

Automated reasoning about variability models with solvers

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Material

[https://github.com/FAMILIAR-project/
HackOurLanguages-SIF](https://github.com/FAMILIAR-project/HackOurLanguages-SIF)

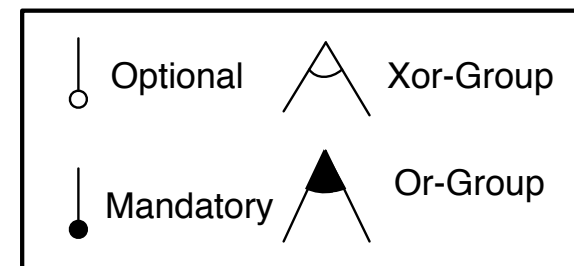
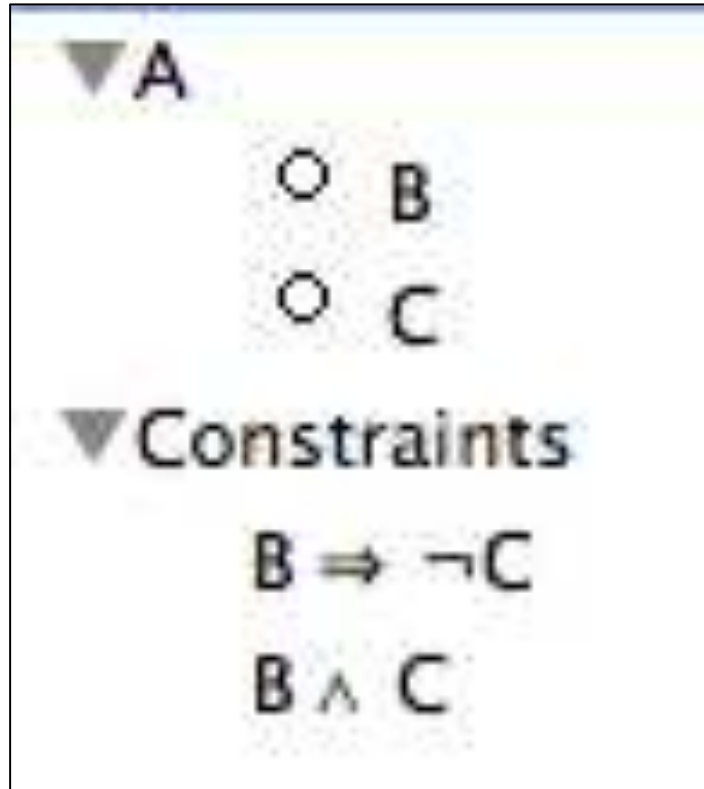
Plan

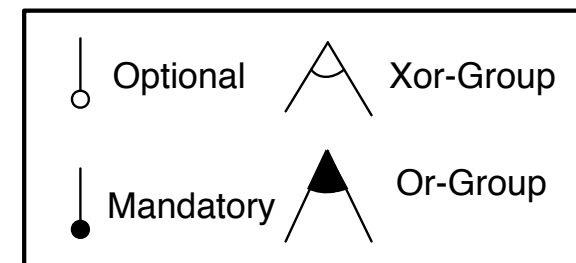
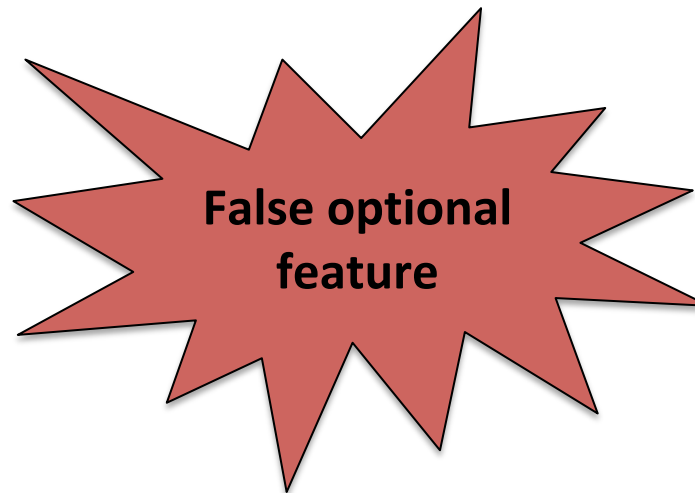
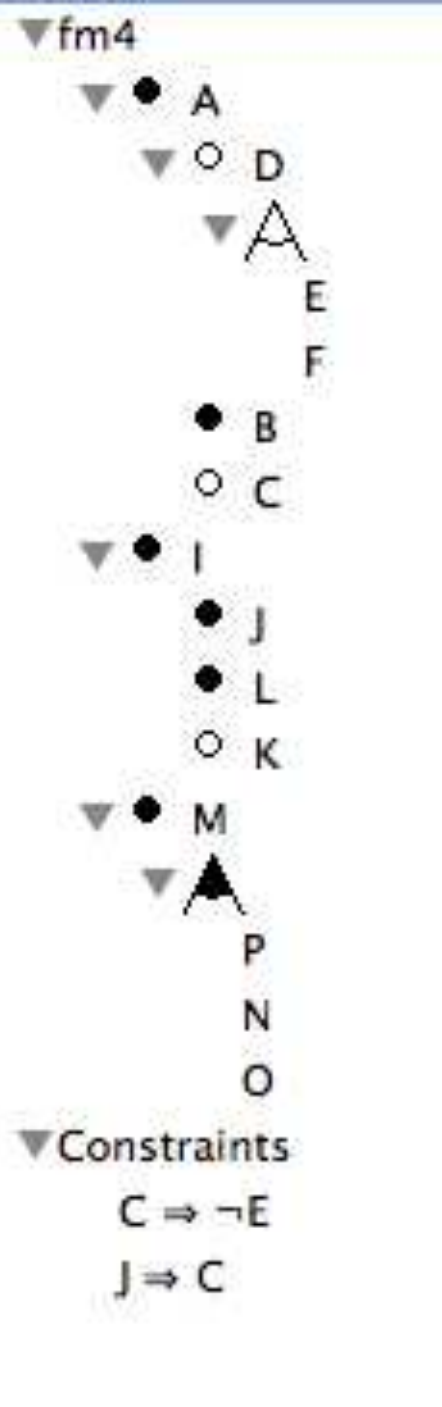
- **Feature Models**
 - **Defacto standard for modeling product lines and variability**
 - **Syntax, semantics, automated reasoning, synthesis**

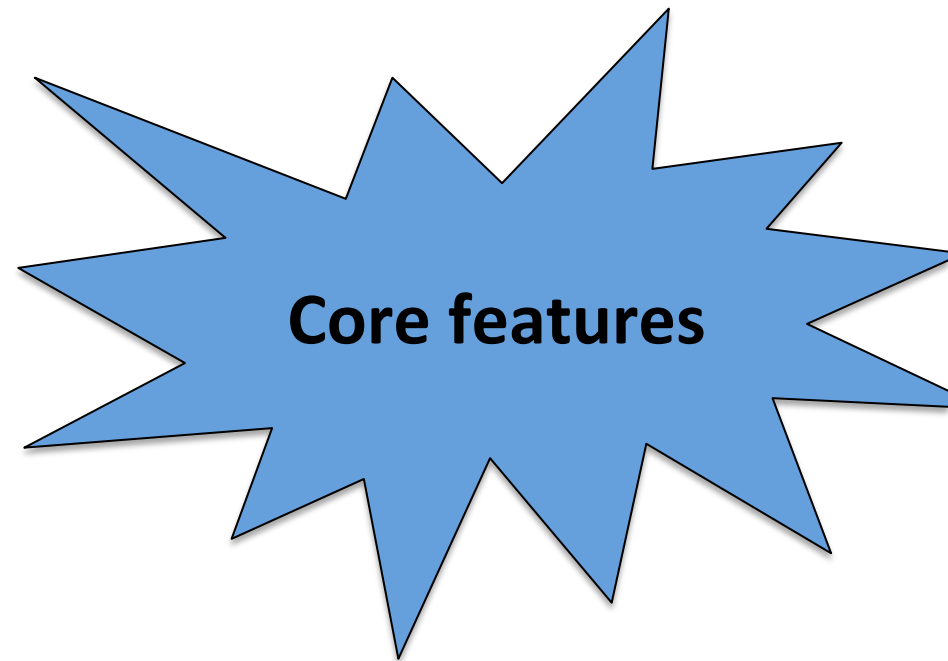
Contract

- The idea of software product lines and variability
 - You will be able to recognize this class of systems
 - Aware of the complexity, the specific development process, and existing techniques
- **Feature modeling**
 - **A widely used formalism for modeling product lines and configurable systems in a broad sense**
- **Composing/Decomposing feature models with a domain-specific language**
- **Reverse engineering variability models**

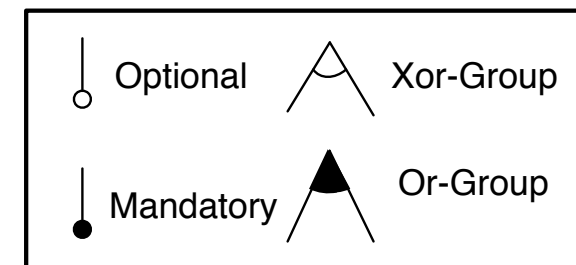
I want to analyze and
play with my specification!

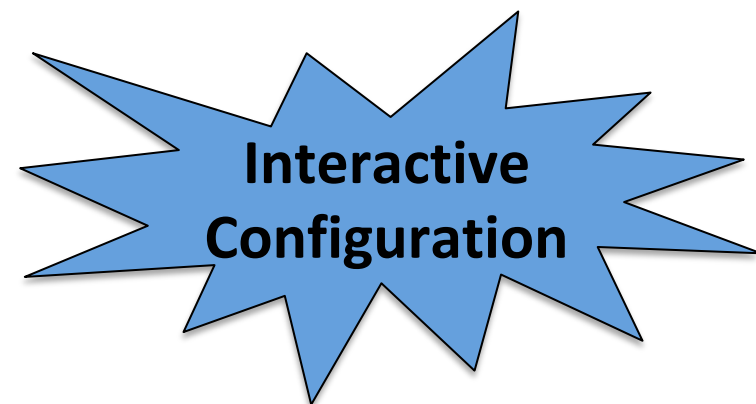
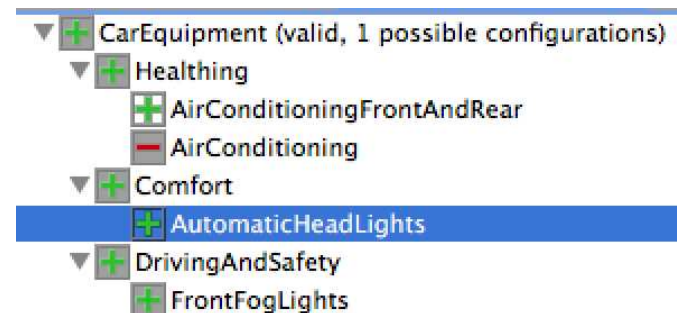
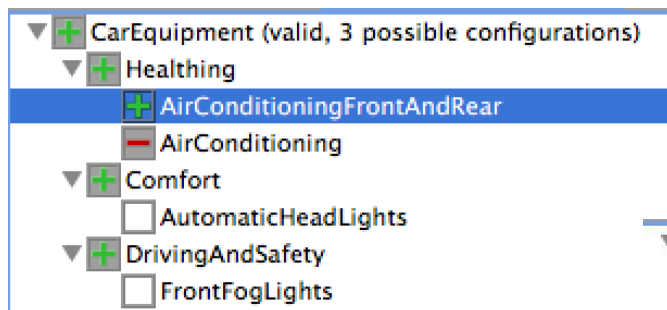
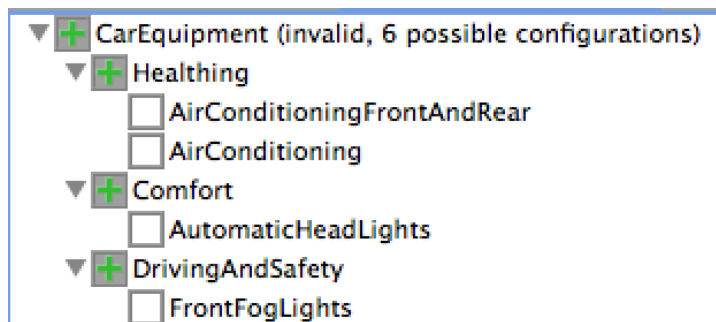
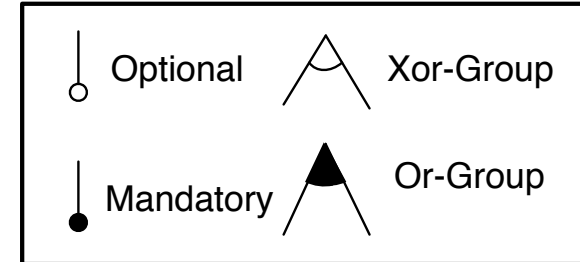






{CarEquipment, Comfort, DrivingAndSafety, Healthing}





Feature Models and Automated Reasoning

Benavides et al. survey, 2010

[illegible]

+	Supported			

			No support
--	--	--	------------

⊕ Supported (first reference)

⊖ No support (first reference)

B	Basic feature model
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C	Cardinality-based feature models
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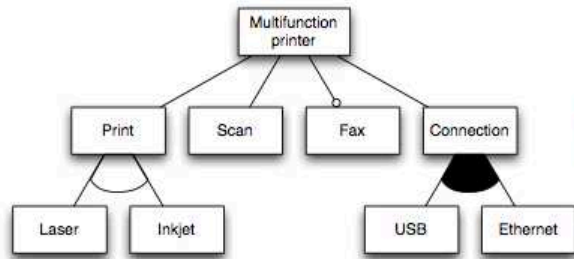
Decision problems and complexity

- Validity of a feature model
- Validity of a configuration
- Computation of dead and core features
- Counting of the number of valid configurations
- Equivalence between two feature models
- Satisfiability (SAT) problem
 - NP-complete

How to automate analysis of your feature models?

