# **Automated Reasoning**

Peter Baumgartner
NICTA, Canberra
and
RSISE, ANU

#### **Contact**

Office: NICTA Bldg, Tower A, 7 London Circuit

Email: <a href="mailto:Peter.Baumgartner@nicta.com.au">Peter.Baumgartner@nicta.com.au</a>

Web: http://users.rsise.anu.edu.au/~baumgart/

Many slides based on material from Scott Sanner

### **Schedule**

- Introduction to Logic (John Slaney)
  - Starting week of March 3
- Automated Reasoning (Peter Baumgartner)
  - Starting week of March 17
- SAT solving (Anbulagan)
  - Starting week of March 31
- Knowledge Compilation (Jinbo Huang)
  - Starting week of April 28
- Temporal Logic (Michael Norrish)
  - Starting week of May 12
- Higher-Order Logic (Jeremy Dawson)
  - Starting week of May 26

### **Automated Reasoning**

#### ... vs. calculation:

- Problem:  $2^2 = ?$   $3^2 = ?$   $4^2 = ?$
- "Easy", often polynomial

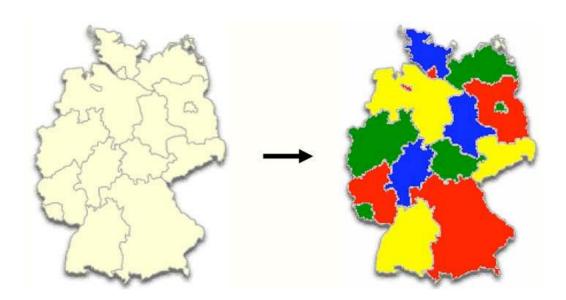
### • ... vs. constraint solving:

- Problem spec:  $x^2 = a$  where x ∈ [1 .. b]
- Problem instance: fix parameter values a and b: a = 16, b = 10
- Find satisfying values then for variable x (from finite domain)
- "Difficult", often exponential (NP-complete problems)
- ... is, among others, about (first-order logic) **theorem proving**:
  - Problem:  $\exists x (x^2 = a \land x \in [1 .. b])$
  - Is is satisfiable? valid?
  - "Very difficult" (often undecidable)

**Logical Analysis of Systems** 

Peter Baumgartner Automated Reasoning 3

# **Logical Analysis Example: Three-Coloring Problem**



**Problem**: Given a map

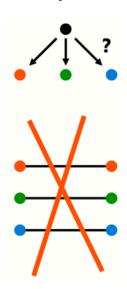
Can it be colored with only three colors?

# **Three-Coloring Problem - Graph Theory Abstraction**

#### **Problem Instance**



### **Problem Specification**



Peter Baumgartner Automated Reasoning 5

# **Three-Coloring Problem - Formalization**

Every node has at least one color

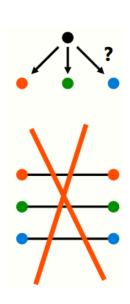
$$\forall N \; (\text{red}(N) \lor \text{green}(N) \lor \text{blue}(N))$$

Every node has at most one color

$$\forall N \ ((\operatorname{red}(N) \to \neg \operatorname{green}(N)) \land \\ (\operatorname{red}(N) \to \neg \operatorname{blue}(N)) \land \\ (\operatorname{blue}(N) \to \neg \operatorname{green}(N)))$$

Adjacent nodes have different color

$$\forall M, N \; (\mathsf{edge}(M, N) \to (\neg(\mathsf{red}(M) \land \mathsf{red}(N)) \land \\ \neg(\mathsf{green}(M) \land \mathsf{green}(N)) \land \\ \neg(\mathsf{blue}(M) \land \mathsf{blue}(N))))$$



## **Three-Coloring Problem - Solving Problem Instances ...**

- ... with a constraint solver
  - Let constraint solver find values for variables such that spec is satisfied.
    - Variables: colors of nodes in the graph
    - Values: red, green or blue
- ... with a first-order logic theorem prover
  - Let the theorm prover prove that the three-colouring formula (see previous slide) + specific graph (as a formula) is satisfiable
- To solve problem instances, a constraint solver is usually much more efficient than a first-order theorem prover (e.g. use a propositional SAT solver)
  - Theorem provers are not even guaranteed to terminate on such problems!

### What is the role of theorem proving then?

Peter Baumgartner Automated Reasoning

## Three-Coloring Problem: The Role of Theorem Proving

- Functional Dependencies
  - The blue coloring functionally depends on the red and green coloring



The blue coloring does not functionally depend on the red coloring



- Theorem proving tasks: are the following valid (expressed as formulas)?
  - The blue coloring functionally depends on the red and green coloring
  - The blue coloring functionally depends on the red coloring
- (Learning about functional dep. might be instructive for modeller and solver)
- These are "proper" theorem proving tasks: analysis wrt **all** instances
- Demo now, files can be downloaded from my web page

### **Abstracting from the Example**

#### AR systems functionality

- Input: a set of formulas in a specific logical language
- Run: analyze these formulas by logical inference for a specific task
- Output: the result of the analysis (proof, counterexample, solution...)
- Rationale deduction: the "ultimate declarative paradigm"
  - Formulas describe possible worlds
  - Draw conclusions by (sound) logical inference
  - Learn something about the "real world"

#### Logical language and semantics

- Propositional, first-order, higher-order, modal, description logic, ...
- monotonic/non-monotonic, probabilistic, ressource-bounded, ...

#### Logical Inference and task

- Calculus (Resolution, ...) -> Proof procedure -> Implementation
- Prove theorem, disprove conjecture, plausible explanation, find a model,...

Peter Baumgartner Automated Reasoning 9

## **History**

### Pre-computer era

- Early: Aristotle, Leibniz
- 19th century: Boole, DeMorgan, Peano, Cantor and others
- 20th century: Hilbert, Skolem, Herbrand, Gödel, Gentzen, Church
- Computer era (among many others)
  - 1960s Calculi
    - Davis-Putnam-Logemann-Loveland (DPLL), Resolution, Model Elimination
  - 1970s Logic programming
    - Prolog
  - 1980s Knowledge representation
    - Description Logics
  - 1990s Modern theory of resolution
  - 2000s (Serious) applications

## **Applications**

### Proofs of Mathematical Conjectures

- Graph theory: Four color theorem
- Boolean algebra: Robbins conjecture

#### Verification

- Hardware: arithmetic units correctness
- Software: functional correctness, safety properties, static checking

#### Query Answering

 Build domain-specific knowledge bases, use theorem proving to answer queries

### Key to Success

- Chose your logic and calculus carefully (e.g. avoid undecidable logic if possible)
- Need domain-specific optimizations (e.g. avoid successor-arithmetic)
- Domain-independent optimization (e.g. "subsumption", good data structures)
- Next: preview of some logics and calculi

Peter Baumgartner Automated Reasoning 11

## **Example of Propositional Logic Sequent Proof**

#### Given:

– Axioms:

None

- Conjecture:

 $A \vee \neg A$ ?

