

ASKeD-BN: Automatic Synthesis of Boolean Networks from Biological Knowledge and Data



Athénaïs Vaginay, Taha Boukhobza, Malika Smaïl-Tabbone

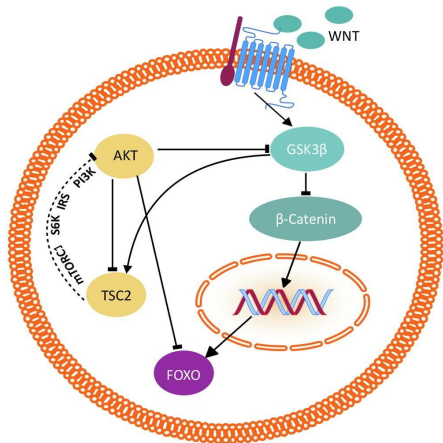
Jun 21-23 2021



Modeling Biological Systems with Boolean Networks

Boolean Networks (BN) are:

- ▶ qualitative formalism, well-suited for biological systems
- ▶ built from experimental data and knowledge from literature
- ▶ the **automatic** synthesis of BNs from biological data and knowledge is still a challenge



from Schwab et al. 2020.

Boolean Networks – Generalities

$$\mathcal{B} = \begin{cases} f_A : a_{t+1} = c_t & \text{in the Boolean world: } \mathbb{B} = \{0, 1\} \\ f_B : b_{t+1} = b_t \wedge \neg c_t & n \text{ Boolean } \mathbf{components} \\ f_C : c_{t+1} = \neg c_t & \mathbf{BN = set of } n \text{ update functions} \end{cases}$$

negation: \neg disjunction: \vee conjunction: \wedge

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Boolean Networks – More About Update Functions

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$$\mathcal{B} = \begin{cases} f_A : a_{t+1} = c_t & \text{"C activates A"} \\ f_B : b_{t+1} = b_t \wedge \neg c_t \\ f_C : c_{t+1} = \neg c_t \end{cases}$$

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$$\mathcal{B} = \begin{cases} f_A : a_{t+1} = c_t & \text{status of child component at } t + 1 \\ f_B : b_{t+1} = b_t \wedge \neg c_t & = f(\text{status of parents components at } t) \\ f_C : c_{t+1} = \neg c_t \end{cases}$$

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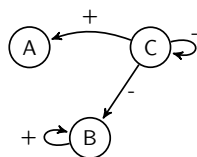
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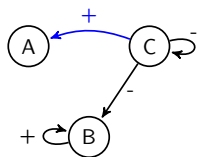
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nodes: components of the BN

edges: influences + polarity

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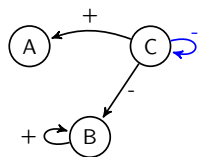
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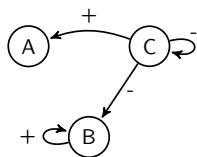
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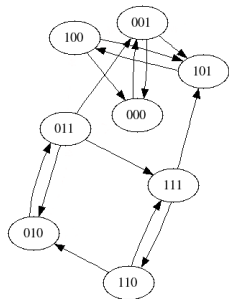


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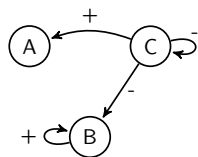
State Transition Graph (STG)

nodes: configurations of the BN (vector $\in \mathbb{B}^n$)

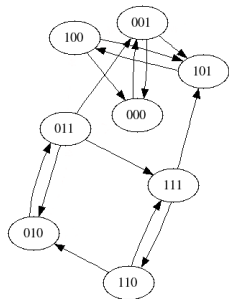
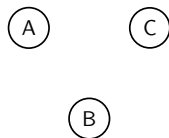
e.g. 001, 010, 111, ...

edge from c to c' if $c' = f(c)$

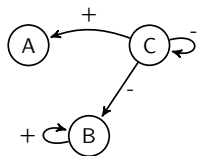
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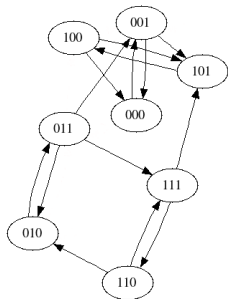
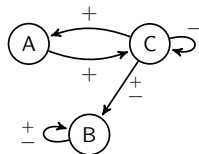


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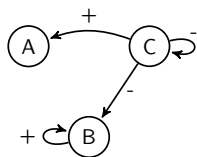


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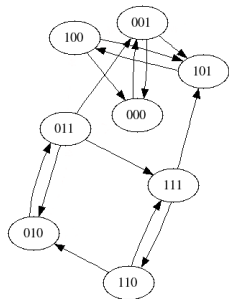
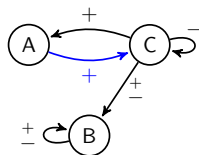


