Compiling Finite Domain Constraints to SAT with BEE

Michael Codish

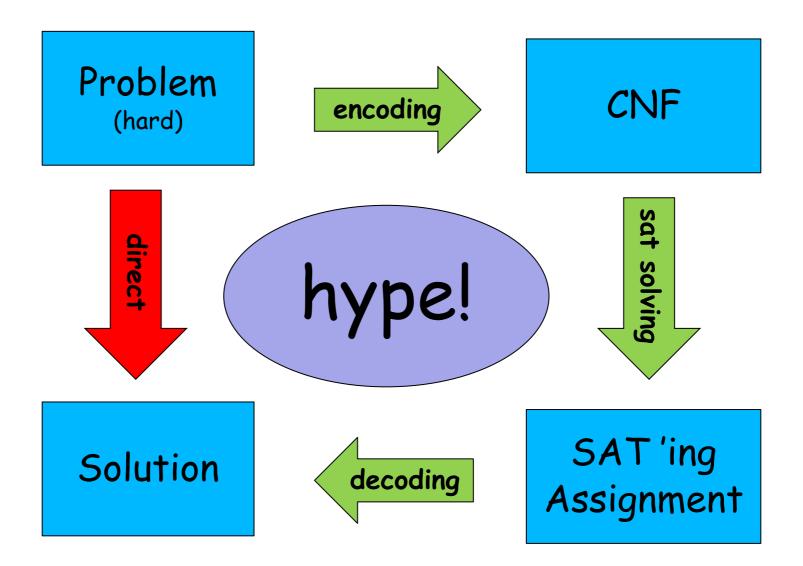


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Joint work: Yoav Fekete & Amit Metodi **cādence**®

In Collaboration with: Vitaly Lagoon & Peter Stuckey

It is all about: Solving hard problems via SAT encodings



Ben-Gurion

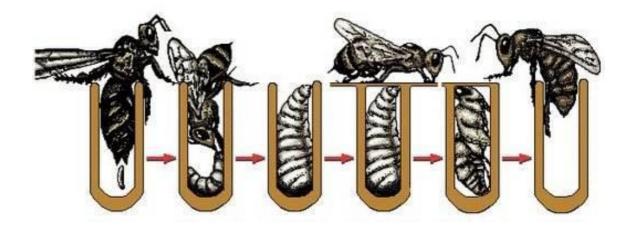
Equi-propagation

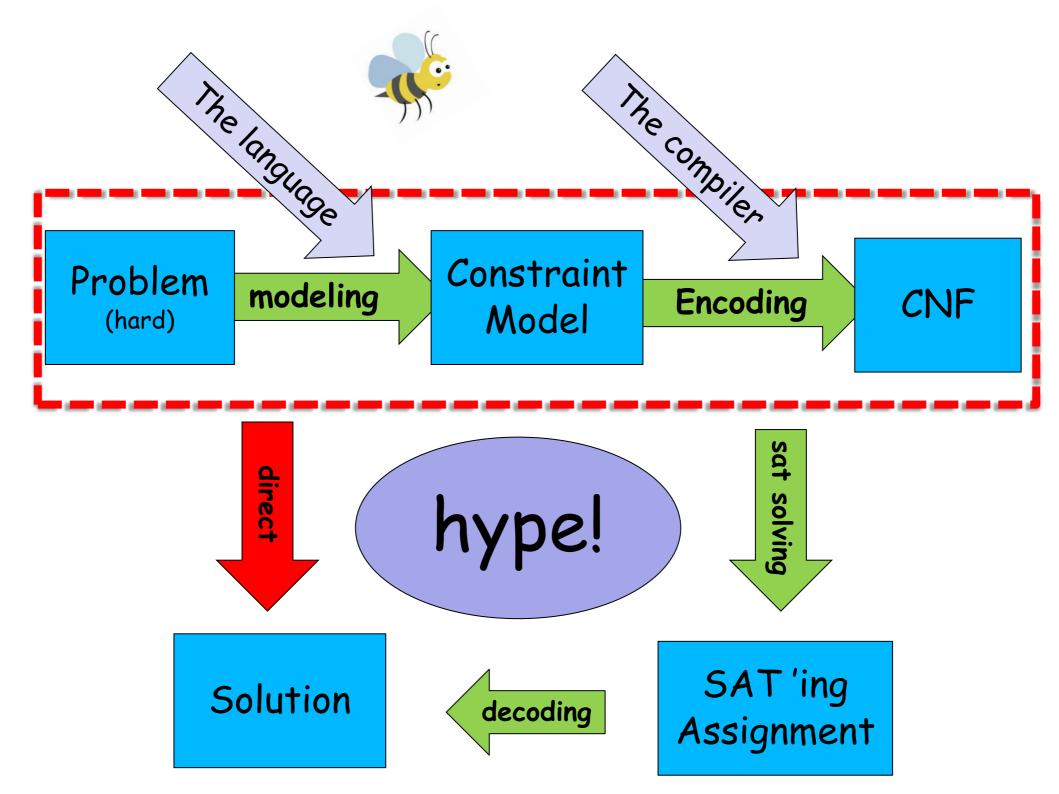
Encoder

was born (*) with two objectives:

- Facilitate the (user) process of <u>encoding</u> a (constraint) problem to CNF
- <u>Compile</u> constraint models to CNF while applying optimizations in order to generate (usually) smaller and better CNF formulas.

 Amit Metodi, Michael Codish, Vitaly Lagoon, Peter J. Stuckey: Boolean Equi-propagation for Optimized SAT Encoding. CP
 2011: 621-636

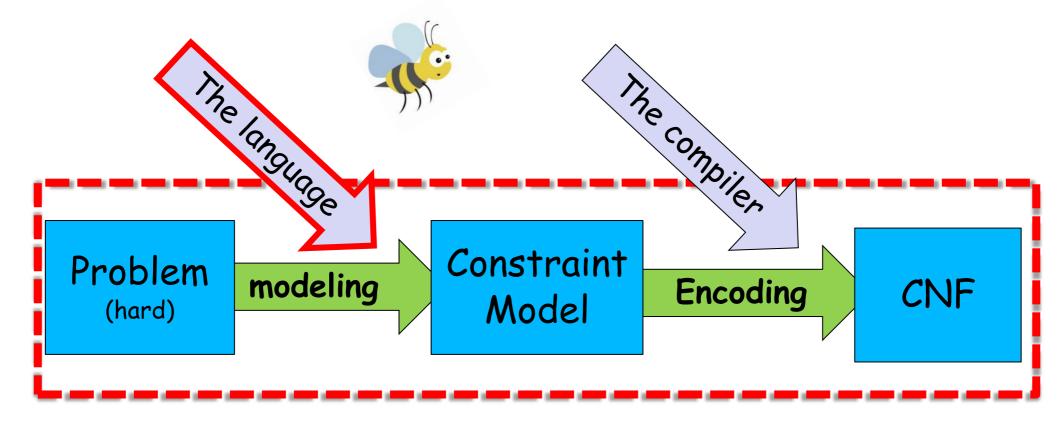




Outline

- Introduction
- BEE in a nutshell
 - Order encoding (representing integers)
 - Equi-propagation (ad-hoc)
- The "new" stuff
 - Complete Equi-Propagation
 - Cardinality Constraints in BEE
 - The binary extension of BEE





