

Synthesis of Domain Specific Encoders for Bit- Vector Solvers

Jeevana Priya Inala

with

Rohit Singh, Armando Solar-Lezama

To appear at SAT'16

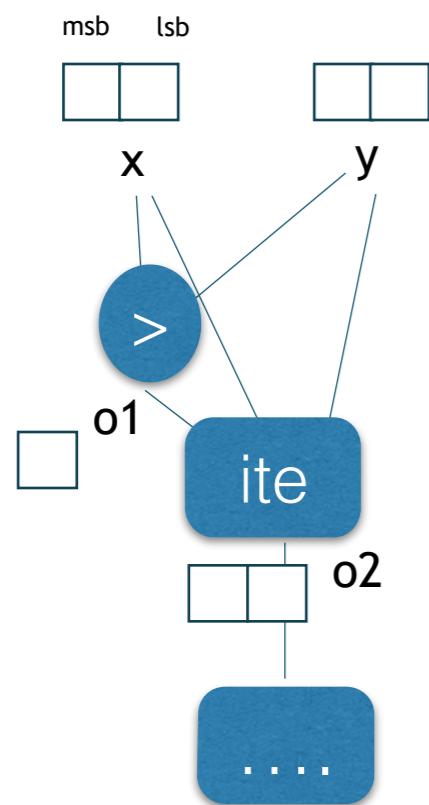
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High-level constraint to CNF clauses

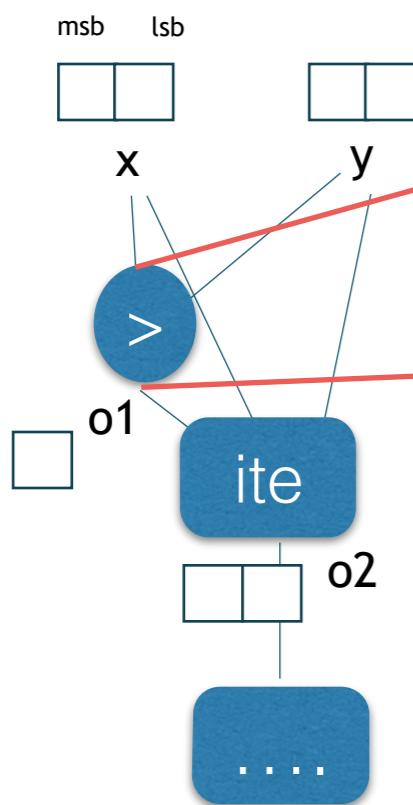
SMT solver
High-level constraint

SAT solver
CNF clauses



High-level constraint to CNF clauses

SMT solver
High-level constraint

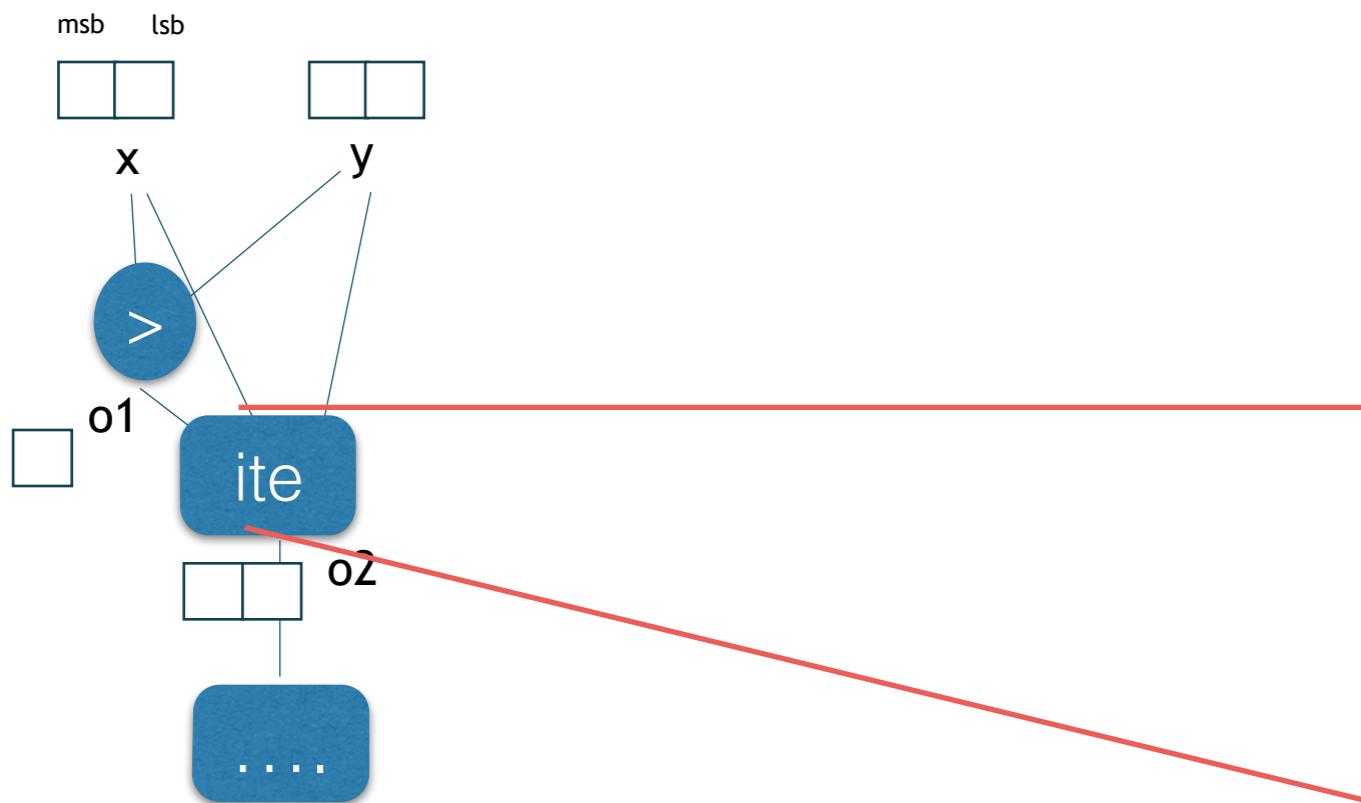


SAT solver
CNF clauses

$$\begin{array}{ll} \overline{y_1} \vee x_1 \vee \overline{t_1} & \overline{t_1} \vee y_0 \vee \overline{x_0} \vee t_2 \\ y_1 \vee \overline{x_1} \vee \overline{t_1} & \overline{t_3} \vee \overline{y_1} \\ \overline{y_1} \vee \overline{x_1} \vee t_1 & \overline{t_3} \vee x_1 \\ y_1 \vee x_1 \vee t_1 & y_1 \vee \overline{x_1} \vee t_3 \\ \overline{t_2} \vee t_1 & o_1 \vee \overline{t_2} \\ \overline{t_2} \vee \overline{y_0} & o_1 \vee \overline{t_3} \\ \overline{t_2} \vee x_0 & t_2 \vee t_3 \vee \overline{o_1} \end{array}$$

