

Dynamic Local Search for SAT: Design, Insights and Analysis

Dave Tompkins

Final PhD Oral Examination

Department of Computer Science, UBC

September 16, 2010

Supervisor: Holger Hoos

Supervisory Committee: Will Evans, Alan Hu

University Examiners: David Kirkpatrick, David Mitchell (SFU)

External Examiner: Steve Prestwich

Chair: Robin Turner (ECE)

Primary Goal

"to advance the state-of-the-art
for SLS algorithms for SAT"

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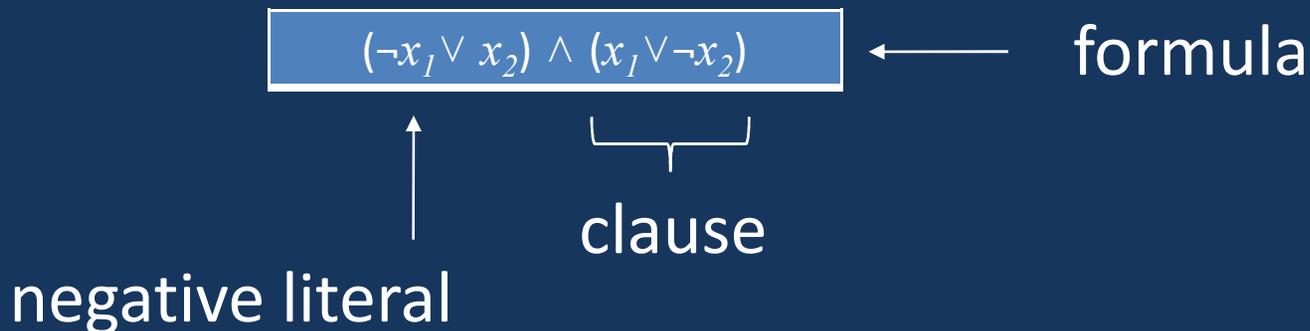
- *Explicitly:* develop new SLS algorithms that can outperform existing algorithms
- *Implicitly:* advance our understanding of current algorithms and introduce tools for developing new algorithms

Overview

- Introduction
 - The Propositional Satisfiability problem (SAT)
 - Stochastic Local Search (SLS) for SAT
 - Summary of key contributions
- Body of Work
- Conclusions
 - Review key contributions
 - Future work

Propositional Satisfiability

- Boolean variables are either (T)rue or (F)alse
 - x_1 : Dave's PhD defence will have a positive outcome
 - x_2 : Dave will celebrate tonight



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F	T
T	F
T	T

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<i>T</i>
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<i>F</i>
<i>T</i>

} satisfying assignments

- Objective: Given a formula (SAT instance)
find a satisfying assignment

Many "Real" SAT Applications



Software Verification

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

Sudoku

Exponential Search Space

x_1	x_2
F	F
F	T
T	F
T	T

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F	F
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x_1	x_2	x_3
F	F	F
F	F	T
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F	T	T
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T	F	T
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x_1	x_2	x_3	x_4
F	F	F	F
F	F	F	T
F	F	T	F
F	F	T	T
F	T	F	F
F	T	F	T
F	T	T	F
F	T	T	T
T	F	F	F
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x_1	x_2	x_3	x_4
F	F	F	F
F	F	F	T
F	F	T	F
F	F	T	T
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F	T	F	T
F	T	T	F
F	T	T	T
T	F	F	F
T	F	F	T
T	F	T	F
T	F	T	T
T	T	F	F
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- n variables:
 2^n assignments
- 250 variables
 $\approx 10^{75}$ combinations
 \approx # atoms in the universe

Stochastic Local Search (SLS) for SAT

randomly initialize all variables
while (formula not satisfied)
 select a variable and “flip” it

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- Selecting a variable:

make = # of clauses that become **satisfied** if we flip x

break = ... **unsatisfied** ...

score = **make** - **break** [GSAT: Selman, Levesque & Mitchell, 1992]



Key Contributions





Key Contributions



1. Developed UBCSAT
2. Created SAPS, a Clause Penalty (CP) algorithm
3. Analyzed CP algorithm behaviour
4. Analyzed random decisions in SLS algorithms
5. Introduced a new conceptual model for SLS algorithms with Variable Expressions (VEs)
 - Developed a new Design Architecture (DAVE)



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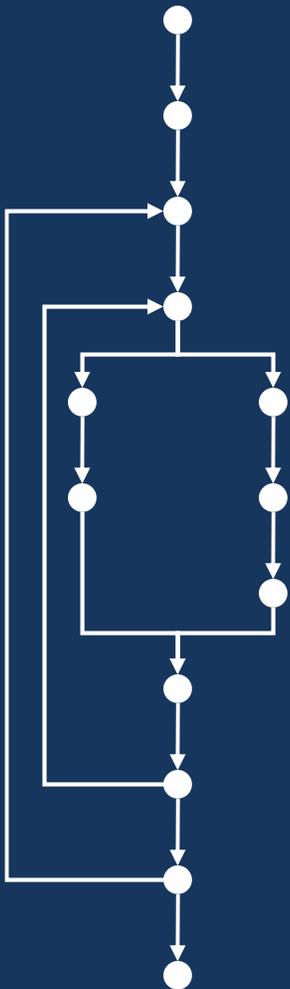
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UBCSAT Architecture

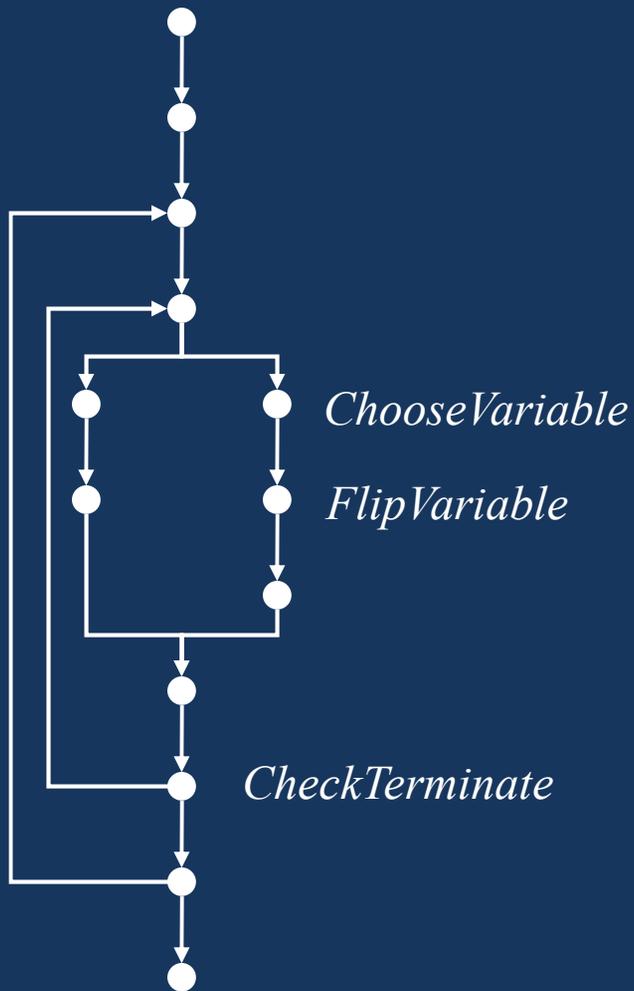
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UBCSAT Architecture