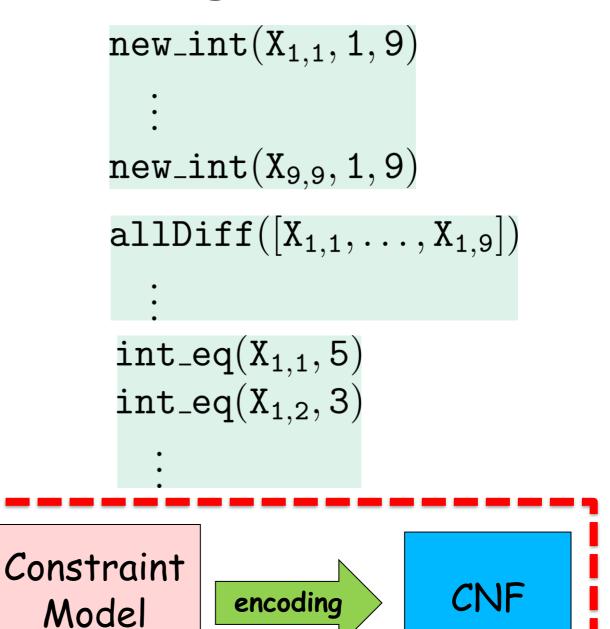
Example: encoding Sudoku

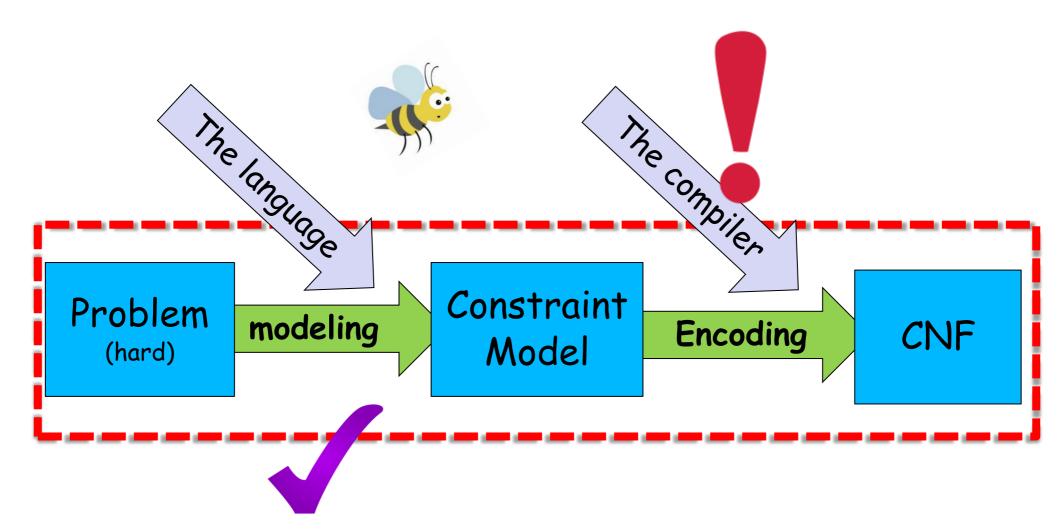
5	3			7				
6			1	9	5			
	9	8					6	
8				6				3
4			8		3			1
7				2				6
	6					2	8	
			4	1	9			5
				8			7	9

Problem

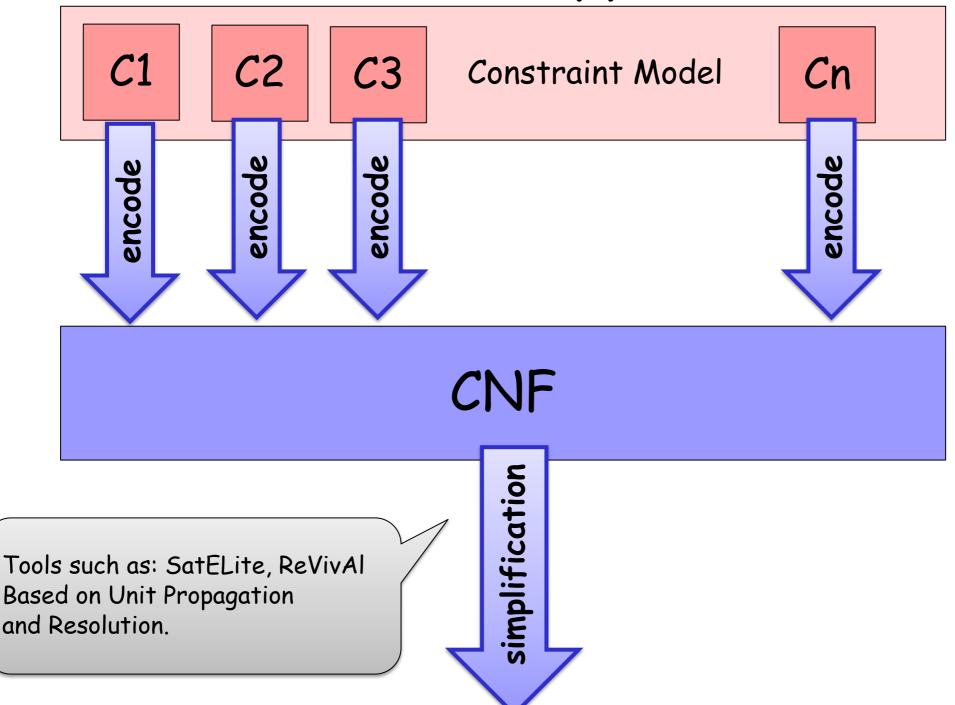
(hard)

