# Logical Engineering with Instance Based Methods 

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## An early IM - The DPLL Procedure

Preprocessing

Outer loop: grounding

Inner loop: propositional DPLL


Obvious problem: how to control the grounding?
Modern IMs address this (and other weaknesses)

## Why Instance Based Methods?

## IMs are different to Resolution, Tableaux, Connection Methods ...

- Conceptually
- Search space
- Decidable classes

IMs capitalize on advances in SAT solving

## Part I

- Some IMs include "the best" SAT solvers as subroutines
- Some IMs lift successful SAT techniques to the first-order level
- All IMs apply successful first-order theorem proving techniques


## Logical Engineering

## Part II

- Exploit strengths of IMs by suitable mapping of application problems
- In particular for SW verification


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## Two-level IMs <br> One-level IMs

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## Two-Level vs One-Level IMs

## Two-Level IMs

- Strict separation between instance generation and SAT solving phase
- Uses (arbitrary) propositional SAT solver as a subroutine
- DPLL, HL, SHL, OSHL [Plaisted et al], PPI [Hooker], InstGen[Ganzinger\& Korovin], Equinox [Claessen] comparison paper [Jacobs\&Waldmann]


InstGen: guide adding instances by model of \$-clause set and unification

## Inst-Gen [Ganzinger\&Korovin]

## Current clauses

$$
\begin{aligned}
& \mathrm{P}(\mathrm{f}(x), x) \vee \mathrm{Q}(x) \\
& \neg \mathrm{P}(z, \mathrm{a}) \vee \neg \mathrm{Q}(z) \\
& \underline{P(f(\$), \$)} \vee Q(\$) \\
& \neg \mathrm{P}(\$, \mathrm{a}) \vee \neg \mathrm{Q}(\$)
\end{aligned}
$$

Model: $\{\mathrm{P}(\mathrm{f}(\$), \$), \neg \mathrm{P}(\$, \mathrm{a})\}$
Model determines literals selection in current clauses for InstGen inference:

$$
\text { InstGen } \frac{\mathrm{P}(\mathrm{f}(x), x) \vee \mathrm{Q}(x) \quad}{\mathrm{P}(\mathrm{f}(\mathrm{a}), \mathrm{a}) \vee \mathrm{Q}(\mathrm{a})} \quad \neg \mathrm{P}(\mathrm{f}(\mathrm{a}), \mathrm{a}) \vee \neg \mathrm{Q}(z) \vee \mathrm{Q}(\mathrm{f}(\mathrm{a}))
$$

Conclusions are obtained by unifying selected literals Add conclusions to "current clauses" and start over

This is just the very basic calculus

## Two-Level vs One-Level IMs

## One-Level IMs

- Monolithic: one single base calculus, two modes of operation
- First-order mode: first-order calculus
- Propositional mode: temporarily replace all variables by \$
- HyperTableauxNG [B], DCTP[Letz\&Stenz], OSHT [Plaisted\&Yahya], FDPLL [B], ME [B\&Tinelli]


Branch unsatisfiable?
Next: One-level IM FDPLL / Model Evolution

## Model Evolution - Motivation

- The best modern SAT solvers (satz, MiniSat, zChaff) are based on the Davis-Putnam-Logemann-Loveland procedure [DPLL 1960-1963]
- Can DPLL be lifted to the first-order level?

How to combine

- DPLL techniques
(unit propagation, backjumping, lemma learning,...)
- first-order techniques?
(unification, subsumption, superposition rule,...)?
- Our approach: Model Evolution
- Directly lifts DPLL. Not: DPLL as a subroutine, i.e. one-level method
- Satisfies additional desirable properties (proof confluence, model computation, ...)


## DPLL procedure

Input: Propositional clause set Output: Model or „unsatisfiable"

## Algorithm components:

- Propositional semantic tree enumerates interpretations
- Propagation
- Split
- Backjumping

$$
\begin{array}{r}
\{A, B\} \stackrel{?}{\models} \not A \vee \mathcal{A} \vee C \vee D \\
\{A, B, C\} \stackrel{?}{\models} \not A \vee \neg B \vee C \vee D
\end{array}
$$

## ME - lifting this idea to first-order level

## ME as First-Order DPLL

Input: First-order clause set Output: Model or „unsatisfiable" if termination

## Algorithm components:

- First-order semantic tree enumerates interpretations
- Propagation

> v is a "parameter" not quite a variable

Interpretation induced by a branch?

