"Systemized" Program Analyses – A "Big Data" Perspective on Static Analysis Scalability

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A Quick Survey

- Have you used a static program analysis?
 What did you use it for?
- Have you designed a static program analysis?
- What are your major analysis infrastructures?
- Have you been bothered by its poor scalability?

This Tutorial Is About

- Big data (graphs)
- Systems
- Static analysis
- SAT solving





This Tutorial Is About

 What inspiration can we take from the big data community?

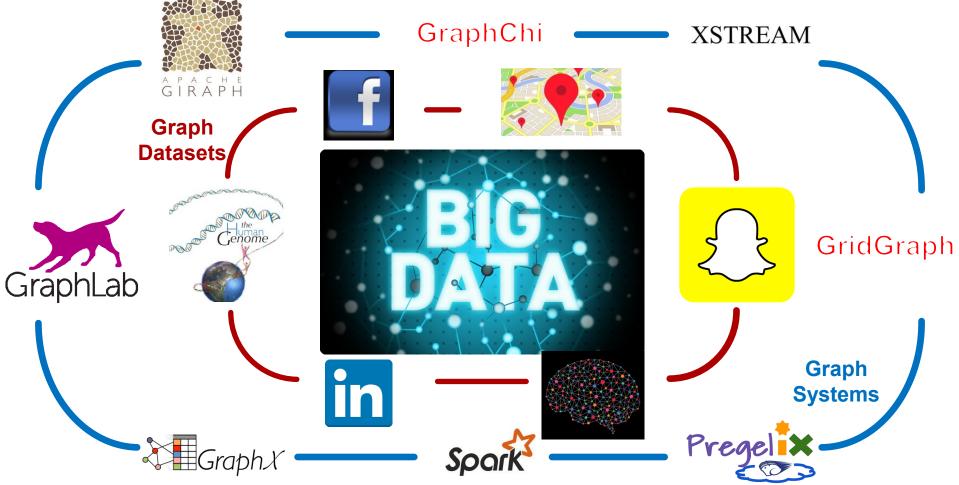


 How shall we shift our mindset from developing scalable analysis algorithms to developing scalable analysis systems?



Outline

- Background: big data/graph processing systems
- Treating static analysis as a big data problem
- Graspan: an out-of-core graph system for parallelizing and scaling static analysis workloads
- BigSAT: distributed SAT solving at scale



Intimacy Between Systems and App. Areas



- Machine Learning
- Information Retrieval
- Bioinformatics
- Sensor Networks

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Large-Scale Graph Processing: Input

- Social network graphs
 - Twitter, Facebook, Friendster
- Bioinformatics graphs
 - Gene regulatory network (GRN)
- Map graphs
 - Google Map, Apple Map, Baidu Map
- Web graphs
 - Yahoo Webmap, UKDomain

Large-Scale Graph Processing: Input Size

- Social network graphs
 - Facebook: 721M vertices (users), 68.7B edges (friendships) in May 2011
- Map graphs
 - Google Map: 20 petabytes of data
- Web graphs
 - Yahoo Webmap: 1.4B websites (vertices) and 6.4B links (edges)

What Do These Numbers Mean

[To analyze the Facebook graph] calculations were performed on a Hadoop cluster with 2,250 machines, using the Hadoop/Hive data analysis framework developed at Facebook.

 Ugander et al., The Anatomy of the Facebook Social Graph, arXiv:1111.4503, 2011

Large-Scale Graph Processing: Core Idea

- Shift our mind from developing specialized graph algorithms to developing simple programs powered by large-scale systems
- Gather-apply-scatter: a graph-parallel abstraction

Think like a vertex

```
PageRank (Vertex v){
Gather foreach (e in v.inEdge) {
total += e.value;
Apply - v.value = 0.15 * (0.85+total);
```

Large-Scale Graph Processing: Classification I

- Distributed systems
 - GraphLab, PowerGraph, PowerLira, GraphX, Gemini
 - Challenges in communication reduction and partitioning
- Single machine systems
 - Shared memory: Ligra, Galois
 - Out of core: GraphChi, X-Stream, GridGraph, GraphQ
 - Challenges in disk I/O reduction

Large-Scale Graph Processing: Classification II

- Vertex-centricity
 - When computation is performed for a vertex, all its incoming/outgoing edges need to be available
 - GraphChi, PowerGraph, etc.
- Edge-centricity
 - Computation is divided into several phases
 - Vertex computation does not need all edges available
 - X-Stream, GridGraph, etc.

