



**SOFTWARE
AND SYSTEMS
ENGINEERING**
research group

Model-based testing under uncertainty

L1: Theoretical aspects & practical applications

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[slides] <https://github.com/matteocamilli/mbt-uncertainty-gssi>

**Formal Methods at Work @
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G S
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Outline

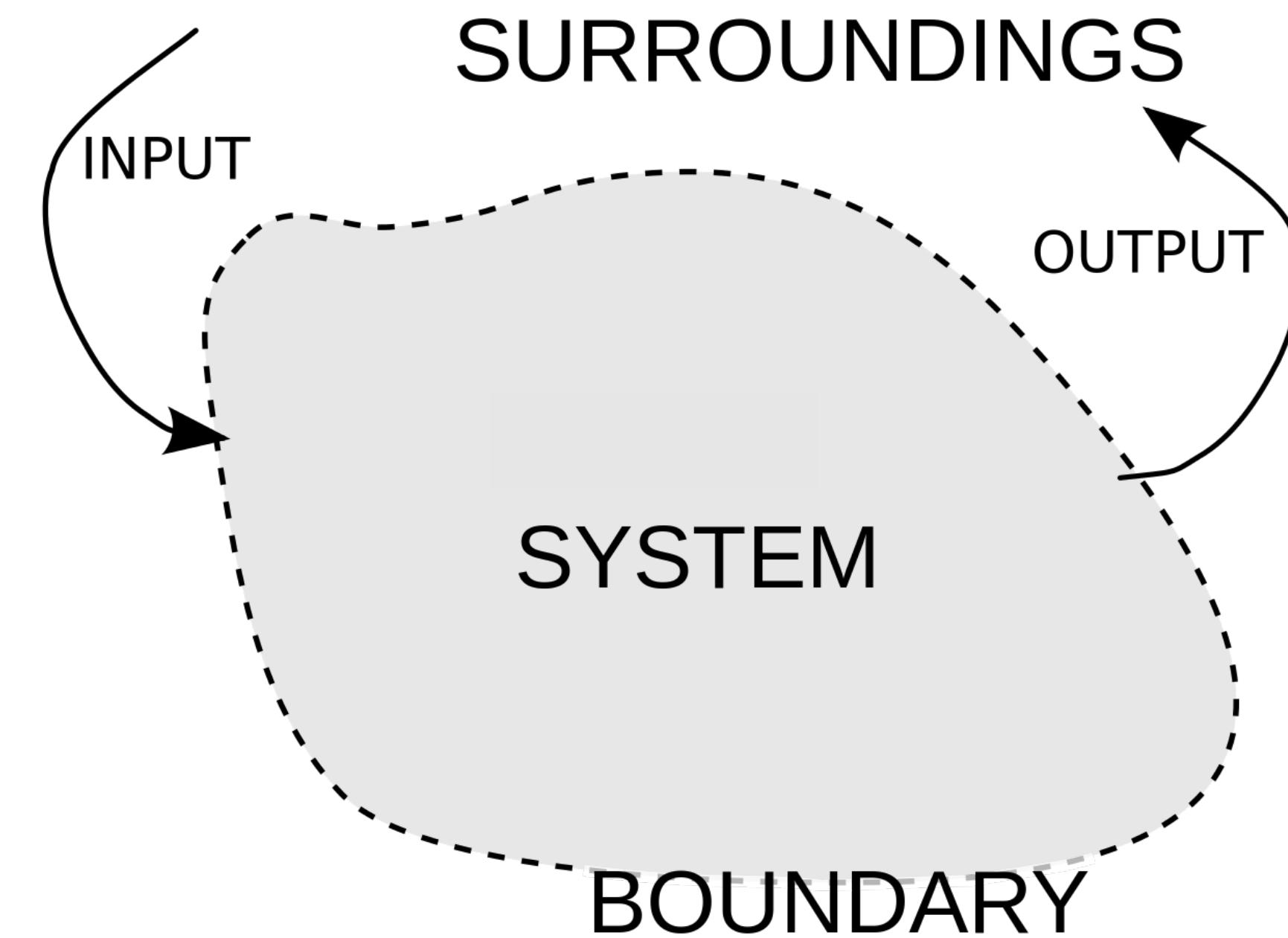
- Introduction
 - The (uncertain) world and the machine
- Markov Decision Process
 - Structure, Rewards
 - Policy, best policy, value iteration
- Model-based testing (MBT)
 - Offline vs online approaches
 - Conformance relation
 - Probabilistic alternating simulation and refinement
- Online MBT under uncertainty
 - Problem statement
 - Uncertain model parameters
 - Bayesian inference
 - Framework and test case generation strategies

Introduction

- The world and the machine
- Requirements vs Specification vs Implementation
- Uncertain assumptions

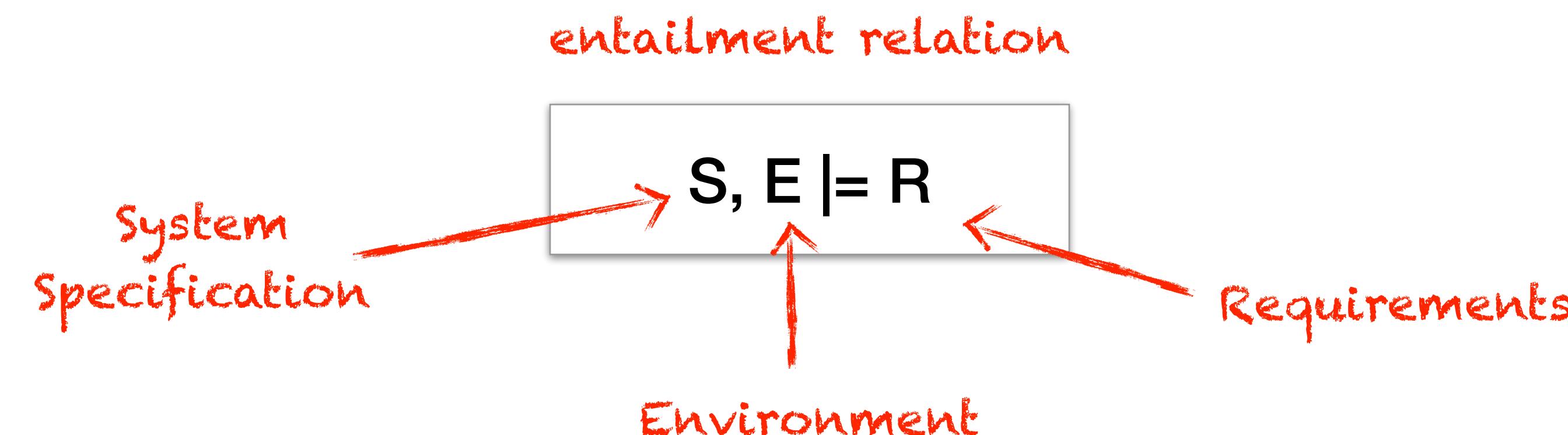
Characterizations of Systems

- **System**
 - Collection of interconnected elements that exist within and interact with an environment



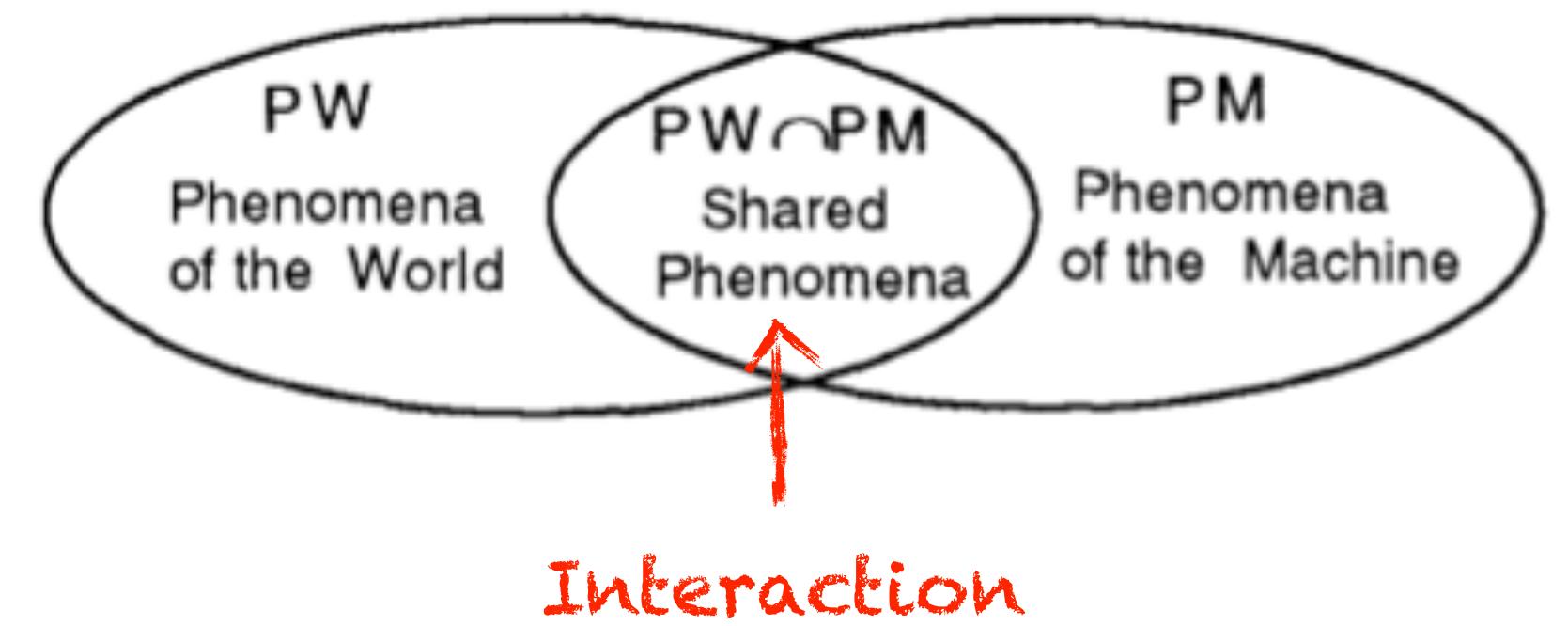
System Boundary

- Collection of elements that exist within the system and directly interact with one or more environments (i.e., part of the external world of interest)
 - Often, sensors + actuators
- [M. Jackson et al., ICSE '95] “The world and the Machine”
 - Engineers are concerned with:
 - The world in which the machine (i.e., the system) serves useful purpose
 - The machine itself