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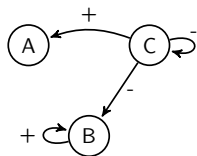


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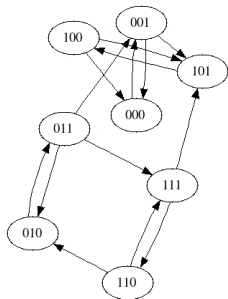
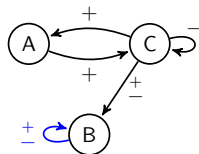


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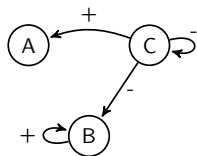


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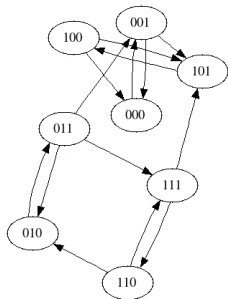
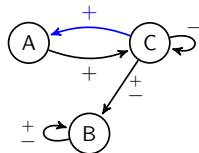


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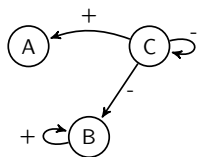


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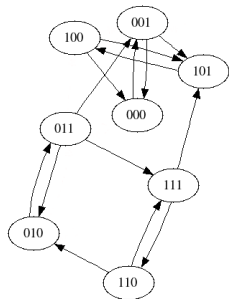
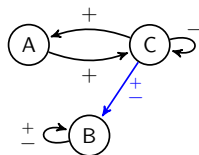


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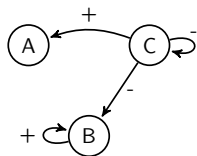


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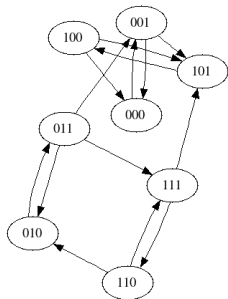
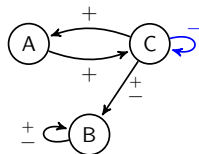


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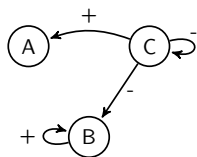


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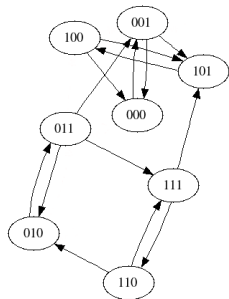
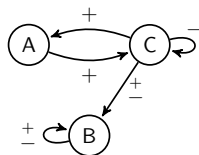


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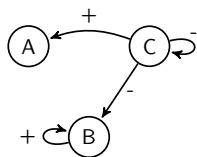


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Prior Knowledge Network (PKN)

Super-set of influences allowed

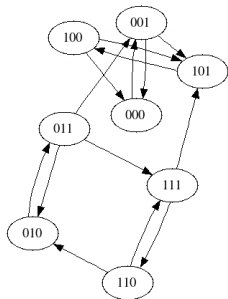
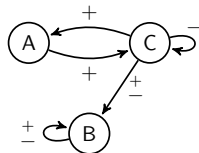
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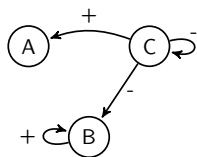
“C activates A”

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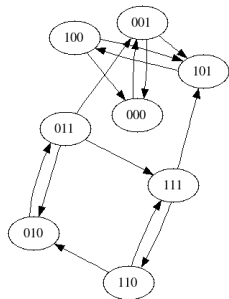
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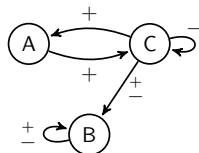
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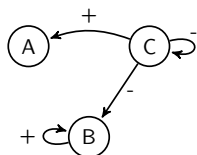


Multivariate Time Series (TS)

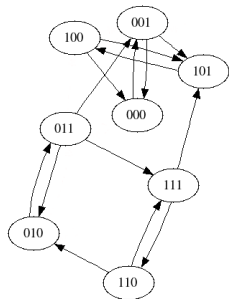
Concentrations of the components over time

t	1	2	3	4	5	6	7	8	9	10	11	12	13	...
A	0	3	7	13	20	30	49	61	100	63	36	25	2	...
B	100	86	64	57	54	53	51	49	45	37	33	28	22	...
C	0	27	36	42	60	75	54	44	38	48	60	72	88	...