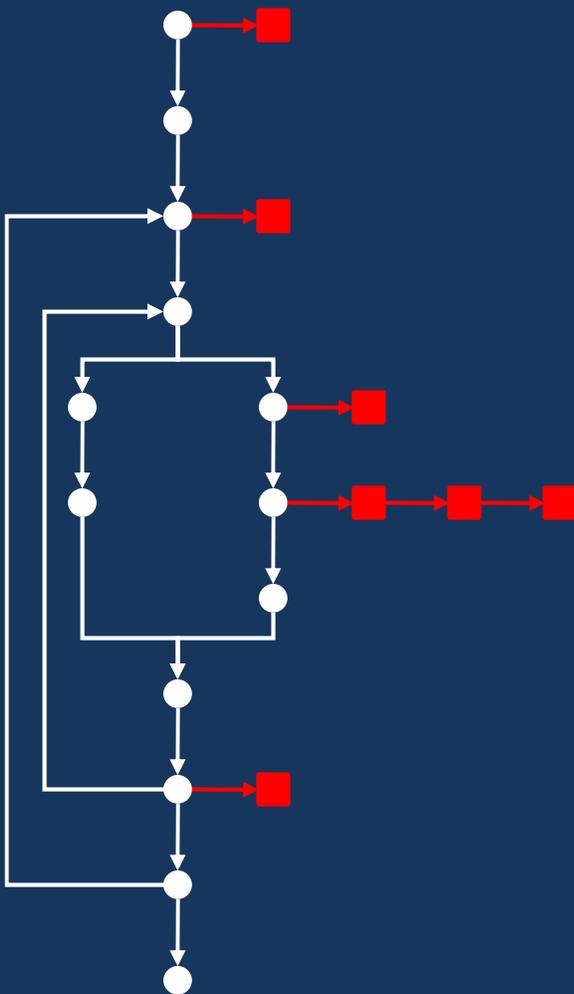
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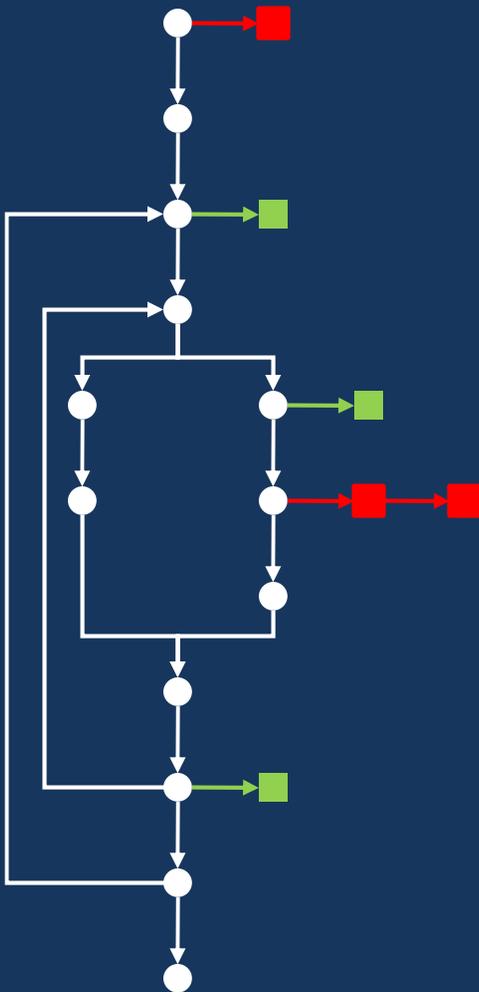
UBCSAT Algorithms



- All (typical) SLS algorithms can be seen as a series of procedures that happen at "event points"
- When you select the algorithm, the appropriate procedures are "triggered"

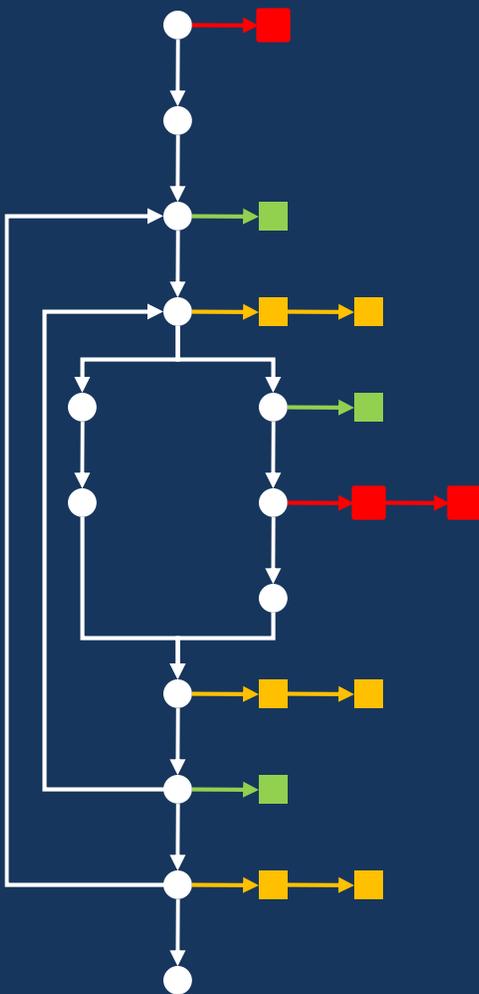
UBCSAT Algorithms

- Similar algorithms can re-use existing triggers



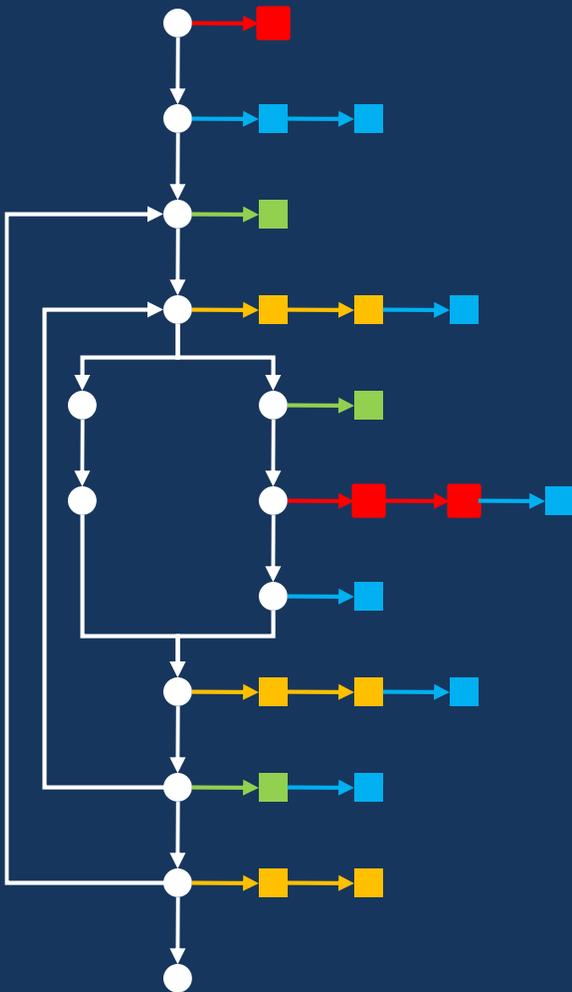
UBCSAT Reports

- Additional Reports and Statistics can be "activated" when needed



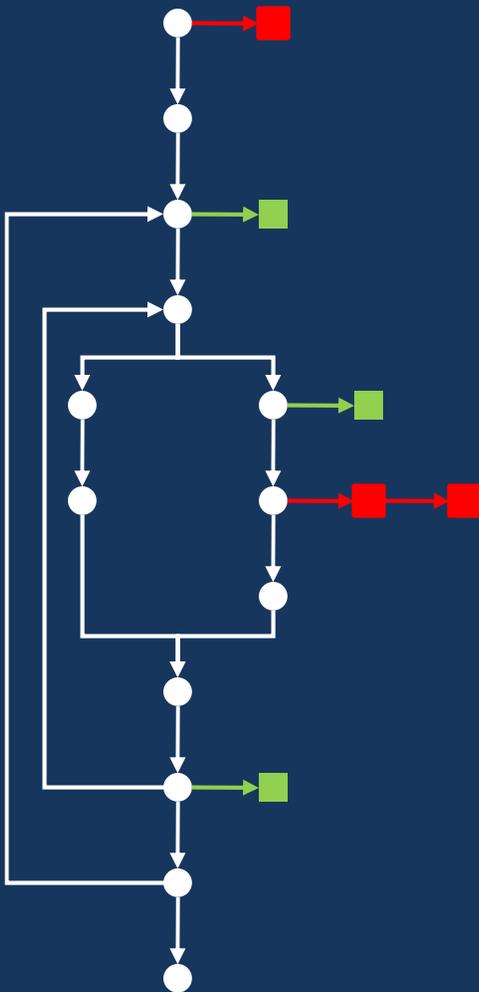
UBCSAT Reports

- Facilitating empirical analysis is an important component of UBCSAT



UBCSAT Efficiency

- UBCSAT is very efficient with little overhead



algorithm	UBCSAT Speedup
WalkSAT/SKC	1.5x – 2.2x
Novelty	1.3x – 2.0x
GSAT	1.7x – 7.6x
GWSAT	2.5x – 7.4x