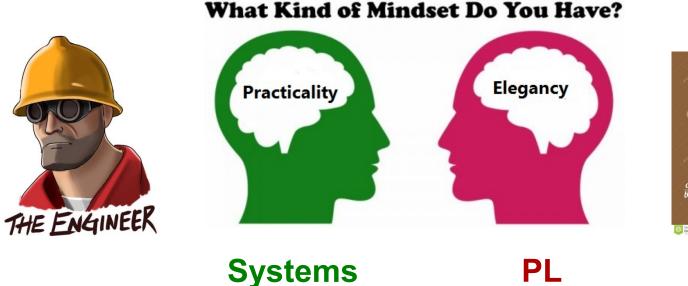
One Stone, Two Birds

- Present a simple interface to the user, making it easy to develop graph algorithms
- Push performance optimizations down to the system, which leverages parallelism and various kind of support to improve performance and scalability

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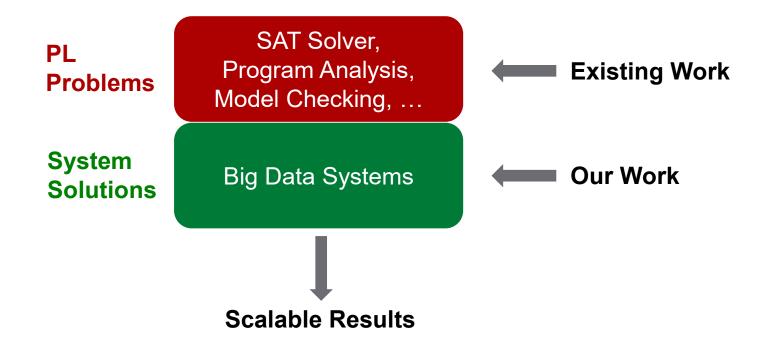
Where Is PL's Position in Big Data?





Programming languages is a big source of data

PL Is Another Source of Big Data



Static Analysis Scalability Is A Big Concern

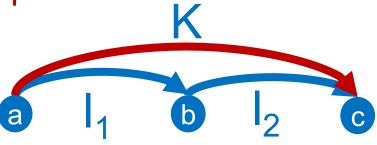
 An important PL problem: Context-sensitive static analysis of very large codebases

- ♦ Pointer/alias analysis
- ♦ Dataflow analysis
- ♦ May/must analysis
- ♦ ...

- ♦ Linux kernel
- ♦ Large server applications
- ♦ Distributed data-intensive systems
- → ...

Context-Free Language (CFL) Reachability

A program graph P



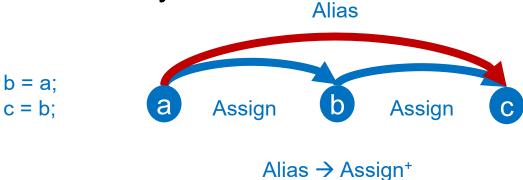
c is K-reachable from a

A context-free Grammar G with balanced parentheses properties

$$K \rightarrow I_1 I_2$$

A Wide Range of Applications

Pointer/alias analysis



 Dataflow analysis, pushdown systems, set-constraint problems can all be converted to context-free-language reachability problems

A Wide Range of Applications (Cont.)

Pointer/alias analysis

```
Alias
b = \& a; // Address-of
c = b;
d = *c; // Dereference
Alias \rightarrow Assign^{+}
| \& Alias *
```

 Address-of & / dereference* are the open/close parentheses



A Typical PL Problem

- Traditional Approach: a worklist-based algorithm
 - the worklist contains reachable vertices
 - no transitive edges are added physically
- Problem: embarrassingly sequential and unscalable
- Solution: develop approximations
- Problem: less precise and still unscalable



No Worry About Memory Blowup

As long as one knows how to use disks and clusters

Big Data thinking:

Solution =

(1) Large Dataset + (2) Simple Computation + System Design

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Turning Big Code Analysis into Big Data Analytics



- Key insights:
 - Adding transitive edges explicitly satisfying (1)
 - Core computation is adding edges satisfying (2)
 - Leveraging disk support for memory blowup
- Can existing graph systems be directly used?
 - No, none of them support dynamic addition of a lot of edges
 - (1) Online edge duplicate check and (2) dynamic graph repartitioning

Graspan: A Graph System for Interprocedural Static Analysis of Large Programs

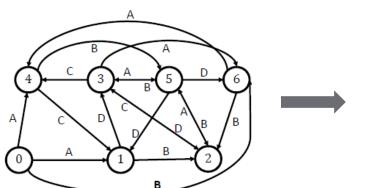
- Scalable
 - Disk-based processing on the developer's work machine
- Parallel
 - Edge-pair centric computation
- Easy to implement a static analysis
 - Developer only needs to generate graphs in mechanical ways and provide a context-free grammar to implement the analysis

How It Works?