Binary Decision Diagram (BDD)
SAT solver

Typical implementations



result



logics



solvers



Z3

Truth table, boolean function

<i>from</i>		<i>to</i>		
x_1	x_2	x_3	x_4	f
0	0	0	0	0
0	0	0	1	1
0	0	1	0	1
0	0	1	1	1
0	1	0	0	0
0	1	0	1	0
0	1	1	0	0
0	1	1	1	1
1	0	0	0	0
1	0	0	1	0
1	0	1	0	0
1	0	1	1	1
1	1	0	0	0
1	1	0	1	0
1	1	1	0	0
1	1	1	1	0

BDDs from Truth Tables

Truth Table



Binary Decision Tree



Binary Decision Diagram (BDD)



Ordered Binary Decision Diagram (OBDD)

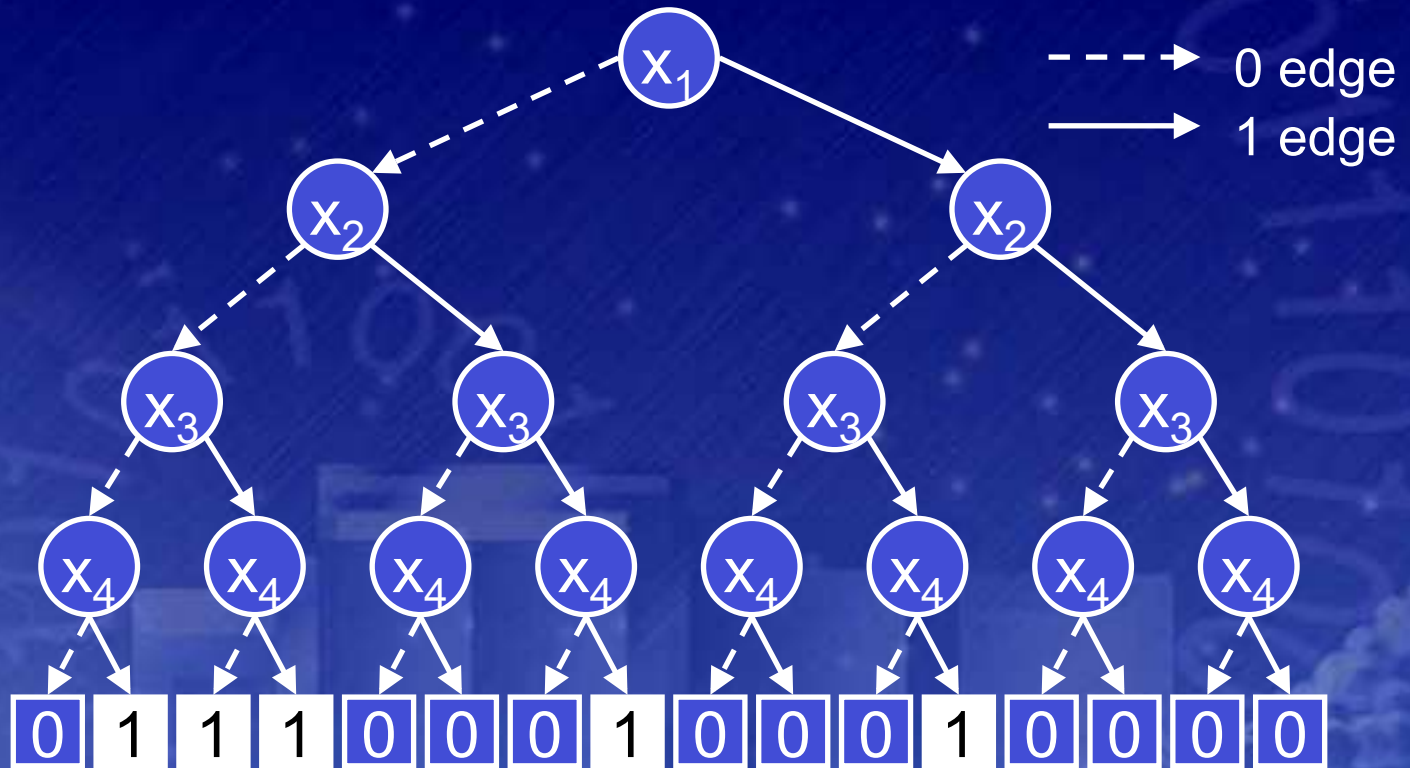


Reduced Ordered Binary Decision Diagram
(ROBDD, simply called BDD)

Binary Decision Diagrams (Bryant 1986)

encoding of a truth table.

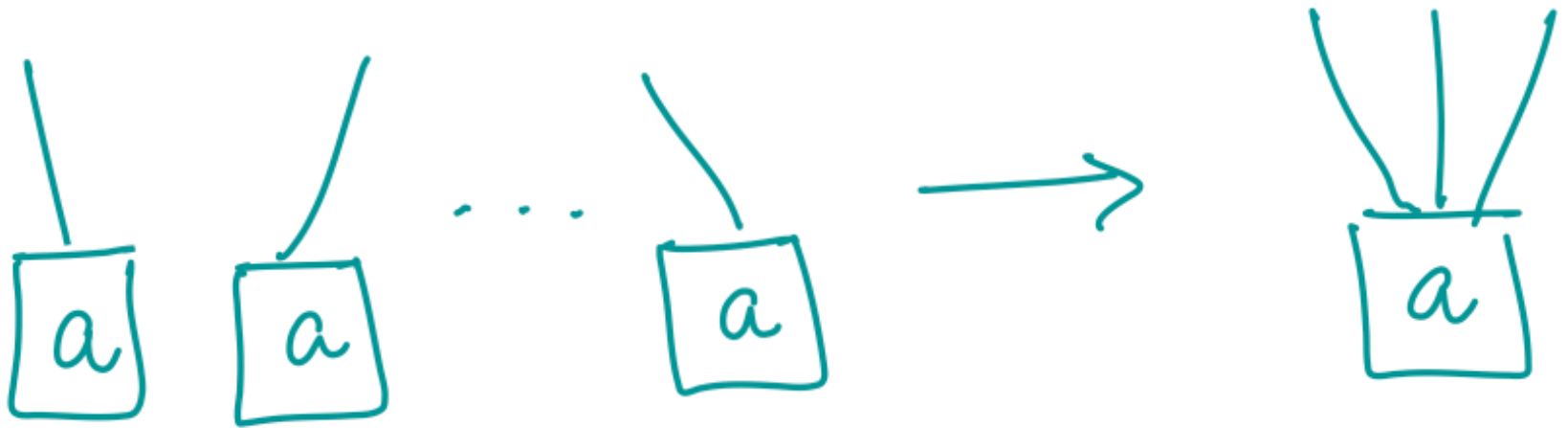
from		to		
x_1	x_2	x_3	x_4	f
0	0	0	0	0
0	0	0	1	1
0	0	1	0	1
0	0	1	1	1
0	1	0	0	0
0	1	0	1	0
0	1	1	0	0
0	1	1	1	1
1	0	0	0	0
1	0	0	1	0
1	0	1	0	0
1	0	1	1	1
1	1	0	0	0
1	1	0	1	0
1	1	1	0	0
1	1	1	1	0



Reduction

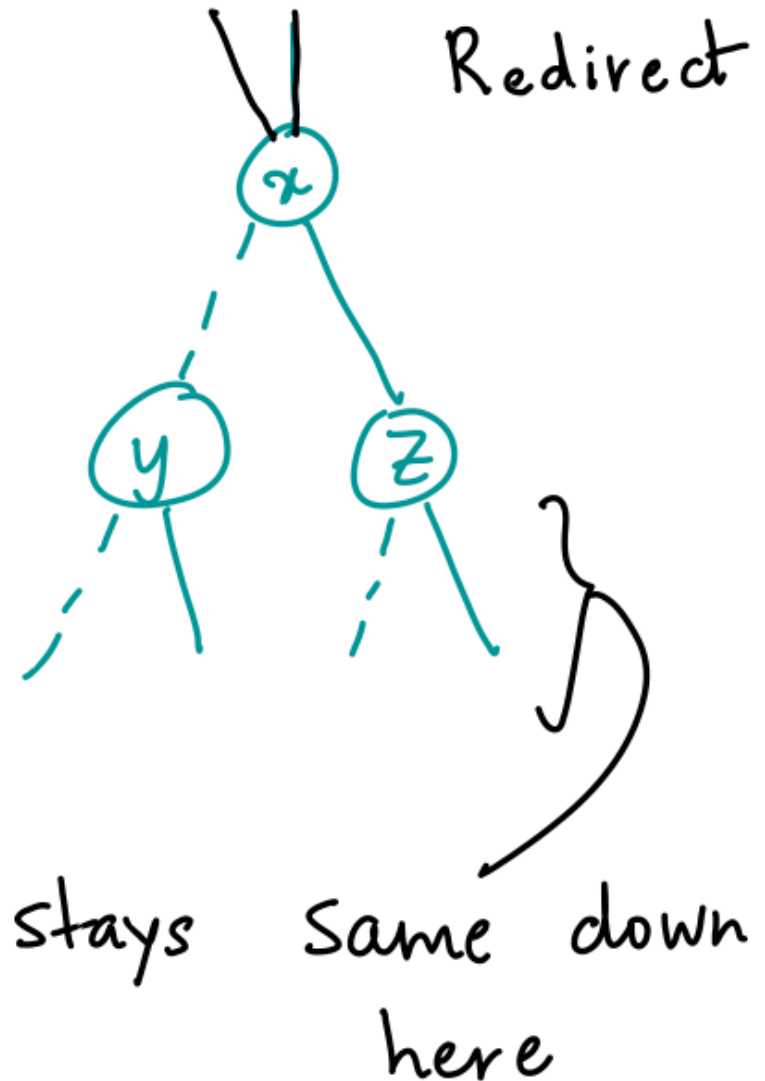
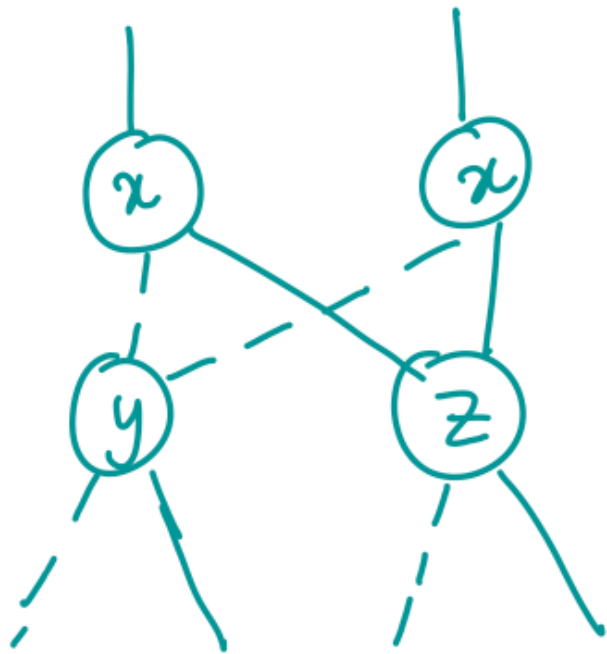
- Identify Redundancies
- 3 Rules
 - Merge equivalent leaves
 - Merge isomorphic nodes
 - Eliminate redundant tests

