Most Permissive Semantics of Boolean Networks Reconciling Qualitative and Abstract Modelling

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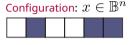


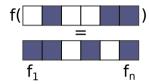


Most permissive semantics of Boolean networks

Introduction

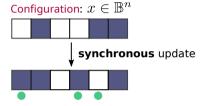
Boolean Network (BN) $f: \mathbb{B}^n o \mathbb{B}^n$

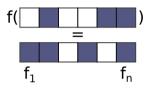




Introduction

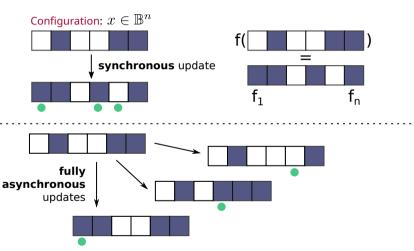
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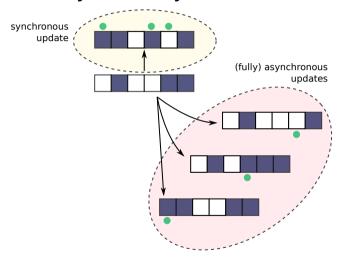


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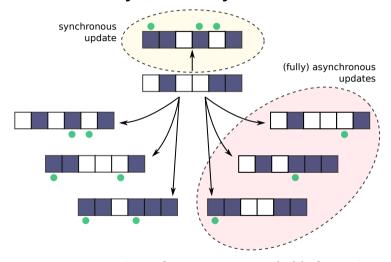
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Generalized Asynchronicity

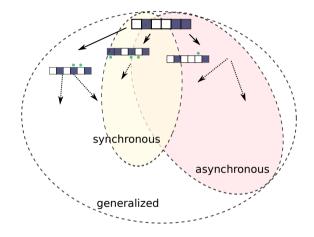


Generalized Asynchronicity



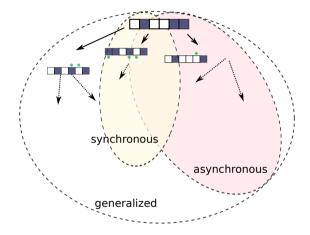
Is configuration x is reachable from y? ⇒ **PSPACE-complete** with update modes

Reachable configurations



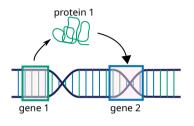
Most permissive semantics of Boolean networks

Reachable configurations



Can we reach configurations beyond generalized asynchronicity?

Boolean networks for biological processes Example with gene regulation

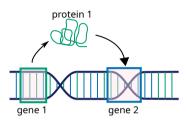






Boolean networks for biological processes

Example with gene regulation

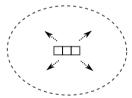


Influence graph



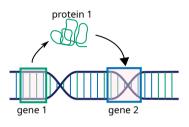
Reachable configurations

Boolean
$$f_1(x) \triangleq \cdots$$
 network $f_2(x) \triangleq \cdots$ + update mode = $f_3(x) \triangleq \cdots$



Boolean networks for biological processes

Example with gene regulation

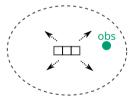


Influence graph



Reachable configurations

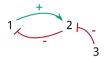
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Validation w.r.t. observations (e.g. time series data)

⇒ we expect measurements match with reachable configurations

Qualitative vs abstract modelling



Consistency analysis at Boolean level transposable to multilevel?

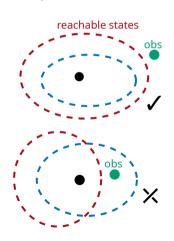
Boolean network

- logic of activity w.r.t. regulators
- update mode (sync, async, etc.)

Multilevel network

+ define activation thresholds

Quantitative model



nformation

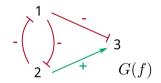
Update modesof Boolean networks:

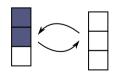
of Boolean networks: a **bug**...