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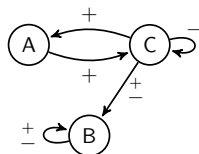
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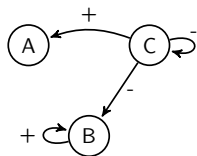


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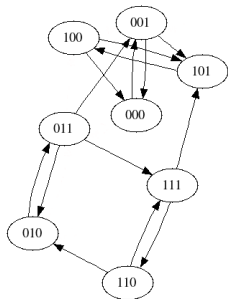
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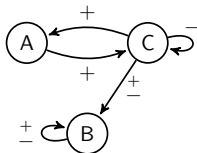
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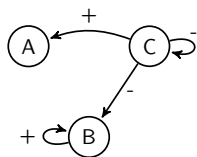


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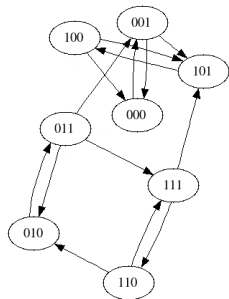
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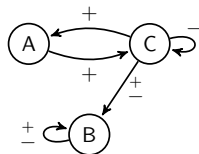
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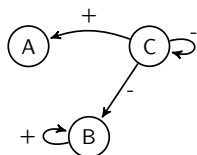


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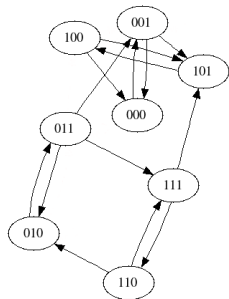
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Boolean Networks – Synthesis from Knowledge and Data



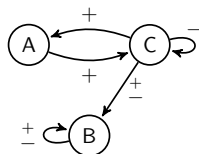
$$\mathcal{B} = \begin{cases} f_A : a_{t+1} = c_t \\ f_B : b_{t+1} = b_t \wedge \neg c_t \\ f_C : c_{t+1} = \neg c_t \end{cases}$$



Prior Knowledge Network (PKN)

Super-set of influences allowed

- “A activates C”
- “B interacts with itself”
- “C activates A”
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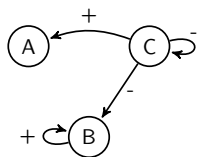


Multivariate Time Series (TS)

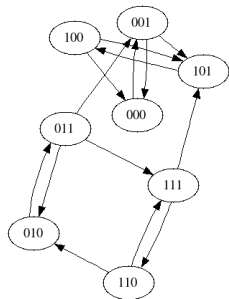
Concentrations of the components over time

t	1	2	3	4	5	6	7	8	9	10	11	12	13	...
A	0	3	7	13	20	30	49	61	100	63	36	25	2	...
B	100	86	64	57	54	53	51	49	45	37	33	28	22	...
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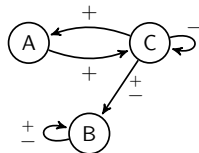
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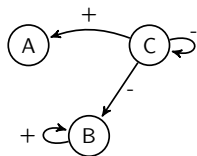


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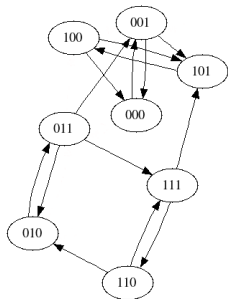
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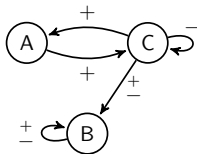
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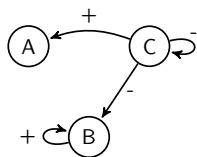


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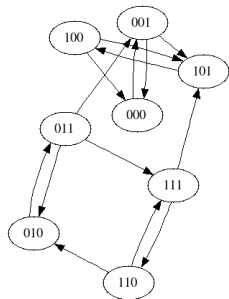
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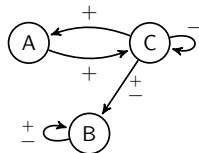
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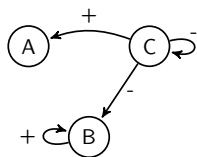


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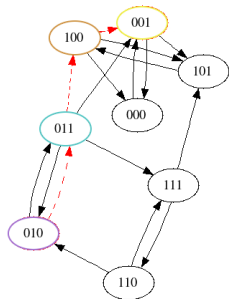
Concentrations of the components over time

	010		→ 011		→ 100		→ 001							
t	1	2	3	4	5	6	7	8	9	10	11	12	13	...
A	Red	Red	Red	Red	Red	Red	Red	Green	Green	Green	Red	Red	Red	...
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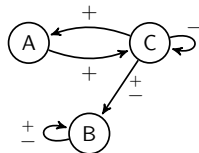
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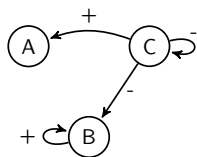


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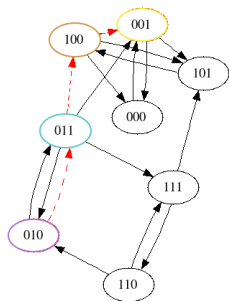
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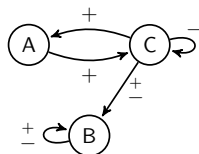
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C	Red	Red	Red	Red	Green	Green	Green	Red	Red	Red	Green	Green	Green	...