- Comparisons with a single-machine Datalog engine:
 - Graspan is a single-machine, out-of-core system
 - Graspan provides better locality and scheduling
 - Graspan is 3X faster than LogicBlox and 5X faster than SociaLite even on small graphs

Granspan Design



	Partition 0			Partition 1			Partition 2		
	Src	Dst	Label	Src	Dst	Label	Src	Dst	Label
1	0	1	Α	3	2	D	5	1	D
		4	Α		4	С		2	В
	1	2	В		5	В		3	Α
		3	D		6	Α		6	D
	2	3	С	4	1	С	6	2	В
		5	Α		5	В		4	Α

- Partitions are of similar sizes
- Each partition contains an adjacency list of edges
- Edges in each partition are sorted

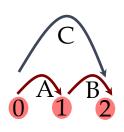
Preprocessing

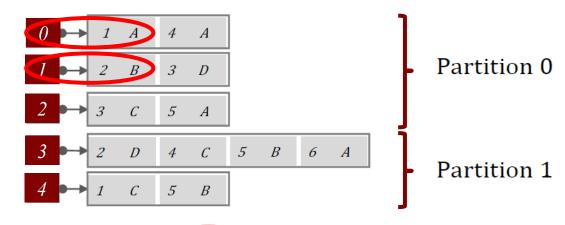
Edge-Pair Centric Computation

Computation Occurs in Supersteps

Edge-Pair Centric Computation

Each Superstep Loads Two Partitions



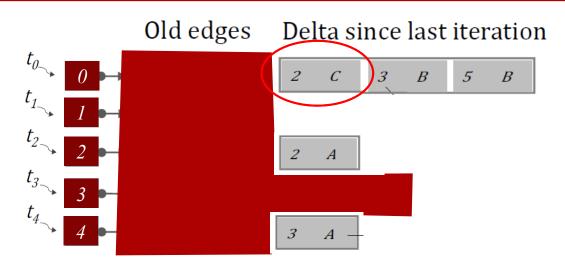


Grammar:
$$C := AB$$
 $D := BC$ $B := AD$ $A := CD$

Preprocessing

Edge-Pair Centric Computation

Each Superstep Loads Two Partitions



GrammalWeckeepleteralling Bucitil Blettales 01:= CD

Preprocessing

Edge-Pair Centric Computation

Post-Processing

- Repartition oversized partitions to maintain balanced load on memory
- Save partitions to disk
- Scheduler favors in-memory partitions and those with higher matching degrees

Preprocessing

Edge-Pair Centric Computation

What We Have Analyzed

Program	#LOC	#Inlines
Linux 4.4.0-rc5	16M	31.7M
PostgreSQL 8.3.9	700K	290K
Apache httpd 2.2.18	300K	58K

- With
 - A fully context-sensitive pointer/alias analysis
 - A fully context-sensitive dataflow analysis
- On a Dell Desktop Computer with 8GB memory and 1TB SSD

Evaluation Questions and Answers I

- Can the interprocedural analyses improve D. Englers' checkers?
 - Found 85 new NULL pointer bugs and 1127 unnecessary NULL tests in Linux 4.4.0-rc5

Checker	BL(4.4.0)		GR(4.4.0)		BL(2.6.1)
	RE	FP	RE	FP	RE
Block	0	0	0	0	43
Null	20	20	+108	23	98
Free	14	14	+4	4	21
Range	1	1	0	0	11
Lock	15	15	+3	3	5
Size	25	23	+11	11	3
UNTest	N/A	N/A	+1127	0	N/A

Evaluation Questions and Answers II

Sample bugs

```
void*probe_kthread_data(
   task struct *task){
 void *data = NULL;
 probe_kernel_read(&data);
 /*data will be
 dereferenced after
 return.*/
return data;
long probe_kernel_read
 (void *dst){
 if(...)
  return -EFAULT;
return
 __probe_kernel_read(dst);
```

```
#define page_private(page)
   ((page)->private)
bool swap_count_continued
(...){
head=vmalloc_to_page(...);
 if (page_private(head)
      != ...){
page*vmalloc_to_page(...){
page *page = NULL;
 if (!pgd_none(*pgd)){
 //...
return page;
```

(a) NULL deref in kernel/kthread.c

(b) NULL deref in mm/swapfile.c

Evaluation Questions and Answers III

Bug breakdown in modules

Modules	NULL pointer defs	Unnecessary NULL Tests
arch	0	75
crypto	0	15
init	0	1
kernel	4(2)	65
mm	3 (0)	84
security	0	78
block	6 (2)	31
fs	19 (3)	84
ipc	0	17
lib	0	39
net	10 (8)	269
sound	15 (5)	83
drivers	25 (3)	286
Total	108 (23)	1127

Evaluation Questions and Answers IV

- Is Graspan efficient and scalable?
 - Computations took 11 mins 12 hrs

Prog	Pointer/Alias Analysis					
	IS=(E,V)	PS=(E,V)	PT	SS	T	
Linux	(249.5M,52.9M)	(1.1B,52.9M)	91 secs	27	1.7 hrs	
PSQL	(25.0M,5.2M)	(862.2M,5.2M)	10 secs	16	6.0 hrs	
httpd	(8.2M, 1.7M)	(904.3M, 1.7M)	3 secs	13	8.4 hrs	