High-level constraint to CNF clauses

SMT solver
High-level constraint

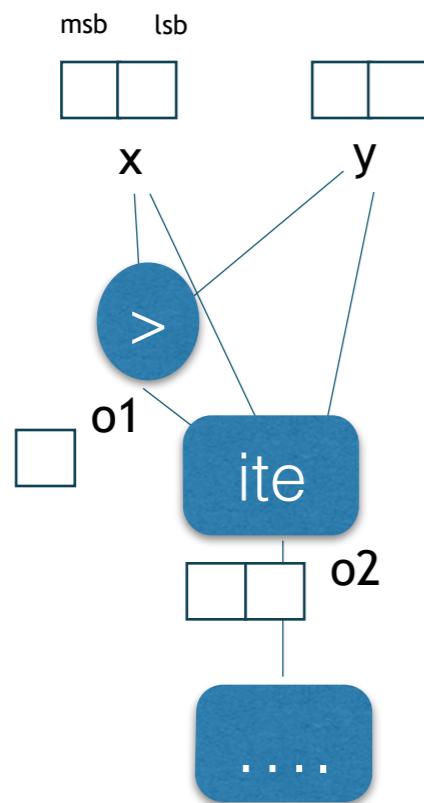


SAT solver
CNF clauses

$\overline{y_1} \vee x_1 \vee \overline{t_1}$	$\overline{t_1} \vee y_0 \vee \overline{x_0} \vee t_2$
$y_1 \vee \overline{x_1} \vee \overline{t_1}$	$\overline{t_3} \vee \overline{y_1}$
$\overline{y_1} \vee \overline{x_1} \vee t_1$	$\overline{t_3} \vee x_1$
$y_1 \vee x_1 \vee t_1$	$y_1 \vee \overline{x_1} \vee t_3$
$\overline{t_2} \vee t_1$	$o_1 \vee \overline{t_2}$
$\overline{t_2} \vee \overline{y_0}$	$o_1 \vee \overline{t_3}$
$\overline{t_2} \vee x_0$	$t_2 \vee t_3 \vee \overline{o_1}$
$\overline{o_1} \vee x_1 \vee \overline{o_{2_1}}$	$\overline{o_1} \vee x_0 \vee \overline{o_{2_0}}$
$\overline{o_1} \vee \overline{x_1} \vee o_{2_1}$	$\overline{o_1} \vee \overline{x_0} \vee o_{2_0}$
$o_1 \vee y_1 \vee \overline{o_{2_1}}$	$o_1 \vee y_0 \vee \overline{o_{2_0}}$
$o_1 \vee \overline{y_1} \vee o_{2_1}$	$o_1 \vee \overline{y_0} \vee o_{2_0}$
$x_1 \vee y_1 \vee \overline{o_{2_1}}$	$x_0 \vee y_0 \vee \overline{o_{2_0}}$
$\overline{x_1} \vee \overline{y_1} \vee o_{2_1}$	$\overline{x_0} \vee \overline{y_0} \vee o_{2_0}$

High-level constraint to CNF clauses

SMT solver
High-level constraint



Not the “best”
encoding

SAT solver
CNF clauses

$$\begin{array}{ll} \overline{y_1} \vee x_1 \vee \overline{t_1} & \overline{t_1} \vee y_0 \vee \overline{x_0} \vee t_2 \\ y_1 \vee \overline{x_1} \vee \overline{t_1} & \overline{t_3} \vee \overline{y_1} \\ \overline{y_1} \vee \overline{x_1} \vee t_1 & \overline{t_3} \vee x_1 \\ y_1 \vee x_1 \vee t_1 & y_1 \vee \overline{x_1} \vee t_3 \\ \overline{t_2} \vee t_1 & o_1 \vee \overline{t_2} \\ \overline{t_2} \vee \overline{y_0} & o_1 \vee \overline{t_3} \\ \overline{t_2} \vee x_0 & t_2 \vee t_3 \vee \overline{o_1} \\ \hline \overline{o_1} \vee x_1 \vee \overline{o_{2_1}} & \overline{o_1} \vee x_0 \vee \overline{o_{2_0}} \\ \overline{o_1} \vee \overline{x_1} \vee o_{2_1} & \overline{o_1} \vee \overline{x_0} \vee o_{2_0} \\ o_1 \vee y_1 \vee \overline{o_{2_1}} & o_1 \vee y_0 \vee \overline{o_{2_0}} \\ o_1 \vee \overline{y_1} \vee o_{2_1} & o_1 \vee \overline{y_0} \vee o_{2_0} \\ x_1 \vee y_1 \vee \overline{o_{2_1}} & x_0 \vee y_0 \vee \overline{o_{2_0}} \\ \overline{x_1} \vee \overline{y_1} \vee o_{2_1} & \overline{x_0} \vee \overline{y_0} \vee o_{2_0} \end{array}$$

....

Goal: Synthesize better code for this translation

What is an optimal encoding?

- Fewer clauses
- Fewer variables
- Maximal propagation

Maximal Propagation

- SAT solvers use unit propagation to infer variable assignments

Maximal Propagation

- SAT solvers use unit propagation to infer variable assignments

Current variables assignment

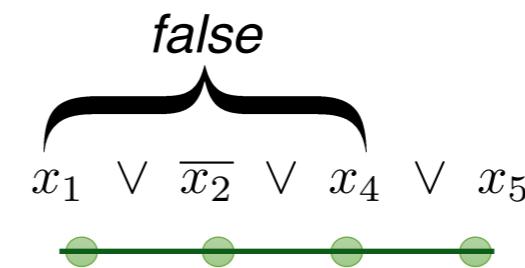
$$\text{true} \rightarrow \overline{x_1}, x_2, \overline{x_3}, \overline{x_4}$$

Maximal Propagation

- SAT solvers use unit propagation to infer variable assignments

Current variables assignment

$$\text{true} \rightarrow \overline{x_1}, x_2, \overline{x_3}, \overline{x_4}$$

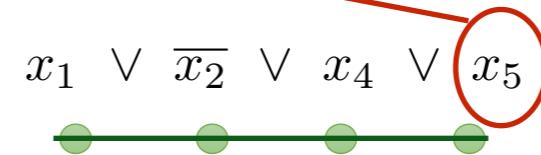


Maximal Propagation

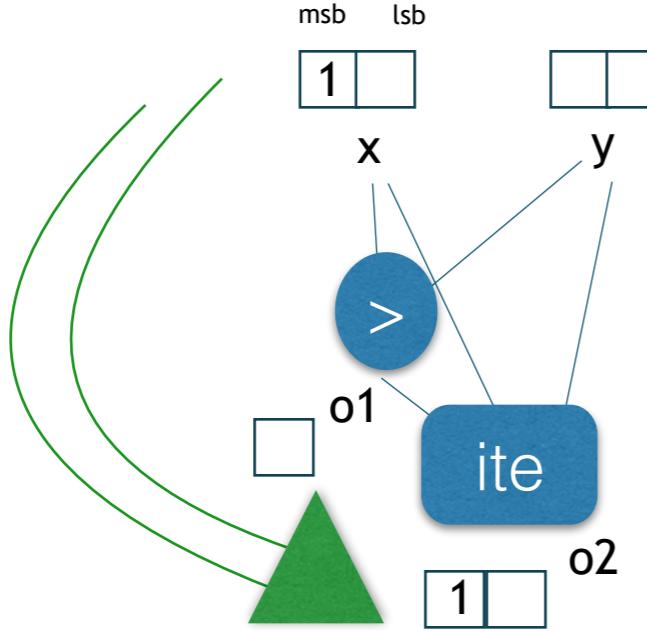
- SAT solvers use unit propagation to infer variable assignments

