

ELECTIVE IN A.I - 2 - REASONING AGENTS

# **Service Composition in Stochastic Settings**

|                        |         |
|------------------------|---------|
| Lomuscio Antonio       | 1647493 |
| Esposito Pierfrancesco | 1642232 |
| Rapi Franci            | 1660405 |



**SAPIENZA**  
UNIVERSITÀ DI ROMA

# Paper: Service Composition in Stochastic Settings

## OUTLINE

- » Introduction of The Paper
- » The Non-Stochastic Model
- » The Valued Requirement Model
- » Computing an Optimal Orchestrator
- » Extensions
- » Examples
- » References

# Introduction Of The Paper

## The “Goal”

- » The goal is to build a controller known as an orchestrator, that uses existing services to satisfy the requirements of the target service
- » We will talk about a simple stochastic model for service composition
- » We will see the target service with the probabilities describing the likelihood of requesting an action:
  - » Each action in a state
  - » Rewards for being able to execute actions.
- » We will show how to solve the resulting problem by solving a certain Markov Decision Process (MDP)

# Introduction Of The Paper

Where we can introduce the Orchestrator?

- » Thanks to growth of "IoT" and "Online Web Services", we can combine multiple services and see how they work
- » For example:
  - » Complete "Vacation" by combining Web services
  - » Flights
  - » Ground Transportation
  - » Event tickets
  - » Home security services
  - » Ect.

# Introduction Of The Paper

Roman Model: 'The Pristine Form'

- » Each available service is modeled as a finite state machine (FSM):
  - » In Each state => Set of Actions
  - » Each action => **Changes** the State of the Service
- » A Scheduler (Orchestrator) use "Actions" provided by existing services to implement action **requested** by the user

# Introduction Of The Paper

## Probabilistic model

- » We make the requirements probabilistic associating a probability with each action chosen in a state
- » This probability captures how likely the user requests the action in that state
- » Moreover a reward is associated with the requirement behavior
- » We observe that rewards can be related to "QoS"
- » We use complex reward specifications in the form of transducers, or formulas in expressive logics such as LTL<sub>f</sub> and LDL<sub>f</sub>

# The Non-Stochastic Model

## Roman Model

- » We adopt the Roman model for *service composition*
- » A *service* is defined as a tuple  $S = (\Sigma, \sigma_0, F, A, \delta)$

$\Sigma$  is the finite set of service's *states*;

$\sigma_0 \in \Sigma$  is the *initial state*;

$F \subseteq \Sigma$  is the set of service's *final states*;

$A$  is the finite set of service's *actions*;

$\delta \subseteq \Sigma \times A \mapsto \Sigma$  is the service's *transition (partial) function*, i.e., *actions are deterministic*.

# The Non-Stochastic Model

## R.M: Execution of Requested Action

- » A *history*  $h$  of a service  $S$  is a sequence alternating states and actions

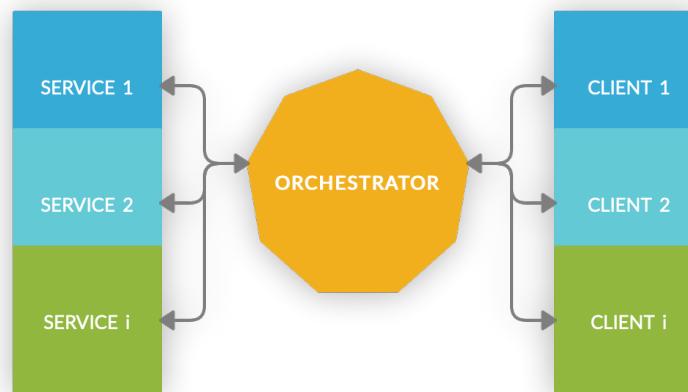
$$\sigma^0 \cdot a_1 \cdot \sigma^1 \cdot a_2 \cdot \dots \cdot a_n \cdot \sigma^n \cdot \dots$$

- » We assume we have a finite set of available services:
  - »  $S_i = (\Sigma_i, \sigma_{i0}, F_i, A, \delta_i)$  (over same actions  $A$ )
  - » Given  $S$ , "target service"  $T = (\Sigma_t, \sigma_{t0}, F_t, A, \delta_t)$
  - » The target represents a business process that one would like to offer to clients, where each state represents a decision point

# The Non-Stochastic Model

The goal of service composition

- » The Goal is to combine the available services as to mimic from a client point of view the behavior of the target service
- » This can be done by interposing:



- » The orchestrator **delegates** the current action requested by the client to some available service
- » The *system service* of S is the service:
  - »  $Z = (\Sigma_z, \sigma_{z_0}, F_z, A_z, \delta_z)$

# The Non-Stochastic Model

## System Service Z

- » Z is the service stemming from the product of the **asynchronous** execution of the services in S
- » An *orchestrator* for a community S is a partial function:
  - »  $\gamma: \Sigma_z \times A \rightarrow \{1, \dots, n\}$
  - »  $\gamma$ : decision maker able to keep track of the way the services in S have evolved up to a certain point
  - » This returns the index of a service
- » The action selected by the user with the orchestrator choice determine a system history
- » The O. Defines a mapping from system state and action to a service and from these elements to the next system state.
- » The O.  $\gamma$  is said to *realize* a target service Z if it realizes all histories of Z.
- » In this case,  $\gamma$  is also called a *composition* of Z (on S)

# The valued requirement model (1)

- » Main limitation: no notion of “good” or “approximate” solution exists
- » Requests not of uniform importance. We introduce:

$P_t \rightarrow$  distribution over the actions given the state

$P_t(s, a) \rightarrow$  likelihood that the user will request  $a$  in the target state  $s$

$R_t \rightarrow$  is the reward function (non negative)

$R_t(s, a) \rightarrow$  value associated to the action  $a$  in the state  $s$

## The valued requirement model (2)

» Formally a target service is:

$$T = (\Sigma_t, \sigma_{t0}, F_t, A, \delta_t, P_t, R_t)$$

where

$$P_t : \Sigma_t \rightarrow \pi(A) \cup \emptyset$$

is the action distribution function

$$R_t : \Sigma_t \times A \rightarrow \mathbb{R}$$

is the reward function

$P_t$  introduces a probability density function over  $P_\infty$

$R_t$  can depend also on  $\Sigma$ . Can assign identical values to pairs  $(\sigma, a)$ .

## The valued requirement model (3)

- » The definition of *value of history*  $h_t$  is the **SUM OF DISCOUNTED REWARDS**

$$v(\sigma_0, a_1, \sigma_1, \dots) = \sum_{i=0}^{\infty} \lambda^i R_t(\sigma_i, a_{i+1})$$

where  $0 < \lambda < 1$  is the discount factor

- » The **EXPECTED VALUE** of an orchestrator  $\gamma$  is defined by:

$$v(\gamma) = E_{h_t \sim P_\infty}(v(h_t) \cdot \text{real}(\gamma, h_t))$$

where  $\text{real}(\gamma, h_t)$  is 1 if  $h_t$  is realizable, 0 otherwise

- » The **OPTIMAL ORCHESTRATOR** is defined as:

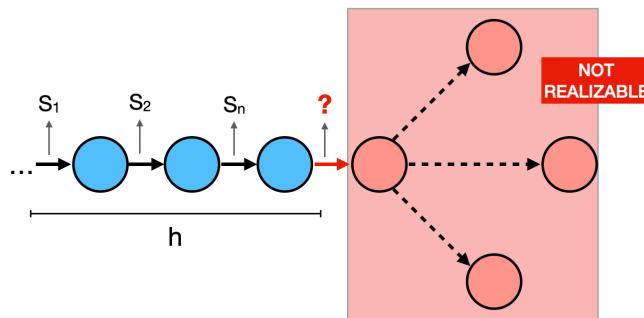
$$\gamma = \arg \max_{\text{orchestrator } \gamma'} v(\gamma')$$

where  $v(\gamma')$  is the expected value of histories realizable

## The valued requirement model (4)

**THEOREM 1:** If the target is realizable and every target history has strictly positive value then  $\gamma$  realizes the target iff it is an optimal orchestrator.

- » If  $h$  is not realizable by  $\gamma'$  there exists a point in  $h$  where  $\gamma'$  does not assign  $a$  in a service that can supply it. So **any history that extends  $h$  is not realizable**.