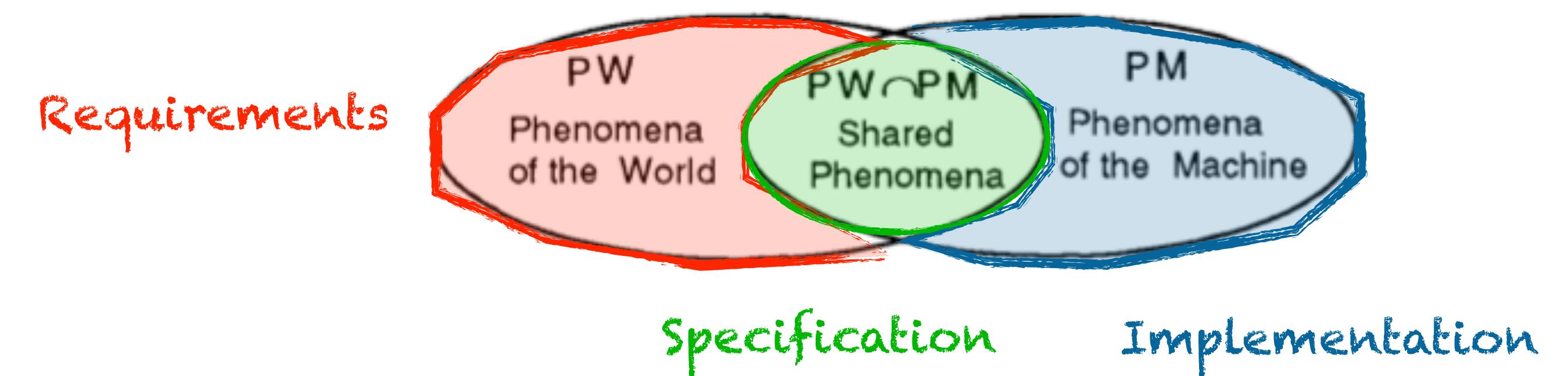
System Boundary – Interface

- Interface between the world and the machine
 - The problem exists in E
 - the solution to the problem is provided by S
 - Interface allow interactions between S and E
- Interaction: participation in shared phenomena (states + events)
 - Often not symmetrical —> E might initiate an event, but S might not have the power to inhibit the event
 - Example (Lift – simple Cyber-Physical System)
 - Lift has buttons (hw) + controller (sw) + on/off switches at floors to recognize the lift car (sensors)
 - Shared state controlled by E
 - Lift at 3rd floor (E) —> Sensor at 3rd floor is on —> should map to the “knowledge” (S)



System Boundary – Engineering

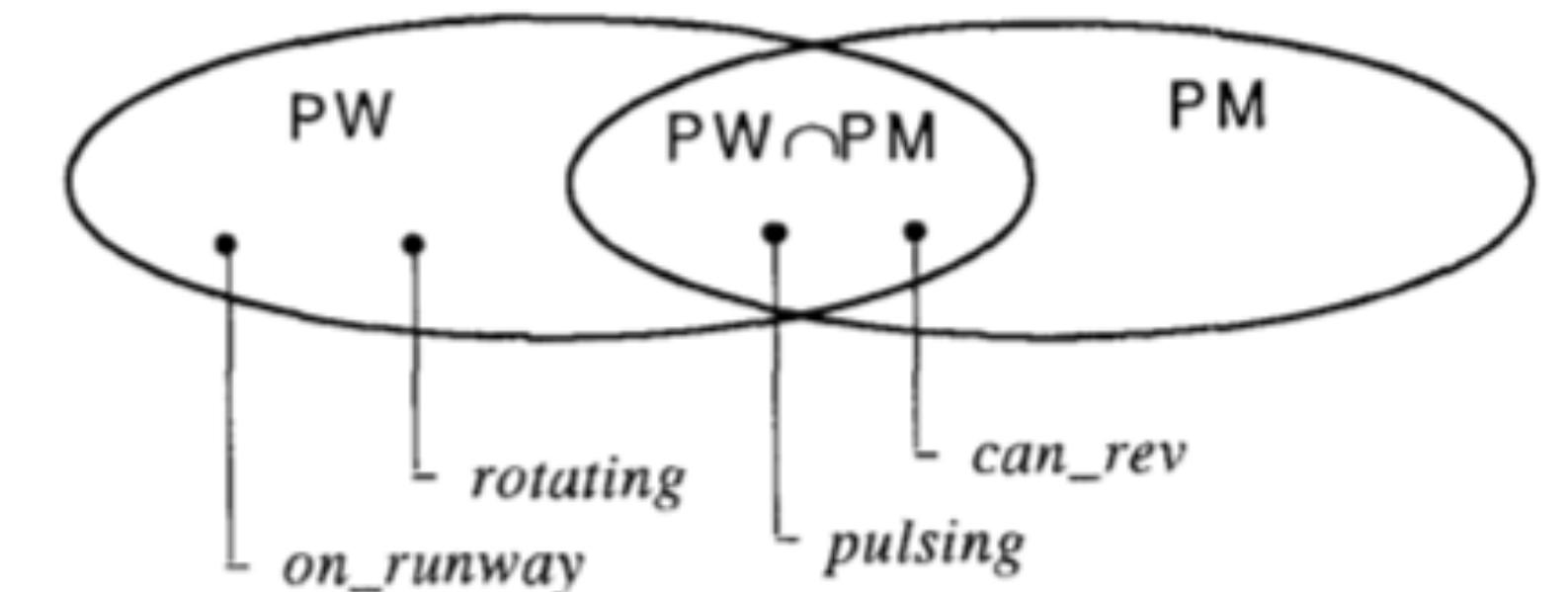
- **Engineering facet**
 - Intersecting phenomena sets suggest systematic usage of terms
 - Requirements
 - Specification
 - Implementation
- **Requirements:** are concerned solely with PW
 - Defined by stakeholders needs
 - Stakeholders want us to engineer effects in the world (not in the machine)
- **Implementation:** concerned solely with PM
 - Properties and behavior of the machine engineered from the specification
- **Specification:** concerned with $PW \cap PM$
 - staging area of the production from requirements to implementation
 - Abstract description of interactions between world and machine



System Boundaries – Engineering

- **Example:** avionic system
 - Requirement: reverse thrust can be engaged iff the plane is landing and already on the runway
 - REQ: $\text{can_rev} \leftrightarrow \text{on_runway}$
- **Controlled by E, Shared with S**
- **Interface:** sensors on landing wheels generate pulses when they rotate
 - State pulsing is now shared with the machine (rotating is not!)
- Engineers decide that the following **assumptions** hold
 - WORLD1: pulsing \leftrightarrow rotating
 - WORLD2: rotating \leftrightarrow on_runway
- Relying on this assumptions, developers can derive the spec
 - SPEC: $\text{can_rev} \leftrightarrow \text{pulsing}$

How does S know??



WORLD1, WORLD2, SPEC \models REQ
Assumptions

System Boundaries – Engineering

- Are the world assumptions reasonable?
 - E.g., does WORLD2 always hold?
 - Heavy rain condition
 - Runway covered with water —> aquaplaning —> on_runway & !rotating
- Problem: engineers shall fully understand the properties of the world
 - full knowledge at design time is hard, or even impossible
 - The phenomena of the world can be uncertain (e.g., precise whether conditions)
 - Uncertainty affect in turn the behavior of the implementation

It holds because we decided that
the world assumptions hold

WORLD1, WORLD2,
SPEC |= REQ

Markov decision processes

- Structure
- Examples
- Rewards
- Policy, best policy
- Value iteration algorithms

Markov Models

- **Basic notions**

- Modeling formalism to describe partially/fully stochastic phenomena of interest
 - the modeled phenomenon meets the **Markov property**^{1,2} (memoryless)
- Formal framework for performance and **dependability** (reliability, availability, safety) analysis
- Dependability modeling (upfront) at design time improves the quality of the system eventually produced

Fully automated by
off-the-shelf tools

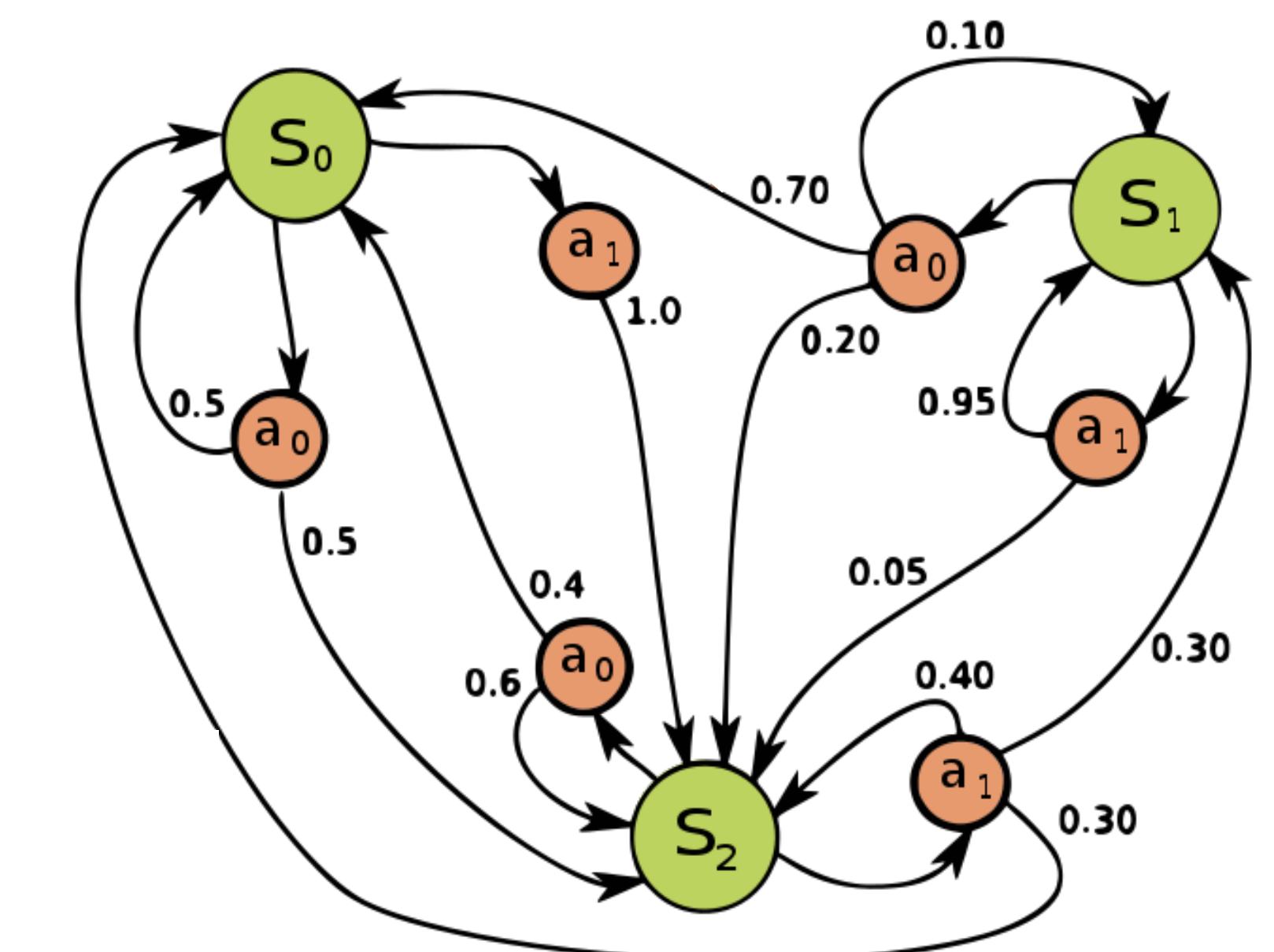
Dependability analysis
(e.g., probabilistic model checking
like PRISM, Storm)



1. The probability of moving to the next state only depends on the current state, not on the history that lead to that state.
2. R. C. Cheung, A user-oriented software reliability model, IEEE TSE, no. 2, pp. 118–125, 1980