Current variables assignment

$$\text{true} \rightarrow \overline{x_1}, x_2, \overline{x_3}, \overline{x_4}, x_5$$

$$x_1 \vee \overline{x_2} \vee x_4 \vee x_5$$


Find an encoding that maximizes what we can learn through unit propagations

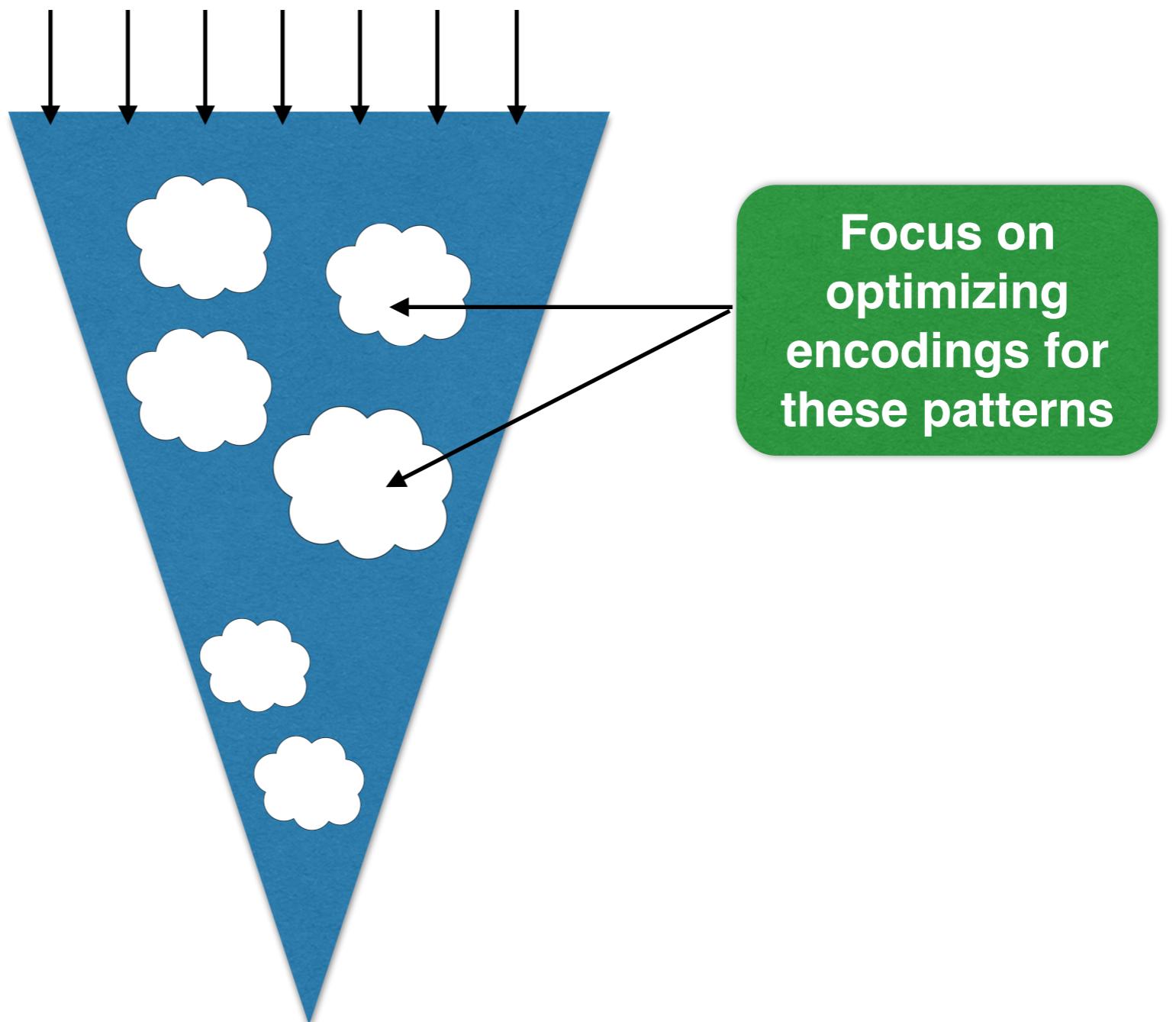


$$\begin{array}{ll}
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 y_1 \vee \overline{x_1} \vee \overline{t_1} & \overline{t_3} \vee \overline{y_1} \\
 \overline{y_1} \vee \overline{x_1} \vee t_1 & \overline{t_3} \vee x_1 \\
 y_1 \vee x_1 \vee t_1 & y_1 \vee \overline{x_1} \vee t_3 \\
 \overline{t_2} \vee t_1 & o_1 \vee \overline{t_2} \\
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 \end{array}$$

$$\begin{array}{ll}
 \overline{o_1} \vee x_1 \vee \overline{o_{2_1}} & \overline{o_1} \vee x_0 \vee \overline{o_{2_0}} \\
 \overline{o_1} \vee \overline{x_1} \vee o_{2_1} & \overline{o_1} \vee \overline{x_0} \vee o_{2_0} \\
 o_1 \vee y_1 \vee \overline{o_{2_1}} & o_1 \vee y_0 \vee \overline{o_{2_0}} \\
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 \overline{x_1} \vee \overline{y_1} \vee o_{2_1} & \overline{x_0} \vee \overline{y_0} \vee o_{2_0}
 \end{array}$$

$$x_1 = 1 \xrightarrow{\text{Unit prop}} o_{2_1} = 1$$

Composing encodings does not preserve optimality





What patterns to target?

How do we come up with “optimal” encoding for a pattern?

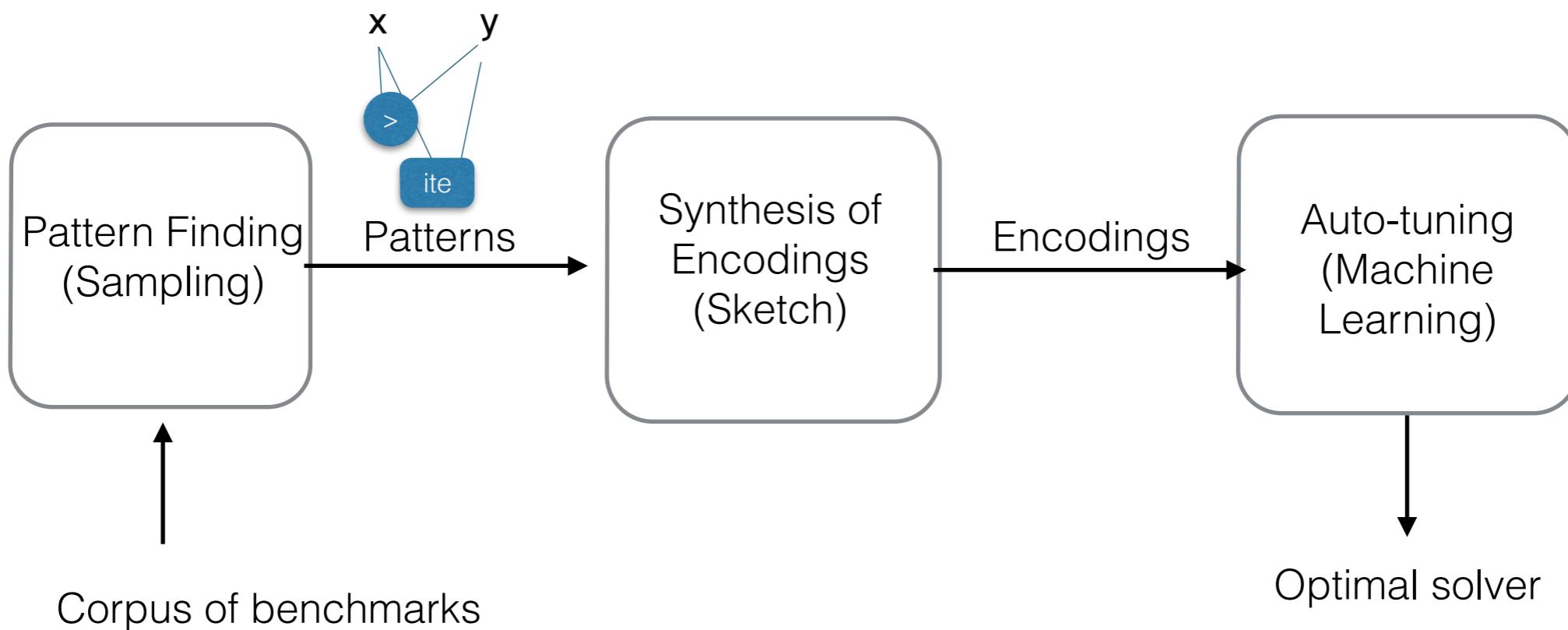
Do these encodings actually improve the performance?