#### Inference:

GentzenSequentCalculus

• Direct Proof:	
(1)	A  - A
(¬R)	- ¬A, A
(∨R2)	- A∨¬A, A
(PR)	- A, A∨¬A
(VR1)	- A∨¬A, A∨¬A
(CR)	- A∨¬A

#### Problem:

- the Sequent Calculus is deduction-complete it can derive every tautology
- Calculi for ATP used nowadays are only refutation-complete (they can only derive a contradiction for a given theorem)

## **Example of First-order Logic Resolution Proof**

- Given:
  - Axioms:

 $\forall x \text{ Man}(x) \Rightarrow \text{Mortal}(x)$ Man(Socrates)

• **Conjecture**: ∃y Mortal(y)?

• Inference:

Resolution calculus

CNF:

 $\neg$ Man(x)  $\vee$  Mortal(x)

Man(Socrates)

¬Mortal(y) (Neg. conj.)

Proof:

1. ¬Mortal(y) (Neg. conj.)

2.  $\neg Man(x) \lor Mortal(x)$  (Given)

3. Man(Socrates) (Given)

4. Mortal(Socrates) (Res. 2,3)

5. ⊥ (*Res. 1,4*)

Contradiction ⇒ Conj. is true

Peter Baumgartner Automated Reasoning 13

# **Example of Description Logic Tableaux Proof**

- Given:
  - Axioms:

None

• Conjecture:

∃ Child.¬Male ⇒

¬∀ Child.Male?

Inference:

**Tableaux** 

Proof:

Check unsatisfiability of

∃Child.¬Male □ ∀ Child.Male

x:  $\exists$ Child. $\neg$ Male  $\sqcap \forall$  Child.Male

x:  $\forall$  Child.Male  $(\neg$ -rule)

x: ∃Child.¬Male (□-rule)

x: Child y (∃-rule)

y: ¬Male (∃-rule)

y: Male (∀-rule)

<CLASH>

Contradiction ⇒ Conj. is true

# **Calculi and Properties**

### For each calculus one has to specify:

- Syntax and semantics of its logic
- Foundational axioms (if any)
- Inference rules
- How to combine inference rules applications into derivations

#### **Derivability and Entailment**

- Let KB be the conjunction of axioms
- Let F be a formula (possibly a conjecture)
- We say  $KB \vdash F$  (read: KB derives F) if F can be derived from KB through rules of inference
- We say  $KB \models F$  (read: KB entails F, or KB models F) if (model-theoretic) semantics hold that F is true whenever KB is true

Peter Baumgartner Automated Reasoning 15

### **Model-Theoretic Semantics**

### Model-theoretic semantics for (propositional) logics

- An interpretation is a truth assignment to atomic elements of a KB:

$$I \langle C,D \rangle \in \{ \langle F,F \rangle, \langle F,T \rangle, \langle T,F \rangle, \langle T,T \rangle \}$$

A model of a formula is an interpretation where it is true:

$$I \langle C,D \rangle = \langle F,T \rangle$$
 models  $C \lor D$ ,  $C \Rightarrow D$ , but not  $C \land D$ 

- Two important properties of a formula C w.r.t. axioms of KB:
  - Entailment, written as KB ⊨ C: C is true in all models of KB
  - Consistency: C is true in ≥1 model of KB

#### Think of truth in a set-theoretic manner

Models of KB  $KB \models C$ C **KB** ⊆ Models of C

## **Calculi and Properties**

- Important properties of calculi:
  - Soundness: If KB ⊢ C then KB ⊨ C
  - Completeness: If KB ⊨ C then KB ⊢ C
  - Refutational completeness: KB ∪ {¬C} ⊢ ⊥)
  - Termination: halts on any KB and C after finite time
- These properties may be incompatible, depending on the logic
  - Decidable logics: all three
    - Example: propositional logic
  - Semi-decidable logics: can have sound and (refutationally) complete calculus
    - Thus terminates if KB ⊨ C . Example: first-order logic
  - Non-r.e. logics: can't have sound and (refutationally) complete calculus
    - Example: second-order logic

Peter Baumgartner Automated Reasoning 17

## **Propositional Logic Syntax**

- Propositional variables: p, rain, sunny
- Connectives: ⇒ ⇔ ¬ ∧ ∨
- Inductive definition of well-formed formula (wff):
  - Base: All propositional vars are wffs
  - Inductive 1: If A is a wff then ¬A is a wff
  - Inductive 2: If A and B are wffs then  $A \wedge B$ ,  $A \vee B$ ,  $A \Rightarrow B$ ,  $A \Leftrightarrow B$  are wffs
- Examples:
  - rain, rain  $\Rightarrow$  ¬ sunny
  - (rain  $\Rightarrow \neg$  sunny)  $\Leftrightarrow$  (sunny  $\Rightarrow \neg$ rain)

## **Prop. Logic Semantics**

- For a formula F, the truth I(F) under interpretation I is recursively defined:
  - Base:
    - F is prop var A then I(F)=true iff I(A)=true
  - Recursive:
    - F is ¬C then I(F)=true iff I(C)=false
    - F is C ∧ D then I(F)=true iff I(C)=true and I(D)=true
    - F is C ∨ D then I(F)=true iff I(C)=true or I(D)=true
    - F is C  $\Rightarrow$  D then I(F)=true iff I( $\neg$ C  $\lor$  D)=true
    - F is C  $\Leftrightarrow$  D then I(F)=true iff I(C  $\Rightarrow$  D)=true and I(D  $\Rightarrow$  C)=true
- Truth defined recursively from ground up
  - Modal logics don't have this property!

