

PBS: A Pseudo-Boolean Solver and Optimizer



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Motivation ...

SAT Solvers

Apps: Verification, Routing,
ATPG, Timing Analysis

Problem Type: **CSP**

Problem Format: CNF

Example: Chaff, GRASP, SATO

Generic ILP Solvers

Apps: Routing, Planning,
Scheduling

Problem Type: **CSP/Optimization**

Problem Format: ILP

Example: CPLEX, LP_Solve

Specialized 0/1 ILP Solvers

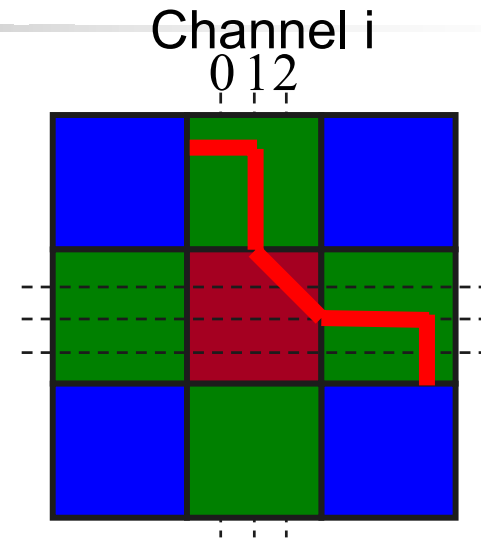
Apps: Verification, Routing,
Binate Covering

Problem Type: **CSP/Optimization**

Problem Format: CNF/PB (0/1 ILP)

Example: Satire, BSOLO, OPBDP, WSAT

Motivation ...



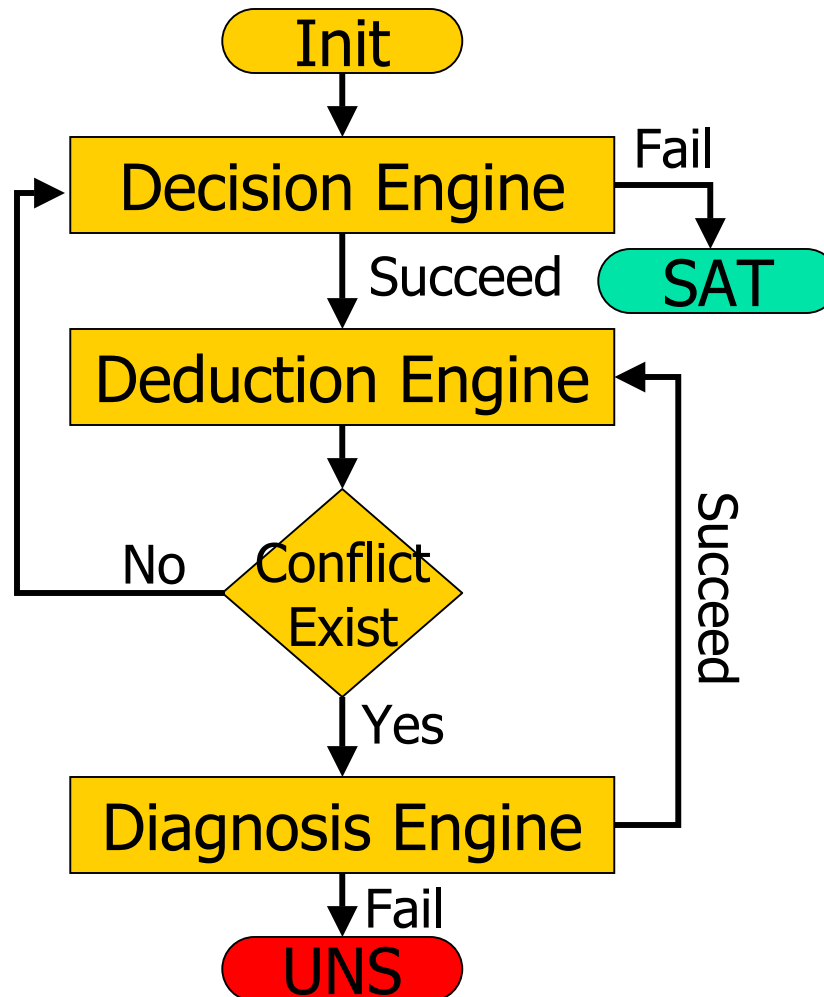
- Many applications require “**Counting Constraints**” that impose upper/lower bounds on number of objects
- Introduce a new specialized 0-1 ILP SAT solver
- Describe Pseudo-Boolean (PB) search algorithms
- Adapt SAT applications expressed in pure CNF to CNF/PB format
- Empirically demonstrate effectiveness in EDA applications