An *optimal orchestrator* works even when the target service is not fully realizable. An *optimal controller* is able to handle more valued histories

# Computing the optimal orchestrator (1)

- » We can solve the model by formulating an **MDP**. It is a four tuple:

$$M' = (S', A', Tr', R')$$

where

$S'$  → finite set of states

$A'$  → finite set of actions

$Tr' \rightarrow S' \times A' \rightarrow \pi(s')$  is the transition function

$R' \rightarrow S' \times A' \rightarrow \mathbb{R}$  is the transition function

## Computing the optimal orchestrator (2)

- » The composition MDP is a function of the system service and the target service as follows:

$$M(Z, T) = (S_M, A_M, Tr_M, R_M)$$

where

$$S_M = \Sigma_Z \times \Sigma_T \times A \cup s_{M0}$$

The **set of states** is defined by this product with a distinguished initial state  $s_{M0}$

$$A_M = \{a_{M0}, 1, \dots, n\}$$

The **actions** correspond to selecting the service with a special initializing action  $a_{M0}$

$$Tr_M(s_{M0}, a_{M0}, (\sigma_{z0}, \sigma_{t0}, a)) = P_t(\sigma_{t0}, a)$$

A **transition in state**  $s_{M0}$  is defined only for **action**  $a_{M0}$ . From this state we can get to  $(\sigma_{z0}, \sigma_{t0}, a)$  with a probability equal to the one that action  $a$  is requested from the target service ad its initial state.

## Computing the optimal orchestrator (3)

$$Tr_M((\sigma_z, \sigma_t, a), i, (\sigma'_z, \sigma'_t, a')) = P_t(\sigma'_t, a')$$

The next system state is determined by  $(a, i)$  and the previous system state.

The next target state is determined by  $a$  and the previous target state.

The probability associated is the one that the action  $a'$  will be requested in the new target state.

$$R((\sigma_z, \sigma_t, a), i) = R_t(\sigma_t, a)$$

The reward function associates a reward to states able to perform  $a$ .

The value of the reward is the value of doing  $a$  at the target state.

**THEOREM 2:** Let  $\rho$  be an optimal policy for  $M(Z, T)$ . Then the orchestrator  $\gamma$  such that  $\gamma((\sigma_z, \sigma_t), a) = \rho(\sigma_z, \sigma_t, a)$  is an *optimal orchestrator*

An optimal policy for MDP is the one **maximizing** the expected sum of rewards with discount factor  $\lambda$

# Extensions

We can now show some useful extensions that improves the system performance, that are:

- » Stochastic available services
- » Handling exceptions
- » Separate rewards specifications
- » Non-Markovian rewards
- » High-level programs as target services

# Extensions

## Stochastic available services

- » We assumed so far deterministic scenarios
- » Let us extend the model to capture stochastic services
- » Service transitions are probabilistic too
- » The MDP has to take also into account the stochastic transitions of the system state and target state

# Extensions

## Handling exceptions

- » In real-world scenarios not everything goes well
- » While booking a vacation, we book a flight but cannot book a hotel, we must cancel the flight reservation, that can be costly!
- » If the target/composite service terminates before a terminal state has been reached, work done so far has to be undone
- » For this reason we need the exception handling!
- » What we do is to augment the MDP definition such that it takes these costs into account by adding a negative reward to states  $(s_z, s_t, a)$  and service choice  $i$  that cannot supply action  $a$  in its current state
- » Reward size depends on the states of various services  $s_z$

# Extensions

## Separate rewards specifications (1)

- » Rewards coupled with likelihood of the client making certain action requests into the target service to be realized
- » Convenient to keep the two specifications separated
- » Use the target service only to specify the likelihood of action request
- » Rewards expressed dynamically on the history of actions executed so far by the target, through a deterministic transition system called transducer

# Extensions

## Separate rewards specifications (2)

- » A transducer is defined as  $R = (\Sigma, \Delta, S, s_0, f, g)$  where:
  - »  $\Sigma$ : input alphabet (that in our case corresponds to the set of actions  $A$ )
  - »  $\Delta$ : output alphabet (possible rewards expressed in real numbers  $R$ )
  - »  $S$ : set of states
  - »  $s_0$ : initial state
  - »  $f: S \times \Sigma \rightarrow S$  is the transition function
  - »  $g: S \times \Sigma \rightarrow \Delta$  is the output (reward) function
- » We obtain that rewards depend on the sequence of actions executed so far and not on the target state

# Extensions

## Non-Markovian rewards

- » Many performance criteria call for more sophisticated reward functions that do not depend on the last state only
- » For example we may want to reward a robot for picking up a cup only if it was requested to do so earlier
- » The idea is to specify rewards by some variants of LTL<sub>f</sub> (linear-time temporal logic over finite traces)
- » One key point is that formulas in these logics can be "translated" into standard DFAs (deterministic finite state automata) that recognize exactly the traces that fulfill the formula
- » Such DFAs can be then combined with probabilistic transition systems to generate suitable MDPs to be used for generating optimal solutions
- » So replace the target specification with a declarative set of logical constraints
- » Then we compute the synchronous product with a target transition system that us the likelihood of action choice

## Extensions

### High-level programs as target services (1)

- » Certain non-Markovian specifications can be expressed more naturally by using procedural constraints, in particular a sort of propositional variant of GOLOG:

$$\delta ::= A \mid \varphi? \mid \delta_1 + \delta_2 \mid \delta_1; \delta_2 \mid \delta^* \mid \\ \textbf{if } \phi \textbf{ then } \delta_1 \textbf{ else } \delta_2 \mid \textbf{while } \phi \textbf{ do } \delta$$

- » Hence we can assign rewards to traces that correspond to successful computations of such programs

# Extensions

## High-level programs as target services (2)

- » **if** and **while** can be seen as abbreviations for regular expression:

$$\begin{aligned}\mathbf{if } \phi \mathbf{ then } \delta_1 \mathbf{ else } \delta_2 &\doteq (\phi?; \delta_1) + (\neg\phi?; \delta_2) \\ \mathbf{while } \phi \mathbf{ do } \delta &\doteq (\phi?; \delta)^*; \neg\phi?\end{aligned}$$

- » Hence these programs can also be translated into *regular expressions* and hence in DFA to be used as above
- » We can combine procedural and declarative temporal constraints by adopting LDL<sub>f</sub> (a variant of LTL<sub>f</sub>, called linear-time dynamic logic on finite traces):

$$[\text{true}^*] \langle \mathbf{while}(cold \wedge heatingOn) \mathbf{ do } (\neg turnOffHeating^*; heat) \rangle$$

- » which says that at every point in time, while it is cold and the heating is on then heat, possibly allowing other action except turning off heating

# Extensions

## Learning

- » For Web services, statistics gathering is very simple and is carried out routinely nowadays
- » So, it is not difficult to learn the stochastic transition function of existing services online, and use it to specify the probabilistic elements of the model

## Example 1 (1)

### Robot Assembly (S1 System)

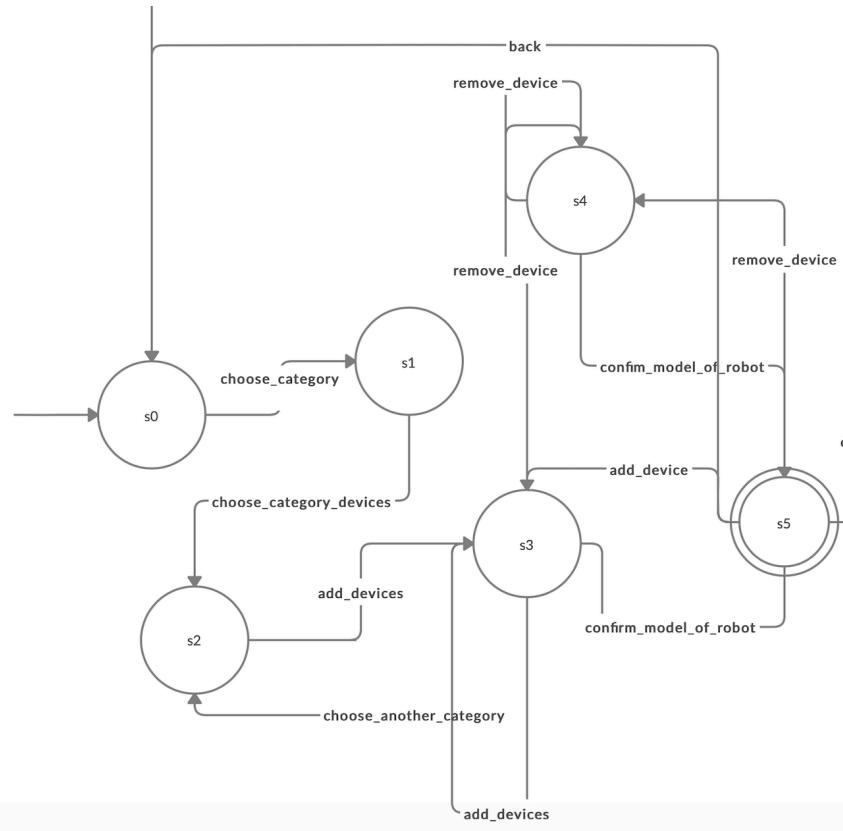
- » Let's consider the ROMAN MODEL (non stochastic case). Service is defined as:  $S = (\Sigma, \sigma_0, F, A, \delta)$
- » The service is a Future Robot Creator with which you can generate from scratch a new robot starting from these category like:
  - » Home
  - » Company..
- » Chosen a category, the Tool shows the Client all the devices which he can put in a robot, for example:
  - » Arm
  - » Wheel..