Peter Baumgartner Automated Reasoning 19

#### **CNF Normalization**

- Many theorem proving techniques req. KB to be in clausal normal form (CNF):
  - Rewrite all C  $\Leftrightarrow$  D as C  $\Rightarrow$  D  $\land$  D  $\Rightarrow$  C
  - Rewrite all C  $\Rightarrow$  D as ¬C ∨ D
  - Push negation through connectives:
    - Rewrite ¬(C ∧ D) as ¬C ∨ ¬D
    - Rewrite  $\neg(C \lor D)$  as  $\neg C \land \neg D$
  - Rewrite double negation ¬ ¬ C as C
  - Now NNF, to get CNF, distribute ∨ over ∧:
    - Rewrite (C ∧ D) ∨ E as (C ∨ E) ∧ (D ∨ E)
- A clause is a disjunction of literals (pos/neg propositional variables)
- Can express KB, a set of clauses, as the conjunction of its clauses

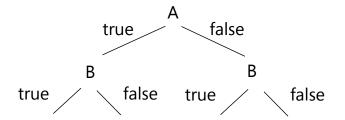
## **CNF Normalization Example**

- Given KB with single formula:
  - ¬ (rain  $\Rightarrow$  wet)  $\Rightarrow$  (inside  $\land$  warm)
- Rewrite all C ⇒ D as ¬C ∨ D
  - ¬¬ (¬ rain ∨ wet) ∨ (inside ∧ warm)
- Push negation through connectives:
  - $(\neg \neg \neg rain \lor \neg \neg wet) \lor (inside \land warm)$
- Rewrite double negation ¬ ¬ C as C
  - (¬ rain ∨ wet) ∨ (inside ∧ warm)
- Distribute ∨ over ∧:
  - (¬rain ∨ wet ∨ inside) ∧ (¬rain ∨ wet ∨ warm)
- CNF KB: {¬rain ∨ wet ∨ inside, ¬rain ∨ wet ∨ warm}

Peter Baumgartner Automated Reasoning 21

## **Prop. Theorem Proving**

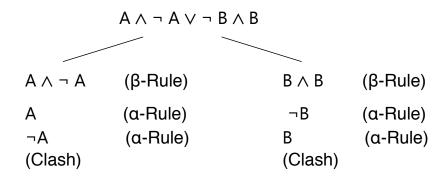
- A ⇒ B iff A ∧ ¬B is unsatisfiable
- Propositional logic is decidable, but NP-complete (reduction to 3-SAT)
- State-of-the-art prop. unsatisfiability methods are DPLL-based
- Many optimizations, more in lecture on SAT solving by Anbulagan



Instantiate prop vars until all clauses falsified, backtrack and do for all instantiations ⇒ unsat!

## **Prop. Tableaux Methods**

- Given negated query F (in NNF), use rules to recursively break down:
  - α-Rule: Given A∧B add A and B
  - β-Rule: Given A∨B branch on A and B
  - Clash: If A and ¬A occur on same branch
- Clash on all branches indicates unsat!



Peter Baumgartner Automated Reasoning 23

## **Propositional Resolution**

One (!) inference rule

Resolution: **Example application:**  $A \lor B \neg B \lor C$ ¬precip ∨ ¬freezing ∨ snow ¬snow ∨ slippery  $A \lor C$ ¬precip ∨ ¬freezing ∨ slippery

- The resolution calculus is sound and (refutationally) complete:  $KB \models C$  if and only if  $KB \cup \{\neg C\} \vdash \bot$ 
  - Simple strategy for completeness is to close clause set under Resolution
- NB: "One inference rule" calculus treats clauses as sets, otherwise need factoring:

Soundness and completeness proof: see blackboard

### **Resolution Strategies**

Need strategies to restrict search:

#### Unit resolution

- Only resolve with unit clauses
- Complete for Horn KB (gives a "bottom-up flavour")
- Intuition: Decrease clause size
- Set of support (see also next two slides)
  - SOS starts with query clauses
  - Only resolve SOS clauses with non-SOS clauses and put resolvents in SOS
  - Intuition: KB should be satisfiable so refutation should derive from query

#### Linear resolution

- Only resolve query clause with KB clauses, resolvent is new query clause
- Complete for Horn KB (gives a "top-down flavour"), basis for Prolog
- Together with ancestor resolution ⇒ complete for non-Horn, too
- Ordered resolution resolve on maximal literals in clause only

Peter Baumgartner Automated Reasoning 25

## The "Given Clause Loop"

- In Otter theorem prover http://en.wikipedia.org/wiki/Otter\_(theorem\_prover)
- Lists of clauses maintained by the algorithm: USABLE and SOS.
- Initialize SOS with the input clauses, USABLE empty.
- Algorithm

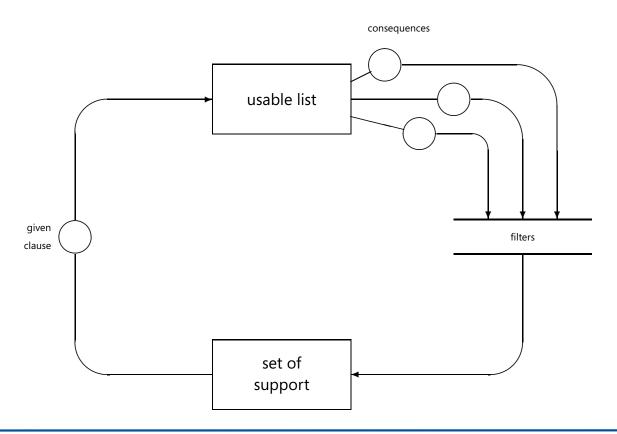
While (SOS is not empty and no refutation has been found)

- Let given\_clause be the `lightest' clause in SOS;
- 2. Move given\_clause from SOS to usable;
- 3. Infer and process new clauses using the inference rules in effect; each new clause must have the given\_clause as one of its parents and members of usable as its other parents; new clauses that pass the retention tests are appended to SOS;

End of while loop.

