Learning any memory-less discrete semantics for dynamical systems represented by logic programs

Learning dynamics from any semantics

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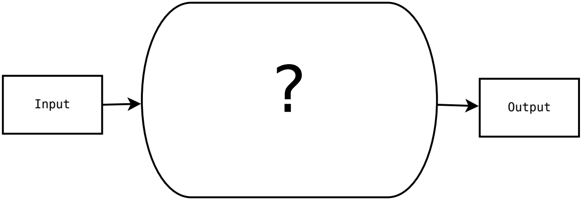
Outline

Outline

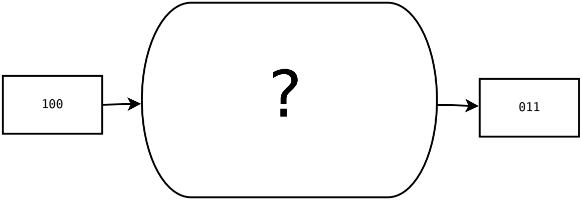
Research area

Idea: given a set of input/output states of a black-box system, learn its internal mechanics.



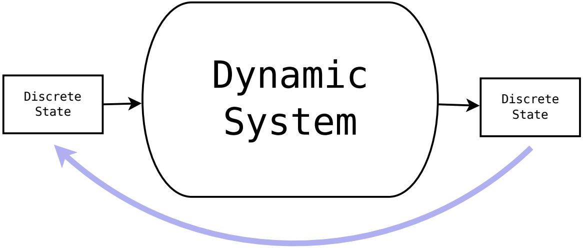
Research area

Discrete system: input/output are vectors of same size which contain discrete values.



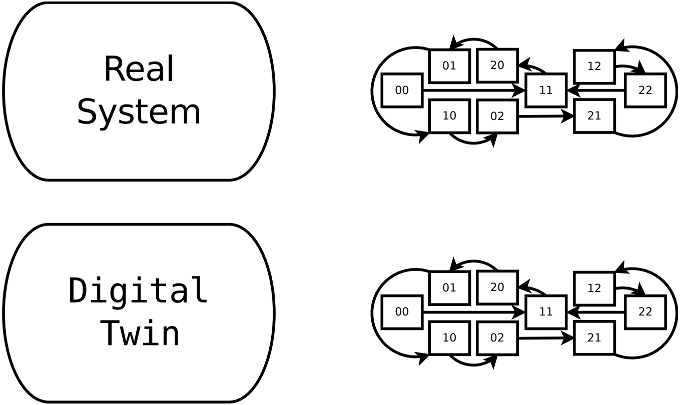
Research area

Dynamic system: input/output are states of the system and output becomes the next input.



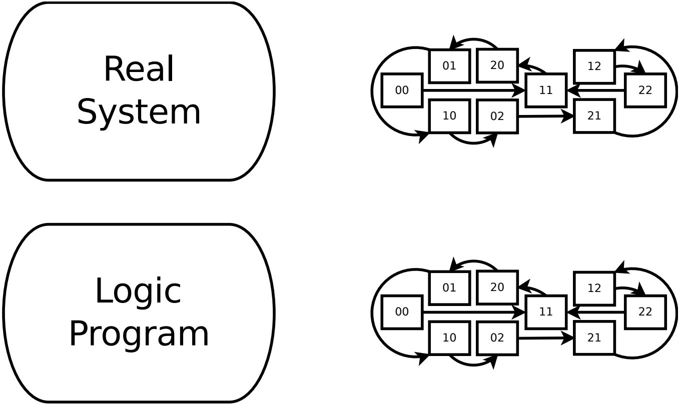
Research area

Goal: produce an artificial system with the same behavior as the one observed, i.e., a digital twin.



Research area

Representation: propositional logic programs with annotated atoms encoding multi-valued variables.

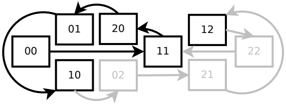


Research area

Method: learn the dynamics of systems from the observations of some of its state transitions.

DATA

?