## Interpretation Induced by a Branch



- A branch literal specifies a truth value for all its ground instances, unless there is a more specific literal specifying the opposite truth value


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## Interpretation Induced by a Branch

$$
\begin{aligned}
& \text { Branch } B \\
& \left\{\begin{array}{l}
\mathrm{P}(x, y), \\
\neg \mathrm{P}(\mathrm{a}, y), \\
\neg \mathrm{P}(\mathrm{~b}, \mathrm{~b}), \\
\mathrm{P}(\mathrm{a}, \mathrm{~b})
\end{array}\right.
\end{aligned}
$$

Interpretation $I_{B}$

$$
P(b, a)
$$

$$
\neg P(b, b)
$$

- A branch literal specifies a truth value for all its ground instances, unless there is a more specific literal specifying the opposite truth value
- The order of the literals on the branch is irrelevant


## Inference Rule: Split



Branch: $\quad\{\neg v, \mathrm{P}(v), \neg \mathrm{P}(\mathrm{a})\}$

| True: | $\mathrm{P}(\mathrm{b})$ |
| ---: | :--- |
| False: | $\neg \mathrm{P}(\mathrm{a}), \neg \mathrm{Q}(\mathrm{a}), \neg \mathrm{Q}(\mathrm{b})$ |

Branch: $\quad\{\neg v, \mathrm{P}(v), \neg \mathrm{P}(\mathrm{a}), \mathrm{Q}(\mathrm{a})\}$

| True: | $\mathrm{P}(\mathrm{b}), \mathrm{Q}(\mathrm{a})$ |
| ---: | :--- |
| False: | $(\mathrm{a}), \neg \mathrm{Q}(\mathrm{b})$ |

$$
\begin{aligned}
&\{\neg v, \mathrm{P}(v), \neg \mathrm{P}(\mathrm{a})\} \stackrel{?}{\models} \mathrm{P}(x) \vee \mathrm{Q}(x) \\
&\{\neg v, \mathrm{P}(v), \neg \mathrm{P}(\mathrm{a}), \mathrm{Q}(\mathrm{a})\} \stackrel{?}{\models} \underline{\underline{\mathrm{P}(x)} \vee \mathrm{Q}(x)}
\end{aligned}
$$

Split - detect falsified instances and repair interpretation Additional rules: Close, Assert, Compact, Resolve, Subsume

## Example - Detecting Functional Dependencies

Graph 3-colorability

$$
\begin{aligned}
& \forall n \mathrm{R}(n) \vee \mathrm{G}(n) \vee \mathrm{B}(n) \\
& \forall n(\mathrm{R}(n) \rightarrow \neg \mathrm{G}(n)) \wedge(\mathrm{R}(n) \rightarrow \neg \mathrm{B}(n)) \wedge(\mathrm{B}(n) \rightarrow \neg \mathrm{G}(n)) \\
& \forall m, n(\mathrm{R}(m) \wedge \mathrm{R}(n) \rightarrow \neg \operatorname{edge}(m, n)) \wedge \\
& \quad(\mathrm{G}(m) \wedge \mathrm{G}(n) \rightarrow \neg \operatorname{edge}(m, n)) \wedge(\mathrm{B}(m) \wedge \mathrm{B}(n) \rightarrow \neg \operatorname{edge}(m, n))
\end{aligned}
$$


$B$ depends on $R$ and $G$
(Dis-)prove functional (non-)dependance
Demo: Darwin theorem prover

