

Logic and Mechanized Reasoning

DP & DPLL

Marijn J.H. Heule

**Carnegie
Mellon
University**

First Midterm Exam

Monday February 19 at 12:30pm

Material covered in the exam:

- ▶ All lectures up to (and including) February 7
- ▶ All homework through Assignment 4
- ▶ Textbook chapters 1-7, excluding Sections 6.3, 6.5, 7.4

Practice exam and solutions on course website

No new homework assigned this week

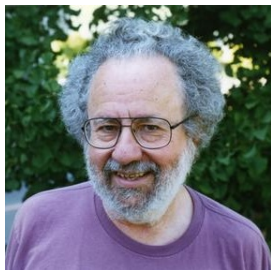
DP Resolution

DPLL

Martin Davis (March 8, 1928 – January 1, 2023)

Martin Davis & Hilary Putnam (1960)
A Computing Procedure for Quantification Theory.
Journal of the ACM 7(3): 201-215

Martin Davis, George Logemann, & Donald W. Loveland (1962)
A machine program for theorem-proving.
Communications of the ACM 5(7): 394-397



DP Resolution

DPLL

DP Resolution / Variable Elimination [DavisPutnam'60]

Definition (Resolution)

Given two clauses $C = (x \vee p_1 \vee \dots \vee p_i)$ and $D = (\bar{x} \vee b_1 \vee \dots \vee b_j)$, the *resolvent* of C and D on variable x (denoted by $C \bowtie_x D$) is $(p_1 \vee \dots \vee p_i \vee b_1 \vee \dots \vee b_j)$

Resolution on sets of clauses Γ_x and $\Gamma_{\bar{x}}$ (denoted by $\Gamma_x \bowtie_x \Gamma_{\bar{x}}$) generates all non-tautological resolvents of $C \in \Gamma_x$ and $D \in \Gamma_{\bar{x}}$.

DP Resolution / Variable Elimination [DavisPutnam'60]

Definition (Resolution)

Given two clauses $C = (x \vee p_1 \vee \dots \vee p_i)$ and $D = (\bar{x} \vee b_1 \vee \dots \vee b_j)$, the *resolvent* of C and D on variable x (denoted by $C \bowtie_x D$) is $(p_1 \vee \dots \vee p_i \vee b_1 \vee \dots \vee b_j)$

Resolution on sets of clauses Γ_x and $\Gamma_{\bar{x}}$ (denoted by $\Gamma_x \bowtie_x \Gamma_{\bar{x}}$) generates all non-tautological resolvents of $C \in \Gamma_x$ and $D \in \Gamma_{\bar{x}}$.

Definition (Variable elimination (VE))

Given a CNF formula Γ , *variable elimination* (or DP resolution) removes a variable x by replacing Γ_x and $\Gamma_{\bar{x}}$ by $\Gamma_x \bowtie_x \Gamma_{\bar{x}}$

DP Resolution / Variable Elimination [DavisPutnam'60]

Definition (Resolution)

Given two clauses $C = (x \vee p_1 \vee \dots \vee p_i)$ and $D = (\bar{x} \vee b_1 \vee \dots \vee b_j)$, the *resolvent* of C and D on variable x (denoted by $C \bowtie_x D$) is $(p_1 \vee \dots \vee p_i \vee b_1 \vee \dots \vee b_j)$

Resolution on sets of clauses Γ_x and $\Gamma_{\bar{x}}$ (denoted by $\Gamma_x \bowtie_x \Gamma_{\bar{x}}$) generates all non-tautological resolvents of $C \in \Gamma_x$ and $D \in \Gamma_{\bar{x}}$.

Definition (Variable elimination (VE))

Given a CNF formula Γ , *variable elimination* (or DP resolution) removes a variable x by replacing Γ_x and $\Gamma_{\bar{x}}$ by $\Gamma_x \bowtie_x \Gamma_{\bar{x}}$

Proof procedure [DavisPutnam60]

VE is a complete proof procedure. Applying VE until fixpoint results in either the empty formula (satisfiable) or empty clause (unsatisfiable)

Example VE by clause distribution [DavisPutnam'60]

Definition (Variable elimination (VE))

Given a CNF formula Γ , *variable elimination* (or DP resolution) removes a variable x by replacing Γ_x and $\Gamma_{\bar{x}}$ by $\Gamma_x \bowtie_x \Gamma_{\bar{x}}$

Example VE by clause distribution [DavisPutnam'60]

Definition (Variable elimination (VE))

Given a CNF formula Γ , *variable elimination* (or DP resolution) removes a variable x by replacing Γ_x and $\Gamma_{\bar{x}}$ by $\Gamma_x \bowtie_x \Gamma_{\bar{x}}$