RESULTS

a(0,T) :- a(2,T-1)
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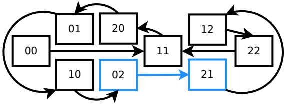
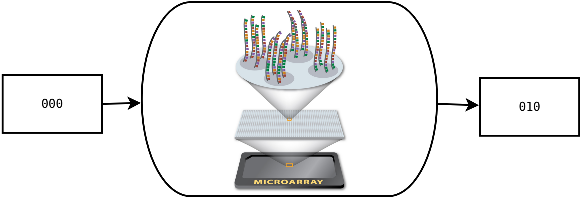


Motivation

Data: time series of gene expression levels in a organic cell.
Goal: model gene interactions to understand their influences.



Example (Possible Applications)

- **Bioinformatics**: Construct gene regulatory networks.
- **Robotics**: Learn action models from robot observations.

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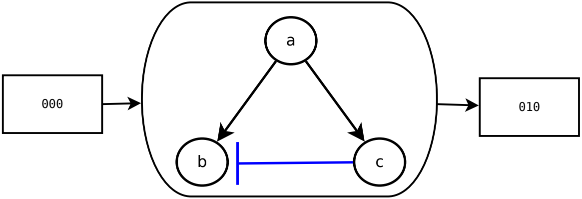

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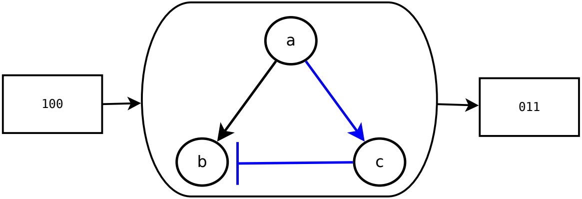

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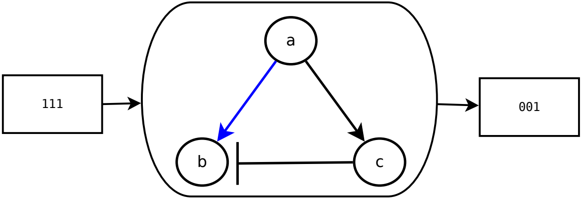
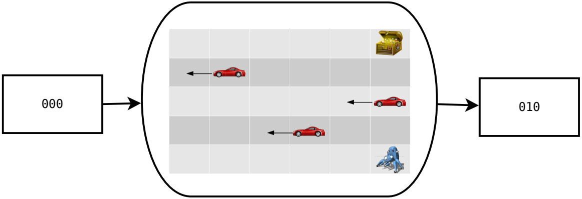


Example (Possible Applications)

- **Bioinformatics**: Construct gene regulatory networks.
- **Robotics**: Learn action models from robot observations.

Motivation

Data: observations of environment evolution according to a robot actions.
Goal: produce a predictive model of the environment for action planning.



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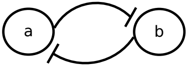
Outline

Dynamical Semantics

Boolean network transitions differ according to the update semantics used.



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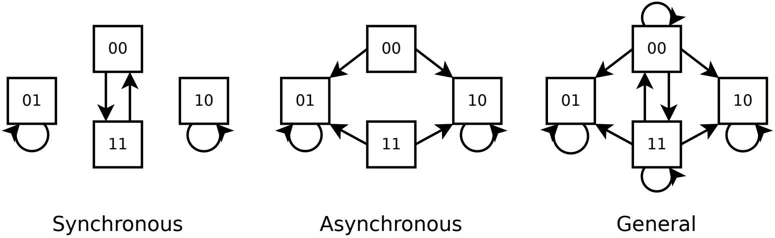

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- Asynchronous: only one variable is updated
- General: any number of variables can be updated

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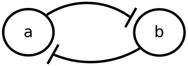

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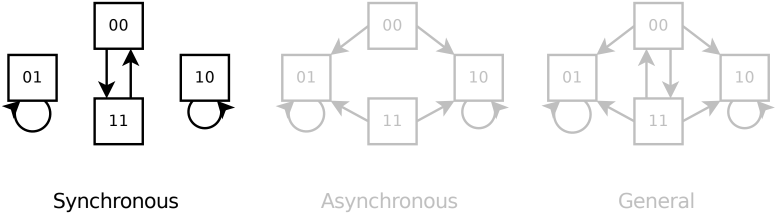