Merge equivalent leaves

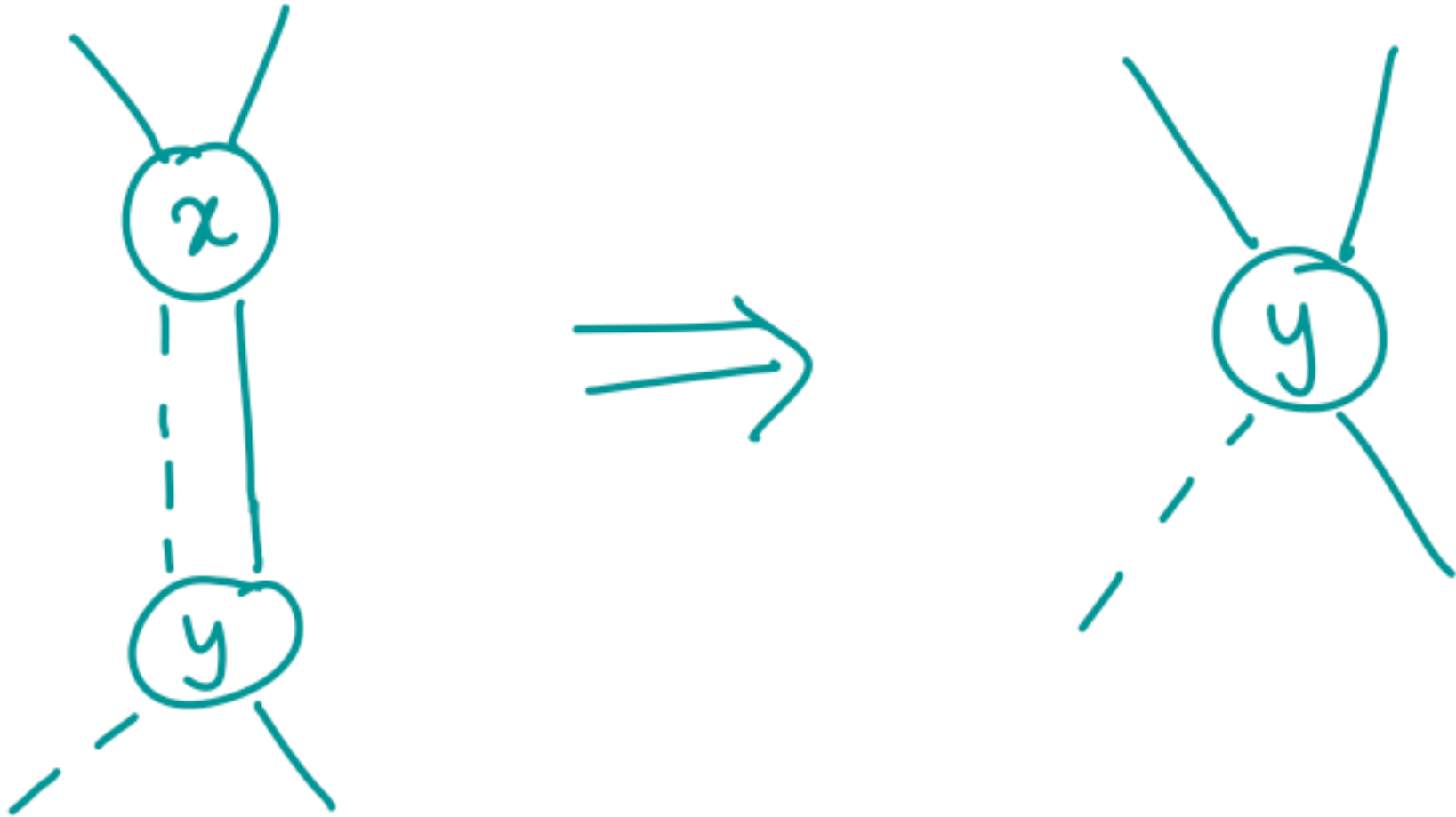


"a" is either 0 or 1

Merge isomorphic nodes

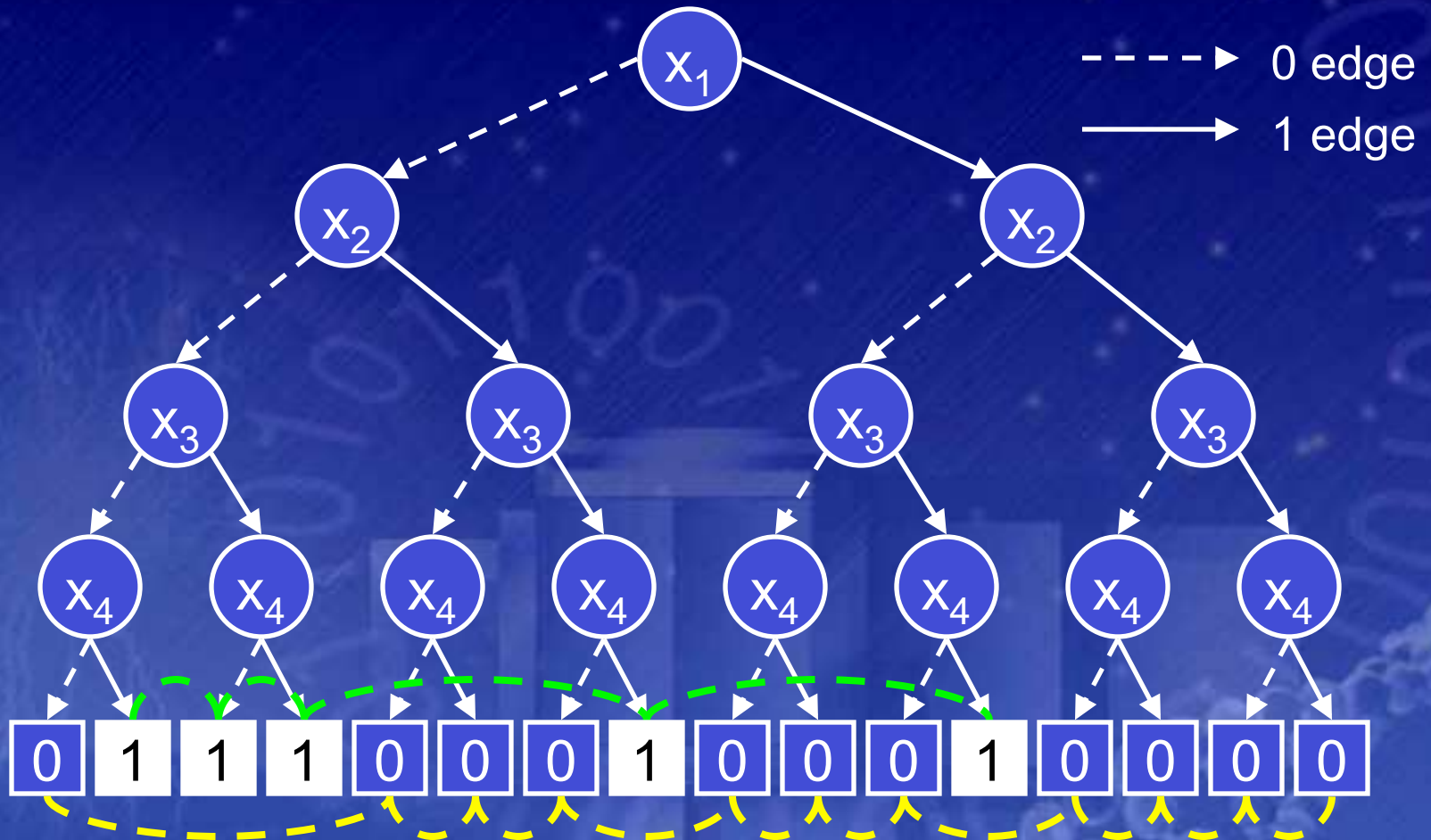


Eliminate redundant tests



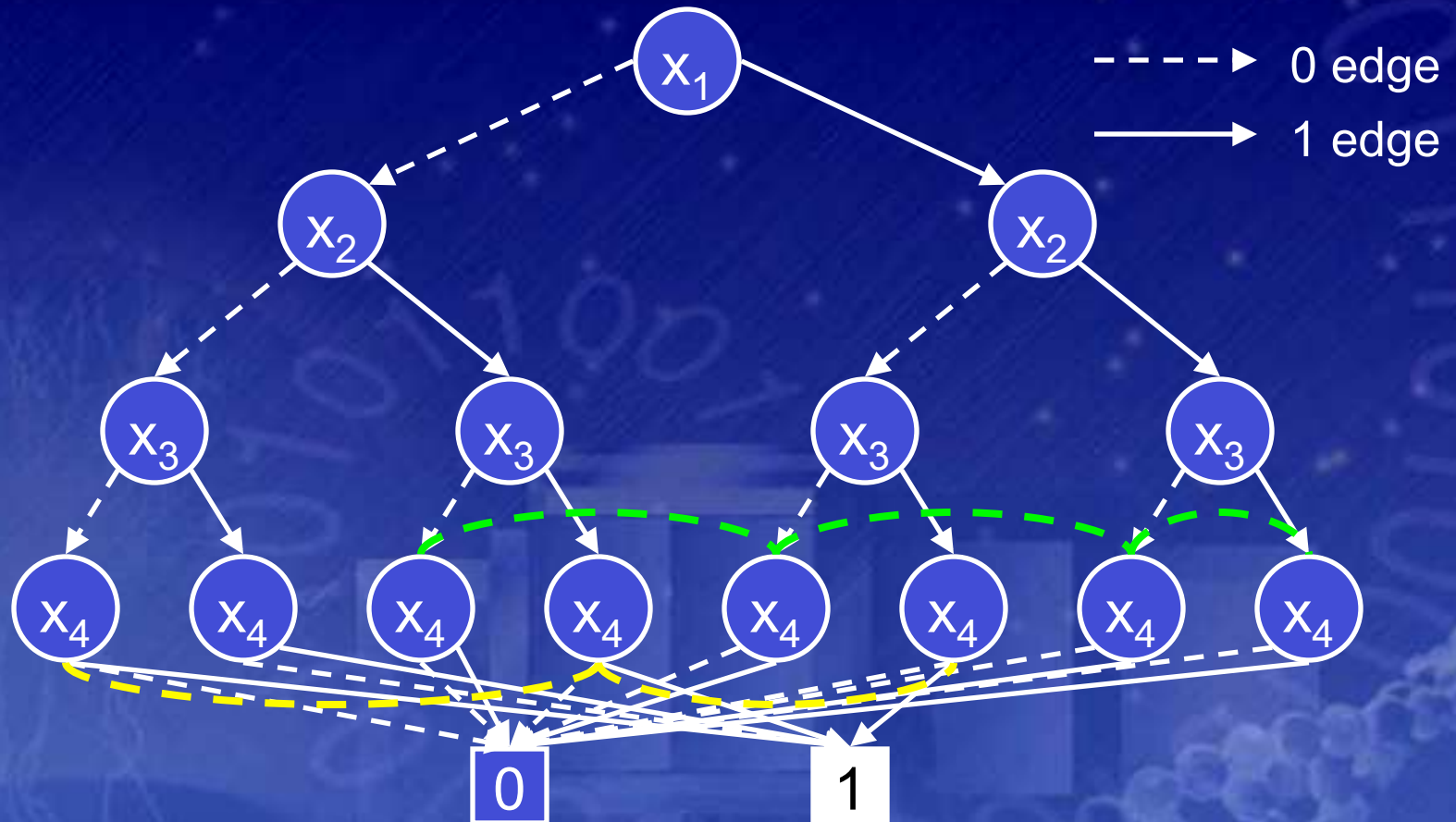
Binary Decision Diagrams

- Collapse redundant nodes.



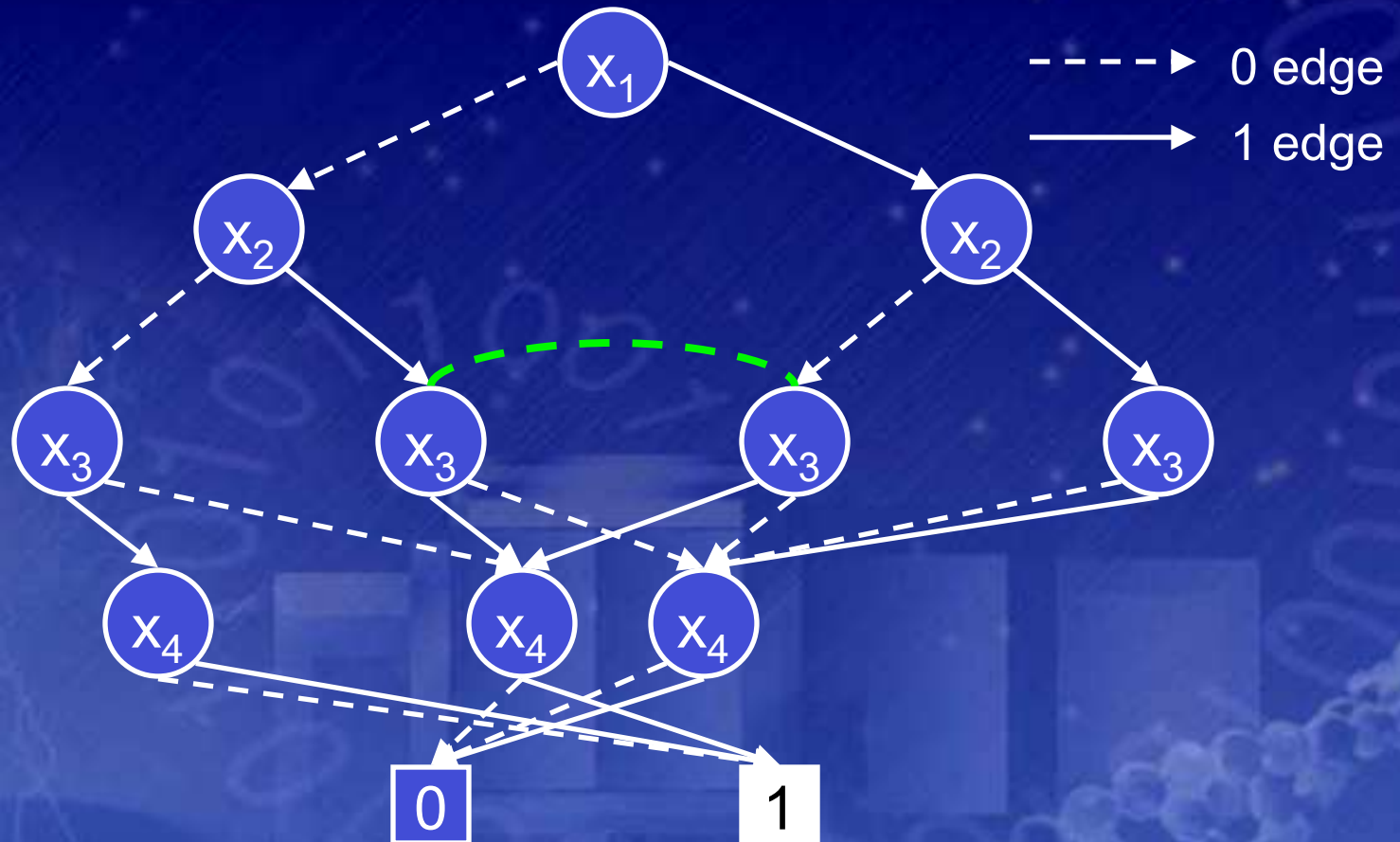
Binary Decision Diagrams

- Collapse redundant nodes.