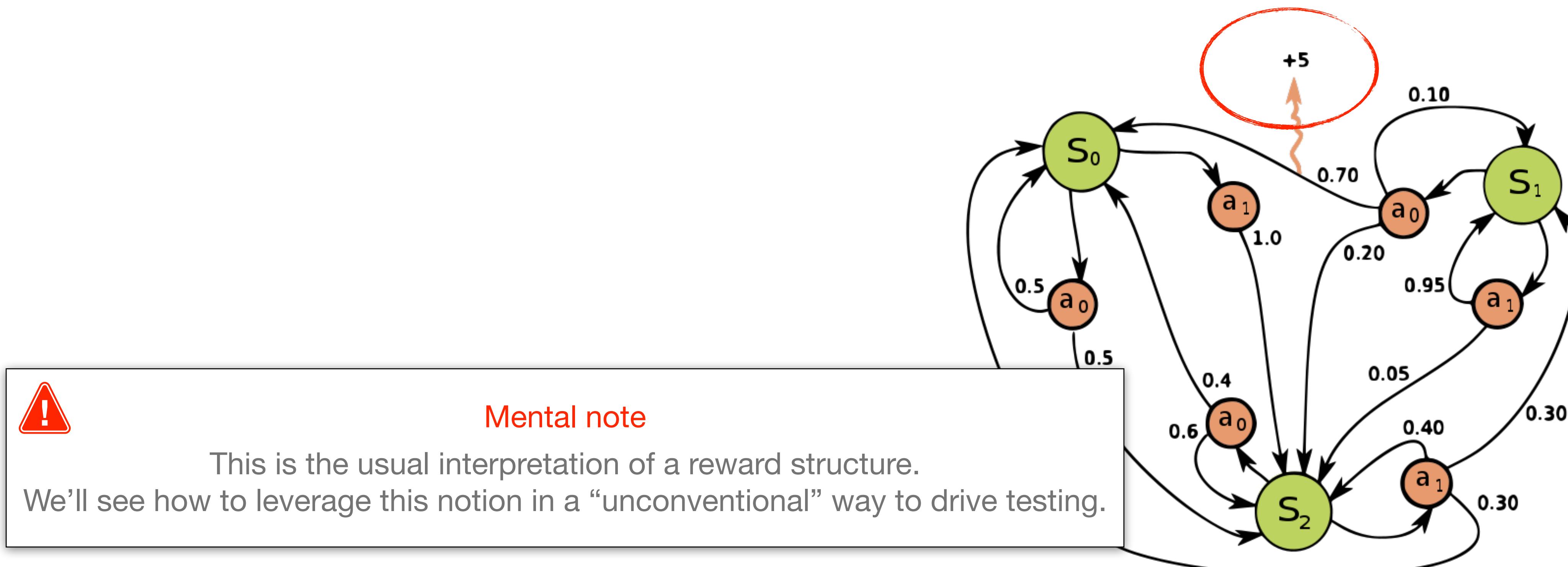
Markov Decision Process

- Mathematical framework for modeling systems whose behavior is partially
 - Nondeterministic — actions (external stimuli) under the control of a decision maker
 - Stochastic — probabilistic outcome out of an executed action
- **Formal structure (S, s_0, A, P)**
 - S : set of states (finite/infinite)
 - s_0 : initial state
 - A : set of actions (alphabet)
 - $P: S \times A \times S \rightarrow [0,1], P(s, a, s') = P(S_{t+1} = s' | S_t = s, a_t = a)$



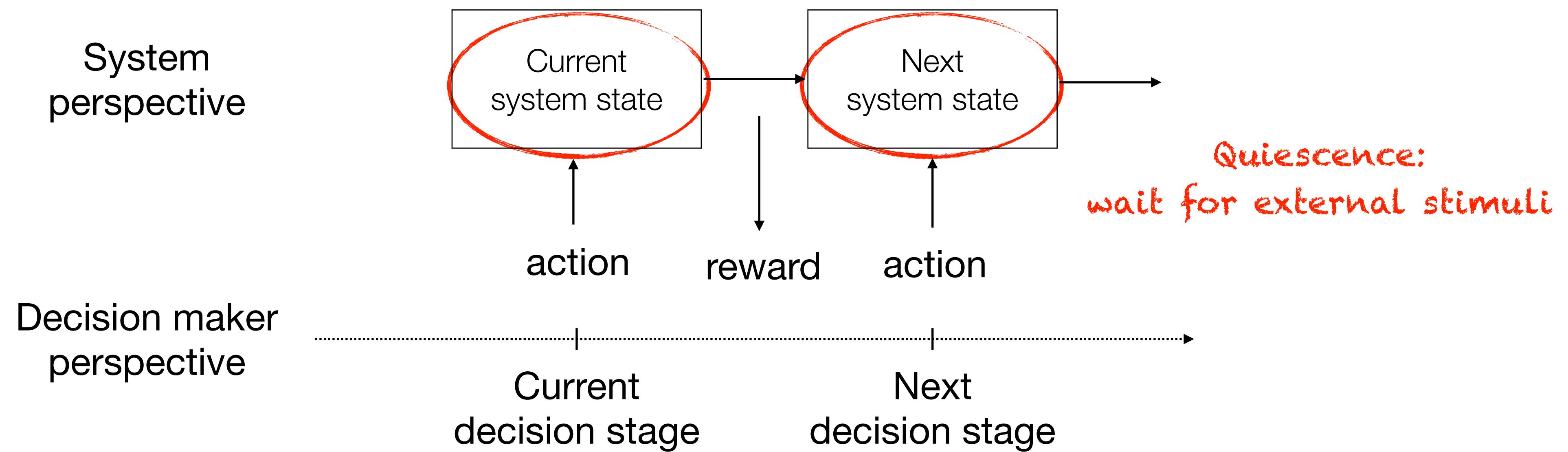
MDP with rewards

- An MDP model can be augmented with one or more reward structures
- **Reward structure**
 - $R: S \times A \times S \rightarrow \mathbb{R}$, $R(s, a, s')$ reward for $(s_{t+1} = s', s_t = s, a_t = a)$
 - Describe nonfunctional aspects (e.g., energy consumption, computational cost, response time, ...)



MDP behavior

- How does the model operate
 - The system must be in one of the states (finite countable set) at a time
 - The system makes a transition $s \rightarrow s'$ when one of the available actions is selected



MDP behavior (2)

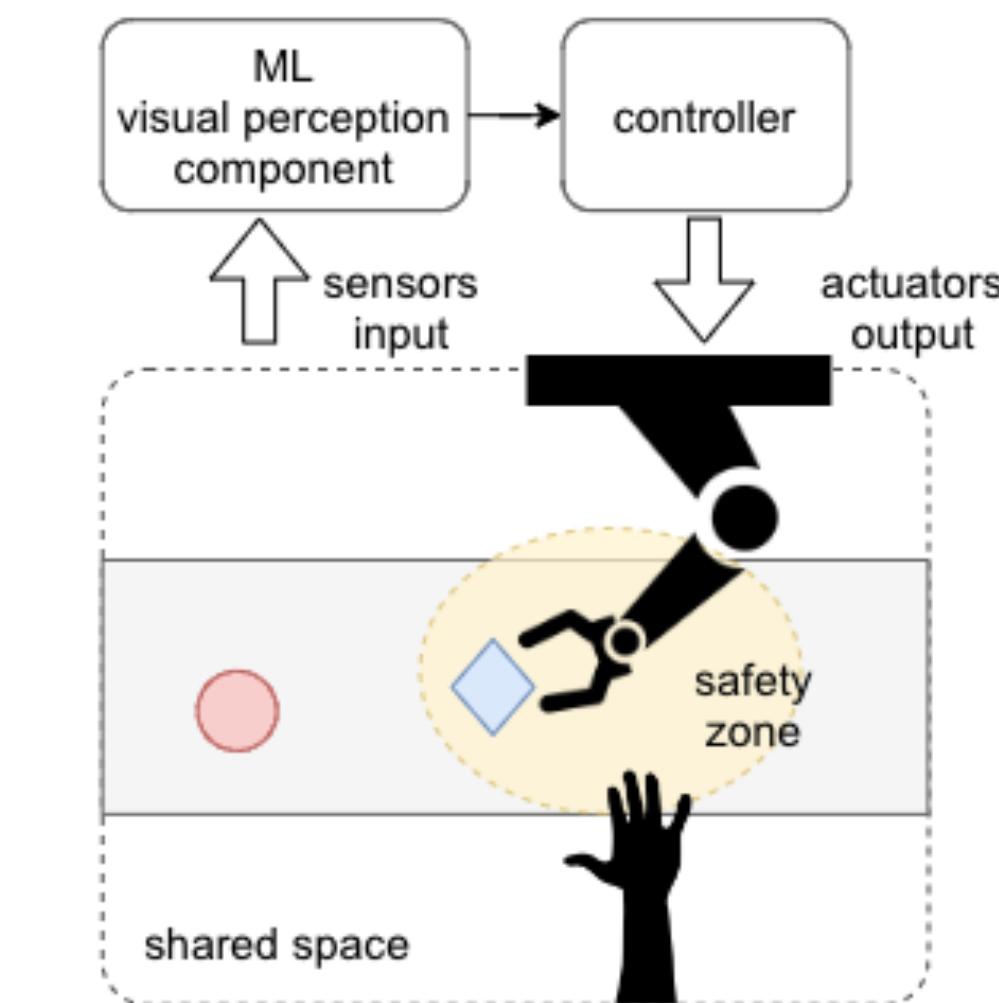
- **States**
 - Describe configurations or status of the shared phenomena
 - E.g., instances of the system where
 - Specific tasks are carried out
 - Operating in a fully-functioning mode, degraded mode, faulty, etc.
 - Undergoing recover/repair
 - Shared state initiated by the world, e.g., “pulsing” (or the other way around)
- **Actions**
 - Possible inputs or external events
- **Transitions**
 - Define whether is possible to go from one state to another
 - Transition probability —> governs the likelihood of observing the transition

MDP examples

- Possible domains
 - Service-based systems
 - Cyber physical systems (CPSs)
 - Control policies in robotics
 - Security protocols
 - etc.
- Selected example
 - Human-robot collaborative system — example of cyber-physical system

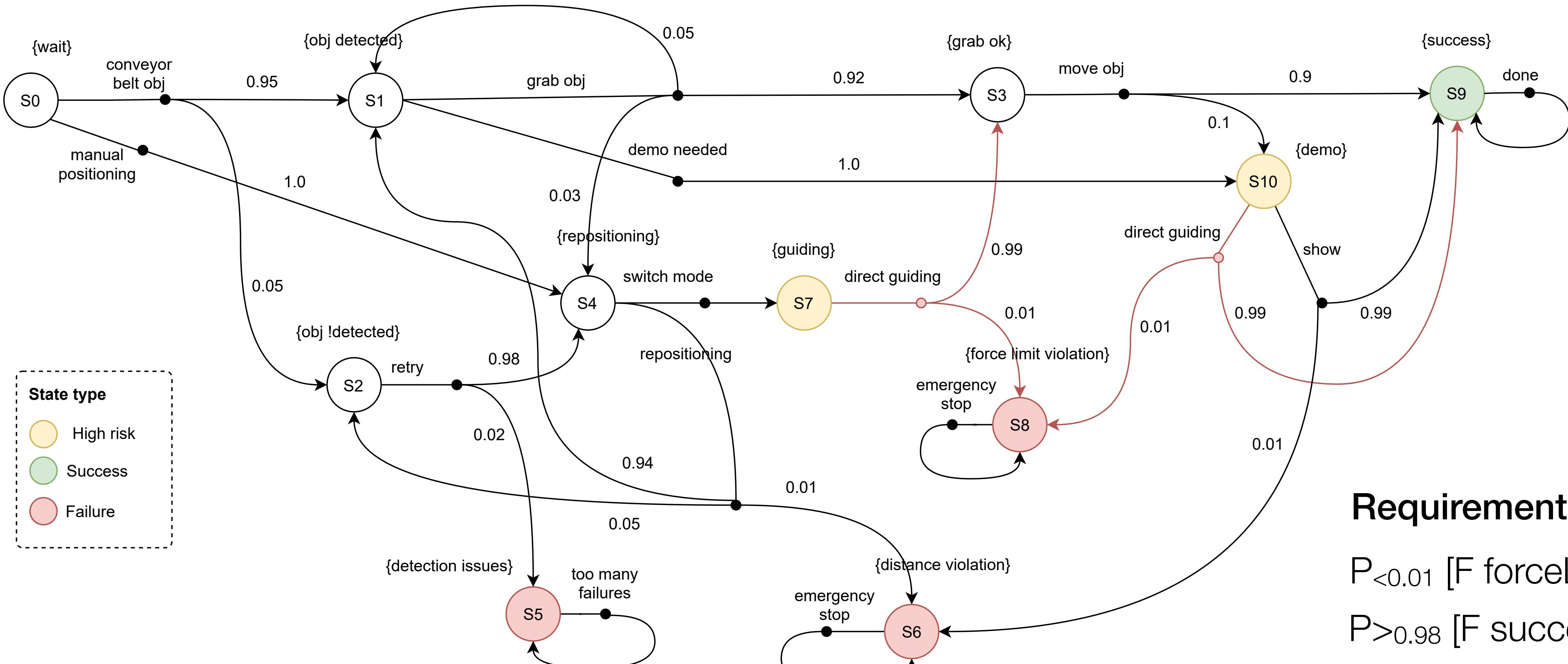
Example – human-robot collaboration

- Industry 4.0 demo running at the ARENA Lab¹ (Fraunhofer Italia)
- Robotic arm detects and moves object from a conveyor belt into the right bucket
- The system is trained online by a human operator that can either:
 - show how to handle objects (protective separation shall be maintained); or
 - guide directly the movements of the arm (power and force limiting shall be applied)