modeling

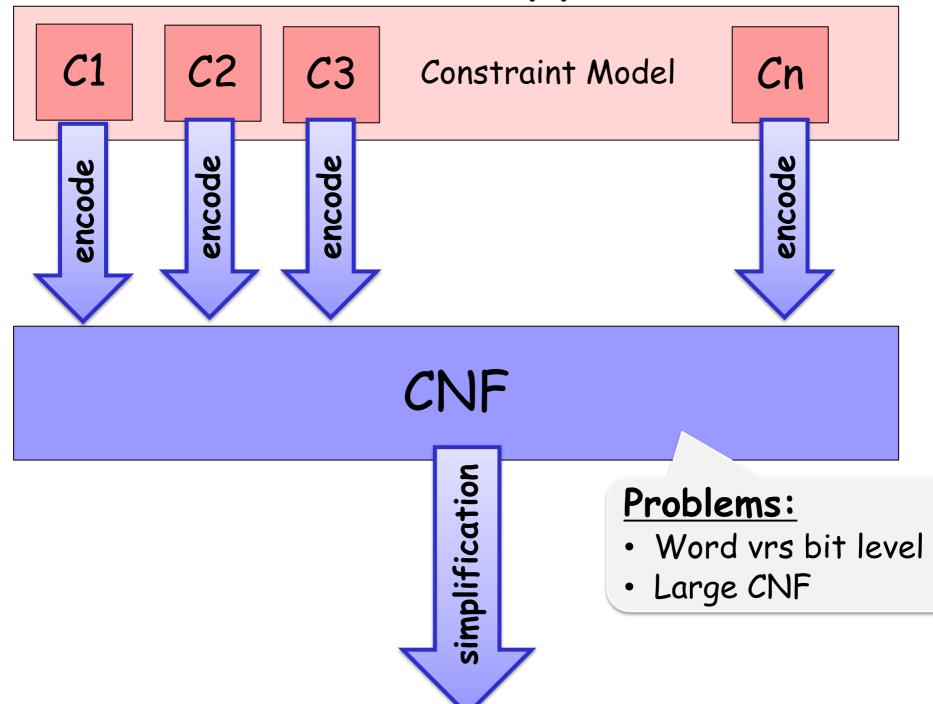


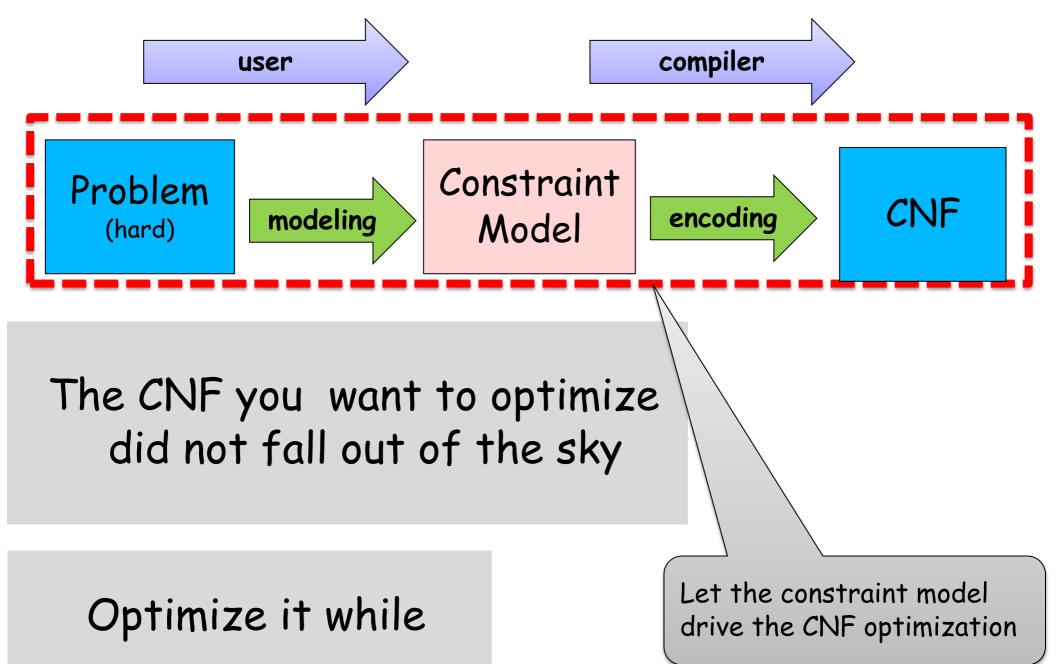


The Usual Approach



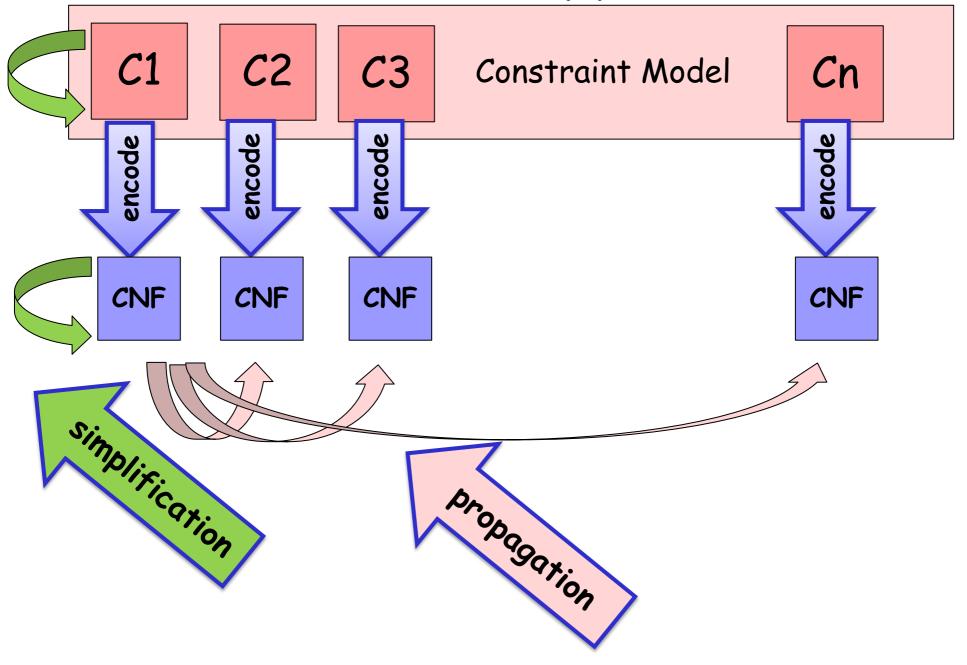
The Usual Approach



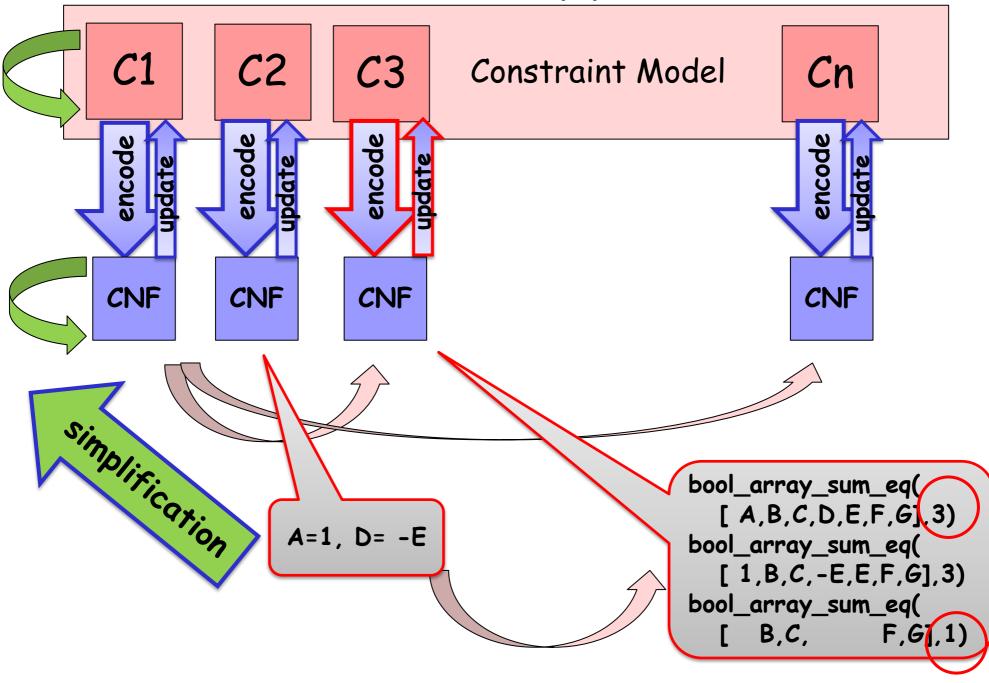


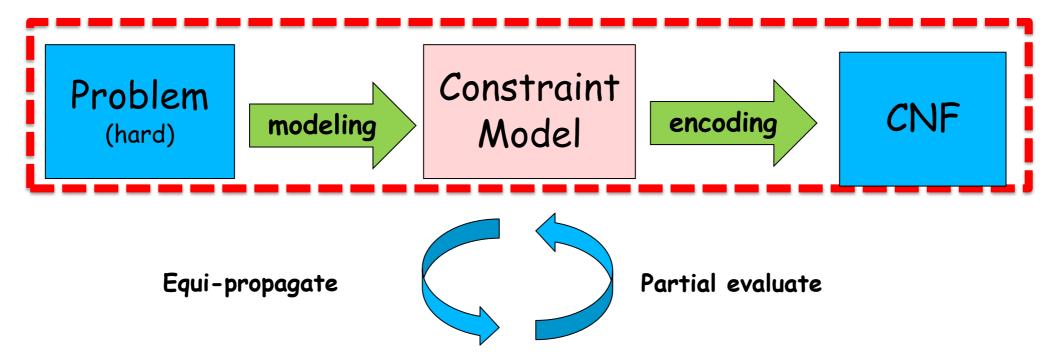
generating it

The BEE Approach



The BEE Approach





- 1. view each "single" constraint as a Boolean formula
- 2. derive ("all") implied equalities between literals and constants
- 3. apply them to simplify <u>all</u> constraints

Equi-propagation is the process of inferring equations implied by a "small chunck " of constraints. more powerful reasoning but on smaller CNF portions