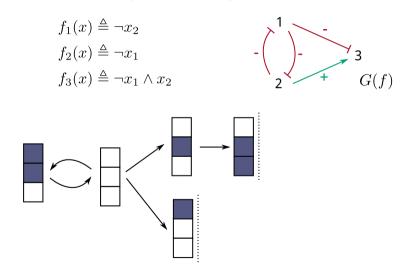
$$f_1(x) \triangleq \neg x_2$$

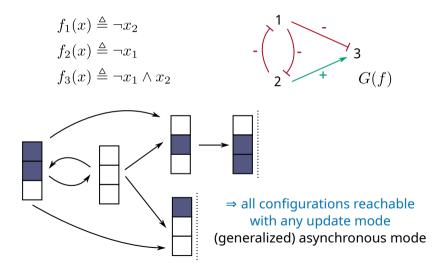
$$f_2(x) \triangleq \neg x_1$$

$$f_3(x) \triangleq \neg x_1 \land x_2$$





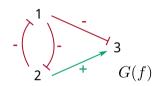




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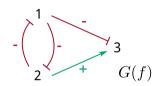




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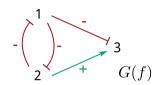


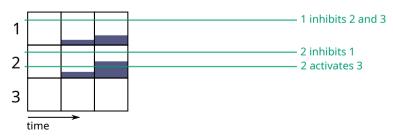


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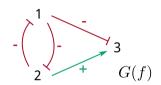
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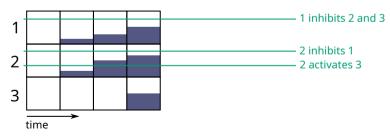
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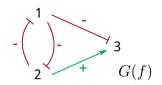


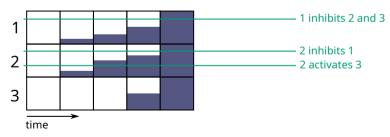


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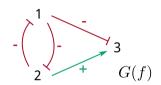


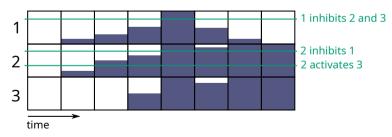


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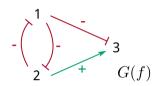


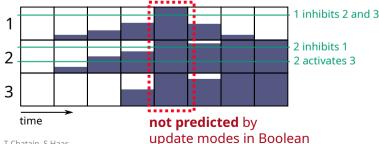


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Practical implications

Any update modes can miss possible transitions

Model inference from observations

⇒ Reject valid models (false negatives)
 (wrongly conclude that some state are not reachable)

Prediction for reprogramming

Find mutations such that

- 1. y (goal phenotype) is reachable from x
- 2. z (bad phenotype) is not reachable from x
- ⇒ False positives (2)
- ⇒ False negatives (1)

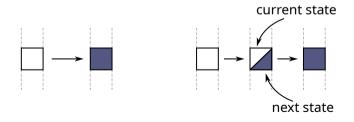
of Boolean networks

enabling new behaviours

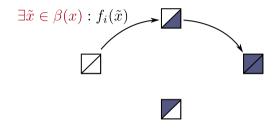
- delay between firing and application of state change
 - ⇒ allow interleaving other state changes
- in "intermediate" states



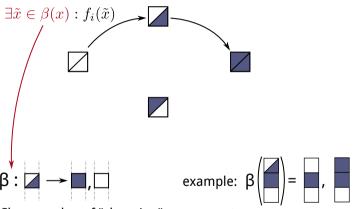
other components choose what they see



Rules for state of component i:

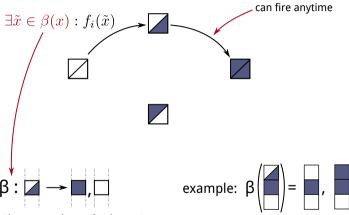


Rules for state of component i:



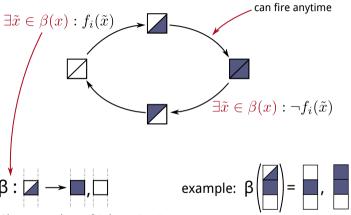
Choose value of "changing" components (act as choosing an activation threshold)

Rules for state of component i:



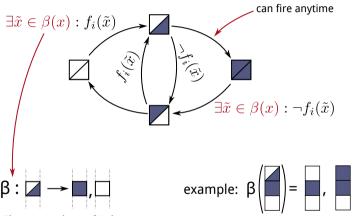
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Application to motivating example

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$$G(f)$$

⇒ valid with respect to multivalued refinements

Properties of the most permissive semantics

Correct abstraction of multilevel/quantitative systems:

- includes all the transitions of every update mode
- multilevel refinements only remove behaviours
- Reachability (configuration y is reachable from x):
 - ⇒ comput. in quadratic iterations

(PTIME with locally-monotonic networks, or encoded as BDDs/Petri nets/...;

NP otherwise: instead of PSPACE-complete with update modes)

- ⇒ no need for simulations / model-checking / ...
 - ⇒ scalable to thousands of components
- Attractors are hypercubes (minimal trap spaces)
 - ⇒ finding attractors is in NP (instead of PSPACE-complete)

Refinements of Boolean Networks

A multivalued network

$$F: \mathbb{M}^n \to \{\uparrow, -, \downarrow\}$$

is a refinement of a Boolean network *f* iff

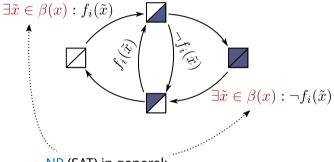
$$F_i(x) = \uparrow \implies \exists x' \in \beta(x) : f_i(x') = 1$$

 $F_i(x) = \downarrow \implies \exists x' \in \beta(x) : f_i(x') = 0$

Most permissive semantics weakly simulates any multivalued refinement with *any update mode*

(can be extended to ODEs)

Cost of one transition in component i



NP (SAT) in general;

Linear with

- locally-monotonic networks
- when f is encoded as BDDs/Petri nets/...

Deciding reachability requires quadratic transitions

Main property:

y reachable from $x \Leftrightarrow$ there exists a path of length $\leq 3n$ transitions

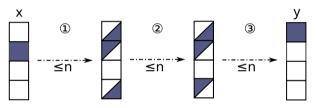




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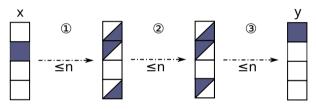
- ① only transitions to "in-between" states*
- 2 orient towards final states
- ③ converge to final states

*: some components must not be updated!

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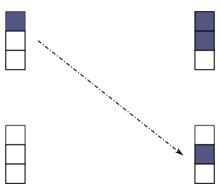


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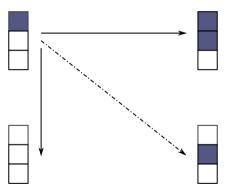
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NP in general PTIME w/ locally-monotonic; BDDs; Petri nets..

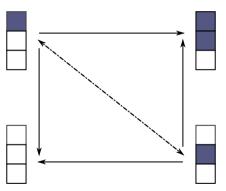
Attractors are hypercubes



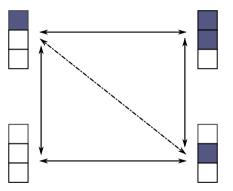
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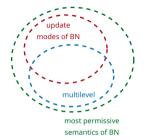


Attractors are hypercubes



Attractors of most permissive semantics = minimal trap spaces Existence of attractor within hypercube is in NP

Is most permissive semantics restrictive?



Minimality of abstraction to any "most permissive" transition, there is corresponding multilevel transition (future work: "most permissive" paths)

- fixpoints (stable states) are preserved
- trap spaces: known to be relevant for reasoning with attractors [Klarner et al in Nat. Comp. 2015] [Naldi in Front. Phys. 2018]
- ⇒ most permissive semantics seems still adequate to model differentiation processes!

Most permissive semantics of Boolean networks

Applications

Prototype python library + ASP (SAT) implementation https://github.com/pauleve/mpbn

Model inference from time series (reachabilty)

→ CaspoTS implements most permissive reachability https://github.com/bioasp/caspots

Computation of reachable attractors

⇒ In the order of ms for networks tested so far (~100 nodes)

WiP with most permissive semantics:

- model inference from differentiation data [Stéphanie Chevalier]
- prediction for reprogramming

Most permissive semantics of Boolean networks

Conclusion

Update modes of Boolean networks (sync, async, etc.):

- difficult to justify (strong implications on dynamics)
- can miss important behaviours [CHP at AUTOMATA'18]
- ⇒ lead to reject valid models of biological systems...
- have limited tractability (model-checking, ...)

Most permissive semantics:

- correct abstraction: guarantees that adding information (multilevel, thresholds) will only remove behaviours
- simpler complexity: reachability PTIME, attractors NP
- ⇒ much higher tractability

Future work: most permissive for multilevel networks