1. <https://www.fraunhofer.it/de/leistungsangebot/fraunhofer-italia-application-center-arena-.html>

Example – human-robot collaboration (MDP)



Requirements (PCTL)

- $P_{<0.01} [F \text{ forceLimitViolation}]$
- $P_{>0.98} [F \text{ success}]$
- $P_{>0.90} [G \text{ !guiding \& !demo}]$

MDP policy

- The notion of policy π refers to the way a Decision Maker (DM) solves nondeterminism of a MDP
- **Deterministic policy**^{1,2}
 - $\pi: S \rightarrow A$, prescribes the action to take given a state
 - DM objective: choose π which maximizes the expected cumulated reward over an infinite horizon
 - This is called best policy π^*
- **Definition of the best deterministic policy**
 - Given $R(s, a)$, i.e., the one-step expected reward
 - We can compute the value function $V(s)$ for each state

Bellman's equation

$$R(s, a) = \sum_{s' \in S} p_{s,a,s'} r_{s,a,s'} \quad V(s) = \max_{a \in A} \{R(s, a) + \gamma \sum_{s' \in S} p_{s,a,s'} V(s')\}$$

Best policy

$$\pi^*(s) = \arg \max_{a \in A} \{R(s, a) + \gamma \sum_{s' \in S} p_{s,a,s'} V(s')\}$$

-
1. Given a deterministic policy, the MDP reduces to a Discrete Time Markov Chain (DTMC).
 2. Martin L. Puterman. 1994. *Markov Decision Processes: Discrete Stochastic Dynamic Programming* (1st. ed.). John Wiley & Sons, Inc., USA

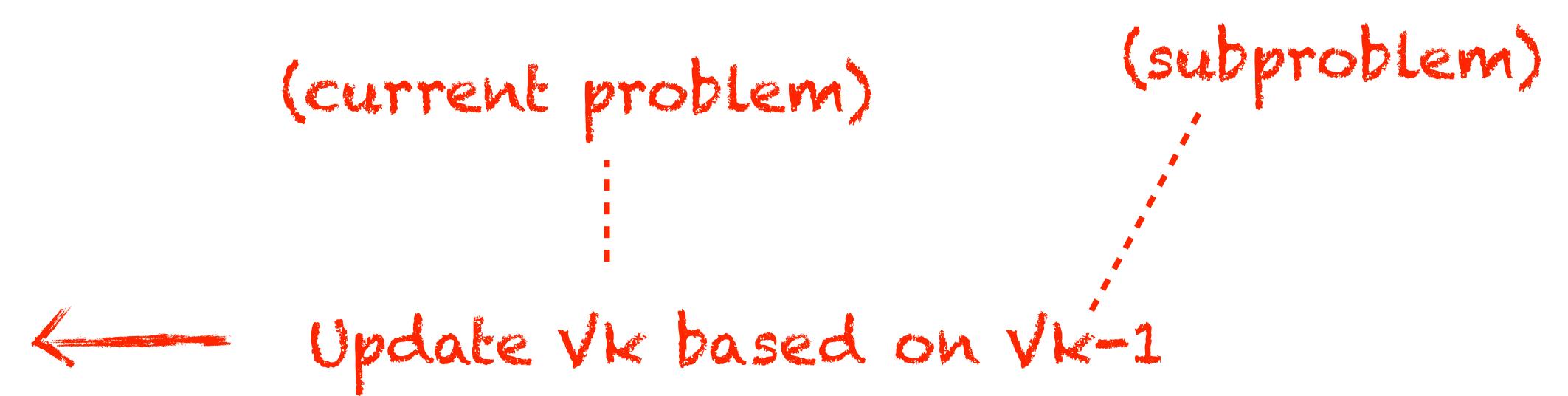
MDP policy – Value iteration

```

1: Procedure ValueIteration(S,A,P,R,θ)
2:   Inputs
3:     S set of all states
4:     A set of all actions
5:     P transition function  $P(s,a,s')$ 
6:     R reward function  $R(s,a,s')$ 
7:     θ a threshold,  $\theta > 0$ 
8:   Output
9:      $\pi[S]$  optimal policy
10:     $V[S]$  value function
11:   Local
12:     real array  $V_k[S]$  is a sequence of value functions
13:     action array  $\pi[S]$ 
14:     assign  $V_0[S]$  arbitrarily
15:      $k \leftarrow 0$ 
16:   repeat
17:      $k \leftarrow k+1$ 
18:     for each state  $s$  do
19:        $V_k[s] = \max_a \sum_{s'} P(s,a,s') (R(s,a,s') + \gamma V_{k-1}[s'])$ 
20:        $\pi[S] = a$ 
21:   until  $\forall s |V_k[s] - V_{k-1}[s]| < \theta$ 
22:   return  $\pi, V_k$ 

```

- The ValueIteration procedure uses **dynamic programming**
 - Memoization + recursion (or iteration)
 - This procedure converges no matter what is the initial value function V_0



Model-based testing of probabilistic systems

- Offline vs online approaches
- Conformance relation
- Probabilistic alternating simulation and refinement

Model-based testing

- Model-based testing vs Formal verification
 - MBT is testing! provides runtime evidence that the SUT behaves as defined in the specification
 - Limitation: testing is not complete (i.e., “*testing can only show the presence of errors, not their absence*” [D. Parnas])
 - Formal verification — prove that the model (i.e., formal specification) satisfies requirements
- Basic idea
 - A model that specifies the behavior of the System Under Test (SUT) is used as baseline of
 - test case generation
 - Construction of the oracle
 - Test suites are automatically extracted from models and then executed

MBT – terminology

- **System (or implementation) Under Test**

- Piece of hardware/software, a software system, an embedded system, a CPS, etc.
- The SUT is viewed as a **black-box** (secret internal structure)
- The tester controls and observes the SUT via its interfaces (e.g., sensors, actuators, APIs)

- **Specification**

- Describes what the SUT should do using a **formal notation** (or language)
- **SPEC** – set of all valid models in a formal notation
 - A specification is $M \in SPEC$

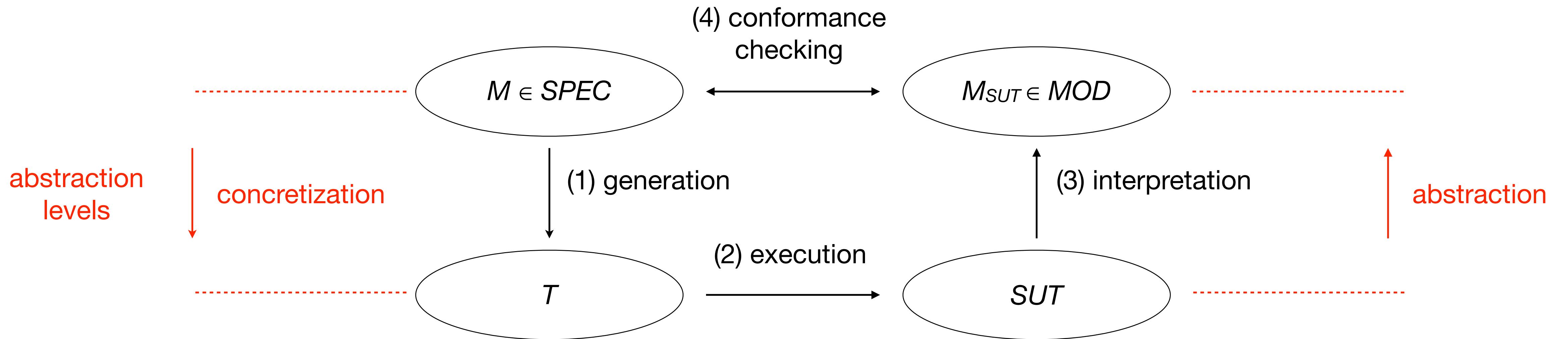
- **Conformance**

- Formalizes the notion of **correct behavior** of a SUT w.r.t. $M \in SPEC$
- **Problem:** we'd like to define a **relation** between elements of different domains
 - M (formal entity) \leftrightarrow SUT (not a formal entity)

MBT – terminology (2)

- Conformance Problem: M (formal domain) \leftrightarrow SUT (not formal domain)
 - Trick – test assumption
 - Interpretation of the SUT behavior using the same level of abstraction of M
 - SUT behavior is a model $M_{SUT} \in MOD \subseteq SPEC$
 - MOD – universe of implementation models
 - M_{SUT} not a-priori known
 - Conformance (under the test assumption)
 - expressed as a binary relation between MOD and $SPEC$ elements
 - $conf \subseteq MOD \times SPEC$
 - M_{SUT} is correct w.r.t. M if $M_{SUT} \ conf \ M$
 - Conformance checking
 - Assess by testing whether $M_{SUT} \ conf \ M$
 - Create T (test suite) s.t. $M_{SUT} \ conf \ M \implies M_{SUT} \ passes \ T$

MBT process

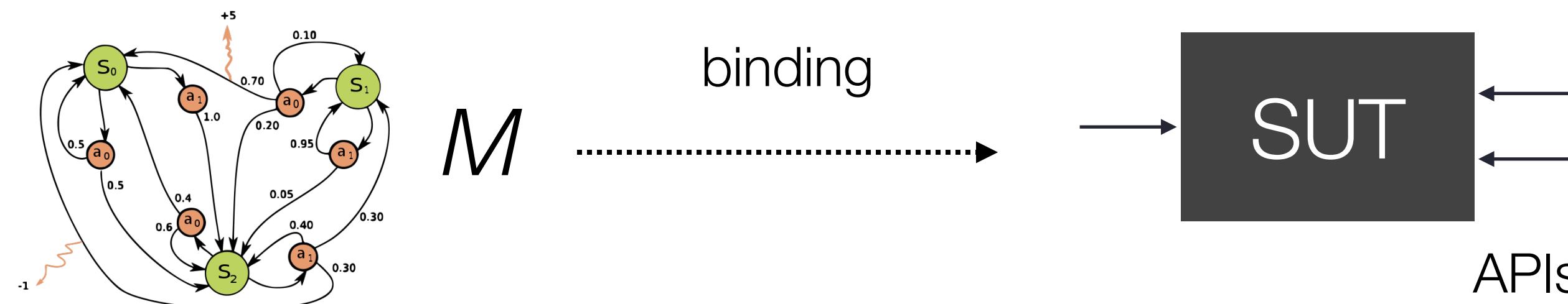


- **Offline vs online**¹
 - Offline – steps 1-4 are separated
 - Online (or on-the-fly) – steps 1-4 are merged into a one-iteration step
 - Test cases are created dynamically and take advantage of the knowledge gained by exploring M
 - Iterative approach –> 2-players game: controller + observer