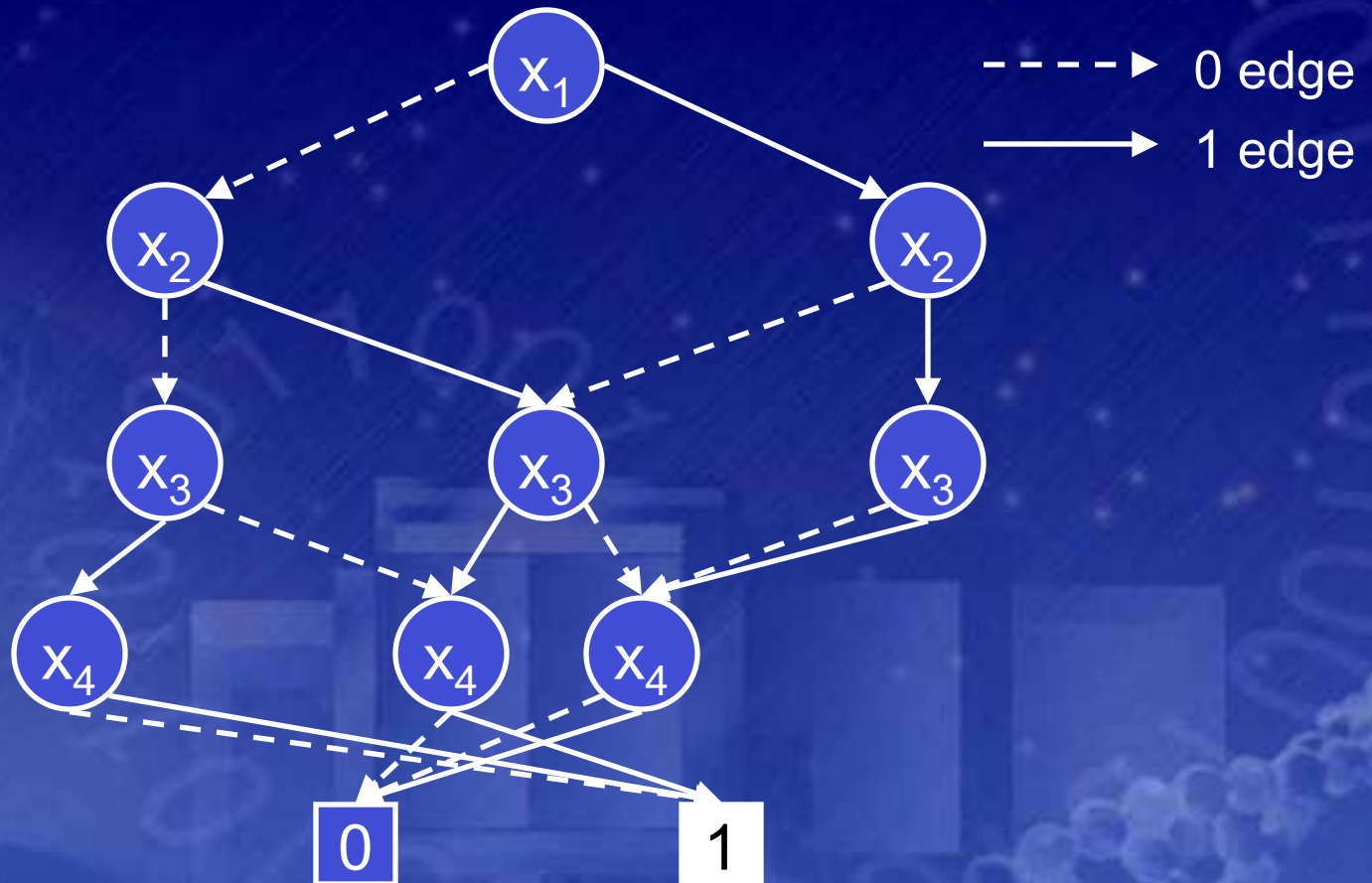
Binary Decision Diagrams

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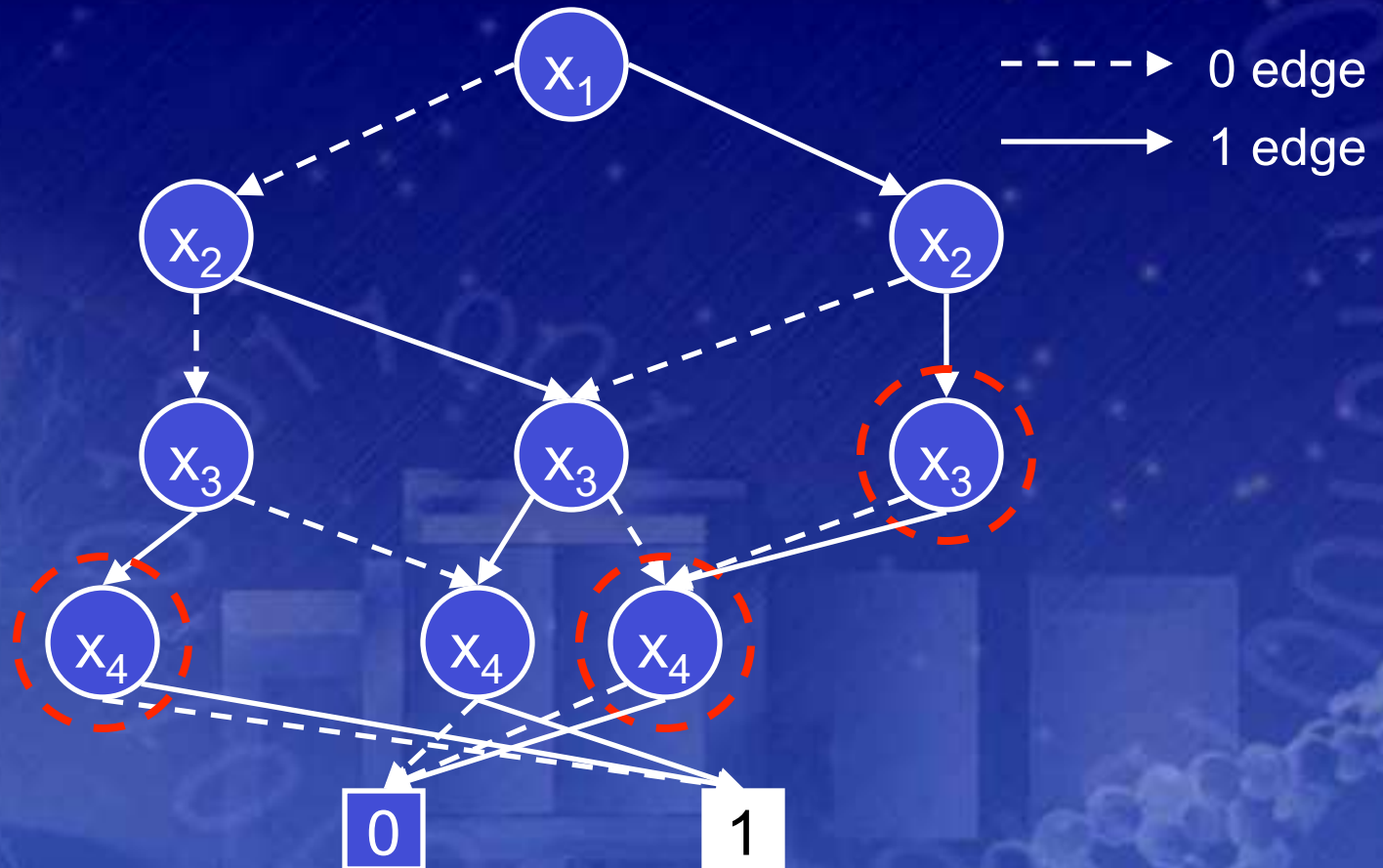
Binary Decision Diagrams

- Collapse redundant nodes.



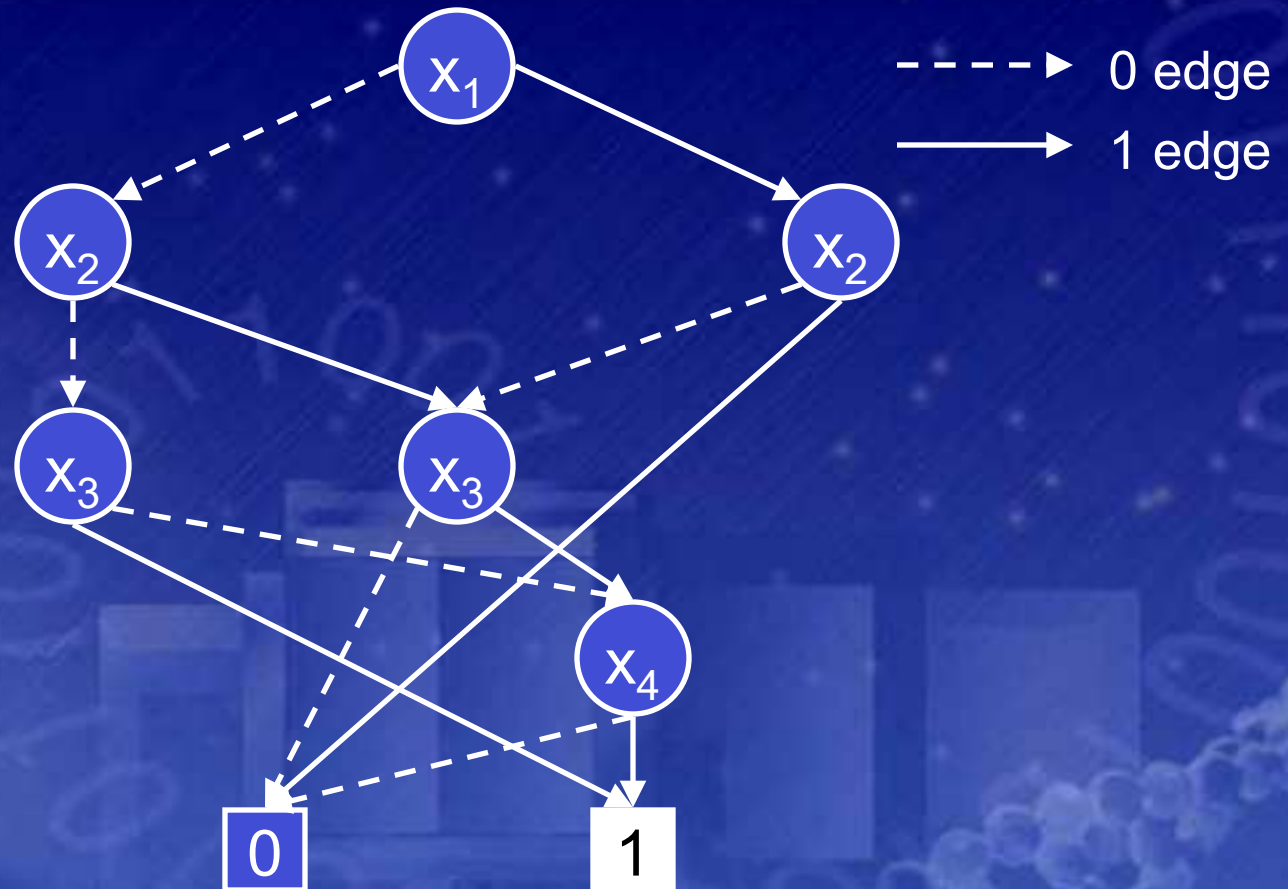
Binary Decision Diagrams

- Eliminate unnecessary nodes.