What patterns to target?

How do we come up with “optimal” encoding for a pattern?

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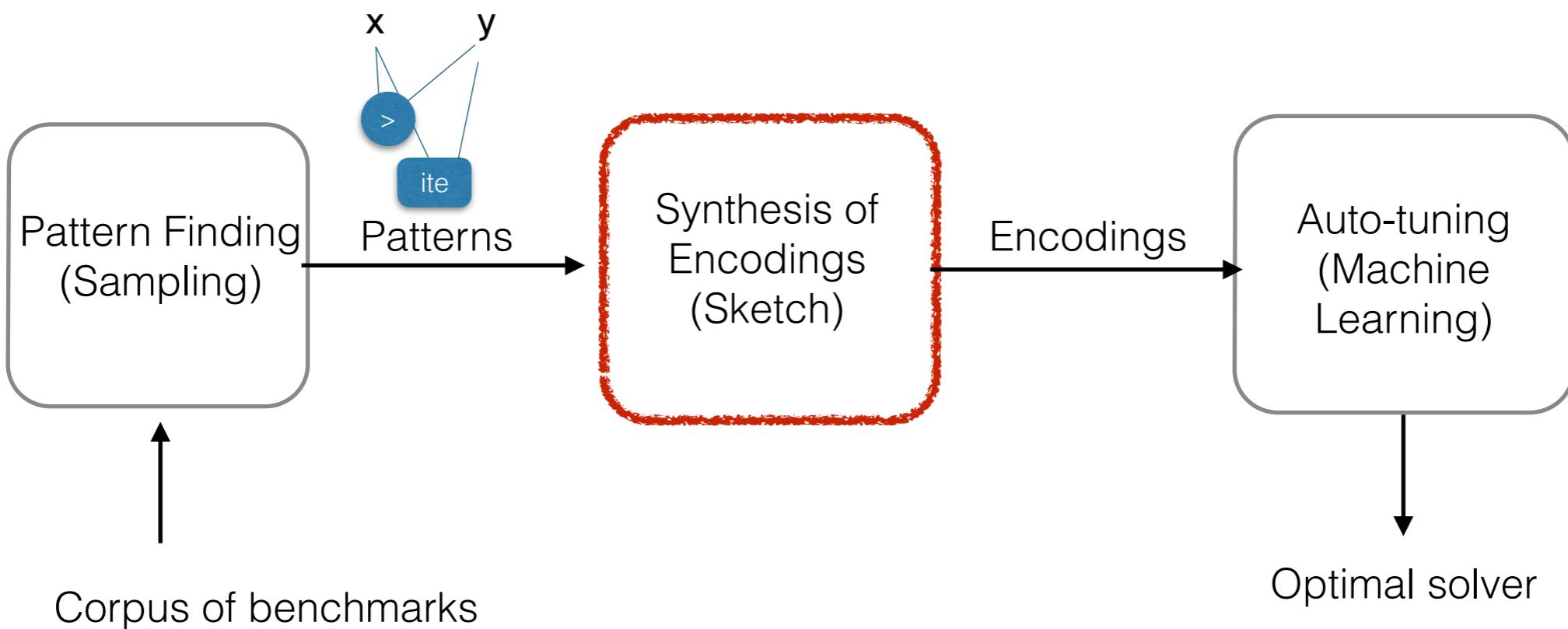


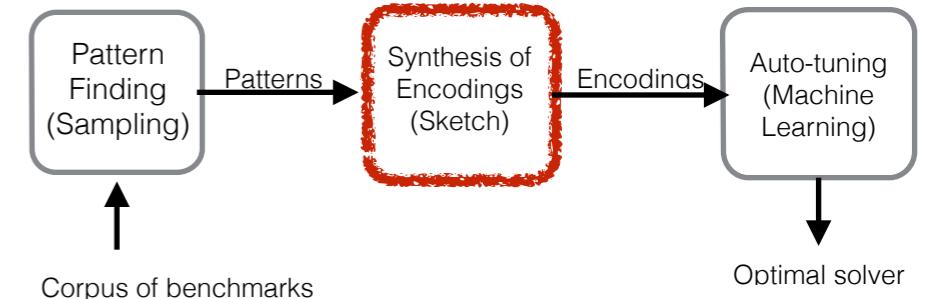


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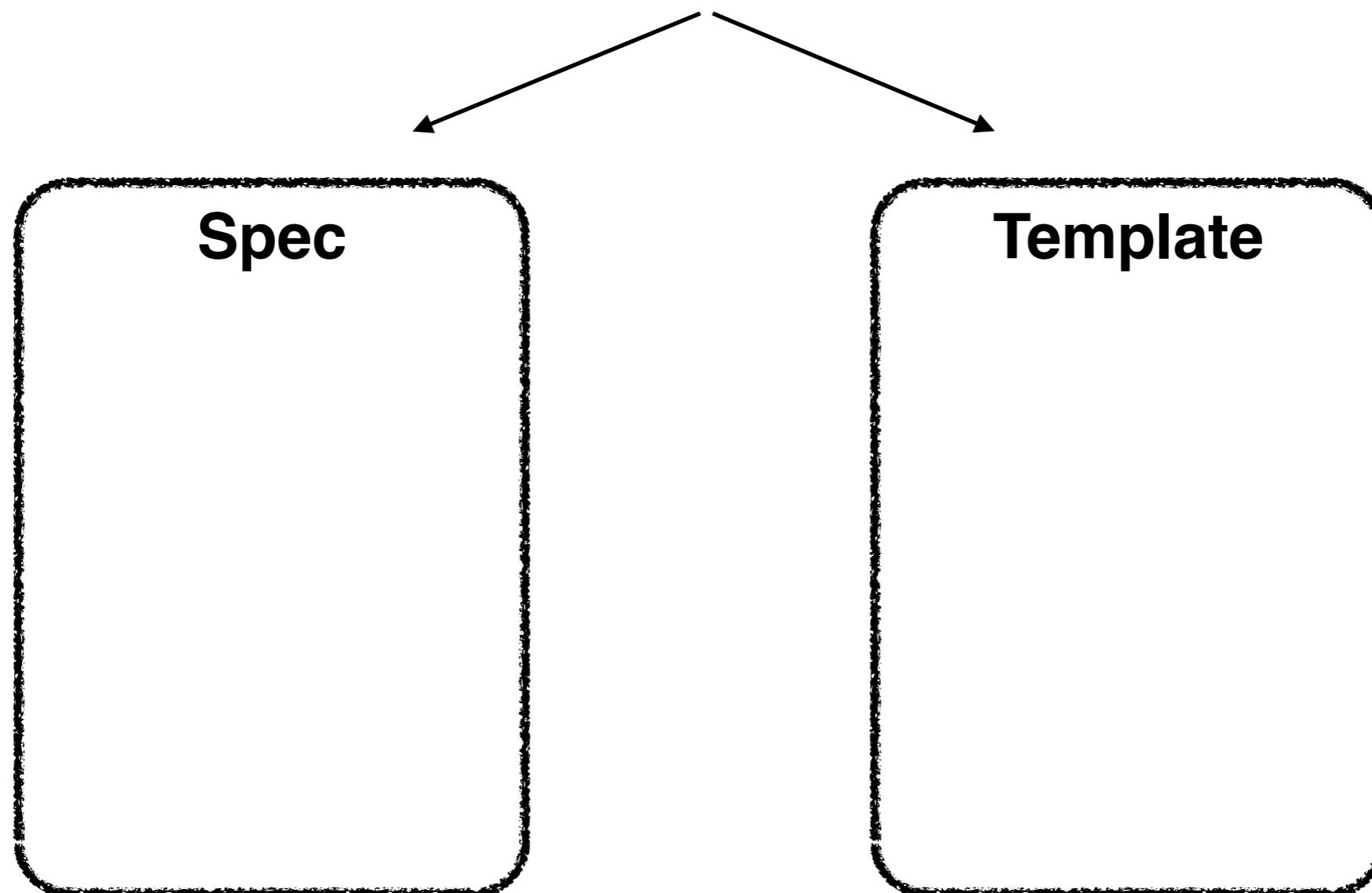
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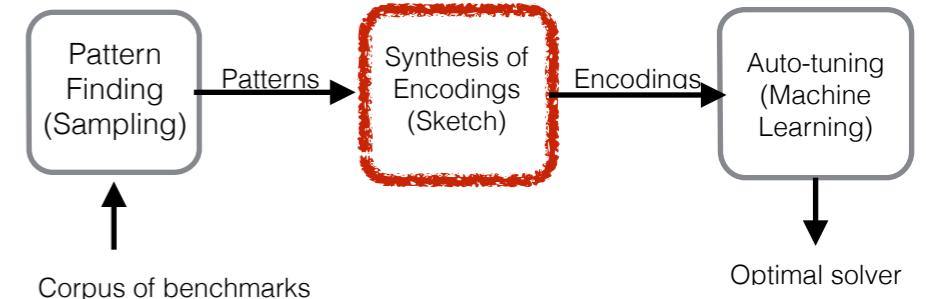




