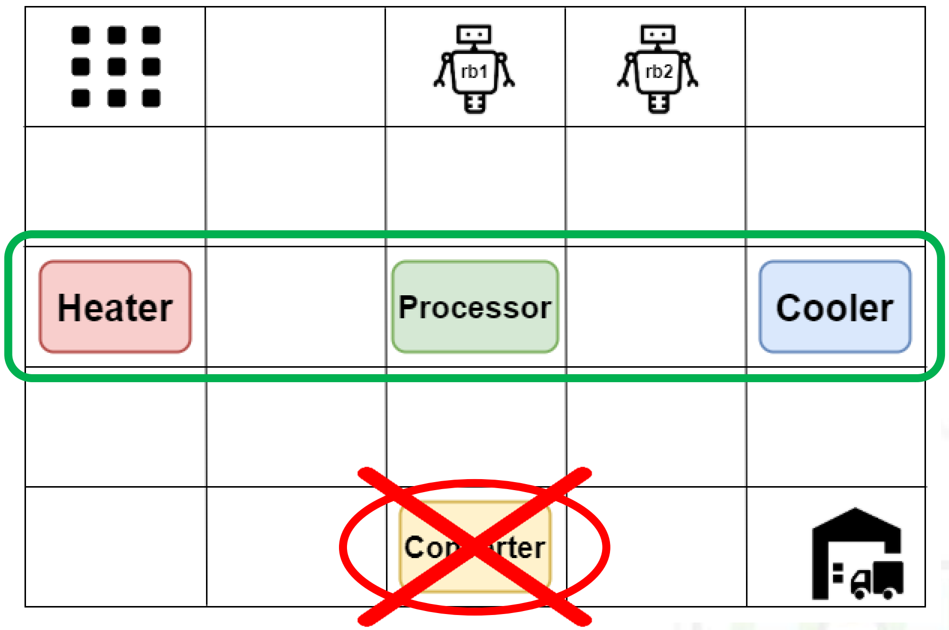
Scenario I: No faults

- All the actors are labelled as not faulty
- The planner synthesize a sequence of actions that involve only the converter, since it is faster
- If during the execution, the actors behave according to the plan, the goal is reached



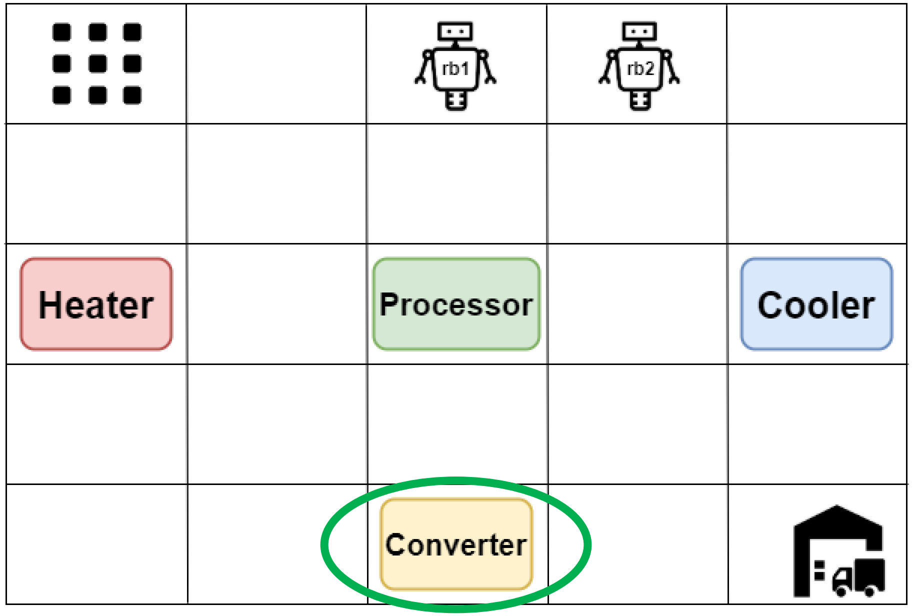
Scenario II: Jammed Converter

- In a previous iteration the converter jammed and therefore it is labelled as faulty
- The converter is ignored in the following iteration
- The planner synthesize a plan that involves the heater, the processor and the cooler



Scenario III: Unsuccesful Task

- In a previous iteration the converter failed to transform an object (due to a transient failure)
- Since the converter is not labelled as faulty, it is included in the following iteration
- The planner synthesize a plan that involves the converter another time



Next Steps

- The execution of a plan requires to know how to translate the state of the world in input parameters
- Things usually wraps physical entities from different vendors → The translation step must be done manually
- Automatic translation

Project Proposals

- Build an adaptive process with DTs and the SmartPM approach
- Apply ontologies to the Smart PM approach for automatic translation
- Design a new way to turn a sensor log into an action log
- Apply a different miner to visual process maps
- …