Specialised vs Declarative Data Mining

Software Testing Applications

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Join works with: M. Maamar, Y. Lebbah, S. Loudni, C. Bessiere, et. al.

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DATA MINING

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- Tree, Geometric structures…

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Aurora Project: - Execution traces - Flow diagram - Source code	Software Engineering	- Program comprehension - Fault localization/prediction

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In market basket analysis:

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Often found patterns are expressed as association rules, for example:

- **If a customer buys bread and wine, then she/he will probably also buy cheese.**

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- **The need:**
  - The set of itemset P s.t.:

$$freq(P) \geq \theta$$

STANDARD ITEMSET MINING

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	A	B	C	D	E	F	G	H
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t2:	A			D			G	
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  - 128 items 10^{68} itemsets (atoms in the universe)

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- **Dealing with basic user's constraints:**

Frequency, Condensed representations (closedness, maximality,…), Size…

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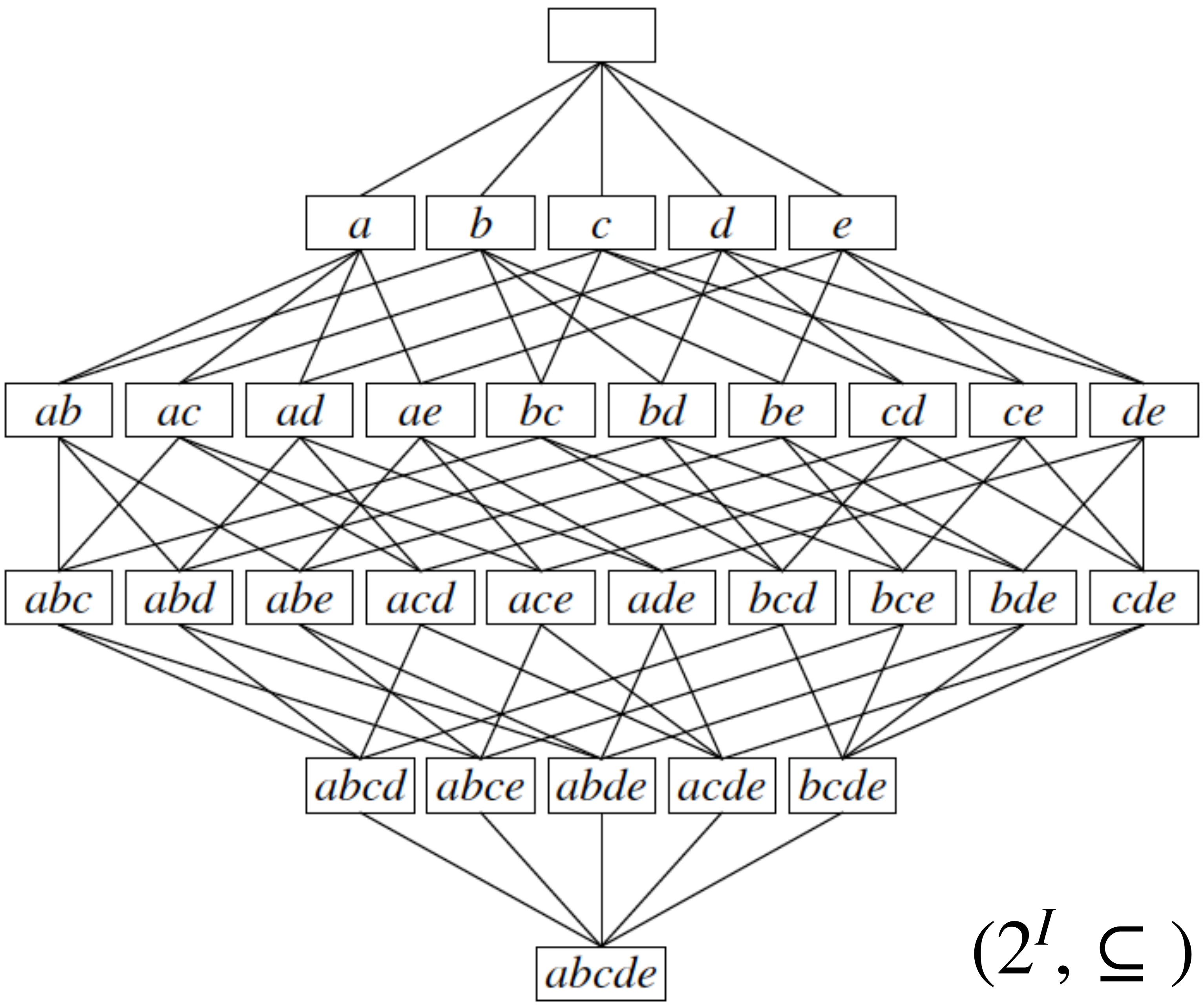

$$(2^I, \subseteq)$$

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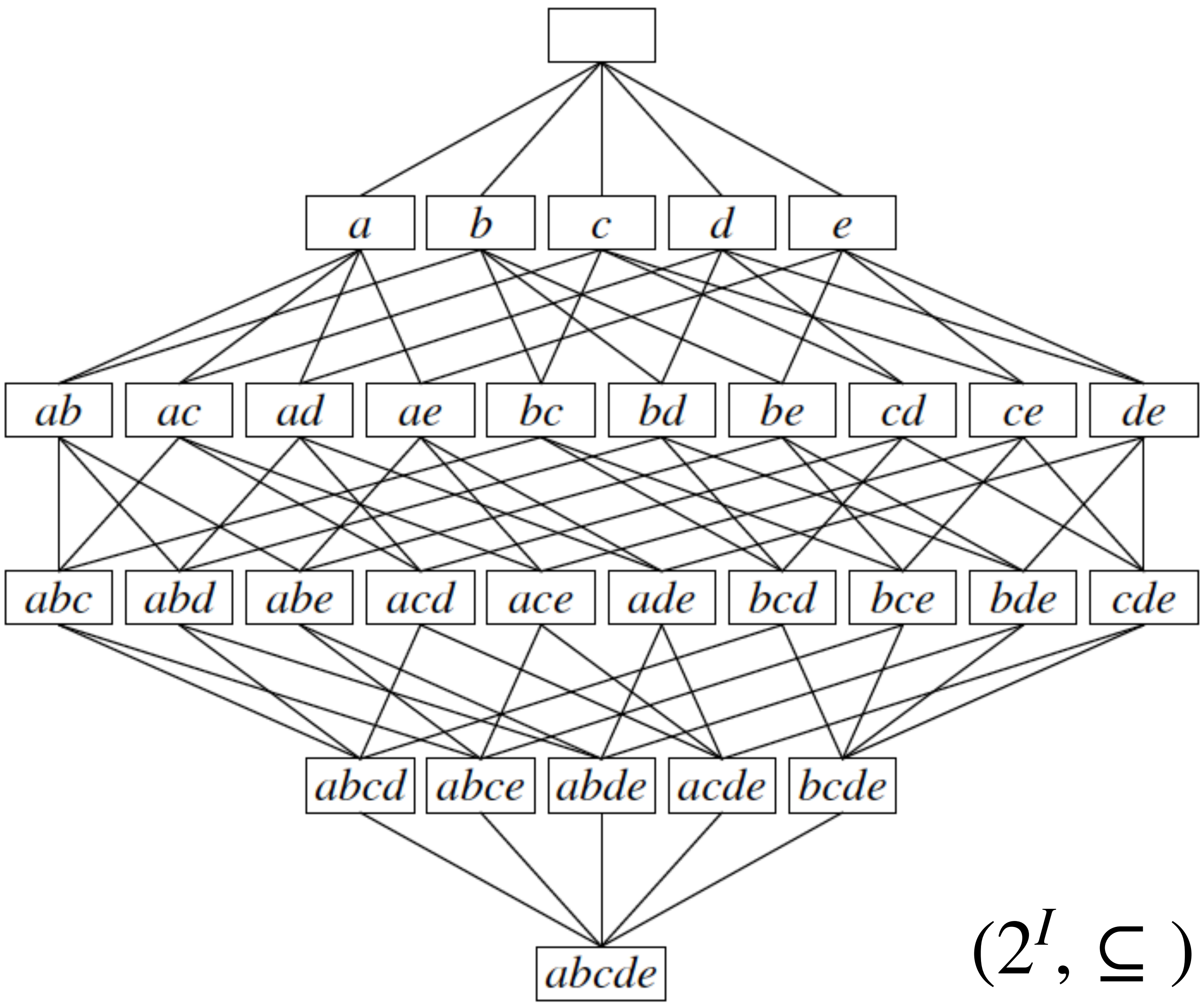

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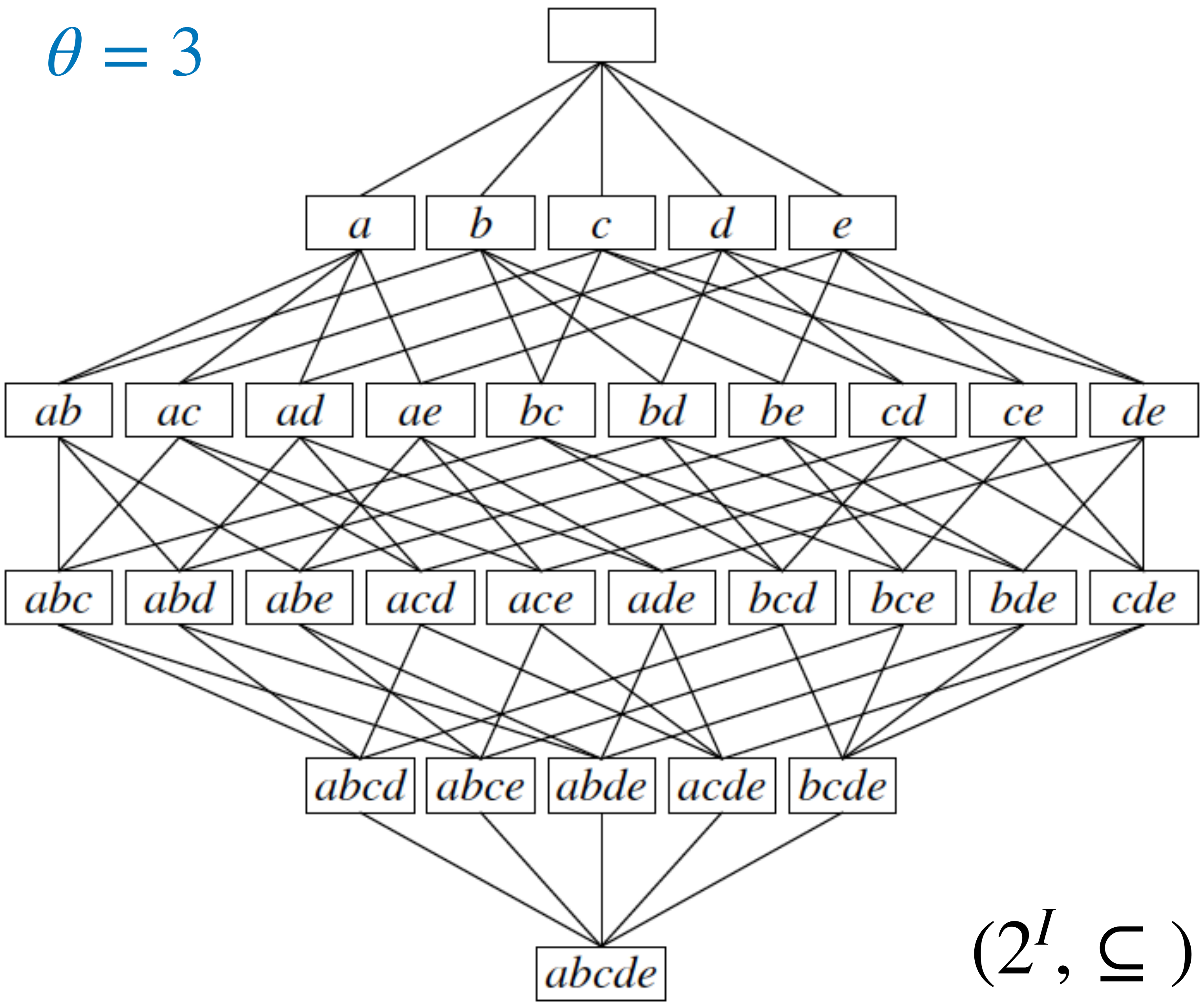

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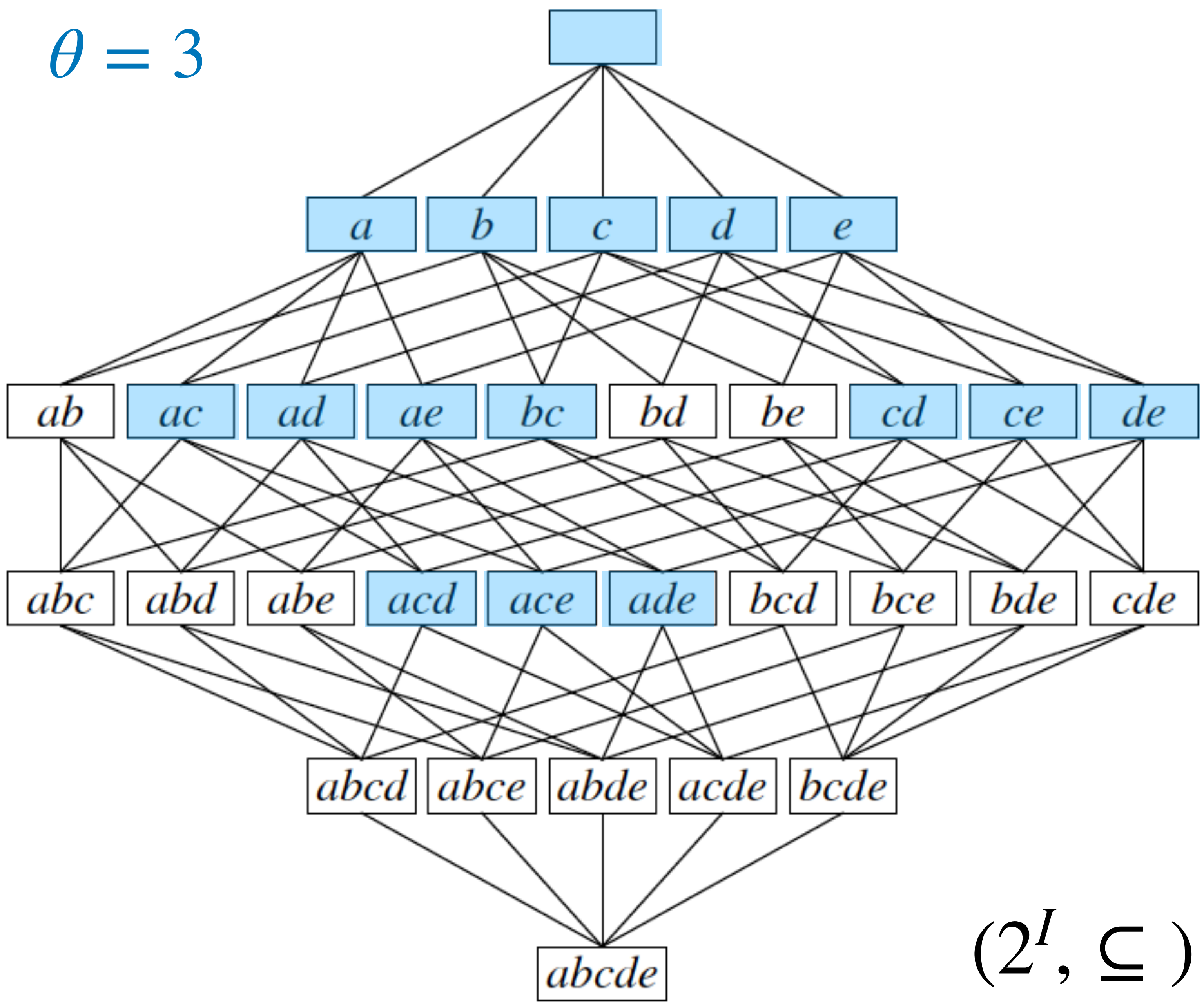