Get the best **coverage** possible

Existing tools

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Automatic synthesis of BNs from a Prior Knowledge Network (PKN)
and a multivariate Time Series (TS)
= hard problem (combinatorial explosion)

REVEAL
Best-Fit
caspo-TS

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1. delimitation of the search space using the PKN as constraint
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Multiple optimal solutions are all returned

ASKeD-BN

Formulation the BN synthesis problem as a logic program with the Answer Set Programming (ASP) framework

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Main parts of the logic program:

1. generates all the possible candidate functions
2. removes the ones that do not respect the PKN
3. acts like an exhaustive evaluation of all the candidates and returns the *parsimonious* candidates which explain best the *binarized* observations from the given time series

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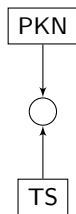
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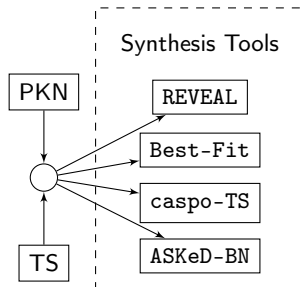
ASP solvers are designed to solve hard combinatorial satisfaction problem. They prune the search space *efficiently* (heuristic from SAT solvers).

Evaluation Procedure

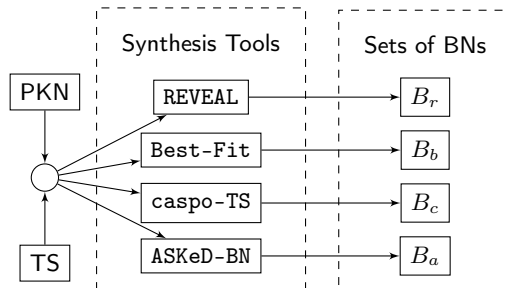
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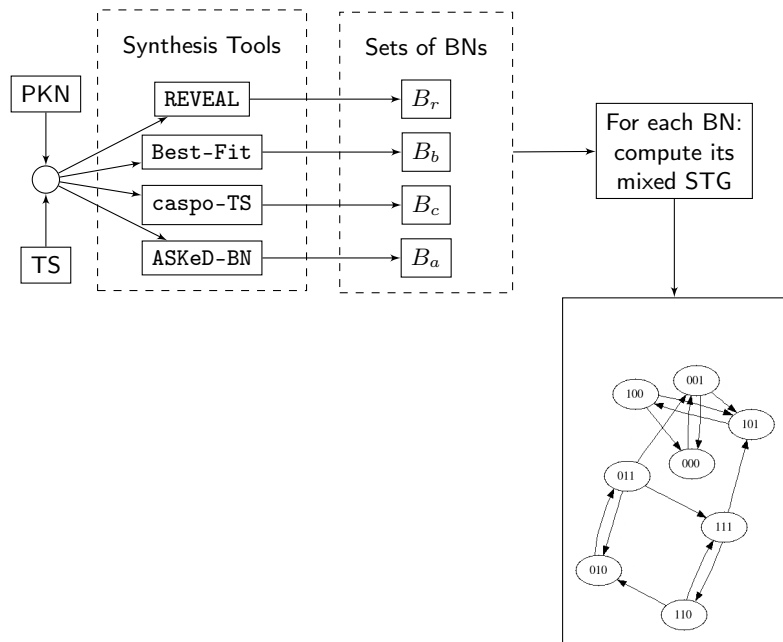
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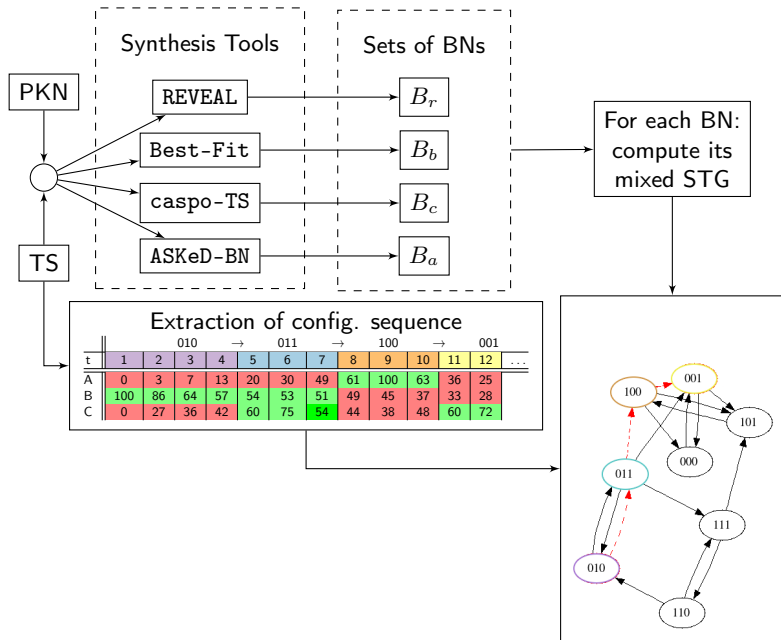
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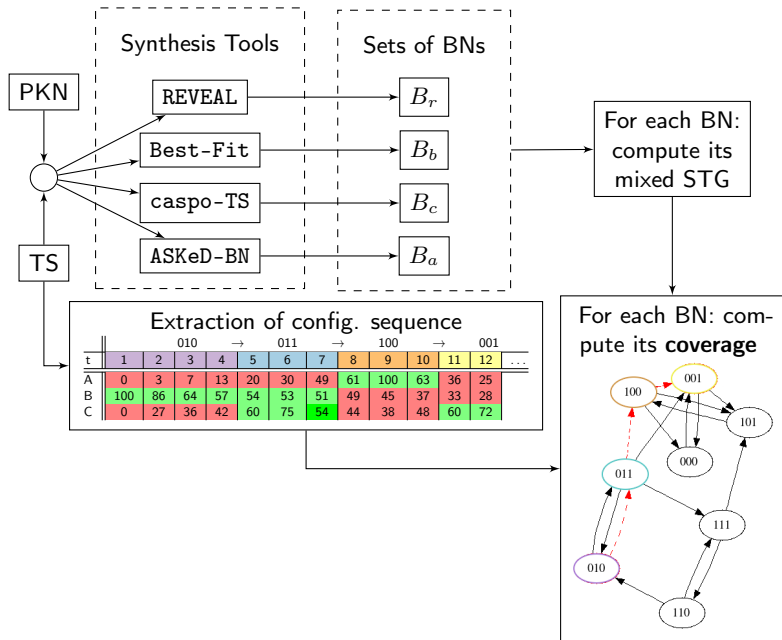
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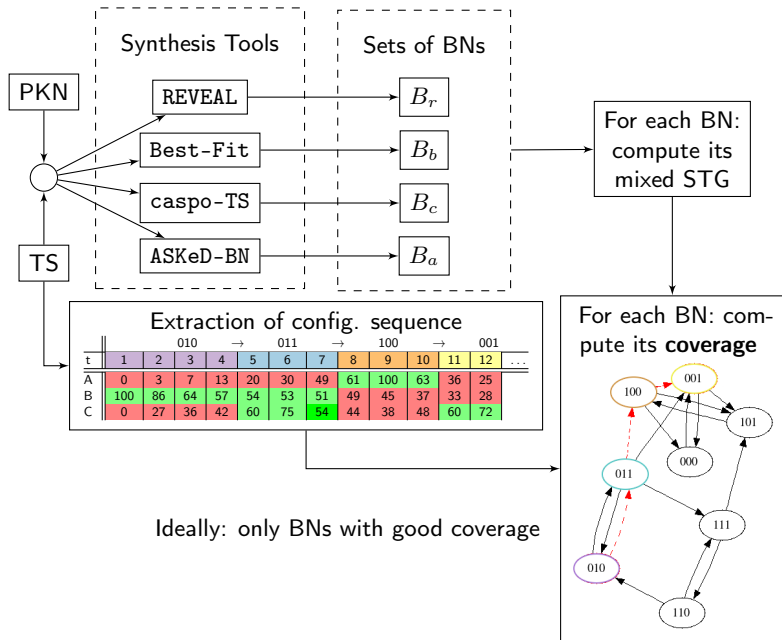
Evaluation Procedure