of the form X=L where L is a constant or a literal: X=Y, X= -Y, X=0, X=1

TWO DESIGN CHOICES

>Representing numbers

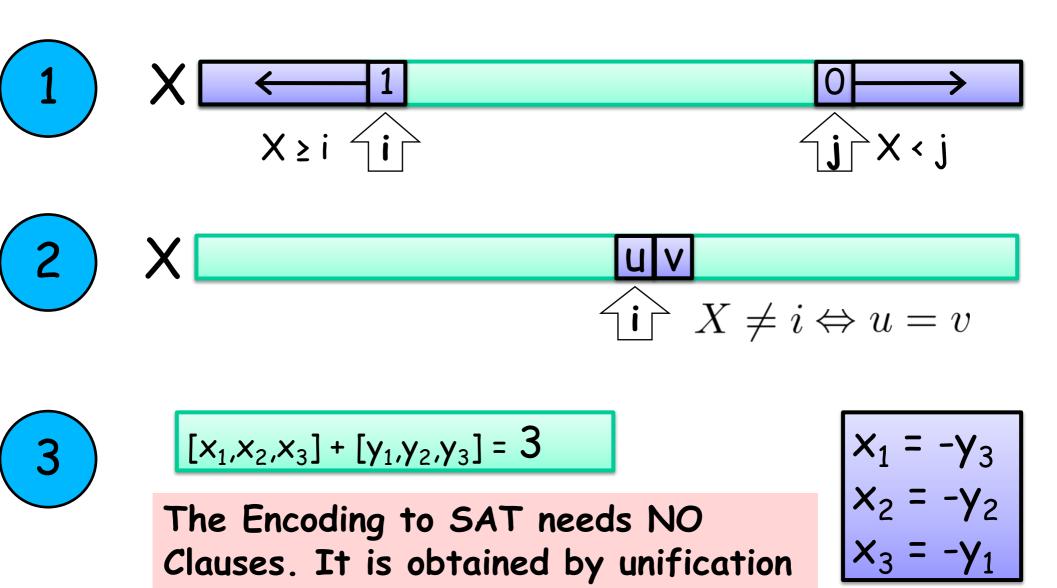
Order encoding (unary)

X =
$$[x_1, ..., x_i, ..., x_n]$$

 $x_i \leftrightarrow (X \ge i)$
(X = 3) = $[1, 1, 1, 0, 0]$



Lots of equi-propagation



TWO DESIGN CHOICES

- >Implementing Equi-Propagation
 - 1. Using BDD's.
 - Prohibitive for global constraints.
 - Complete
 - 2. Using SAT (on small groups of constraints)
 - In practice, surprisingly, "not slow"
 - Complete
 - .) Ad-Hoc rules (per constraint type)
 - Fast, precise in practice
 - Incomplete