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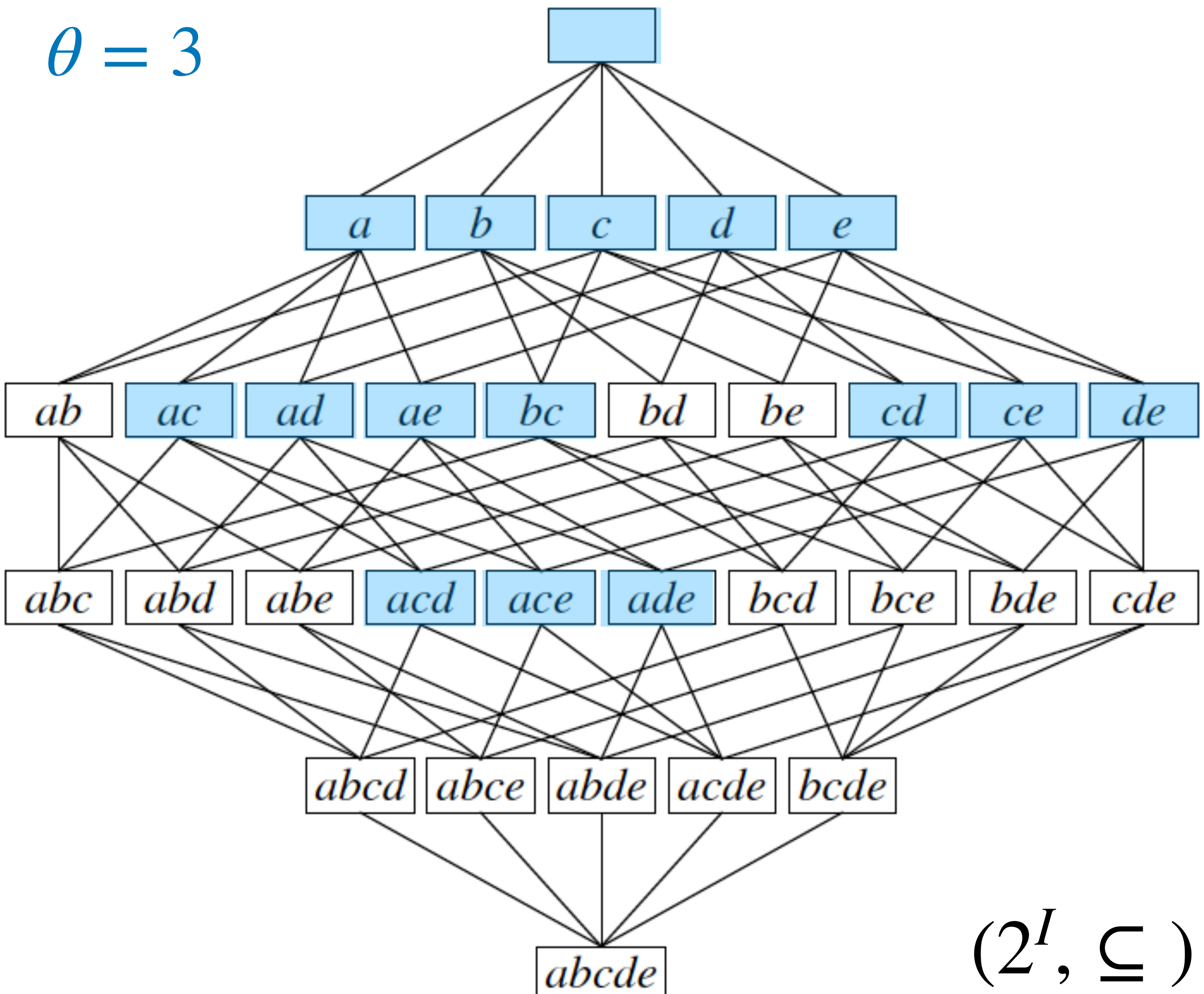

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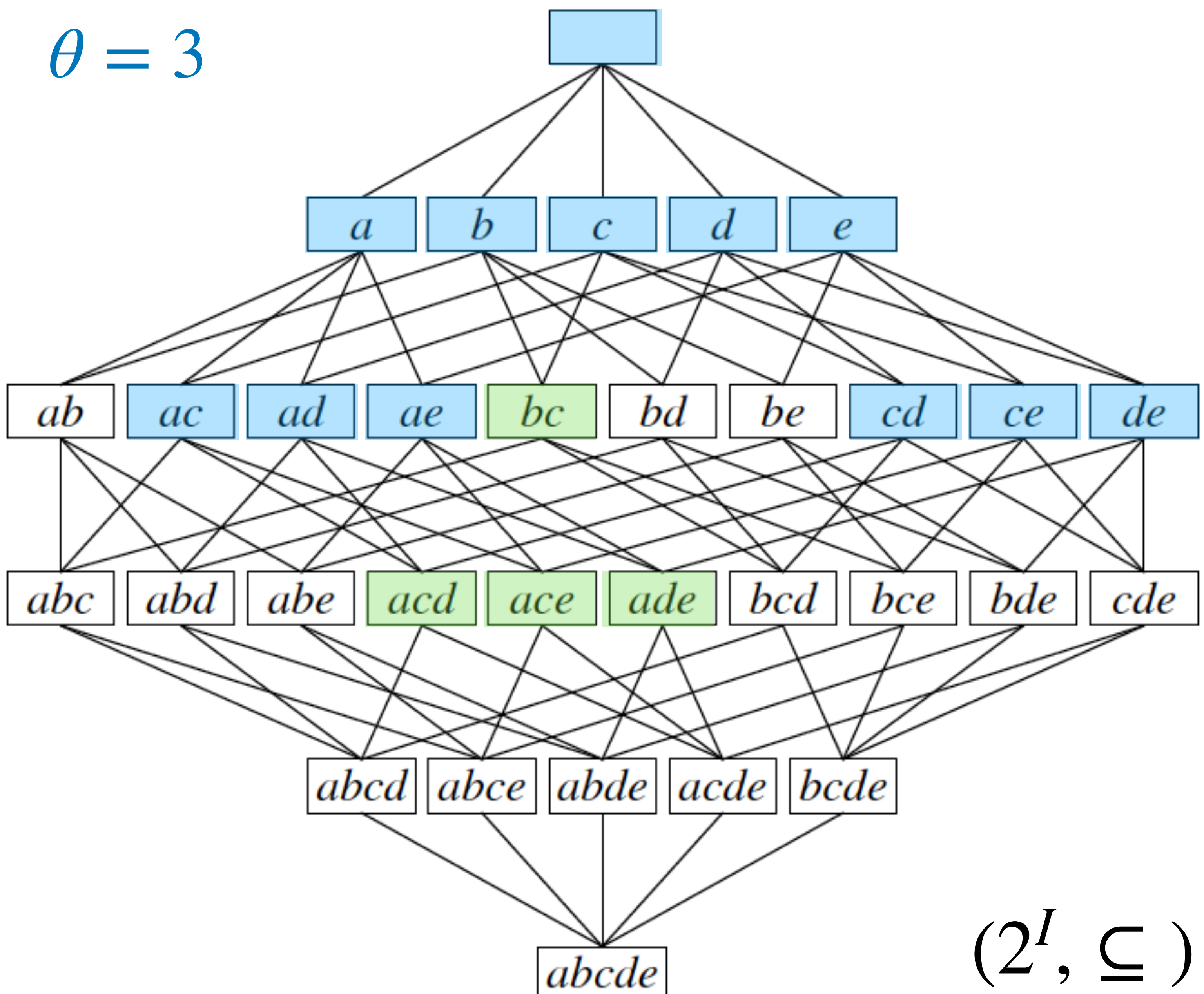

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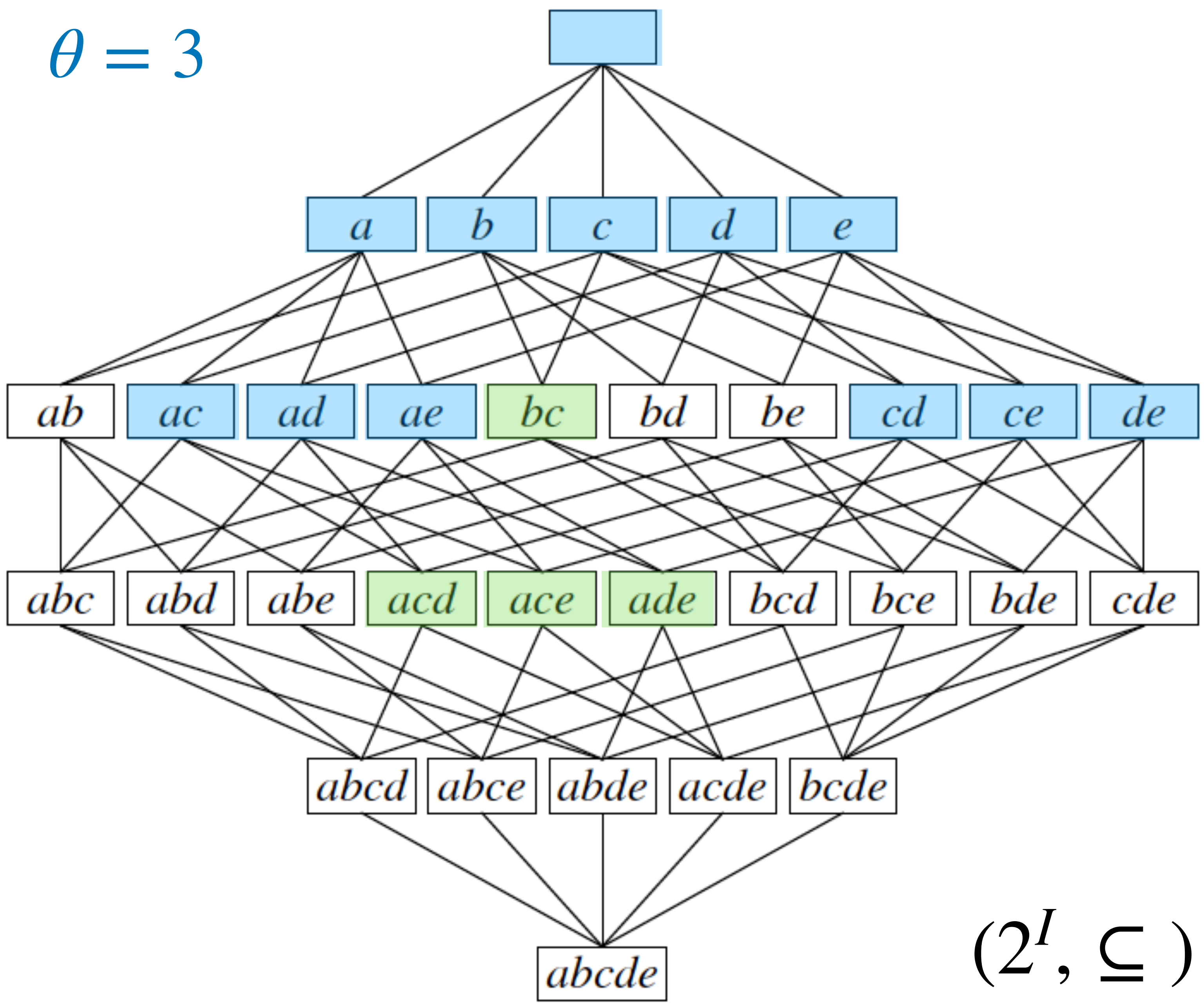

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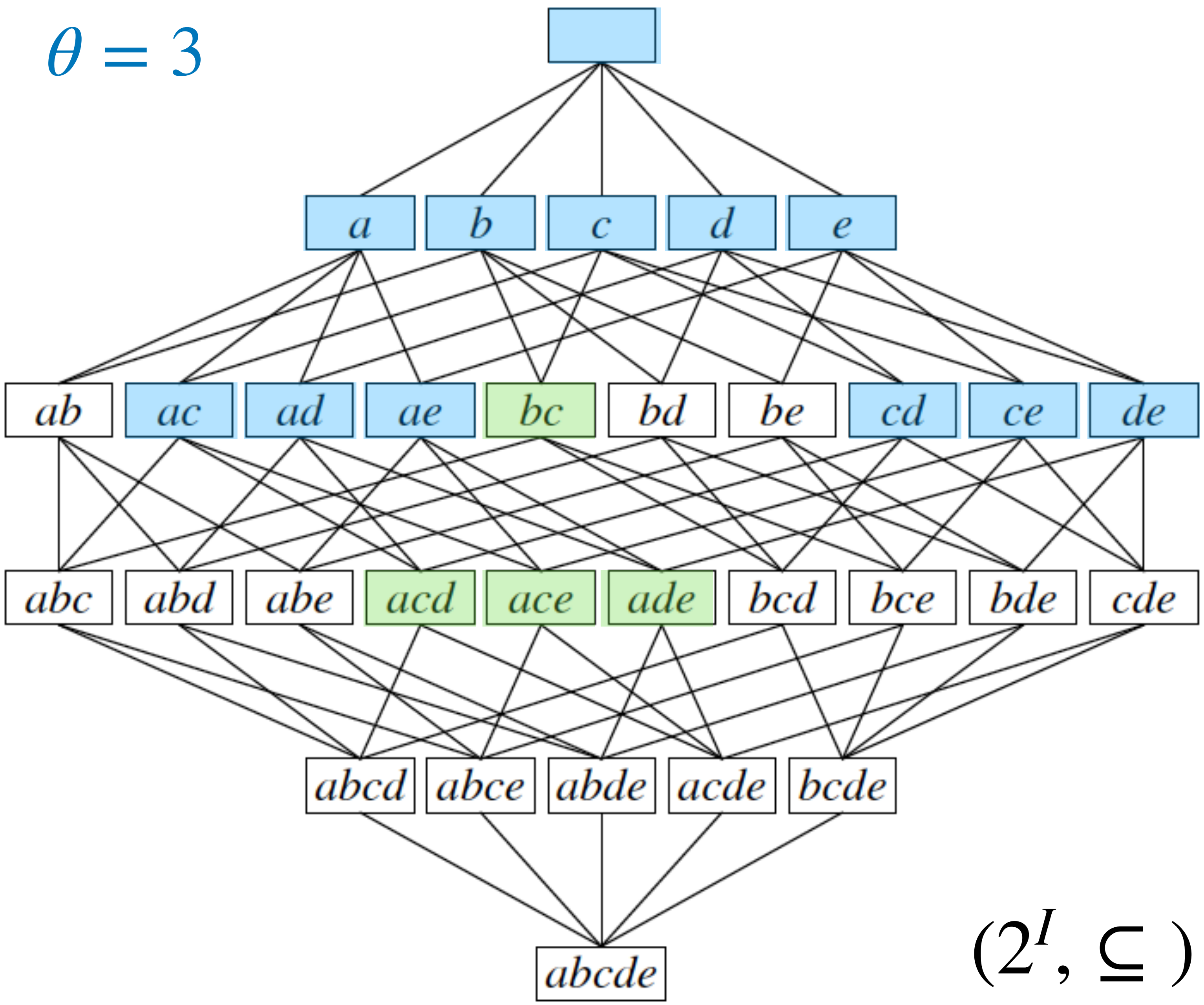