Evaluation Procedure



Evaluation Procedure



Evaluation on Real Datasets

Evaluation on Real Datasets

yeast

A. thaliana

Evaluation on Real Datasets

yeast

4 components, 7 transitions

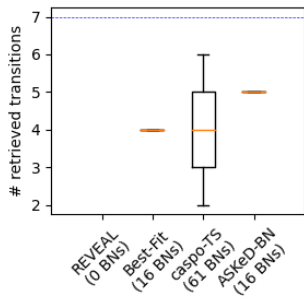
A. thaliana

5 components, 10 transitions

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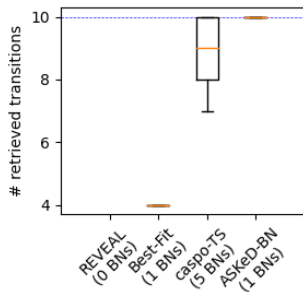
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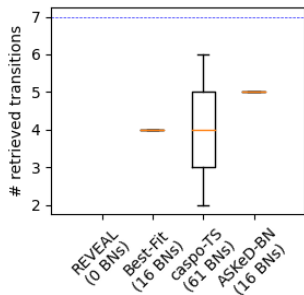
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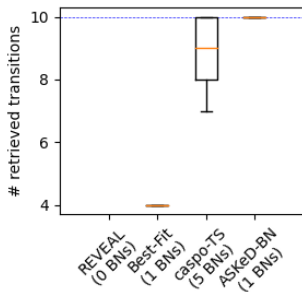
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► REVEAL fails

A. thaliana

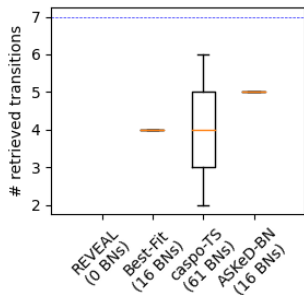
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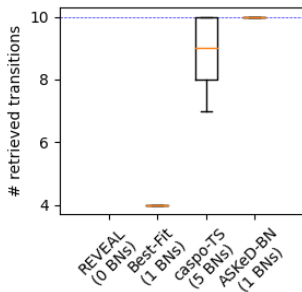
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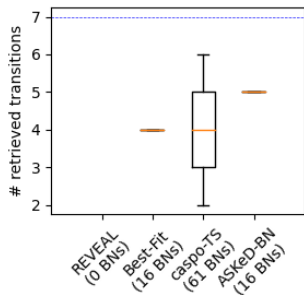
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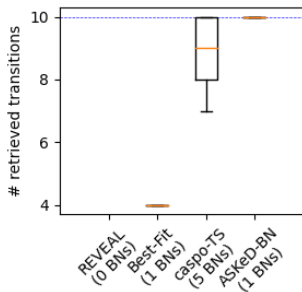
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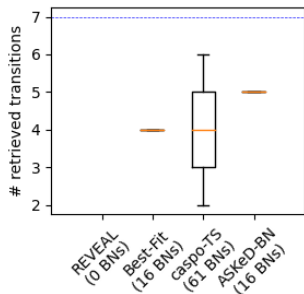
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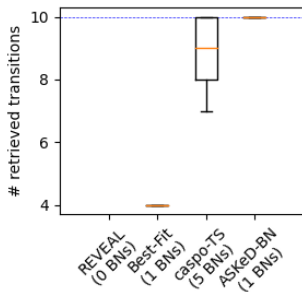
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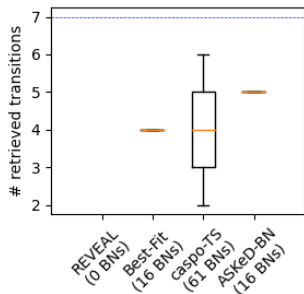
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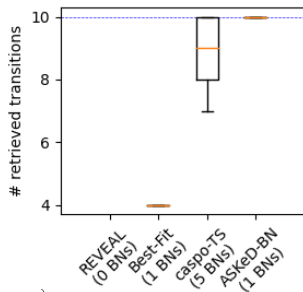
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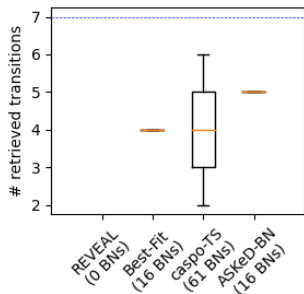
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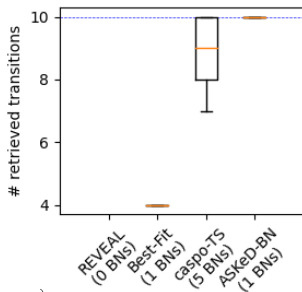
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} confirmed on synthetic datasets

→ ASKeD-BN returns a small number of BN, with good coverage and low variance ✓

Conclusion

Contribution:

- ▶ ASKeD-BN: Automatic Synthesis of Boolean Networks constrained in their structure (PKN knowledge) and their dynamics (TS data)
- ▶ Approach free of strong / restraining assumptions
- ▶ Formulation as a logic program (Answer-Set Programming)
- ▶ ASKeD-BN gives good results

All data + code available at:

<https://gitlab.inria.fr/avaginay/OLA2021>

Work in progress:

- ▶ Apply ASKeD-BN on PKN and TS directly extracted from existing biological models (ODE-like)

The end. Any questions ?