Synthesis as a SyGus problem

Boolean predicate P → CNF clauses C

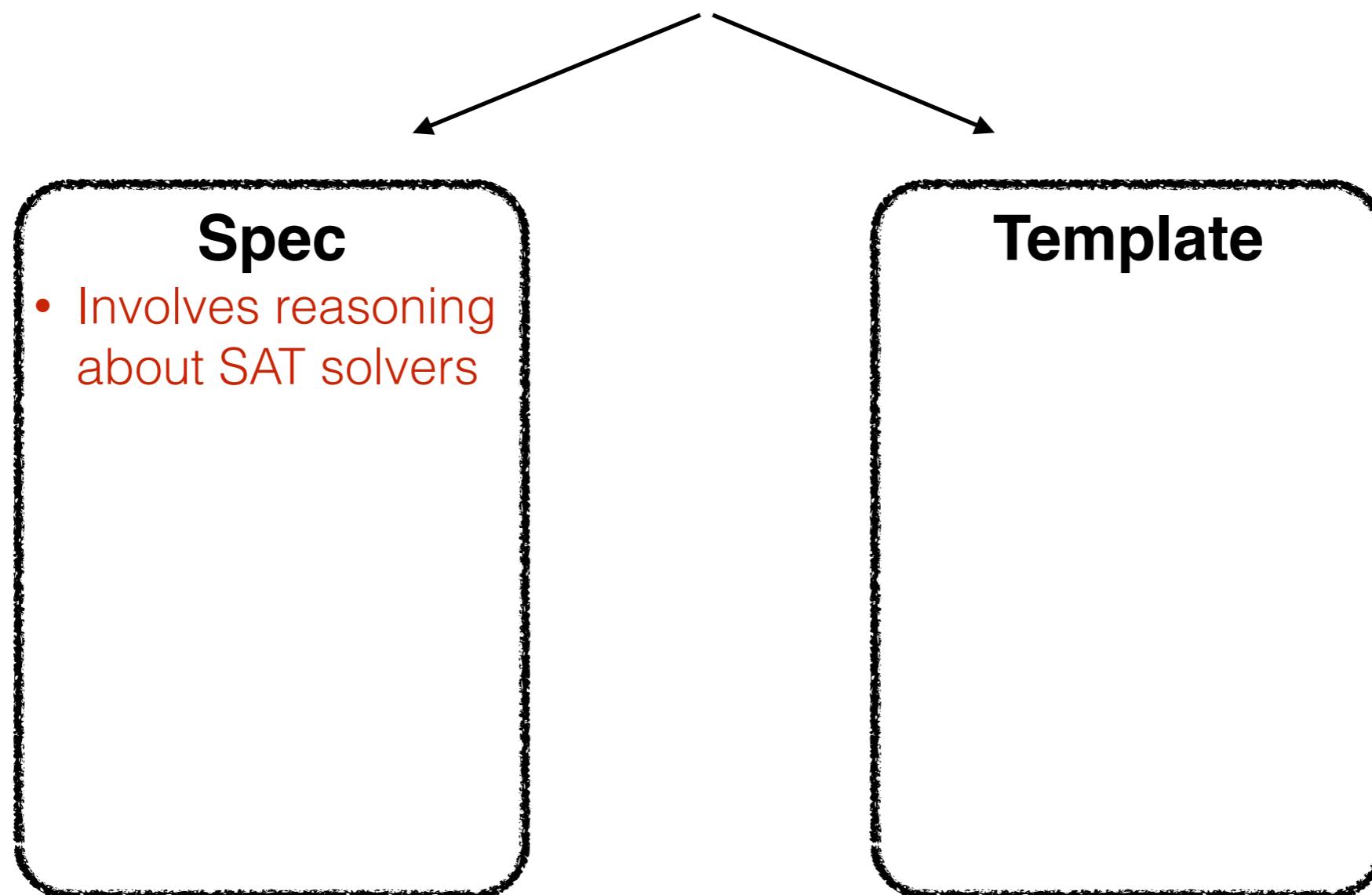


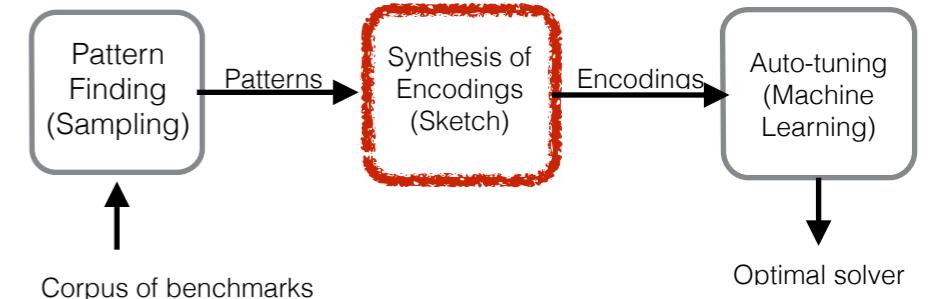


Synthesis as a SyGus problem

Boolean predicate P