- Fairness here: define clause weight e.g. as "depth + length" of clause
  - Important property: no clause is delayed infinitely long in (1)

# The Given Clause Loop - Graphically



Peter Baumgartner Automated Reasoning 27

# **First-order logic**

- Refer to objects and relations between them
- · Propositional logic requires all relations to be propositionalized
  - Peter-at-home, Peter-at-work,
     Jim-at-subway, etc...
- Really want a compact relational form:
  - at(Peter, home), at(Peter, work), at(Jim, subway), etc...
- Then can use variables and quantify over all objects:
  - $\forall$ x (person(x)  $\Rightarrow$   $\exists$ y at(x,y)  $\land$  place(y))

### From Propositional Logic to First-Order Logic

- Generalize Syntax
- Generalize Semantics
  - Work with Herbrand interpretations
- Clause normal form generation
  - Involves Skolemization now
- Calculi for first-order clause logic
  - Involve substitutions and unification now

Peter Baumgartner Automated Reasoning 29

# **First-order Logic Syntax**

- Terms (technical definition is inductive because of function symbols)
  - Variables: w, x, y, z
  - Constants: a, b, c, d
  - Functions over terms: f(a), f(x,y), f(x,c,f(f(z)))
- Atoms: P(x), Q(f(x,y)), R(x, f(x,f(c,z),c))
- Connectives: ⇒ ⇔ ¬ ∧ ∨
- Quantifiers: ∀ ∃
- Inductive definition of wff:
  - Same as propositional logic but with following modifications
  - Base: All atoms over terms are wffs
  - Inductive: If A is a wff and x is a variable term
     then ∀x A and ∃x A are wffs

### **First-order Logic Semantics**

- Interpretation I = (ΔI,•I)
  - ΔI is a non-empty domain
  - •I maps each function symbol f of arity n to a total function  $(\Delta I)^n \mapsto \Delta I$
  - I maps each predicate symbol P of arity n into a set of n-tuples over ΔI
- **Herbrand** interpretations (Th: KB is satisfiable iff it has a Herbrand model)
  - ΔI is set of ground terms { Peter, Jim, loc(Peter), loc(Jim), loc(loc(Peter)), ... }
  - I maps each f to the identity function. Thus, I(loc(Peter)) = loc(Peter)
  - I maps each predicate symbol P of arity n into a set of n-tuples over ΔI
  - Logical connectives interpreted as in propositional logic; new:  $I \models \forall x \land iff I \models A[x/t]$ , for all ground terms  $t \in ΔI$
- Example
  - •I may map at(•,•) into { ⟨Peter, loc(Peter)⟩ , ⟨Jim, loc(Jim)⟩ }
  - All other ground predicates are false in I, e.g. at(Jim, Jim)

Peter Baumgartner Automated Reasoning 31

### **Skolemization**

- Skolemization is the process of getting rid of all ∃ quantifiers from a formula while preserving (un)satisfiability:
  - If  $\exists x$  quantifier is the outermost quantifier, remove the  $\exists$  quantifier and substitute a new constant for x
  - If ∃x quantifier occurs inside of ∀ quantifiers, remove the ∃ quantifier and substitute a new function of all ∀ quantified variables for x
- Examples:
  - Skolemize(  $\exists w \; \exists x \; \forall y \; \forall z \; P(w,x,y,z)$  ) =  $\forall y \; \forall z \; P(c,d,y,z)$
  - Skolemize(  $\forall w \exists x \forall y \exists z P(w,x,y,z)$  ) =  $\forall w \forall y P(w,f(w),y,g(w,y))$

#### **CNF Conversion**

- CNF conversion is the same as the propositional case up to NNF, then do:
  - Standardize apart variables (all quantified variables get different names)
    - e.g.  $(\forall x \ A(x)) \land (\exists x \ \neg A(x))$  becomes  $(\forall x \ A(x)) \land (\exists y \ \neg A(y))$
  - Shift all quantifiers in front of formula (obtain, ultimately, prenex normal form)
    - $(\forall x \ A(x)) \land (\exists y \ \neg A(y))$  becomes  $\exists y \ \forall x \ (A(x) \land \neg A(y))$
  - Skolemize formula
    - e.g.  $\exists y \ \forall x \ (A(x) \land \neg A(y)) \ becomes \ \forall x \ (A(x) \land \neg A(c))$
  - Drop universals
    - e.g.  $\forall x (A(x) \land \neg A(c))$  becomes  $A(x) \land \neg A(c)$
  - Distribute ∨ over ∧
  - Write result as a clause set (trivial)
    - e.g.  $A(x) \land \neg A(c)$  becomes { A(x),  $\neg A(c)$  }

Peter Baumgartner Automated Reasoning 33

### **Herbrand's Theorem**

- · Refutational theorem proving calculi are based on the following chain of reasoning
  - Any FO-formula is unsatisfiable iff its clause form is unsatisfiable (Non-trivial part is Skolemization)
  - A clause set is unsatisfiable iff it has no satisfying Herbrand interpretation (i.e. no Herbrand model)
  - A clause set has no Herbrand model iff some finite set of ground instances of its clauses is unsatisfiable (Herbrand's theorem)
- A naive application of the chain leads to Gilmore's method
  - It searches for this unsatisfiable set of ground instances in a direct way

### **Gilmore's Method**

**Preprocessing:** 

Given Formula

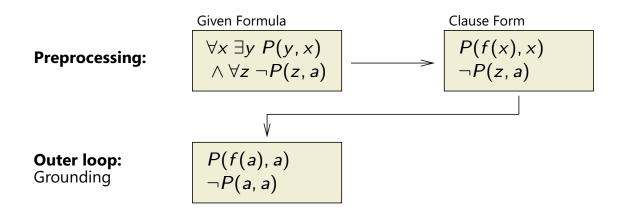
$$\forall x \exists y \ P(y, x) \\
\land \forall z \neg P(z, a)$$
Clause Form
$$P(f(x), x) \\
\neg P(z, a)$$

**Outer loop:** Grounding

**Inner loop:**Propositional Method

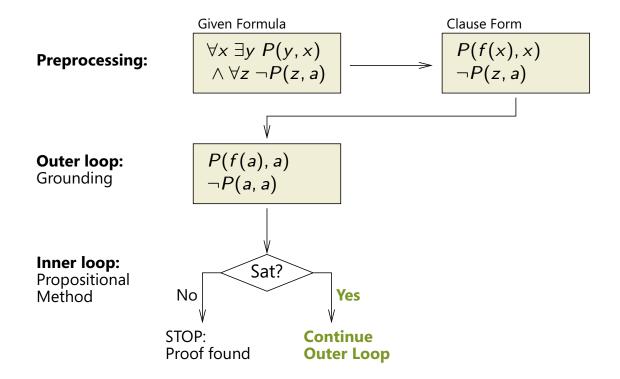
Peter Baumgartner Automated Reasoning 35

