

Sudoku

An application of message passing

Heiko Bauke, Andrzej Görlich, Satish Korada,
Cyril Measson, Thierry Mora, Olivier Rivoire

数独

Classical Sudoku



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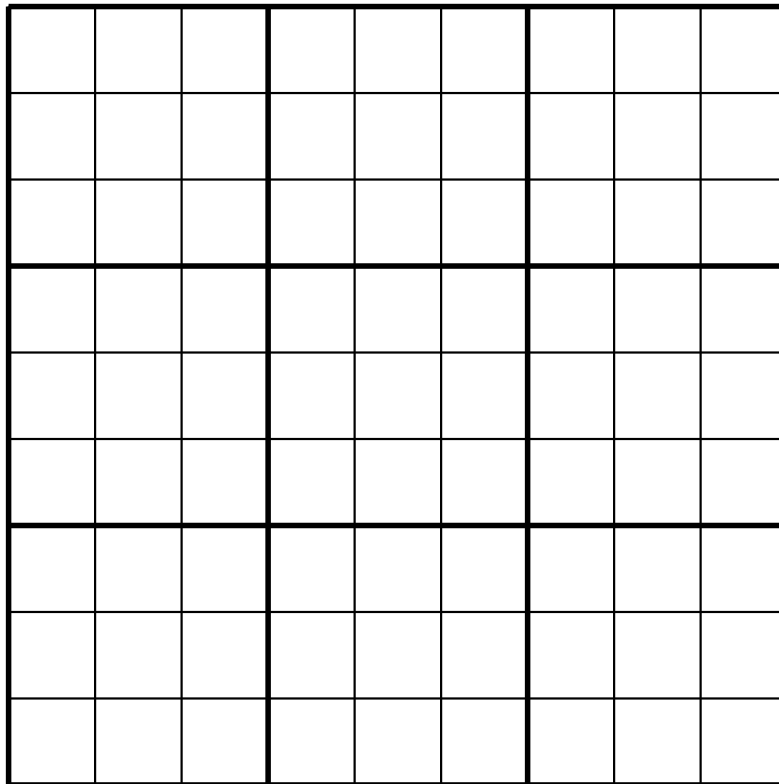
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	7		5		8		3	
		2				9		