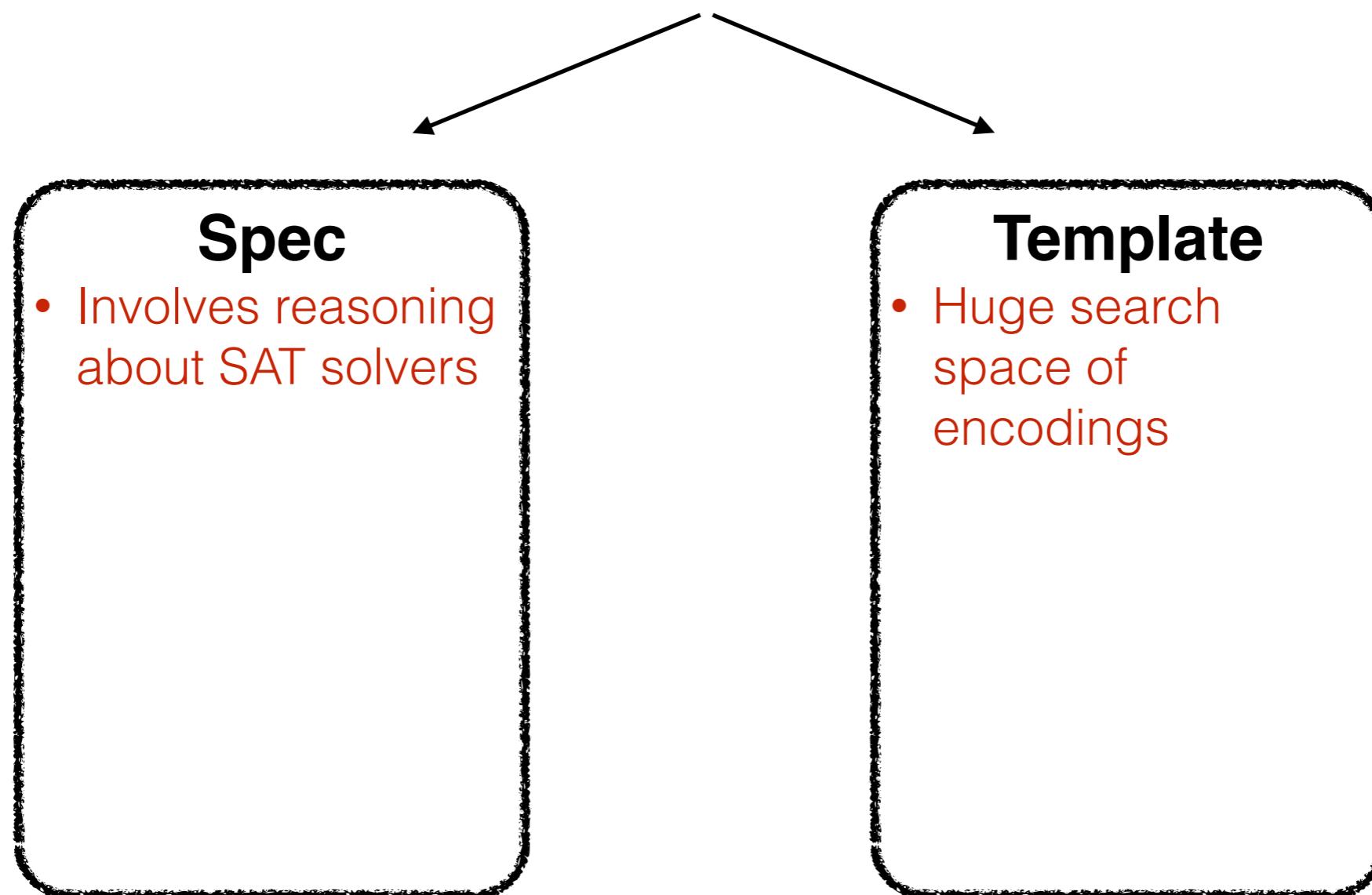
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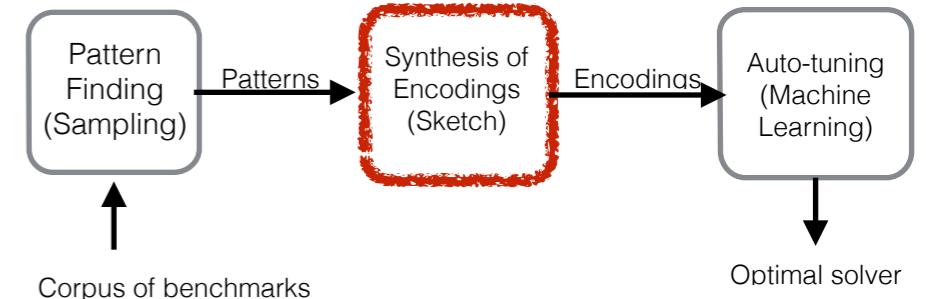




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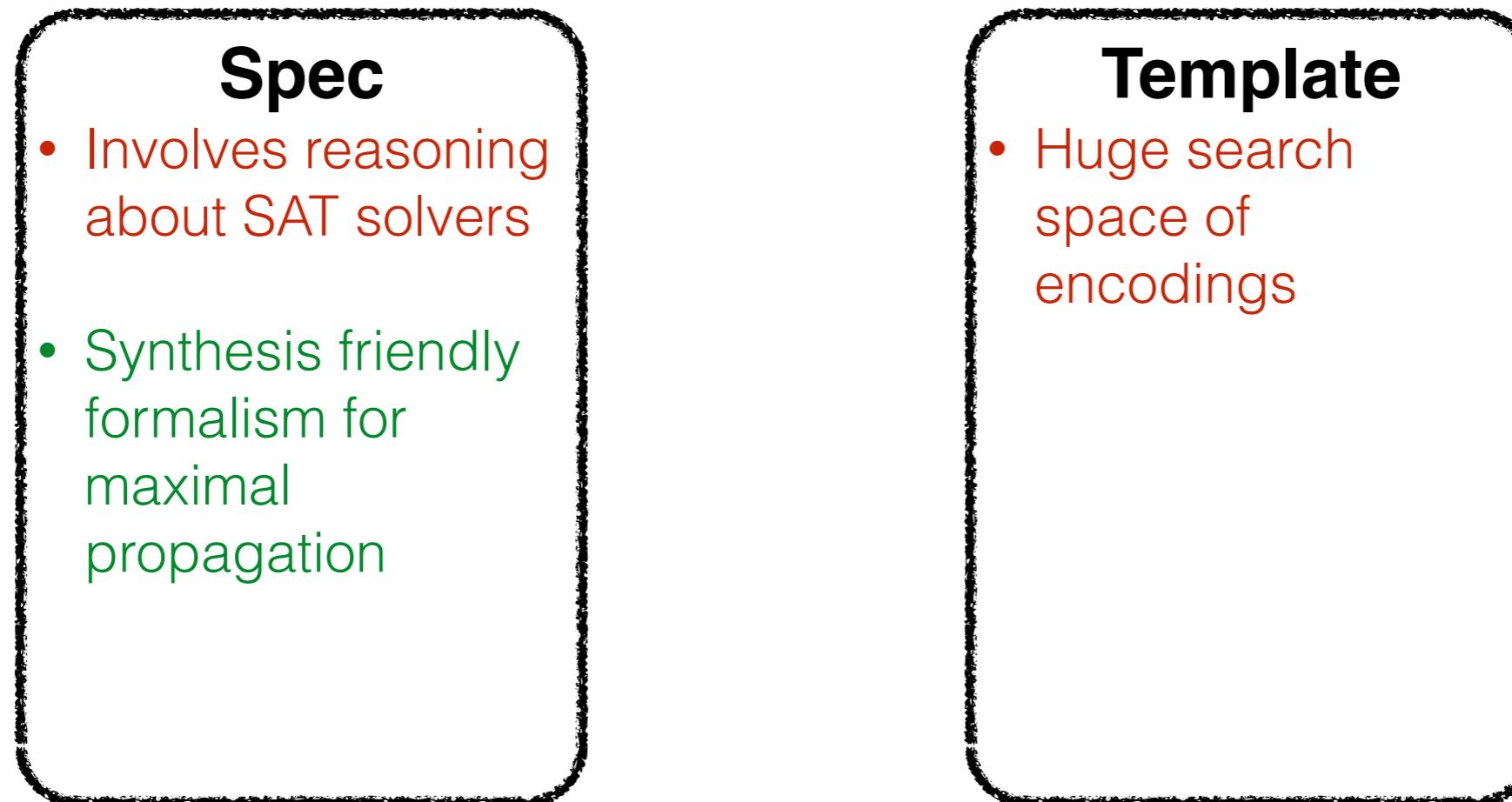