### **Gilmore's Method**



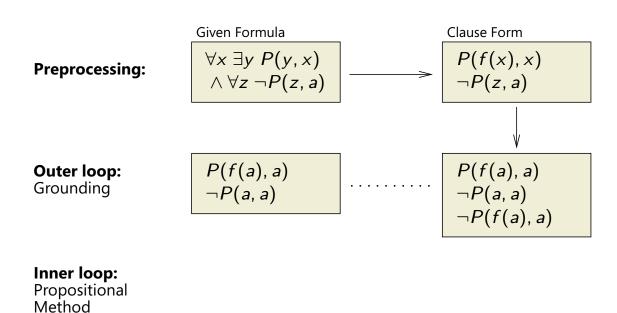
**Inner loop:** Propositional Method

### **Gilmore's Method**

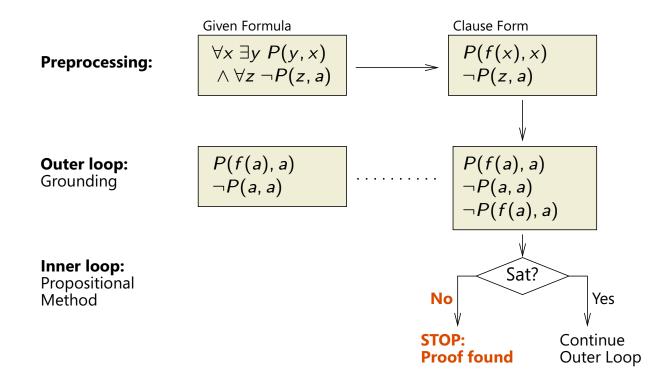


Peter Baumgartner Automated Reasoning 37

### **Gilmore's Method**



#### Gilmore's Method



Peter Baumgartner Automated Reasoning 39

### **Problems with Gilmore's Method**

- Gilmore's method reduces proof search in first-order logic to propositional logic unsatisfiability problems
- Main problem is the unguided generation of (very many) ground clauses
- All modern calculi address this problem in one way or another. e.g.
  - Guidance

Instance-Based Methods are similar to Gilmore's method but generate ground instances in a guided way

Avoidance

Resolution calculi need not generate the ground instances at all, they work directly on first-order clauses, not on their ground instances. This way, infinitely many ground resolution steps can be represented compactly with one first-order resolution step (sometimes)

They use the unification operation to enable this

### **Better Methods for First-order Theorem Proving**

#### Tableaux methods

- Highly successful for description and modal logics,
   which conform to certain (syntactically restricted) fragments of FOL
- Not treated here

#### Resolution Methods

- Most successful technique for a variety of KBs
- But... search space grows very quickly
- Need a variety of optimizations in practice
  - · strategies, ordering, redundancy elimination

#### Instance Based Methods

- Reduce proof search in FOL to proof search in propositional logic
- Comparably new and interesting paradigm
- All methods are based on Herbrand interpretations
  - which justifies the use of unification

Peter Baumgartner Automated Reasoning 41

### **Substitution and Unification**

#### Substitution

- A substitution list  $\theta$  is a list of variable-term pairs
  - e.g.,  $\theta = \{x/3, y/f(z)\}$
- When  $\theta$  is applied to an FOL formula, every free occurrence of a variable in the list is replaced with the given term
  - e.g.  $(P(x,y) \land \exists x P(x,y))\theta = P(3,f(z)) \land \exists x P(x,f(z))$

#### Unification / Most General Unifier

- The unifier UNIF(x,y) of two atoms/terms is a substitution that makes both arguments identical
  - e.g. UNIF(  $P(x,f(x)), P(y, f(f(z))) ) = \{x/f(1), y/f(1), z/1\}$
- The most general unifier MGU(x,y) is just that...
   all other unifiers can be obtained from the MGU
   by additional substitution (MGU exists for unifiable args)
  - e.g. MGU(  $P(x,f(x)), P(y, f(f(z))) ) = \{x/f(z), y/f(z)\}$

### An Instance-Based Method ("InstGen")

#### Current clauses

$$\begin{array}{c} P(\mathsf{f}(x),x) \vee \mathsf{Q}(x) \\ \neg \mathsf{P}(z,\mathsf{a}) \vee \neg \mathsf{Q}(z) \end{array} \begin{array}{c} \text{ground} \\ \hline x_{\mathsf{,}z} \to \$ \end{array} \left( \begin{array}{c} \underline{\mathsf{P}(\mathsf{f}(\$),\$)} \vee \mathsf{Q}(\$) \\ \hline \underline{\neg \mathsf{P}(\$,\mathsf{a})} \vee \neg \mathsf{Q}(\$) \end{array} \right)$$

Model: 
$$\{P(f(\$),\$), \neg P(\$,a)\}$$

Model determines literals selection in current clauses for InstGen inference:

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

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

Peter Baumgartner Automated Reasoning 43

# **Lifting Propositional Resolution to First-Order Resolution**

### **Propositional Resolution**

Clauses	Ground instances
P(f(x), y)	$P(f(a),a),\ldots,P(f(f(a)),f(f(a))),\ldots\}$
$\neg P(z,z)$	$\{\neg P(a), \ldots, \neg P(f(f(a)), f(f(a))), \ldots\}$

Only common instances of P(f(x), y) and P(z, z) give rise to inference:

$$\frac{P(f(f(a)), f(f(a)))}{|} \neg P(f(f(a)), f(f(a)))$$

Observation (leading to "lifting lemma of resolution inferences")

All common instances of P(f(x), y) and P(z, z) are instances of P(f(x), f(x))P(f(x), f(x)) is computed deterministically by *unification* 

**First-Order Resolution** 

$$\frac{P(f(x),y) \qquad \neg P(z,z)}{|}$$

Justified by existence of P(f(x), f(x)) via unification; observation above tells us that these are the only inferences neccessary

### **Resolution for First-Order Clauses**

#### Inference rules

$$\frac{C \vee A \qquad D \vee B}{(C \vee D)\sigma} \quad \text{if } \sigma = \mathsf{MGU}(A,B) \qquad [\mathsf{resolution}]$$

$$\frac{C \vee A \vee B}{(C \vee A)\sigma} \qquad \text{if } \sigma = \mathsf{MGU}(A,B) \quad [\mathsf{factorization}]$$

In both cases, A and B have to be renamed apart (made variable disjoint).

### Example

$$\frac{Q(z) \vee P(z, z) \quad \neg P(x, y)}{Q(x)} \quad \text{where } \sigma = [z/x, y/x] \qquad [\text{resolution}]$$

$$\frac{Q(z) \vee P(z, a) \vee P(a, y)}{Q(a) \vee P(a, a)} \quad \text{where } \sigma = [z/a, y/a] \quad [\text{factorization}]$$

Peter Baumgartner Automated Reasoning 45

# **Example of First-Order Resolution Proof**

Given: CNF:

**Axioms**:  $\neg Man(x) \lor Mortal(x)$ 

 $\forall x \, \mathsf{Man}(x) \Rightarrow \mathsf{Mortal}(x)$  Man(Socrates)

Man(Socrates) ¬Mortal(y) [Neg. conj.]