	1		6		4		5	
5								6
	2		1		5		9	
		4				7		
	8		7		2		4	
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8	6	2	3	4	7	9	1	5
9	1	3	6	8	4	2	5	7
5	4	7	2	9	3	1	8	6
6	2	8	1	7	5	3	9	4
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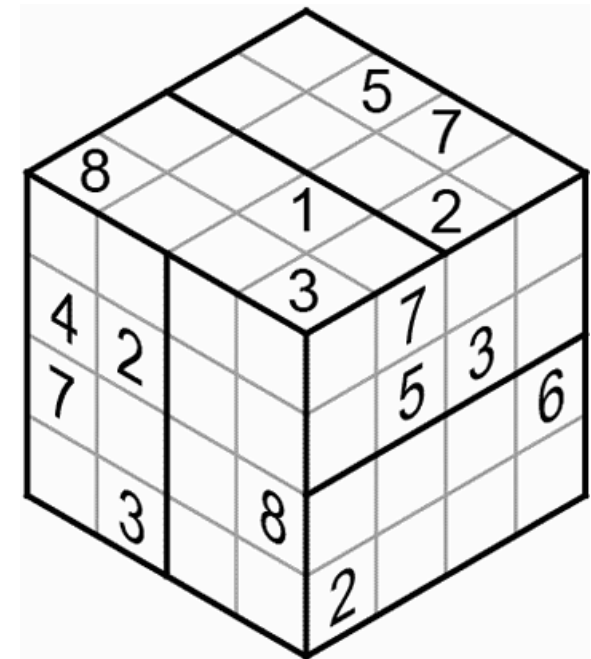
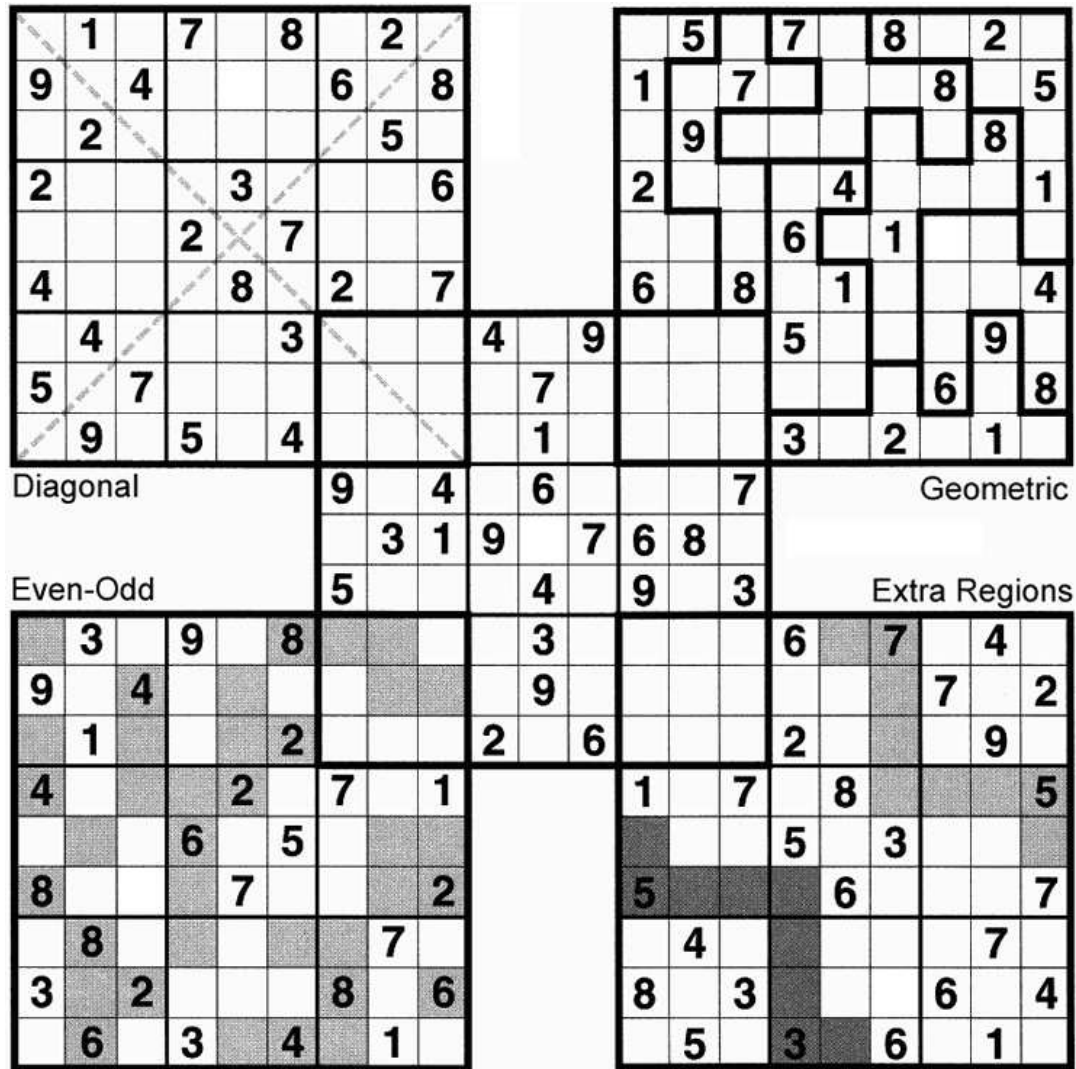
Sudoku variants