## ME - Achievements so far

- FDPLL [CADE-17]
- Basic ideas, predecessor of ME
- ME Calculus [CADE-19, AI Journal]
- Proper treatment of universal variables and unit propagation
- Semantically justified redundancy criteria
- ME+Equality [CADE-20]
- Superposition inference rules, currently being implemented
- ME+Lemmas [LPAR 2006]
- Darwin prover [JAIT 2006]
http://combination.cs.uiowa.edu/Darwin/
- Won CASC-J3 and CASC-21 EPR division
- FM-Darwin: finite model computation [JAL 2007]


## Resolution vs IMs

## Resolution

$$
\text { Res } \frac{C \vee L \quad \overline{L^{\prime}} \vee D}{(C \vee D) \sigma}
$$

- Inefficient in propositional case
- Clauses can grow in length
- Recombination of clauses
- Subsumption deletion
- Selection by A-ordering
- Difficult to extract model
- Decides many classes
- Wins CASC FOF


## Instance Based Methods

$$
\text { InstGen } \frac{C \vee L}{} \frac{\overline{L^{\prime}} \vee D}{(C \vee L) \sigma} \quad\left(\overline{L^{\prime}} \vee D\right) \sigma \quad \curvearrowright L
$$

- Efficient in propositional case
- Clauses do not grow in length
- No recombination of clauses
- Limited subsumption deletion
- Selection by interpretation
- Easy to extract model
- Decides Bernays-Schönfinkel Class
- Does not win CASC FOF

Complementary methods

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## Exploiting Strengths of IMs

... in particular as decision procedures for the Bernays-Schönfinkel class:

- CASC-competition: EPR category
- Optimized functional translation of modal logics [Ohlbach\&Schmidt]
- DQBF satisfiability $\forall P_{1} \exists Q_{1}\left(P_{1}\right) \forall P_{2} \exists Q_{2}\left(P_{2}\right) \cdots$
- LTL model checking [Navarro-Pérez\&Voronkov CADE-21]
- Planning [Voronkov et al CP 2007]
- CEGAR [Klaessen]
- Back-end for DL reasoning (SHOIQ), cf [Motik et al])
- Strong equivalence (under answer sets semantics) of logic programs
- Finite model computation (FM-Darwin)
- Within constraint modelling
- Analysis of constraint models (functional dependencies ...)
- Model expansion [Ternovska\&Mitchell]


## Application for SW Verification

Applications of formal methods often rely on proving or disproving firstorder logic formulas over a fixed (background) theory $\mathcal{T}$

- E.g. proving properties of programs involving arrays and integers Core Problem: SMT - Satisfiability Modulo Theories
- Is a given formula satisfiable modulo a given theory $\mathcal{T}$ ?


## One Main Approach: DPLL(T)

- Prop. DPLL + solver for conjunctions of ground $\mathcal{T}$-literals ( $\mathcal{T}$-solver)
- Issue: works inherently with propositional abstractions
- DPLL cannot analyze term structure
- Non-ground formulas grounded by "external" heuristic
- Still a hot topic (cf. SMT session, R. Leino talk @ CADE-21)
- Here: contribution from the viewpoint of First-Order ATP

Plan: address issues by using "ME(T)" instead of DPLL(T)

## DPLL(T) Approach to SMT

- DPLL computes candidate model of propositional abstraction
- Check candidate model with $\mathcal{T}$-solver

- $\mathcal{T}$-solver reports relevant literals
- Theory propagation ( $\mathcal{T}$-solver computes unit consequences)

Lifting $\operatorname{DPLL}(\mathcal{T})$ to $\operatorname{ME}(\mathcal{T})$ ?

## ME(T) - Basic Approach

- Replace DPLL by ME
- Rename all theory literals as positive literals
- $\neg(5>3)$ becomes $5 \ngtr 3$
- Turn args of negative non-theory literals into vars

$c>5 \quad \neg(c>5)$
- $\neg P(5)$ becomes $x \neq 5 \vee \neg P(x)$


ME(T) proper generalization of $\operatorname{DPLL}(\mathcal{T})$

## Theory Lemmas Application I: Theory Propagation

- Theory propagation - important efficiency improvement for $\operatorname{DPLL}(\mathcal{T})$
- $\mathcal{T}$-solver computes $\mathcal{T}$-implied literals which avoids branching
- Approximated in $\operatorname{ME}(\mathcal{T})$ by theory lemmas
- Doesn't rely on $\mathcal{T}$-solver in any way