Prog	Dataflow Analysis					
	IS=(E,V)	PS=(E,V)	PT	SS	T	
Linux	(69.4M, 63.0M)	(211.3M, 63.0M)	65 secs	33	11.9 hrs	
PSQL	(34.8M,29.0M)	(56.1M, 29.0M)	35 secs	16	2.4 hrs	
httpd	(10.0M, 5.3M)	(19.3M, 5.3M)	9 secs	16	11.4 mins	

Evaluation Questions and Answers V

- Graspan v/s other engines?
 - GraphChi crashed in 133 secs

Analysis Graspan			ODA [101]	SociaLite [45]
	CT	I/O		
Linux-P	99.7 mins	46.6 secs	OOM	OOM
Linux-D	713.8 mins	4.2 mins	-	OOM
PostgreSQL-P	353.1 mins	4.5 mins	> 1 day	OOM
${\sf PostgreSQL\text{-}D}$	143.8 mins	57.1 secs	-	OOM
httpd-P	497.9 mins	7.6 mins	> 1 day	> 1 day
httpd-D	11.3 mins	3.3 secs	-	4 hrs

[101] X. Zheng and R. Rugina, Demand-driven alias analysis for C, POPL, 2008
 [45] M. S. Lam, S. Guo, and J. Seo. SociaLite: Datalog extensions for efficient social network analysis. ICDE, 2013.

Evaluation Questions and Answers VI

- How easy to use Graspan?
 - 1K LOC of C++ for writing each of points-to and dataflow graph generators
 - Provide a grammar file
- Data structure analysis in LLVM
 - More than 10K lines of code

Download and Use Graspan

- https://github.com/Graspan
- Two versions available at GitHub
 - https://github.com/Graspan/graspan-cpp
 - https://github.com/Graspan/graspan-java
- Data structure analysis in LLVM
 - More than 10K lines of code

Outline

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Outline

- Preliminaries
- DPLL & CDCL
- Parallelizability of SAT solving
- BigSAT

Boolean Satisfiability Problem (SAT)

 A propositional formula is built from propositional variables, operators (and, or, negation) and parentheses.

$$(x1'\vee x2')\wedge(x1'\vee x2\vee x3')\wedge(x1'\vee x3\vee x4')\wedge(x1\vee x4)$$

- SAT problem
 - Given a formula, find a satisfying assignment or prove that none exists.

CNF formula

$$(x1)^2 \vee x2) \wedge (x1)^2 \vee x2 \vee x3) \wedge (x1)^2 \vee x3 \vee x4) \wedge (x1 \vee x4)$$

- Literal: a variable or negation of a variable
- Clause: a disjunction of literals
- CNF: a conjunction of clauses

Why is SAT important?

- Theoretically,
 - First NP-completeness problem [Cook,1971]
- Practically,
 - Hardware/software verification
 - Model checking
 - Cryptography
 - Computational biology
 - **—** ...

- Backtrack search
- Boolean constraint propagation (BCP)
 (x1')∧(x1∨x2)∧(x2'∨x3')

- Backtrack search
- Boolean constraint propagation (BCP)

$$(x1')\wedge(x1\vee x2)\wedge(x2'\vee x3') => x1=F$$

- Backtrack search
- Boolean constraint propagation (BCP)

$$(x1')\land(x1\lor x2)\land(x2'\lor x3') => x1=F x2=T$$

- Backtrack search
- Boolean constraint propagation (BCP)

$$(x1')\land(x1\lorx2)\land(x2'\lorx3') => x1=F x2=T$$

- Backtrack search
- Boolean constraint propagation (BCP)

$$(x1')\land(x1\lor x2)\land(x2'\lor x3') => x1=F x2=T x3=F$$

- Algorithm
 - Select a variable and assign T or F
 - Apply BCP
 - If there's a conflict, backtrack to previous decision level
 - Otherwise, continue until all variables are assigned

x1 +x4

x1 + x3' + x8'

x1 + x8 + x12

x2 + x11

x7' + x3' + x9

x7' + x8 + x9'

