Binary Decision Diagrams in Product-Line Analysis

FOSD Online Meeting 2021 | **Tobias Heß**, Chico Sundermann, Thomas Thüm | 15.04.2021

SP Software Engineering Programming Languages

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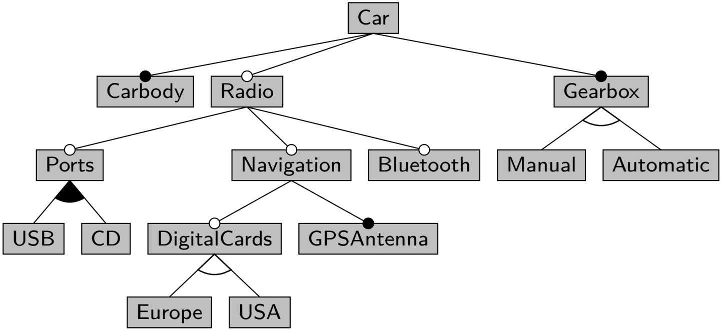
Feature Models



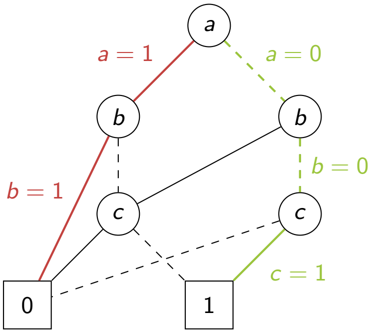
Feature Diagram

$$USA \Rightarrow \neg Manual$$

Constraints

Binary Decision Diagrams (BDD)

Let $f(a, b, c) = (\neg a \vee \neg b) \wedge (\neg a \vee \neg c) \wedge (\neg b \vee \neg c) \vee (a \vee b \vee c)$.



Why should we use BDDs?

$\underbrace{\text{SAT}}_{\text{const.}}$, $\underbrace{\text{Verification,}}_{\text{linear wrt. \#variables}}$ $\underbrace{\text{\#SAT, Commonality}}_{\text{linear wrt. \#nodes}}$

$\boxed{\underbrace{\text{Negation,}}_{\text{const.}}\ \underbrace{\text{Composition, Disjunction}}_{\text{polynomial time \& space wrt. size of BDDs}}}$

Not feasible with CNF or d-DNNF.

Feature Model Differences

Mathieu Acher[1], Patrick Heymans[1,2], Philippe Collet[3], Clément Quinton[2], Philippe Lahire[3], and Philippe Merle[2]

Reasoning about Edits to Feature Models

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$\underbrace{\text{Existential Quantification, QBF}}_{\text{polynomial wrt. size of BDDs}}$

Slicing Feature Models

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Why aren't we using BDDs?

Slicing Feature Models

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"[..] the size of the BDD and that are known to scale for up to **2,000** features. [..] very large FMs (i.e., with more than 5,000 features) [..] For this order of complexity, **BDDs do not scale**."

Feature Model Differences

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"[BDDs] scale up to **2,000** features."

Propagating Configuration Decisions with Modal Implication Graphs

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"A problem with BDDs is that they typically do not scale for feature models larger than **1,000** features."

"BDDs scale for feature models with $\leq$ 2,000 features"

Efficient Compilation Techniques for Large Scale Feature Models

Marcilio Mendonca[1], Andrzej Wasowski[2], Krzysztof Czarnecki[1] and Donald Cowan[1]
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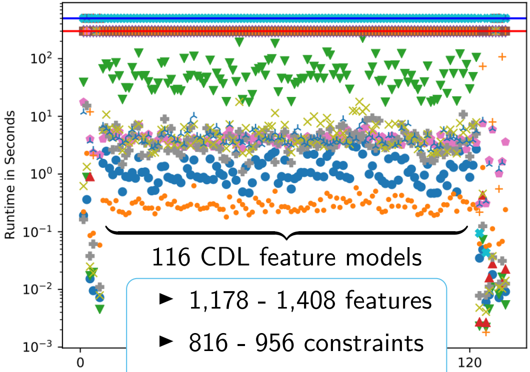
2009

- **Def.:** $ECR(FM) = \dfrac{\text{\# unique features in constraints}}{\text{\# features}}$
- Based on experiments with artificial feature models
  - ECR settings: 10%, 20%, 30%
  - Parameters founded on real-world FMs of the time
  - Largest: *e-Shop*, 326 features, 21 constraints, ECR: 10.4%

And today?