- larger Sudokus

									M	W	B	P	E	U	K	Y	A	X	F	T	D	R	I	V	
I		W	O	U	L	D				H	M	V	F	N	Q	T	J	B	E	A	C	S	G	Y	
		D	E	S	I	G	N									P	L	M	U	X	F	K	B	W	
								A		G	R	I	D								L	Q	E	M	N
												L	A	C	K	I	N	G							
																D	U	P	L	I	C	A	T	E	S
		I	N		E	A	C	H																	
S						R	O	W							E	A	H	C	Q	V	N	G	B	D	X
H	P	A	D						B	L	O	C	K			E	G	F	Y	N	M	U	J	W	I
E	Q	C	X	B	G					A	N	D									F	L	Y	H	O
V	W	J	G	T	S	B	F					C	O	L	U	M	N				I	E	Q	K	H
R	X	B	S	F	D	P	K	N	J												O	M	W	A	C
Y	A	U	K	D	O	Q	I	L	C	M	W	R	N	B	F	J	E	H	S	V	P	G	X	T	
Q	O	P	C	L	H	M	E	G	Y	T	K	F	A	V	W	B	I	D	X	U	J	N	S	R	
N	H	M	I	E	V	W	A	T	U	Q	X	J	S	G	P	O	K	C	R	Y	B	F	L	D	
C	S	L	M	H	J	N	D	I	P	K	G	U	T	R	X	F	O	V	B	E	W	A	Y	Q	
W	T	G	R	N	X	V	U	M	O	E	P	B	J	D	H	A	Y	K	Q	S	I	C	F	L	
P	D			X	W	E	T	F					L	C	G	I					N				
U											Q	W	T							R					
O	V			B						I										H		U			
G	L	V		P	F	T		U		R	H		X	W	Y	Q									
	M		Q				L	K	G	J	U			O		R	V								
	U			R	Q	I		S			N														
X	E	Y		M																					

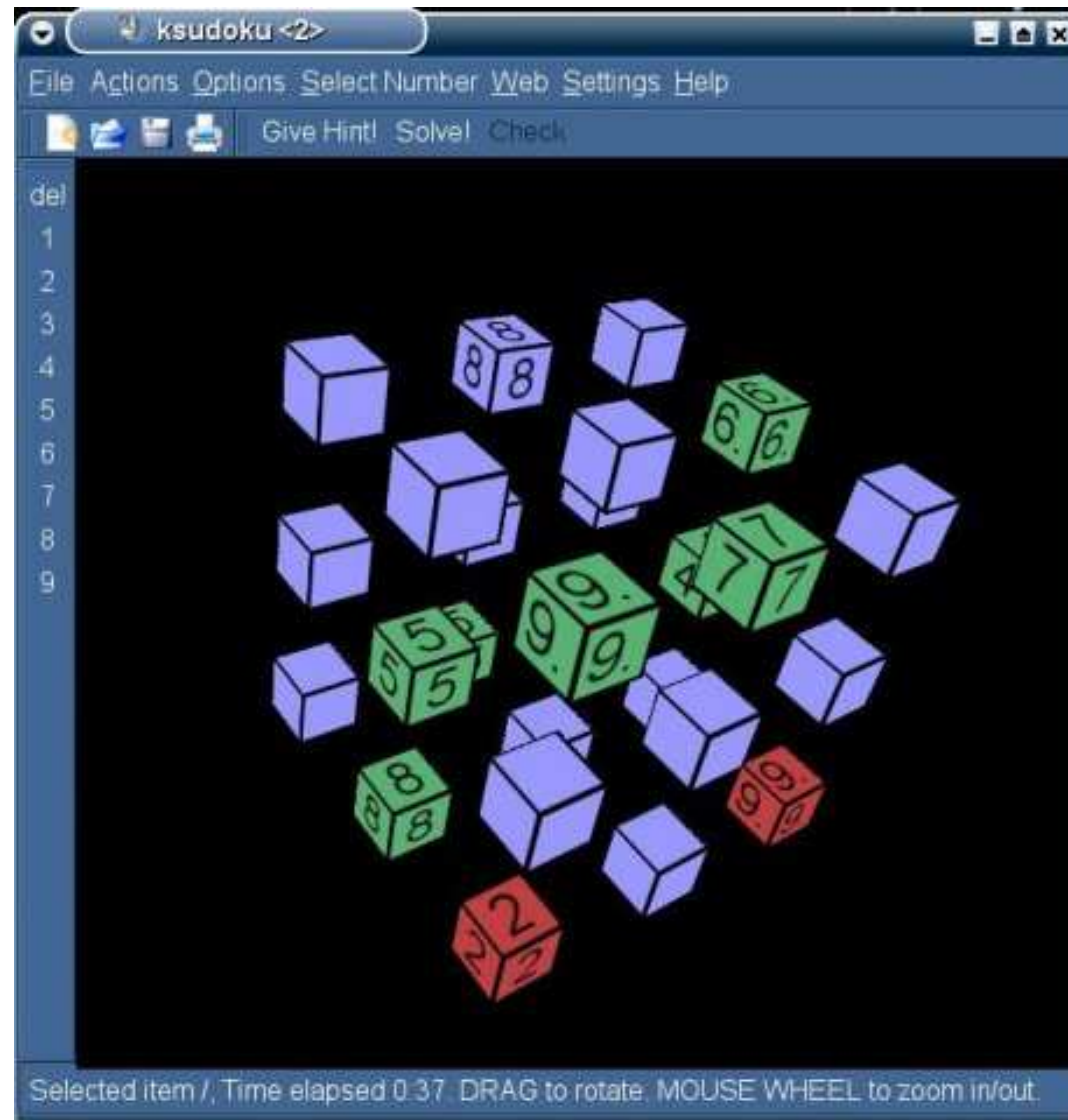
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Sudoku variants