Ad-Hoc Rules: int_plus

> Equi-Propagation

$c = \operatorname{int_plus}(X, Y, Z)$ where $X = \langle x_1, \ldots, x_n \rangle$,				
$Y = \langle y_1, \ldots, y_m \rangle$, and $Z = \langle z_1, \ldots, z_{n+m} \rangle$				
if in E	then add in $\mu_{c}(E)$			
$X \ge i, Y \ge j$	$Z \ge i + j$			
X < i, Y < j	Z < i + j - 1			
$Z \ge k, X < i$	$Y \ge k - i$			
$Z < k, X \ge i$	Y < k - i			
X = i	$z_{i+1} = y_1, \dots, z_{i+m} = y_m$			
Z = k	$x_1 = \neg y_k, \dots, x_k = \neg y_1$			

> Partial Evaluation

$c = \text{int}_{plus}(X, Y, Z)$ where $X = \langle x_1, \dots, x_n \rangle$,				
$Y = \langle y_1, \ldots, y_m \rangle$, and $Z = \langle z_1, \ldots, z_{n+m} \rangle$				
if	then replace with			
X = i	true			
Z = k	true			
$X \ge i, Z \ge i$	$\operatorname{int_plus}([x_{i+1},\ldots,x_n],Y,$			
	$[z_{i+1},\ldots,z_{n+m}])$			
$X \le i, Z \le i+m$	$\operatorname{int_plus}([x_1,\ldots,x_i],Y,$			
$\Lambda \leq \iota, \Sigma \leq \iota + m$	$[z_1,\ldots,z_{i+m}])$			



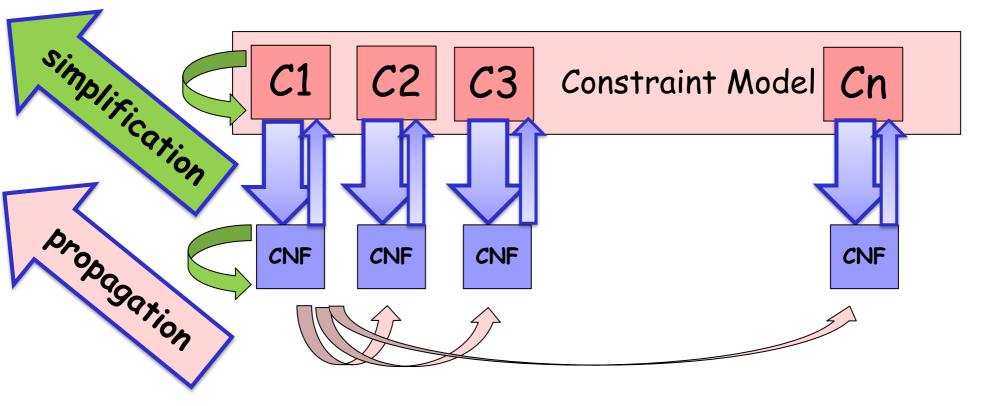
- Introduction
- BEE in a nutshell

http://amit.metodi.me/research/bee/

- The "new" stuff
 - Complete Equi-Propagation
 - Cardinality Constraints in BEE
 - The binary extension of BEE

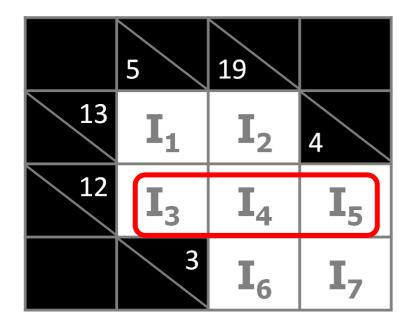


Complete Equi-propagation



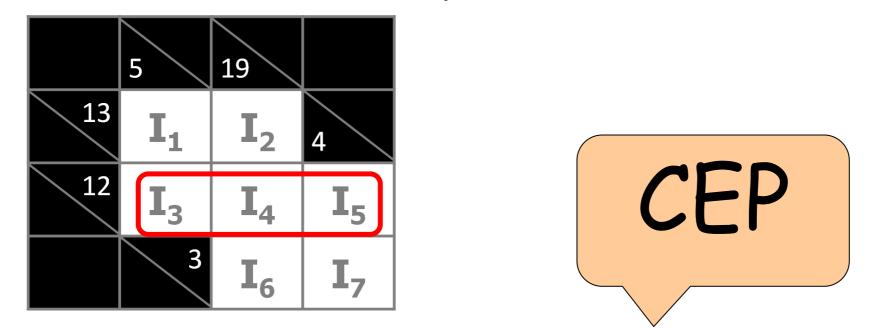
designate specific **sets** of constraints for **complete** equi-propagation (using a SAT solver)

Example: Kakuro



$\boxed{\texttt{new_int}(I_1, 1, 9)}$	$int_array_plus([I_1, I_2], 13)$	$allDiff([I_1, I_2])$
$ \operatorname{new_int}(I_2, 1, 9) $	$int_array_plus([I_1, I_3], 5)$	$allDiff([I_1, I_3])$
$ \operatorname{new_int}(I_3, 1, 9) $	$[int_array_plus([I_3, I_4, I_5], 12)]$	$ \texttt{allDiff}[[I_3, I_4, I_5]) $
$ \operatorname{new_int}(I_4, 1, 9) $	$[int_array_plus([I_2, I_4, I_6], 19])$	$ allDiff([I_2, I_4, I_6]) $
$ \operatorname{new_int}(I_5, 1, 9) $	$int_array_plus([I_6, I_7], 3)$	$allDiff([I_6, I_7])$
$ \operatorname{new_int}(I_6, 1, 9) $	$int_array_plus([I_5, I_7], 4)$	$allDiff([I_5, I_7])$
$ \operatorname{new_int}(I_7, 1, 9) $		

Example: Kakuro



$new_int(I_1, 1, 9)$	$int_array_plus([I_1, I_2], 13)$	$allDiff([I_1, I_2])$
$ \operatorname{new_int}(I_2, 1, 9) $	$int_array_plus([I_1, I_3], 5)$	$allDiff([I_1, I_3])$
$new_int(I_3, 1, 9)$	$[int_array_plus([I_3, I_4, I_5], 12)]$	$\texttt{allDiff}([I_3, I_4, I_5])$
$\texttt{new_int}(I_4, 1, 9)$	$int_array_plus([I_2, I_4, I_6], 19)$	$\texttt{allDiff}([I_2, I_4, I_6])$
$\texttt{new_int}(I_5, 1, 9)$	$ int_array_plus([I_6, I_7], 3) $	$allDiff([I_6, I_7])$
$ \operatorname{new_int}(I_6, 1, 9) $	$int_array_plus([I_5, I_7], 4)$	$allDiff([I_5, I_7])$
$ \operatorname{new_int}(I_7, 1, 9) $		

