ucc
Coláiste na hOllscoile Corcaigh, Éire
University College Cork, Ireland

CS4618 Artificial Intelligence I

Today: Uninformed Search

Thomas Jansen

September 28th

Plans for Today

Looking at 'Dimensions of Task Environments'

Remember task environment encompasses
performance measure, environment, actuators, sensors

- fully observable vs. partially observable
- single agent vs. multiagent
- deterministic vs. stochastic
- episodic vs. sequential
- static vs. dynamic
- discrete vs. continuous
- known vs. unknown

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now examples

Seven Examples of Task Environments

Seven Examples of Task Environments

Task Environment	observable	agents	determ.	episodic	static	discrete

Seven Examples of Task Environments

Task Environment	observable	agents	determ.	episodic	static	discrete
Crossword puzzle						

Seven Examples of Task Environments

Task Environment	observable	agents	determ.	episodic	static	discrete
Crossword puzzle	fully					

Seven Examples of Task Environments

Task Environment	observable	agents	determ.	episodic	static	discrete
Crossword puzzle	fully	single				

Seven Examples of Task Environments

Task Environment	observable	agents	determ.	episodic	static	discrete
Crossword puzzle	fully	single	determ.			

Seven Examples of Task Environments

Task Environment	observable	agents	determ.	episodic	static	discrete
Crossword puzzle	fully	single	determ.	sequential		

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Crossword puzzle	fully	single	determ.	sequential	static	

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Chess with clock	fully	multi				

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Chess with clock	fully	multi	determ.	sequential	semi	

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Poker	partially					

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Taxi driving						

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Medical diagnosis	partially					

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Image analysis						

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Image analysis	fully					

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Image analysis	fully	single				

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Medical diagnosis	partially	single	stochastic	sequential	dynamic	continuous
Image analysis	fully	single	determ.			

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Image analysis	fully	single	determ.	episodic		

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Medical diagnosis	partially	single	stochastic	sequential	dynamic	continuous
Image analysis	fully	single	determ.	episodic	static	

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Image analysis	fully	single	determ.	episodic	static	discrete

Note

- in many examples different properties possible

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Medical diagnosis	partially	single	stochastic	sequential	dynamic	continuous
Image analysis	fully	single	determ.	episodic	static	discrete

Note

- in many examples different properties possible
- known vs. unknown both possible in all examples

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Medical diagnosis	partially	single	stochastic	sequential	dynamic	continuous
Image analysis	fully	single	determ.	episodic	static	discrete

Note

- in many examples different properties possible
- known vs. unknown both possible in all examples
- in particular for complex task environments, simulators useful

Structure of Agents

Structure of Agents

Agents consist of

- architecture
- program

Structure of Agents

Agents consist of

- architecture
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Agent Architecture

- physical sensors
- physical actuators
- computing platform

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Agent Program

- run on computing platform

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Note agent function vs. agent program

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Agent Program

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Note agent function vs. agent program

- agent function maps sequences of percepts ($\widehat{=}$ percept history) to action
- agent program maps single percept (and current state of the agent) to action

Agent Programs

in general	maps percept to action based on agent's state

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in general maps percept to action
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Classes of agent programs

- table-driven agent
- simple reflex agent
- model-based reflex agent
- goal-based agent
- utility-based agent

Table-Driven Agent

Idea direct implementation of agent function

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Table-Driven Agent

```
function Table-Driven-Agent(percept) returns action
    persistent   sequence of percepts, initially empty
                 table of actions, initially fully specified
    append percept to end of percepts
    return lookup(table, percepts)
```

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+ completely flexible

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− requires very large (maybe infinite) table

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- \+ very simple
- \+ completely flexible
- − requires very large (maybe infinite) table
- − not very practical

Simple Reflex Agent

Idea choose action based on current percept (ignoring history)

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Simple Reflex Agent

function Simple-Reflex-Agent(percept) returns action
  persistent a set of condition-action rules, initially fully specified
  state = interpret-input(percept)
  rule = rule-match(state, rules)
  return rule.action

Simple Reflex Agent

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+ very simple
+ easy to understand
+ requires almost no memory

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+ very simple
+ easy to understand
+ requires almost no memory
− limited flexibility

Two Tiny Examples

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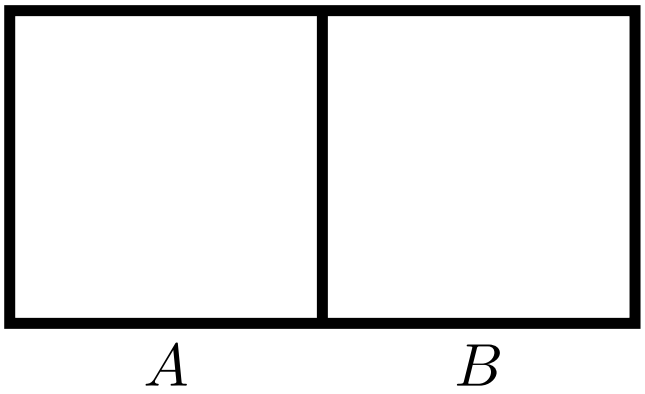
Vacuum Cleaner World 1



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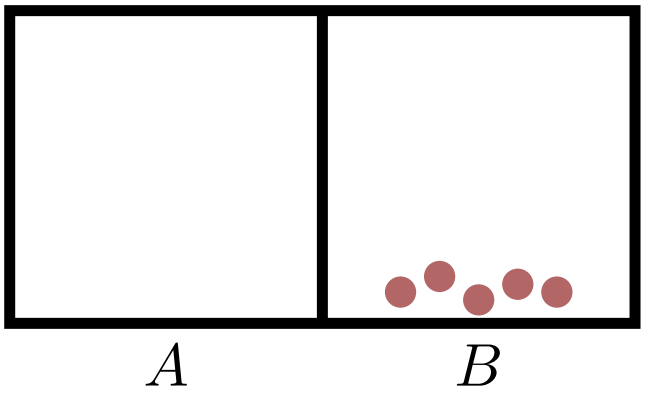

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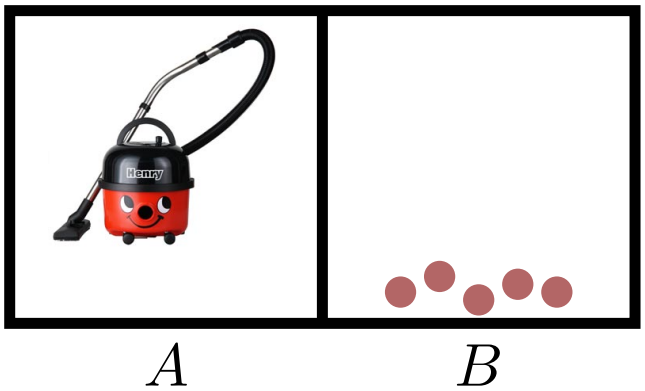