1. Utting, Mark, and Bruno Legeard. Practical model-based testing: a tools approach. Elsevier, 2010

Online MBT with MDPs

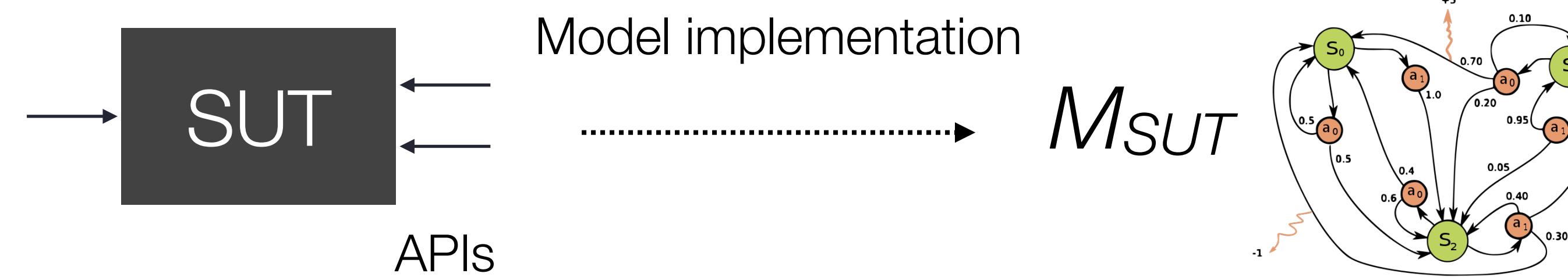
- **Binding** (concretization)
 - Defines a mapping between the MDP model spec and the SUT behavior



- **Formal definition**
 - Given a MDP $M = (S, s_0, A, P)$ and a SUT, i.e., a set of exported operations H (having signature and arguments), a binding is a tuple of partial functions $(h, i, post)$ s.t.
 - $h(s, a)$, $a \in A(s)$ identifies an operation in H
 - $i(s, a)$, $a \in A(s)$ identifies a vector v_{in} for $h(s, a)$
 - $post(s, a, s')$, $a \in A(s)$ maps to a post-condition that must hold for v_{out} outcome of $h(s, a)$ on input v_{in}
- Controllable
SUT components →
 Observable
SUT behavior ←

Online MBT with MDPs (2)

- Model implementation (abstraction)
 - Defines the abstract interpretation of the SUT behavior in terms of MDP model



- Formal definition
 - Given a MDP $M = (S, s_0, A, P)$ and a binding $(h, i, post)$ the model implementation is a MDP $M_{SUT} = (S', s'_0, A', P')$ s.t.
 - $S' \subseteq S$
 - $A' \subseteq A$
 - $P'(s, a, s') > 0$ iff $post(s, a, s')$ holds for v_{out} with $v_{out} = h(s, a)(v_{in})$

ALL observable SUT states exist in M

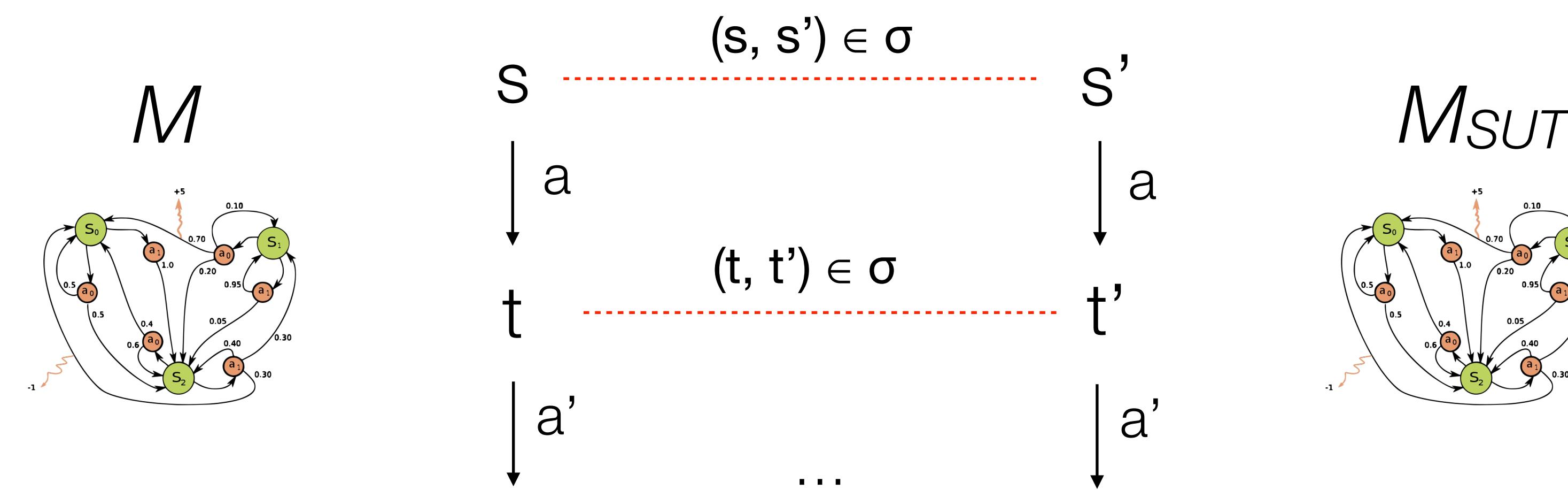
ALL controllable actions in M are feasible in SUT

MsUT transitions are defined in terms
of SUT behavior

Online MBT with MDPs (3)

- Conformance checking
 - Defined in terms of probabilistic alternating simulation + refinement

- Probabilistic alternating simulation
 - between M and M_{SUT} is a binary relation $\sigma \subseteq S \times S'$, s.t. for all $(s, s') \in \sigma$
 - $A(s) \subseteq A'(s')$
 - For each $t \in S : P(s, a, t) > 0$, there exists $t' \in S' : P(s', a, t') > 0$ and $(t, t') \in \sigma$



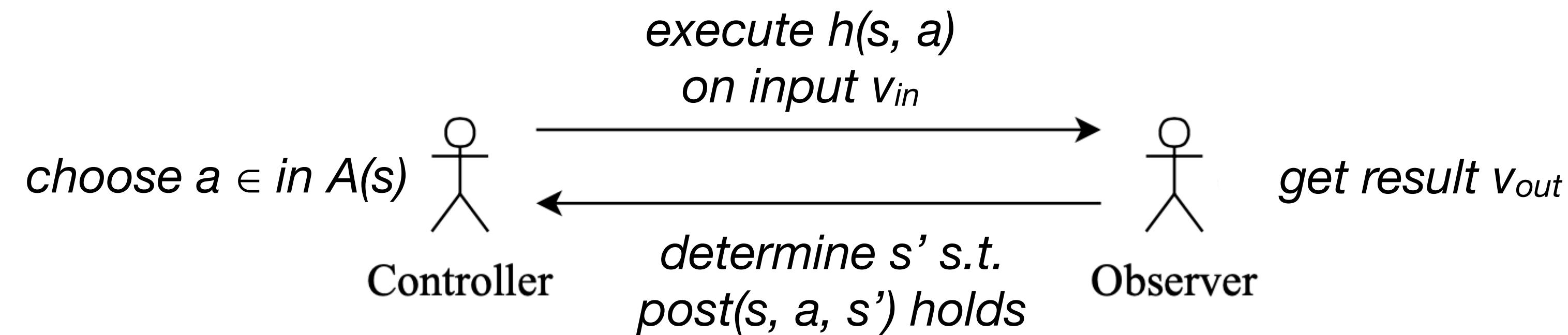
Online MBT with MDPs (4)

- **Refinement**

- M_{SUT} refines M iff there exists a probabilistic alternating simulation σ s.t. $(s_0, s'_0) \in \sigma$

- **Conformance game**

- The notion of refinement is verified in practice by means of a conformance game between
 - Controller —> chooses actions based on a given test case generation strategy
 - Observer —> verifies the result out of a test execution



Online MBT under Uncertainty

- Problem statement
- Uncertain model parameters
- Bayesian inference
- Framework and test case generation strategies

Problem statement



Is it complete?
or is it based on partial knowledge?

How to refine the partial knowledge in
 M based on runtime evidence?

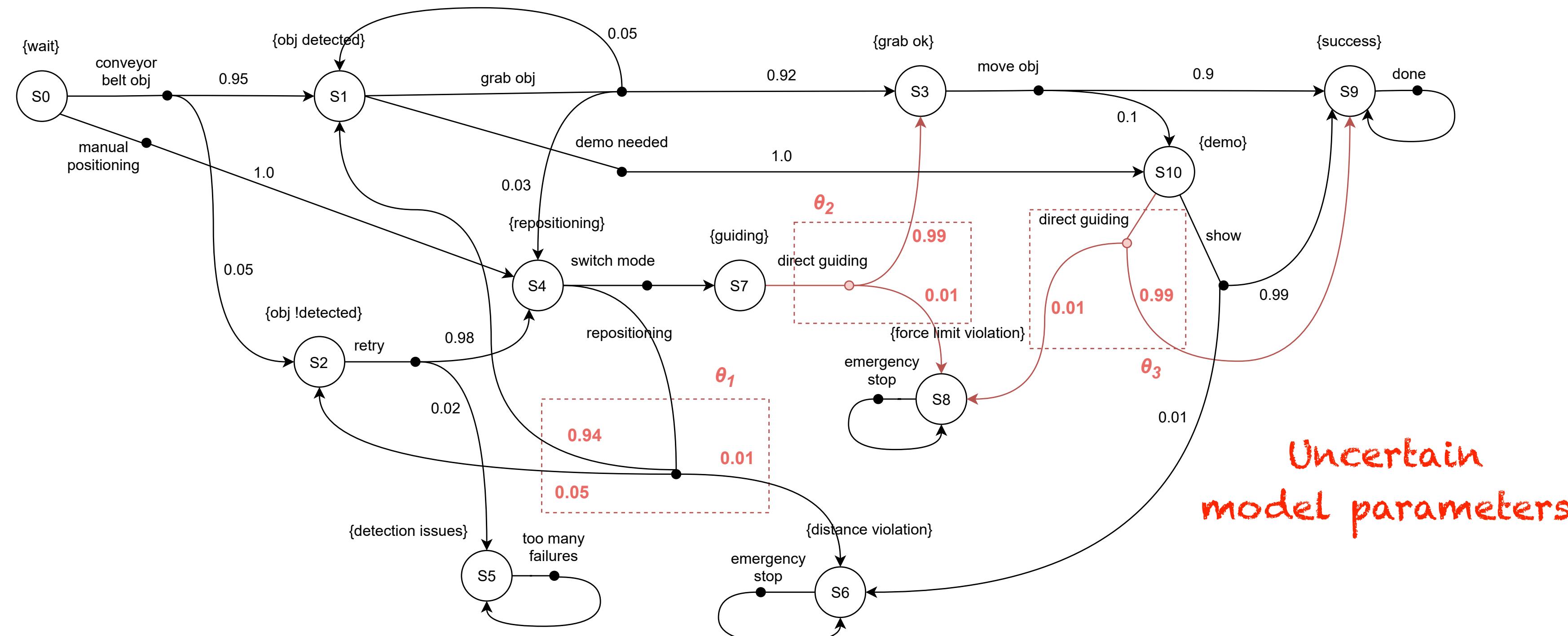
- Problem
 - Design-time models are imperfect and include assumptions
 - Assumptions are affected uncertainty = partial knowledge of the phenomena of the world and their effect on the behavior of the machine
 - E.g., human-robot interaction scenario:
 - Outcome of the visual perception component (luminance of the area, color and contrast of objects)
 - Safety guarantees in close-collaboration settings (human misbehavior, emergency brake latency)