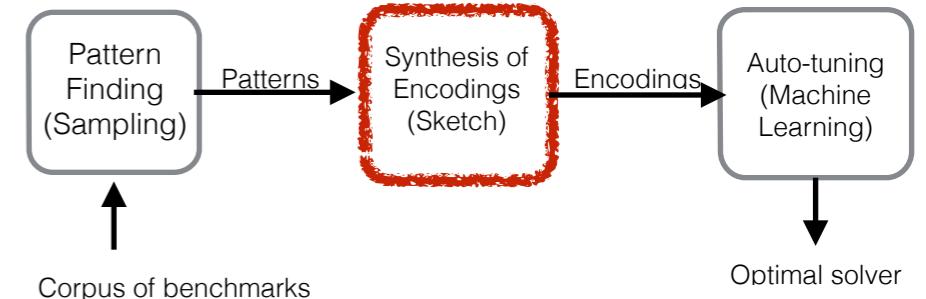
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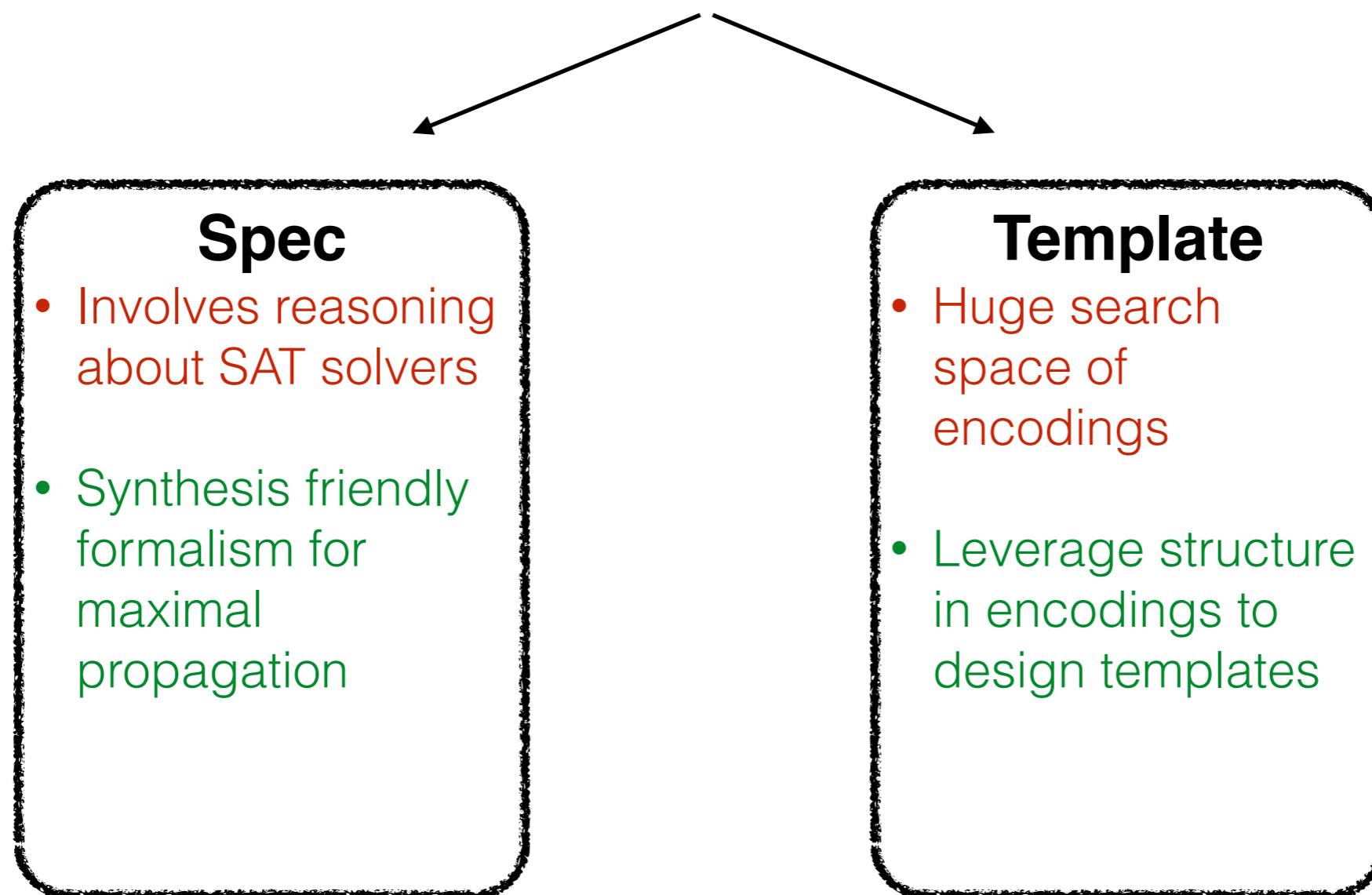