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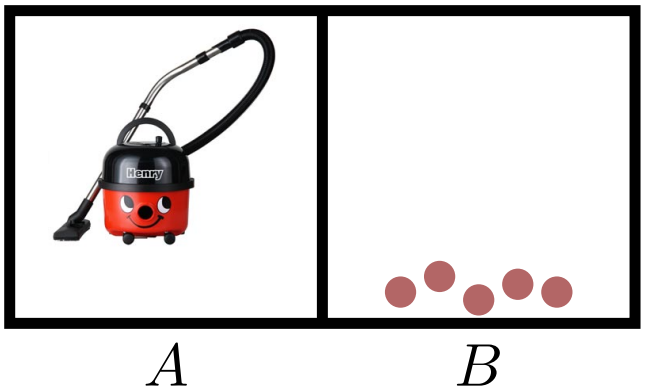

- initial set-up never changes

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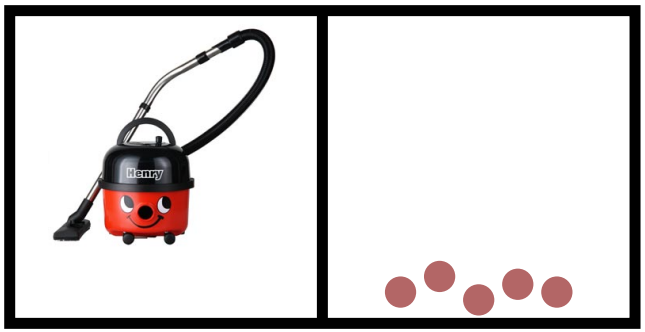

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- sensors perceive percept
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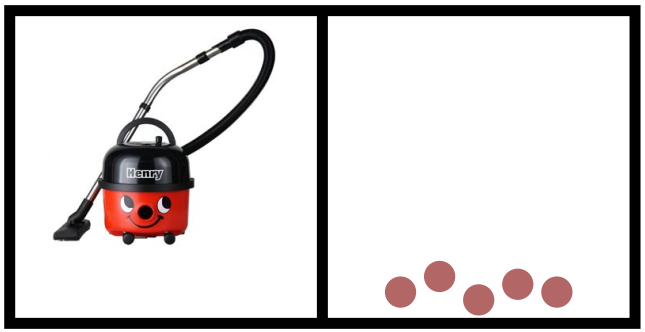

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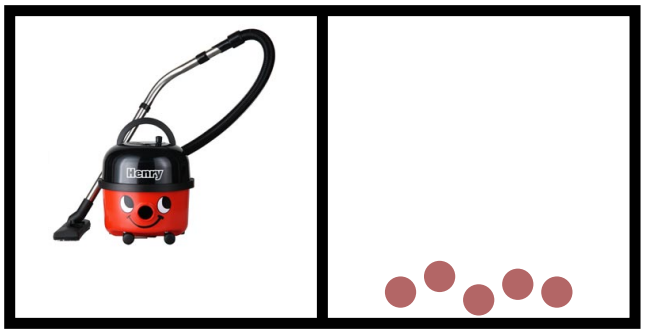

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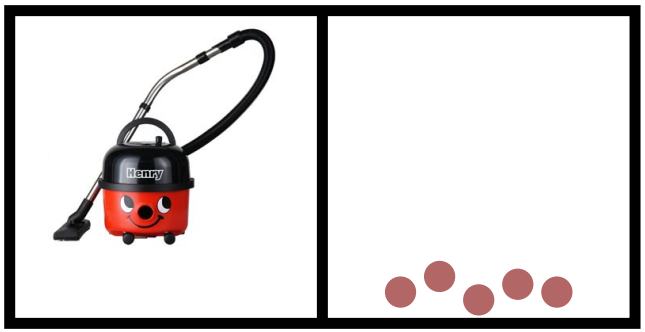

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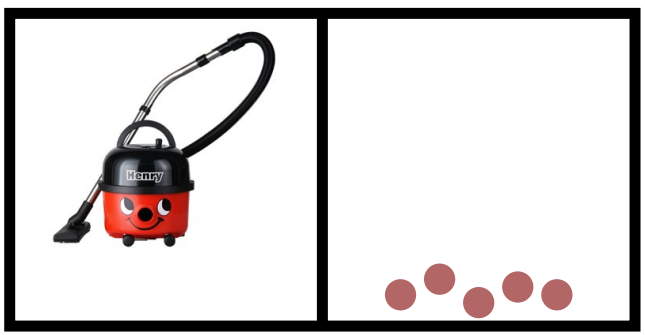

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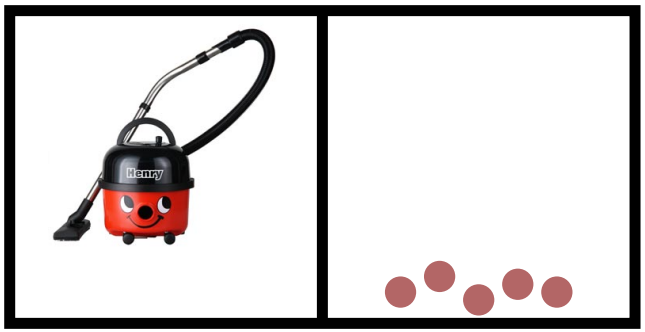

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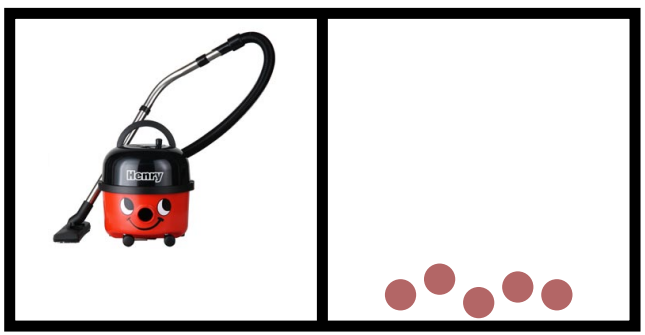

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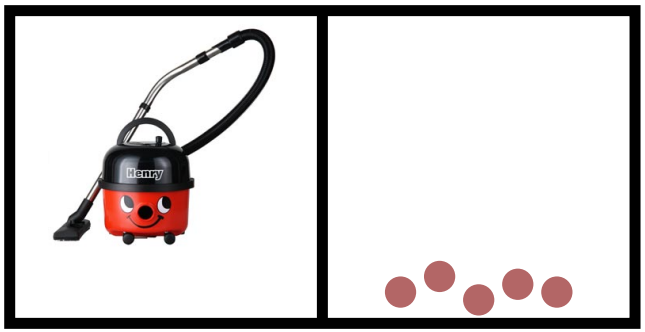