- three-dimensional Sudoku



Sudoku factor graph

- 81 fields $\hat{=}$ variables x_i

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$$p(x_1, x_2, \dots, x_{81}) = \frac{1}{Z} \prod_{i \in \text{cols, rows, squares}} f(x_{i_1}, x_{i_2}, \dots, x_{i_9})$$

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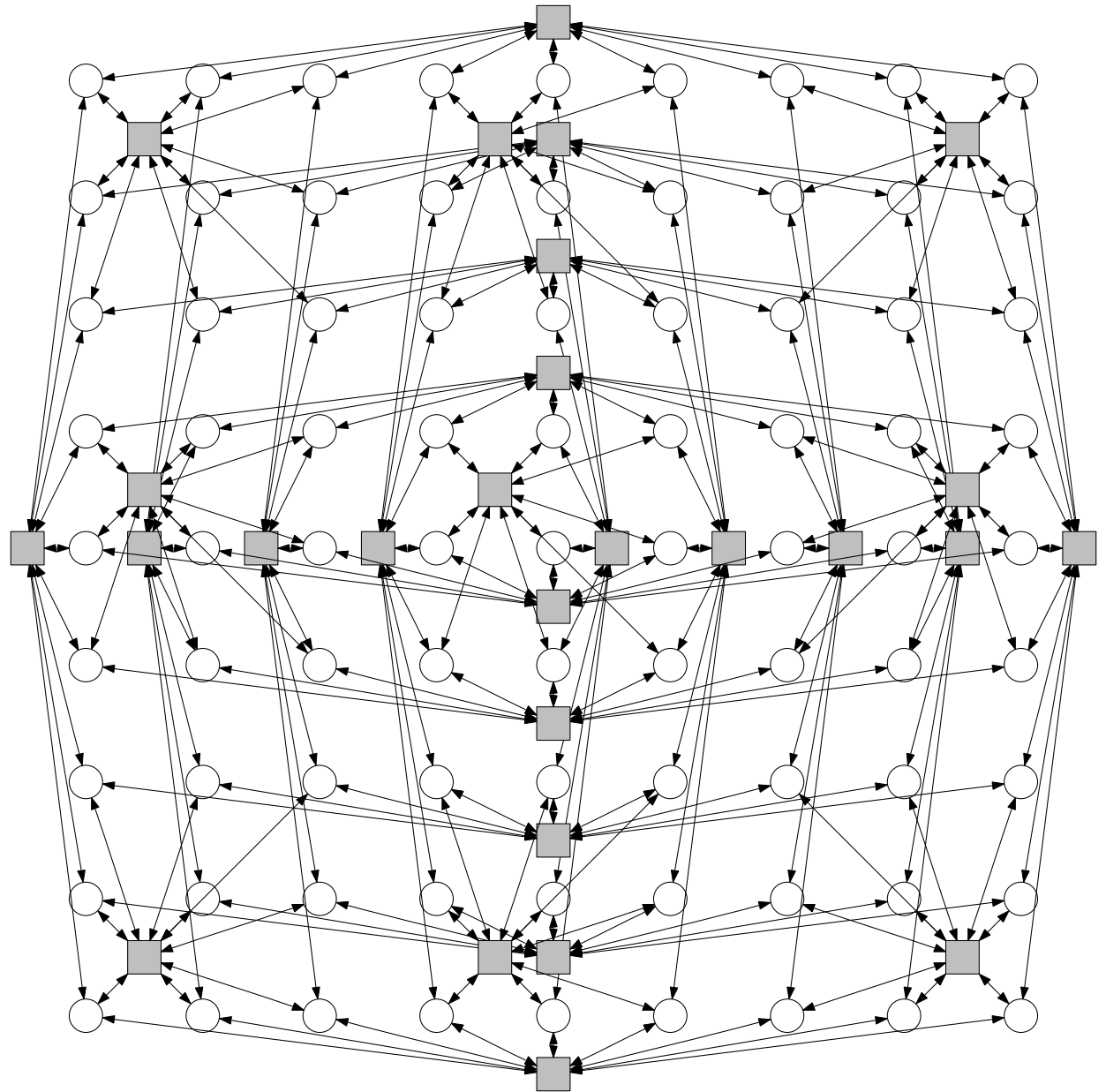
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- probability distribution can be expressed in terms of a factor graph