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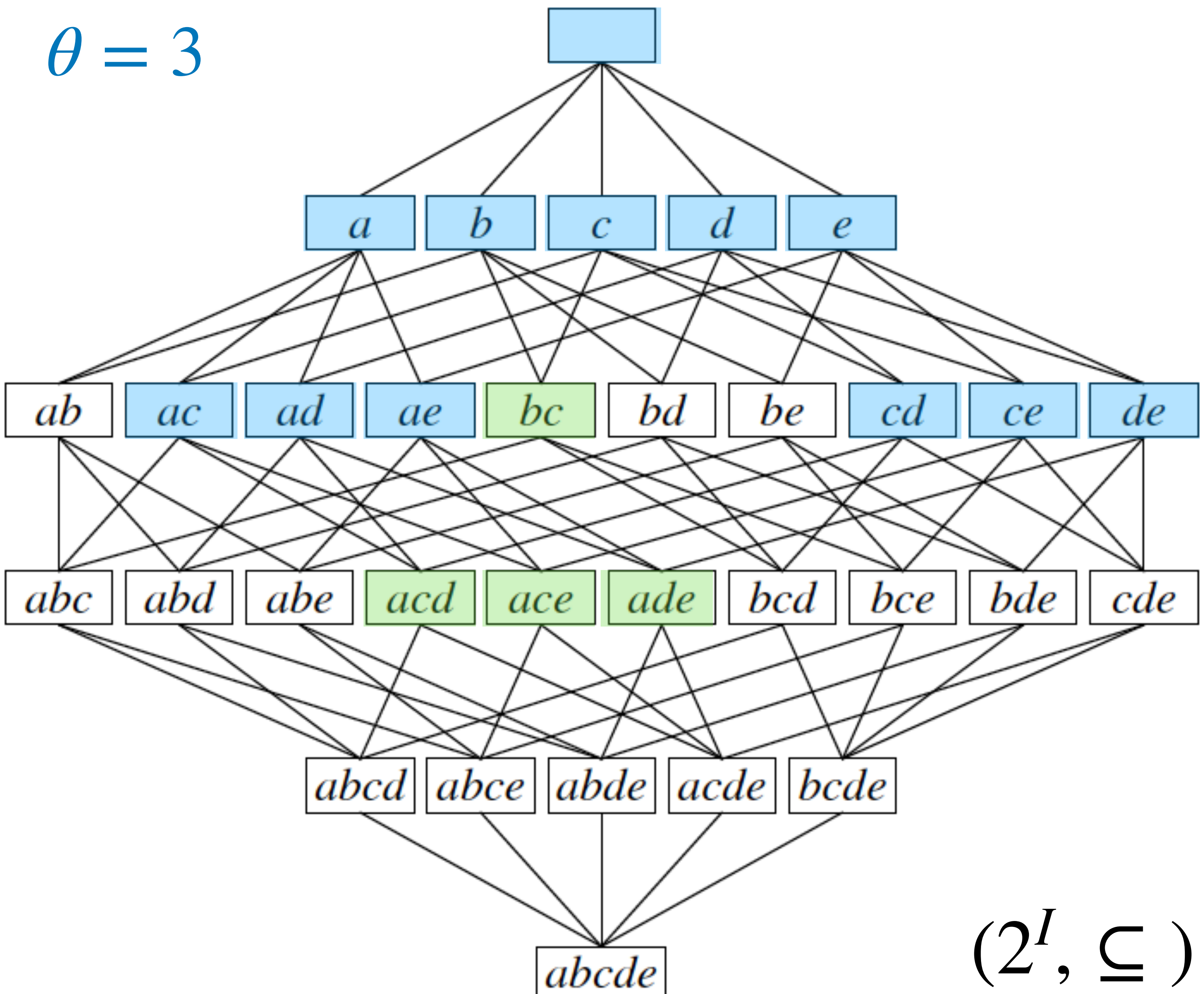

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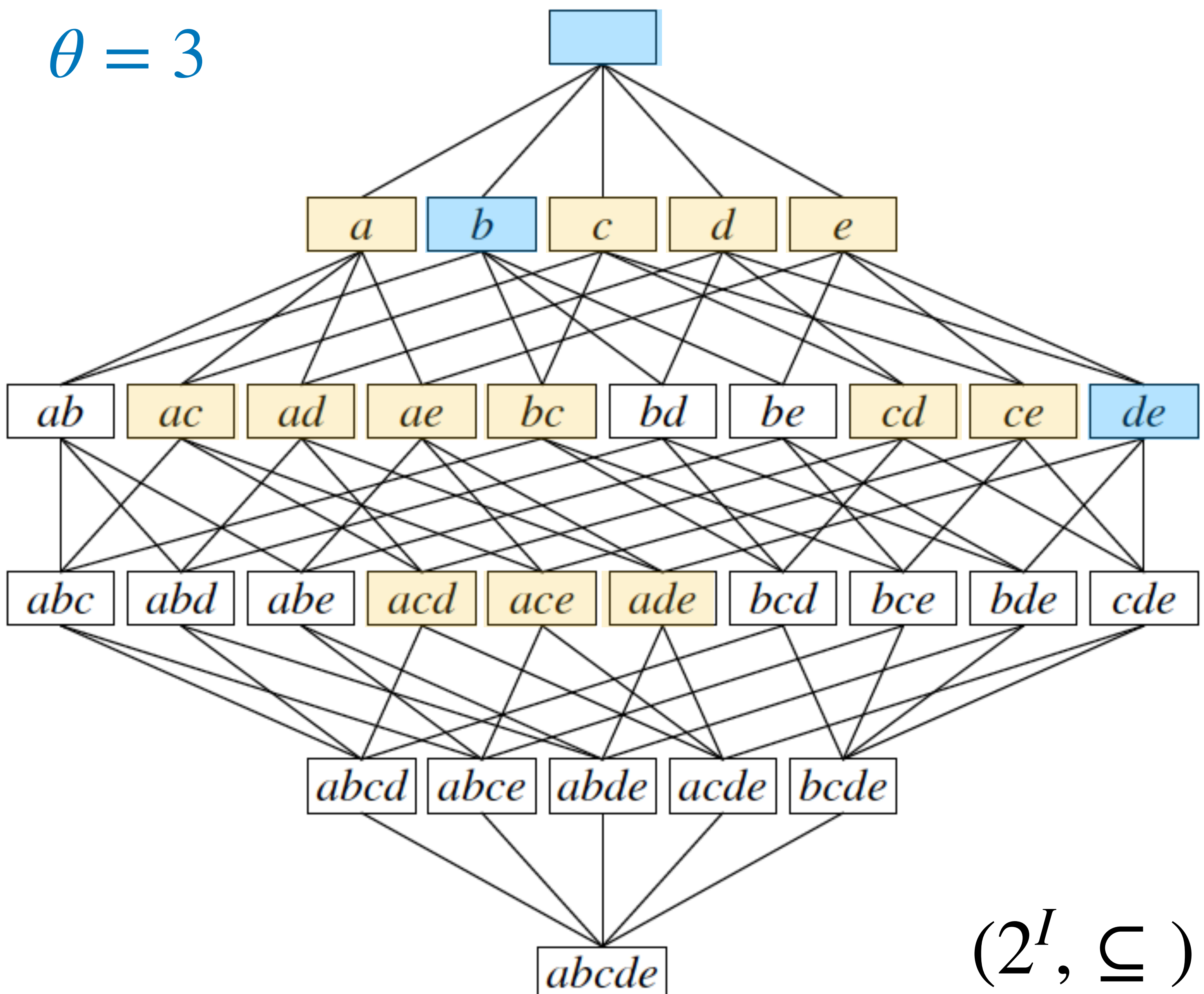

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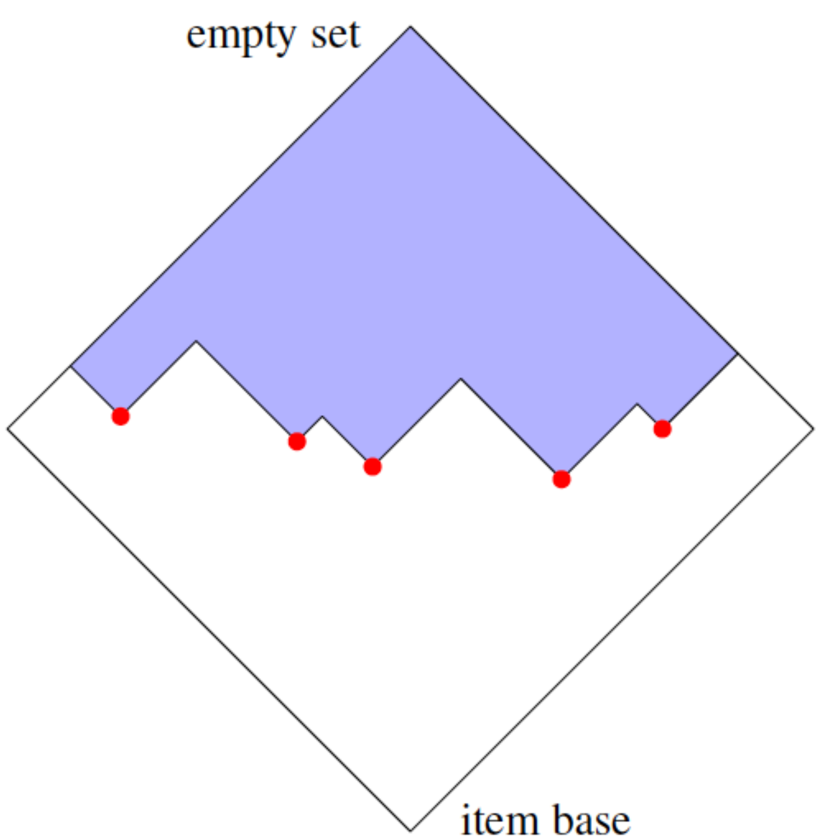

maximal (frequent) item sets

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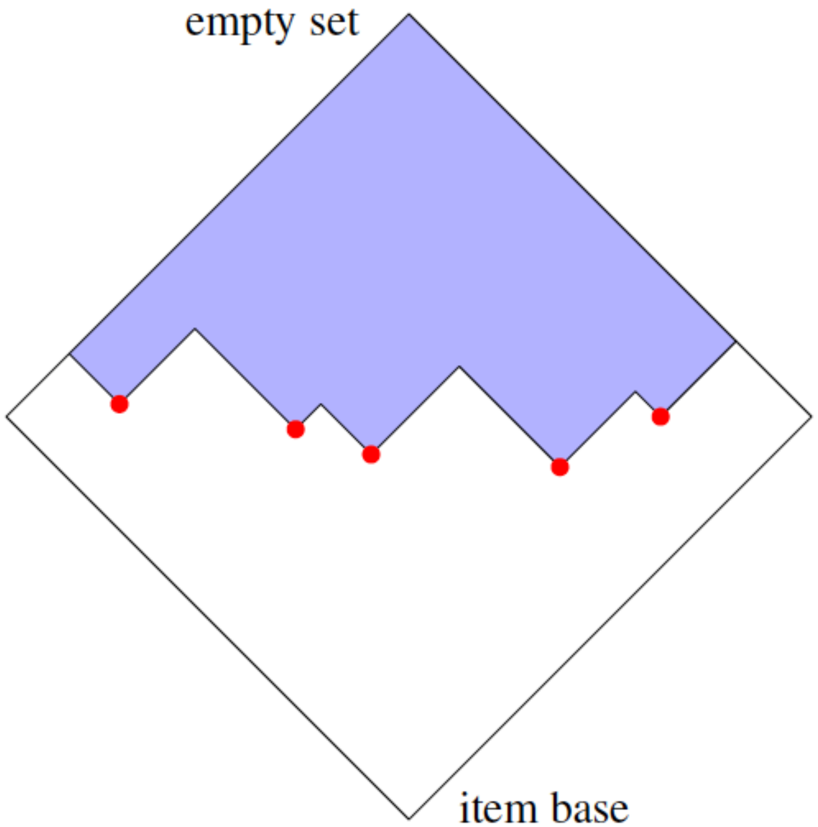

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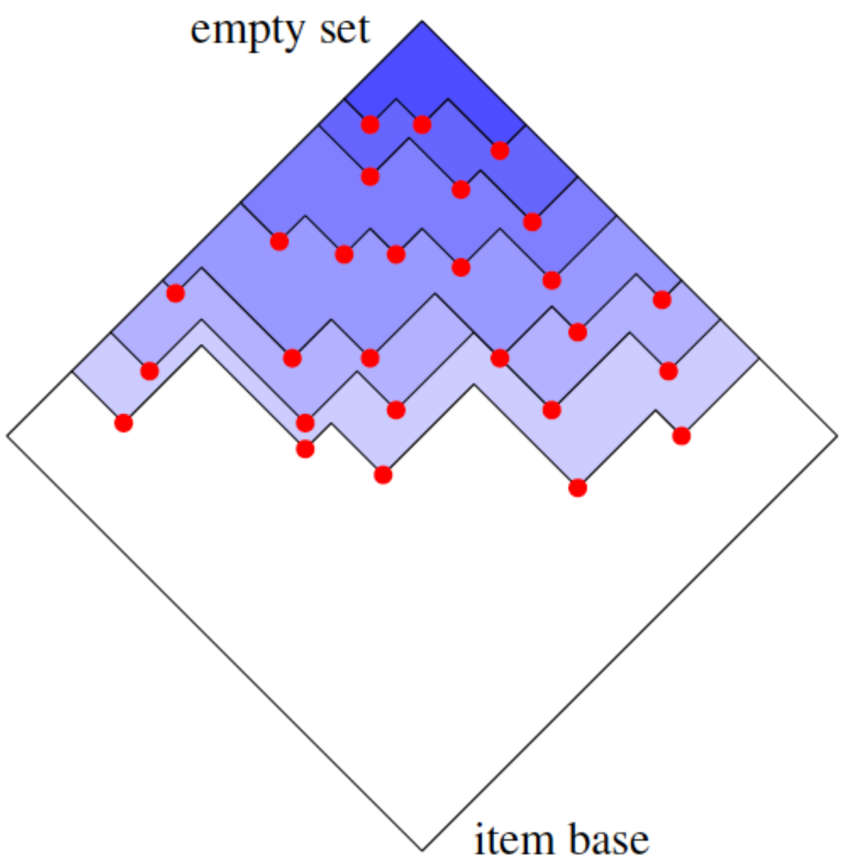

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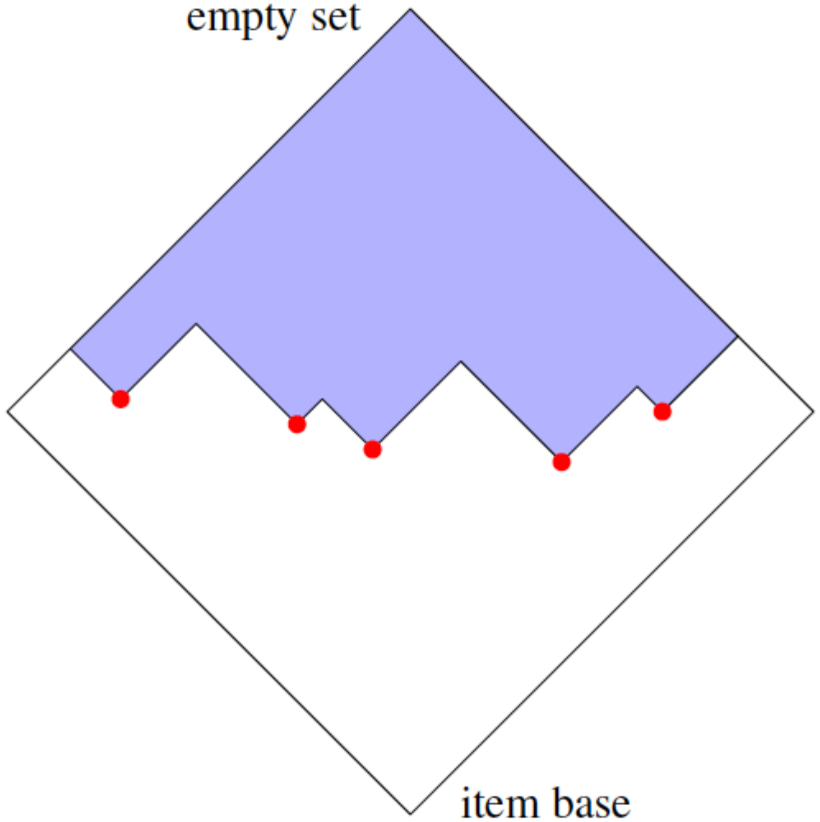