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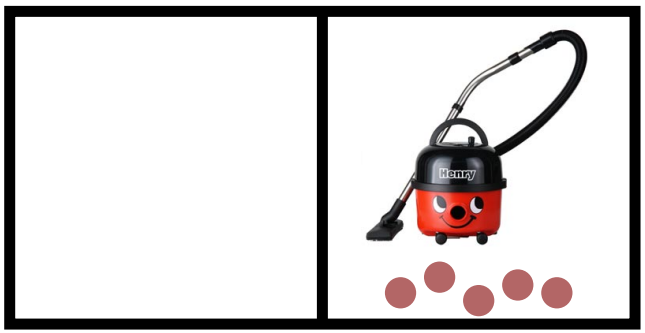

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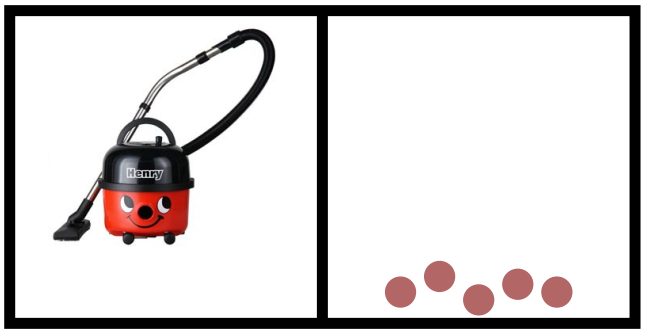

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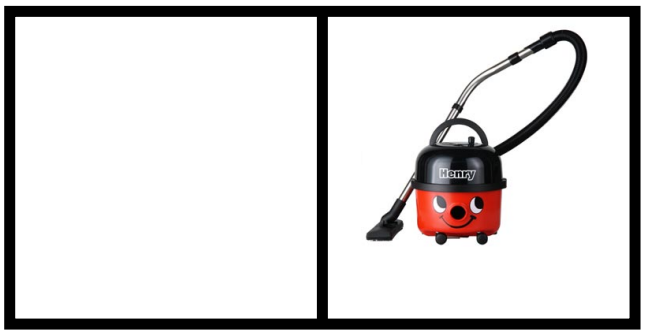

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Idea choose action based on current percept & model of world

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function Model-Based-Reflex-Agent(percept) returns action

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Consequence solution to problem is fixed sequence of actions for any problem

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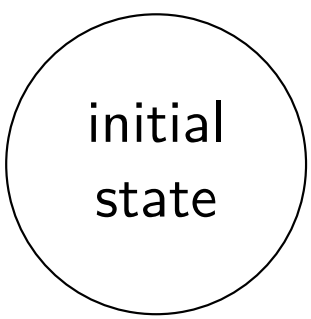

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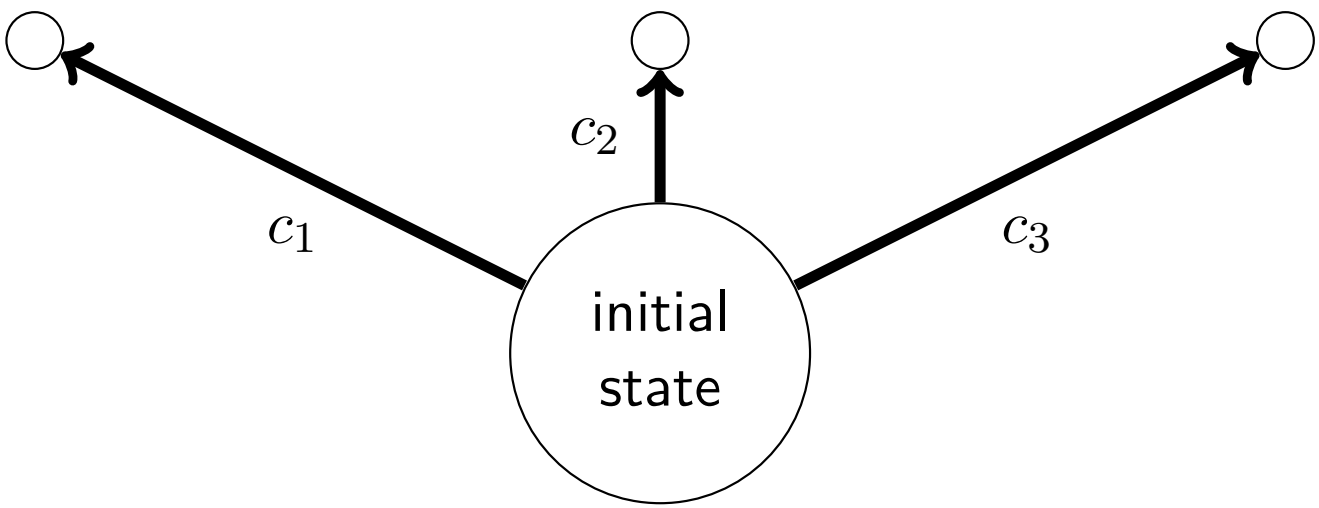

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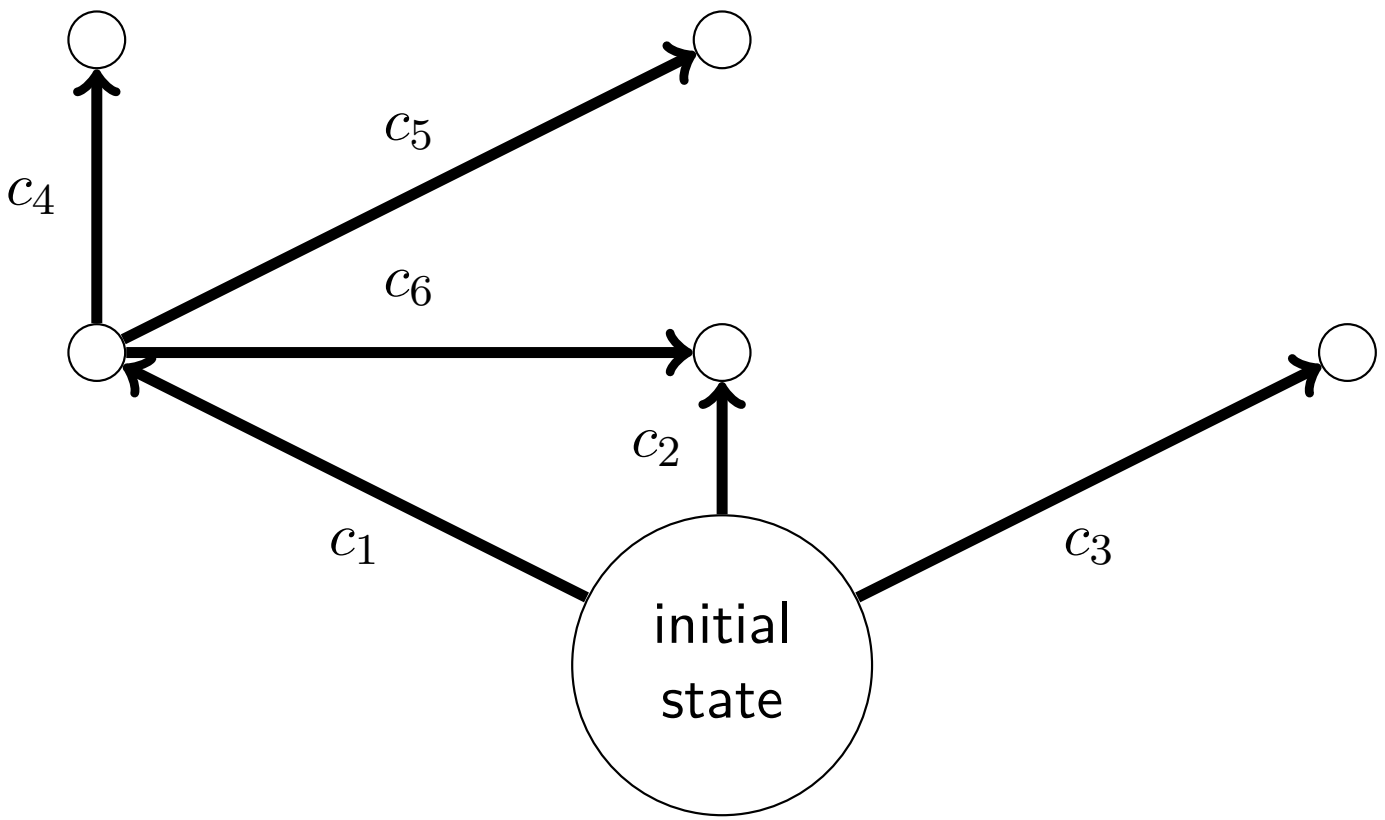