Binary Decision Diagrams

- Eliminate unnecessary nodes.

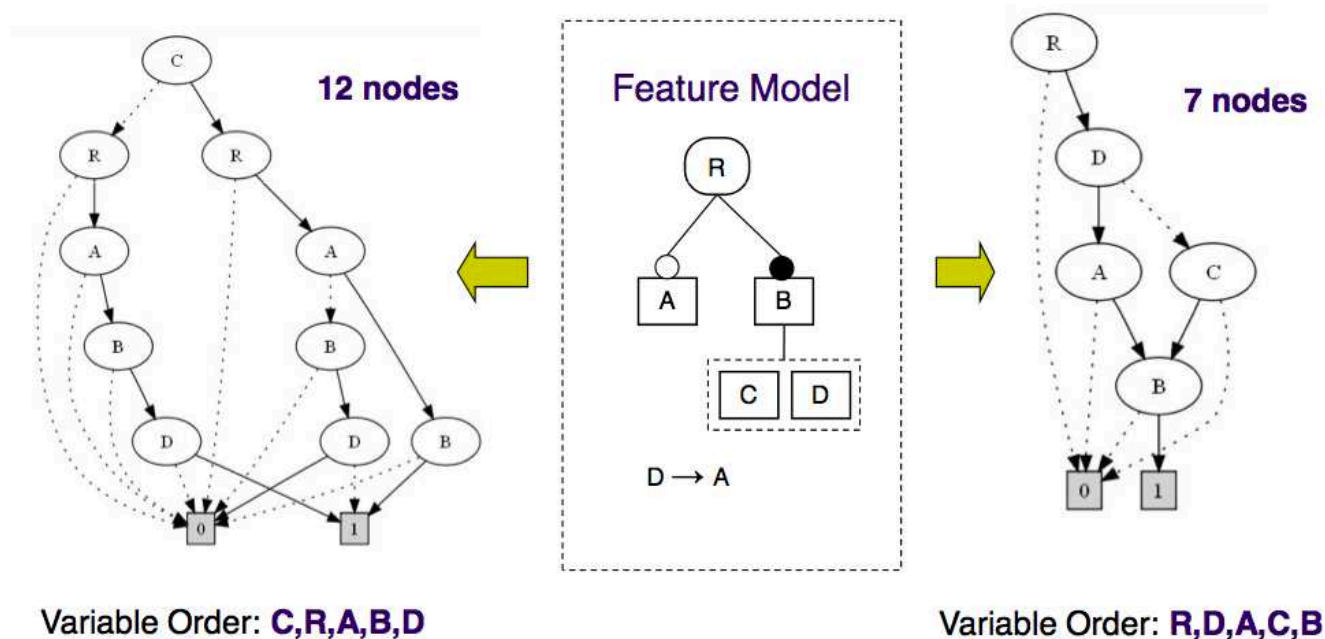


Binary Decision Diagrams (BDDs)

- Very efficient structure for most of the satisfiability operations
- Polynomial in time for checking satisfiability and determining equivalence between two BDDs
- Graph traversal
- So great?

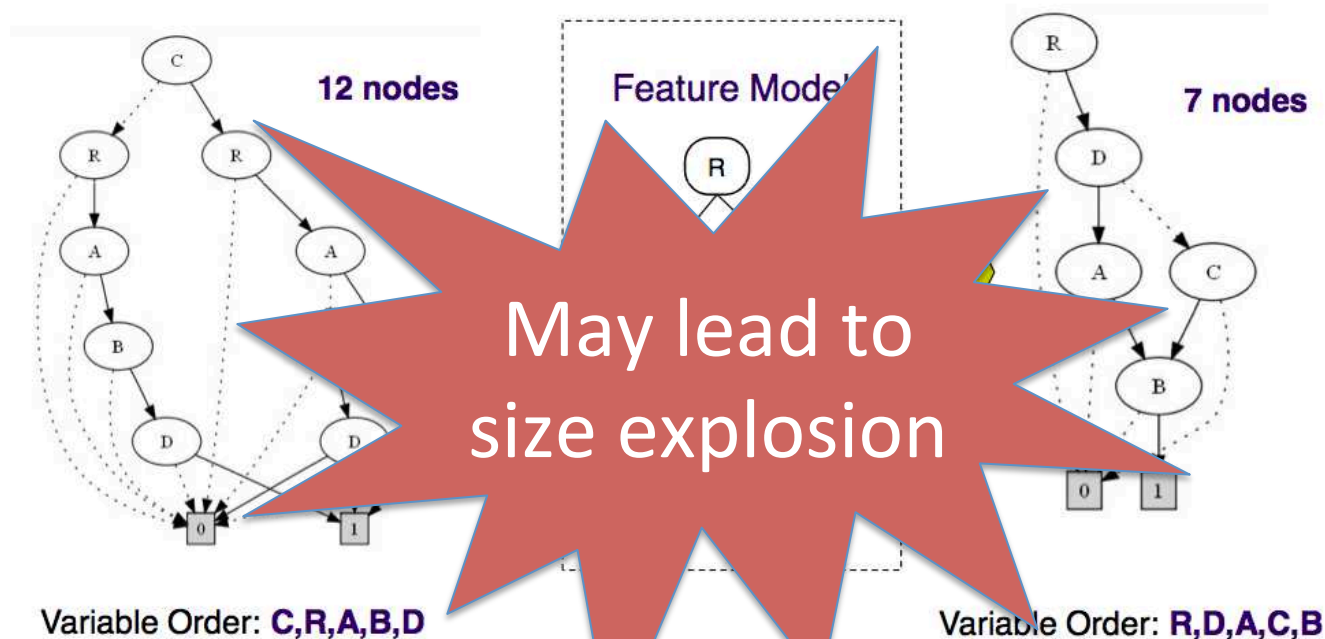
Binary Decision Diagrams (BDDs): Theoretical Problem

- The size of the BDD is very sensitive to the order of the BDD variables
 - e.g. two equivalent BDDs for the same feature



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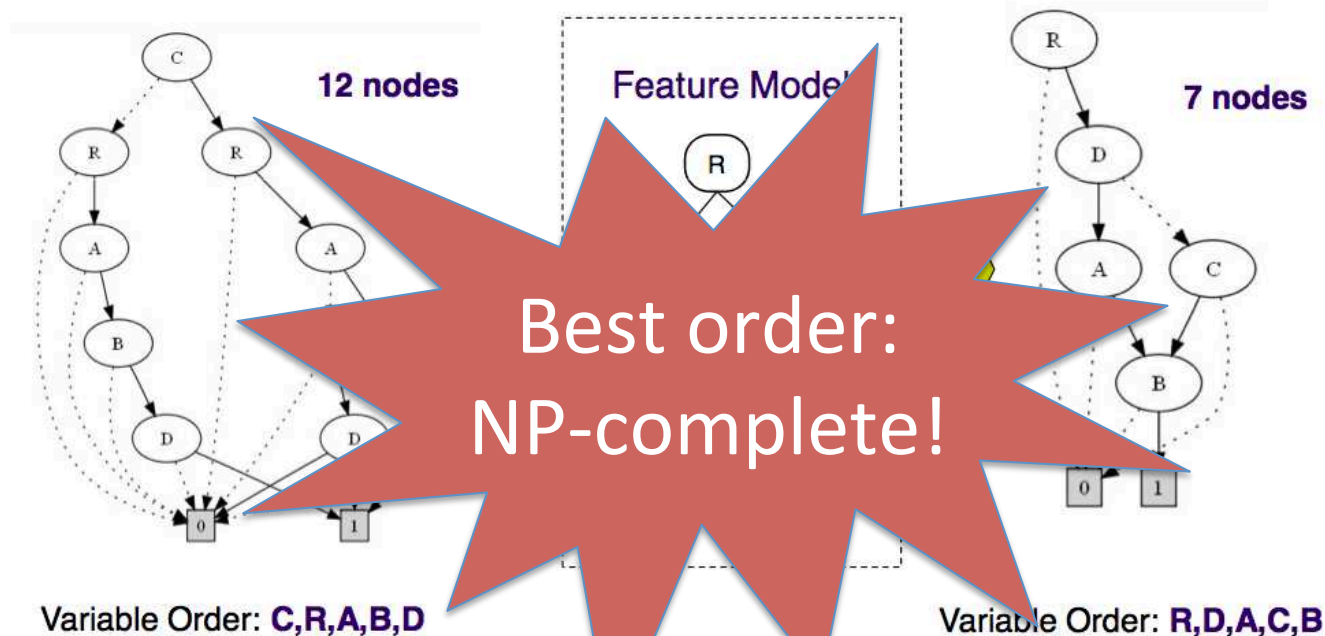
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[Mendonca, slide]

Binary Decision Diagrams (BDDs): Theoretical Problem

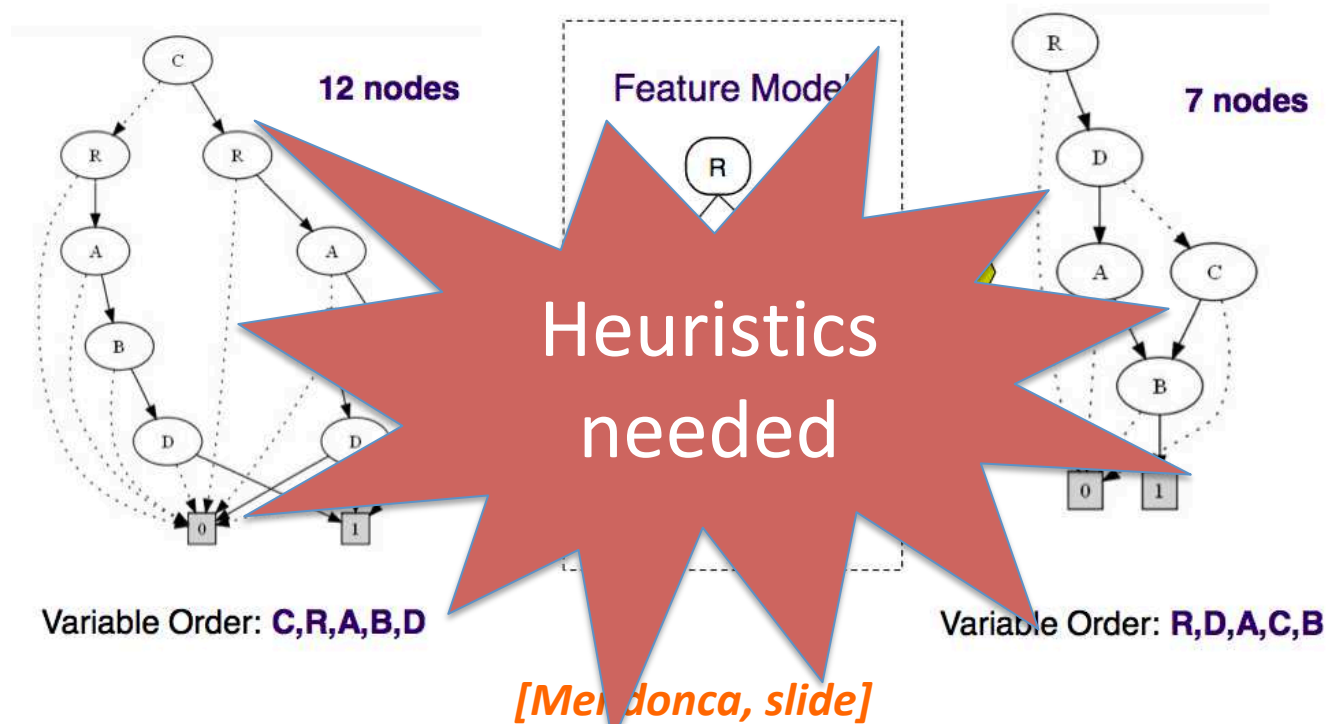
- The size of the BDD is very sensitive to the order of the BDD variables
 - e.g. two equivalent BDDs for the same feature



[Mendonca, slide]

Binary Decision Diagrams (BDDs): Practical Problem

- The size of the BDD is very sensitive to the order of the BDD variables. In practice: **BDDs cannot be build for feature models with 2000+ features**

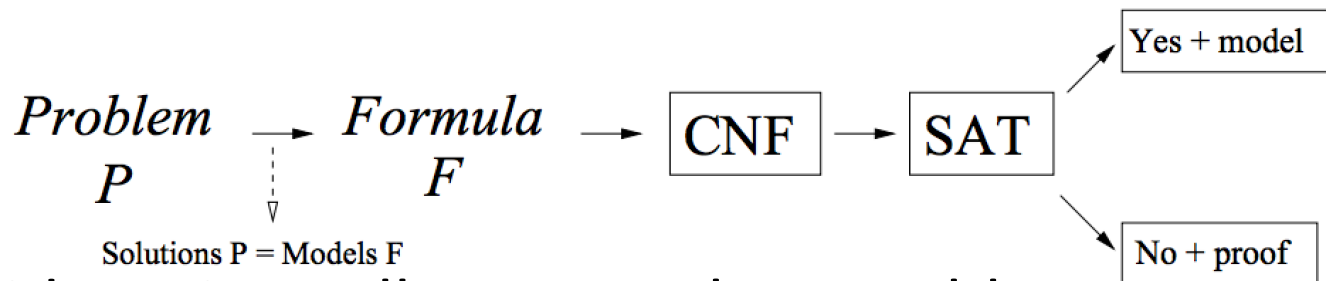


How to automate analysis of your feature models?