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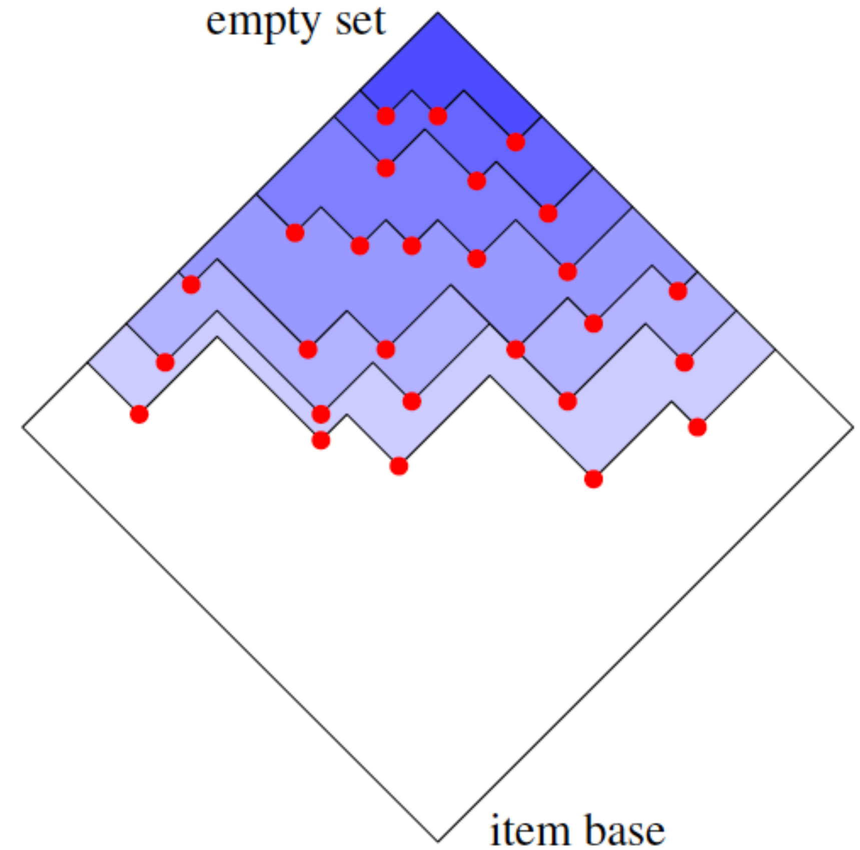

closed (frequent) item sets

Dataset	#Frequent	#Closed	#Maximal
Zoo-1	151 807	3 292	230
Mushroom	155 734	3 287	453
Lymph	9 967 402	46 802	5 191
Hepatitis	27 . 10^7	1 827 264	189 205

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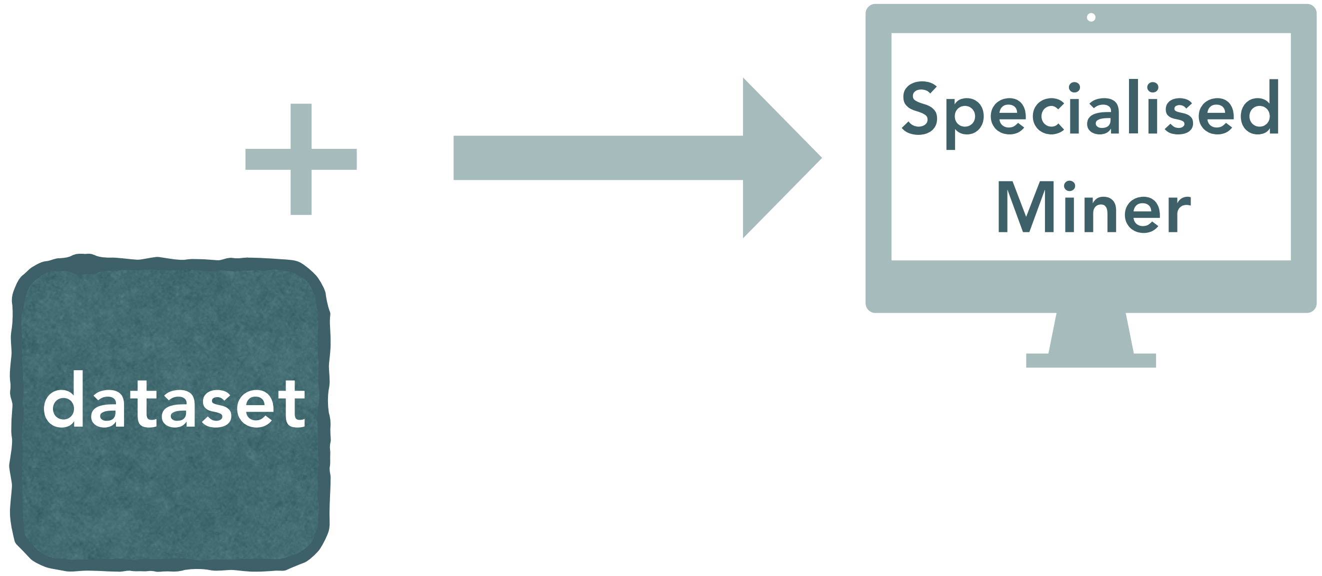

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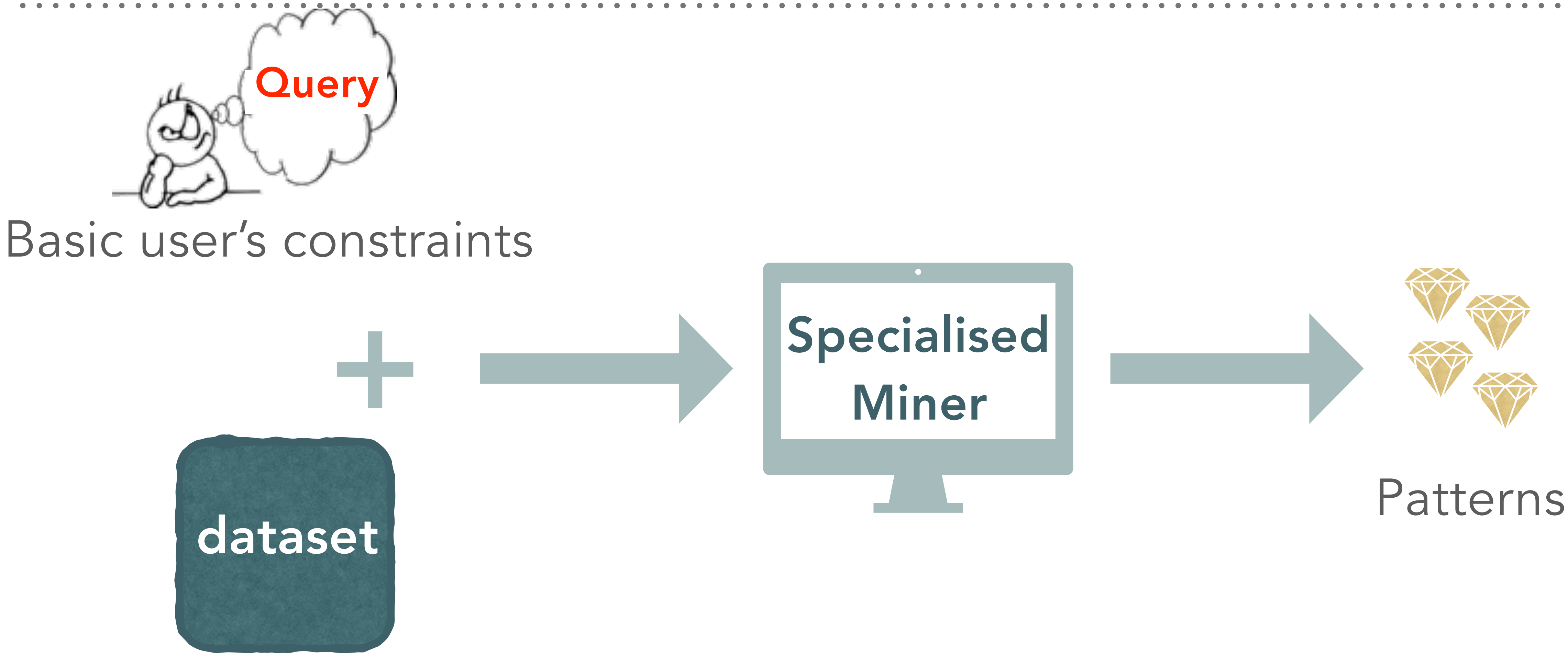

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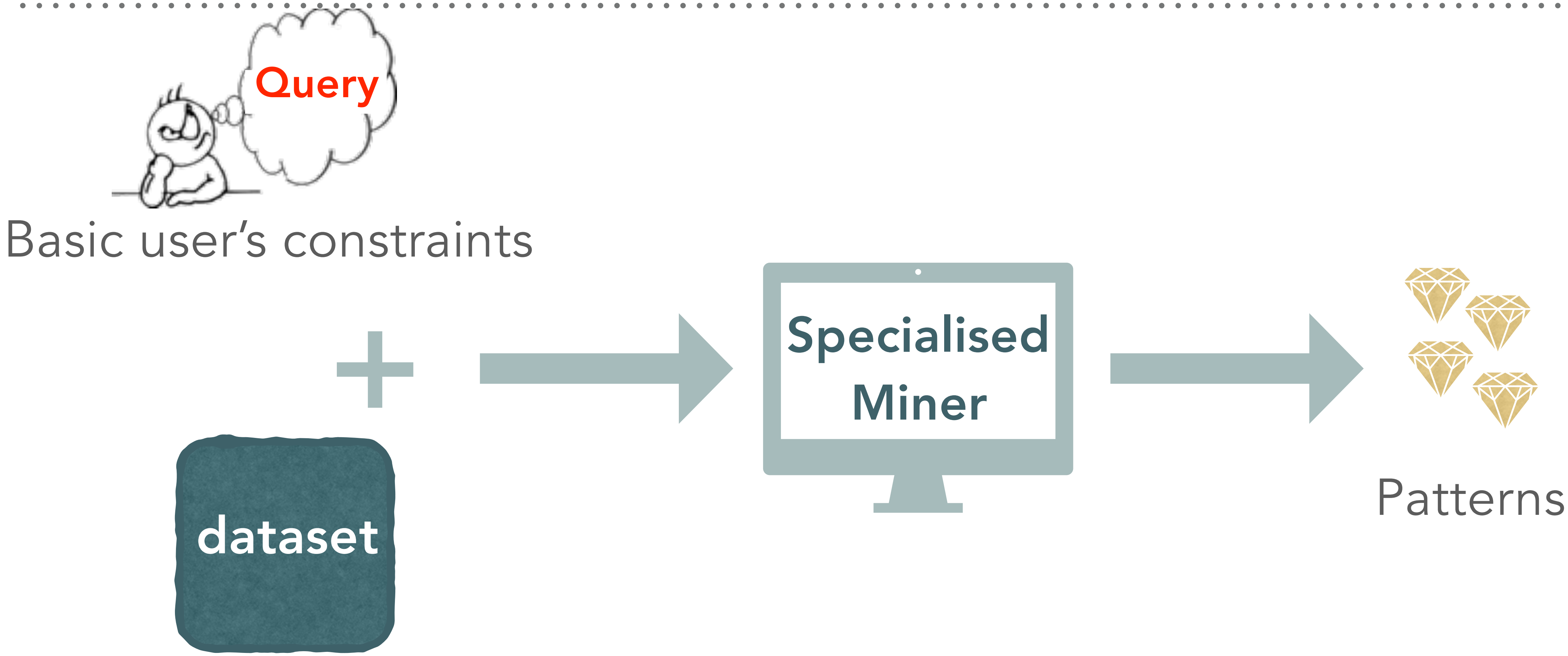

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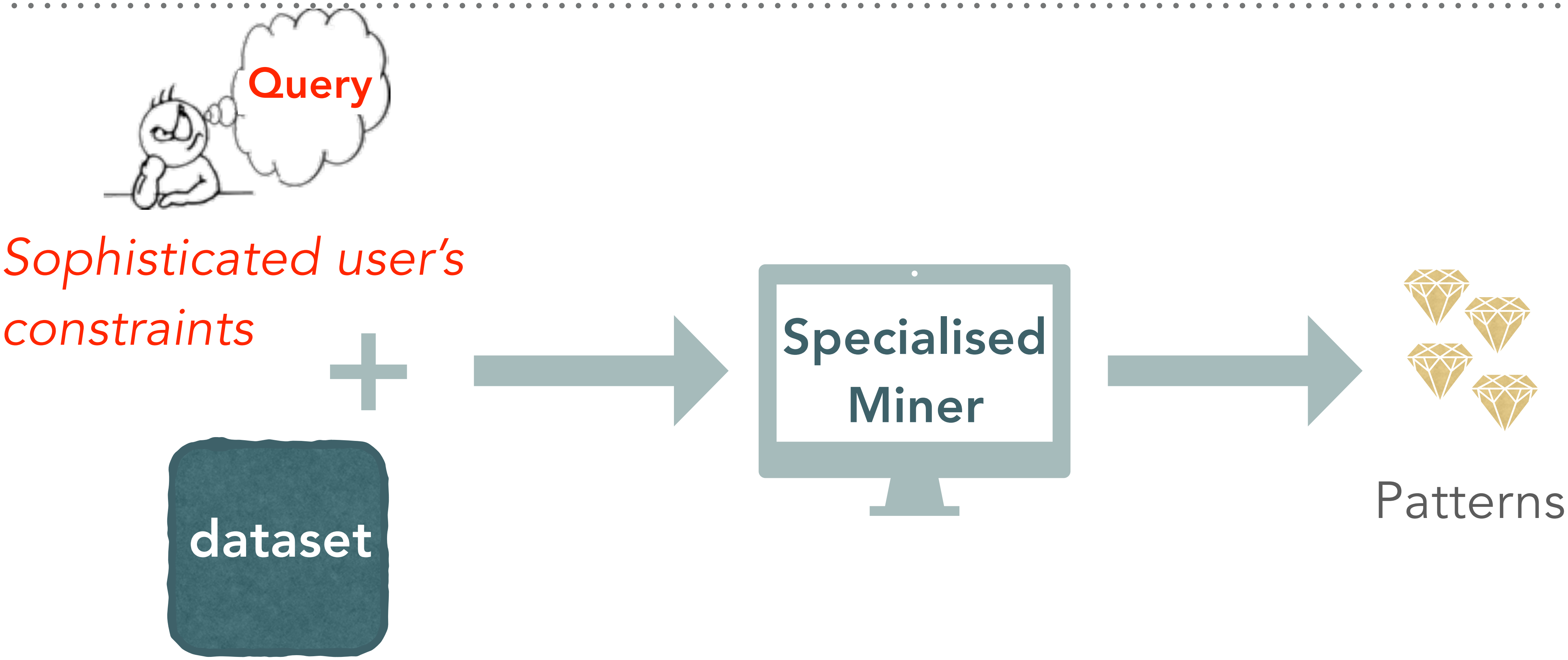