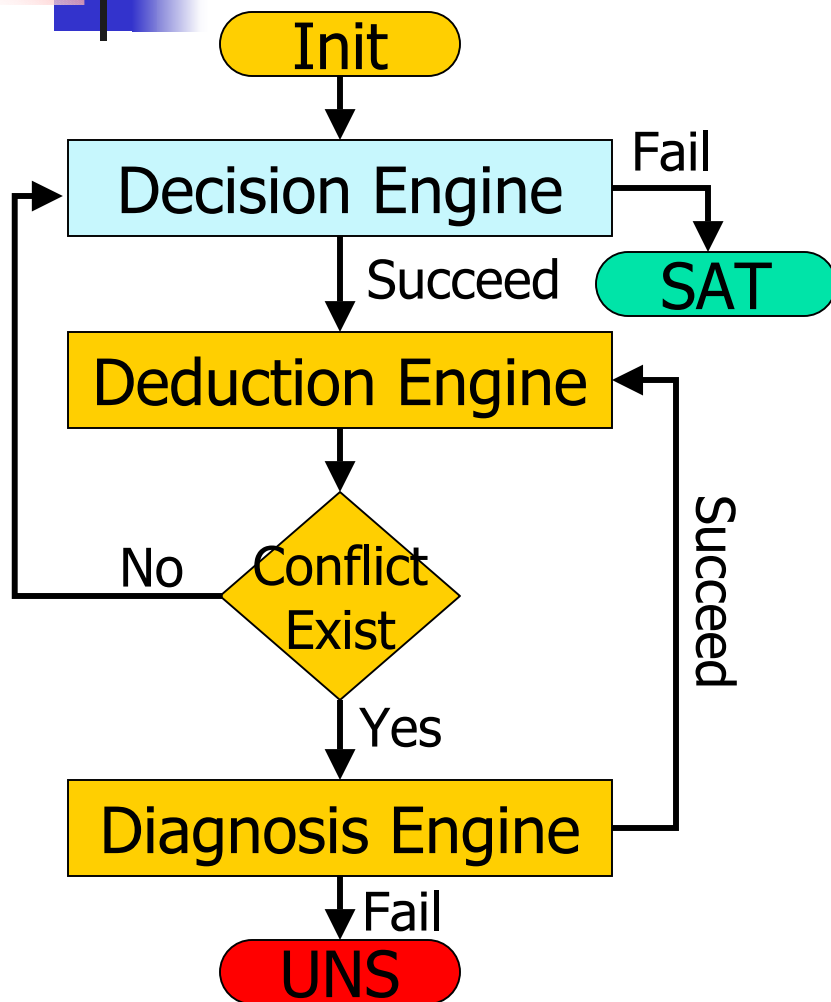
Outline

- Boolean Satisfiability advances
- Processing Pseudo-Boolean constraints
- Applications
 - CSP
 - Optimization
- Experimental evaluation
- Conclusions

Backtrack Search (DPLL)