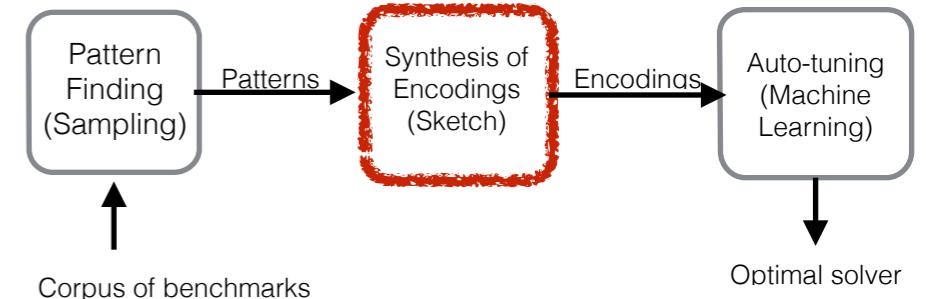
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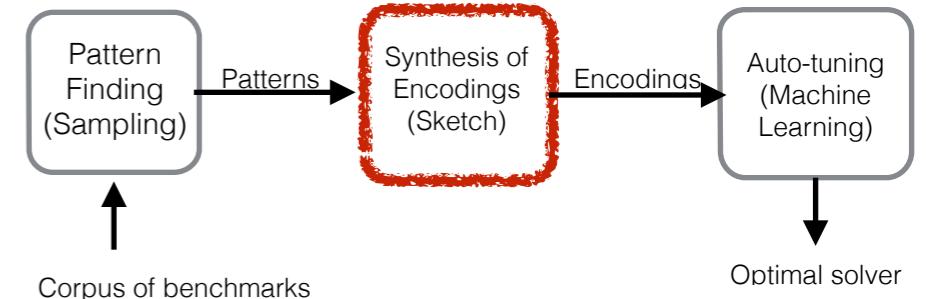
$o = ITE_N((GT_N, x, y), x, y)$



```

t1 = true
t2 = true
for i from N to 1 :
  t3 = newVar
  t4 = newVar
  clause({t1, t2,  $\overline{t4}$ })
  clause({t1,  $\overline{t2}$ , t4})
  clause({t1,  $\overline{t3}$ })
  clause({ $\overline{t1}$ ,  $\overline{x}$ , t3,  $\overline{t4}$ })
  ....
  clause({ $\overline{t1}$ ,  $\overline{y}$ ,  $\overline{x}$ , t3})
  clause({ $\overline{t1}$ ,  $\overline{y}$ , t3, t4})
  clause({ $\overline{t1}$ ,  $\overline{y}$ ,  $\overline{o}$ })
  clause({ $\overline{t1}$ ,  $\overline{x}$ ,  $\overline{o}$ })
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Synthesis as a SyGus problem

Boolean predicate P



CNF clauses C

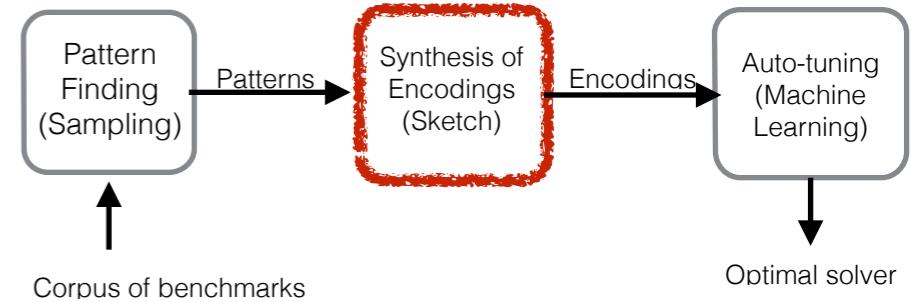
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    ....
    clause({t̄1, ȳ, x̄, t3})
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Synthesis as a SyGus problem

Boolean predicate P



CNF clauses C

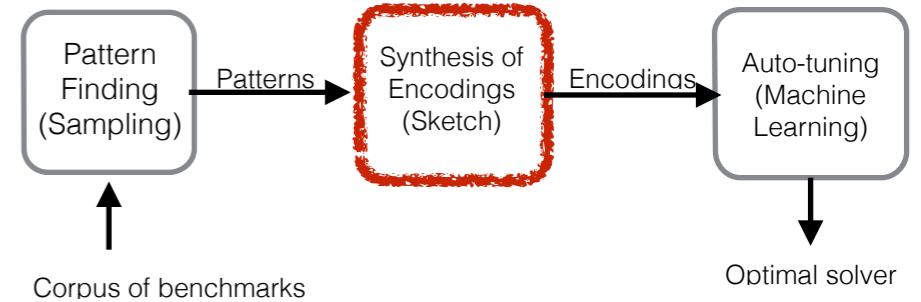
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Synthesis as a SyGus problem

Boolean predicate P



CNF clauses C

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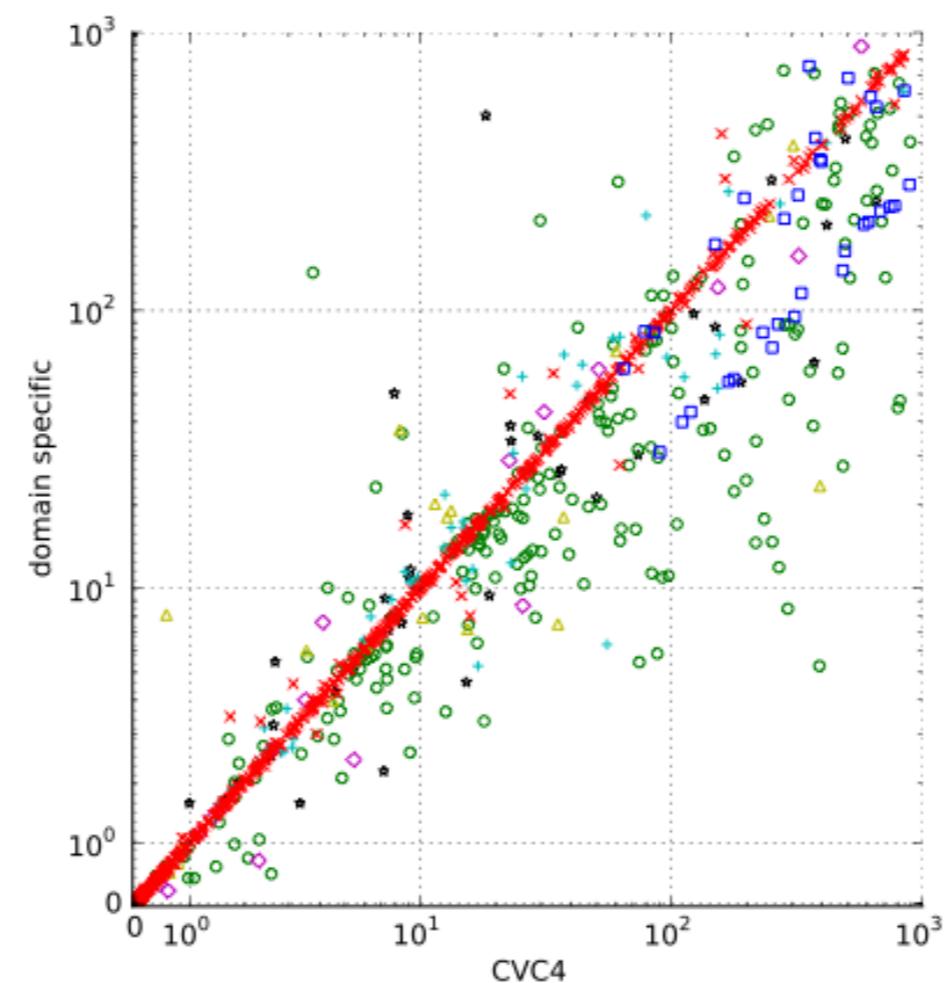


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  clause({t̄1, y, x, t3})
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  clause({t̄1, y, o})
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```

Does this buy you anything?



Solve more problems

Benchmark Family	Solved by CVC4 → Our Solver
<i>Log-slicing</i> (79)	33 → 62
ASP (365)	240 → 288
Mcm (61)	40 → 43
<i>Brummayerbiere2</i> (33)	28 → 29
Float (62)	59 → 60
<i>Brummayerbiere3</i> (40)	23 → 24
Bruttomesso (676)	623 → 623
TOTAL	1046 → 1129

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TOTAL	1046 → 1129



**83 more
problems in total**

Cross domain performance

Solver Domain	→ ↓	log-slicing	asp	mcm	brumma2	float	brumma3	brutto
<i>log-slicing</i>		62	58	36	59	32	35	35
<i>asp</i>		227	288	255	227	236	253	240
<i>mcm</i>		39	38	43	40	39	39	41
<i>brumma2</i>		29	28	28	29	29	29	29
<i>float</i>		57	57	59	57	60	60	59
<i>brumma3</i>		22	22	25	22	23	24	23
<i>brutto</i>		607	606	623	609	623	623	623



What did it take?

- Around 2000 benchmarks across 7 domains
- Over 200 million nodes in the high level SMT constraints
- Sampling generated ~2000 patterns (size ≤ 5)
- ~2000 SyGus problems to solve
- Generated ~40k to 160k lines of code per domain (30 lines per encoding)
- 8 hours of auto-tuning per domain
- On total, took 10-20 hours per domain with parallelism of 30