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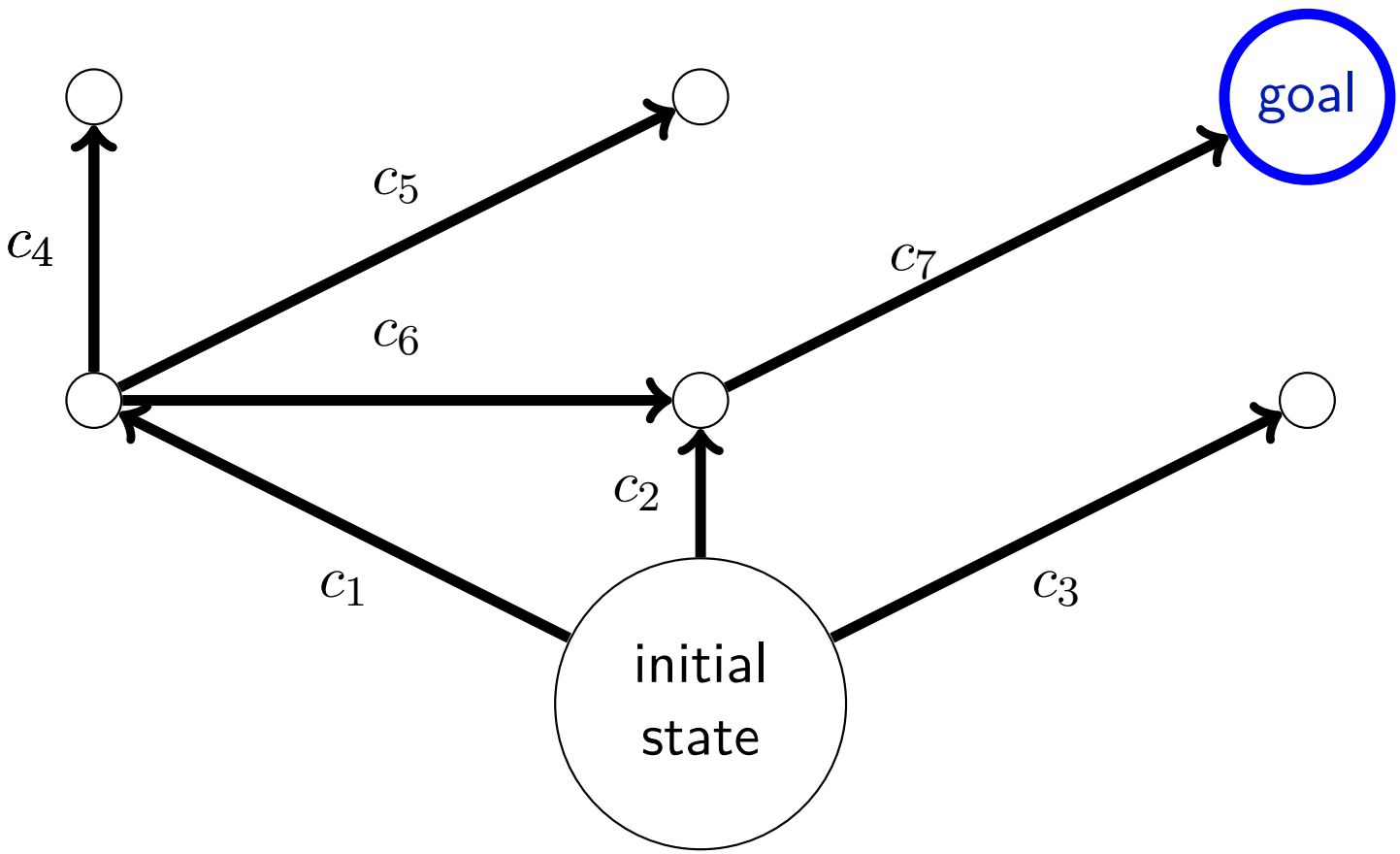