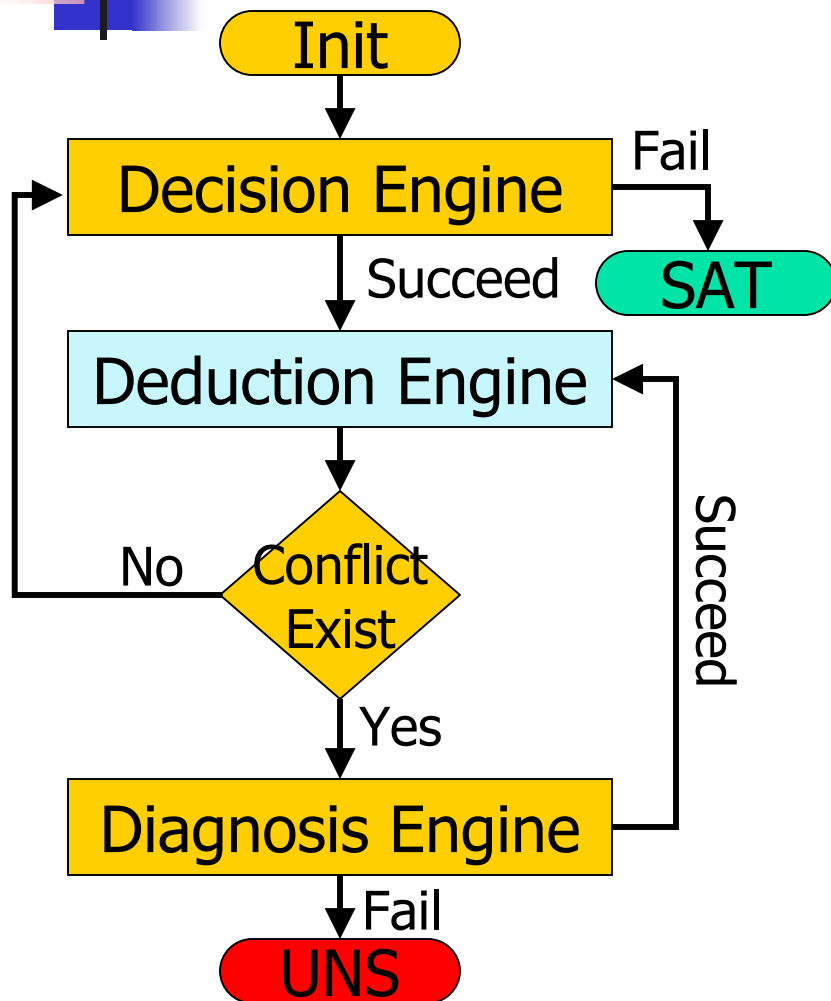


Decision Strategy



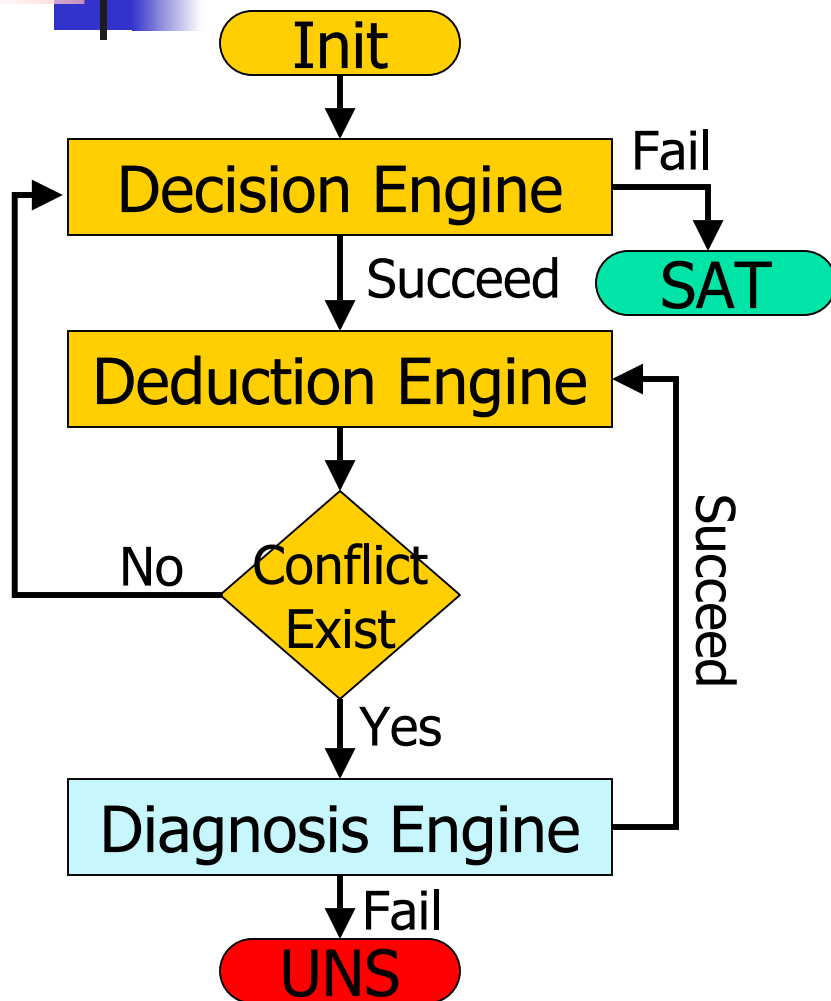
- Significantly improves the search performance
- Classified as:
 - Static
 - Dynamic
- Chaff introduced dynamic VSIDS:
 - Shown to be effective on most benchmarks
 - Selects most common literal and emphasizes variables in recent conflicts