## Theory Lemmas Application II: Problem Reduction

To prove: $(x+y)^{2}=x^{2}+2 x y+y^{2}$
Sufficient set of axioms:

$$
\begin{aligned}
x y & =y x \\
x(y z) & =(x y) z \\
1 x & =x \\
x(y+z) & =x y+x z
\end{aligned}
$$

$$
\begin{align*}
x+y & =y+x  \tag{Comm}\\
x+(y+z) & =(x+y)+z \\
0+x & =x \\
2 x & =x+x
\end{align*}
$$

FO theorem proving, axioms above: very easy e.g. for SPASS, KeY
DPLL(T), T=UFLIA, left column axioms+(2): CVC3 fails
ME(T), T=UFLIA, left column axioms+(2) as theory lemmas:
reduce (Binom) to $(x x+x y)+(x y+y y)=x x+((x y+x y)+y y)$, then complete proof with call to UFLIA-solver

Can (E.g.) KeY taclets modeled as clauses, for contextual rewriting? Related to [Bonacina\&Echenim] this CADE

## Theory Lemmas Application III: Non-ground Input

## Typical scenario

- $\mathcal{T}=$ Linear arithmetic + Arrays $+\ldots$
- Uninterpreted function and/or predicate symbols

The theory of arrays

$$
\begin{align*}
\operatorname{select}(\operatorname{store}(a, i, j, e), i, j) & =e  \tag{A1}\\
\operatorname{select}\left(\operatorname{store}(a, i, j, e), i^{\prime}, j^{\prime}\right) & =\operatorname{select}\left(a, i^{\prime}, j^{\prime}\right) \leftarrow \neg\left(i=i^{\prime}\right)  \tag{A2}\\
\operatorname{select}\left(\operatorname{store}(a, i, j, e), i^{\prime}, j^{\prime}\right) & =\operatorname{select}\left(a, i^{\prime}, j^{\prime}\right) \leftarrow \neg\left(j=j^{\prime}\right) \tag{A3}
\end{align*}
$$

Challenging example problem [Ranise]
Define
$\forall a, n \operatorname{symmetric}(a, n) \leftrightarrow(\forall i, j 1 \leq i, j \leq n \rightarrow \operatorname{select}(a, i, j)=\operatorname{select}(a, j, i))$
Prove $\{\operatorname{symmetric}(\mathrm{a}, \mathrm{n})\} \quad \mathrm{a}[0,0]:=\mathrm{e}_{0} ; \ldots ; \mathrm{a}[\mathrm{k}, \mathrm{k}]:=\mathrm{e}_{\mathrm{k}} \quad\{\operatorname{symmetric}(\mathrm{a}, \mathrm{n})\}$

## Results in non-ground clause set Required instances are not obvious

## Theory Lemmas = Array Axioms Relational Translation

Array axioms (1-dimensional, for simplicity)

$$
\begin{align*}
& \operatorname{select}(\operatorname{store}(a, i, e), i)=e  \tag{A1}\\
& \operatorname{select}(\operatorname{store}(a, i, e), j)=\operatorname{select}(a, j) \leftarrow \neg(i=j) \tag{A2}
\end{align*}
$$

$$
\begin{align*}
& r 1=r 2 \leftarrow \operatorname{select}(a, i, r 1) \wedge \operatorname{select}(a, i, r 2)  \tag{Func-1}\\
& r 1=r 2 \leftarrow \operatorname{store}(a, i, e, r 1) \wedge \operatorname{store}(a, i, e, r 2)
\end{align*}
$$

$\operatorname{select}(a, i, \operatorname{skf}(a, i)) \leftarrow$
(Totality) is problematic

- Generates a huge search space
- Without it all function symbols have gone (good for ME)
- Approximate (Totality) by $\operatorname{select}(a, i, \operatorname{skf}(a, i)) \leftarrow \operatorname{index}(i)$ index?
(Definedness)