Evaluating #SAT Solvers on Industrial Feature Models

Chico Sundermann, Technische Universität Braunschweig
Thomas Thüm, University of Ulm
Ina Schaefer, Technische Universität Braunschweig



116 CDL feature models

- 1,178 - 1,408 features
- 816 - 956 constraints
- ECR: 80% - 90%

0% success rate

And today?

Feature models have “evolved”

- 1-2 orders of magnitude larger
- Often: #features ≈ #constraints
- ECR: 5% - 95%

BDD tooling has not “evolved”

- BuDDy (1996) and CUDD (1995)
- Expert knowledge required
- Not included in current frameworks

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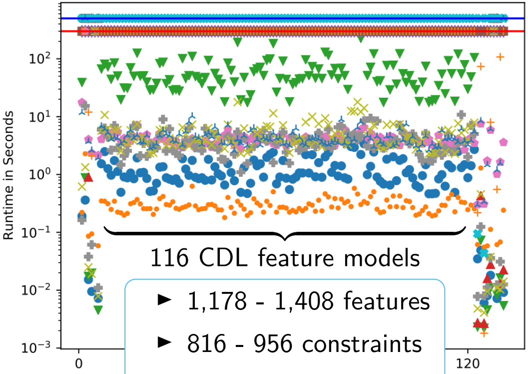

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What can we do?

Variable Ordering

- *Future work*™ in many papers
- linear size $\leftrightarrow$ exponential size

Graph-Based Algorithms for Boolean Function Manipulation

RANDAL E. BRYANT, MEMBER, IEEE

Exploit feature diagram structure

- Feature diagram induces variable ordering $\rightarrow$ **BDD of linear size** (w/o constraints)

Using Extended Logical Primitives for Efficient BDD Building

David Fernandez-Amoros *, Sergio Bra, Ernesto Aranda-Escolástico and Ruben Heradio

Efficient Compilation Techniques for Large Scale Feature Models

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- **Consequence:** Don't use CNF (e.g., DIMACS) as input for BDD construction.

What are we doing?

- 1^{st} stage: ~~Denial~~ **Community, we have a problem!**

Applications of #SAT Solvers on Feature Models

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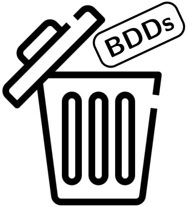
$\Rightarrow$



- 2^{nd} stage: ~~Anger~~ **Address future work!** (e.g., finding good variable orderings)
- 3^{nd} stage: ~~Bargaining~~ **What can we do different?** (e.g., BDD variants like ZDD)

With proper variable ordering, BDDs scale to CDL feature models!

`ddueruem`

A wrapper for BuDDy and CUDD written in Python.

Features

- command line interface

```
./ddueruem.py input.uvl    --preorder force    --dynorder sift-converge
```

`./ddueruem.py input.uvl`: parse input, build BDD, analyse

`--preorder force`: opt. specify variable ordering

`--dynorder sift-converge`: opt. specify variable ordering during build

- downloads & builds BuDDy and CUDD for you
- parses DIMACS or UVL (Unified Variability Language)

Feature requests welcome!

~~Take~~ Stay Home Messages

The Good

BDDs solve many problems in product-line analysis.

The Bad

BDD construction is hard, requires care (variable ordering!), and tooling is insufficient.

The Ugly

Some feature models may force BDDs of exponential size.