s0: startingPage (initial state)  
s1: category of robots  
s2: category devices  
s3: add device  
s4: remove device

## Example 1 (2)

### The System Services Z

» Now we show the System (S1) which composes Z:



## Example 1 (3)

### Robot Store Assembly (S2 System)

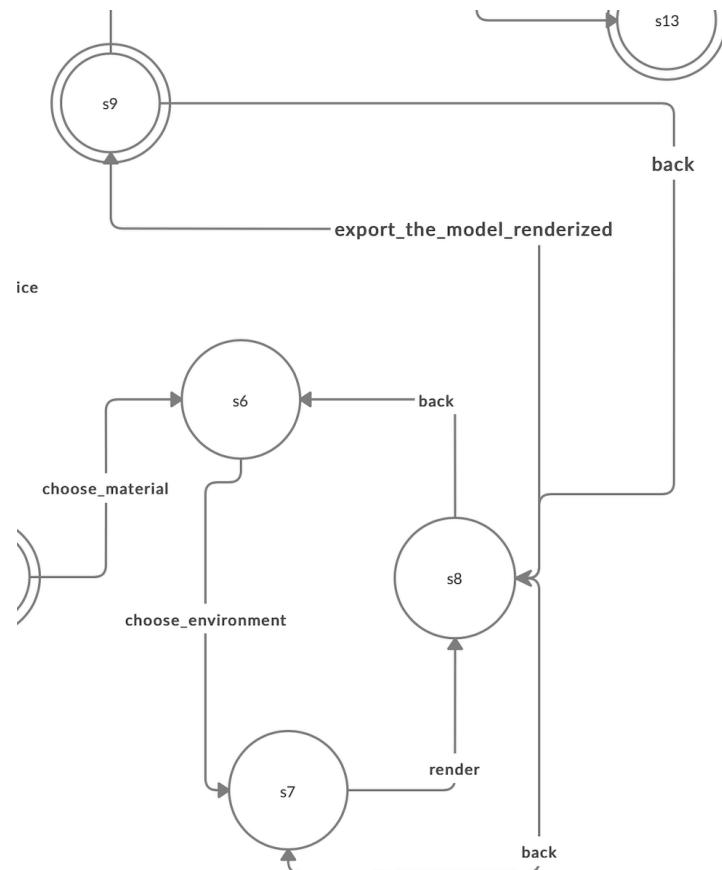
- » Finished to assembly the Robot, the System shows:
  - » Generate Model or return Back
  - » Choose the Material
  - » Choose the Environment where the robot have to work (like Rain, Snow ect..)
  - » Generate the rendering of the model

```
s5: robotModelConfirmed (init_state)
s6: finalComponent
s7: chooseEnvironment
s8: renderingModel
```

## Example 1 (4)

### The System Services Z

» Now we show the System (S2) which composes Z:



## Example 1 (5)

### Robot Store Assembly (S3 System)

- » If the client is satisfied with the created model, he can:
  - » "Export the model"
  - » Choose the "extension file"
  - » "Rename" the file
  - » "Save" Model
  - » Export the model to the Store of application
  - » And maybe, in future, "sell" the virtual model!

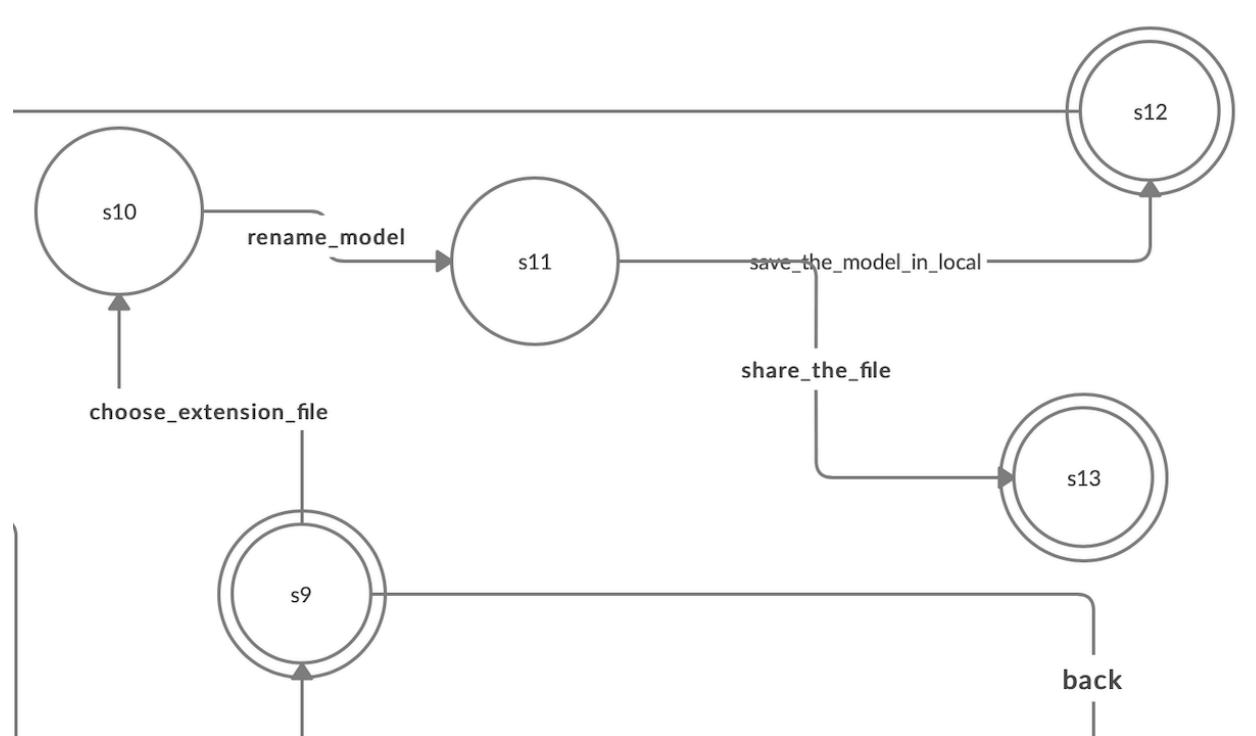
```
s9: exportModel (init_state)
s10: extensionFile
s11: renameModel
s12: saveModel
s13: shareToStore
```

Now the SERVICE COMMUNITY can be expressed like:  $S = \{S1, S2, S3\}$

## Example 1 (6)

### The System Services Z

» Now we show the System (S3) which composes Z:



## Example 1 (7)

### The System Services Z

» Now we conclude with the History of Z:

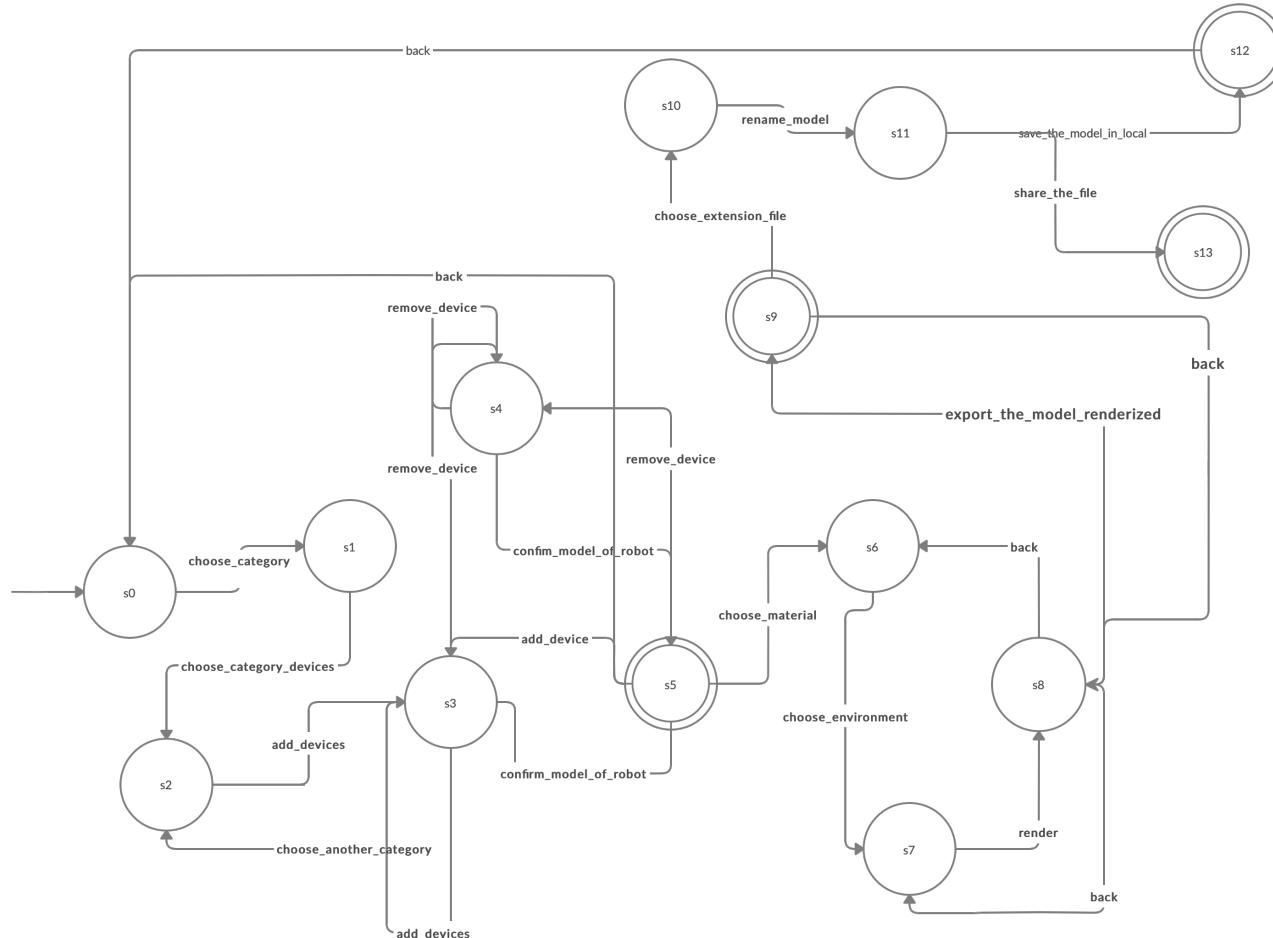
#### Ex. of History of Z:

```
s0 · choose_category · s1 · choose_cat_devices · s2  
· add_devices · s3 · confirm_robot · s5  
· chose_material · s6 · chose_env · s7  
· chose_render_model · s8 · export_the_model · s9  
· choose_extension · s10 · rename_the_model · s11  
· save_model · s12  
[...]
```

## Example 1 (8)

### The System Services Z

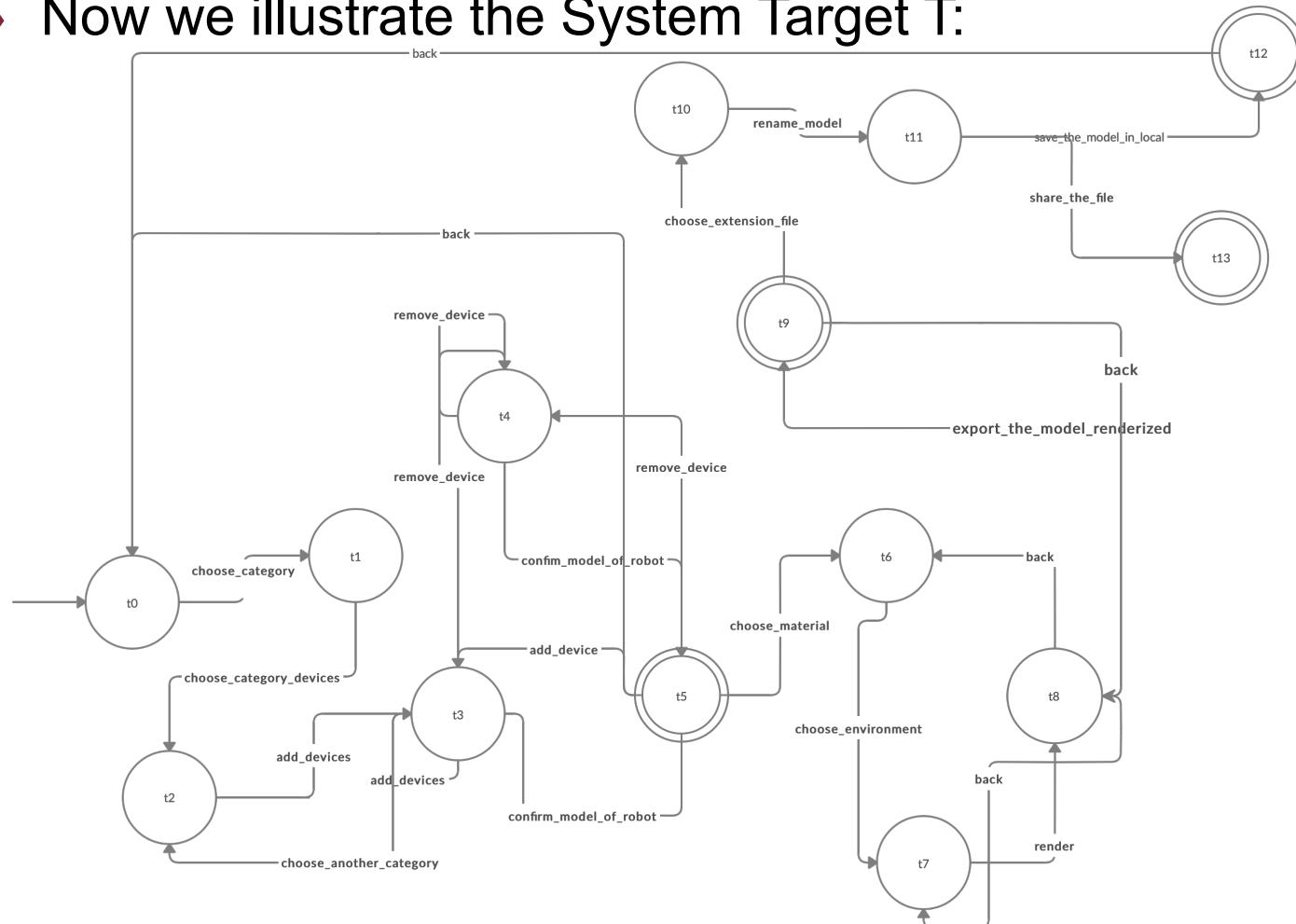
» Now we illustrate the Automata of System Services Z:



# Example 1 (9)

## The System Services T

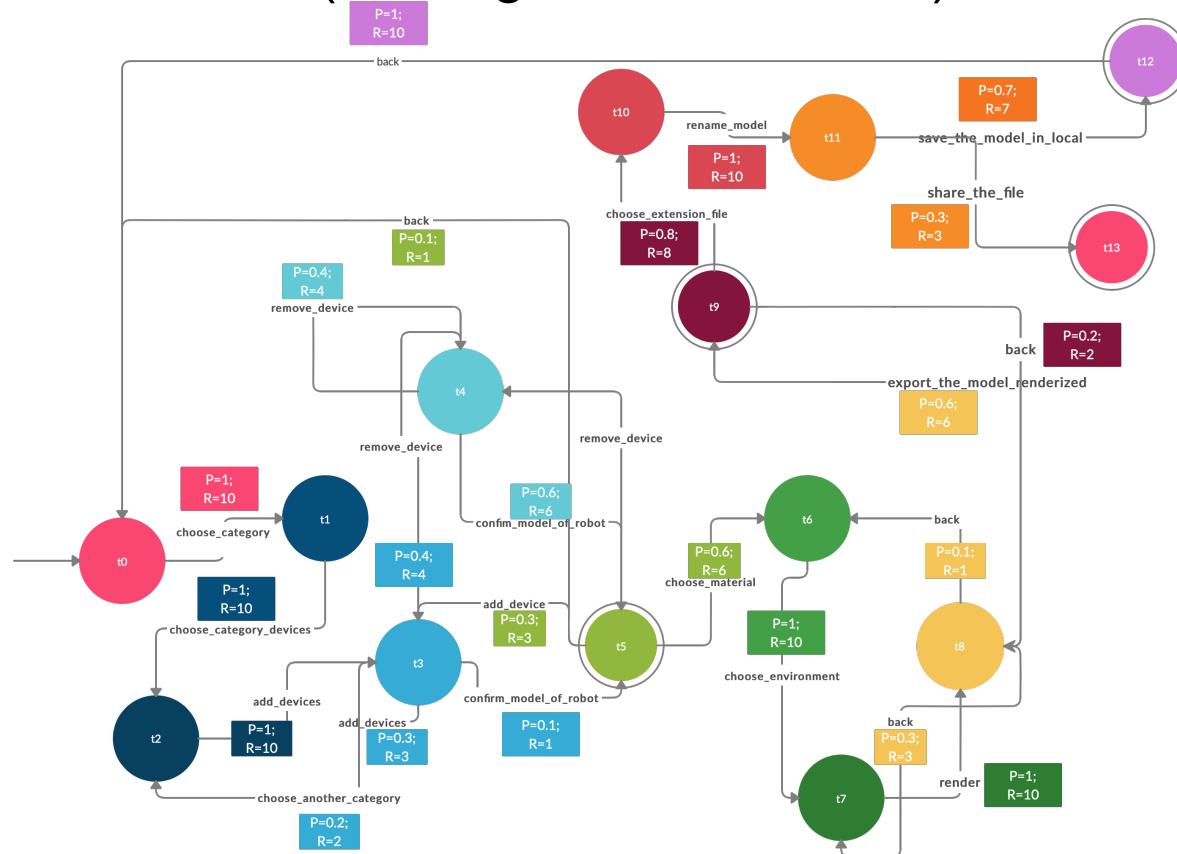
» Now we illustrate the System Target T:



# Example 1 (10)

## The System Services T

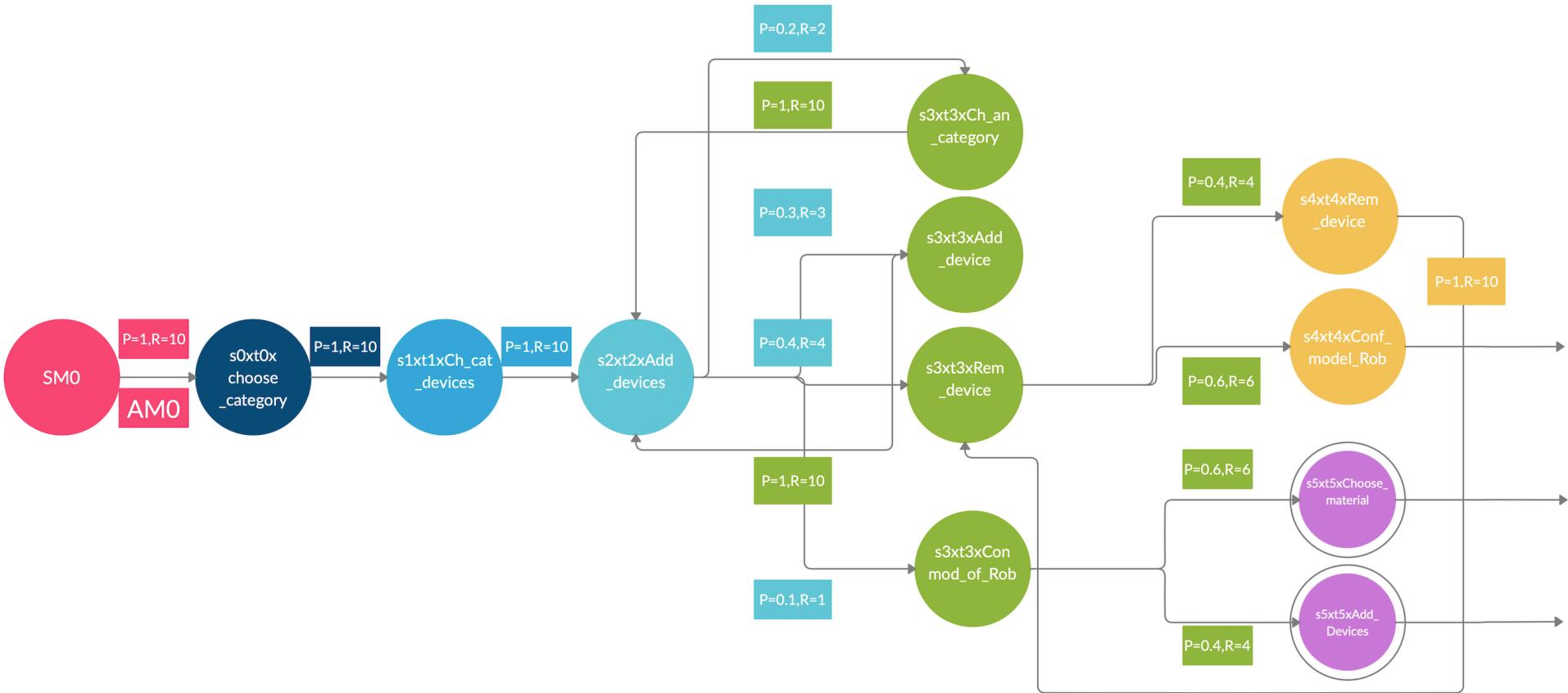
- » The System Target T has the intrinsic characteristics of:
  - » **P<sub>t</sub>** and **R<sub>t</sub>** (coming out from action)



# Example 1 (11)

## Markov Decision Process

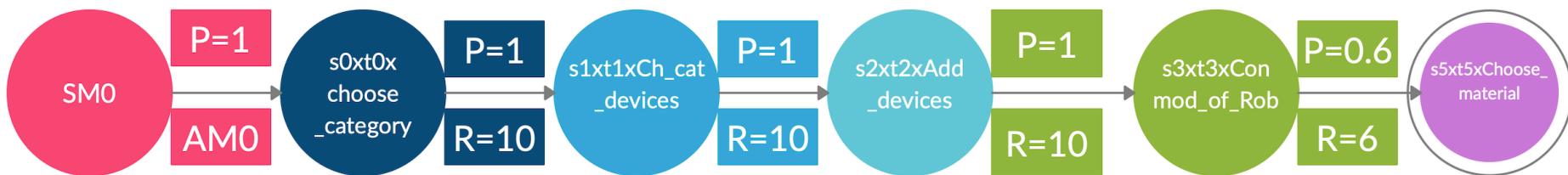
» Now we show the MDP of The First System:



# Example 1 (12)

## Markov Decision Process

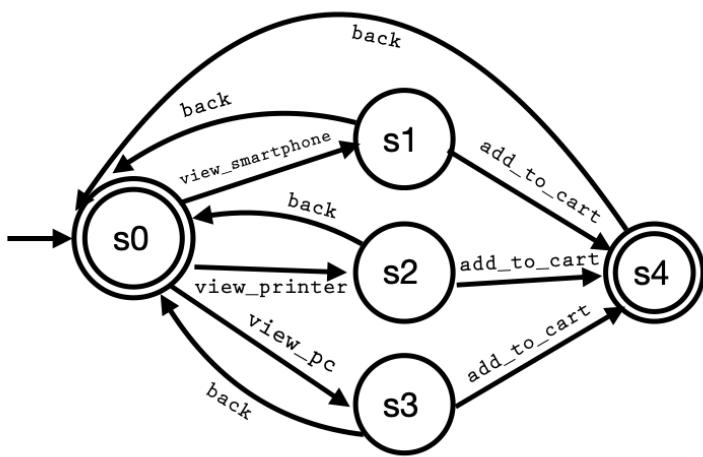
- » Now we show the best Trace of the MDP (S1):
  - » Chosen  $\lambda = 0.9$
  - » Now we calculate SUM OF DISCOUNTED REWARDS (seen s.13)
  - » " $10 + 0.9^1 \times 10 + 0.9^2 \times 10 + 0.9^3 \times 10 + 0.9^4 \times 6 = 38.33$ "



## EXAMPLE 2 (1)

### The S1 system

- » Let's consider the **ROMAN MODEL** (non stochastic case). Service is defined as:  $S = (\Sigma, \sigma_0, F, A, \delta)$
- » This service allows the user to choose among **different electronic products**. Once he has done his choice, can visualize the information about the product. If it is not satisfied about it, he can go **back** and chose another product.



s0: initial state  
s1: smartphone description  
s2: printer description  
s3: pc description  
s4: product in the cart