The very idea

- **Objective**
 - Refine partial knowledge of design-time assumptions through runtime evidence
- **Assumption**
 - Sources of uncertainty affect model parameters (i.e., uncertain transition probability values in the MDP)
- **How**
 - Calibration of uncertain model parameters during system testing by combining
 - Online Model-based Testing
 - Bayesian inference

Uncertain model parameters

- **Uncertainty in the human-robot collaboration**
 - World phenomena might affect: visual perception component + ability to promptly actuate the right movements
 - Possible violations: protective distance or the power and force limit during close interaction with the operator
 - Model parameters (probability values) governing such a behavior are uncertain



Uncertain regions

- **Uncertain region**
 - Set of uncertain transition probability values θ_i identified by a **<state, action>** pair
 - θ_i is formally described through a Categorical distribution $\theta_i \sim Cat(p_1, \dots, p_k)$

region	state-action	target states	distribution
θ_1	$(s_4, repositioning)$	s_1, s_2, s_6	$Cat(0.94, 0.05, 0.01)$
θ_2	$(s_7, directGuiding)$	s_3, s_8	$Cat(0.99, 0.01)$
θ_3	$(s_{10}, directGuiding)$	s_8, s_9	$Cat(0.99, 0.01)$

Uncertain parameters
(hypothesis)

- **Intuition**
 - Mitigate the uncertainty of θ regions by observing (multiple times) the SUT
 - Run-time observations provide evidence to update the uncertain regions

Bayesian inference

- Statistical machinery used to update a probability distribution that describes θ based on the evidence
- **Formulation**¹
 - To learn θ we collect a sample $y = (y_1, \dots, y_n)$
 - *Posterior \propto Likelihood \cdot Prior*
 - *Posterior $f(\theta | y)$ – updated knowledge given the evidence*
 - *Prior $f(\theta)$ – hypothesis*
 - *Likelihood $f(y | \theta)$ – compatibility of the evidence given the hypothesis*
- **In our context**
 - The natural conjugate Prior of the Categorical distribution is the Dirichlet distribution
 - $f(\theta_i) \sim Dir(\alpha_1, \dots, \alpha_k), \alpha_i > 0$

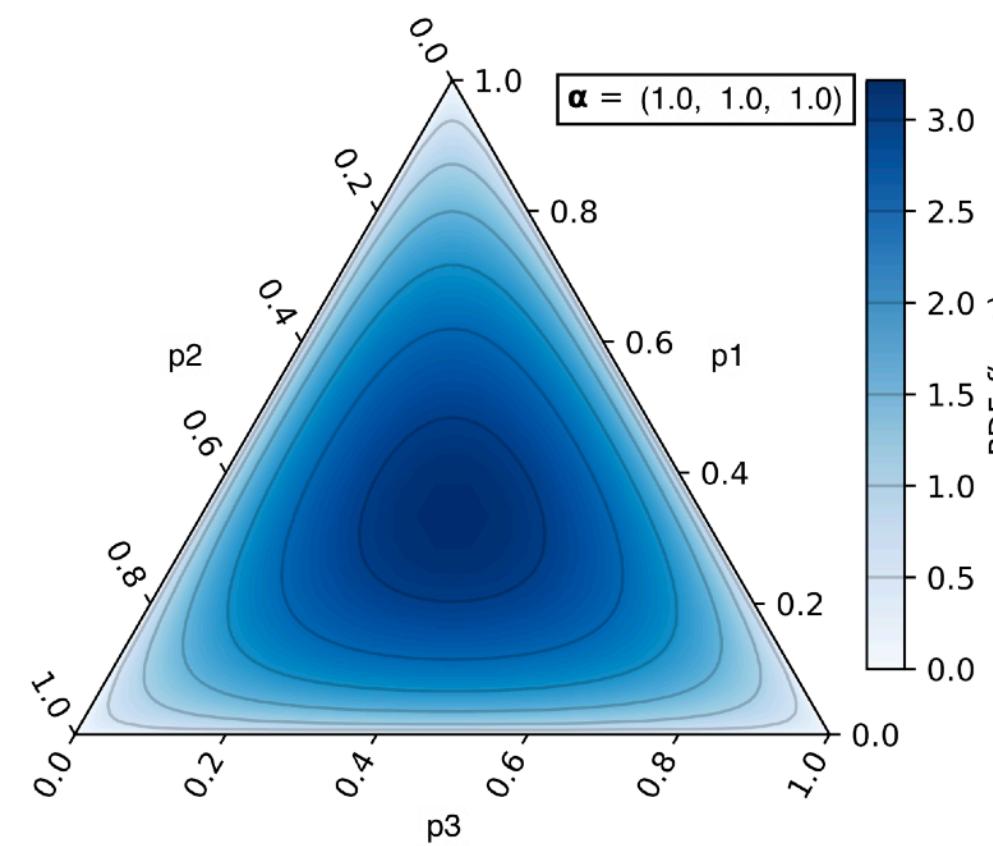
1. Robert, Christian. The Bayesian choice: from decision-theoretic foundations to computational implementation. Springer Science & Business Media, 2007

Bayesian inference (2)

- Updating rule

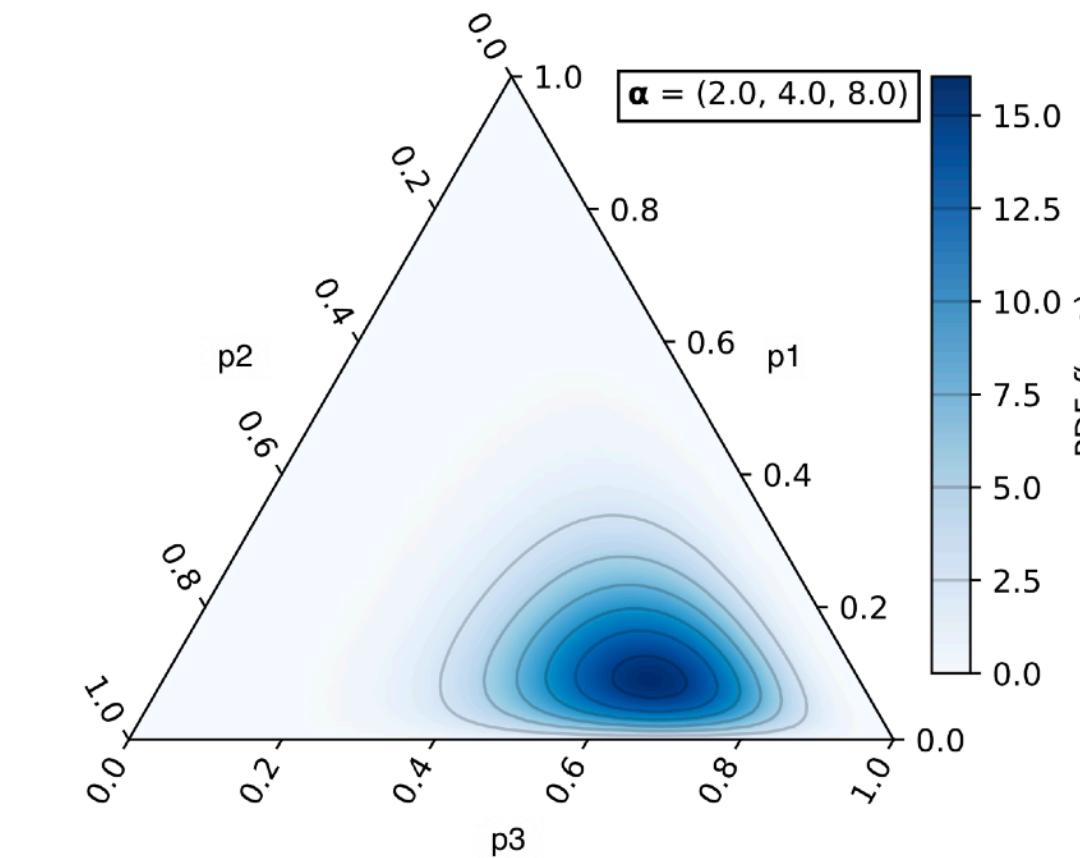
$$\cdot f(\theta) \sim Dir(\alpha_1, \dots, \alpha_k) \rightarrow f(\theta | y) \sim Dir(\alpha_1 + n_1, \dots, \alpha_k + n_k)$$

$$f(\theta_1) \sim Dir(1.0, 1.0, 1.0)$$



$$f(\theta_1 | y) \sim Dir(1.0 + 1.0, 1.0 + 4.0, 1.0 + 7.0)$$

Observations:
1x51, 4x52, 7x56



Bayesian inference (2)

- **Summarization**

- Prior/Posterior knowledge can be summarized by using

- Punctual summarization Mean: $p_i = \alpha_i / \sum_{j=1}^k \alpha_j$

- Interval summarization Highest Density Region $HDR : P(\theta \in HDR) \geq 0.95$