Let us try with SAT solvers

Satisfiability (SAT) solver

- A “SAT solver” is a program that automatically decides whether a propositional logic formula is satisfiable.
 - If it is satisfiable, a SAT solver will produce an example of a truth assignment that satisfies the formula.



- Basic idea: since all NP-complete problems are mutually reducible:
 - Write one really good solver for NP-complete problems (in fact, get lots of people to do it. Hold competitions.)
 - Translate your NP-complete problems to that problem.

SAT solver and CNF

- All current fast SAT solvers work on CNF
- Terminology:
 - A literal is a propositional variable or its negation (e.g., p or $\neg q$).
 - A clause is a disjunction of literals (e.g., $(p \vee \neg q \vee r)$). Since \vee is associative, we can represent clauses as lists of literals.
- A formula is in conjunctive normal form (CNF) if it is a conjunction of clauses
 - e.g., $(p \vee q \vee \neg r) \wedge (\neg p \vee s \vee t \vee \neg u)$

SAT solver and Unit Propagation

- Whenever all the literals in a clause are false except one, the remaining literal must be true in any satisfying assignment (such a clause is called a **unit clause**).
 - Therefore, the algorithm can assign it to true immediately. After choosing a variable there are often many unit clauses.
 - Setting a literal in a unit clause often creates other unit clauses, leading to a cascade.

$$\{\neg p \vee q, \neg p \vee \neg q \vee r, p, \neg r\}.$$

$\neg p \vee q$		q
$\neg p \vee \neg q \vee r$		$\neg q \vee r$
p		
$\neg r$		
		$\neg r$

- A good SAT solver often spends 80-90% of its time in unit propagation.

$$\begin{aligned} \mathcal{F}_{\text{unit}} := & (\neg x_1 \vee \neg x_3 \vee x_4) \wedge (\neg x_1 \vee \neg x_2 \vee x_3) \\ & (\neg x_1 \vee x_2) \wedge (x_1 \vee x_3 \vee x_6) \wedge (\neg x_1 \vee x_4 \vee \neg x_5) \\ & (x_1 \vee \neg x_6) \wedge (x_4 \vee x_5 \vee x_6) \wedge (x_5 \vee \neg x_6) \end{aligned}$$

$$\begin{aligned}\mathcal{F}_{\text{unit}} := & (\neg \textcolor{red}{x}_1 \vee \neg x_3 \vee x_4) \wedge (\neg \textcolor{red}{x}_1 \vee \neg x_2 \vee x_3) \\ & (\neg \textcolor{red}{x}_1 \vee x_2) \wedge (\textcolor{green}{x}_1 \vee x_3 \vee x_6) \wedge (\neg \textcolor{red}{x}_1 \vee x_4 \vee \neg x_5) \\ & (\textcolor{green}{x}_1 \vee \neg x_6) \wedge (x_4 \vee x_5 \vee x_6) \wedge (x_5 \vee \neg x_6)\end{aligned}$$

$$\varphi = \{x_1=1\}$$

$$\begin{aligned}\mathcal{F}_{\text{unit}} := & (\neg x_1 \vee \neg x_3 \vee x_4) \wedge (\neg x_1 \vee \neg x_2 \vee x_3) \\ & (\neg x_1 \vee x_2) \wedge (x_1 \vee x_3 \vee x_6) \wedge (\neg x_1 \vee x_4 \vee \neg x_5) \\ & (x_1 \vee \neg x_6) \wedge (x_4 \vee x_5 \vee x_6) \wedge (x_5 \vee \neg x_6)\end{aligned}$$

$$\varphi = \{x_1=1, x_2=1\}$$

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$$\varphi = \{x_1=1, x_2=1, x_3=1\}$$

$$\begin{aligned}\mathcal{F}_{\text{unit}} := & (\neg x_1 \vee \neg x_3 \vee x_4) \wedge (\neg x_1 \vee \neg x_2 \vee x_3) \\ & (\neg x_1 \vee x_2) \wedge (x_1 \vee x_3 \vee x_6) \wedge (\neg x_1 \vee x_4 \vee \neg x_5) \\ & (x_1 \vee \neg x_6) \wedge (x_4 \vee x_5 \vee x_6) \wedge (x_5 \vee \neg x_6)\end{aligned}$$

$$\varphi = \{x_1=1, x_2=1, x_3=1, x_4=1\}$$

SAT solver and Unit Propagation

BCP():

Repeatedly search for unit clauses, and
set unassigned literal to required value.

If a literal is assigned conflicting values, return F
else return T;

satisfy(ϕ) {

if every clause of ϕ has a true literal, return T;

if BCP() == F, return F;

assign appropriate values to all pure literals;

choose an $x \in V$ that is unassigned in A ,

and choose $v \in \{T, F\}$.

$A(x) = v$;

if satisfy(ϕ) return T;

$A(x) = \neg v$;

if satisfy(ϕ) return T;

unassign $A(x)$; // undo assignment for backtracking.

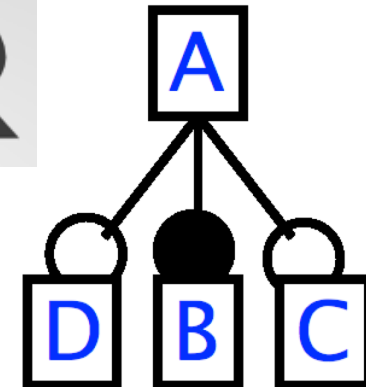
return F; }

How to automate analysis of your feature models?

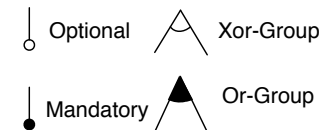
Let us use BDDs and SAT solvers

$A \wedge$
 $A \Leftrightarrow B \wedge$
 $C \Rightarrow A \wedge$
 $D \Rightarrow A$

FAMiliAR



FM



Φ

```

fm1bis = FM ("foo3.dimacs")
fm1bisbis = FM ("foo3.constraints")

```

```

fm1> fm1 = FM ("output/fm1.tvl")
root A {
  group [ 3..3 ] {
    opt D {
    },
    B {
    },
    opt C {
    }
  }
}
fm1: (FEATURE_MODEL) A: [D] B [C] ;

```

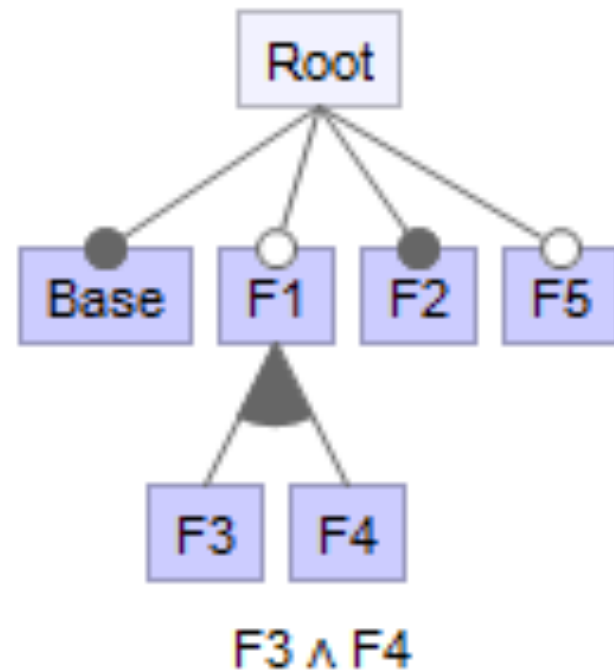
```

fm1> c1 = cores fm1
fm1> s1 c1: (SET) {B;A}
s1: (SET) {B;A}
fm1> c1bis = cores fm1bis
c1bis: (SET) {B;A}
fm1> compare fm1 fm1bis
res7: (STRING) REFACTORING {A;B;D}}
fm1> compare fm1bis fm1bisbis
res8: (STRING) REFACTORING {A};{B;A}}
fm1> s1 res3: (BOOLEAN) true
fm1> s1 res6: (BOOLEAN) true
res4: (BOOLEAN) true

```

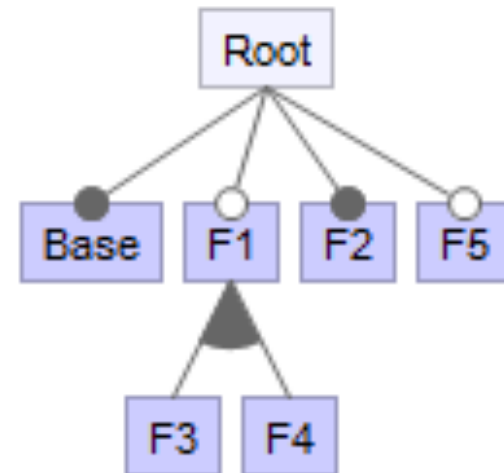
Consistency

- SAT-Solver
 - SAT(FM)



Core and dead features

- Dead : $\text{SAT}(\text{FM} \wedge F)$
- Core: $\text{SAT}(\text{FM} \wedge \text{not}(F))$



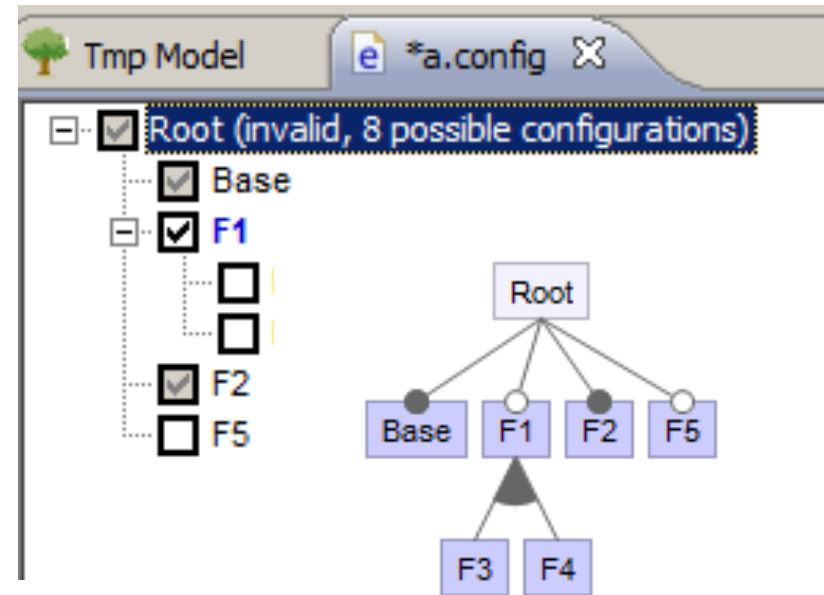
$F5 \Rightarrow F4 \vee \text{Base}$

$F3 \Rightarrow F2 \wedge F5$

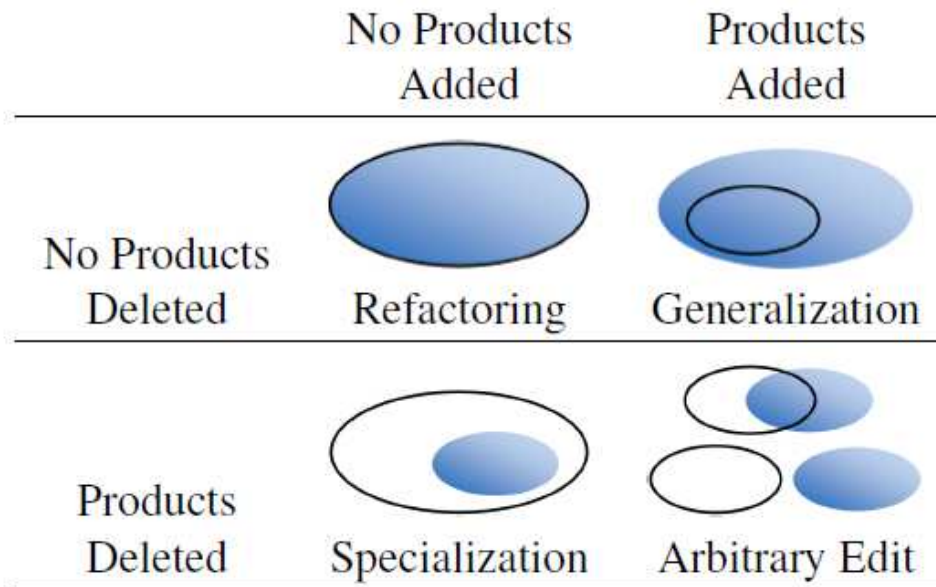
$\neg(F4 \wedge F2)$

Partial configuration

- $\text{SAT}(\text{FM} \wedge \text{PK} \wedge \text{F})$
- $\text{SAT}(\text{FM} \wedge \text{PK} \wedge \text{not}(\text{F}))$