Conjecture: Proof:

∃y Mortal(y) ? 1. ¬Mortal(y) [Neg. conj.]

2.  $\neg$ Man(x)  $\vee$  Mortal(x) [Given]

**Inference**: 3. Man(Socrates) [Given]

Refutation 4. Mortal(Socrates) [Res. 2,3]

Resolution 5.  $\perp$  [Res. 1,4]

Contradiction ⇒ Conj. is true

## **Importance of Factoring**

- · Without the factoring rule, resolution is incomplete
- For example, take the following refutable clause set:
  - $\{ A(w) \lor A(z), \sim A(y) \lor \sim A(z) \}$
- All binary resolutions yield clauses of the same form
- Clause set is only refutable if one of the clauses is first factored

Peter Baumgartner Automated Reasoning 47

### **Search Control**

- Goal-directed / bottom-up search, as in propositional logic
  - SLD Resolution
    - KB of definite clauses (i.e. Horn rules), e.g.
       Uncle(x,y) :- Father(x,z) ∧ Brother(z,y)
    - Resolution backward chains from goal of rules
    - With negation-as-failure semantics, SLD- resolution is logic programming,
       i.e. Prolog
  - Negative and Positive Hyperresolution
    - All negative (positive) literals in nucleus clause are simultaneously resolved with completely positive (negative) satellite clauses
    - Positive Hyperresolution yields backward chaining
    - Negative Hyperresolution yields forward chaining
- Such search strategies prevent the generation of resolvents,
   they don't explain when clauses can be deleted (redundancy control)

### **Redundancy Control**

- Redundancy of clauses is a huge problem in FOL resolution
  - For clauses C & D, C is redundant if  $\exists \theta$  s.t. Cθ ⊆ D as a multiset, a.k.a. θ-subsumption
  - If true, D is redundant and can be removed
    - Intuition: If D used in a refutation, Cθ could be substituted leading to even shorter refutation
- Two types of subsumption where N is a new resolvent and A is a current clause:
  - Forward subsumption: A  $\theta$ -subsumes N, delete N
  - Backward subsumption: N  $\theta$ -subsumes A, delete A
- Forward / backward subsumption expensive but saves many redundant inferences
- Leads to saturation-based theorem proving (with orderings, in general)

Peter Baumgartner Automated Reasoning 49

## **Saturation Theorem Proving**

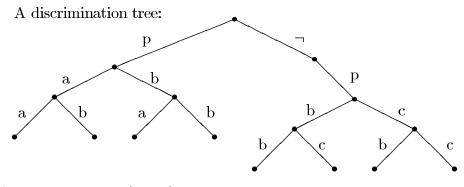
- Given a set of clauses S:
  - S is saturated if all possible inferences from clauses in S generate forward subsumed clauses
  - All new inferences are "redundant" then and need not be carried out, without sacrificing completeness
  - If S does not contain the empty clause then S is satisfiable
- Saturation without deriving the empty clause implies no proof possible!
   And the clause set is satisfiable then.
- Usually need ordering restrictions to reach finite saturation.

## **Term Indexing**

- Term indexing is an implementation technique for fast retrieval of sets of terms / clauses matching criteria
- Common uses in modern theorem provers:
  - Term q (query) is unifiable with term t (in index), i.e.,  $\exists \theta$  s.t.  $q\theta = t\theta$
  - Term t is an instance of q, i.e.,  $\exists \theta$  s.t.  $q\theta = t$
  - Term t is a generalization of q, i.e.,  $\exists \theta$  s.t.  $q = t\theta$
  - Clause q subsumes clause t, i.e.,  $\exists \theta$  s.t.  $q\theta$  ⊆ t
  - Clause q is subsumed by clause t, i.e.,  $\exists \theta$  s.t. t $\theta$  ⊆ q
- Techniques: (Google for "term indexing")
  - Path indexing
  - Substitution tree indexing, discrimination trees

Peter Baumgartner Automated Reasoning 51

# **Discrimination Tree Indexing**



Stores P(a,a), P(a,b), P(b,a), ... -P(c,c)

- Tree structure to look up terms or literals from a (large) database
  - Branches store terms as written down (from left to right)
- Doesn't distinguish different variables P(x,y) becomes P(?,?)
   (Can overretrieve)
- More efficient for common uses than linear search.
- Can be combined with hashing of symbols, if branching is high

# **Equality**

- A predicate w/ special interpretation
- · Could axiomatize:
  - x=x (reflexive)
  - $x=y \Rightarrow y=x$  (symmetric)
  - $= x=y \land y=z \Rightarrow x=z$  (transitive)
  - For each function symbol f:

$$x_1 = y_1 \land ... \land x_n = y_n \Rightarrow f(x_1,...,x_n) = f(y_1,...,y_n)$$
 (congruence)

For each predicate symbol P:

$$x_1=y_1 \land ... \land x_n=y_n \land P(x_1,...,x_n) \Rightarrow P(y_1,...,y_n)$$
 (congruence)

- · Lead to bad search space
- Better to use dedicated inference rules (Paramodulation)

Peter Baumgartner Automated Reasoning

# **Inference Rules for Equality**

Demodulation (incomplete, based on matching)

Literal containing t Example application:  $\frac{|x|}{|x|} = \frac{|x|}{|x|} =$ 

Paramodulation (complete, based on unification)

## **Equality Reasoning: Conclusions**

 The inference rule of paramodulation together with the resolution and factoring inference rules constitute a sound a complete calculus for first-order logic with equality, i.e. can semi-decide the question whether

$$E \models \phi$$

holds, where E is the theory of equality (Ref, Sym, Trans, Congruence) and  $\phi$  is an (arbitrary) formula.

- Caution: some search strategies no longer work (are incomplete), e.g. SOS
  - Unless "paramodulation into and below variables is permitted" (inpractical)
  - The practically most successful theorem provers are saturation-based, heavily use term orderings ("Replace bigger terms by smaller ones"), and the main inference rule is called "superposition"
- Natural question: can one "build-in" other/richer theories than E?
  - Answer: yes, the keyword is "Theory Reasoning"

Peter Baumgartner Automated Reasoning 55

## **Theory Reasoning**

Let T be a first-order theory of signature  $\Sigma$ 

Let L be a class of  $\Sigma$ -formulas

#### **The T-validity Problem**

Given  $\phi$  in L, is it the case that  $T \models \phi$ ?

More accurately:

Given  $\phi$  in L, is it the case that  $T \models \forall \phi$ ?