Improved BCP



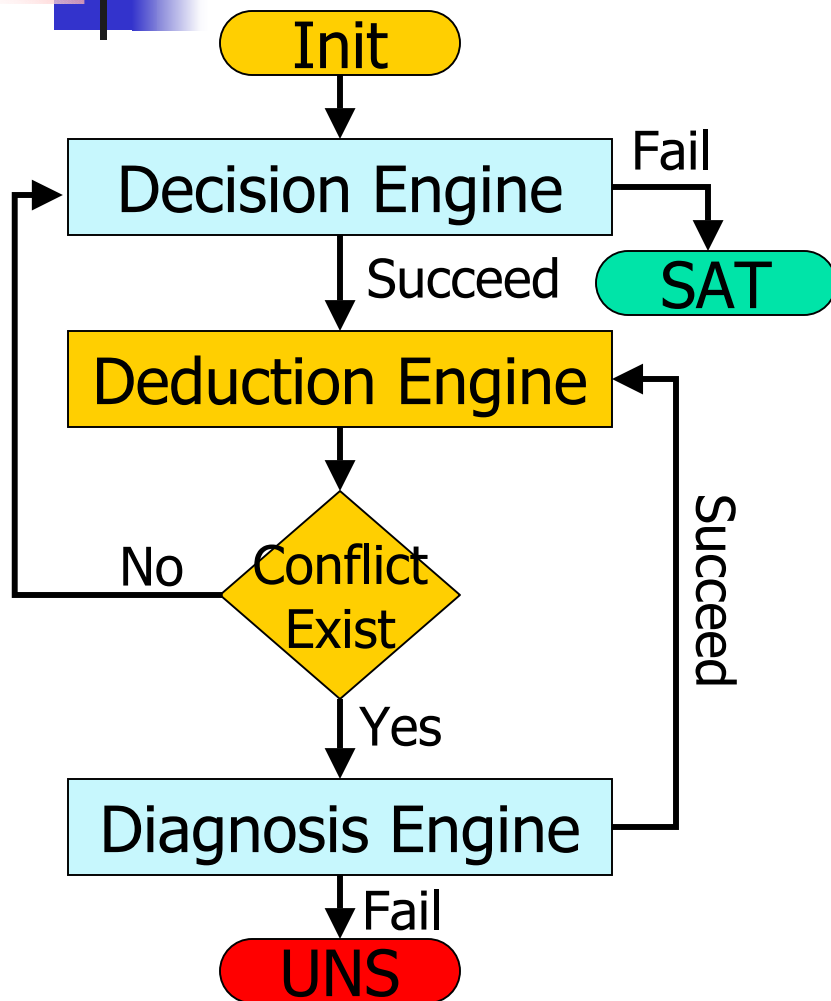
- Keeps track of any two unresolved literals in each clause instead of keeping track of all literals
- Leads to significant improvements over conventional BCP [Moskewicz et al., Zhang et al.]

Conflict Diagnosis and Clause Deletion



- Add conflict-induced clauses to avoid regenerating similar conflicts in future parts of the search process
- Very effective in expediting the search process
- Allows non-chronological backtracking
- 1UIP learning scheme shown to perform best among other learning schemes [Zhang et al.]

Random Restarts and Backtracking



- Solver often gets stuck in local non-useful search space
- Random restarts periodically unassigns all decisions and randomly selects a new decision sequence
- Restarts ensures that different sub-trees are searched at every restart
- Randomization can be combined with backtracking



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Pseudo-Boolean Constraints

$$c_1x_1 + \dots + c_nx_n \sim g$$

$$c_i, g \in \mathbb{Z}$$

$$\sim \in \{=, \leq, \geq\}$$

$$x_j \in \text{Literals}$$

- Clauses can be generalized as a PB constraint:
 $(x + y) \rightarrow (x + y \geq 1)$
- None of the presented algorithms rely on the integrality of c_i and can be implemented for floating-point c_i