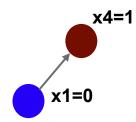
x7 + x8 + x10

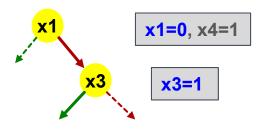
x7 + x10 + x12

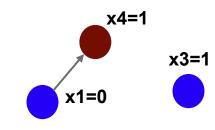


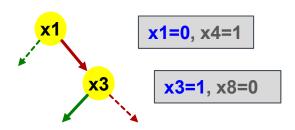


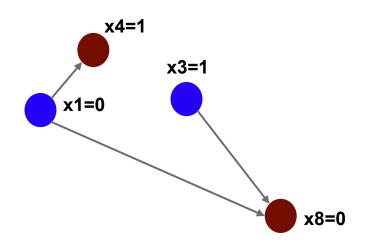


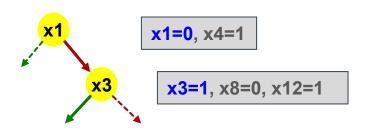


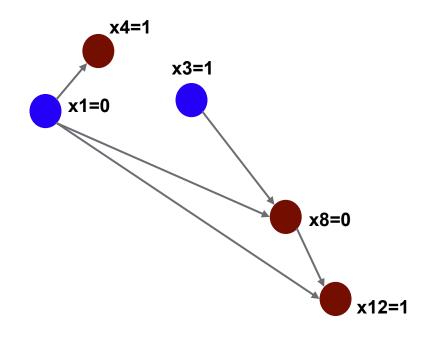


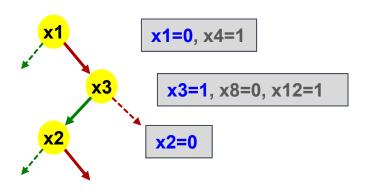


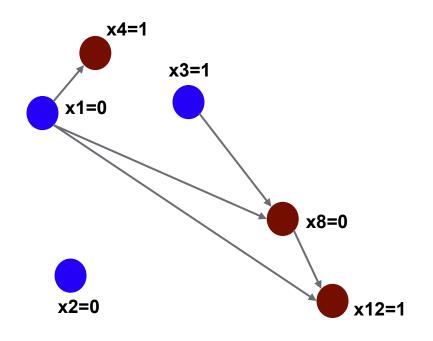


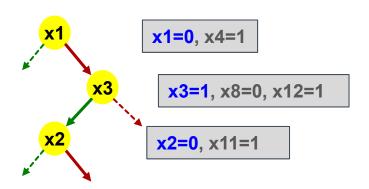


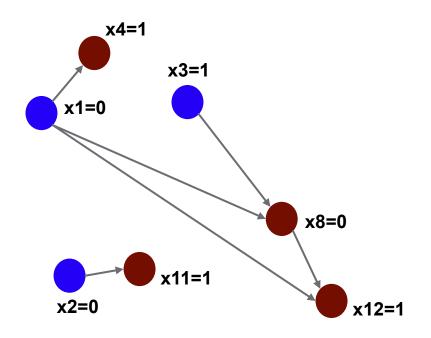


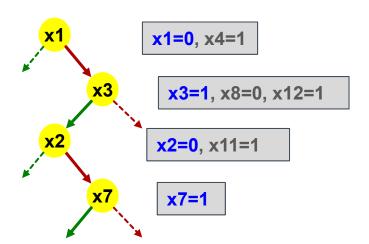


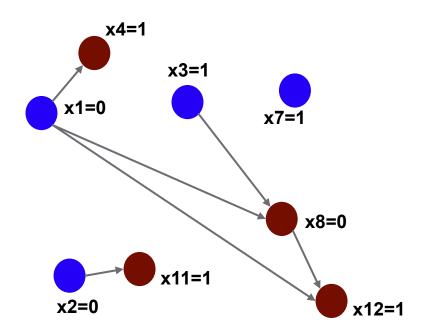


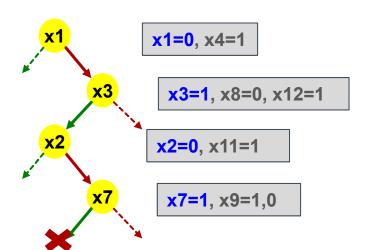


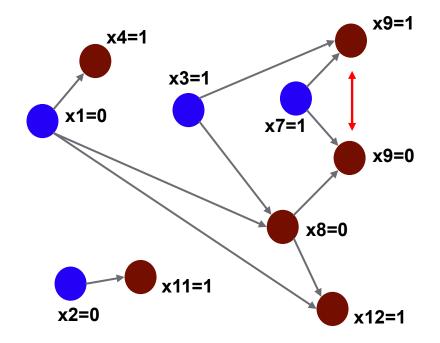


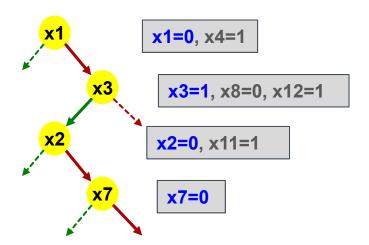


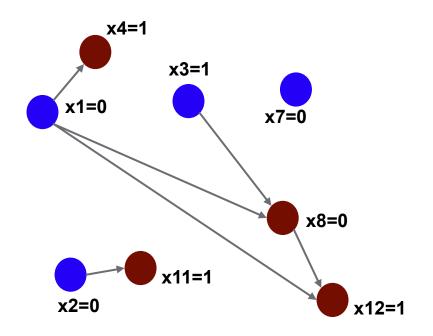


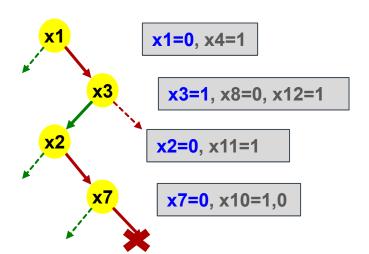


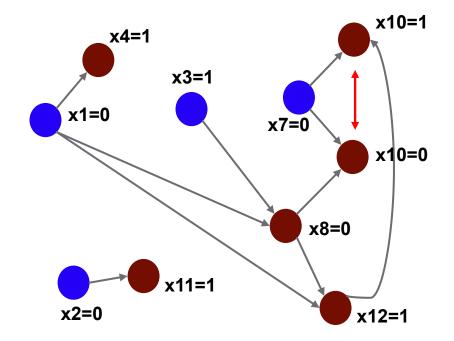


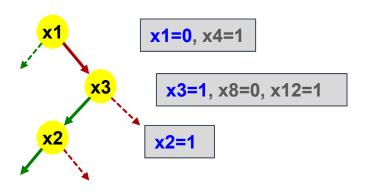