Annexe

Datasets for Evaluation

2 real datasets:

System	PKN		TS	
	# nodes	# edges	# time steps	# transitions
<i>yeast</i> (cell cycle)	4	28	14	6
<i>A. thaliana</i> (circadian clock)	5	8	50	11

6 synthetic datasets:

Various complexity: from 3 to 10 nodes.

Various conditions: synch. or async. update scheme, with or without repetition, with or without noise

336 experiments at total including 42 with the ARN setting.

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Comparison time and RAM

	<i>yest</i>		
method	running time (s)	cputime (s)	max_rss (MB)
REVEAL	1.0095	0.55	72.97
Best-Fit	1.4069	1.10	92.77
caspo-TS	24.6545	12.91	183.08
ASKeD-BN	5.4209	4.90	186.80

	<i>A. thaliana</i>		
method	running time (s)	cputime (s)	max_rss (MB)
caspo-TS	7.0394	1.85	139.93
ASKeD-BN	8.5820	8.19	163.38

observed in general:

- ▶ caspo-TS faster and less RAM usage than ASKeD-BN
- ▶ but not on some datasets, where ASKeD-BN terminated in less than 100 hours while caspo-TS is still running after more than 300 hours. ← to investigate...

Synthetic Data – Comparison of the Number of BN Returned

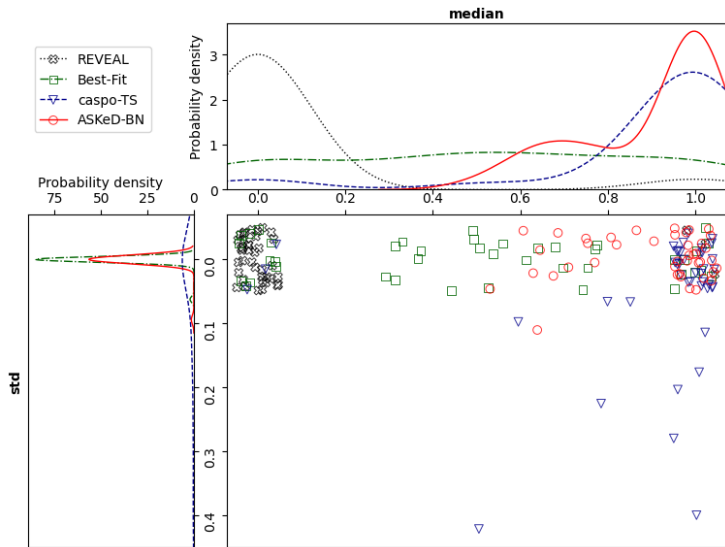
336 experiments at total including 42 with the ARN* setting.

	setting	REVEAL		Best-Fit		caspo-TS	ASKeD-BN
		before filter	after filter	before filter	after filter		
# failing xp	all	230	240	0	64	20	0
# total returned BNs	all	100 677 500	406	100 678 198	724	8481	1210
# total returned BNs	ARN	3	3	51	35	720	85

- ▶ REVEAL often fails
- ▶ REVEAL and Best-Fit return a lots of BNs which are not respecting the PKN
- ▶ caspo-TS returns in average between 5 and 7 times more BNs than ASKeD-BN (depending on the setting)

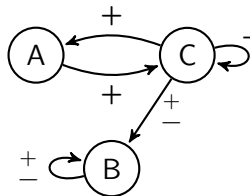
*: ARN = Asyn. update scheme, with repetition and noise

Synthetic data, ARN setting – Quality of the BNs



ASKeD-BN: Hard Constraints

- “A activates C”
 - “B interacts with itself”
 - “C activates A”
 - “C interacts with B”
 - “C inhibits itself”
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ASKeD-BN: Hard Constraints

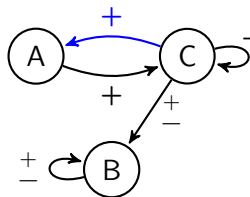
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For A:

3 choices:

A := C

A := 0

A := 1

but not:

A := B

A := \neg C

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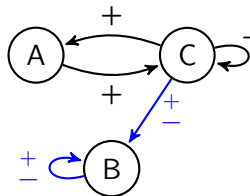
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3 choices:

$A := C$

$A := 0$

$A := 1$

but not:

$A := B$

$A := \neg C$

For B:

16 choices:

$B := B \wedge \neg C$

$B := (B \wedge \neg C) \vee (\neg B \wedge C);$

...