Motivating Example

- Objective:
 - limit the **true** assignments to **k** vars out of the **n** vars
- Solution:
 - **CNF:**
 $\binom{n}{k+1}$ clauses
Each of size $(k+1)$
 - **PB:** single PB constraint
- “at most 2 out of v_1, v_2, v_3, v_4, v_5 , can be true”
 - **Pure CNF:**
 $(\bar{v}_1 + \bar{v}_2 + \bar{v}_3) \cdot (\bar{v}_1 + \bar{v}_2 + \bar{v}_4) \cdot$
 $(\bar{v}_1 + \bar{v}_2 + \bar{v}_5) \cdot (\bar{v}_1 + \bar{v}_3 + \bar{v}_4) \cdot$
 $(\bar{v}_1 + \bar{v}_3 + \bar{v}_5) \cdot (\bar{v}_1 + \bar{v}_4 + \bar{v}_5) \cdot$
 $(\bar{v}_2 + \bar{v}_3 + \bar{v}_4) \cdot (\bar{v}_2 + \bar{v}_3 + \bar{v}_5) \cdot$
 $(\bar{v}_2 + \bar{v}_4 + \bar{v}_5) \cdot (\bar{v}_3 + \bar{v}_4 + \bar{v}_5)$
 - **PB form:**
 $(1v_1 + 1v_2 + 1v_3 + 1v_4 + 1v_5 \leq 2)$



PB Constraint Data Structure

- Struct PBConstraint {
 - Goal n ; constraint type \sim ; list of c_i and x_i 's;
 - `initLHS`; // sum of all c_i 's
 - `LHS`; // value of LHS based on current variable assignment
 - `maxLHS`; // maximal possible value of LHS given the current variable assignment }

- For efficiency:
 - Sort the list of $c_i x_i$ in order of increasing c_i
 - Convert all negative c_i to positive:

i.e. $c_1 x_1 - c_2 x_2 \leq n$

$$c_1 x_1 - c_2 (1 - \bar{x}_2) \leq n$$

$$c_1 x_1 + c_2 \bar{x}_2 \leq n + c_2$$

Algorithms for PB Search

- Assigning v_i to 1:
For each literal x_i of v_i
 - If positive x_i , LHS += c_i
 - If negative x_i , maxLHS -= c_i
- Unassigning v_i from 1:
For each literal x_i of v_i
 - If positive x_i , LHS -= c_i
 - If negative x_i , maxLHS += c_i
- PB constraint state:
 - \geq type
 - SAT: LHS \geq goal
 - UNS: maxLHS < goal
 - \leq type
 - SAT: maxLHS \leq goal
 - UNS: LHS > goal

$$5x_1 + 6x_2 + 3x_3 \leq 12$$



$$\begin{aligned} \text{LHS} &= 0 \\ \text{maxLHS} &= 14 \end{aligned}$$

$$5x_1 + 6x_2 + 3x_3 \leq 12$$



$$\begin{aligned} \text{LHS} &= 5 \\ \text{maxLHS} &= 14 \end{aligned}$$

$$5x_1 + 6x_2 + 3x_3 \leq 12$$

$$\begin{aligned} \text{LHS} &= 5 \\ \text{maxLHS} &= 8 \\ \text{SATISFIABLE} \end{aligned}$$

Algorithms for PB Search

- Identifying implications
 - \leq type
 - if $c_i > \text{goal} - \text{LHS}$, $x_i = 0$
 - Implied by literals in PB assigned to 1
 - \geq type
 - if $c_i > \text{maxLHS} - \text{goal}$, $x_i = 1$
 - Implied by literals in PB assigned to 0

$$5x_1 + 6x_2 + 3x_3 \leq 12$$



$$\begin{aligned} \text{LHS} &= 0 \\ \text{maxLHS} &= 14 \\ \text{goal} - \text{LHS} &= 12 \end{aligned}$$

$$5x_1 + 6x_2 + 3x_3 \leq 12$$

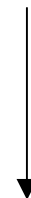


$$\begin{aligned} \text{LHS} &= 8 \\ \text{maxLHS} &= 14 \\ \text{goal} - \text{LHS} &= 4 \\ \text{Imply } x_2 &= 0 \end{aligned}$$