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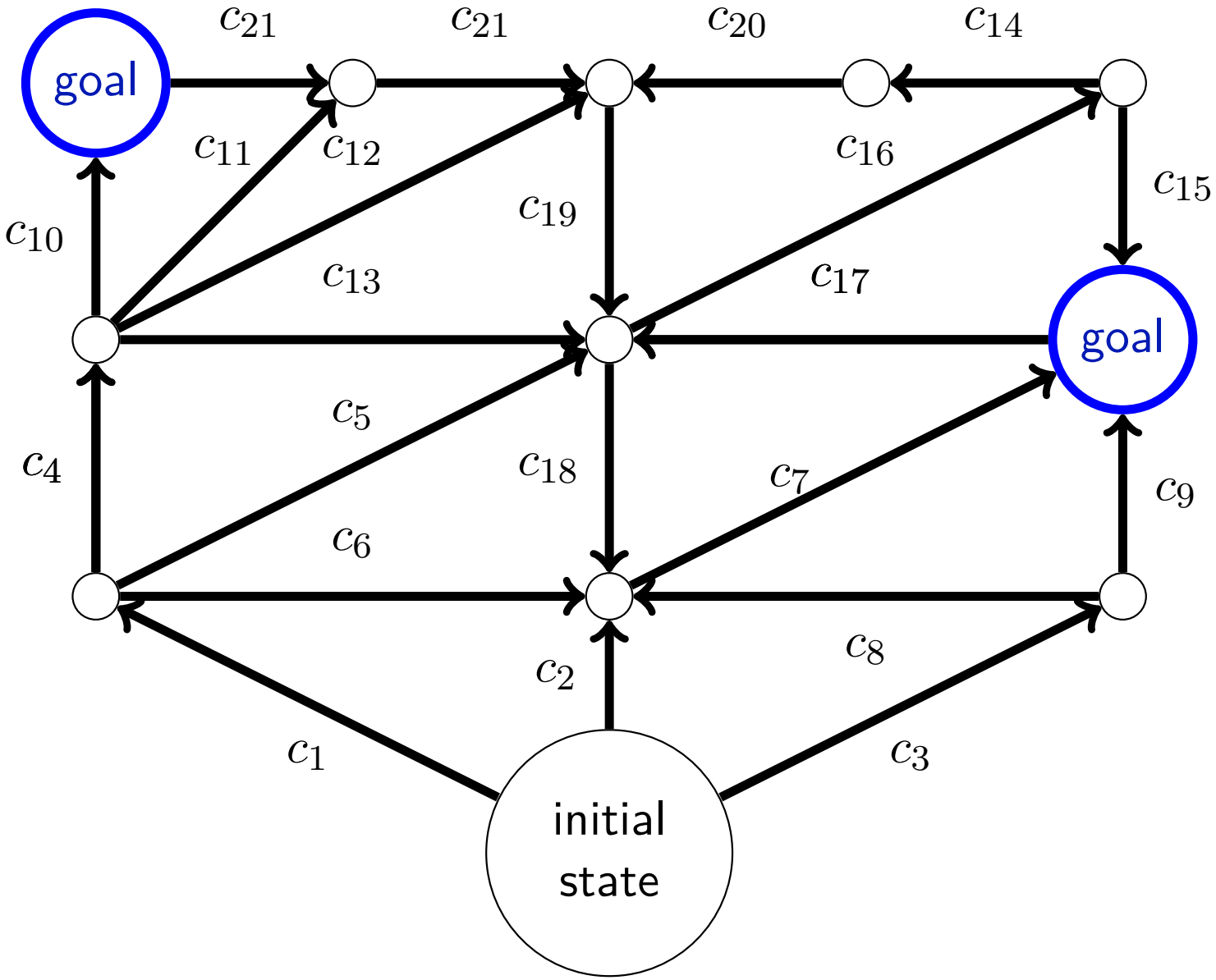

Visualisation Vacuum Cleaner World

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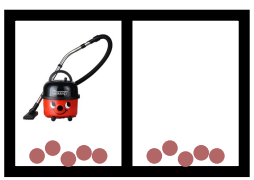

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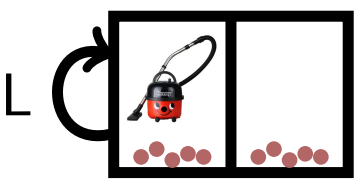

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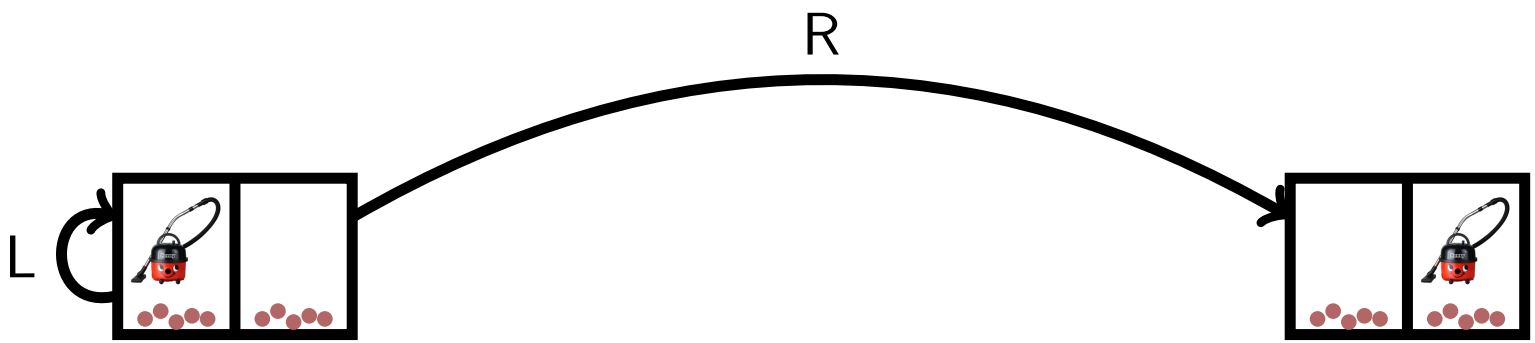

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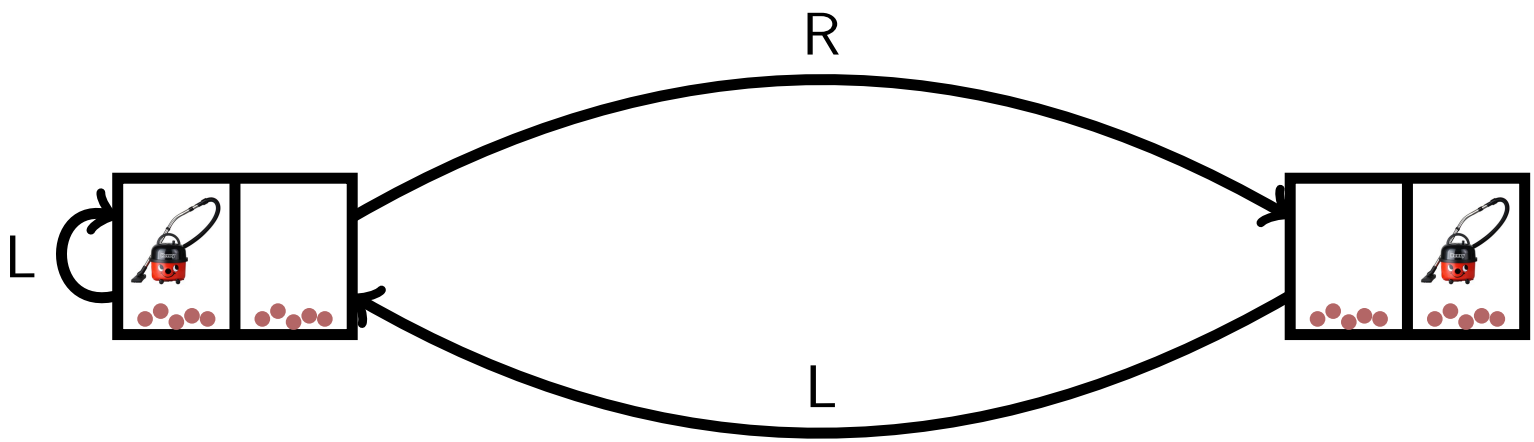