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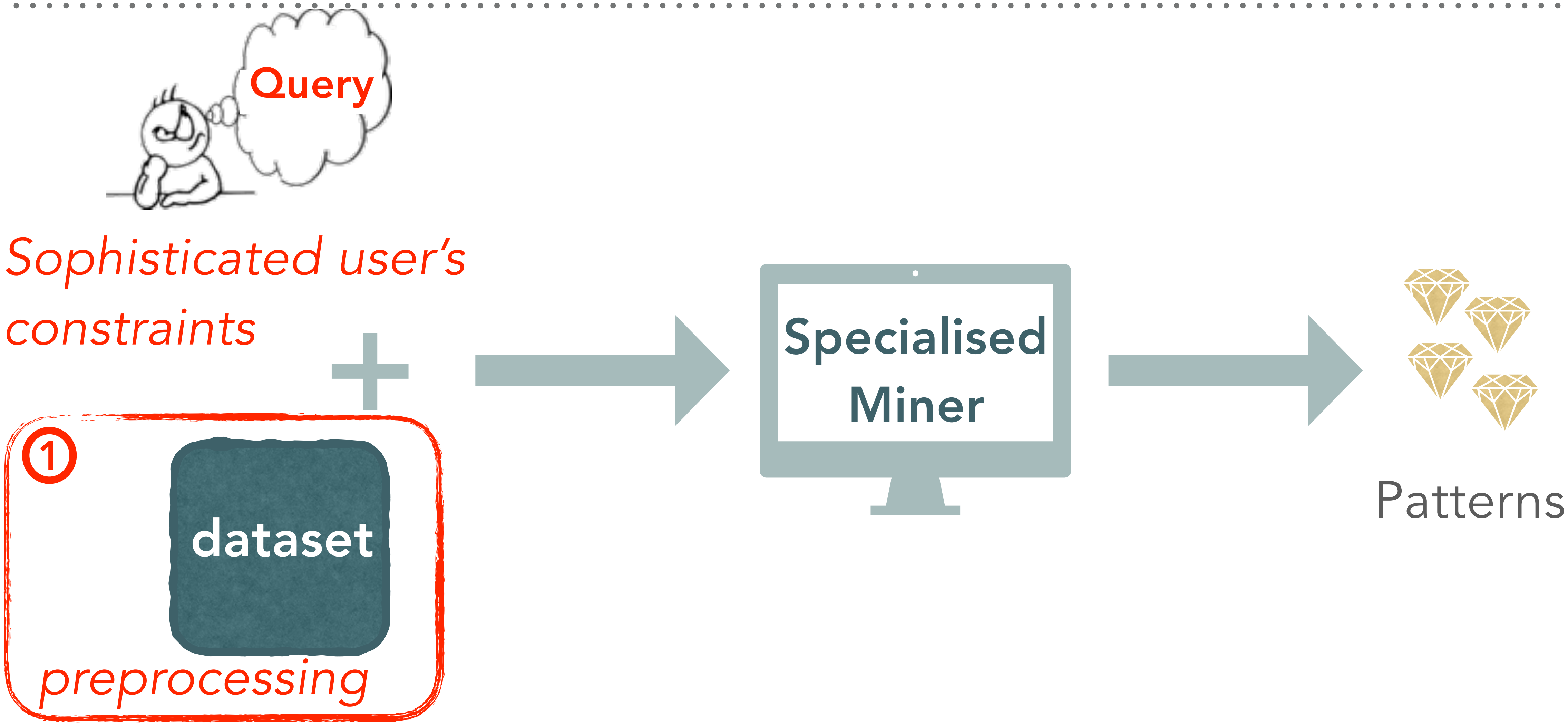

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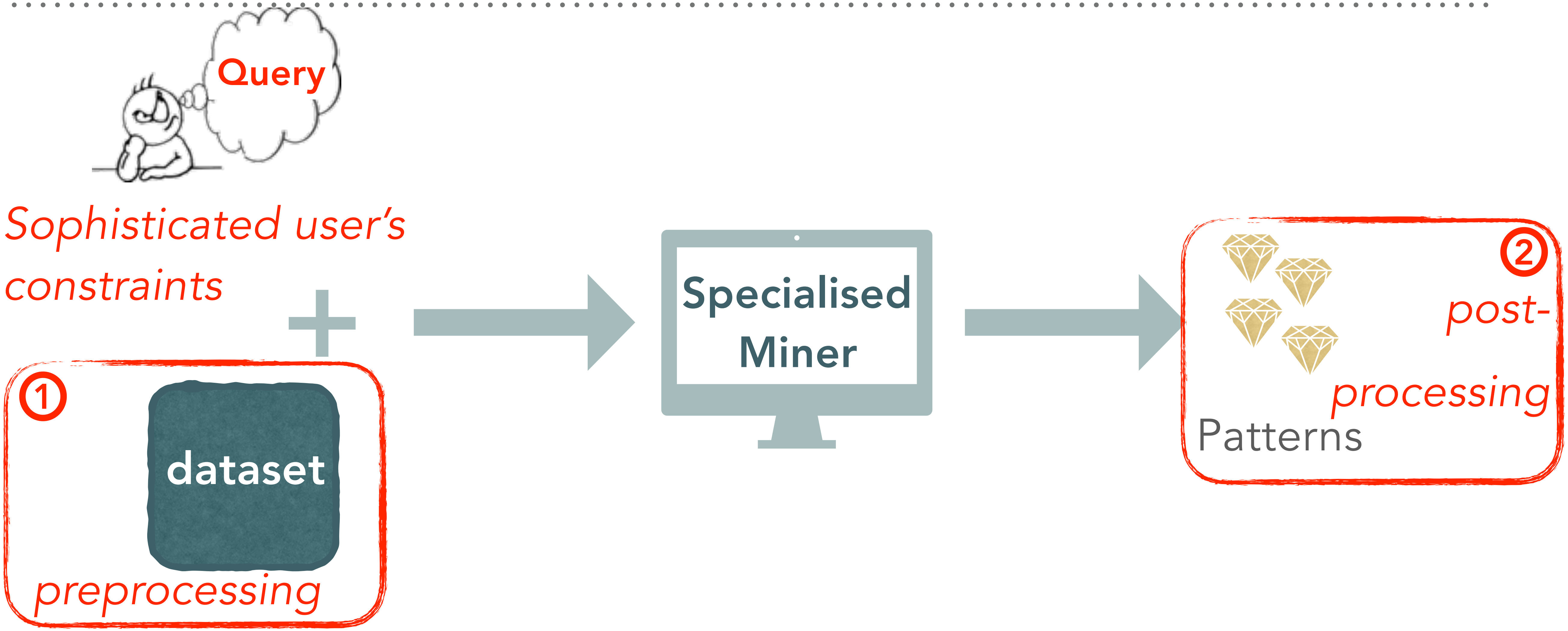

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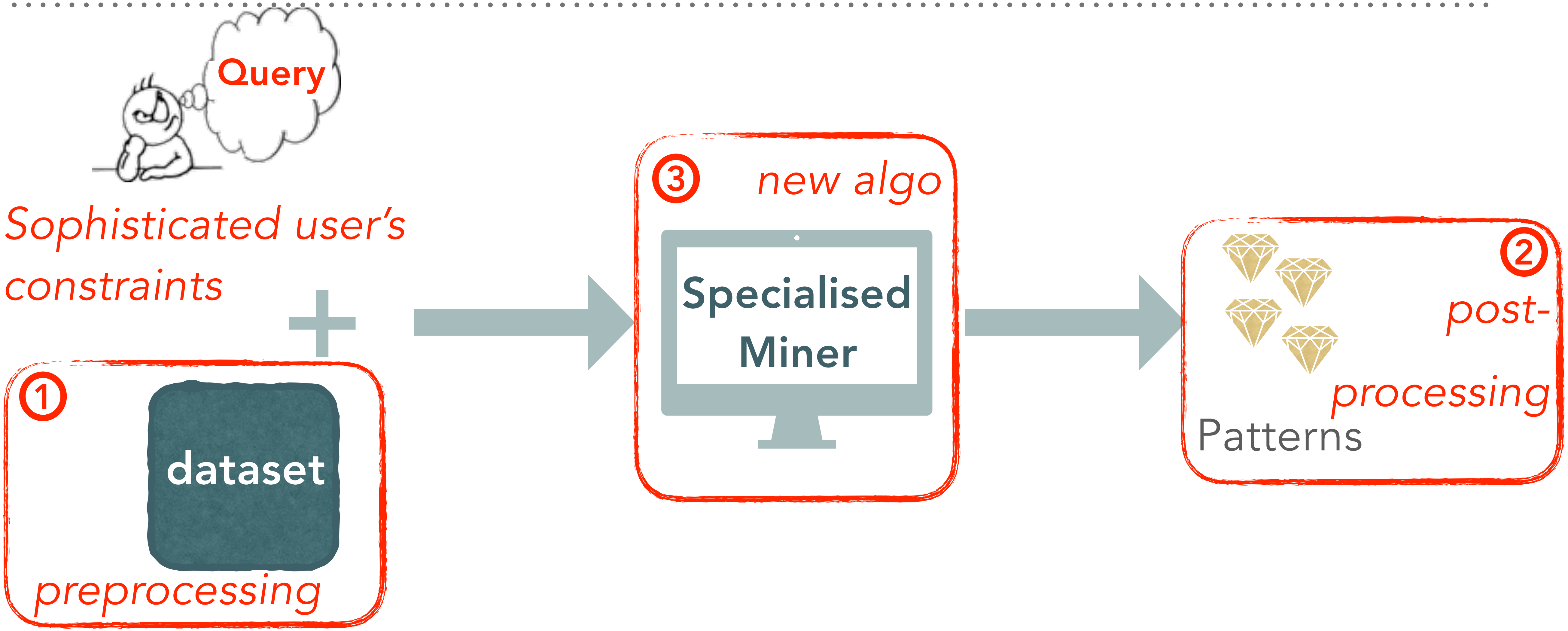

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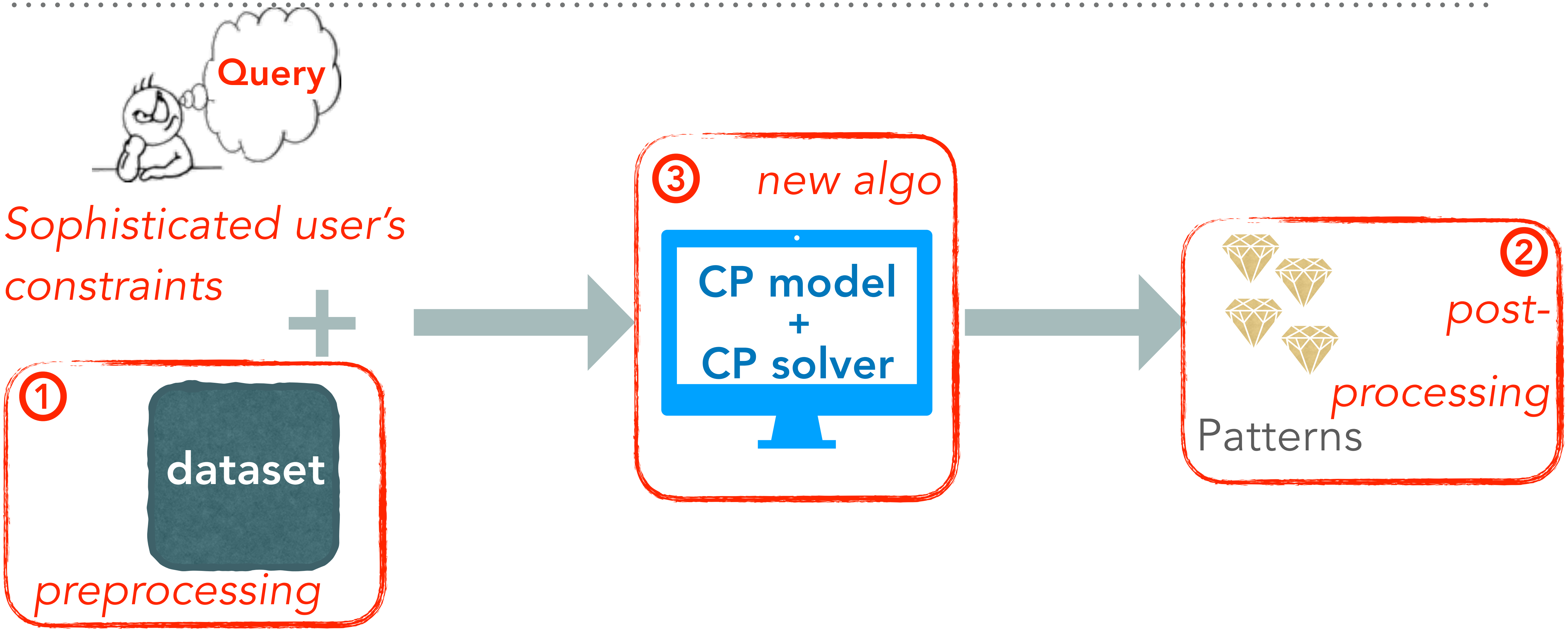

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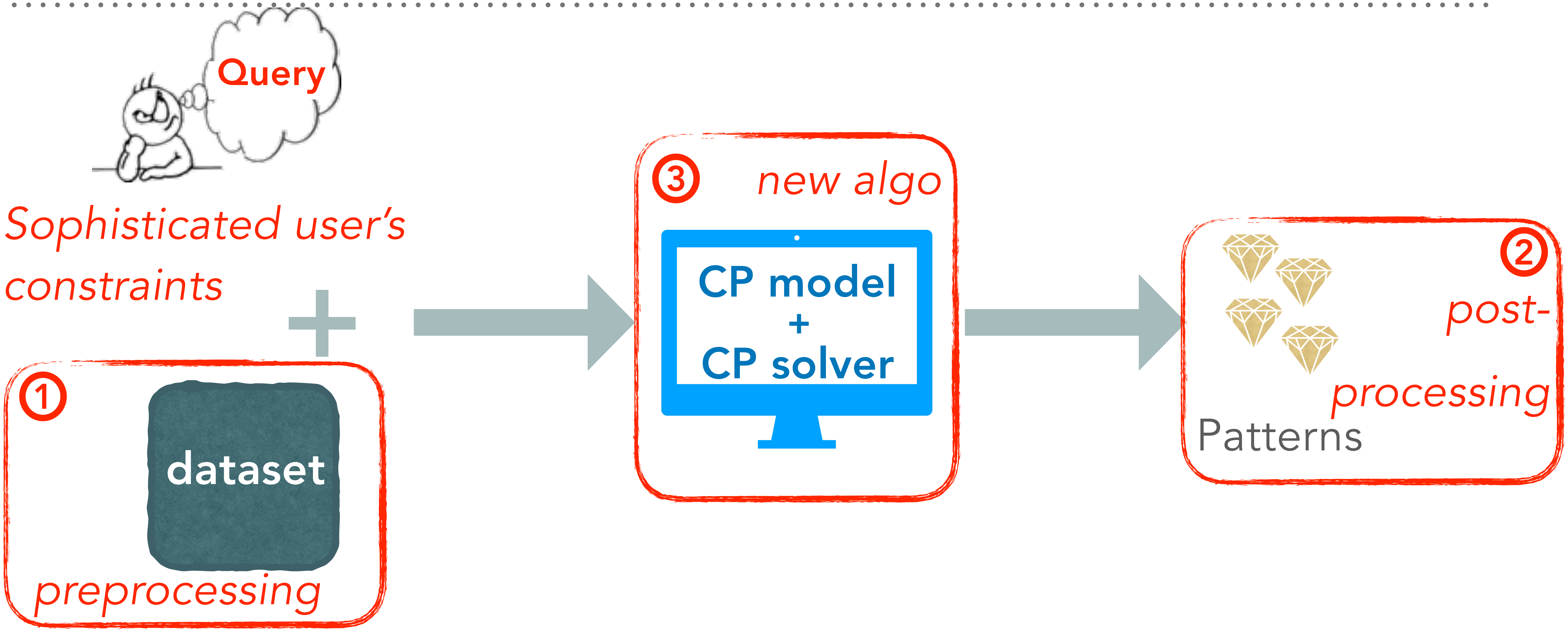