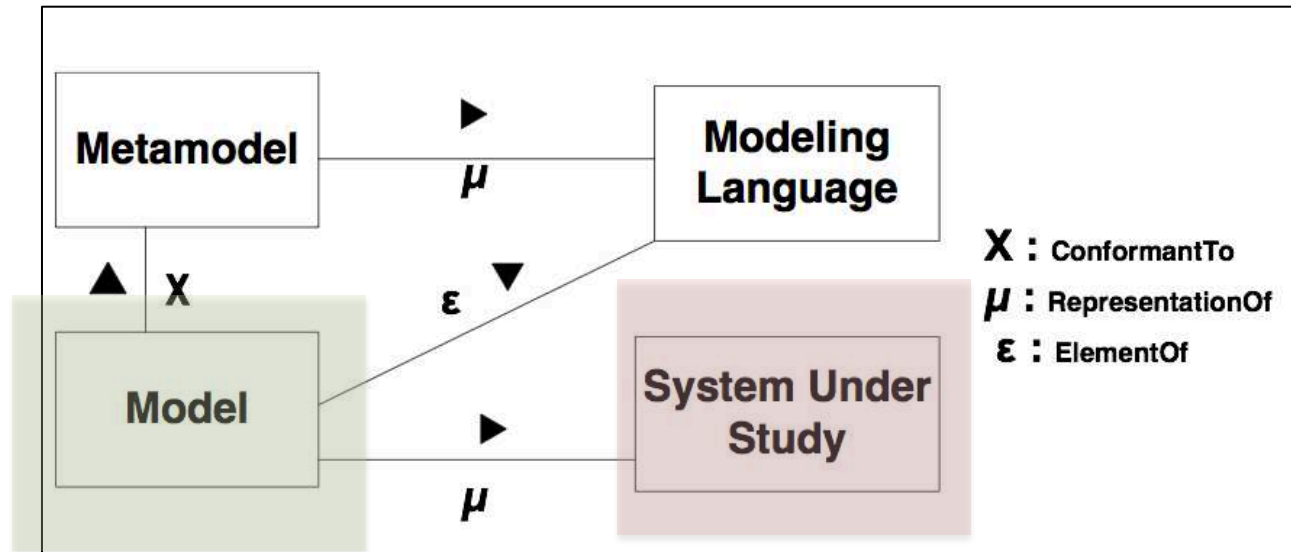
Relationship between feature models



- Refactoring
 - Tautology: $(FM1 \Leftrightarrow FM2)$
= not SAT(not $(FM1 \Leftrightarrow FM2)$)

Recap

Feature Models



▼ CarEquipment

- ▼ ● Healing
 - ▼ A
 - AirConditioningFrontAndRear
 - AirConditioning
- ▼ ● Comfort
 - AutomaticHeadLights
- ▼ ● DrivingAndSafety
 - FrontFogLights

▼ Constraints

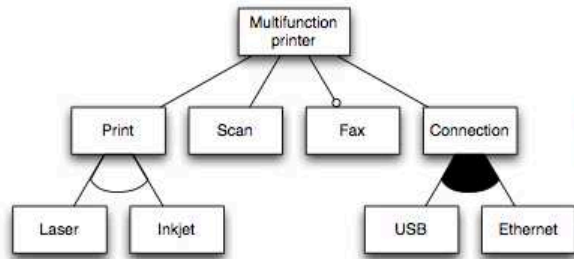
AutomaticHeadLights \Rightarrow FrontFogLights

The screenshot shows the Audi R8 Spyder configuration interface. It includes images of the car from different angles and a detailed list of optional equipment with their respective prices.

Option	Price (EUR)
Régulateur de vitesse	320,65
Système d'aide au stationnement APS avant / arrière	931,70
Système d'aide au stationnement APS avant / arrière avec affichage dans l'écran MMI	1.373,35
Système d'aide au stationnement Advanced : APS avant et arrière et caméra arrière	1.790,80

Other visible options include: Châssis, Freins, Système d'assistance, Aides, Sécurité & technique, Intégration, Pack d'équipements, Extérieur, Jantes & pneumatiques, Intérieur, Volants, Sièges, and Intégration.

Typical implementations



result



logics



solvers

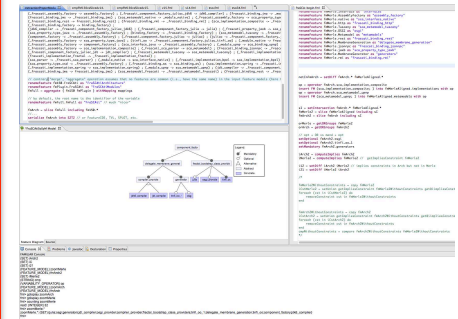
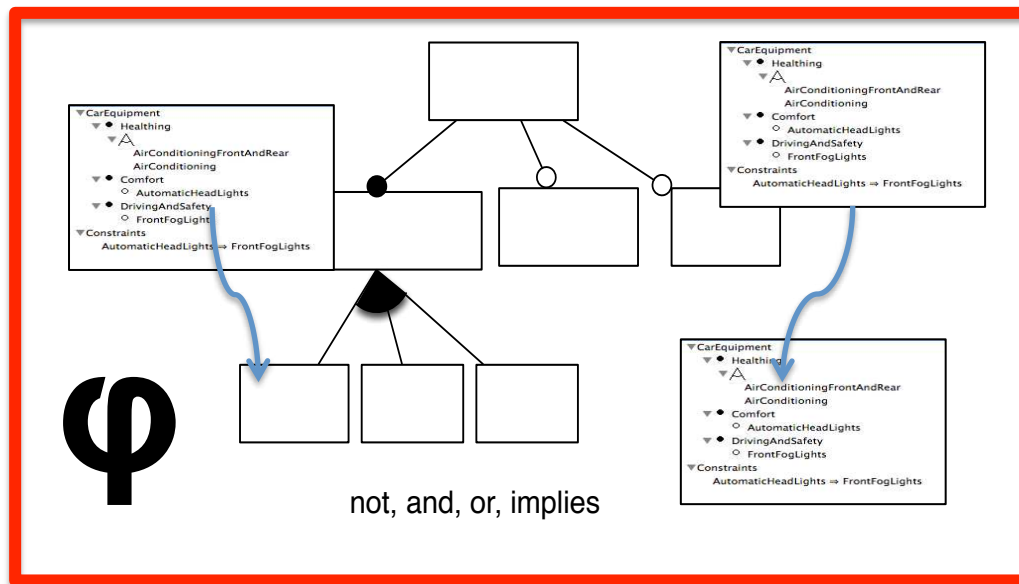


Z3

FAMiliAR

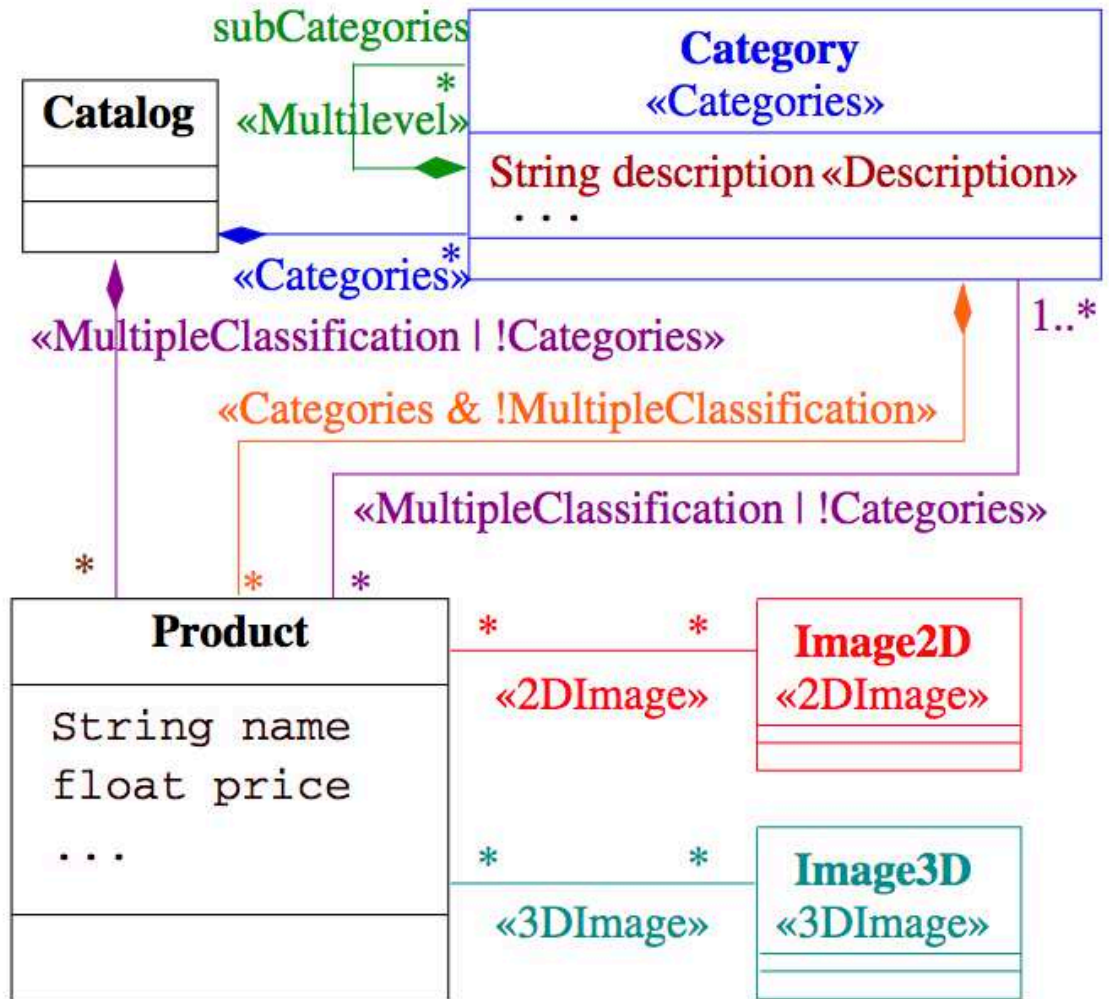
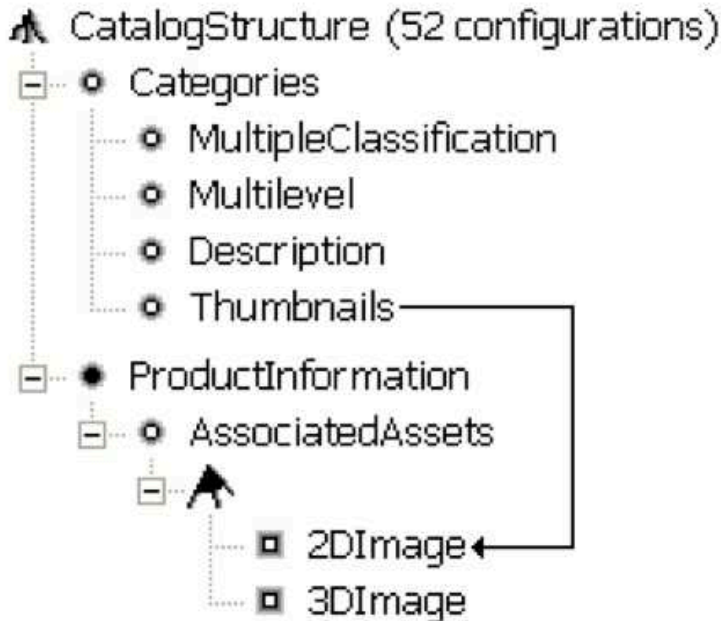
(FeAture Model script Language for manipulation and Automatic Reasoning)