## Controlling the Search Space with the index Predicate

Relational translation of array axioms

$$
\begin{align*}
\operatorname{select}(h, i, e) & \leftarrow \operatorname{store}(a, i, e, h)  \tag{A1}\\
\operatorname{select}(h, j, r) & \leftarrow \operatorname{store}(a, i, e, h) \wedge \operatorname{select}(a, j, r) \wedge \neg(i=j)  \tag{A2}\\
r 1=r 2 & \leftarrow \operatorname{select}(a, i, r 1) \wedge \operatorname{select}(a, i, r 2) \\
r 1=r 2 & \leftarrow \operatorname{store}(a, i, e, r 1) \wedge \operatorname{store}(a, i, e, r 2)
\end{align*}
$$

$\operatorname{select}(a, i, \operatorname{skf}(a, i)) \leftarrow \operatorname{index}(i)$
(Definedness)
Options for defining the index predicate
(1) add a clause "index $(i)$ " - select is total
(2) add a clause " $\neg$ index $(i)$ " - select is partial
(3) add clauses "index(t)" for all input ground terms $t$
(4) add clauses "index $(i) \leftarrow P(\ldots, i, \ldots)$ " for all/some predicate symbols $P$

## Options (2) - (4) are incomplete

## But target logic LIA + free predicate symbols is incomplete anyways

## Experiments with Symmetric Array Problem

Definition of "symmetric array":
$\forall a, n \operatorname{symmetric}(a, n) \leftrightarrow(\forall i, j 1 \leq i, j \leq n \rightarrow \operatorname{select}(a, i, j)=\operatorname{select}(a, j, i))$
Prove $\{\operatorname{symmetric}(a, n)\} \quad a[0,0]:=\mathrm{e}_{0} ; \ldots ; \mathrm{a}[\mathrm{k}, \mathrm{k}]:=\mathrm{e}_{\mathrm{k}} \quad\{\operatorname{symmetric}(\mathrm{a}, \mathrm{n})\}$

## Systems tried

CVC3: $\operatorname{DPLL}(\mathcal{T})$ prover (with instantiation heuristics) - cannot solve KeY: Interactive verification system, "taclets" - cannot solve SPASS: Hyper-resolution setting, equality array axioms (performed best) Darwin: Relational array axioms, heuristics (4)

| k | SPASS | Darwin |
| ---: | ---: | ---: |
| 2 | $<1$ | $<1$ |
| 3 | 142 | 3 |
| 4 | $>5 h$ | 7 |
| 5 | $>5 \mathrm{~h}$ | 20 |
| 6 | $>5 \mathrm{~h}$ | 63 |

[^0]
## ME(T)- Conclusion (1)

- View from DPLL(T)
- Proper extension of DPLL( $\mathcal{T})$ by integrating FO reasoning
- Advantages derive from being able to analyze term structure
- New way to handle non-ground formulas
- Implemented by theory lemmas instead of meta-logical: "Points of definedness" (cf. "select" above) computed by calculus itself, by first-order reasoning, in a by need fashion
- View from First-Order Theorem Proving
- This is "total theory reasoning" + "partial theory reasoning" ( $\mathcal{T}$-propagation by theory lemmas)
- Goal: better functionality of ATP systems
- Useful explanation for failure, e.g. a model
- Reasoning with integers

> Message of the day

## Conclusion (2)

- Related Work
- Big engines approach [Armando\&Bonacina\&Ranise\&Schulz]:
E.g. $\operatorname{DPLL}(\mathcal{T})$ where $\mathcal{T}$ is implemented by a first-order theorem prover
- SPASS+ $\mathcal{T}$ [Prevosto\&Waldmann]: two-level architecture with SMT-solver as black box
- Future
- Implement the coupling ME + CVC3
- Experiments
- In particular proof obligations from KeY
- $\mathrm{ME}_{\mathcal{T}}$ - non-ground $\mathcal{T}$-interpretations

$$
P(v)|v<5-\neg P(v)| v<5
$$


[^0]:    To be fair:
    no arithmetic in this example: SPASS is a complete prover, whereas

    Darwin setup is incomplete
    but allows good control of search space