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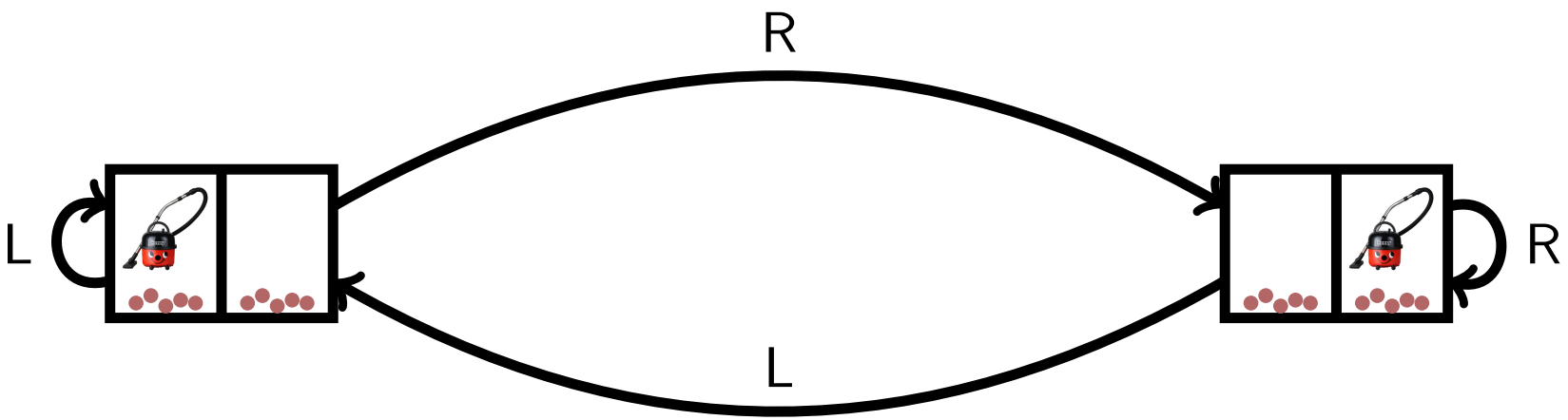

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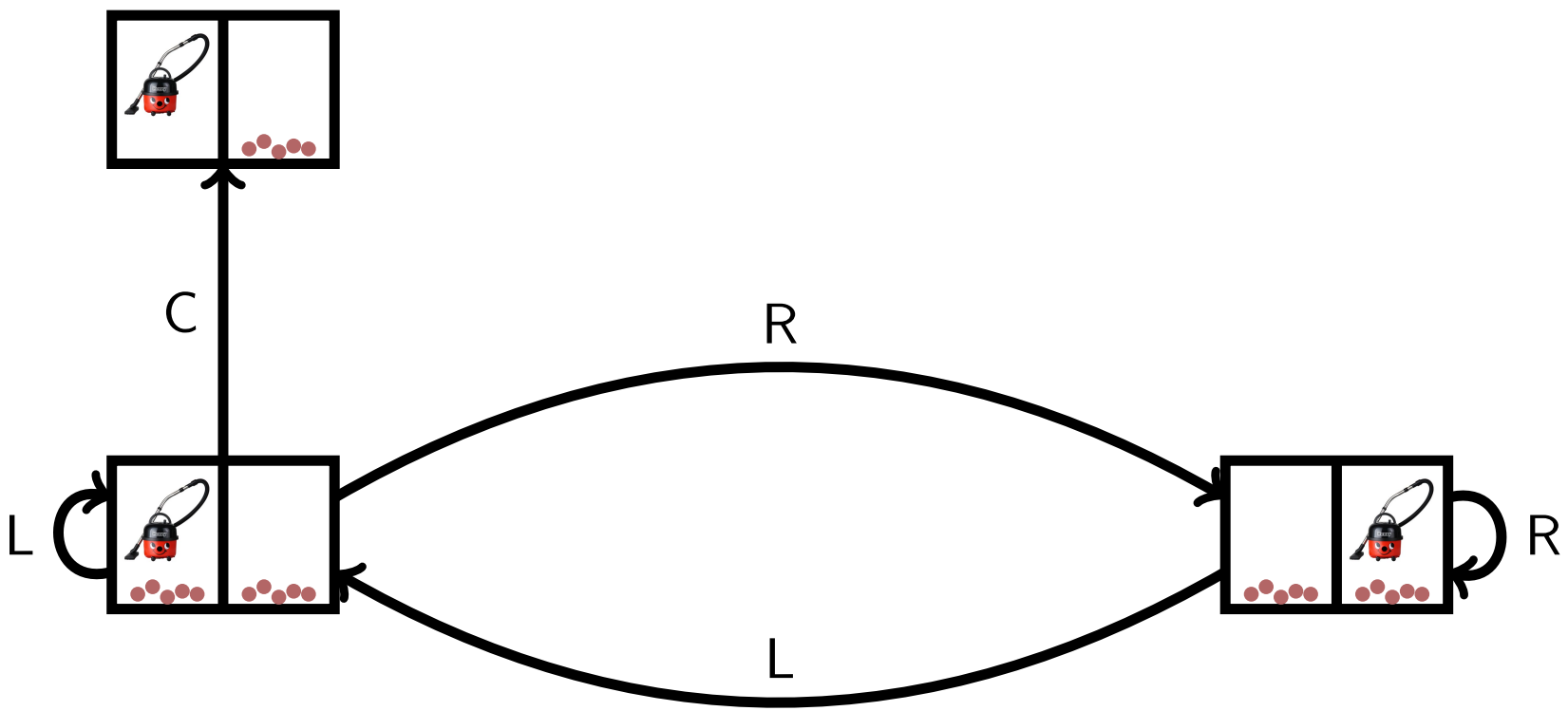