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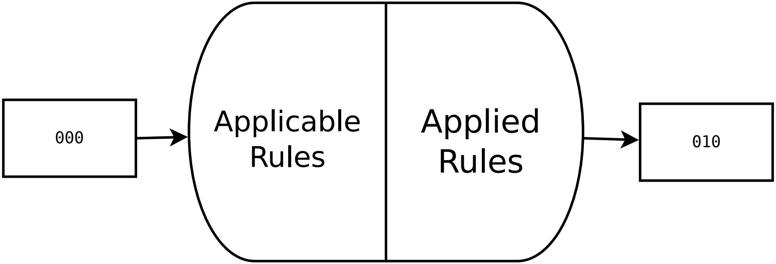
What is a semantics?

For those three semantics at least, it is about computing the next state by selecting among applicable local rules the ones that will be applied.



Semantics: what is an applicable rule and what is a valid set of applied rule.

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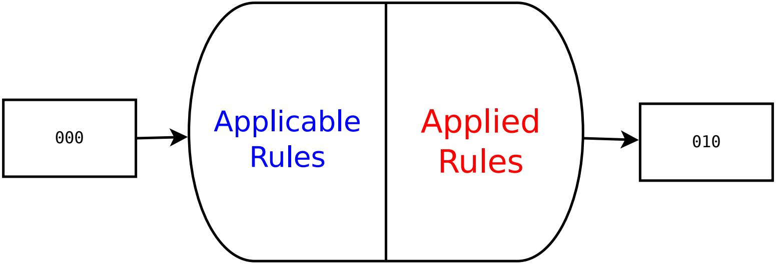

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Learning algorithm intuition: classification problem

What is an applicable rule?

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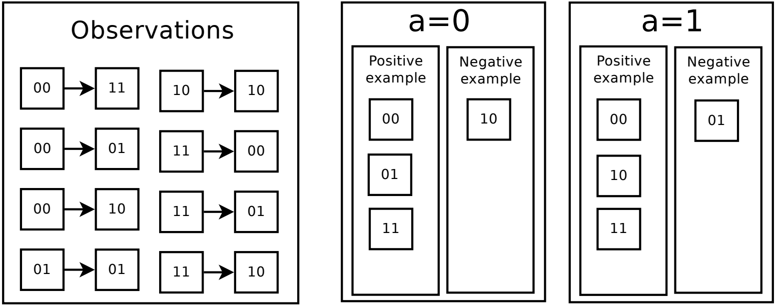

Equivalent to a classification problem: for each value of a variable, what is a typical state where the variable can takes this value in the next state ?

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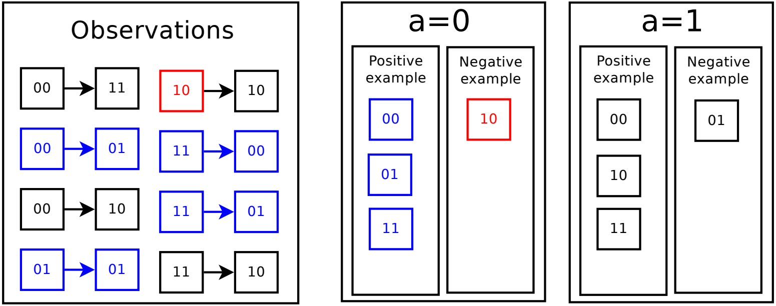

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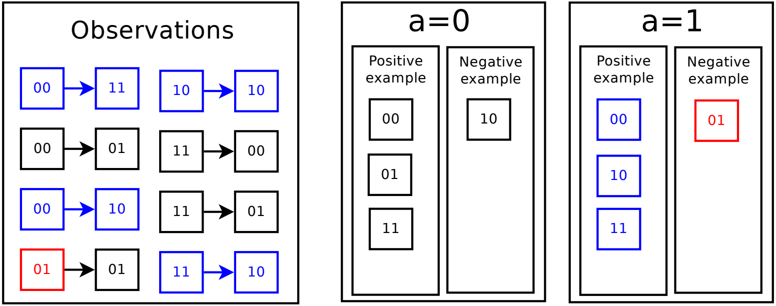