UBCSAT

A software framework for SLS algorithms

- Incorporates existing SLS algorithms
 - highly efficient, accurate implementations
- Facilitate development of new SLS algorithms
- Advanced empirical analysis of algorithms
- Open-source
- Cornerstone of the dissertation



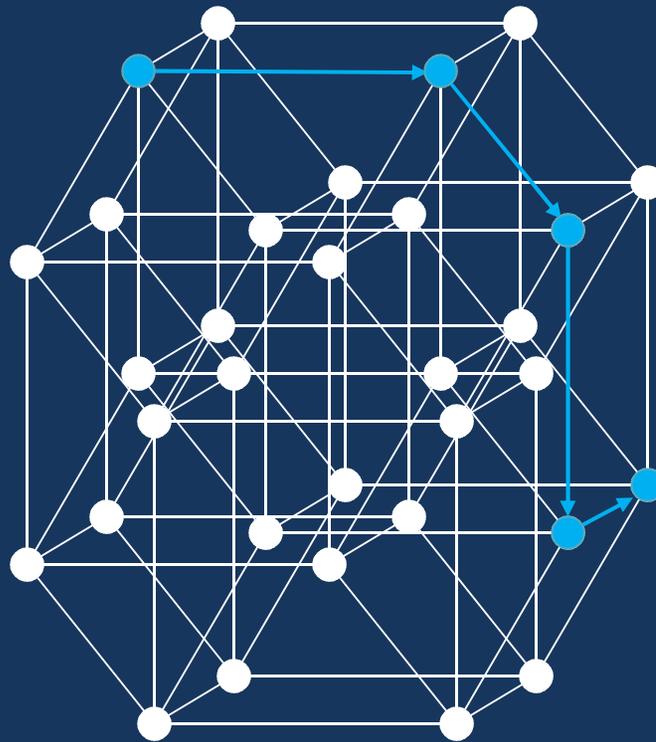
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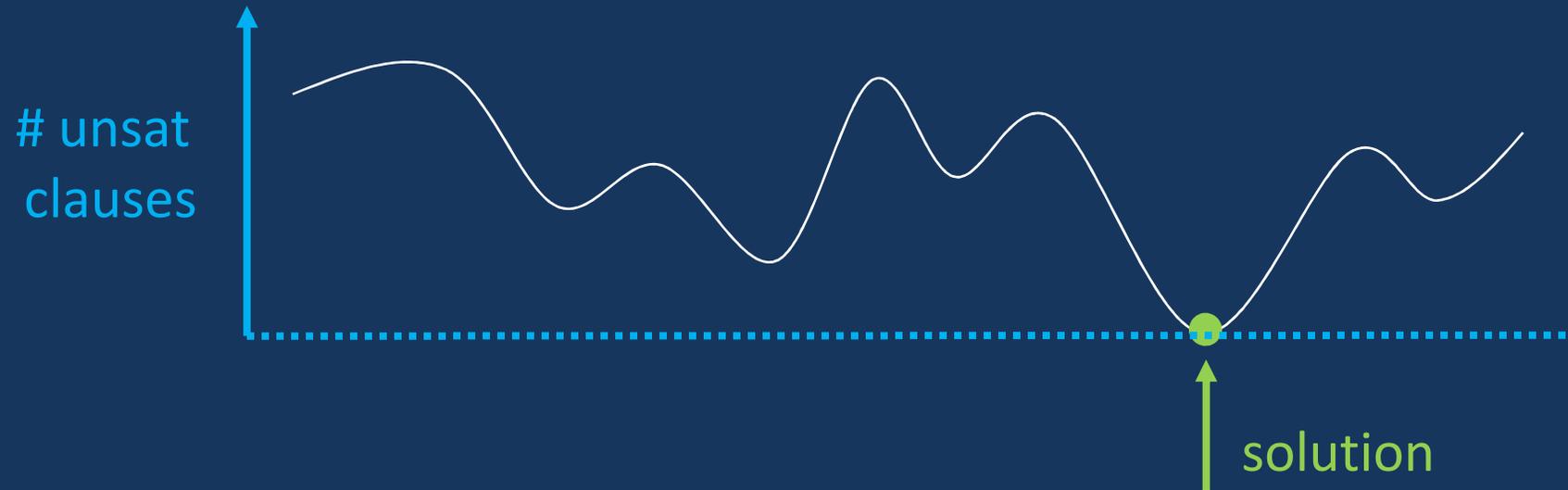
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SAT Search Space