CEP is similar to Backbones

Backbones are about detecting variables which take fixed values in all solutions

 $\begin{array}{c} \varphi \models x = 1 \\ \varphi \models x = 0 \end{array}$

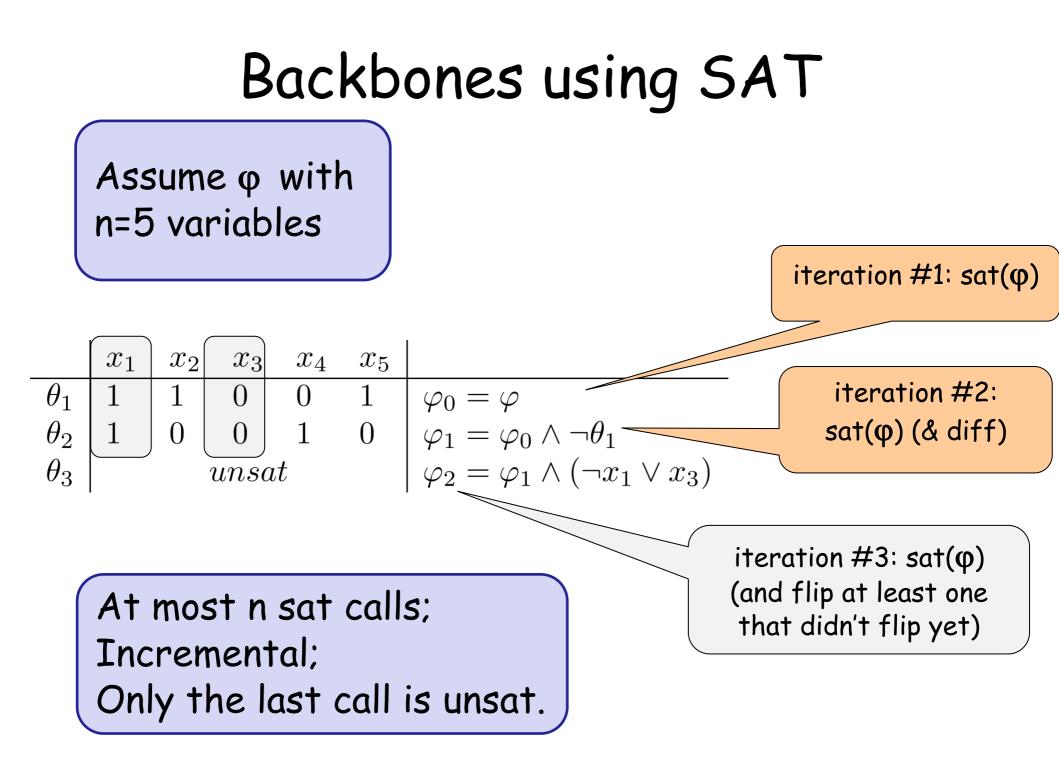
 $\varphi \models x = 1$

 $\varphi \models x = 0$

 $\varphi \models x = y$

 $\models x = -y$

CEP is also about detecting equations between variables which take fixed values in all solutions



Backbones for Equality (CEP)

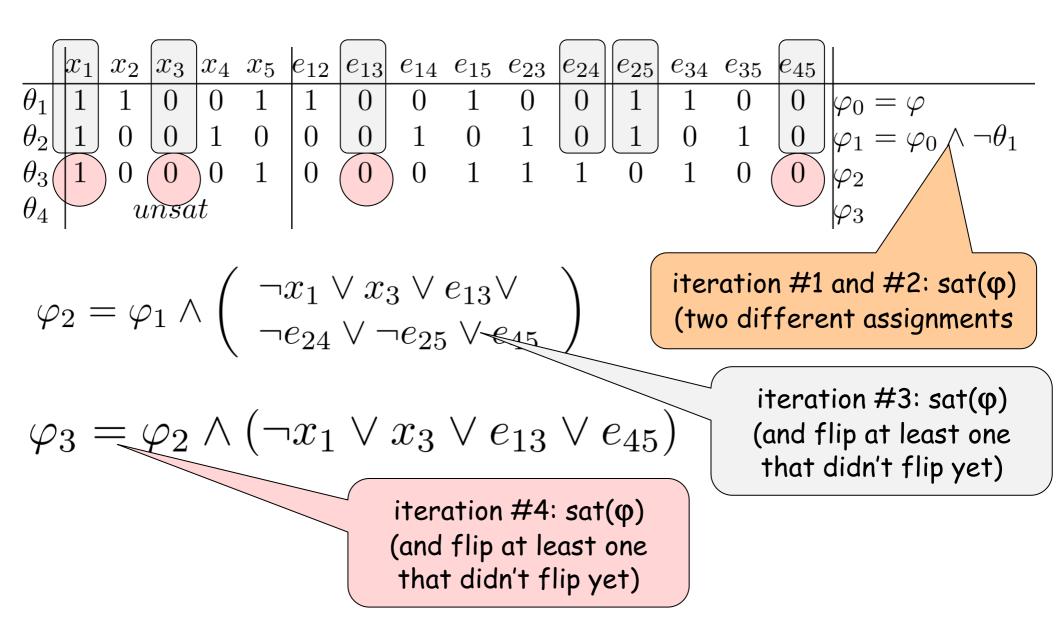
Essentially the same: Define

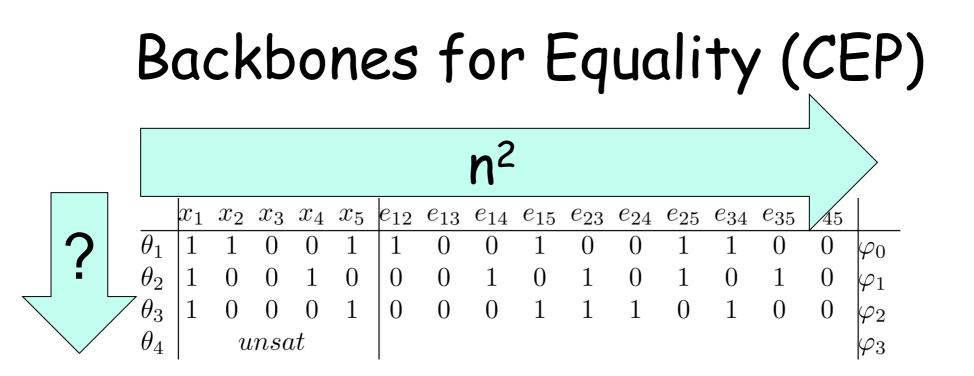
$$\varphi' = \varphi \land \{ e_{ij} \leftrightarrow (x_i \leftrightarrow x_j) \mid 0 \le i < j \le n \}$$

and then apply a backbone algorithm

But, we have added $O(n^2)$ new variables (???)