Algorithms for PB Search

- Identifying implications
 - \leq type
 - if $c_i > \text{goal} - \text{LHS}$, $x_i = 0$
 - Implied by literals in PB assigned to 1
 - \geq type
 - if $c_i > \text{maxLHS} - \text{goal}$, $x_i = 1$
 - Implied by literals in PB assigned to 0

$$5x_1 + 6x_2 + 3x_3 \geq 10$$



$$\text{LHS} = 0$$

$$\text{maxLHS} = 14$$

$$\text{maxLHS} - \text{goal} = 4$$

$$\text{Imply } x_1 = x_2 = 1$$

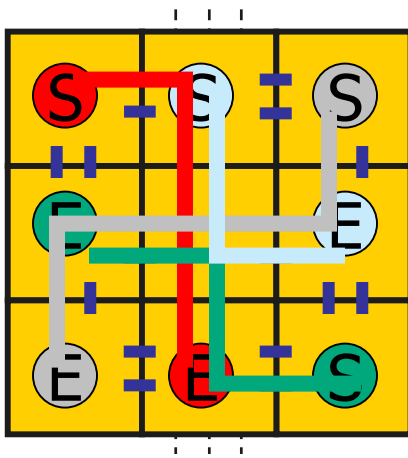


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Applications - CSP

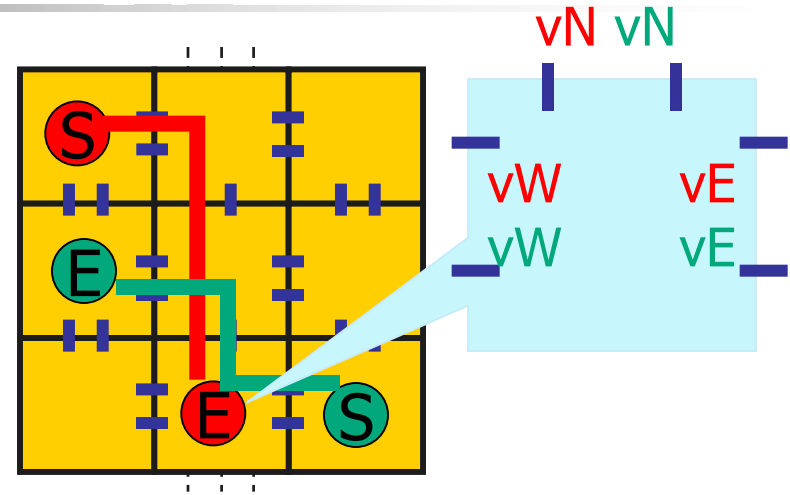
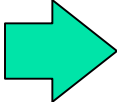
- Global Routing



- 2-D grid of cells arranged in rows/columns
- Cell boundaries are edges
- Capacity C is associated with each edge (no more than C routes can pass)
- Goal: route number of 2-pin connections in the grid with edge capacities
- Generate satisfiable instances using randomized flooding

Global Routing Formulation

- Connectivity constraints (for each net)
 - Exactly one edge selected at start/end point
 - If cell is a mid-point, either two or no edges are selected
- Capacity constraints
 - A net can use a single track across an edge
 - No two nets can use the same track across an edge



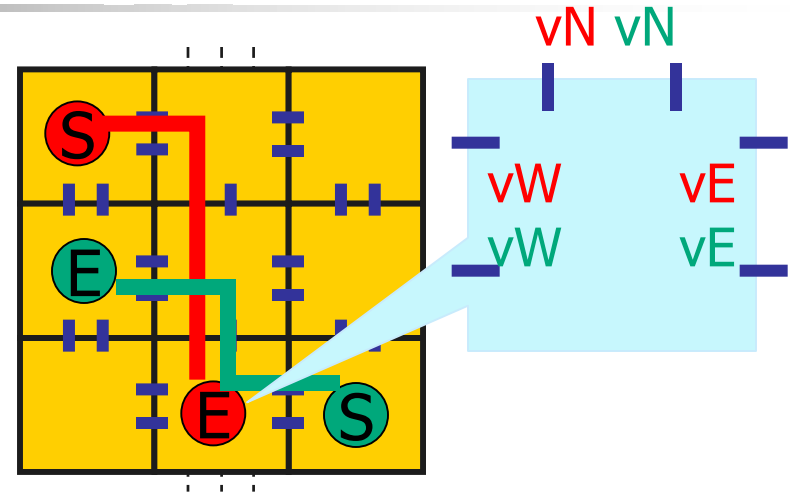
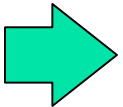
- Create a variable for each edge/net
 $2 \times 12 = 24$ variables

$$(\overline{vN} + \overline{vW})(\overline{vN} + \overline{vE})(\overline{vW} + \overline{vE})$$