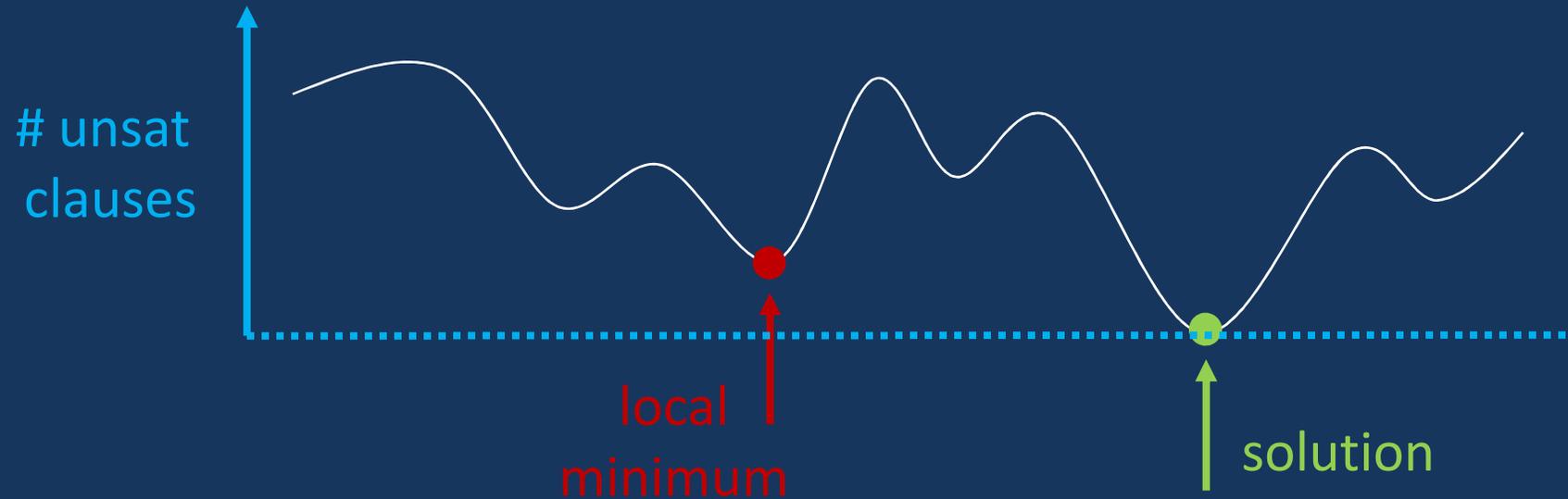
- n-dimensional hypercube



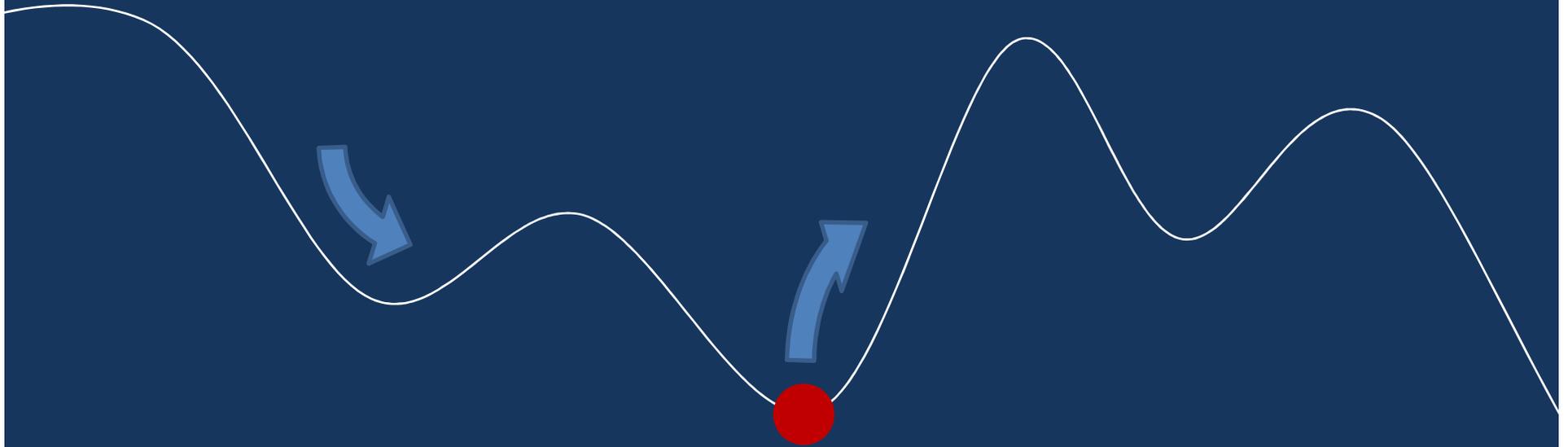
"2D" Search Landscape



"2D" Search Landscape



Intensification & Diversification



Clause Penalties

- Each clause is assigned a penalty value
- Score is no longer just **make** – **break**

$$\text{score} = \sum_{\text{make}} \text{c.penalty} - \sum_{\text{break}} \text{c.penalty}$$

Original Idea:

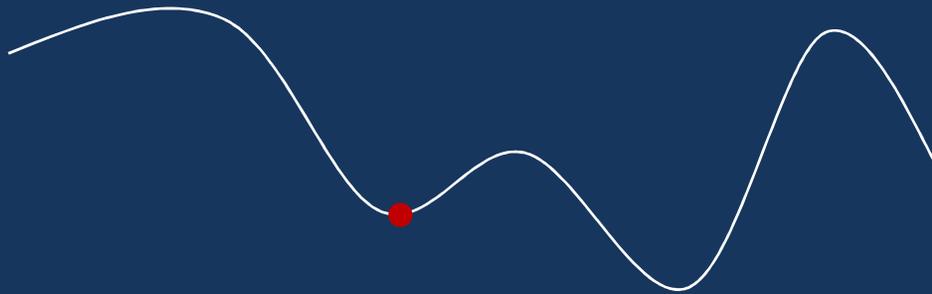
- Breakout Method [Morris, 1993]
- GSAT+CW [Selman & Kautz, 1993]

"Breakout" Approach

- When a local minimum occurs:

$$\sum_{\text{make}} \text{c.penalty} \leq \sum_{\text{break}} \text{c.penalty}$$

increment the penalty for unsatisfied clauses



"Breakout" Approach

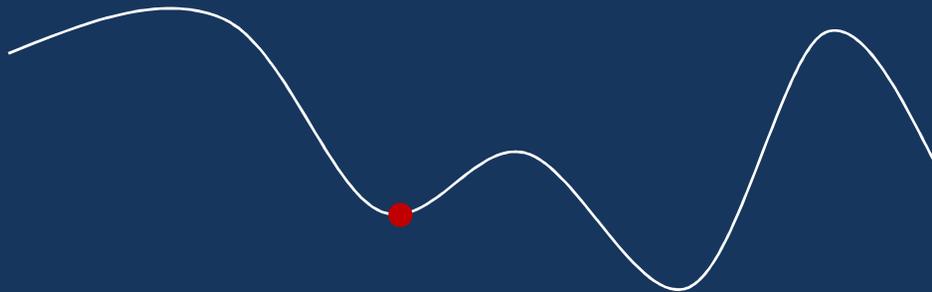
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- Eventually, will no longer be in a local minimum

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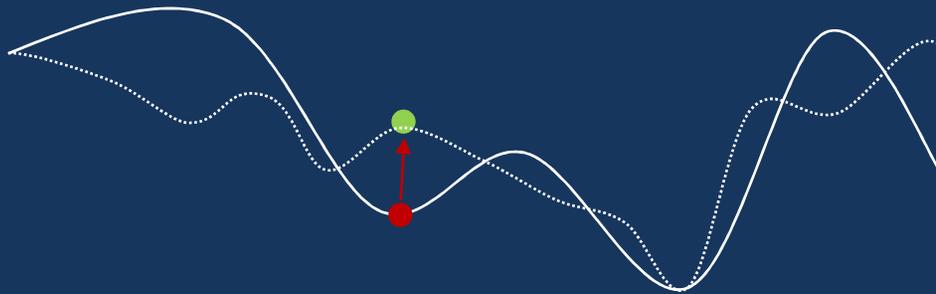
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SAPS Algorithm

- Enhancement of existing algorithm
 - Exponentiated Sub-Gradient (ESG)
[Schuurmans et. al, 2002]
- Multiplicative Scaling
 $c.\text{penalty} := c.\text{penalty} \cdot \alpha$
- Probabilistic Smoothing
with probability (P_s):
 $c.\text{penalty} := c.\text{penalty} + (1-\rho) \cdot \text{avg.penalty}$
- Scaling And Probabilistic Smoothing (SAPS)

SAPS Algorithm

- Dominated the performance of its predecessor (ESG)
- Still amongst the state-of-the-art solvers
- Led to the work in other chapters