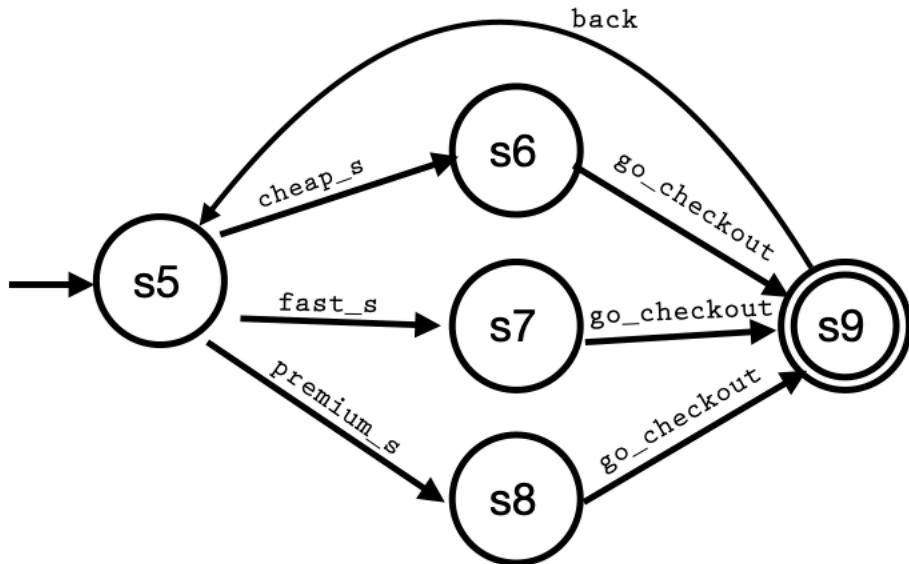
History of S:

s0 · view\_smartphone · s1 · add\_to\_cart · s4  
s0 · view\_smartphone · s1 · back · s0  
s0 · view\_printer · s2 · add\_to\_cart · s4  
[...]

## EXAMPLE 2 (2)

### The S2 system

- » Once the product is in the cart, the user can chose among different types of shipping: **cheap**, **fast** or **premium**. The type of shipping influences the delivery time and the supplier reward.

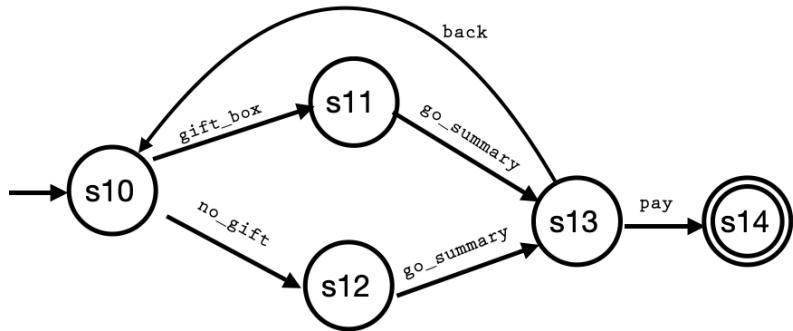


$s_5$ : product in the cart  
(initial state)  
 $s_6$ : cheap shipping chosen  
 $s_7$ : fast shipping chosen  
 $s_8$ : premium shipping chosen  
 $s_9$ : checkout page

## EXAMPLE 2 (3)

### The S3 system

- » Once the checkout page is visualized, the user can choose to add a **gift box** to the order, or not. Then he can see a summary before proceeding with the payment. From the summary page, if the user pays, then the order is marked as **completed**.



s10: checkout page (initial state)  
s11: gift box added  
s12: gift box not added  
s13: summary page  
s14: order completed

We can express the SERVICE COMMUNITY as:  $S = \{S_1, S_2, S_3\}$

## EXAMPLE 2 (4)

### Target and orchestrator

- » Suppose to have the following target service where, in the optimistic case, the user chooses a smartphone, the premium shipping, a gift box and pays the order without any afterthought. It can be expressed by:

```
t0 · view_smartphone · t1 · add_to_cart · t4 · premium_s · t8 · go_checkout ·  
· t9 · gift_box · t11 · go_summary · t13 · pay · t14
```

We need to **combine** the available services.

Once we have collected all the services in the Z virtual entity, the orchestrator  $\gamma$  will return the **index** of the service able to solve the action.

$$\gamma \begin{cases} \text{action: add_to_cart} \\ \text{service: S1} \end{cases}$$

If the action is not available in any of the services?

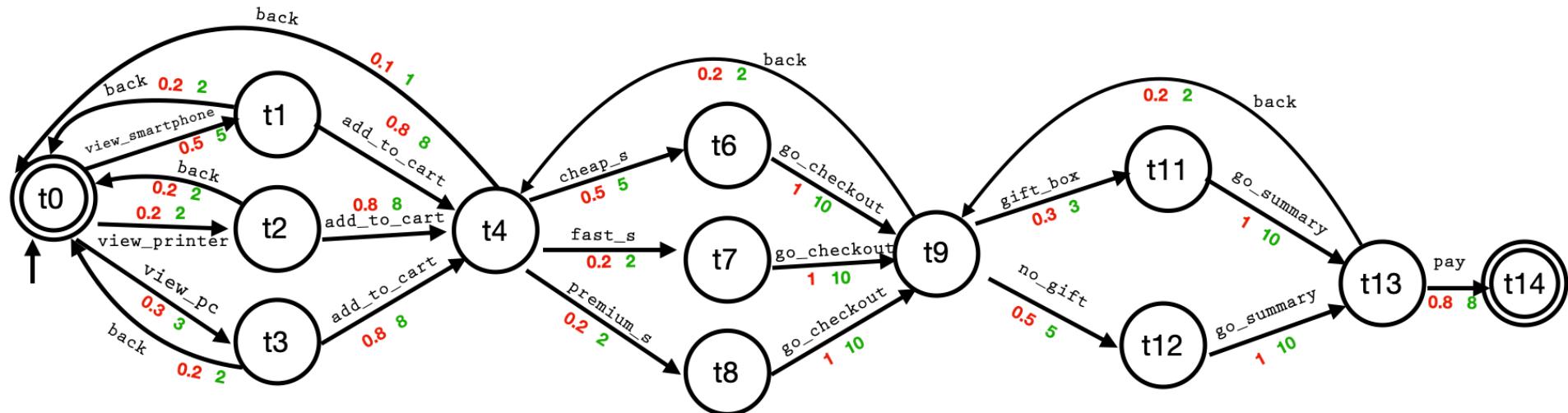
$$\gamma \begin{cases} \text{action: add_another_object} \\ \text{service: ???} \end{cases}$$

Target service is not FULLY REALIZABLE. No solution in this case, but...

## EXAMPLE 2 (5)

### The valued requirement model

» We introduce the probability  $P_t$  and  $R_t$



The value associated to the target, choosing  $\lambda = 0.9$  is:

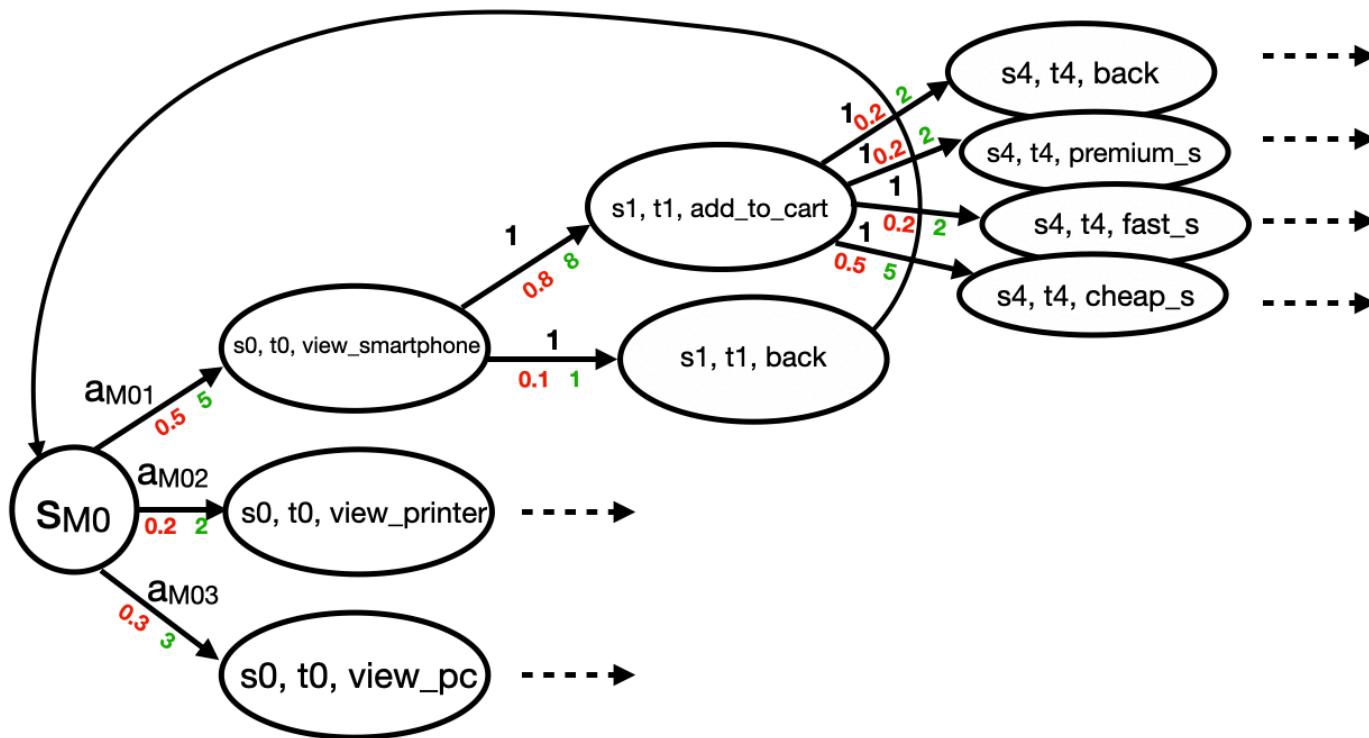
$$t_0 \cdot \text{view\_smartphone} \cdot t_1 \cdot \text{add\_to\_cart} \cdot t_4 \cdot \text{premium\_s} \cdot t_8 \cdot \text{go\_checkout} \cdot \\ \cdot t_9 \cdot \text{gift\_box} \cdot t_{11} \cdot \text{go\_summary} \cdot t_{13} \cdot \text{pay} \cdot t_{14}$$

$$5 + 0.9^8 + 0.9^{2*2} + 0.9^{3*10} + 0.9^{4*3} + 0.9^{5*10} + 0.9^{6*8} = 33.23$$

## EXAMPLE 2 (6)

### The MDP formulation

» Now we can formulate the MDP (partial), considering also  $P_t$  and  $R_t$

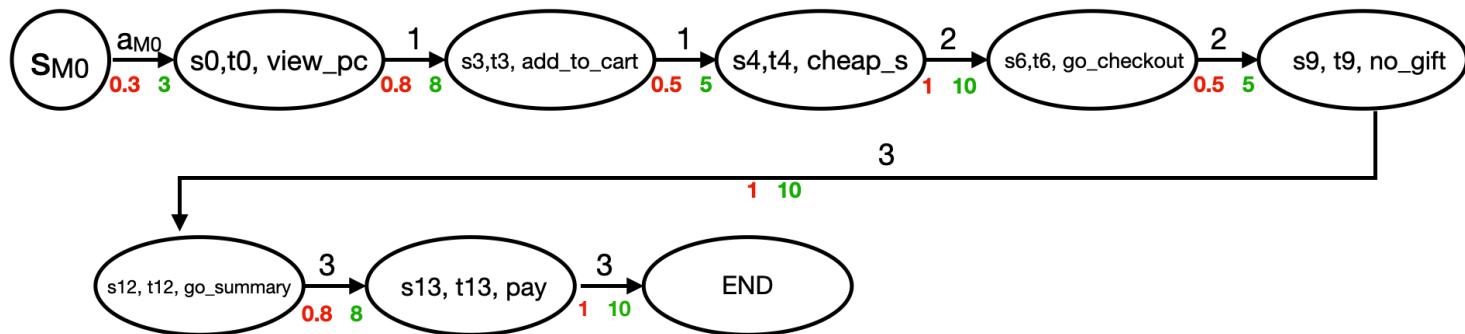


## EXAMPLE 2 (6)

### The MDP formulation

- » Suppose to have the following target that will define a path in the MDP

```
t0 · view_pc · t3 · add_to_cart · t4 · cheap_s · t6 · go_checkout · t9 · no_gift · t12 ·  
· go_summary · t13 · pay · t14
```



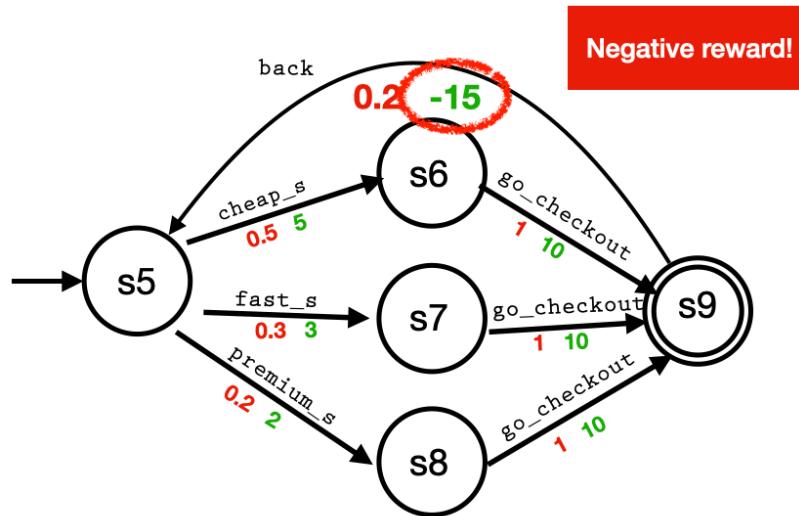
The **optimal policy** for the MDP is the one maximizing the expected discounted sum of rewards

## EXAMPLE 2 (7)

### Improvement

- » It can happen that, when the buyer is viewing the checkout page, he decides that the price is too high and he wants to go **back** and choose another product.
- » He can also decide to change the shipping method after having seen that the delivery days are too much. Since it can be translated into a loss of the work done so far, we can define the **size of the reward** in a way that **reflects the work that needs to be undone** in each of the existing services.

For example, considering S2:



# Food delivery (1)

## Service Systems

- » Let us consider the ROMAN MODEL (non stochastic case). Service is defined as:  $S = (\Sigma, \sigma_0, F, A, \delta)$
- » We will consider 3 services:
  - » Service 1: this service allows the Client to order a **first dish**
  - » Service 2: this service allows the Client to order a **side dish**
  - » Service 3: this service allows the Client to order a **dessert**
  - » Service 4: this service allows to finalize the order
- » The services are composed by some states as below:

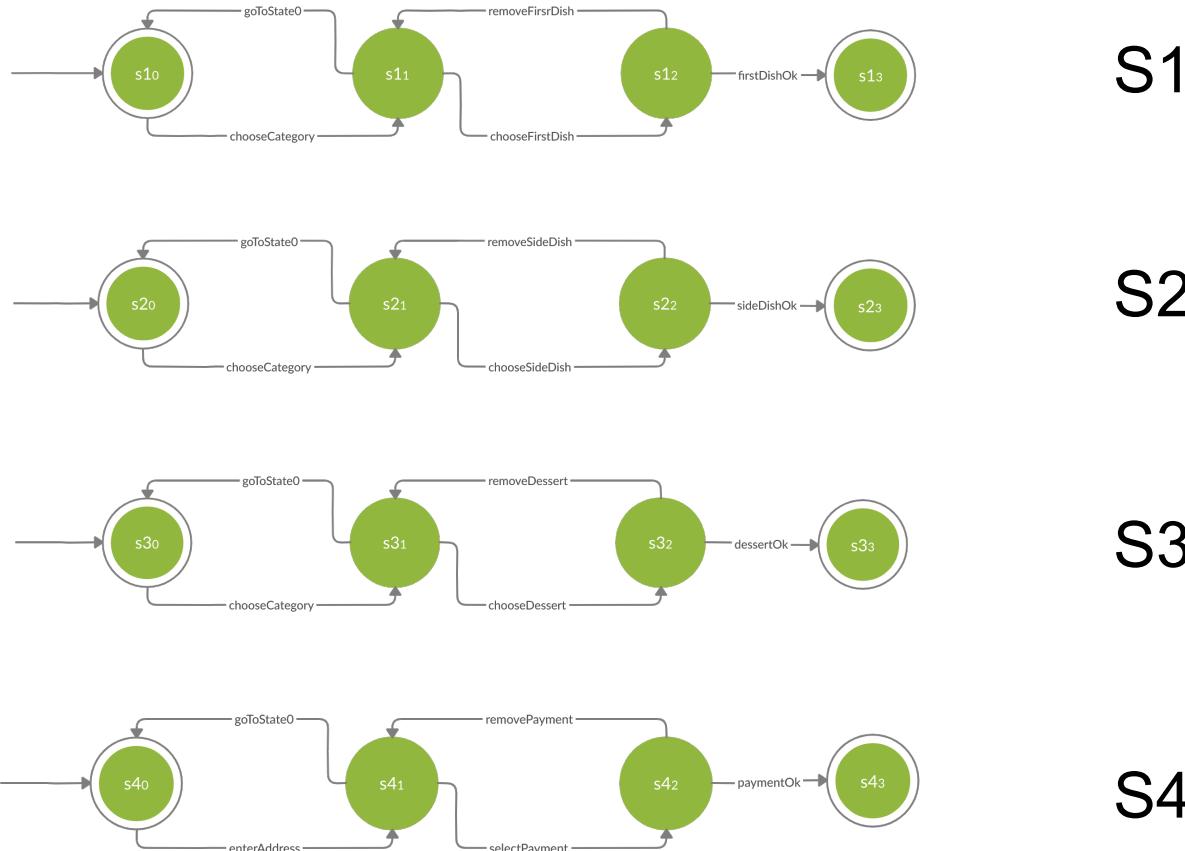
s0: initial state  
s1: chosenCategory/addedAddress  
s2: chosenDish/selectedPayment  
s3: dishOk/paymentOk