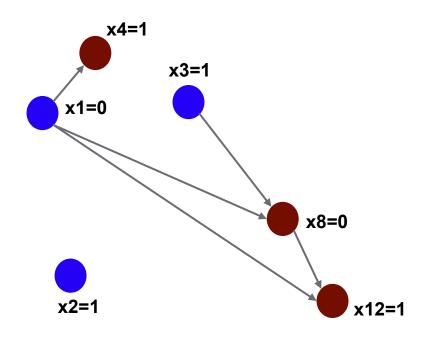






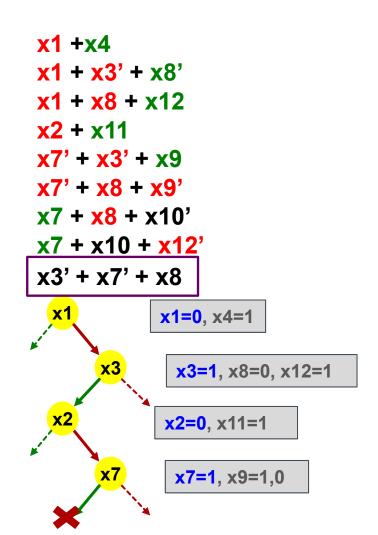


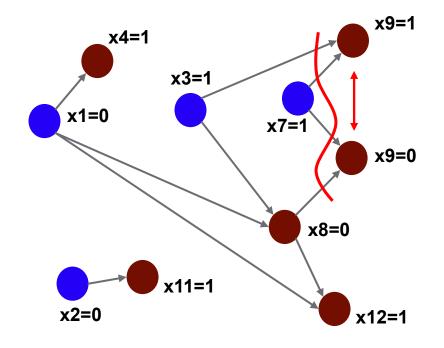




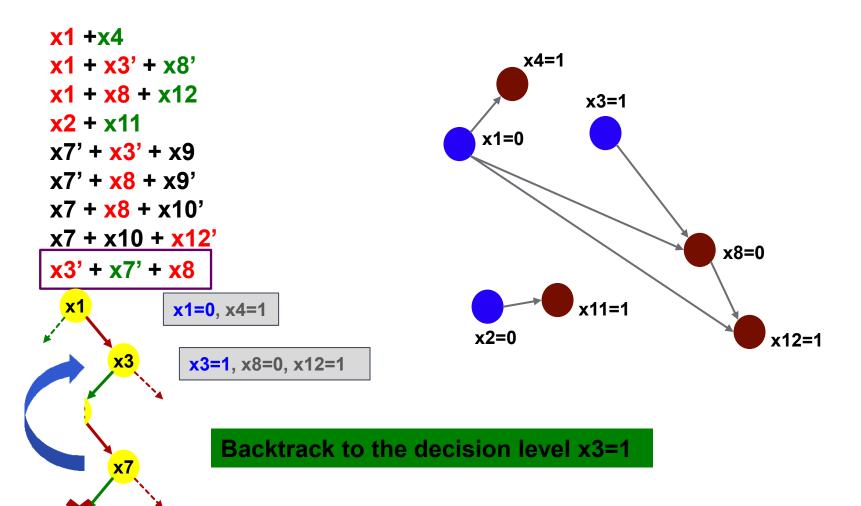
Conflict-driven clause learning (CDCL)

- Clause learning from conflicts
- Non-chronological backtracking
- Algorithm
 - Select a variable and assign T or F
 - Apply BCP
 - If there's a conflict, conflict analysis to learn clauses and backtrack to the appropriate decision level
 - Otherwise, continue until all variables are assigned





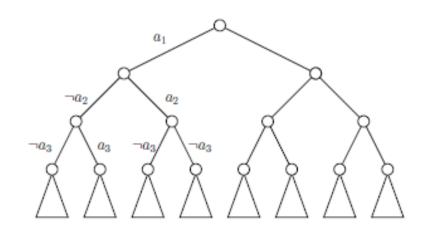
$$x3=1 \land x7=1 \land x8=0$$
 \longrightarrow conflict
 $(x3=1 \land x7=1 \land x8=0)$ '
 $x3' + x7' + x8$



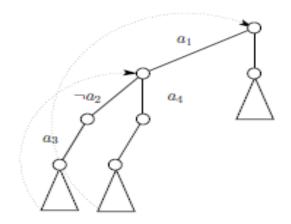
Conflict-driven clause learning (CDCL)

- Clause learning from conflicts
- Non-chronological backtracking
- Others
 - Lazy data structures
 - Branching heuristics
 - Restarts
 - Clause deletion
 - etc.