$B := 0$

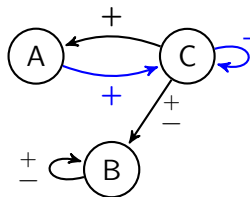
$B := 1$

but not:

$B := A$

ASKeD-BN: Hard Constraints

- “A activates C”
- “B interacts with itself”
- “C activates A”
- “C interacts with B”
- “C inhibits itself”



For A:

3 choices:

$A := C$

$A := 0$

$A := 1$

but not:

$A := B$

$A := \neg C$

For B:

16 choices:

$B := B \wedge \neg C$

$B := (B \wedge \neg C) \vee (\neg B \wedge C);$

...

$B := 0$

$B := 1$

but not:

$B := A$

For C:

6 choices:

$C := \neg C$

$C := A$

...

$C := 0$

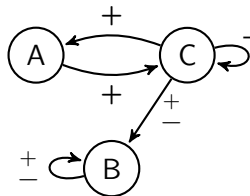
$C := 1$

but not:

$C := A \wedge B$

ASKeD-BN: Hard Constraints

- “A activates C”
- “B interacts with itself”
- “C activates A”
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3 choices:

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...

$B := 0$

$B := 1$

but not:

$B := A$

For C:

6 choices:

$C := \neg C$

$C := A$

...

$C := 0$

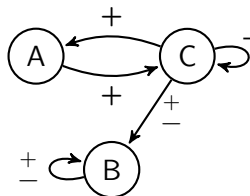
$C := 1$

but not:

$C := A \wedge B$

ASKeD-BN: Hard Constraints

- “A activates C”
- “B interacts with itself”
- “C activates A”
- “C interacts with B”
- “C inhibits itself”



For A:

3 choices:

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but not:

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For B:

16 choices:

$B := B \wedge \neg C$

$B := (B \wedge \neg C) \vee (\neg B \wedge C);$

...

$B := 0$

$B := 1$

but not:

$B := A$

For C:

6 choices:

$C := \neg C$

$C := A$

...

$C := 0$

$C := 1$

but not:

$C := A \wedge B$

ASKeD-BN: Soft constraints — Example 1

	010		→ 011		→ 100		→ 001													
t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
A	0	3	7	13	20	30	49	61	100	63	36	25	2	3	1	1	3	0	0	0
B	100	86	64	57	54	53	51	49	45	37	33	28	22	19	14	12	9	5	2	0
C	0	27	36	42	60	75	54	44	38	48	60	72	88	90	100	100	100	100	100	100

\mathcal{U} set of unexplained timesteps

$$\text{Mean Absolute Error MAE}_X = \frac{\sum_{t' \in \mathcal{U}} |\theta_X - x_{t'}|}{T}$$

	$a_{t+1} = c_t$	✓	$a_{t+1} = 0$
\mathcal{U}	\emptyset		$\{8\}$
MAE	0	✓	0.55

ASKeD-BN: Soft constraints — Example 2

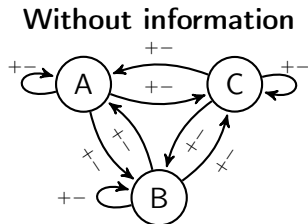
	010		→ 011		→ 100		→ 001													
t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
A	0	3	7	13	20	30	49	61	100	63	36	25	2	3	1	1	3	0	0	0
B	100	86	64	57	54	53	51	49	45	37	33	28	22	19	14	12	9	5	2	0
C	0	27	36	42	60	75	54	44	38	48	60	72	88	90	100	100	100	100	100	100

\mathcal{U} set of unexplained timesteps

$$\text{Mean Absolute Error MAE}_X = \frac{\sum_{t' \in \mathcal{U}} |\theta_X - x_{t'}|}{T}$$

	$b_{t+1} = b_t \wedge \neg c_t$	✓	$b_{t+1} = (b_t \wedge \neg c_t) \vee (\neg b_t \wedge c_t)$	
\mathcal{U}	\emptyset		\emptyset	
MAE	0	✓	0	✓
# influences	2	✓	4	

How does the PKN help reducing the search space?



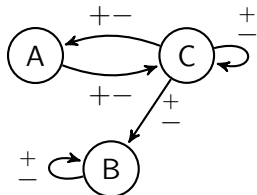
$2^{2^3} = 256$ candidates for each components

→ $256 \times 256 \times 256 = 16777216$ candidate BNs

How does the PKN help reducing the search space?

With PKN

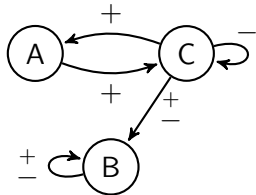
directions only
(REVEAL & Best-Fit)



A	B	C
4	16	16

$\rightarrow 4 \times 16 \times 16 = 1024$
candidate BNs

direction + signs
(caspo-TS & ASKeD-BN)



	A	B	C
all	3	16	6
monotonous	3	14	6

$\rightarrow 3 \times 16 \times 6 = 288$
candidate BNs
including 252 locally
partial-monotonous.