Backup Slides

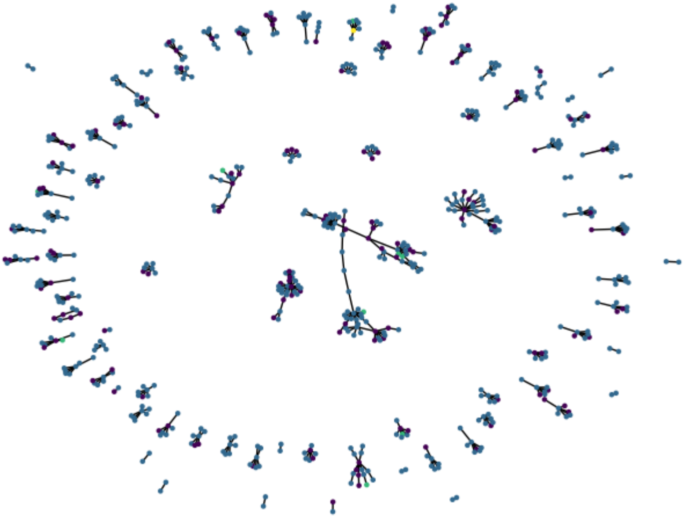
Automotive02_v1 vs. *Automotive02_v4*

	#Features	#CTCs	#Nodes	Max #Nodes	Average Time (s)
Automotive02_v1	14,010	666	70,003	111,000	**20.3**
Automotive02_v2	17,742	914	90,254	90,254	1,275
Automotive02_v3	18,343	1,300	65,022	192,000	1,654
Automotive02_v4	18,616	1,369	76,156	185,000	**1,680**

What makes *Automotive02_v4* **8,000%** harder than *Automotive02_v1*?

- **28%** more features
- **105%** more cross-tree constraints
- features to cross-tree constraints ratio: **4%** vs. **7%**
- ECR: **5.7%** vs. **8%**

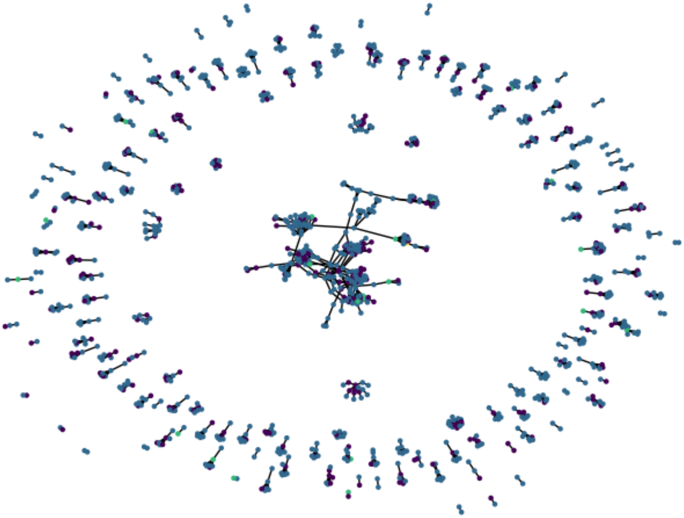
Graph Metrics



Automotive02_v1

- **88** components
- Minimum Size: **2**
- Average Size: **7.2**
- Maximum Size: **43**

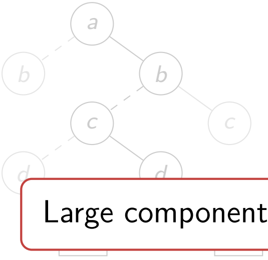
Graph Metrics cont.

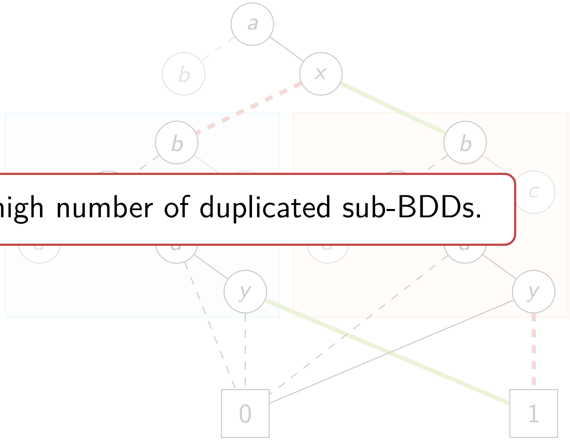


Automotive02_v4

- **167** components
- Minimum Size: **2**
- Average Size: **7.2**
- Maximum Size: **198**

Why are large components a problem?





Large components lead to a high number of duplicated sub-BDDs.

Variable Order: $\pi = (a, x, b, c, y, d)$

Add cross-tree constraint:

$$C = (x \vee y) \wedge (\neg x \vee \neg y)$$

Automotive01: Cross-Tree Constraint Structure