Example of clause distribution

	Γ_x			
	$(x \vee c)$	$(x \vee \bar{d})$	$(x \vee \bar{a} \vee \bar{b})$	
$\Gamma_{\bar{x}}$ {	$(\bar{x} \vee a)$	$(a \vee c)$	$(a \vee \bar{d})$	$(a \vee \bar{a} \vee \bar{b})$
	$(\bar{x} \vee b)$	$(b \vee c)$	$(b \vee \bar{d})$	$(b \vee \bar{a} \vee \bar{b})$
	$(\bar{x} \vee \bar{e} \vee f)$	$(c \vee \bar{e} \vee f)$	$(\bar{d} \vee \bar{e} \vee f)$	$(\bar{a} \vee \bar{b} \vee \bar{e} \vee f)$

Example VE by clause distribution [DavisPutnam'60]

Definition (Variable elimination (VE))

Given a CNF formula Γ , *variable elimination* (or DP resolution) removes a variable x by replacing Γ_x and $\Gamma_{\bar{x}}$ by $\Gamma_x \bowtie_x \Gamma_{\bar{x}}$

Example of clause distribution

	Γ_x		
	$(x \vee c)$	$(x \vee \bar{d})$	$(x \vee \bar{a} \vee \bar{b})$
$\Gamma_{\bar{x}}$	$(\bar{x} \vee a)$	$(a \vee c)$	$(a \vee \bar{d})$
	$(\bar{x} \vee b)$	$(b \vee c)$	$(b \vee \bar{d})$
	$(\bar{x} \vee \bar{e} \vee f)$	$(c \vee \bar{e} \vee f)$	$(\bar{d} \vee \bar{e} \vee f)$
		$(a \vee \bar{a} \vee \bar{b})$	$(b \vee \bar{a} \vee \bar{b})$
			$(\bar{a} \vee \bar{b} \vee \bar{e} \vee f)$

Example VE by clause distribution [DavisPutnam'60]

Definition (Variable elimination (VE))

Given a CNF formula Γ , *variable elimination* (or DP resolution) removes a variable x by replacing Γ_x and $\Gamma_{\bar{x}}$ by $\Gamma_x \bowtie_x \Gamma_{\bar{x}}$

Example of clause distribution

	Γ_x		
	$(x \vee c)$	$(x \vee \bar{d})$	$(x \vee \bar{a} \vee \bar{b})$
$\Gamma_{\bar{x}}$	$(\bar{x} \vee a)$	$(a \vee c)$	$(a \vee \bar{d})$
	$(\bar{x} \vee b)$	$(b \vee c)$	$(b \vee \bar{d})$
	$(\bar{x} \vee \bar{e} \vee f)$	$(c \vee \bar{e} \vee f)$	$(\bar{d} \vee \bar{e} \vee f)$
		$(a \vee \bar{a} \vee \bar{b})$	$(b \vee \bar{a} \vee \bar{b})$
			$(\bar{a} \vee \bar{b} \vee \bar{e} \vee f)$

In the example: $|\Gamma_x \bowtie \Gamma_{\bar{x}}| > |\Gamma_x| + |\Gamma_{\bar{x}}|$

Exponential growth of clauses in general

DP Resolution and Pure Literals

Proposition

Given a CNF formula Γ with pure literal p , the effect of applying the pure literal rule on p is the same as the effect of applying DP resolution on p .

True or false?

DP Resolution and Pure Literals

Proposition

Given a CNF formula Γ with pure literal p , the effect of applying the pure literal rule on p is the same as the effect of applying DP resolution on p .

True or false?

Proof.

True. The pure literal rule assign p to true, which has the effect that all clauses containing p are removed. Applying DP resolution on p also removes all clauses containing literal p , because $\Gamma_p \bowtie \Gamma_{\neg p}$ is empty. □

VE by substitution [EenBiere07]

General idea

Detect definitions $x = \text{DEF}(p_1, \dots, p_n)$ in the formula and use them to reduce the number of added clauses

VE by substitution [EenBiere07]

General idea

Detect definitions $x = \text{DEF}(p_1, \dots, p_n)$ in the formula and use them to reduce the number of added clauses

Possible gates

definition	D_x	$D_{\bar{x}}$
AND(p_1, \dots, p_n)	$(x \vee \bar{p}_1 \vee \dots \vee \bar{p}_n)$	$(\bar{x} \vee p_1), \dots, (\bar{x} \vee p_n)$
OR(p_1, \dots, p_n)	$(x \vee \bar{p}_1), \dots, (x \vee \bar{p}_n)$	$(\bar{x} \vee p_1 \vee \dots \vee p_n)$
ITE(c, t, f)	$(x \vee \bar{c} \vee \bar{t}), (x \vee c \vee \bar{f})$	$(\bar{x} \vee \bar{c} \vee t), (\bar{x} \vee c \vee f)$