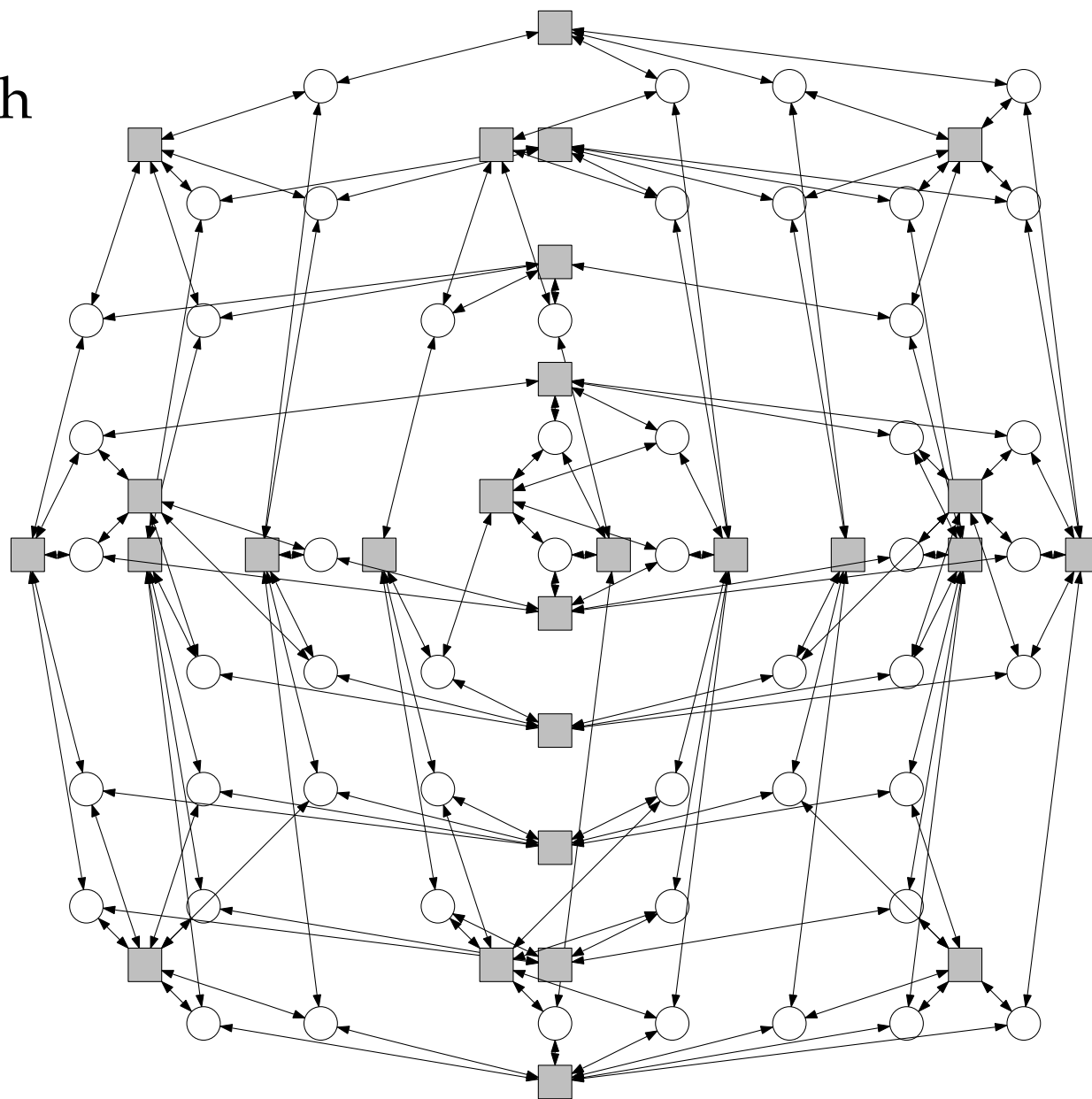
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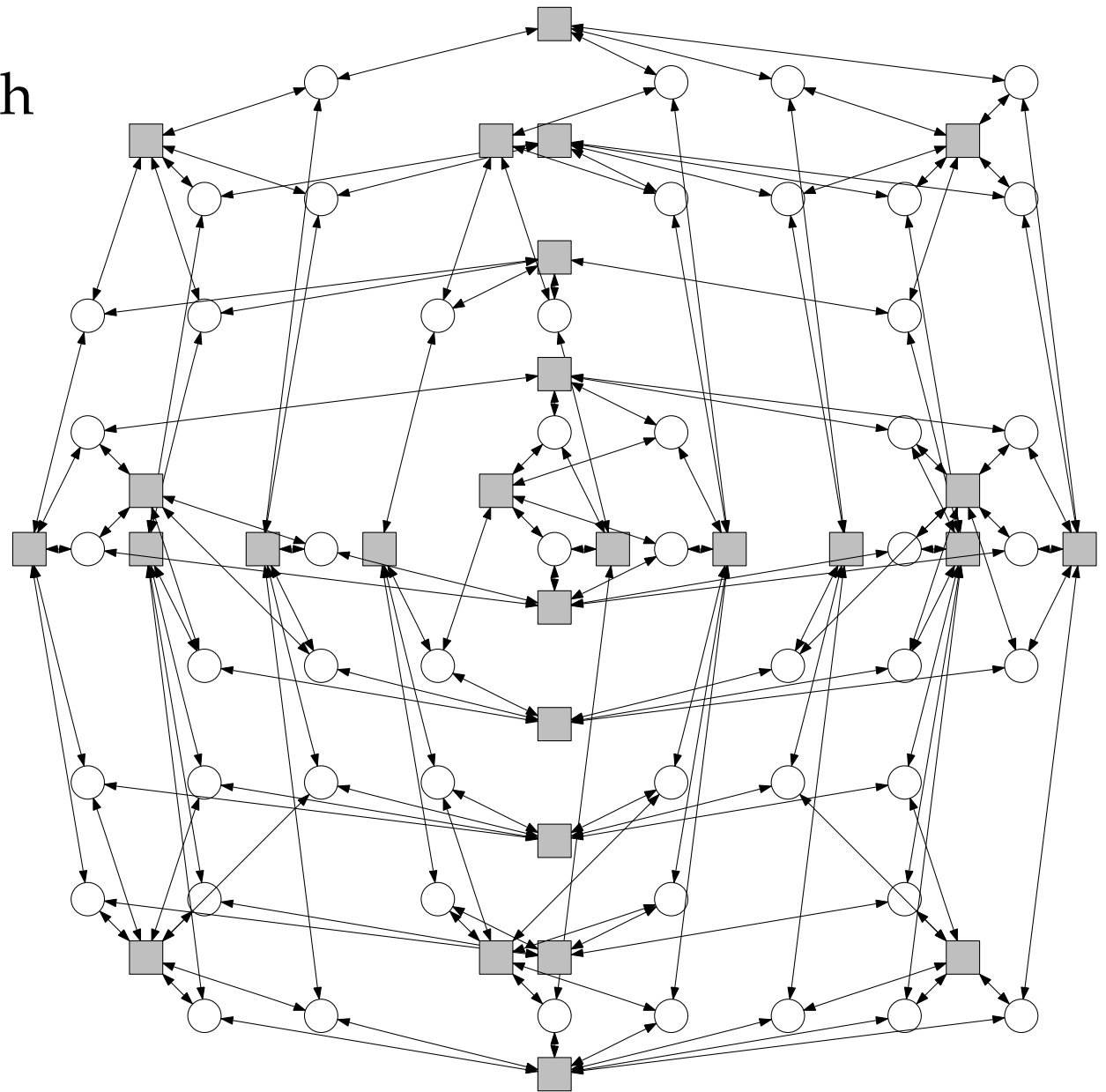
8	2		7	5			4	
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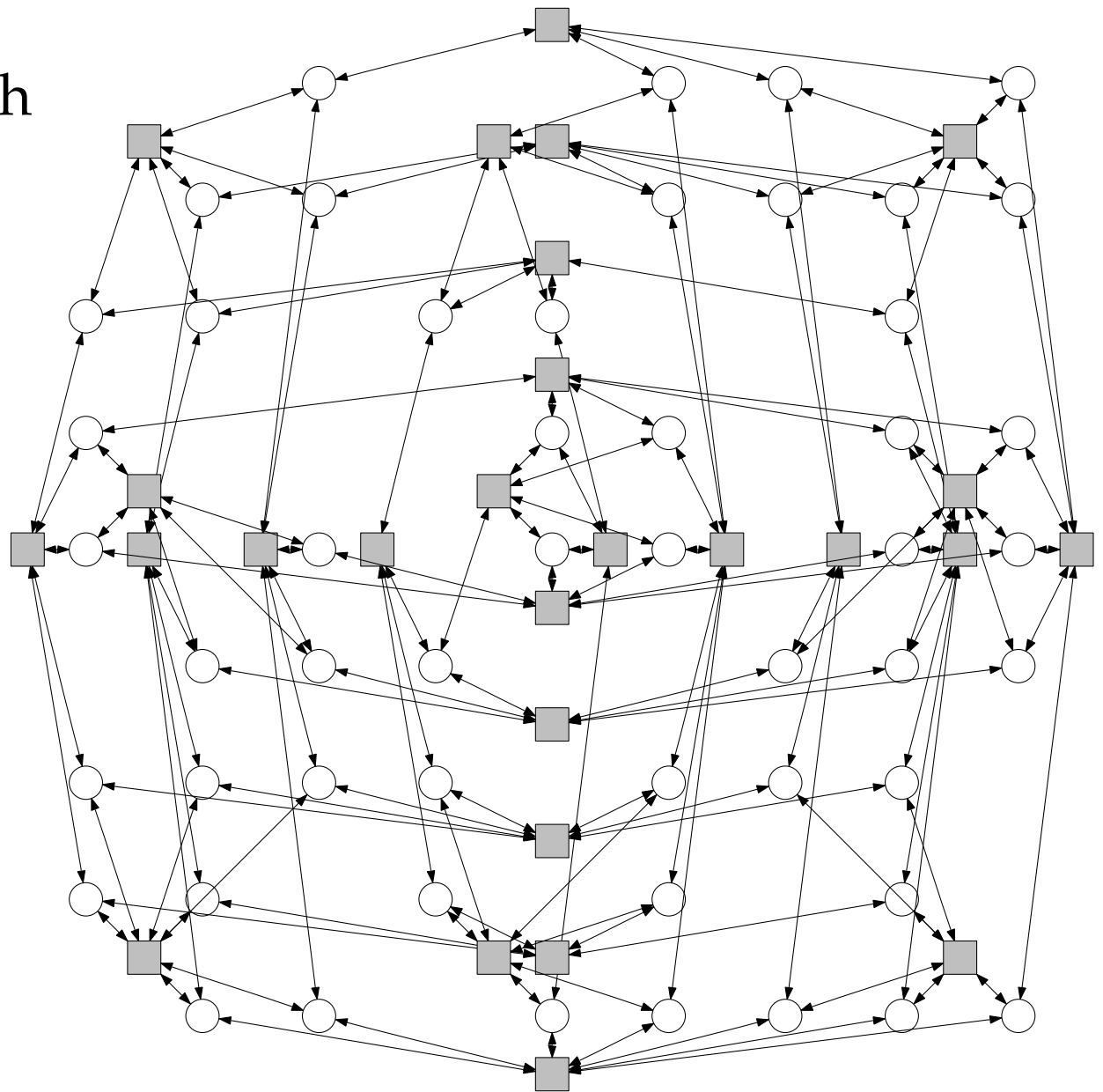
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- Will message passing work?

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- function node processing: marginalisation with respect to x

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\mathbb{K}	“(+, 0)”	“(·, 1)”	algorithm
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$\mathbb{R} \cup \{\infty\}$	(min, ∞)	(+, 0)	min sum
$\mathbb{R} \cup \{-\infty\}$	(max, $-\infty$)	(+, 0)	max sum

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- no numerical instabilities, outperforms sum product algorithm slightly (solves 71 % of Sudokus with 17 givens)

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- What about other message passing schemes, e. g. formulations with binary variables?