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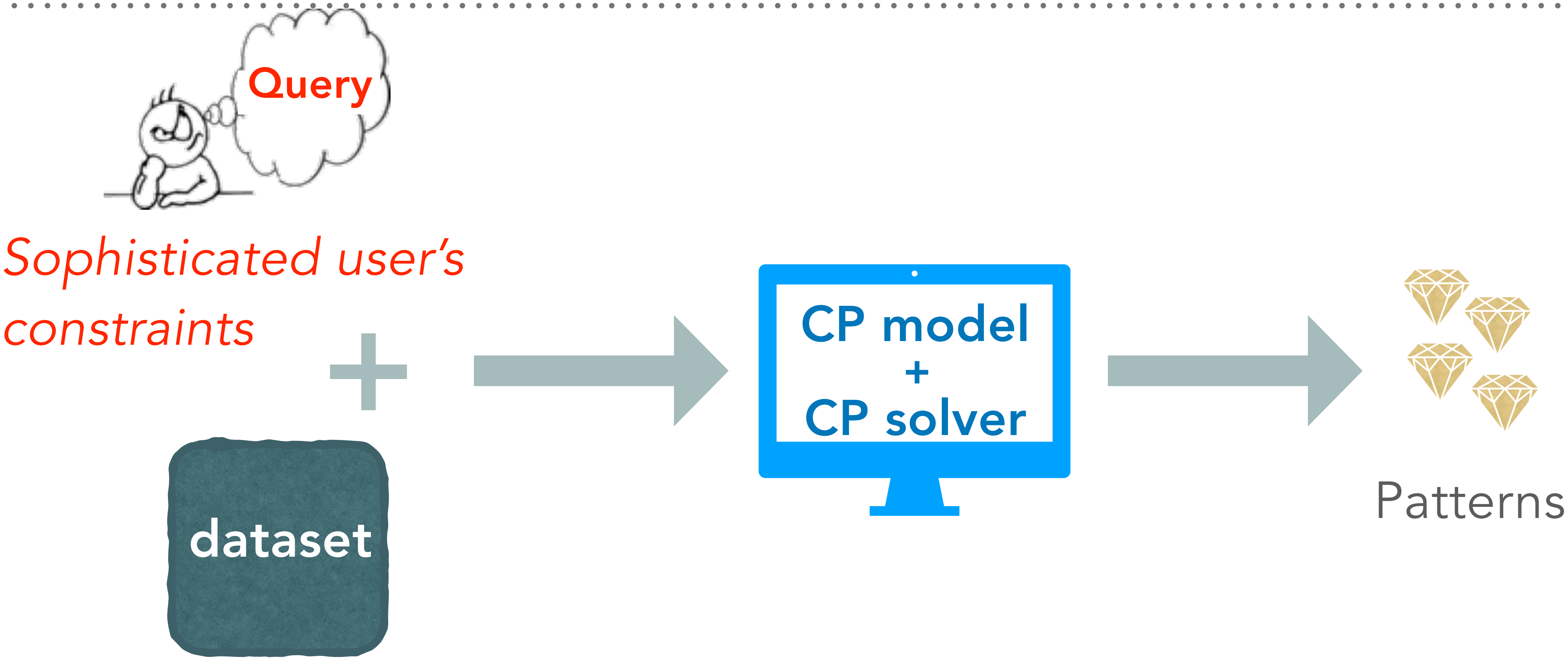

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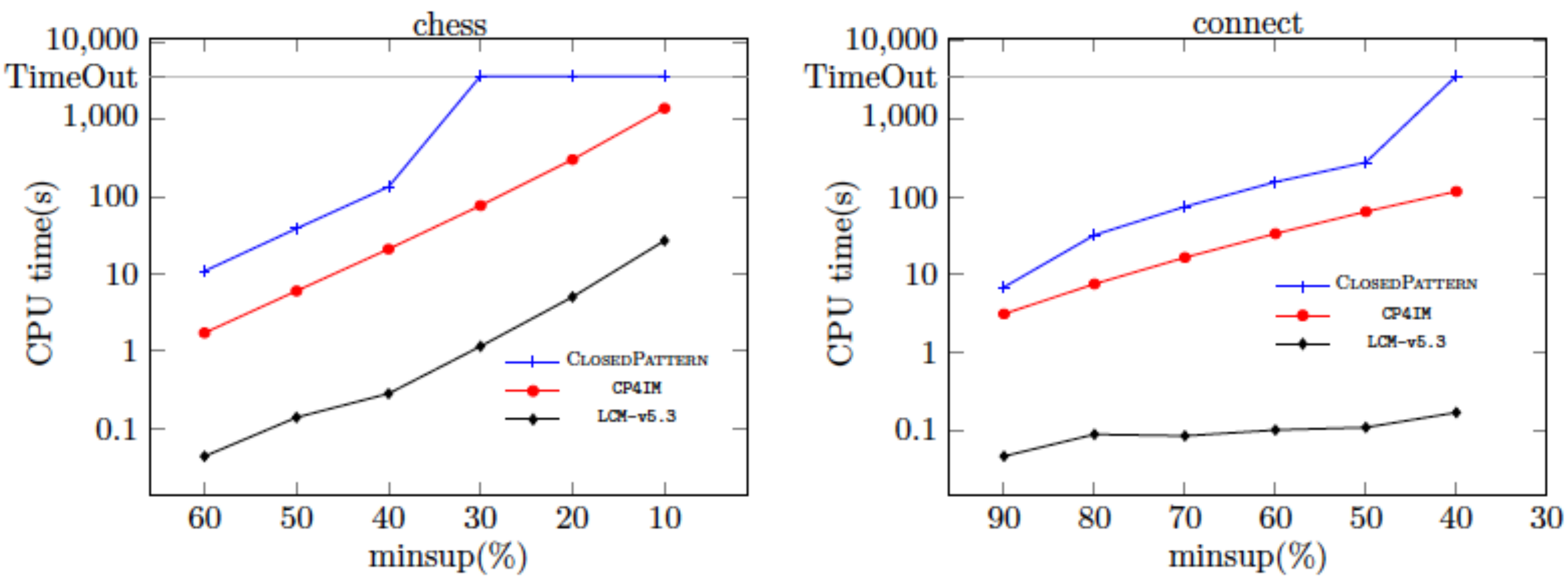

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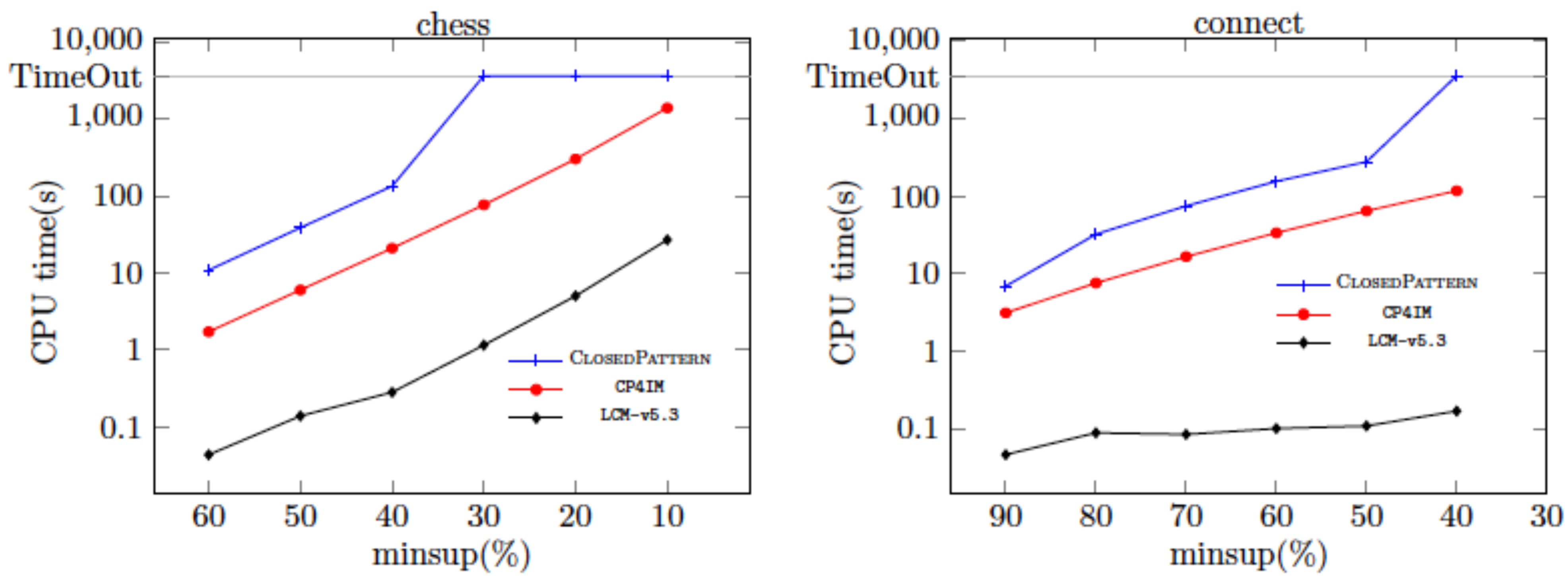

Specialised
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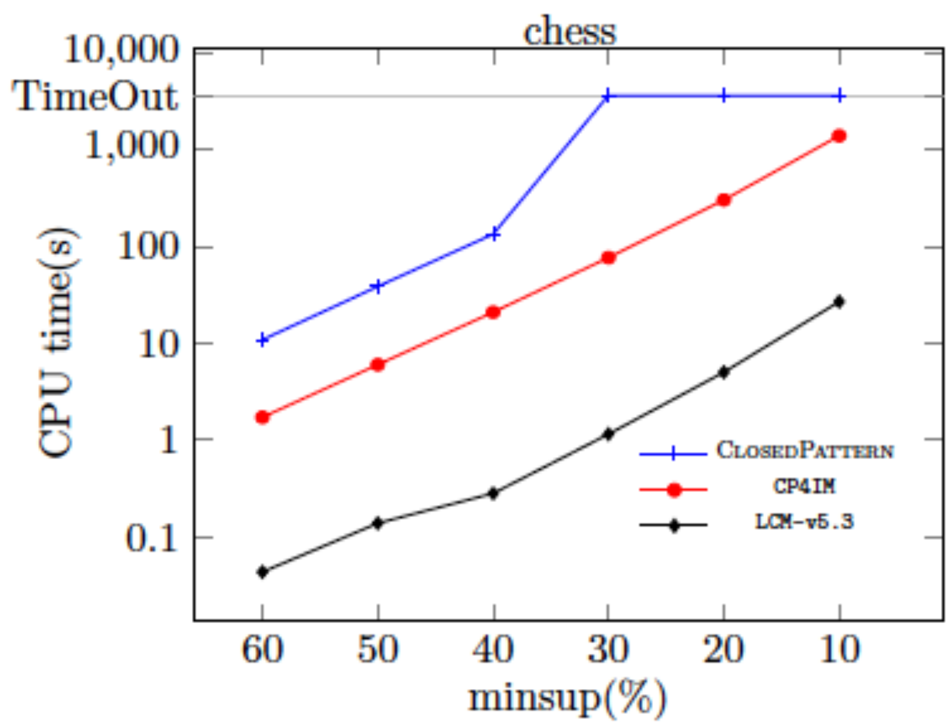

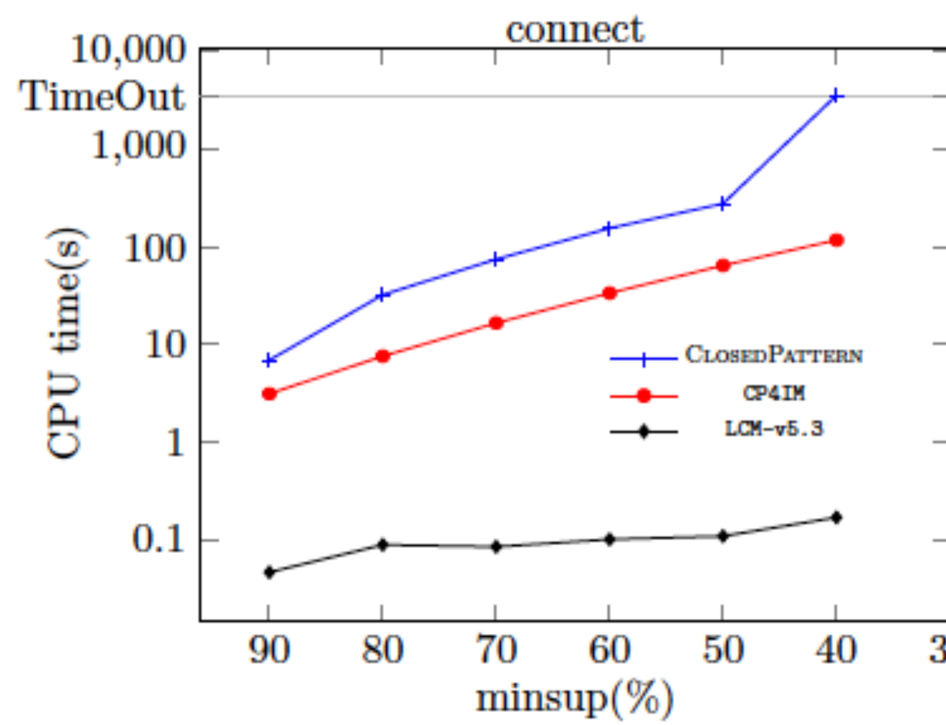

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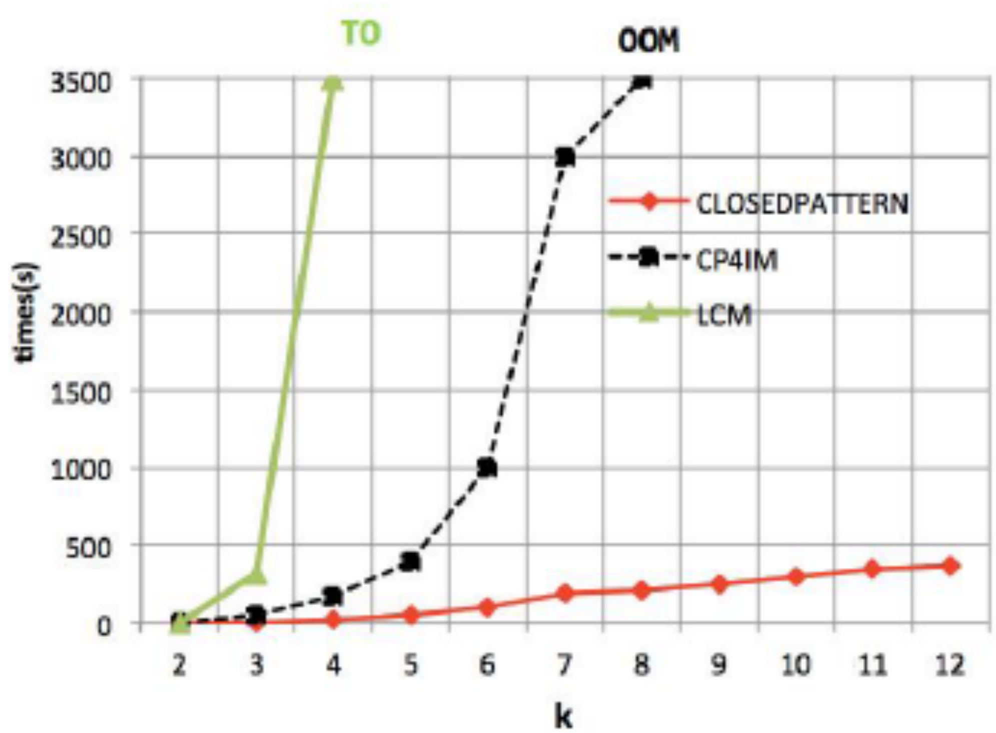
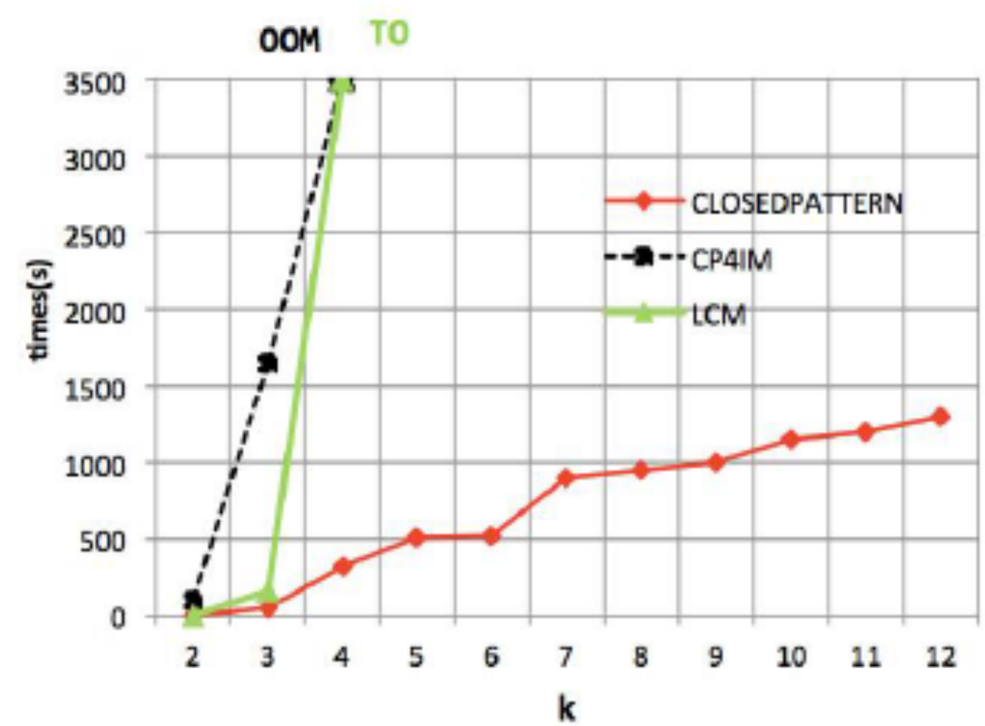


chess (θ = 80%, *lb* = 2, *ub* = 10)



connect (θ = 90%, *lb* = 2, *ub* = 10)