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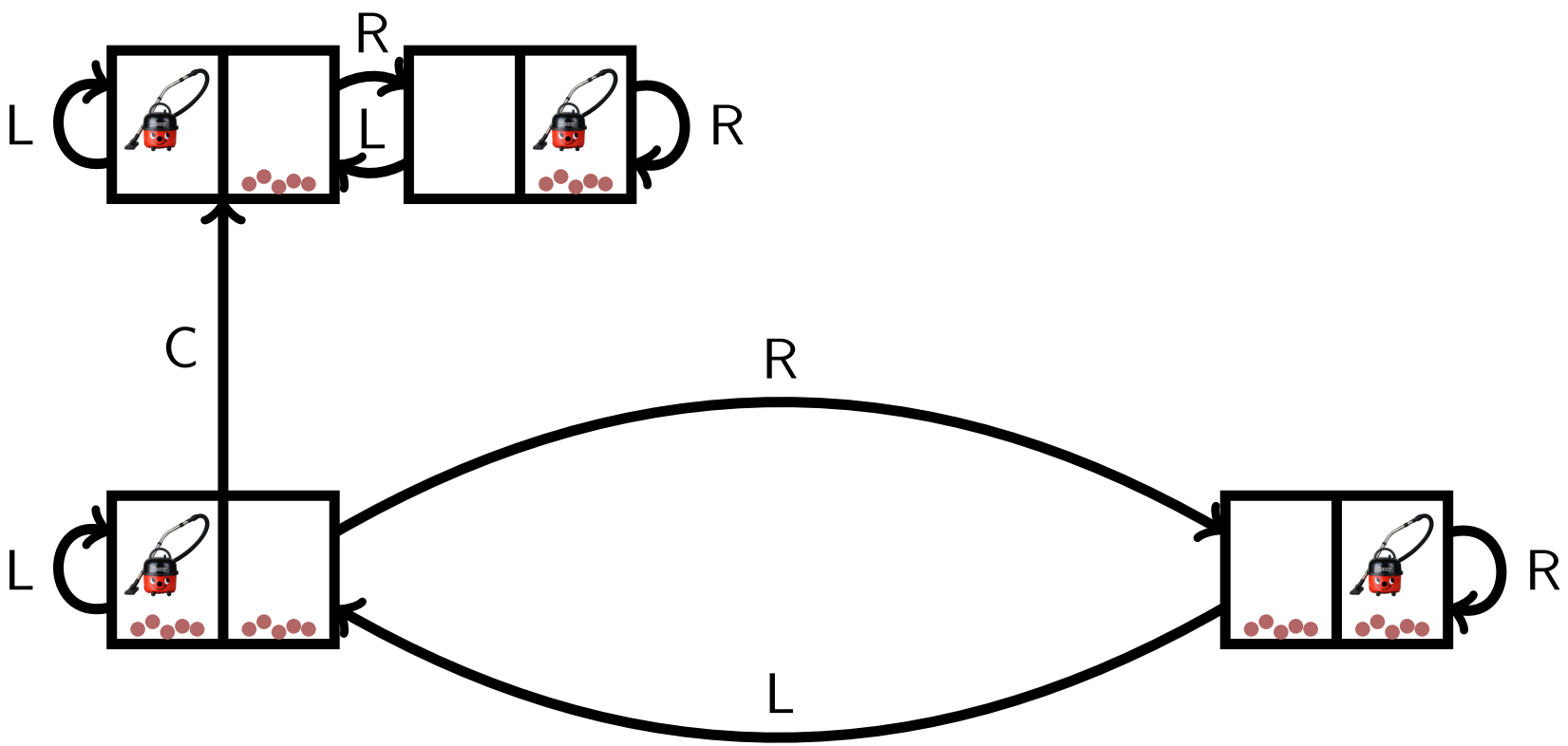

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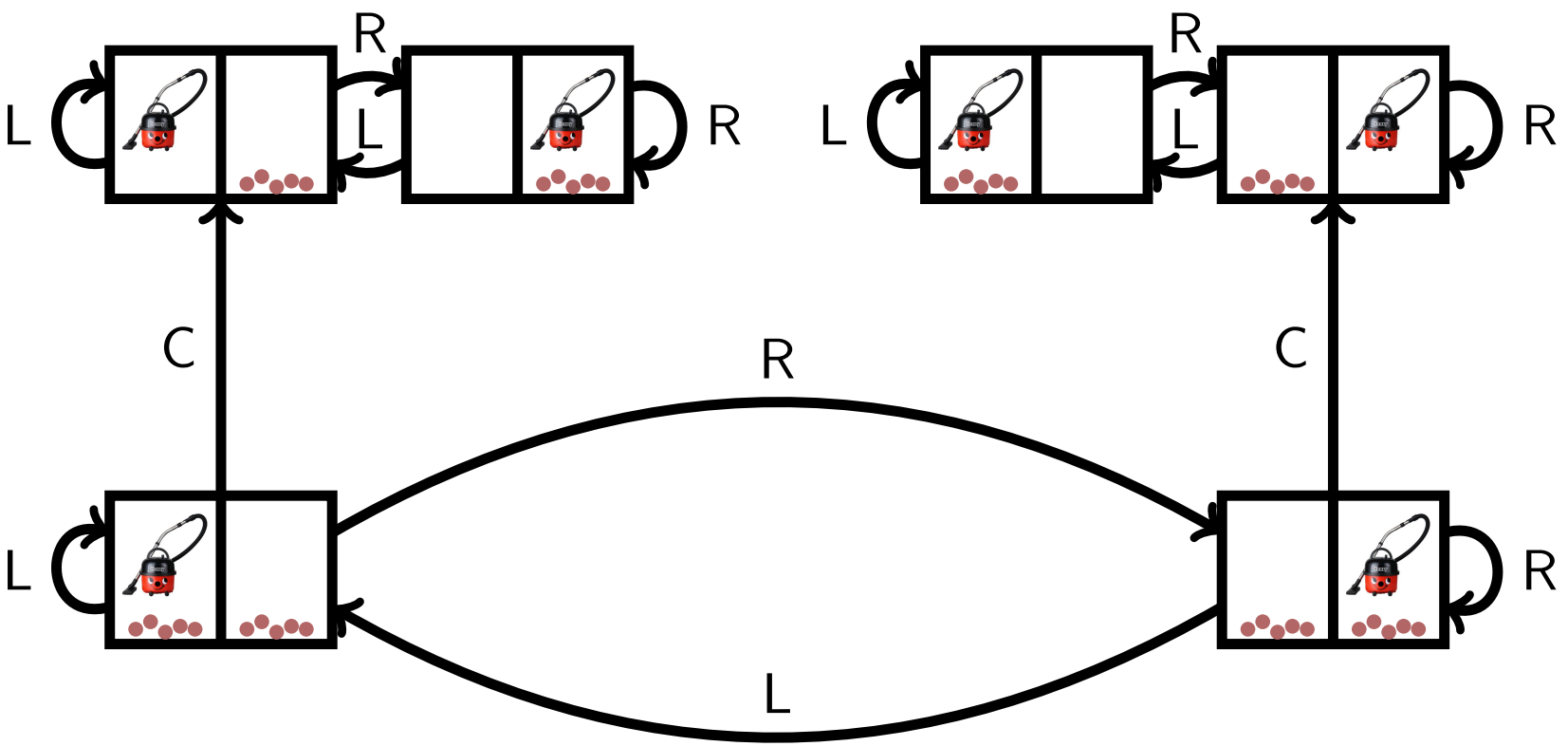