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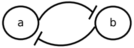
General Usage LFIT Algorithm (**GULA**) ouptut



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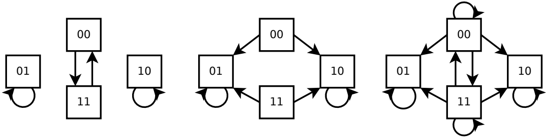

Synchronous

// f(a) := not b
$a_t^0 \leftarrow b_{t-1}^1$
$a_t^1 \leftarrow b_{t-1}^0$

// f(b) := not a
$b_t^0 \leftarrow a_{t-1}^1$
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Asynchronous

// f(a) := not b
$a_t^0 \leftarrow b_{t-1}^1$
$a_t^1 \leftarrow b_{t-1}^0$

// f(b) := not a
$b_t^0 \leftarrow a_{t-1}^1$
$b_t^1 \leftarrow a_{t-1}^0$

// Default rules
$a_t^0 \leftarrow a_{t-1}^0$
$a_t^1 \leftarrow a_{t-1}^1$
$b_t^0 \leftarrow b_{t-1}^0$
$b_t^1 \leftarrow b_{t-1}^1$

General

// f(a) := not b
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// f(b) := not a
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// Default rules
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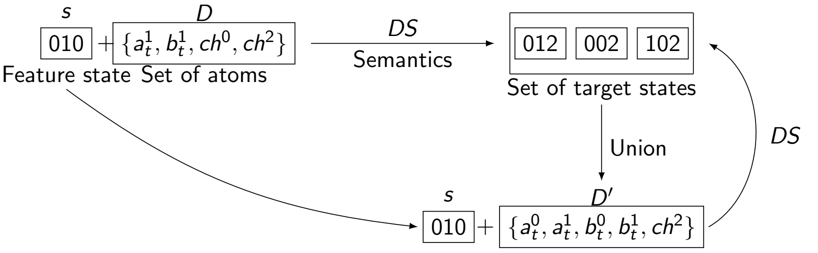
Pseudo-idempotent semantics

GULA can model observations from any pseudo-idempotent semantics.



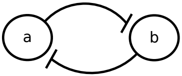
$$\longrightarrow DS(s, D) = DS\Big(s, \bigcup_{s' \in DS(s,D)} s'\Big)$$

where DS is the dynamical semantics, and D is the head of rules of a multi-valued logic program that match the sate s.

Outline

What about others semantics?

Three examples of arbitrary semantics.



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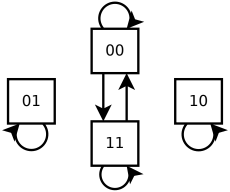
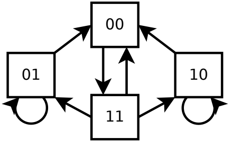
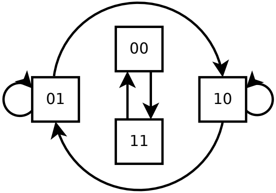


All or nothing change



Degradation

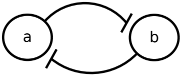


Inverse all values

How can we learn a program able to reproduce these behaviors?

What is impossible?

Problem: If GULA learns a program from those transitions and we apply the synchronous semantics, this is what happens:



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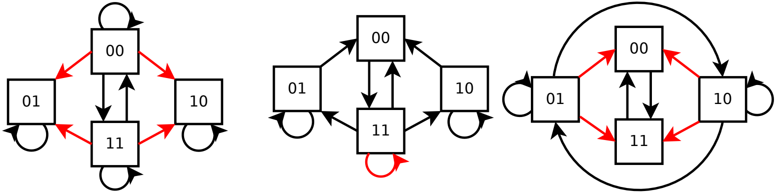

All or nothing change   Degradation   Inverse all values

Can we prevent impossible transitions?