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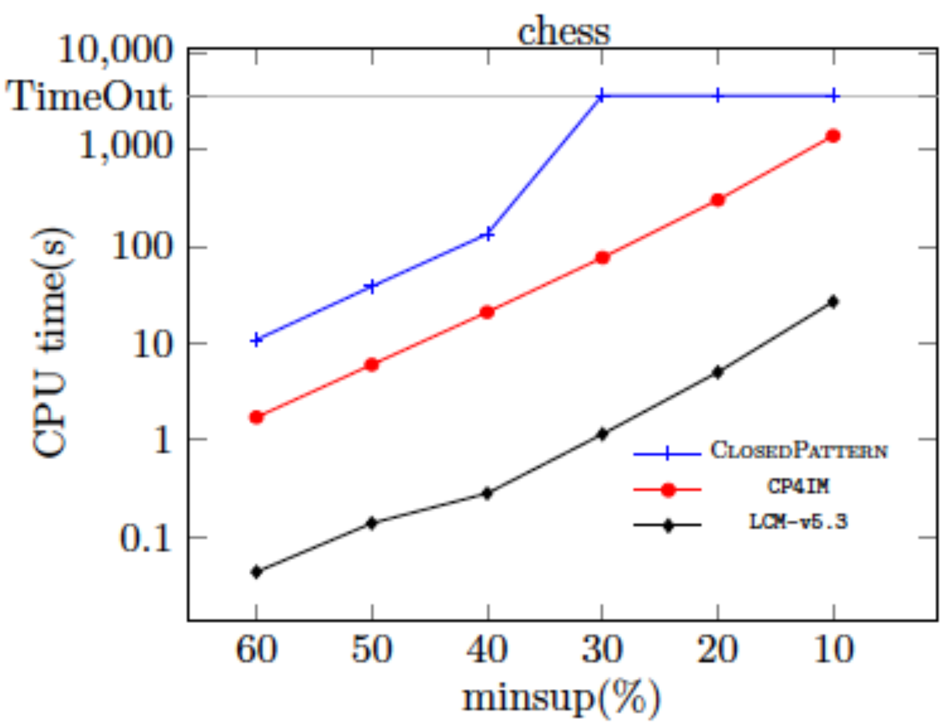

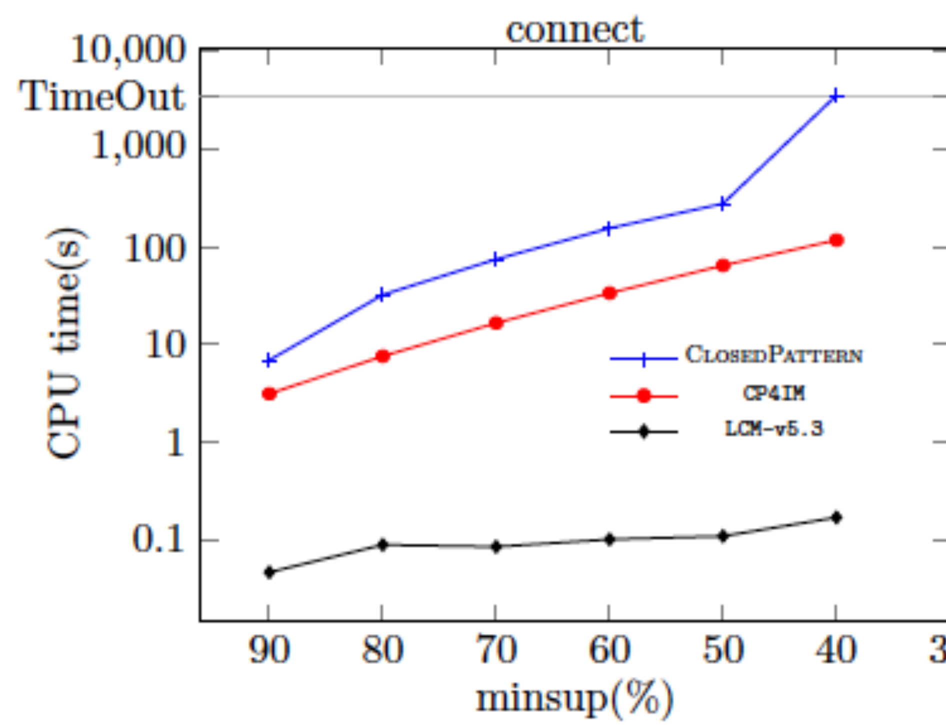

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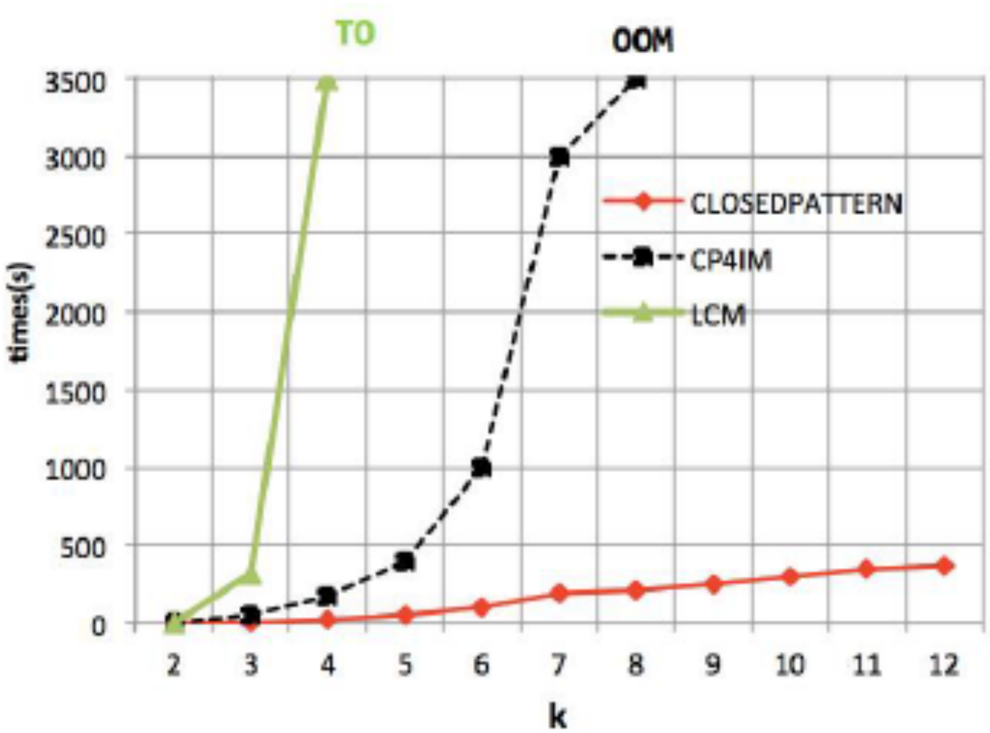

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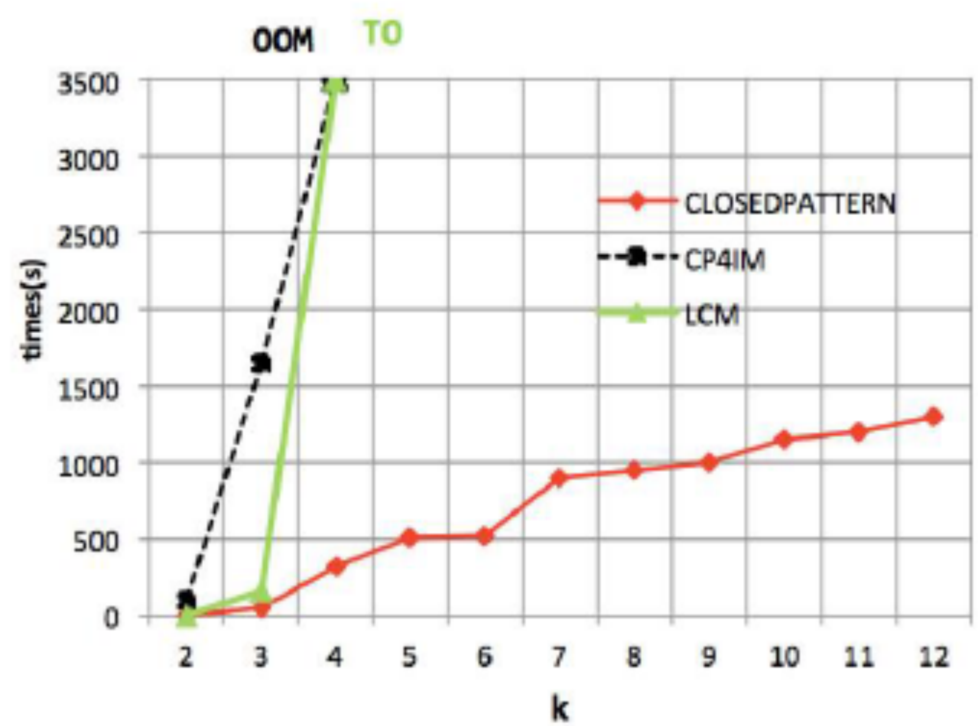

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Declarative
is the winner!

SPECIALISED VS DECLARATIVE DATA MINING

SPECIALISED VS DECLARATIVE DATA MINING

Preprocessing + Specialised step vs Declarative

Instances	$\#\mathcal{I}_i$	$\#\mathcal{T}_i$	(lb_I, ub_I)	(lb_T, ub_T)	$\#D$	#FCIs	PP-LCM	CP-ItemSet
Zoo_70_6	6	10	(2,3)	(2,3)	5,775	8	39.69	**1.75**
Zoo_50_11	6	10	(3,4)	(3,4)	11,550	9	88.66	**3.36**
Zoo_85_5	6	10	(2,6)	(2,10)	57,741	8	521.89	**31.86**
Primary_82_5	3	12	(2,3)	(2,10)	16,280	8	199.58	**36.13**
Vote_70_6	6	29	(2,3)	(2,3)	142,100	2	TO	**118.67**
Vote_72_5	8	29	(2,3)	(2,3)	341,040	2	TO	**201.79**
Mushroom_80_5	17	12	(2,2)	(2,2)	8,976	10	446.42	**102.68**
Mushroom_82_5	17	12	(2,2)	(3,3)	29,920	7	TO	**455.19**
Chess_90_16	5	34	(2,3)	(2,2)	11,220	3	286.42	**87.22**

TO: **timeout**

SPECIALISED VS DECLARATIVE DATA MINING

SPECIALISED VS DECLARATIVE DATA MINING

Specialised + postprocessing vs Declarative

Instances	*ub*	*lb*	ECLAT-Z-PP	SAT	CP	#TOT
Zoo_5	2	11	479.26	3.92	**0.36**	27
Zoo_5	1	9	491.48	0.17	**0.06**	12
Vote_5	4	8	37.69	282.25	**0.66**	13
Vote_5	1	2	38.49	1.41	**0.05**	23
Anneal_80	2	13	1567.48	1.14	**0.26**	76
Anneal_80	1	12	1622.19	0.53	**0.15**	73
Chess_60	2	9	280.60	2.17	**0.20**	20
Chess_60	1	8	284.22	1.07	**0.08**	24
Mushroom_10	1	11	249.00	47.52	**0.07**	14
Connect_90	1	11	61.80	30.41	**0.26**	12
T10_0.02	1	11	84.47	TO	**5.44**	0
T40_0.1	1	11	TO	TO	**8.33**	39
Pumsb_80	1	12	741.49	OOM	**0.34**	32

TO: timeout OOM: out-of-memory

CONCLUSIONS (PART I)

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Time left?

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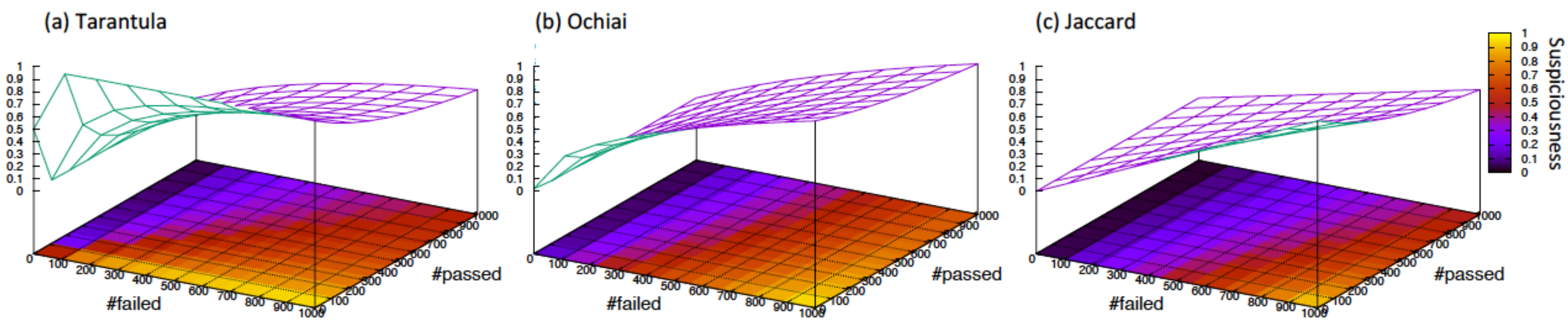
- Spectrum-based approaches: (ranking metrics - suspiciousness score)
  - Tarantula [Jones and Harrold 05]
  - Ochiai [Abreu et al. 07]
  - Jaccard [Abreu et al. 07]
  - …

FAULT LOCALISATION (MOTIVATIONS)