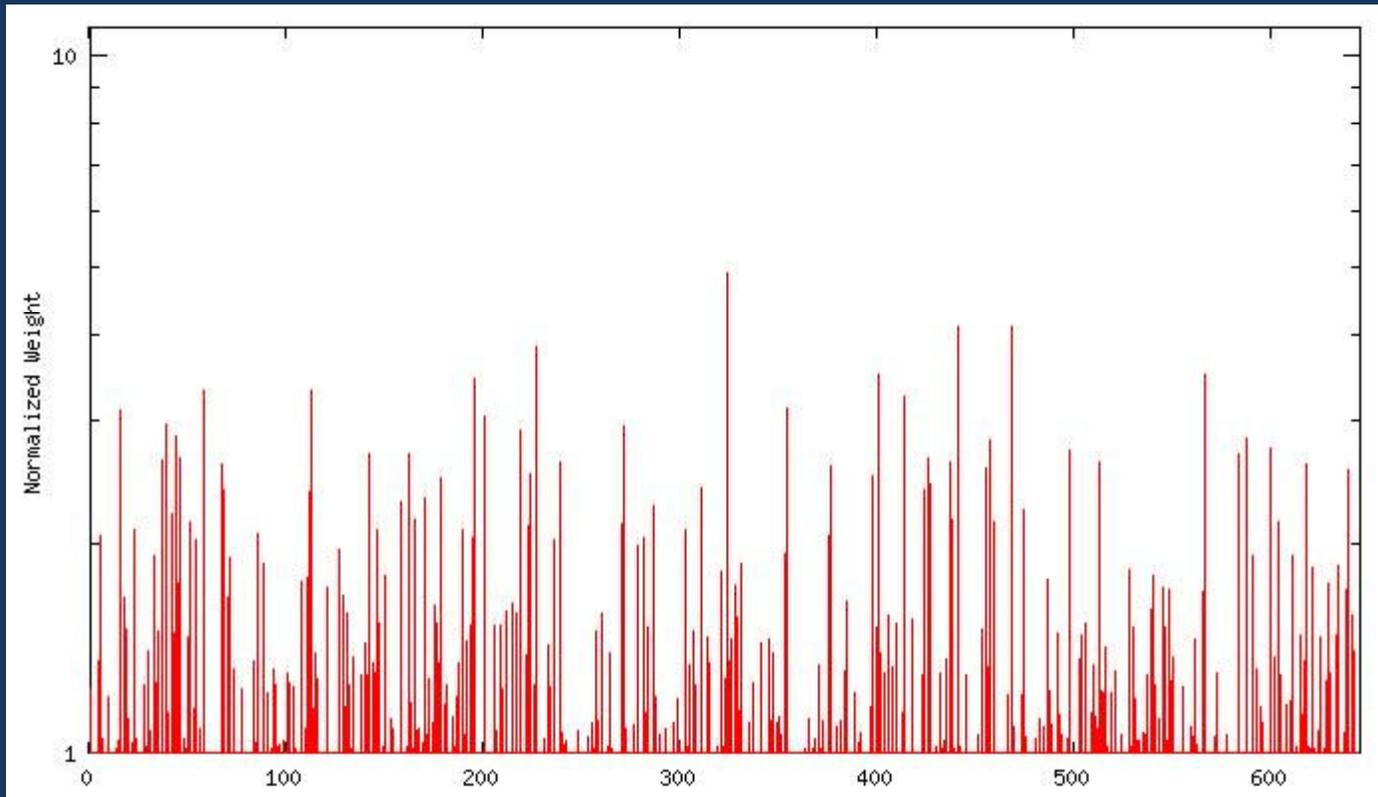


Key Contributions

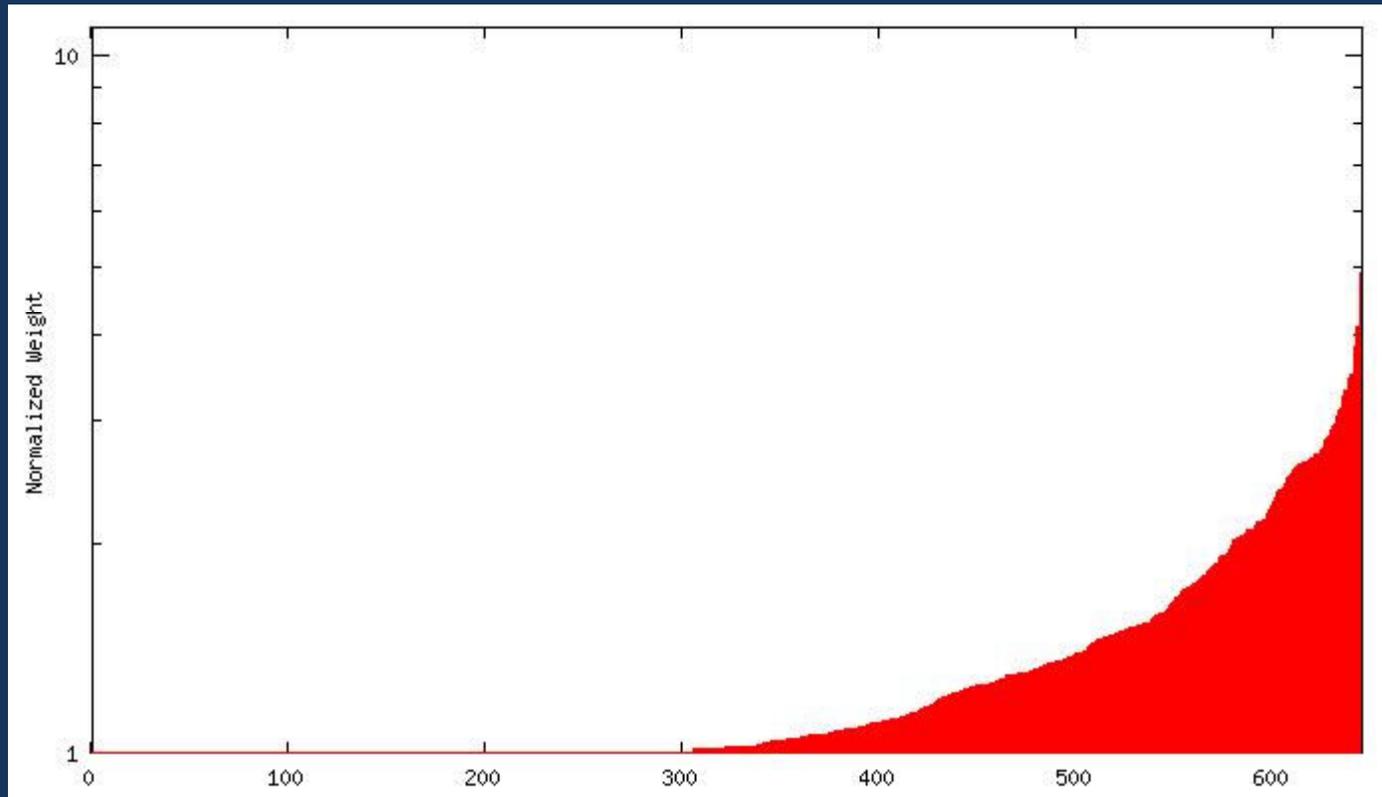


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Dynamic Clause Penalties



Clause Penalty Distributions



Clause Penalty Analysis

- We identified instances with "Problem Clauses"
 - We constructed *weighted* instances...
... that were *easier* for SLS algorithms to solve
(80x faster for Adaptive Novelty⁺)

Clause Penalty Analysis

- A quest for problem clauses
- Analyzed penalty behaviour
- Hardness of warped landscapes
- History ("memory") of the search

- Ultimately: problem clauses are rarely helpful
- Key element of CP algorithms: diversification



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Random Decisions

- Stochastic Local Search
- *Quality* of random decision
 - SLS Algorithms are robust (existing random number generators are good enough)
- *Quantity* of random decisions
 - Simple derandomizations can be effective
 - SLS Algorithms exhibit 'chaotic'-like behaviour
 - No real advantage to derandomizing



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Variable Properties

- Scoring Properties

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- Dynamic Properties

age = # of steps since x was flipped [TABU, Glover 1986]

flips = # of times x has been flipped [HSAT, Gent & Walsh 1992]

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- Static Properties

Variable Expressions (VEs)

- combinations of variable *properties* in mathematical expressions:

make – break

age

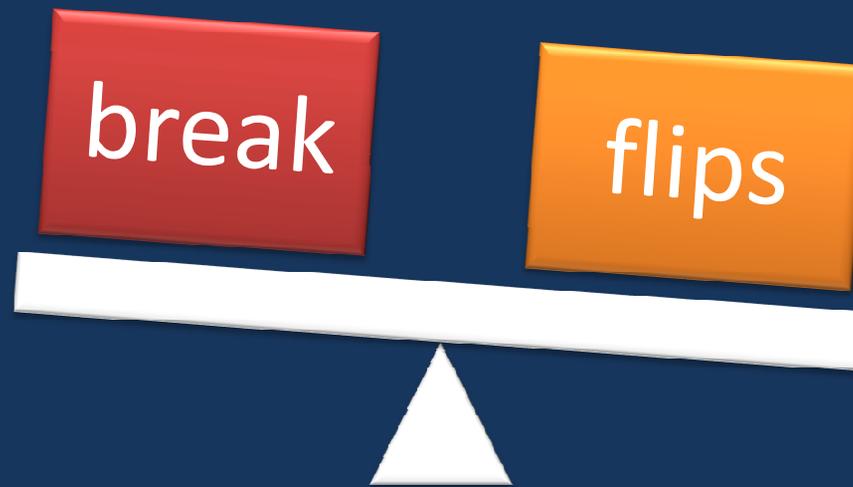
$(\text{make} - \text{break}) + 3 \cdot \log_2(\text{age}) + \text{age}/\text{flips}$

- Most existing SLS algorithms use straightforward VEs
... we explore more complex VEs
- Our work was inspired by:
Variable Weighting Algorithm VW2 [Prestwich, 2005]

Combining Properties

Select variable with minimum value of:

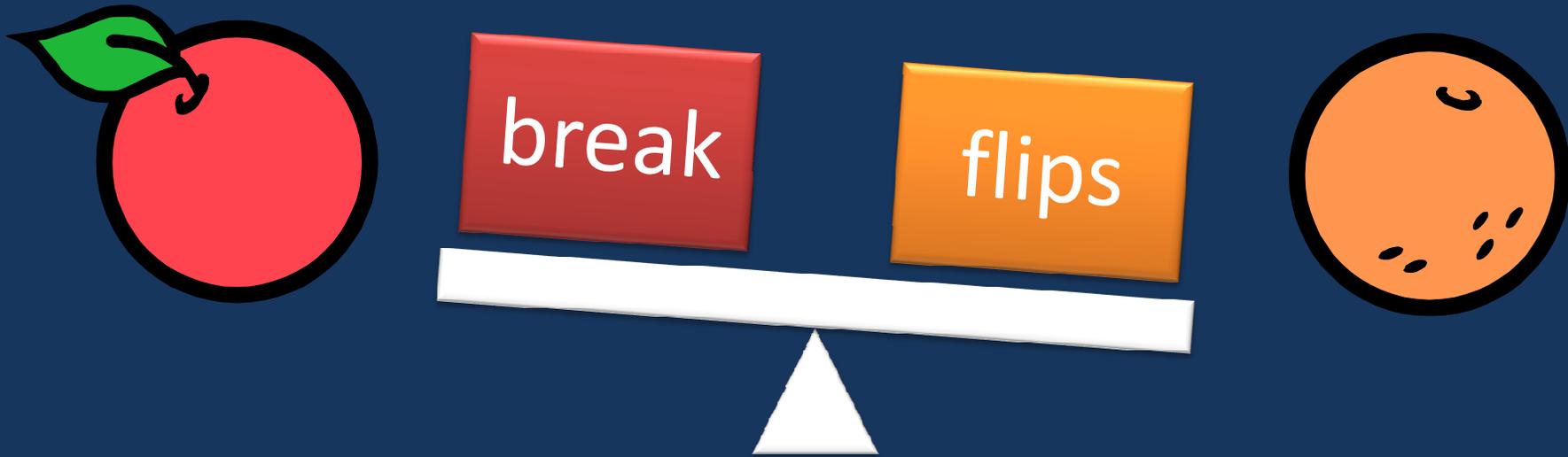
$$\text{break} + c \cdot \text{flips}$$



Combining Properties

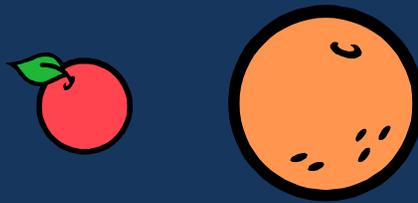
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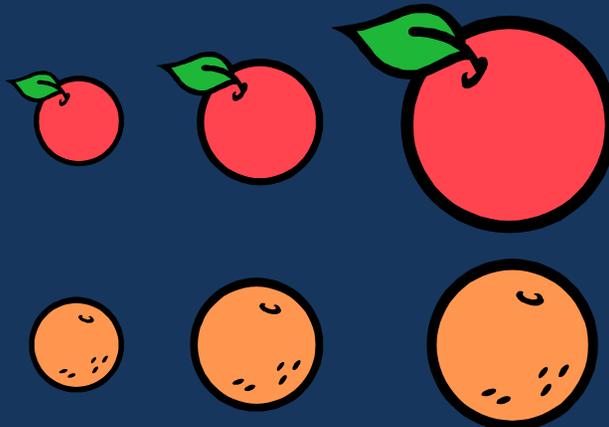


Combining Properties

- **Normalize** properties values to $[0..1]$ amongst the “candidate” variables

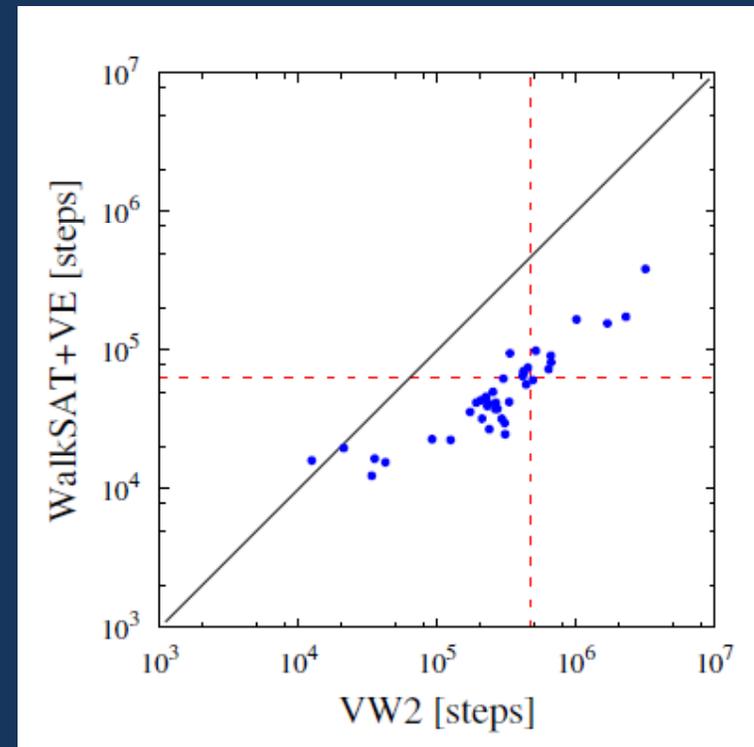


- Allow for **non-linear** normalization



Modifying Existing Algorithms with VEs

- WalkSAT with more complex VE
- Speedup factor:
 - 7.2x (steps)
 - 3.1x (time)
- (compared to original WalkSAT)
 - > 4000x (steps)
 - > 2000x (time)



Our New SLS Model



Our New SLS Model



Separation of: VEs & Selection Mechanism

- Novelty Algorithm [McAllester, Selman & Kautz, 1997]
- Select “best” variable with maximum of:
(make – break)
breaking ties by
(age)
- If the best variable has the minimum
(age)
then, with probability p , select 2nd best var.

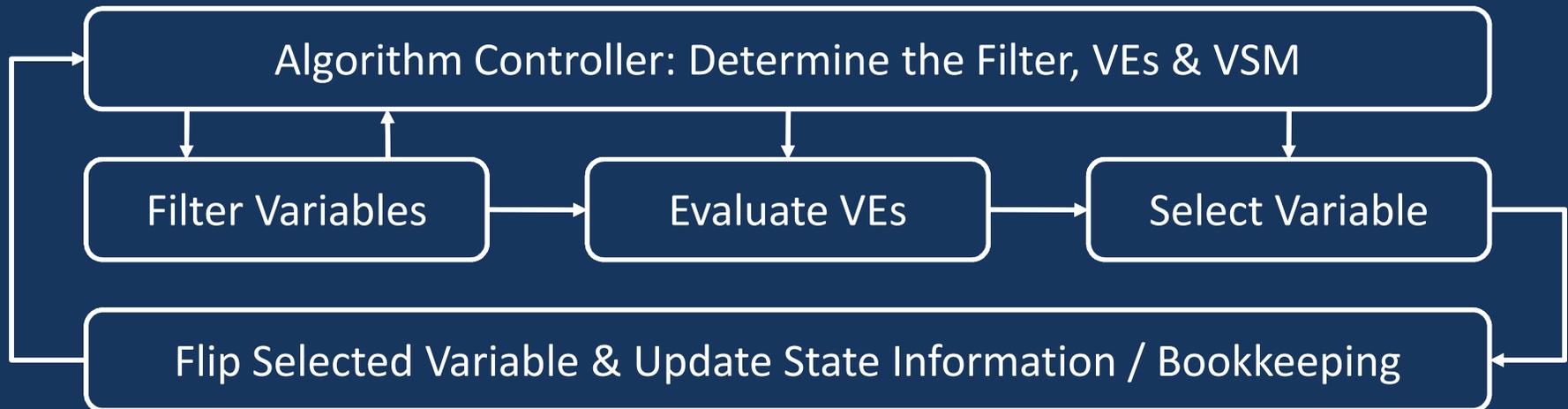
Separation of: VEs & Selection Mechanism

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 (VE_1)
breaking ties by
 (VE_2)
- If the best variable has the minimum
 (VE_3)
then, with probability p , select 2nd best var.