$$(vW + vN + vE)$$

Global Routing Formulation

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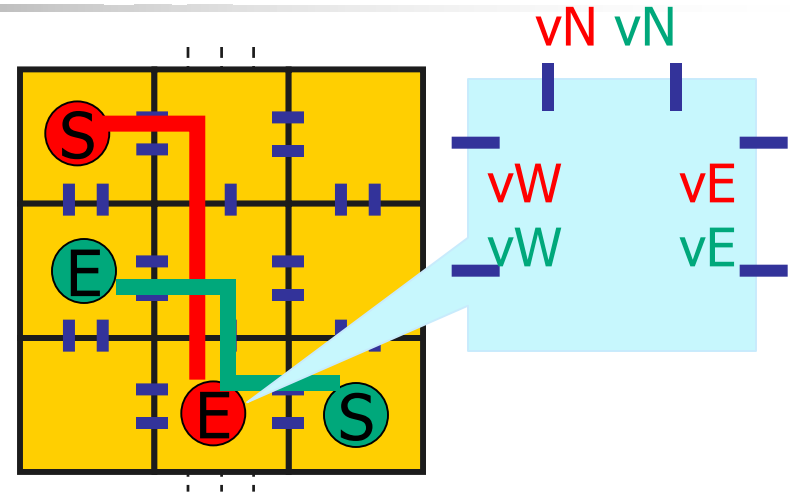
- Create a variable for each edge/net
 $2 \times 12 = 24$ variables

$$(\overline{vN} + vE + vW)(vN + \overline{vE} + vW)$$

$$(vN + vE + \overline{vW})(\overline{vN} + \overline{vE} + \overline{vW})$$

Global Routing Formulation

- Connectivity constraints (for each net)
 - Exactly one edge selected at start/end point
 - If cell is a mid-point, either two or no edges are selected



- Capacity constraints
 - A net can only occupy one track across the grid
 - No two nets can occupy the same track

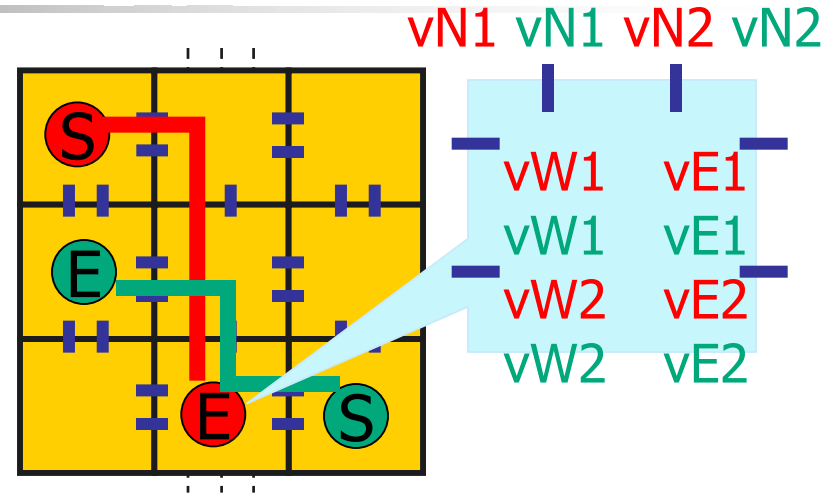
30 Nets
10 Cap
#Cl = 55M
vs.
1 PB

Create a variable for each edge/net
 $2 \times 12 = 24$ variables

pureCNF	CNF/PB
$\#Cl = \begin{pmatrix} \#Nets \\ Cap + 1 \end{pmatrix}$	$\sum v_i \leq Cap$ all $_nets$

Global Routing Formulation

- Connectivity constraints (for each net)
 - Exactly one edge selected at start/end point
 - If cell is a mid-point, either two or no edges are selected



- Capacity constraints
 - A net can only occupy one track across an edge
 - No two nets can occupy the same track across an edge

Additional Variables & Clauses

- Create *Cap* variables per edge/net
 $2 \times 2 \times 12 = 48$ variables

pureCNF

$$\#Cl = (\#Nets) \binom{Cap}{2} + (Cap) \binom{\#Nets}{2}$$



Applications - optimization

- Max-ONEs
 - Seeks an assignment that
 - Satisfies all constraints
 - Maximizes the number of variables assigned to true
 - Useful to represent “Max-Clique” problems
 - “Vertex Cover” can be reduced to Min-ONEs
 - Use a single PB constraint of type “ \geq ” that includes each variable with coefficient “1”
 - Iteratively increase the lower bound until the problem becomes unsatisfiable
 - Extendable to “Weighted Max-ONEs”