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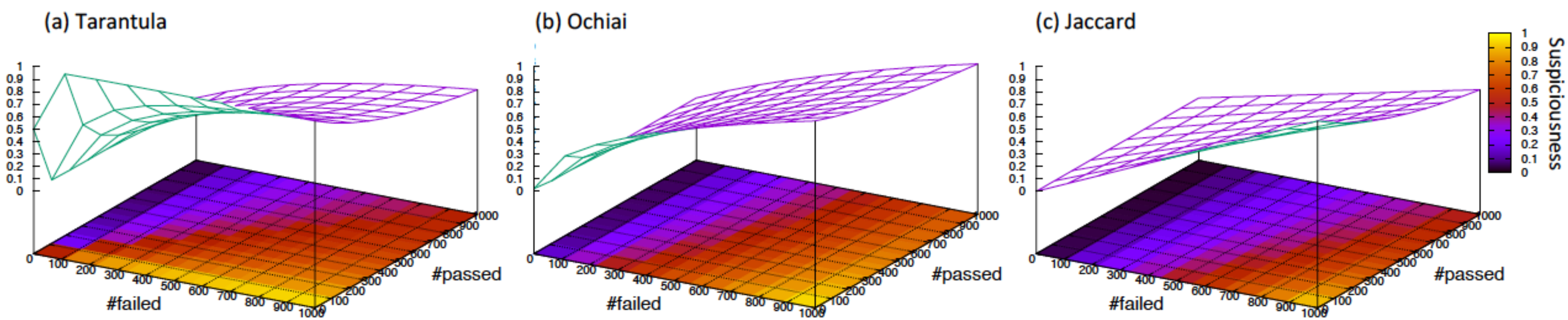

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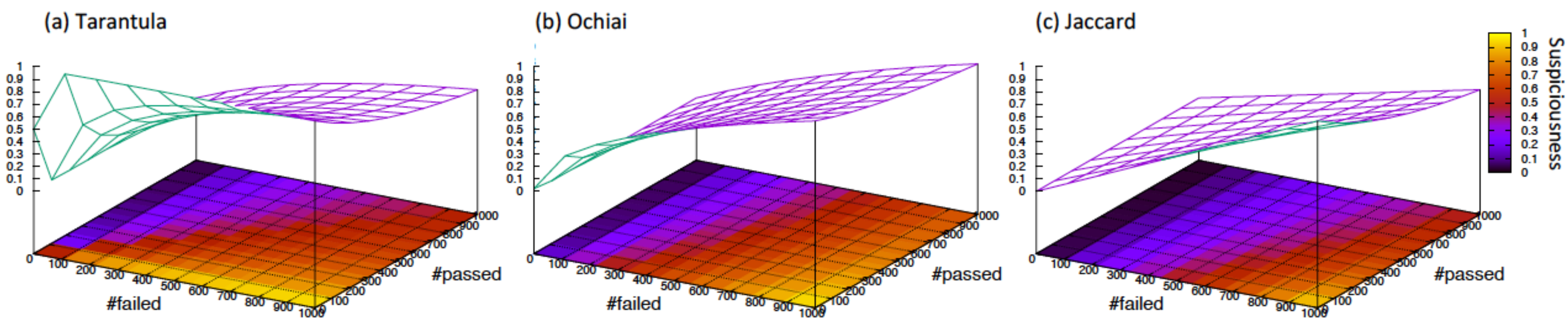

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Program : Character counter	Test cases							
	tc_1	tc_2	tc_3	tc_4	tc_5	tc_6	tc_7	tc_8
`function count (char *s) {`								
`int let, dig, other, i = 0;`								
`char c;`								
e_1: `while (c = s[i++]) {`	1	1	1	1	1	1	1	1
e_2: `if('A'<=c && 'Z'>=c)`	1	1	1	1	1	1	0	1
e_3: `let += 2; //- fault -`	1	1	1	1	1	1	0	0
e_4: `else if ( 'a'<=c && 'z'>=c )`	1	1	1	1	1	0	0	1
e_5: `let += 1;`	1	1	0	0	1	0	0	0
e_6: `else if ( '0'<=c && '9'>=c )`	1	1	1	1	0	0	0	1
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e_8: `else if (isprint (c))`	1	0	1	0	0	0	0	1
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Passing/Failing	F	F	F	F	F	F	P	P

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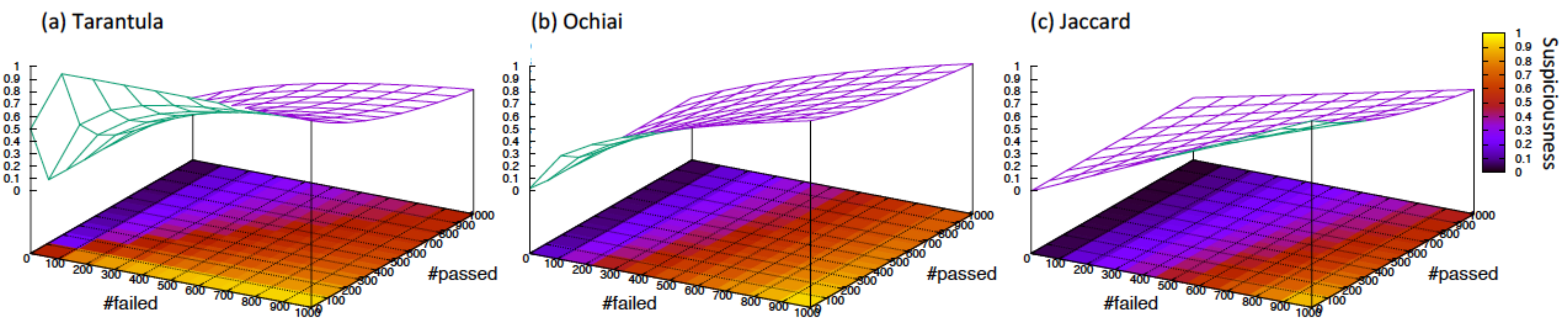

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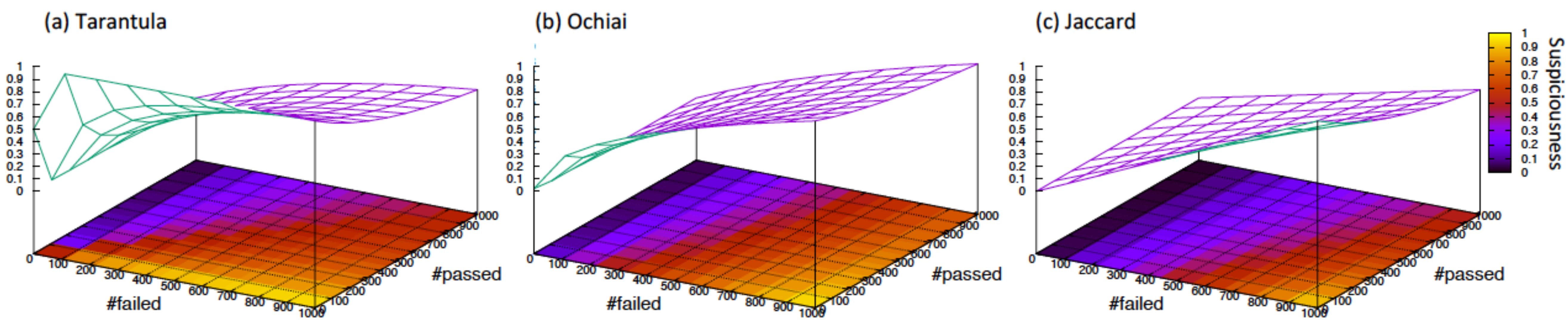

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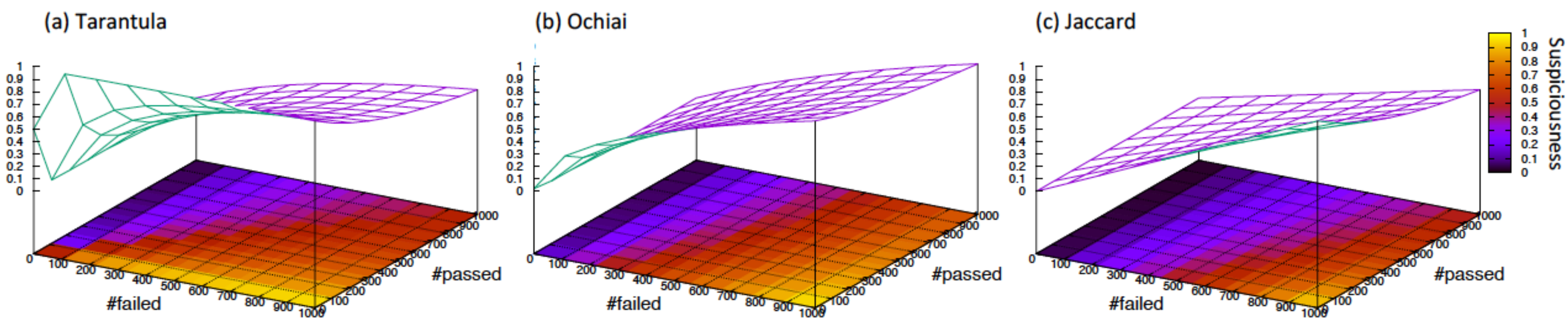

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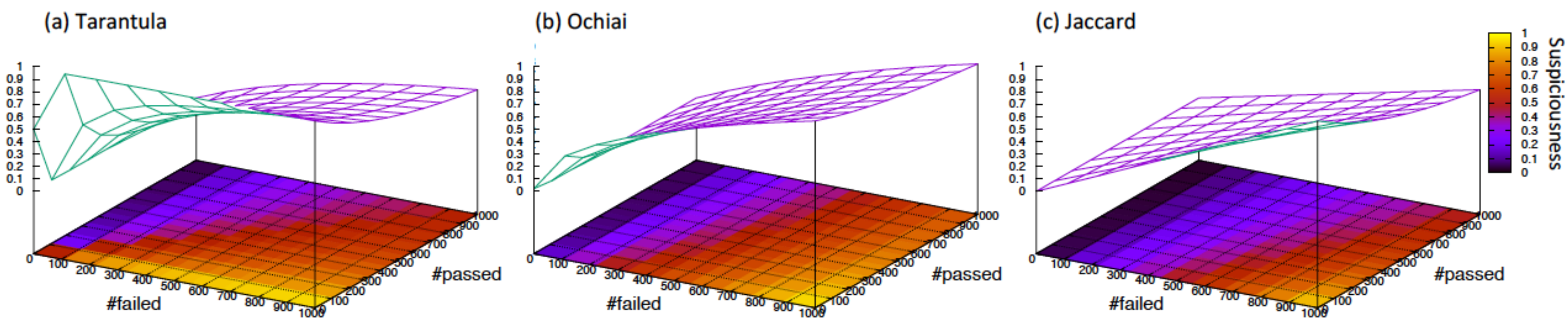

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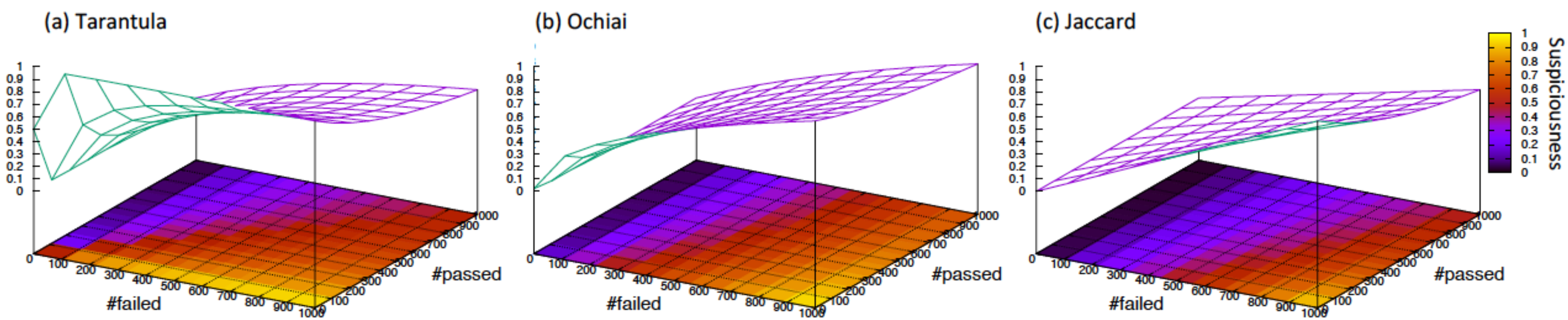

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Fault localisation

=

Mining Task

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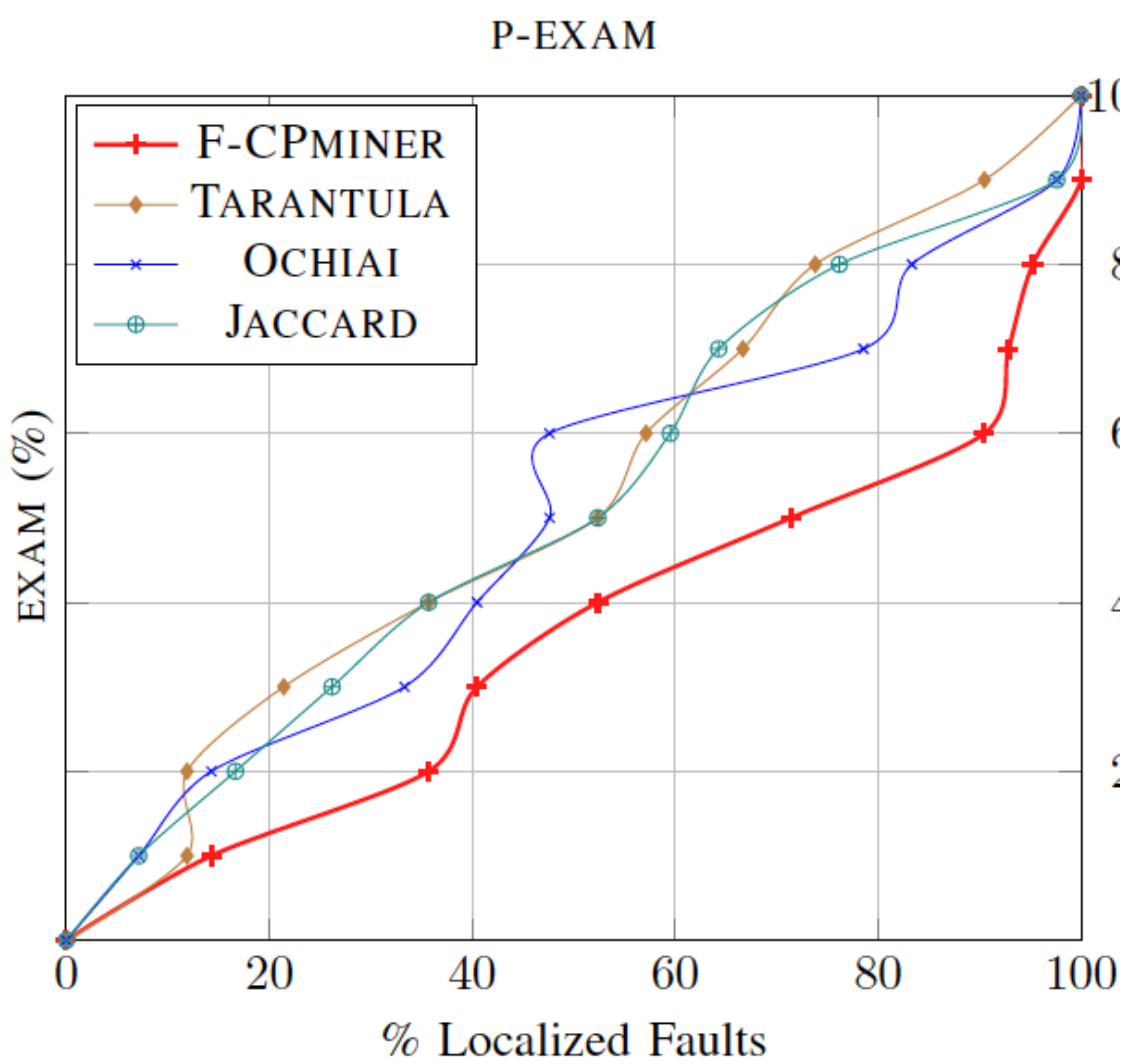
- Top-k suspicious patterns.

$$\boxed{\text{top-k} = \{P | \; \nexists P_1, \ldots, P_k : \forall 1 \leq j \leq k, \; P_j \rhd_{PSD} P\}}$$

FCP-MINER TOOL (SOME RESULTS)



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