$$f(\theta_1) \sim Dir(1.0, 1.0, 1.0)$$



$$f(\theta_1 | y) \sim Dir(2.0, 4.0, 8.0)$$

Mean = { 0.33, 0.33, 0.33 }

HDR = { [3.6E-6, 7.8E-1], [2.7E-6, 7.7E-1], [1.4E-5, 7.8E-1] }

HDR magnitude = 0.78

Mean = { 0.14, 0.29, 0.57 }

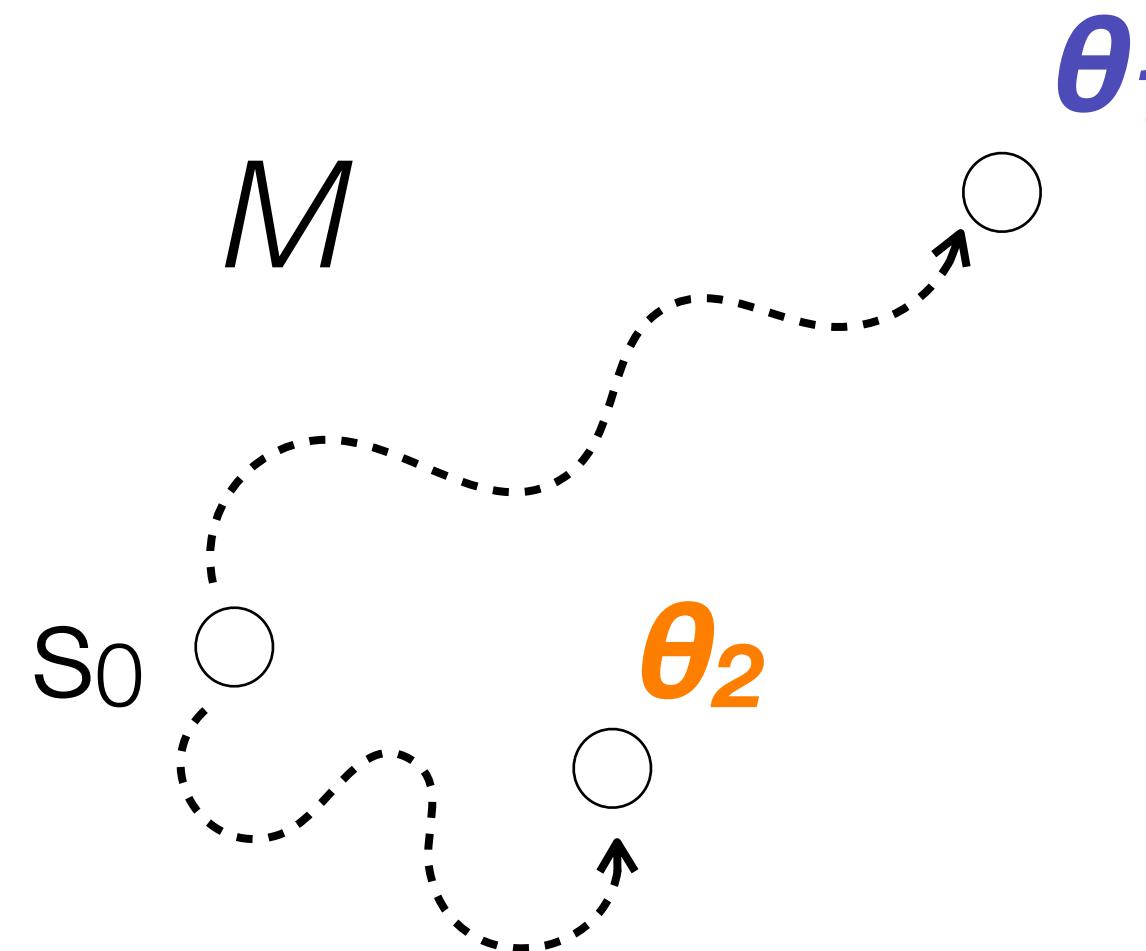
HDR = { [0.0, 0.31], [0.07, 0.51], [0.32, 0.81] }

HDR magnitude = 0.41

Lower value → higher accuracy

Online MBT + Bayesian inference

- **Objective** (reminder)
 - Collect runtime evidence and refine uncertain assumptions
- **How**
 - Perform a controlled exploration using online MBT to stress the uncertain model regions
 - Collect evidence and run bayesian inference to mitigate the uncertainty

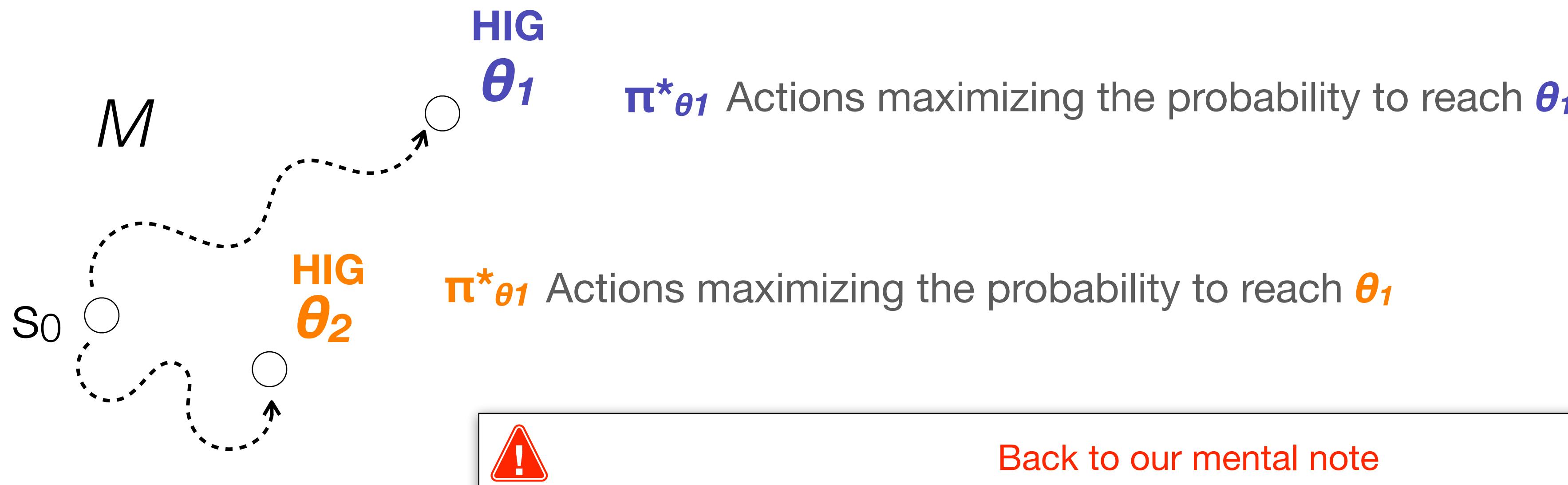


- **Uncertainty-aware MBT strategy (decision maker)**
 - Explore by maximize the probability of reaching θ regions
 - Reduces to an **optimization problem**:
 - Find out the actions a decision maker should take to maximize the execution of θ regions

Uncertainty-aware strategy

- Computation of the best policies

- For each θ_i
 - construct a reward structure that assigns HIG reward to θ_i transitions, LOW elsewhere
 - Compute the best policy $\pi^*_{\theta_i}$ (e.g, using value iteration)
 - For each state, it selects the action that maximizes the probability to reach θ_i



Uncertainty-aware strategy (2)

- How to combine the best policies $\pi^*_{\theta_i}$?
 - Simple scenario —> there exists just a single θ region
 - Otherwise —> different exploration strategies may be constructed/adopted
 - A strategies represents decision maker (i.e., tester) that uses a probabilistic function like:

$$\mathcal{P}(s, a) = \begin{cases} 0 & \omega(s, a) = 0 \\ \omega(s, a) / \sum_{a' \in A(s)} \omega(s, a') & \text{otherwise} \end{cases}$$

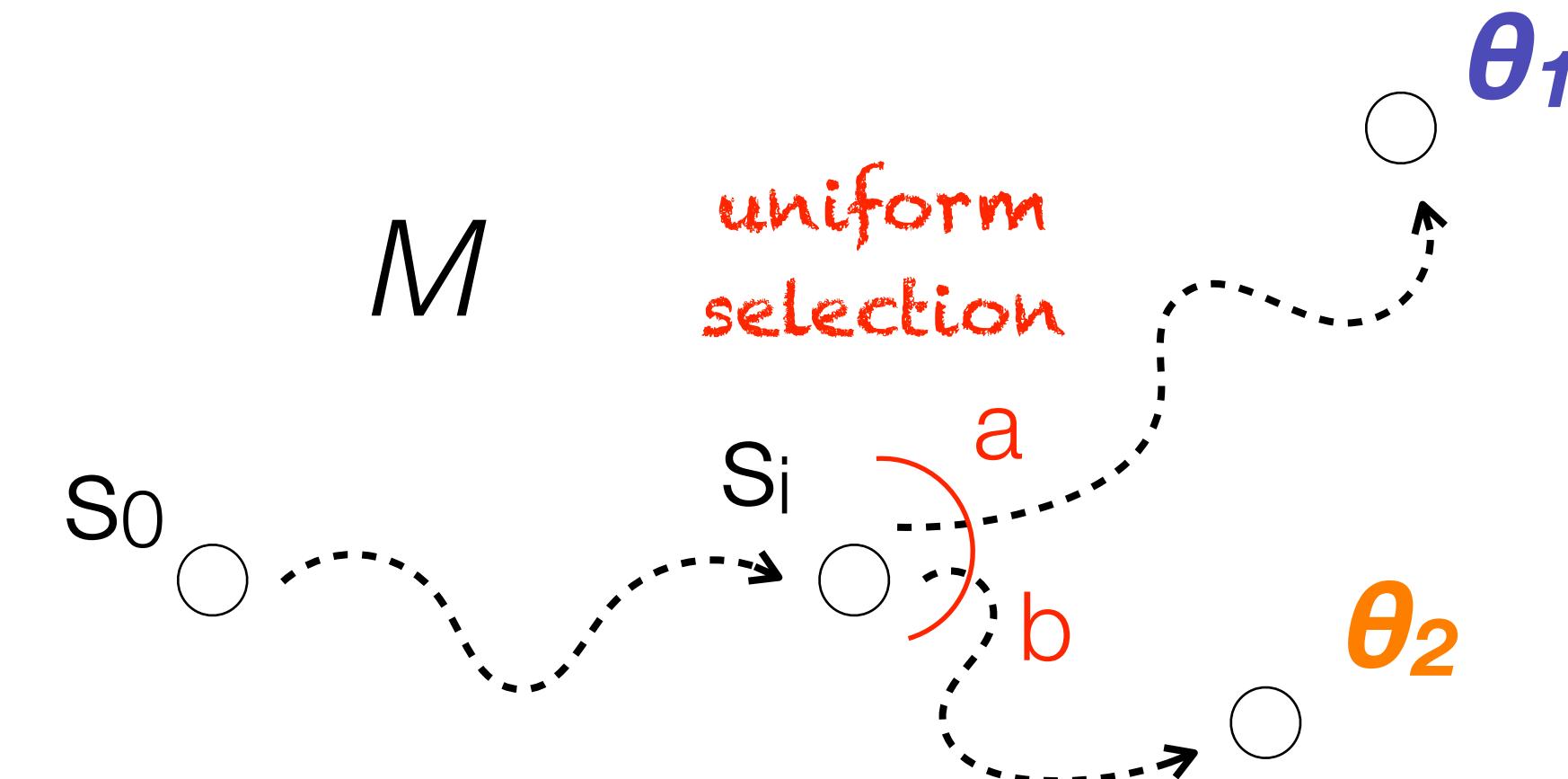
- The ω weight selectively increase/decrease the probability of choosing a specific action a from state s

Uncertainty-aware strategy (3)

- **Flat strategy**

- Actions selected by different policies $\pi^*_{\theta_i}$ have equal probability
- Uniform random sampling of the available policies

$$\omega^{RT}(s, a) = \begin{cases} 1 & \exists i : \pi_i^*(s) = a \\ 0 & \text{otherwise} \end{cases}$$

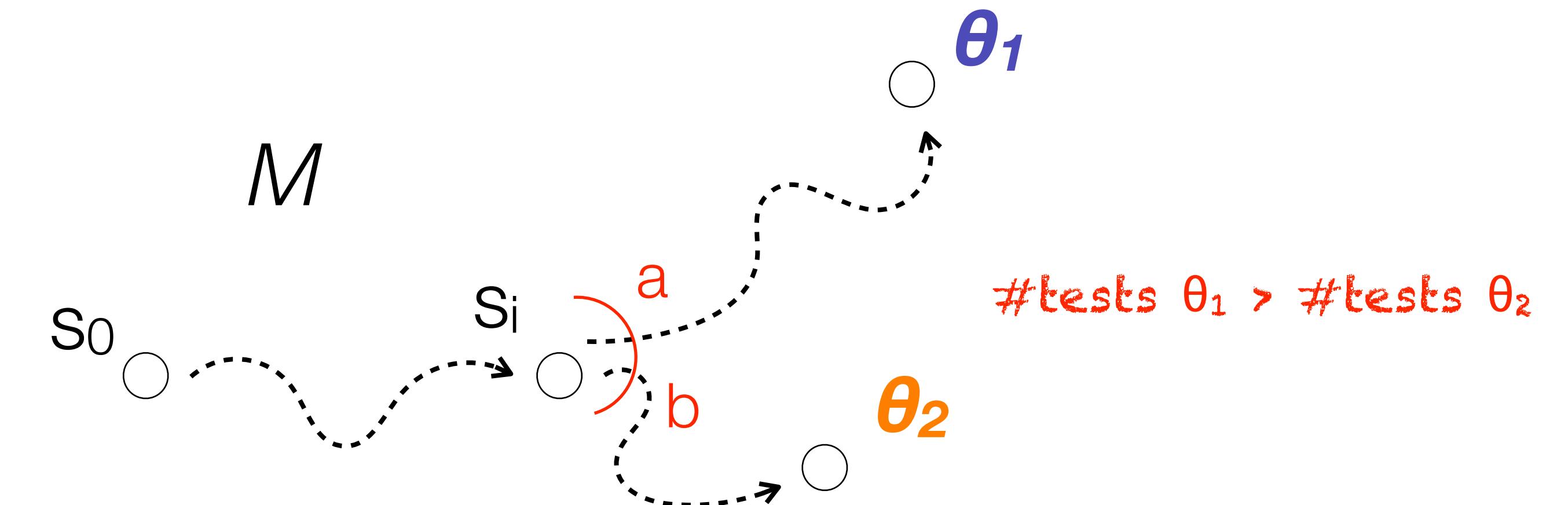


Uncertainty-aware strategy (4)