DPLL vs. CDCL



DPLL: no learning and chronological backtracking



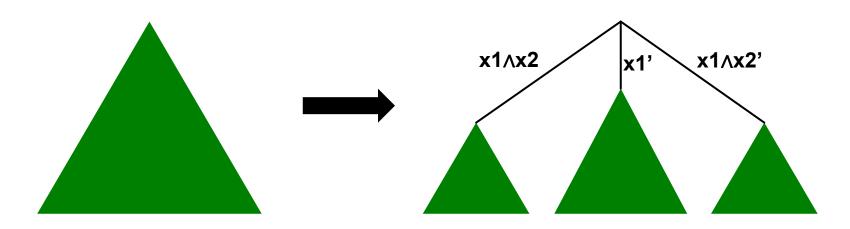
CDCL: clause learning and nonchronological backtracking

Parallel SAT solvers

- Why?
 - Sequential solvers are difficult to improve
 - Can't scale to large problems
- Category
 - Divide-and-conquer
 - Portfolio-based

Divide-and-conquer

 Divide search space into multiple independent sub-trees via guiding-paths



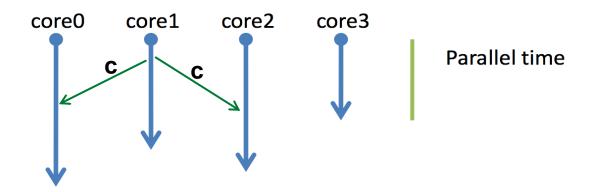
Problem: load imbalance

Portfolio-based

- Observations
 - Modern SAT solvers are sensitive to parameters

- Principle
 - Run multiple CDCLs with different parameters simultaneously
 - Let them compete and cooperate

Portfolio-based



- Diversification
 - Restart, variable heuristics, polarity, learning scheme
- Clause sharing

Parallelization Barriers

- Poor scalability
 - 3x faster on 32-cores
- Reasons
 - BCP is P-complete, hard to parallelize
 - Bottlenecks [AAAI'2013]
 - Load imbalance for divide & conquer
 - Diversity for portfolio-based

Bottlenecks in CDCL proofs

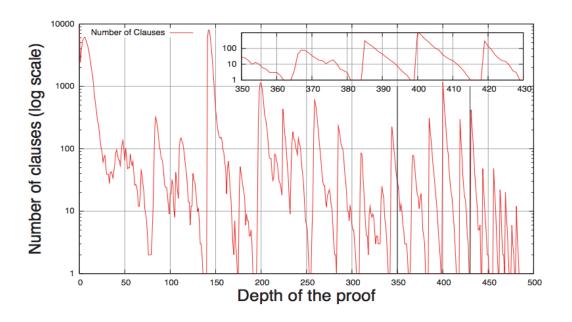


Figure 1: Number of clauses derived at each depth of a typical CDCL proof

BigSAT: Turning SAT (DP) into Big Data Analytics



Big Data thinking:

Big Data Solution

II

(1) Large Dataset + (2) Simple Computation + System Design

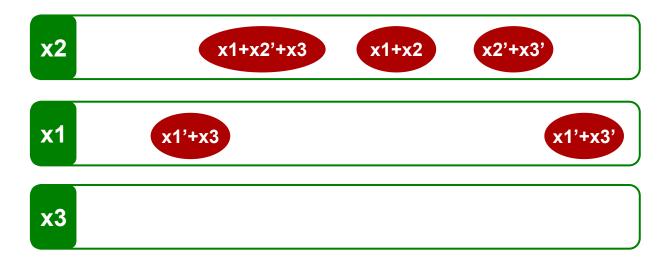
- DPLL?
- Others?

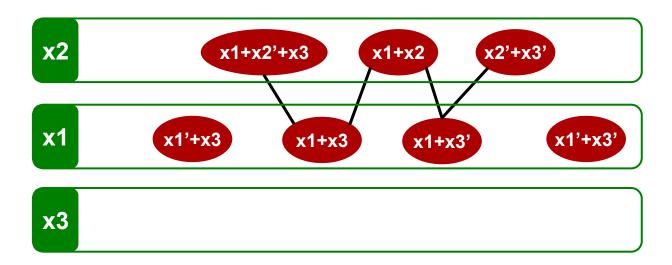
DP

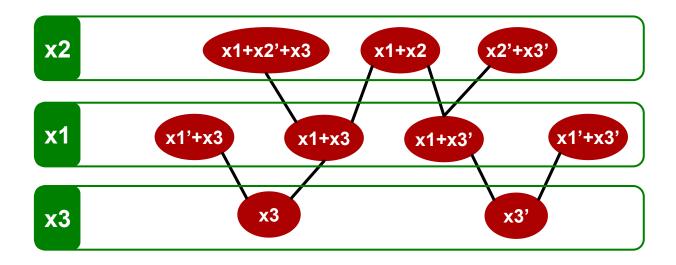
- Introduced by Davis and Putnam in 1960
- Resolution