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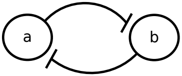

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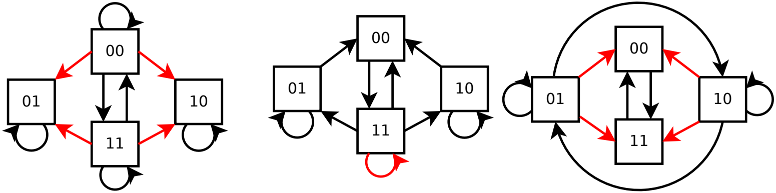
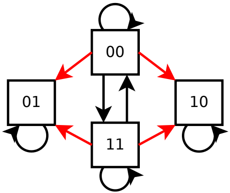


All or nothing change　　Degradation　　Inverse all values

Can we prevent impossible transitions? Yes: with constraints!

Classification modeling of impossibility

Idea: **GULA** can learn constraints using observations as negative examples.



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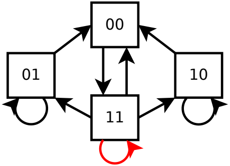

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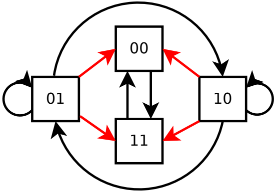

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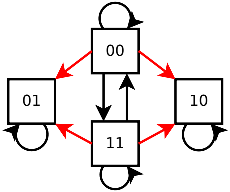

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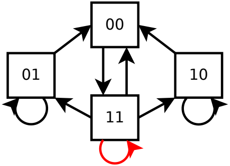

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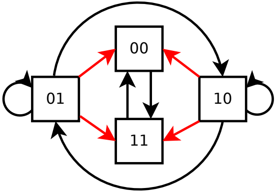

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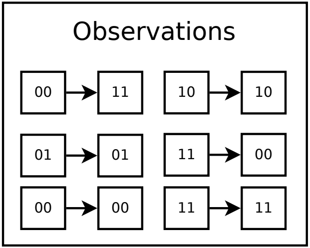
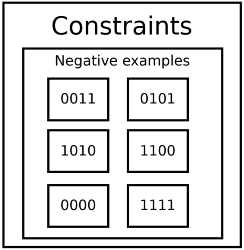
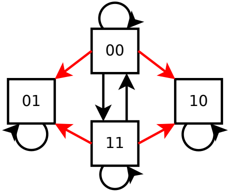




Examples of learned programs



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b := not a
b(0,T) :- a(1,T-1).
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Conservation rules
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a(1,T) :- a(1,T-1).
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b(1,T) :- b(1,T-1).
Constraints
:- a(0,T), b(1,T), b(0,T-1).
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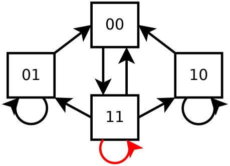

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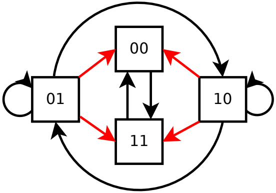

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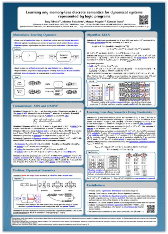
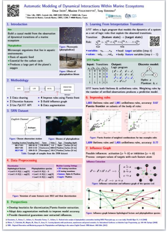
Outline

Conclusions

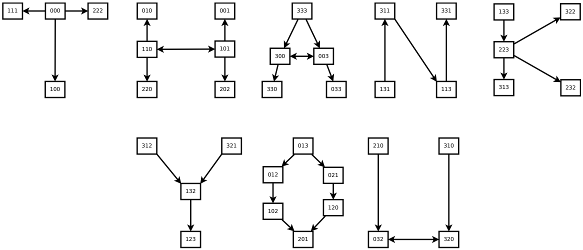
- **Previous works:** Synchronous deterministic transitions only.
- **Novelty:** Learn from any memory-less discrete dynamical semantics.
- **Application:** Selection of a semantics, can be done a posteriori.
- **Weakness:** Too costly/sensitive to deal with real systems.
- **Outlook:** Development of heuristic approaches to tackle real data.
- Source code (Python) available as open source on Github.
- Join us at posters session for details about theory and applications.

Manuscript





Source Code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