#### **Examples**

- "0/0, s/1, +/2, =/2, ≤/2"  $\vDash \exists y. y > x$
- "The theory of equality  $E'' \models \phi$  ( $\phi$  arbitrary formula, as above)
- "An equational theory"  $\models \exists s_1 = t_1 \land ... \land s_n = t_n$  (E-Unification problem)
- "Some group theory"  $\models$  s = t (Word problem)

### The T-validity problem is decidably only for restricted L and T

### **Theory Reasoning**

#### **The T-validity Problem**

Is it the case that  $T \models \phi$ ?

More accurately:

Is it the case that  $T \models \forall \phi$ ?

I.e., Free vars are constants

### The Dual Problem: T-satisfiability

Is it the case that  $\phi$  is T-satisfiable?

More accurately:

Is it the case that  $\exists \phi$  is T-satisfiable?

I.e., Free vars are constants

**Prop:**  $T \models \Phi$  iff  $\neg \Phi$  is T-unsatisfiable

Peter Baumgartner Automated Reasoning 5

# **Approaches to Theory Reasoning**

- Theory-Reasoning in Automated First-Order Theorem Proving:
  - Semi-decide the T-validity problem,  $T \models \phi$ ?
  - φ arbitrary first-order formula, T universal theory
  - Generality is strength and weakness at the same time
  - Really successful only for specific instance:
    - T = equality and equality inference rules like paramodulation

### **Approaches to Hybrid Reasoning**

#### Satisfiability Modulo Theories (SMT)

- Decide the T-validity problem,  $T \models \phi$ ?
- Usual restrictions:
  - φ quantifier-free, i.e. all variables implicitly universally quantified
  - The T-satisfiability of conjunctions of literals must be decidable
- SMT is the perhaps most advanced approach among those mentioned
- Applications in particular to Formal verification

Peter Baumgartner Automated Reasoning 59

## **Checking Satisfiability Modulo Theories**

#### **Usual Formulation**

#### Given:

A decision procedure for T-satisfiability of sets of literals

A quantifier-free formula φ (implicitly existentially quantified)

**Task:** Decide whether  $\phi$  is T-satisfiable?

#### **Approaches:**

#### Eager translation into SAT

- Encode problem and theory into an equisatisfiable propositional formula
- Feed formula to a SAT-solver

### Lazy translation into SAT

- Couple a SAT solver with a decision procedure for T-satisfiability of ground literals
- For instance if T is "equality" then the Nelson-Oppen congruence closure method can be used

### **Lazy Translation Into SAT**

$$g(a) = c \land f(g(a)) \neq f(c) \lor g(a) = d \land c \neq d$$

**Theory: Equality** 

Peter Baumgartner Automated Reasoning 61

## **Lazy Translation Into SAT**

$$\underbrace{g(a) = c}_{1} \quad \land \quad \underbrace{f(g(a)) \neq f(c)}_{\overline{2}} \lor \underbrace{g(a) = d}_{3} \quad \land \quad \underbrace{c \neq d}_{\overline{4}}$$

- Send  $\{1, \overline{2} \vee 3, \overline{4}\}$  to SAT solver.
- SAT solver returns model  $\{1, \overline{2}, \overline{4}\}$ . Theory solver finds  $\{1, \overline{2}\}$  *E*-unsatisfiable.
- Send  $\{1, \overline{2} \vee 3, \overline{4}, \overline{1} \vee 2\}$  to SAT solver.
- SAT solver returns model  $\{1, 2, 3, \overline{4}\}$ . Theory solver finds  $\{1, 3, \overline{4}\}$  *E*-unsatisfiable.
- Send  $\{1, \overline{2} \lor 3, \overline{4}, \overline{1} \lor 2, \overline{1} \lor \overline{3} \lor 4\}$  to SAT solver. SAT solver finds  $\{1, \overline{2} \lor 3, \overline{4}, \overline{1} \lor 2, \overline{1} \lor \overline{3} \lor 4\}$  unsatisfiable.

## **Lazy Translation Into SAT: Summary**

- Mapping atoms to propositions is abstraction
- SAT solver computes a solution,
   i.e. boolean assignment for atoms in literal set
- Solution from SAT solver may not be true solution, i.e. the literal set is T-unsatisfiable
- Refine (strengthen) propositional formula by incorporating reason for false solution
- Reason provided by theory decision procedure, typically in form of subset of given literal set

Peter Baumgartner Automated Reasoning 63

## **More Optimizations**

### Theory Consequences

The theory solver may return consequences (typically literals) to guide the SAT solver

### Online SAT solving

 The SAT solver continues its search after accepting additional clauses (rather than restring from scratch)

### Backjumping

- Instead of chronological backtracking

### Preprocessing atoms

Atoms are rewritten into normal form, using theory-specific atoms (e.g. associativity, commutativity)

### Several layers of decision procedures

- "Cheaper" ones are applied first

### **Some SMT Systems**

• Argo-lib, University of Belgrade

DPLL(T), Technical University of Catalonia, U Iowa

• CVC Lite, Stanford

• haRVey, Loria

• ICS, SRI

• Math-SAT, ITC

• Tsat++, University of Genova

• UCLID, CMU

Peter Baumgartner Automated Reasoning 65

# **Combining Theories**

### Theories:

R: theory of rationals

$$\Sigma_{\mathcal{R}} = \{ \leq, +, -, 0, 1 \}$$

£: theory of lists

$$\Sigma_{\mathcal{L}} = \{=, \text{hd}, \text{tl}, \text{nil}, \text{cons}\}$$

- $\bullet$   $\mathcal{E}$ : theory of equality
  - $\Sigma$ : free function and predicate symbols

Problem: Is

$$x \le y \land y \le x + \operatorname{hd}(\operatorname{cons}(0, \operatorname{nil})) \land P(h(x) - h(y)) \land \neg P(0)$$

satisfiable in  $\mathcal{R} \cup \mathcal{L} \cup \mathcal{E}$ ?

G. Nelson and D.C. Oppen: Simplification by cooperating decision procedures, ACM Trans. on Programming Languages and Systems, 1(2):245-257, 1979.

### Given:

- $\mathcal{T}_1$ ,  $\mathcal{T}_2$  first-order theories with signatures  $\Sigma_1$ ,  $\Sigma_2$
- $\phi$  quantifier-free formula over  $\Sigma_1 \cup \Sigma_2$

Obtain a decision procedure for satisfiability in  $\mathcal{T}_1 \cup \mathcal{T}_2$  from decision procedures for satisfiability in  $\mathcal{T}_1$  and  $\mathcal{T}_2$ .