Applications - optimization

- Max-SAT
 - Finds an assignment that
 - Satisfies maximum possible number of clauses
 - Generalization of SAT
 - Provides more info for unsatisfiable instances
 - Used to represent “Max-CUT” problems
 - Expressed using a single PB constraint
 - Solved using PBS
 - Addressed indirectly using WalkSAT



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Experimental Setup

- Platform: Pentium-II 300 MHz with 512MB RAM running Linux
- Runtime limit: 5000 sec
- PBS Implemented in C++
- PBS settings:
 - VSIDS decision heuristic
 - Optimized BCP
 - Random Restarts
 - 1st UIP conflict analysis learning scheme
 - Clause deletion/random backtracking disabled



Global Routing Experiment

Instance	CNF + pseudo-Boolean						pure CNF			PBS Speedup		
	V	C	#PB	PBS	SATIRE	OPBDP	V	C	Chaff	Satire	OPBDP	Chaff
grout3.3-1	216	572	12	1.72	0.41	4.51	864	7592	40.43	0	3	24
grout3.3-2	264	700	12	0.33	0.96	4.65	1056	10864	11.3	3	14	34
grout3.3-3	240	636	12	0.09	1.1	6.65	960	9156	37.21	12	74	413
grout3.3-4	228	604	12	1.29	0.2	4.73	912	8356	103.13	0	4	80
grout3.3-5	240	634	12	0.84	0.35	6.88	960	9154	71.21	0	8	85
grout4.3-1	672	2004	24	3.46	109.7	5000	2688	33924	1361.6	32	1445	394
grout4.3-2	648	1928	24	1.92	32.13	5000	2592	31736	5000	17	2604	2604
grout4.3-3	648	1930	24	5.52	319.47	5000	2592	31738	5000	58	906	906
grout4.3-4	696	2072	24	16.3	3772	5000	2784	36176	2523	231	307	155
grout4.3-5	720	2144	24	2.06	567.12	5000	2880	38504	3915	275	2427	1900
grout4.3-6	624	1860	24	134	5000	5000	2496	29628	5000	37	37	37
grout4.3-7	672	2006	24	55	5000	5000	2688	33926	772.6	91	91	14
grout4.3-8	432	1280	24	2.9	177.8	5000	1728	15320	125	61	1724	43
grout4.3-9	840	2502	24	376	5000	5000	3360	51222	3203	13	13	9
grout4.3-10	840	2504	24	7.4	5000	5000	3360	51224	3465	676	676	468



MaxONE Experiment

Bench- mark	Satisfiable Instance	V	C	Max- ONEs	PBS	SATIRE	OPBDP	PBS Speedup	
								SATIRE	OBPD
DIMACS	aim-50-1_6-yes1-1	50	80	29	0.01	0.01	0.02	1	2
	aim-100-1_6-yes1-1	100	160	43	0.01	0.02	7.19	2	719
	aim-200-2_0-yes1_1	200	400	96	0.01	0.06	5000	6	500000
	ii8b1	336	2068	275	4.69	3180	56.2	678	12
	jnh1	100	850	55	0.32	2.2	0.12	7	0.38
	jnh204	100	800	58	0.28	1.63	0.14	6	0.50
	par8-1	350	1149	79	0.01	0.06	0.05	6	5
	par8-2-c	68	270	20	0.01	0.02	0.01	2	1
Beijing	3blocks	283	9690	63	4.83	49.53	4494	10	930
QG	qg7-09	729	22060	81	0.1	5.41	9.8	54	98
	qg6-09	729	21844	81	0.21	5.56	45	26	214
Planning	bw_a	459	4675	73	0.03	0.43	0.21	14	7
	bw_b	1087	13772	136	0.58	6.39	17.86	11	31
	bw_c	3016	50457	272	24.37	315.5	5000	13	205



Conclusions

- Adapting SAT apps to use CNF/PB constraints
 - leads to memory savings and runtime reductions
- Proposed new specialized 0-1 ILP solver, PBS
- Confirmed effectiveness on real world examples:
 - Global routing **consistency** instances
 - Max-ONEs **optimization** problems (extendable to Max-SAT, Min-ONEs)



Future Works

- Compare state-of-the-art Generic ILP solvers, such as CPLEX, to specialized 0-1 ILP solvers
- Apply PBS to Max-SAT and Min-ONEs problems
- Study applications to Max-Clique, Max Independent Set, and Min Vertex Cover