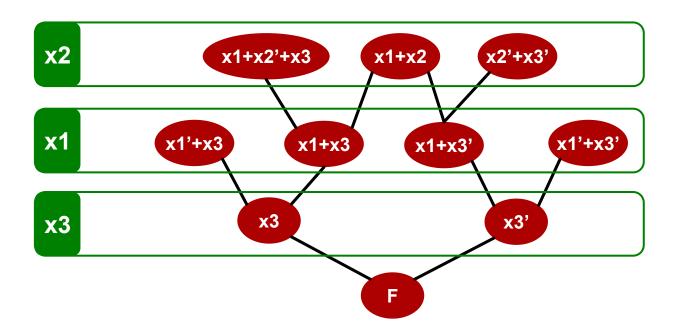
$$\frac{(x \vee y) \wedge (x' \vee z)}{(y \vee z)}$$

- Algorithm
 - Select a variable x, and add all resolvents
 - Remove all clauses containing x
 - Continue until no variable left for resolution









BigSAT: Turning SAT (DP) into Big Data Analytics



Big Data thinking:

Big Data Solution

II

(1) Large Dataset + (2) Simple Computation + System Design

- DP exhibits data parallelism
 - (1) Large Num. of Clauses + (2) Simple Resolution + BigSAT

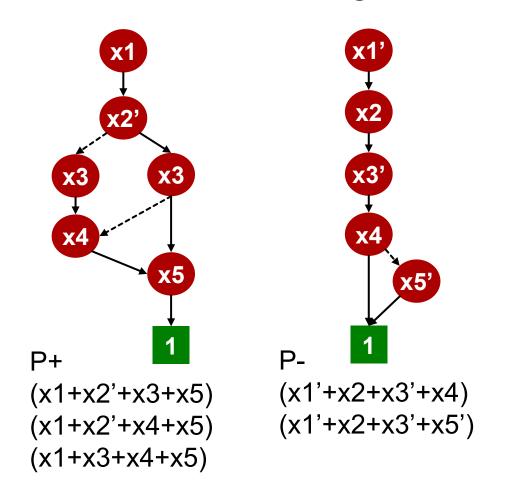
ZBDD-based resolution

- ZBDD clauses representation
 - Common prefix and suffix compression

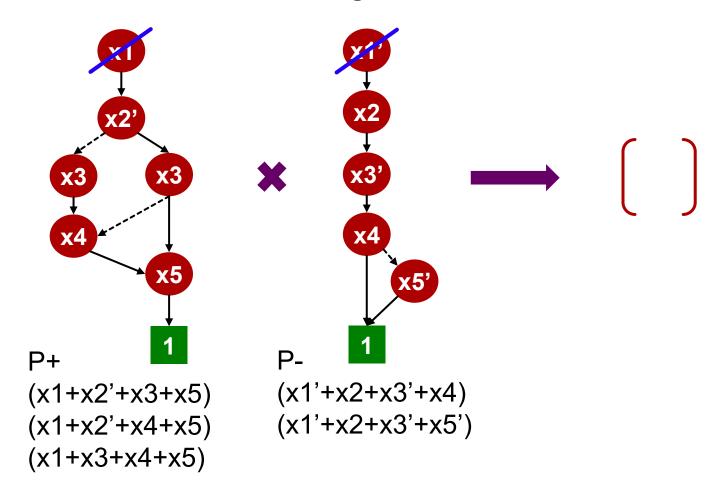
- Multi-resolution on ZBDD
 - Resolution on a pair of sets of clauses

Clause subsumption elimination

Ordering: x1>x2>x3>x4>x5

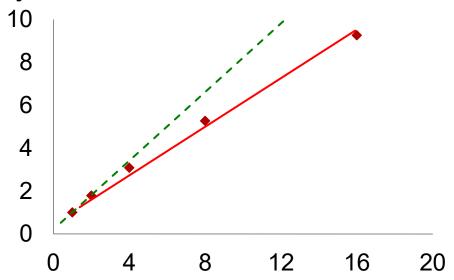


Ordering: x1>x2>x3>x4>x5



BigSAT-parallel

Good scalability factor



Incremental DP

BigSAT-distributed

- Bulk Synchronous Parallel DP
 - Do resolutions as soon as possible
 - Do resolutions on all buckets
- Load balancing
 - Skewed join on Spark

In progress

Conclusion

- "Big data" thinking to solve problems that do not appear to generate big data
- Two example problems
 - Interprocedural static analysis
 - SAT solving
- Future problems
 - Symbolic execution
 - Program synthesis

- ...