Backbones for Equality (CEP)





Theorem

Let φ be a CNF, X a set of n variables, and $\Theta = \{\theta_1, \dots, \theta_m\}$ the sequence of assignments encountered by the CEP algorithm for φ and X. Then, $m \leq n+1$.

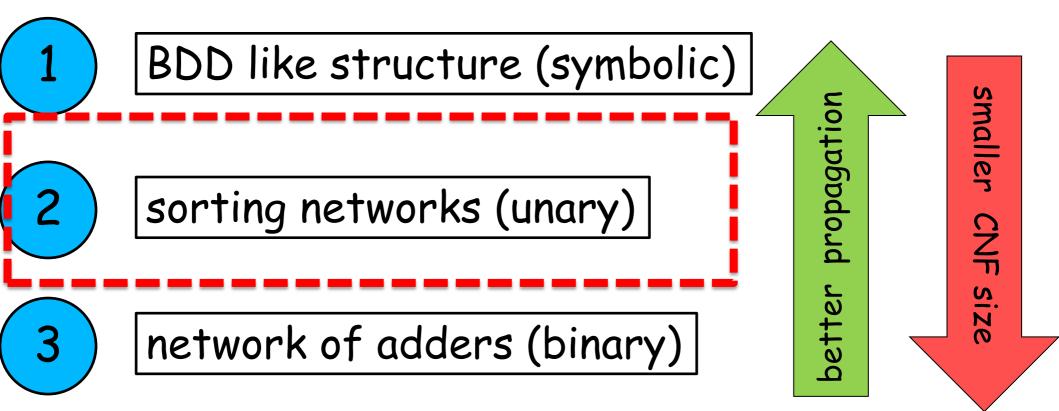


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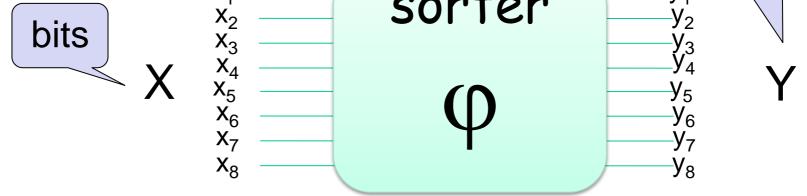
http://amit.metodi.me/research/bee/

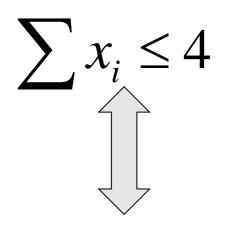
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Cardinality Constraints

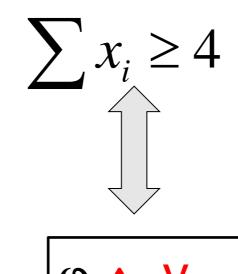


Sat encoding - cardinality constraints unarynumber (OE) x_1 x_2 Sorter y_1 y_2

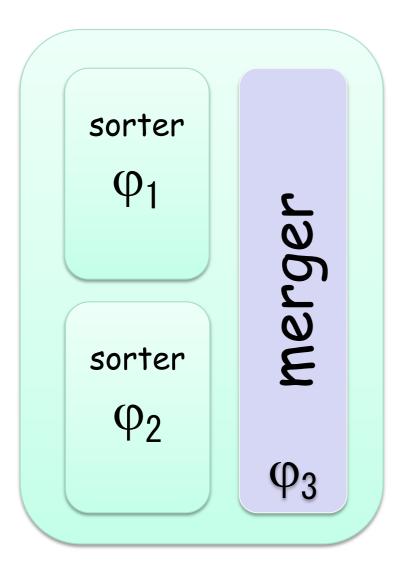








sorting networks (defined recursively)



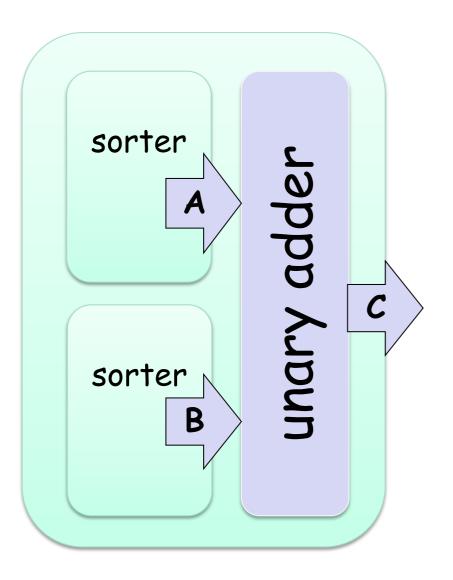
defined recursively; so it is all in the merger

Many adapt this approach applying Batcher's Odd Even Sorting Network

Another option is Parberry's "pairwise" sorting networks

The odd-even merger is basically a unary adder and consists of **O(n log n)** "comparators".

Totalizers (same but with different merger)



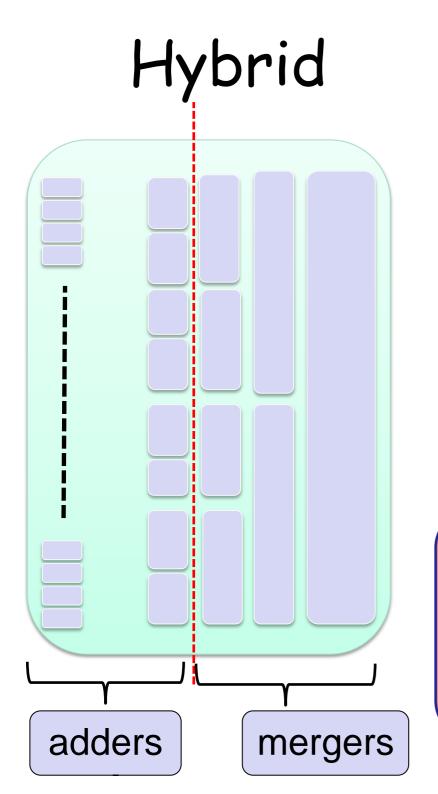
Totalizers: define the merger with a direct encoding **O(n²)** clauses

$$A \ge i \& B \ge j \rightarrow C \ge i+j$$

$$A \le i \& B \le j \rightarrow C \le i+j$$

$$i,j$$

(direct) adders are larger than mergers but have better propagation properties



(direct) adders are larger than mergers but have better propagation properties

But, for small n, adders are actually smaller than mergers

Anyway, the size penalty can pay off (if under control)

While constructing, first use mergers. Then, as things get smaller, introduce adders Experiments illustrating the advantage of the hybrid approach:

Ignasi Abio, Robert Nieuwenhuis, Albert Oliveras, Enric Rodriguez-Carbonell; A parametric approach for smaller and better encodings of cardinality constraints; CP 2013

bSettings.pl (for cardinality constraints)

Name: 'unaryAdderType'

Constraint: 'int_plus'

Possible values:

'uadder' - (default) use O(N^2) encoding

'merger' - decompose to comparators O(NlogN) encoding

'hybrid' - hybrid approach:

BEE will decide if to decompose like merger or encode like uadder - based on the generated CNF size.