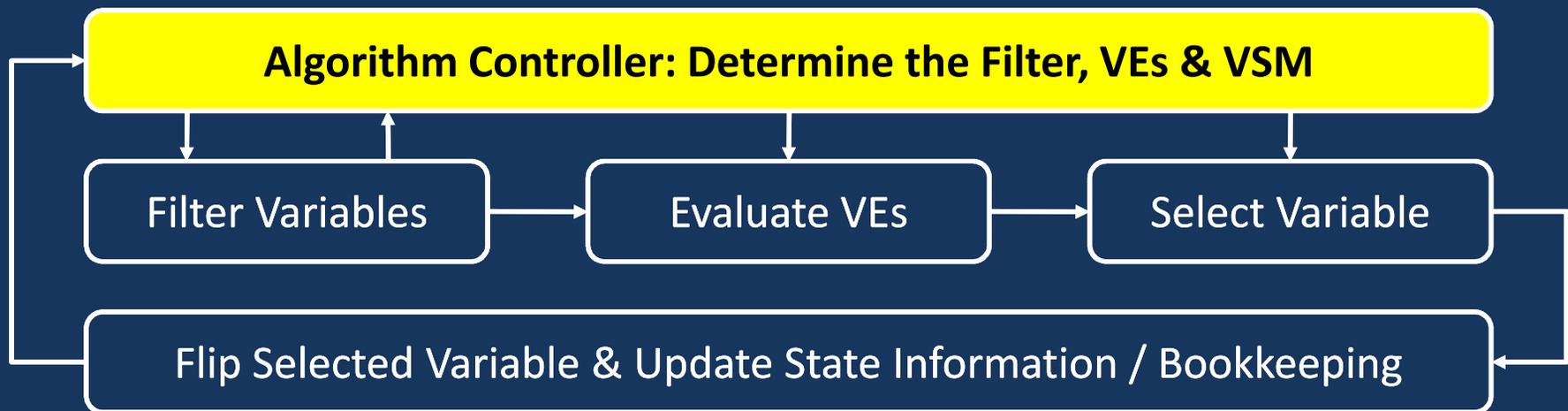
Our New SLS Model



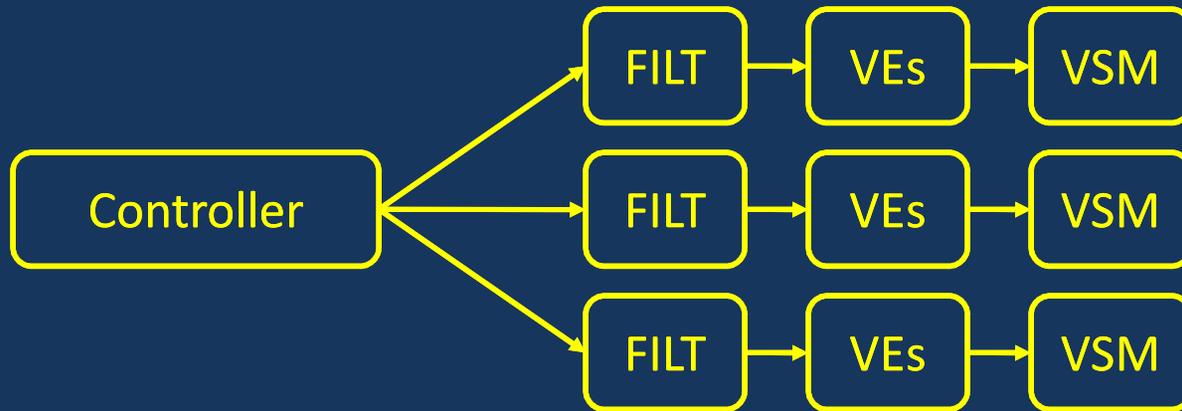
Our New SLS Model



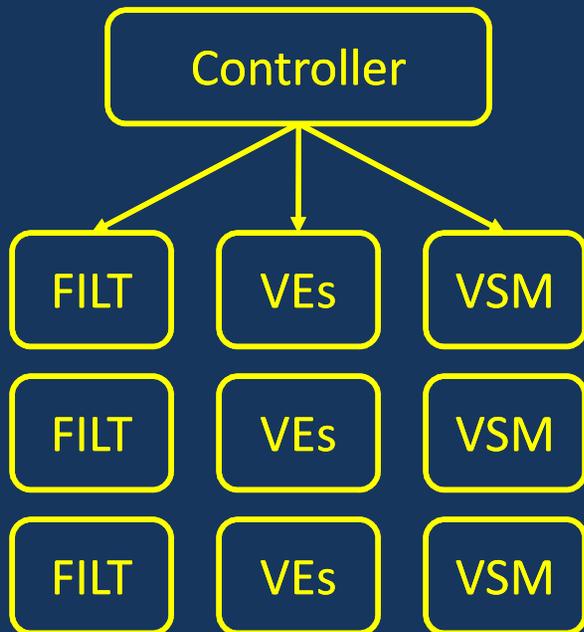
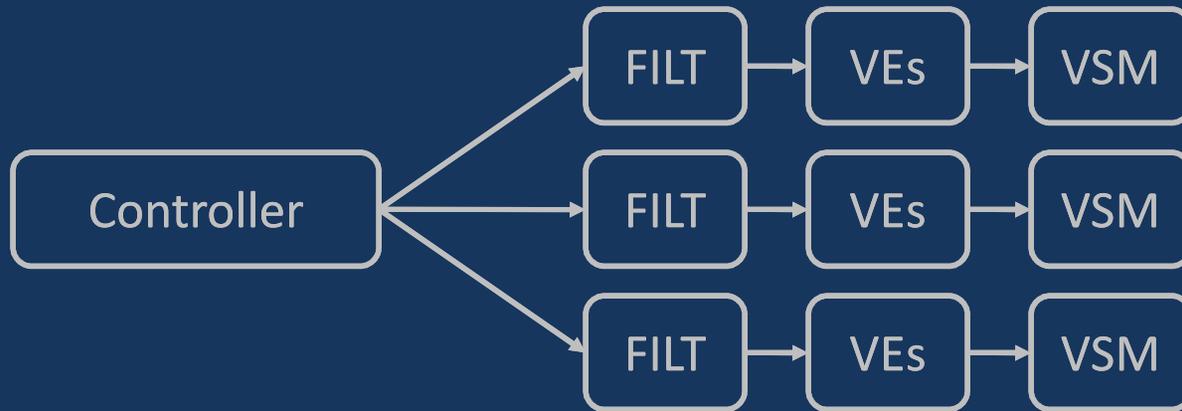
Our New SLS Model



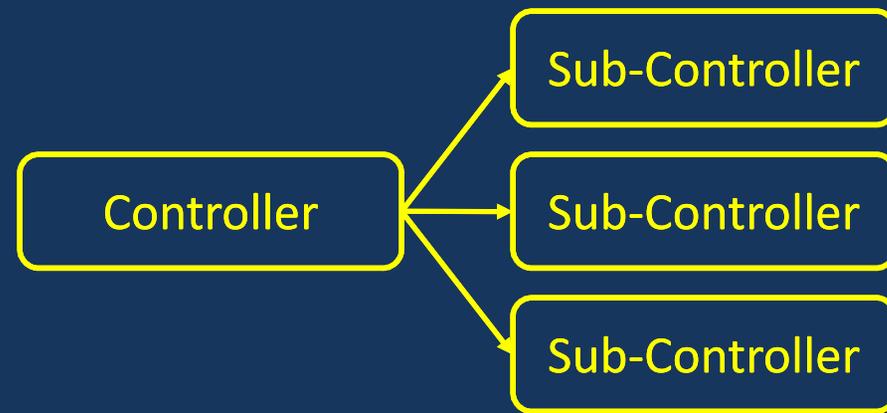
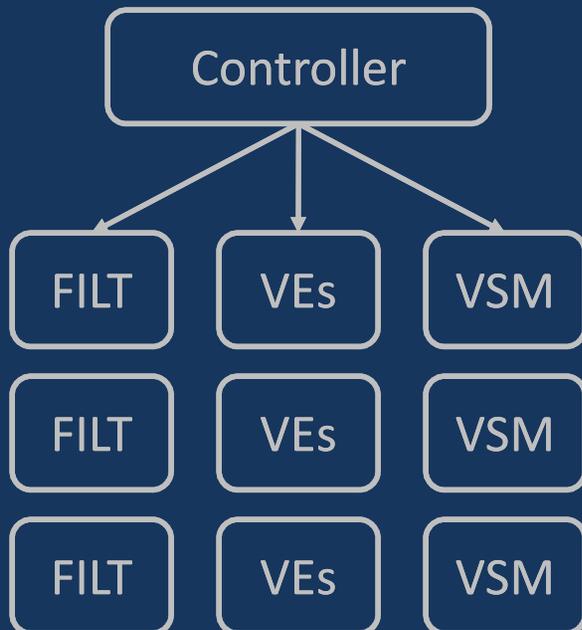
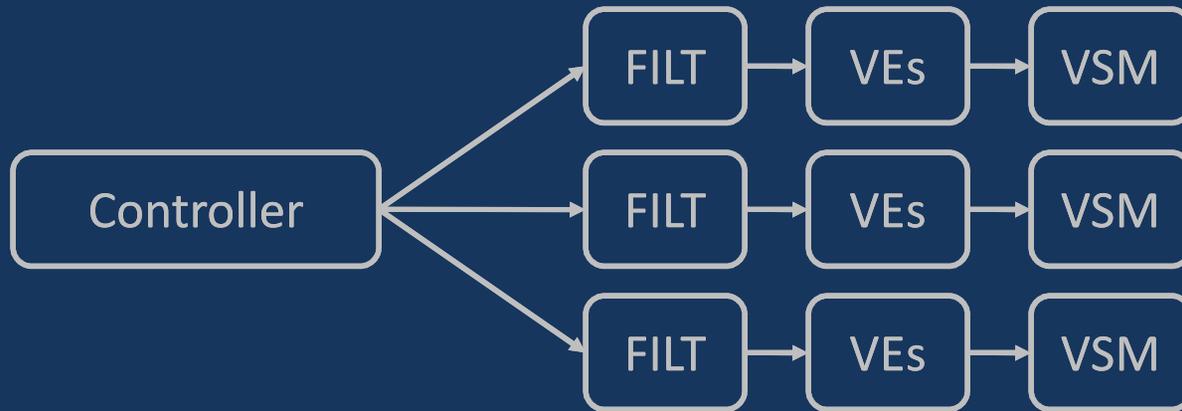
Algorithm Controllers