Now the SERVICE COMMUNITY can be expressed as  $S = \{S1, S2, S3, S4\}$

# Food delivery (2)

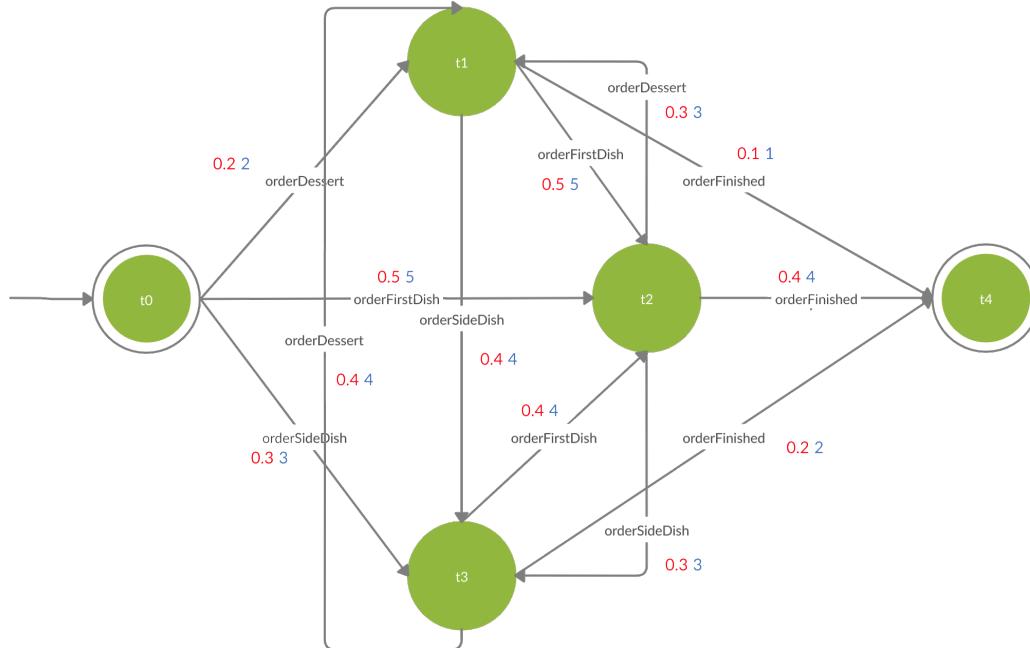
## Service System

» These are the four automata service systems considered:



# Food delivery (4)

## The valued requirement model



We introduce the probability  $P_t$  and  $R_t$

The value associated to the target, choosing  $\lambda = 0.9$  is:

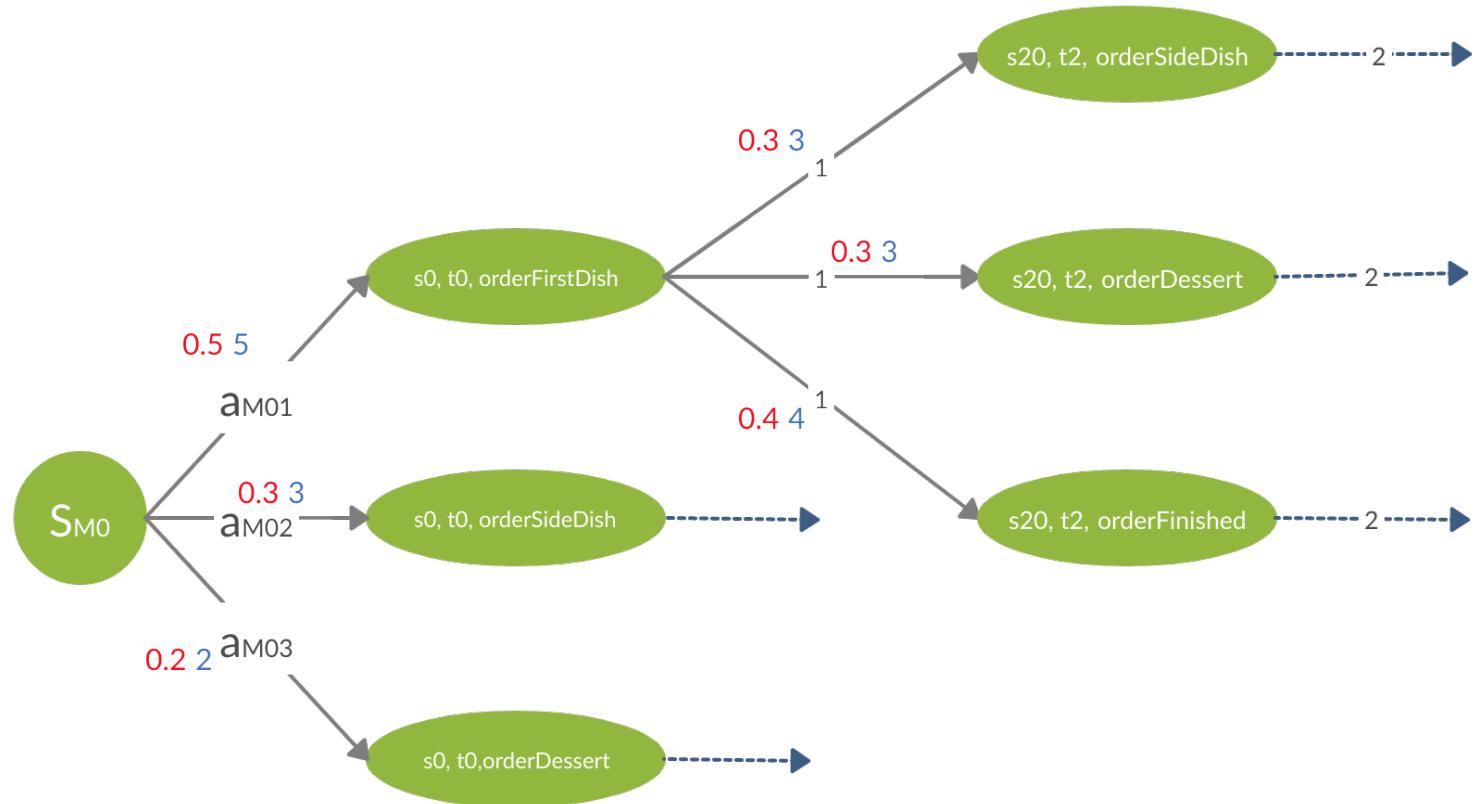
t0 -> orderDessert-> t1 -> orderSideDish -> t3 -> orderFirstDish -> t2 -> orderFinished -> t4

$$====> 2 + 0.9^4 + 0.9^{2*4} + 0.9^{3*4} = \mathbf{11.75}$$

# Food delivery (5)

## The MDP formulation

» Now we can formulate the MDP (partial), considering also  $P_t$  and  $R_t$



## References

- » Ronen I. Brafman, Giuseppe De Giacomo, Massimo Mecella, Sebastian Sardina - *Service Composition in Stochastic Settings*. AI\*IA 2017 Advances in Artificial Intelligence, Springer (2017)