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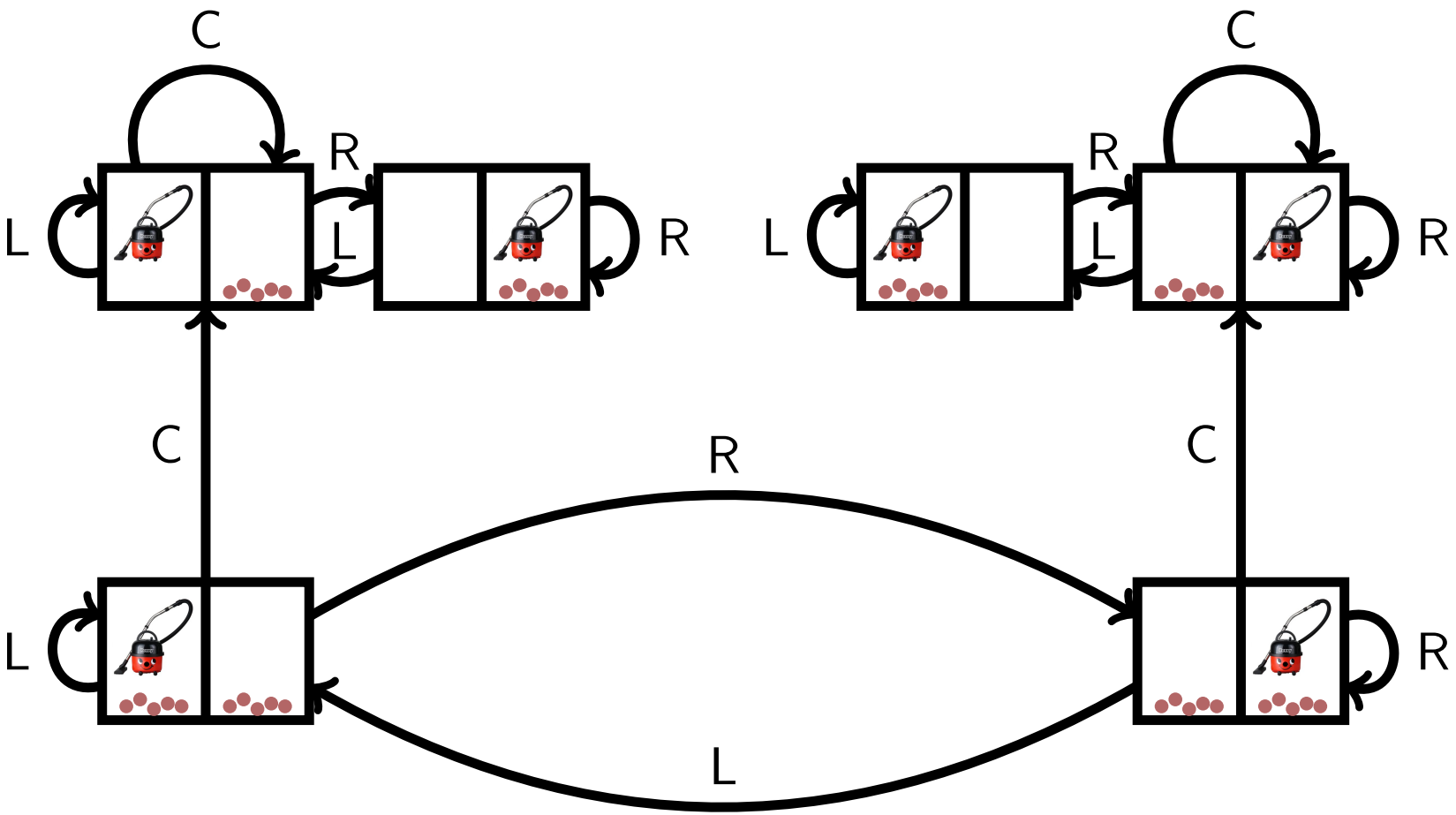

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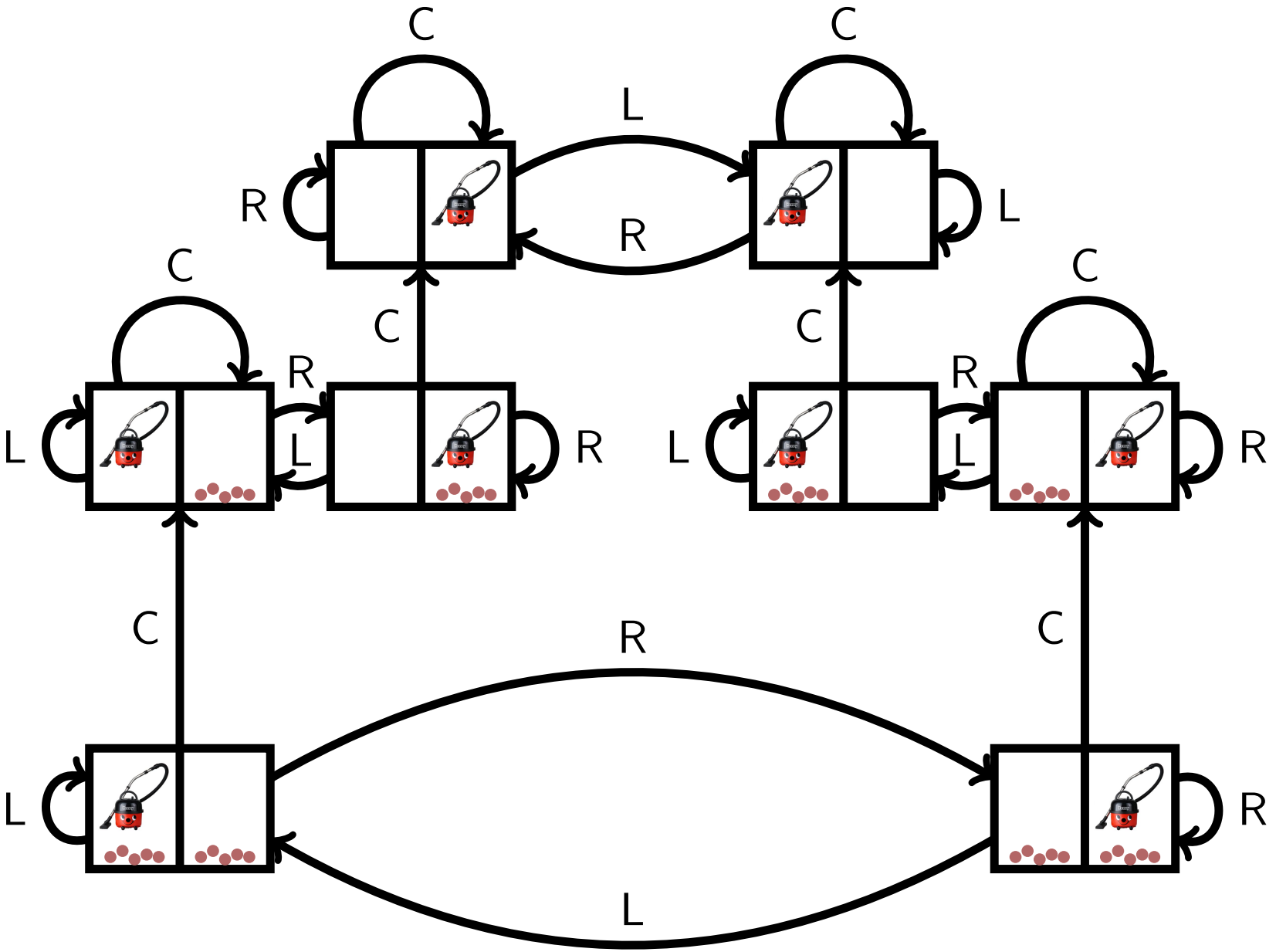

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- Stack (LIFO: last in first out)
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