- History-based strategy

- Tries to keep balanced the number of times θ regions are tested
- We leverage decrementing weights inversely proportional to #selections of state-action pairs

$$\omega^{HT}(s, a) = \begin{cases} 1/\#(s, a) & \exists i : \pi_i^*(s) = a \\ 0 & \text{otherwise} \end{cases}$$

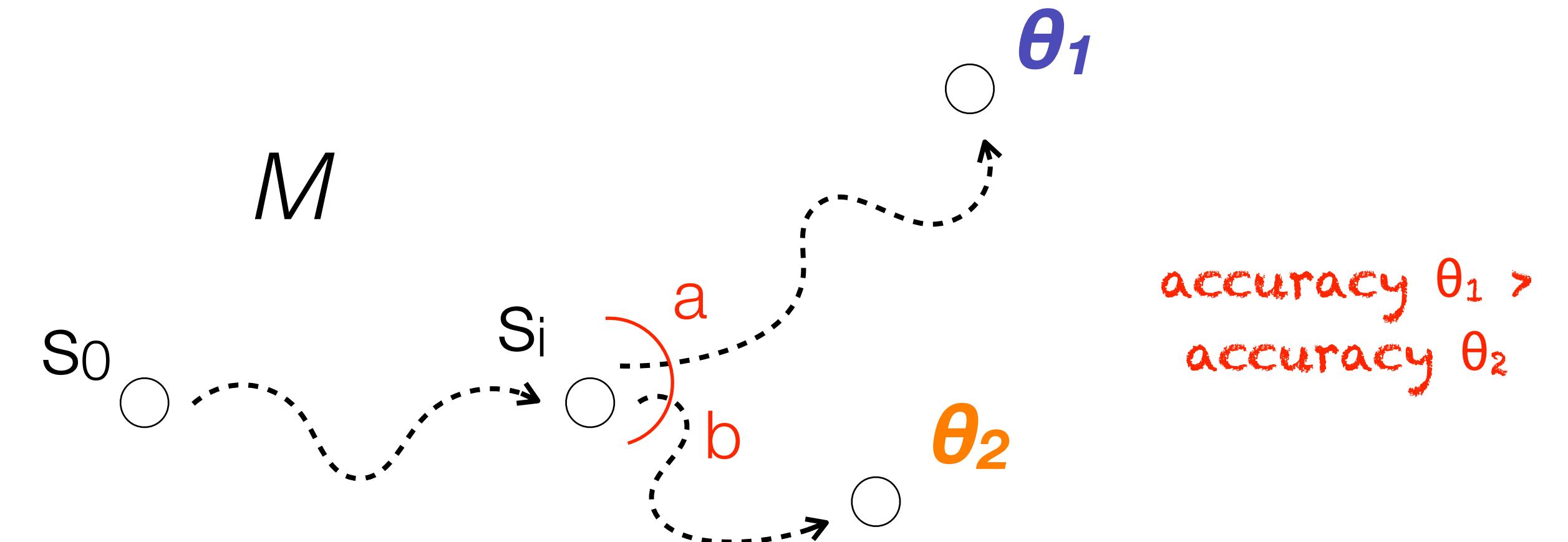


Uncertainty-aware strategy (5)

- **Distance strategy**

- Tries to deliver uniform degree of accuracy for all θ
- The weight is proportional to the HDR magnitude of θ_i

$$\omega^{DT}(s, a) = \begin{cases} |HDR_{\theta_i}| & \exists i : \pi_i^*(s) = a \\ 0 & \text{otherwise} \end{cases}$$



the larger the $|HDR|$ of the target θ ,
the higher the likelihood of selecting the corresponding action

Termination condition

- Limit on the effort
 - Traditional termination condition based on #tests limit
- Bayes factor
 - Tries to recognize when the inference process converges

$$\mathcal{F} = \frac{f(y|\theta)}{f(y|\theta')}$$

Likelihood that data y are produced under different assumptions θ and θ'

$$\mathcal{F} \in [10^0, 10^{1/2}]$$

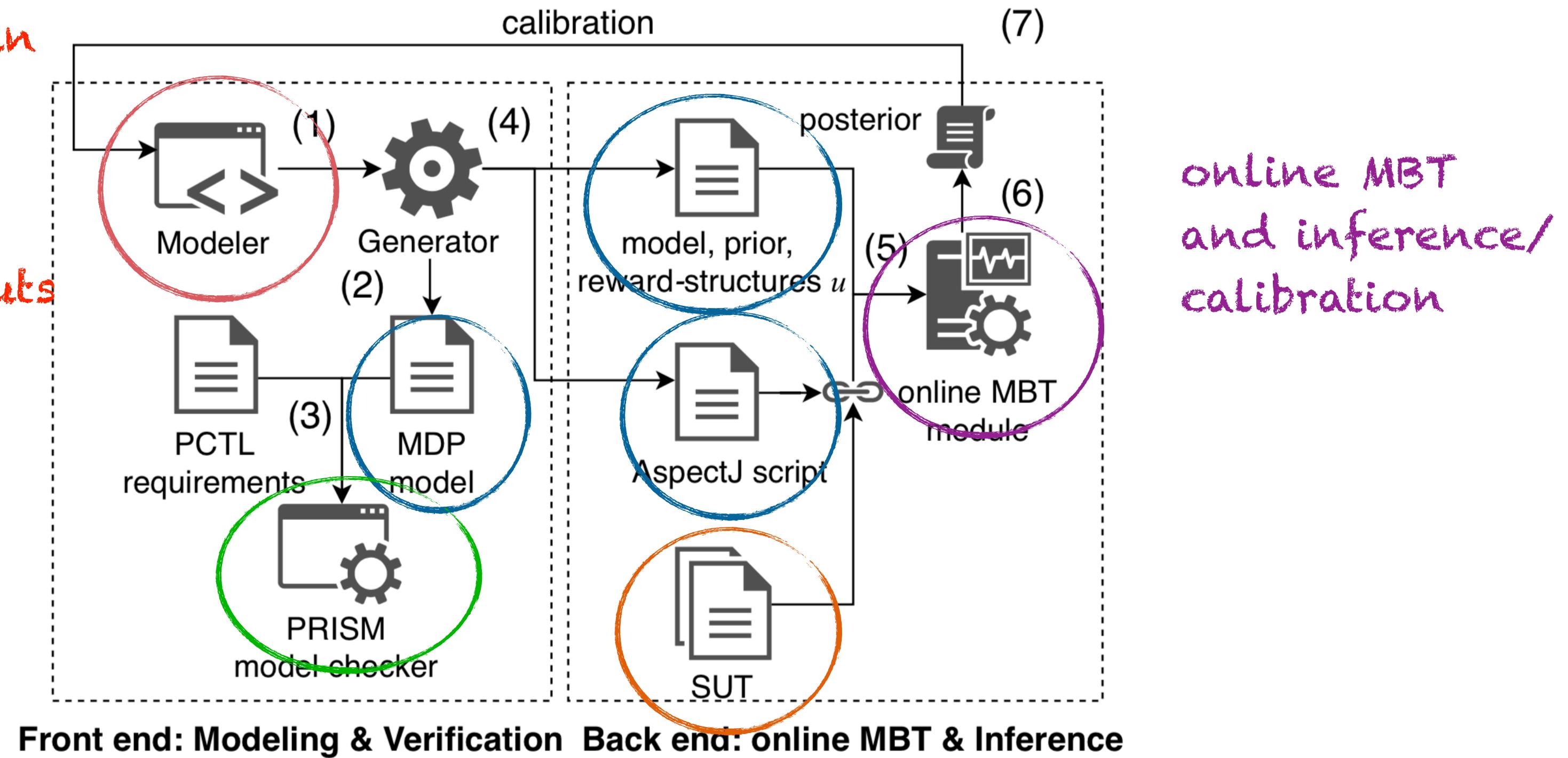
Difference between assumptions θ and θ' is not substantial

Current toolchain implementation

MDP definition + uncertain transition probabilities θ

binding to the SUT:
actions → methods + inputs
acs → postconditions

automatic generation



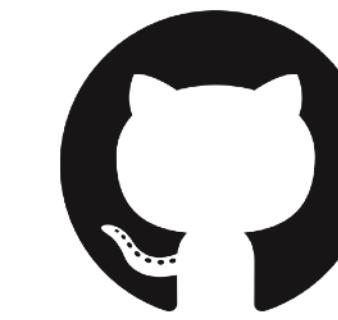
model checking of
PCTL requirements

Java program

Current toolchain implementation (2)

MBT module

<https://github.com/SELab-unimi/mbt-module>



- Java 99.3%
- Other 0.7%

- Current stage
 - Implemented uncertainty-aware strategies: flat, history-based, distance, frequency
 - Systematic evaluation of their cost-effectiveness¹

1. M Camilli, A Gargantini, P Scandurra, C Trubiani. Uncertainty-aware Exploration in Model-based Testing. IEEE ICST 2021

Current toolchain implementation (3)

- **Evaluation summary**
 - We assessed statistical difference (Mann-Whitney U test ¹)
 - We evaluated practical value (Vargha & Delaney's \hat{A}_{12} measure ¹)
 - Assuming same effort (i.e., #tests), the probability that target strategy yields smaller HPD width values than flat one (i.e., baseline)

Table 3: Vargha and Delaney's \hat{A}_{12} measure

%uncertainty			#actions		
balanced	20	50	80	5	10
hist	1.000	0.716	0.531	0.617	0.704
	1.000	0.790	0.679	0.741	0.802
unbalanced	20	50	80	5	10
	0.963	0.716	0.556	0.531	0.642
			20	0.901	
dist	0.988	0.951	0.691	0.741	0.741
				0.975	

1. Andrea Arcuri and Lionel Briand, A practical guide for using statistical tests to assess randomized algorithms in software engineering, ICSE'11, New York, NY, USA

Summary

- We discussed the importance of understanding the world where the machine runs —> uncertain phenomena
- We discussed MBT and the problem of testing with uncertain model regions
- We put into place major aspects by using Markov Decision Processes as modeling formalism of choice
- We derived different uncertainty-aware exploration MBT strategies that leverage runtime evidence to mitigate uncertainty and refine model parameters
- **Next**
 - Hands on session with the MBT module
 - Design/develop an additional exploration strategy

Collaboration opportunities

- Testing using Model-based Reinforcement Learning (based on MDP theory)
 - Discover the location of the uncertain regions
- PCTL falsification
 - Combination of metaheuristic optimizing search and MBT to find environment conditions that leads to violate PCTL requirements

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