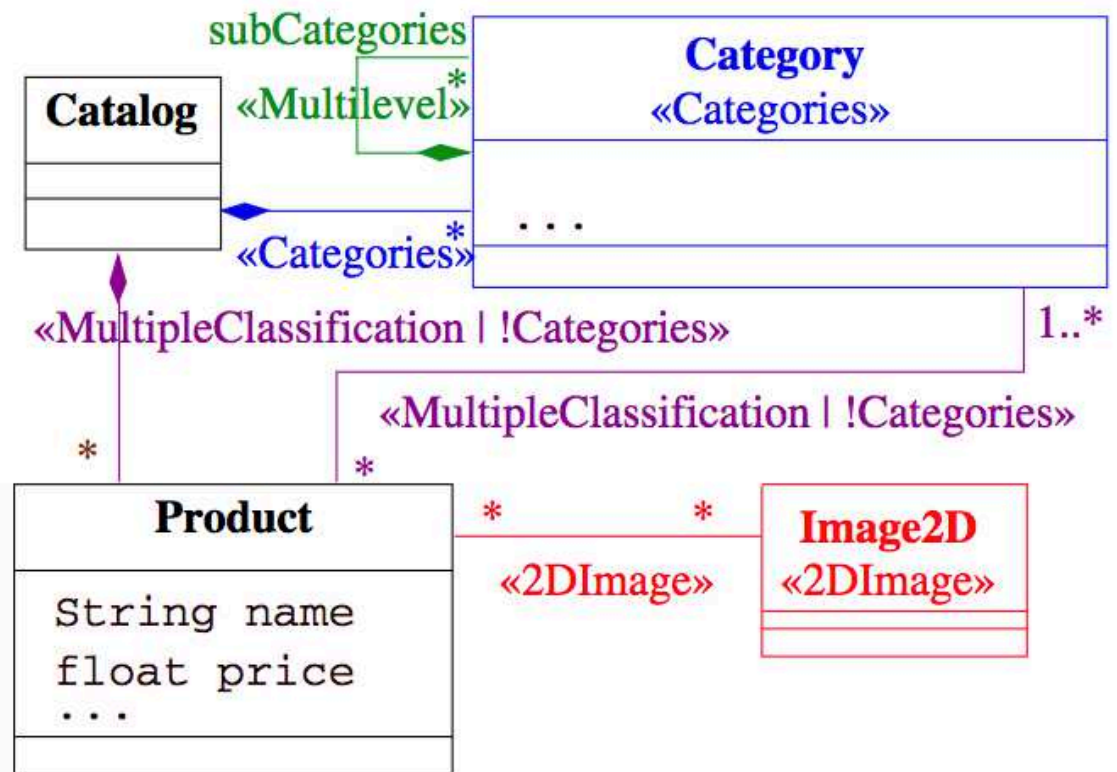
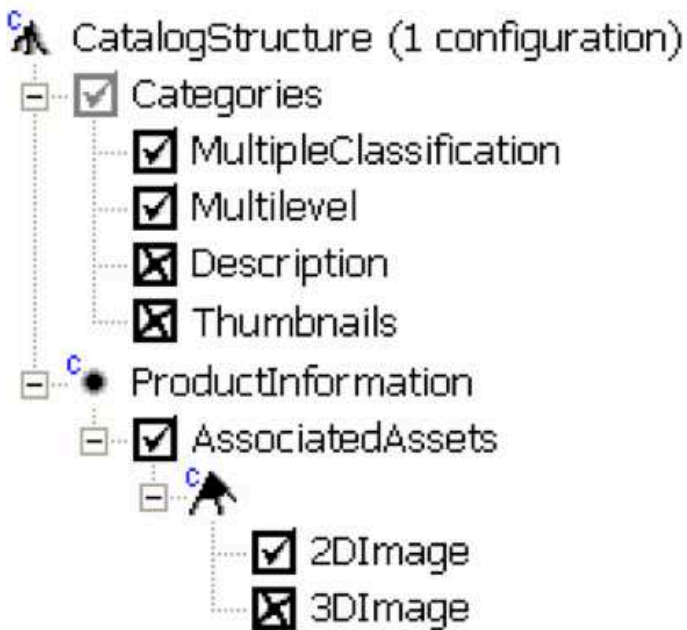
<http://familiar-project.github.com/>



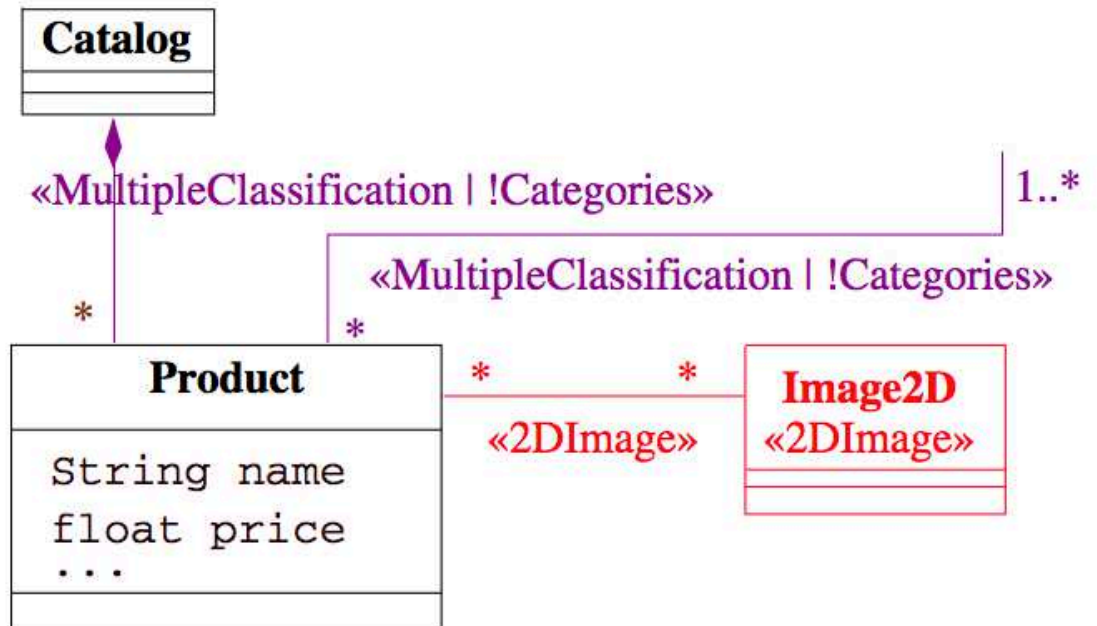
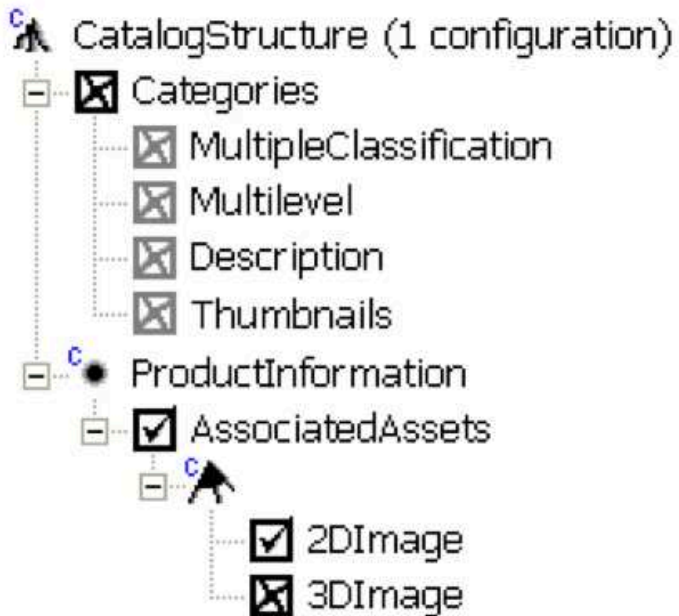
importing, exporting, composing, decomposing, editing, configuring, reverse engineering, computing "difs", refactoring, testing, and reasoning about (multiple) variability models

Mathieu Acher, Philippe Collet, Philippe Lahire, Robert B. France « A Domain-Specific Language for Large-Scale Management of Feature Models » Science of Computer Programming (SCP), 2013

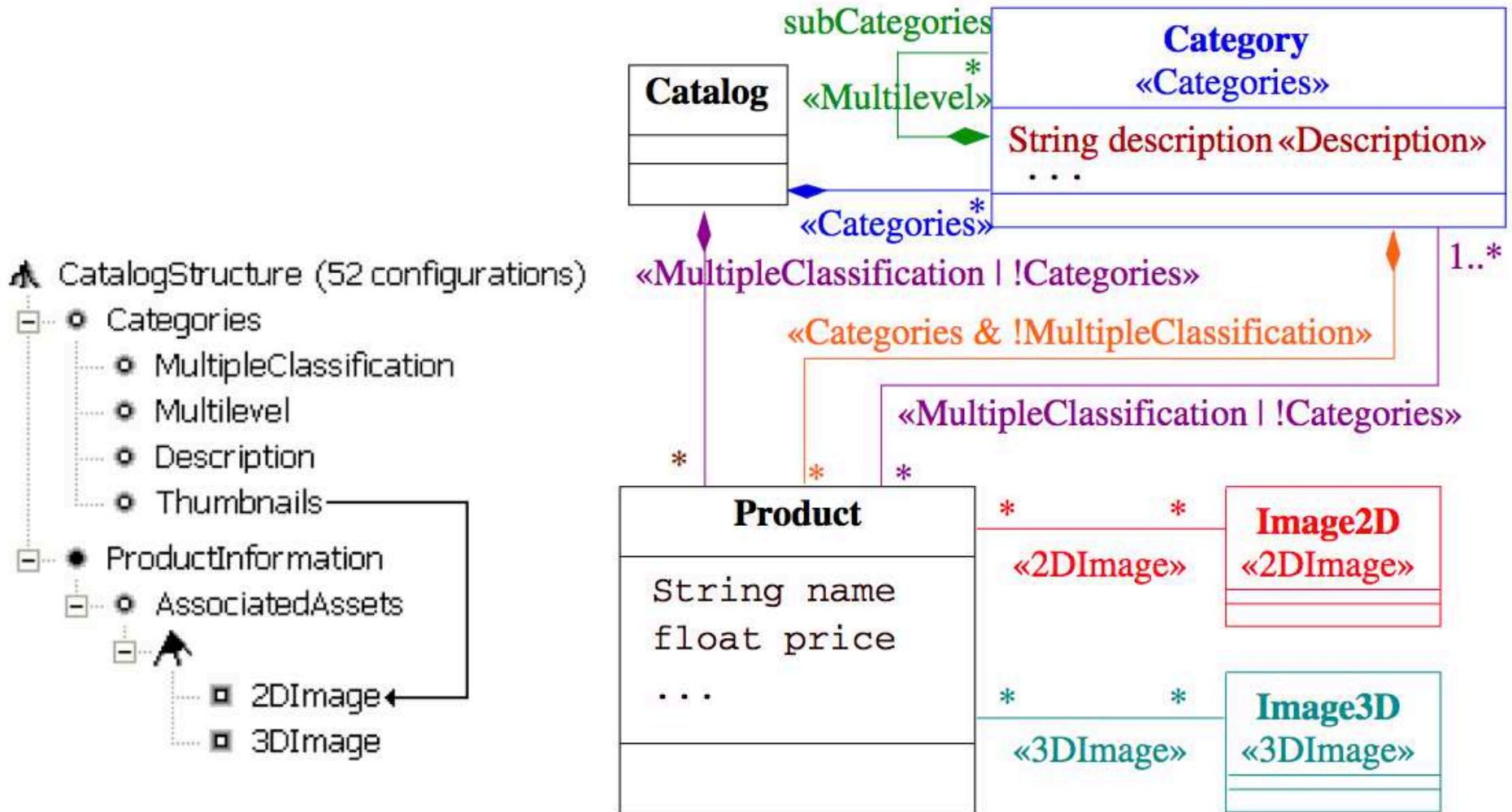




Ooops



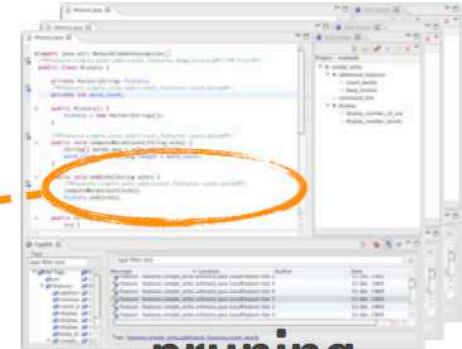
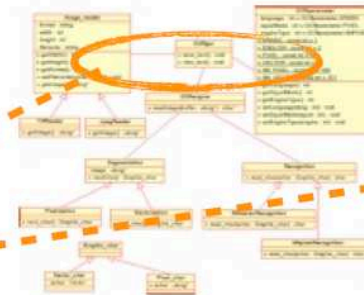
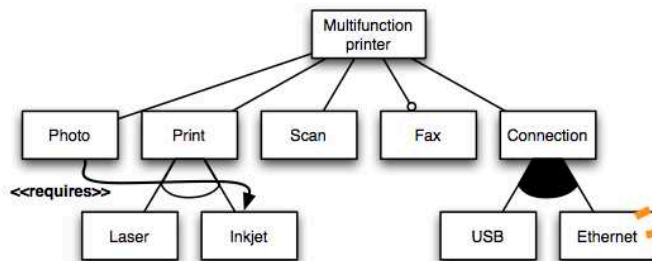
Safe composition? No!



Product Derivation

feature model

variable model and
code assets



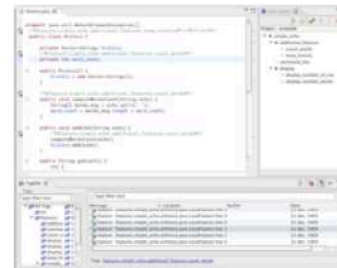
configuration

pruning,
composition,
weaving,
transformation
...

{ MP, Photo, Print, Inkjet, Scan,
Fax, Connection, USB, Ethernet }

product spec

product



Safe composition: how does it work?