*/

/*

:- defineSetting(unaryAdderType,uadder).

/*

Name: 'sumBitsDecompose'

Constraint: 'bool_array_sum_op' / 'bool_array_pb_op' Possible values:

'simple' - (default) divide and conquer technique

'buckets' - split to buckets, sum each bucket and use linear constraints to sum buckets

'pairwise' - pairwise sorting network

*/

:- defineSetting(sumBitsDecompose,simple).



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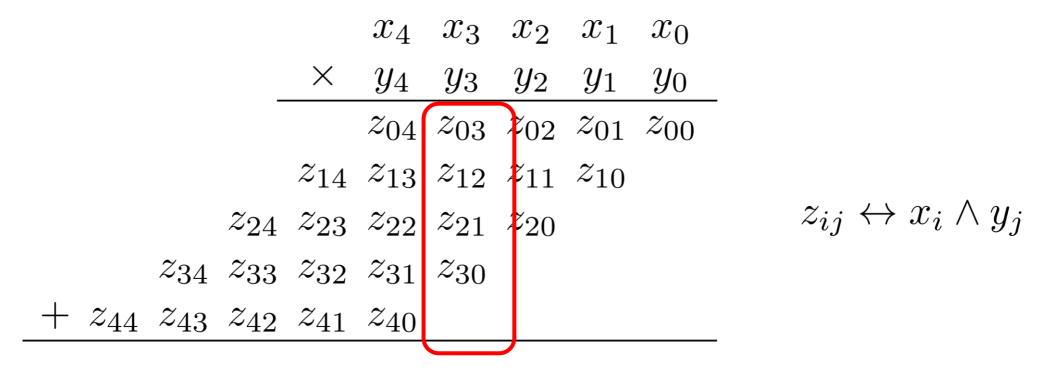
The binary extension of BEE

Binary Extension of BEE

Bit Blasting is obvious; But it is more about how the simplifications work

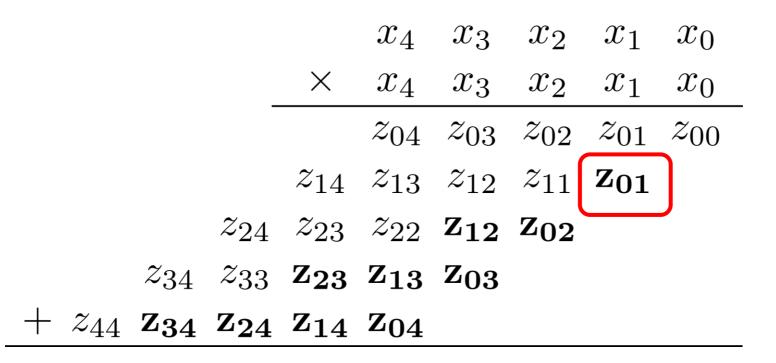
Where possible, blast into the unary core

Binary Multiplication



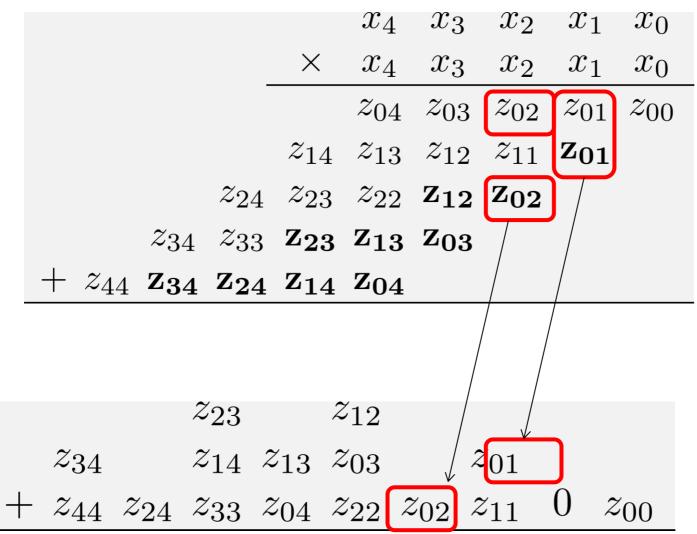
unary sums

Binary Multiplication (square)

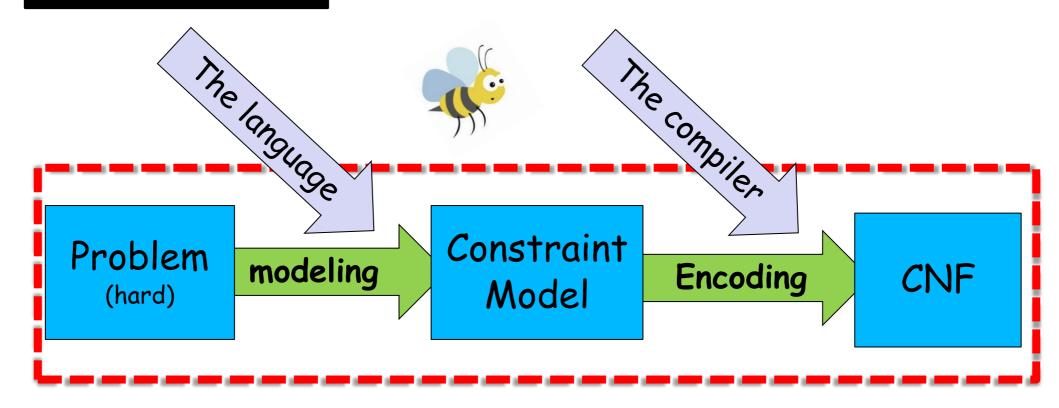


equi propagation:
$$z_{ij} = z_{ji}$$

Binary Multiplication (square)



Conclusion



- The "new" stuff
 - Complete Equi-Propagation
 - Cardinality Constraints in BEE
 - The binary extension of BEE