Satisfied lity Modulo Theories p.7/107

# **Nelson-Oppen Combination Method**

Variable abstraction + equality propagation:

$$x \le y \land y \le x + \operatorname{hd}(\operatorname{cons}(0, \operatorname{nil})) \land P(h(x) - h(y)) \land \neg P(0)$$

# Variable abstraction + equality propagation:

$$x \le y \land y \le x + \underbrace{\operatorname{hd}(\operatorname{cons}(0,\operatorname{nil}))}_{v_1} \land P(\underbrace{h(x)}_{v_3} - \underbrace{h(y)}_{v_4}) \land \neg P(\underbrace{0}_{v_5})$$

Sat aliceflity Mocale Theories \_p.2/109

# **Nelson-Oppen Combination Method**

# Variable abstraction + equality propagation:

$$x \le y \land y \le x + \underbrace{\operatorname{hd}(\operatorname{cons}(0,\operatorname{nil}))}_{v_1} \land P(\underbrace{h(x)}_{v_3} - \underbrace{h(y)}_{v_4}) \land \neg P(\underbrace{0}_{v_5})$$

$\mathcal R$	$\mathcal L$	${\cal E}$
$x \le y$		$P(v_2)$
$y \le x + v_1$		$\neg P(v_5)$

# Variable abstraction + equality propagation:

$$x \le y \land y \le x + \underbrace{\operatorname{hd}(\operatorname{cons}(0,\operatorname{nil}))}_{v_1} \land P(\underbrace{h(x)}_{v_3} - \underbrace{h(y)}_{v_4}) \land \neg P(\underbrace{0}_{v_5})$$

$\mathcal R$	${\cal L}$	${\cal E}$
$x \le y$		$P(v_2)$
$y \leq x + v_1$		$\neg P(v_5)$
$v_2 = v_3 - v_4$	$v_1 = \operatorname{hd}(\operatorname{cons}(v_5, \operatorname{nil}))$	$v_3 = h(x)$
$v_5 = 0$		$v_4=h(y)$

Satisficality Modulo Treories \_p.8/10[

# **Nelson-Oppen Combination Method**

# Variable abstraction + equality propagation:

$$x \le y \land y \le x + \underbrace{\operatorname{hd}(\operatorname{cons}(0,\operatorname{nil}))}_{v_1} \land P(\underbrace{h(x)}_{v_3} - \underbrace{h(y)}_{v_4}) \land \neg P(\underbrace{0}_{v_5})$$

$$\mathcal{R}$$
  $\mathcal{L}$   $\mathcal{E}$   $P(v_2)$   $y \le x + v_1$   $\neg P(v_5)$   $v_2 = v_3 - v_4$   $v_1 = \operatorname{hd}(\cos(v_5, \operatorname{nil}))$   $v_3 = h(x)$   $v_4 = h(y)$   $v_1 = v_5$ 

Satisfiedlity Modulo Theories \_p.9/102

# Variable abstraction + equality propagation:

$$x \le y \land y \le x + \underbrace{\operatorname{hd}(\operatorname{cons}(0,\operatorname{nil}))}_{v_1} \land P(\underbrace{h(x)}_{v_3} - \underbrace{h(y)}_{v_4}) \land \neg P(\underbrace{0}_{v_5})$$

$\mathcal R$	$\mathcal L$	${\cal E}$
$x \le y$		$P(v_2)$
$y \le x + v_1$		$\neg P(v_5)$
$v_2 = v_3 - v_4$	$v_1 = \operatorname{hd}(\operatorname{cons}(v_5, \operatorname{nil}))$	$v_3 = h(x)$
$v_5 = 0$		$v_4=h(y)$
x = y	$v_1 = v_5$	

Sat alicability Mocolo Theories \_p.8/103

# **Nelson-Oppen Combination Method**

# Variable abstraction + equality propagation:

$$x \le y \land y \le x + \underbrace{\operatorname{hd}(\operatorname{cons}(0,\operatorname{nil}))}_{v_1} \land P(\underbrace{h(x)}_{v_3} - \underbrace{h(y)}_{v_4}) \land \neg P(\underbrace{0}_{v_5})$$

$\mathcal{R}$	$\mathcal L$	$\mathcal{E}$
$x \leq y$		$P(v_2)$
$y \le x + v_1$		$\neg P(v_5)$
$v_2 = v_3 - v_4$	$v_1 = \operatorname{hd}(\operatorname{cons}(v_5, \operatorname{nil}))$	$v_3 = h(x)$
$v_5 = 0$		$v_4 = h(y)$
x = y	$v_1 = v_5$	$v_3 = v_4$

Satisfiedlity Modulo Theories \_p.9/104

# Variable abstraction + equality propagation:

$$x \le y \land y \le x + \underbrace{\operatorname{hd}(\operatorname{cons}(0,\operatorname{nil}))}_{v_1} \land P(\underbrace{h(x)}_{v_3} - \underbrace{h(y)}_{v_4}) \land \neg P(\underbrace{0}_{v_5})$$

$\mathcal{R}$	$\mathcal L$	$\mathcal{E}$
$x \le y$		$P(v_2)$
$y \le x + v_1$		$\neg P(v_5)$
$v_2 = v_3 - v_4$	$v_1 = \operatorname{hd}(\operatorname{cons}(v_5, \operatorname{nil}))$	$v_3 = h(x)$
$v_5 = 0$		$v_4=h(y)$
x = y	$v_1 = v_5$	$v_3 = v_4$
$v_2 = v_5$		

Satisficiality Modulo Toporius ... p.2/105

# **Nelson-Oppen Combination Method**

# Variable abstraction + equality propagation:

$$x \le y \land y \le x + \underbrace{\operatorname{hd}(\operatorname{cons}(0,\operatorname{nil}))}_{v_1} \land P(\underbrace{h(x)}_{v_3} - \underbrace{h(y)}_{v_4}) \land \neg P(\underbrace{0}_{v_5})$$

$\mathcal R$	$\mathcal L$	$\mathcal E$
$x \le y$		$P(v_2)$
$y \leq x + v_1$		$\neg P(v_5)$
$v_2 = v_3 - v_4$	$v_1 = \operatorname{hd}(\operatorname{cons}(v_5, \operatorname{nil}))$	$v_3 = h(x)$
$v_5 = 0$		$v_4 = h(y)$
x = y	$v_1 = v_5$	$v_3 = v_4$
$v_2 = v_5$		Τ