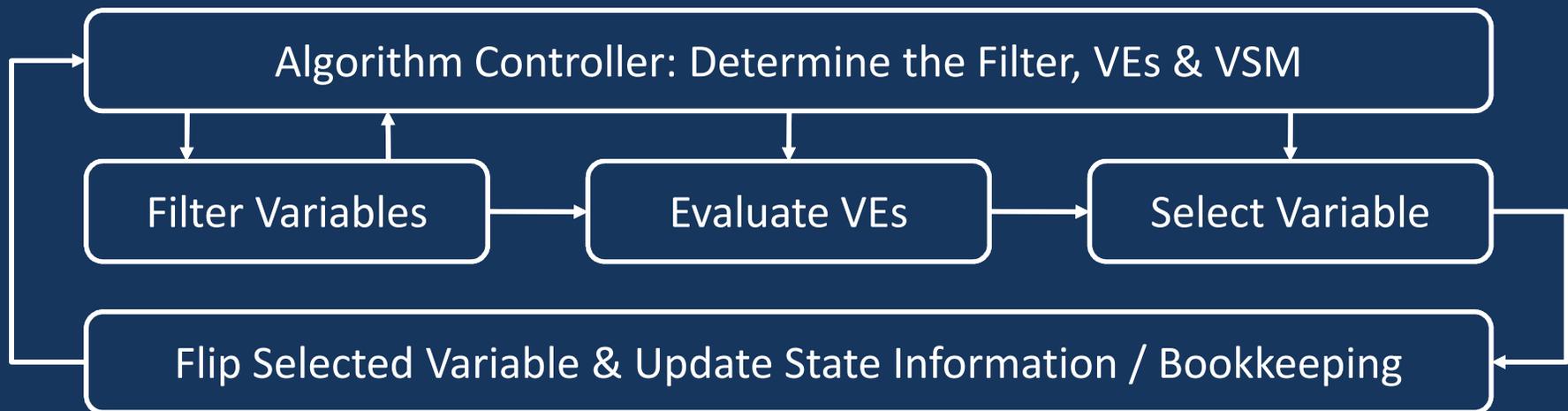
Algorithm Controllers



Algorithm Controllers



Our New SLS Model

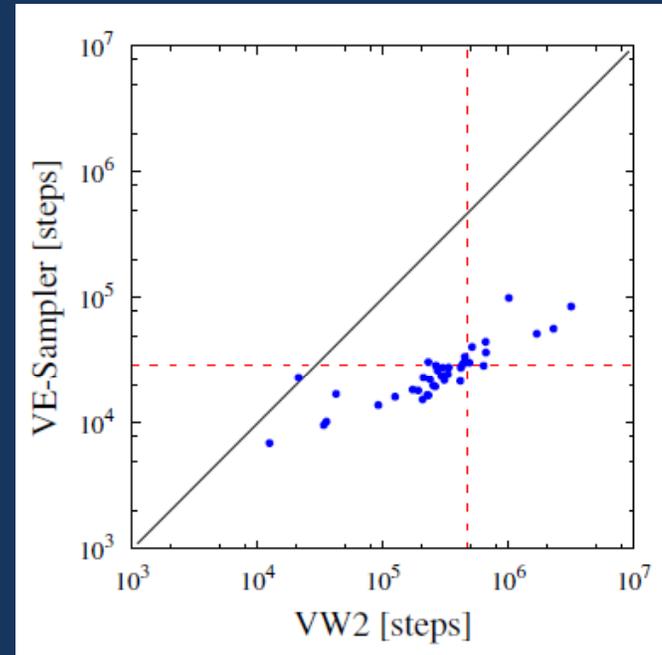


Software Implementation

- Design Architecture for Variable Expressions (DAVE)
 - Entire algorithm specified at runtime
 - Controllers, filters, VEs, selection mechanisms
 - Arbitrary complex VEs (interpreted)
 - Sophisticated macro system
 - Aids the use of automated configurators
- Extension of UBCSAT (2.0)

New Model & DAVE

- Concept of VEs
- New Model
- New Architecture
- Demonstrated our work in conjunction with an automated configurator



- Speedup factor:
16.2x (steps)
9.0x (time)



Key Contributions



1. Developed UBCSAT
2. Created SAPS, a Clause Penalty (CP) algorithm
3. Analyzed CP algorithm behaviour
4. Analyzed random decisions in SLS algorithms
5. Introduced a new conceptual model for SLS algorithms with Variable Expressions (VEs)
 - Developed a new Design Architecture (DAVE)

Primary Goal

"to advance the state-of-the-art
for SLS algorithms for SAT"

- *Explicitly:* develop new SLS algorithms that can outperform existing algorithms
- *Implicitly:* advance our understanding of current algorithms and introduce tools for developing new algorithms

Future Work

- Extend our methods to other domains
- Incorporate the use of automated tools
- Dynamic instances, distributed systems
- Generalized clause penalty solver
- Problem clauses & encodings
- New algorithm constructions

Selected Publications

- Dave A. D. Tompkins and Holger H. Hoos. **Dynamic Scoring Functions with Variable Expressions: New SLS Methods for Solving SAT** in SAT 2010, p. 278-292, 2010.
- Dave A.D. Tompkins and Holger H. Hoos, **On the Quality and Quantity of Random Decisions in Stochastic Local Search for SAT** in AI 2006, p. 146-158, 2006.
[Awarded Best Paper]
- Dave A.D. Tompkins and Holger H. Hoos, **UBCSAT: An Implementation and Experimentation Environment for SLS Algorithms for SAT and MAX-SAT** in SAT 2004, p. 306-320, 2005. [Google Scholar citations: 62]
- Dave A. D. Tompkins and Holger H. Hoos. **Warped Landscapes and Random Acts of SAT Solving** in AI&M 2004. [Google Scholar citations: 25]
- Frank Hutter, Dave A. D. Tompkins, and Holger H. Hoos, **Scaling and Probabilistic Smoothing: Efficient Dynamic Local Search for SAT** in CP 2002, p. 233-248, 2002.
[Google Scholar citations: 119]

Special Thanks To:

- Supervisor:
 - Holger H. Hoos



Special Thanks To:

- Committee members:
 - Will Evans, Alan Hu (& Lee Iverson)
- Co-Authors:
 - Holger H. Hoos & Frank Hutter
- Additional technical help
 - Kevin Smyth, Lin Xu, Chris Fawcett
- BETA lab members
- Proofreaders
- Family & friends

Special Thanks To:



Questions...