VE by substitution [EenBiere07]

General idea

Detect definitions $x = \text{DEF}(p_1, \dots, p_n)$ in the formula and use them to reduce the number of added clauses

Possible gates

definition	D_x	$D_{\bar{x}}$
AND(p_1, \dots, p_n)	$(x \vee \bar{p}_1 \vee \dots \vee \bar{p}_n)$	$(\bar{x} \vee p_1), \dots, (\bar{x} \vee p_n)$
OR(p_1, \dots, p_n)	$(x \vee \bar{p}_1), \dots, (x \vee \bar{p}_n)$	$(\bar{x} \vee p_1 \vee \dots \vee p_n)$
ITE(c, t, f)	$(x \vee \bar{c} \vee \bar{t}), (x \vee c \vee \bar{f})$	$(\bar{x} \vee \bar{c} \vee t), (\bar{x} \vee c \vee f)$

Variable elimination by substitution [EenBiere07]

Let $R_x = \Gamma_x \setminus D_x$; $R_{\bar{x}} = \Gamma_{\bar{x}} \setminus D_{\bar{x}}$.

Replace $\Gamma_x \wedge \Gamma_{\bar{x}}$ by $D_x \bowtie_x R_{\bar{x}} \wedge D_{\bar{x}} \bowtie_x R_x$.

Always less than $\Gamma_x \bowtie_x \Gamma_{\bar{x}}$! (if x is a definition)

VE by substitution [EenBiere'07]

Example of gate extraction: $x = \text{AND}(a, b)$

$$\Gamma_x = (x \vee c) \wedge (x \vee \bar{d}) \wedge (x \vee \bar{a} \vee \bar{b})$$

$$\Gamma_{\bar{x}} = (\bar{x} \vee a) \wedge (\bar{x} \vee b) \wedge (\bar{x} \vee \bar{e} \vee f)$$

VE by substitution [EenBiere'07]

Example of gate extraction: $x = \text{AND}(a, b)$

$$\Gamma_x = (x \vee c) \wedge (x \vee \bar{d}) \wedge (x \vee \bar{a} \vee \bar{b})$$

$$\Gamma_{\bar{x}} = (\bar{x} \vee a) \wedge (\bar{x} \vee b) \wedge (\bar{x} \vee \bar{e} \vee f)$$

Example of substitution

	R_x		D_x
	$(x \vee c)$	$(x \vee \bar{d})$	$(x \vee \bar{a} \vee \bar{b})$
$D_{\bar{x}} \left\{ \begin{array}{l} (\bar{x} \vee a) \\ (\bar{x} \vee b) \end{array} \right.$	$(a \vee c)$	$(a \vee \bar{d})$	
$R_{\bar{x}} \left\{ (\bar{x} \vee \bar{e} \vee f) \right.$	$(b \vee c)$	$(b \vee \bar{d})$	$(\bar{a} \vee \bar{b} \vee \bar{e} \vee f)$

VE by substitution [EenBiere'07]

Example of gate extraction: $x = \text{AND}(a, b)$

$$\Gamma_x = (x \vee c) \wedge (x \vee \bar{d}) \wedge (x \vee \bar{a} \vee \bar{b})$$

$$\Gamma_{\bar{x}} = (\bar{x} \vee a) \wedge (\bar{x} \vee b) \wedge (\bar{x} \vee \bar{e} \vee f)$$

Example of substitution

	R_x		D_x
	$(x \vee c)$	$(x \vee \bar{d})$	$(x \vee \bar{a} \vee \bar{b})$
$D_{\bar{x}} \left\{ \begin{array}{l} (\bar{x} \vee a) \\ (\bar{x} \vee b) \end{array} \right.$	$(a \vee c)$	$(a \vee \bar{d})$	
$R_{\bar{x}} \left\{ (\bar{x} \vee \bar{e} \vee f) \right.$	$(b \vee c)$	$(b \vee \bar{d})$	$(\bar{a} \vee \bar{b} \vee \bar{e} \vee f)$

using substitution: $|\Gamma_x \bowtie \Gamma_{\bar{x}}| < |\Gamma_x| + |\Gamma_{\bar{x}}|$

DP Resolution

DPLL

SAT Solver Paradigms Overview

DPLL: Aims at finding a small search-tree by selecting effective splitting variables (e.g. via looking ahead).

Strength: Effective on small, hard formulas.

Weakness: Expensive.



SAT Solver Paradigms Overview

DPLL: Aims at finding a small search-tree by selecting effective splitting variables (e.g. via looking ahead).

Strength: Effective on small, hard formulas.

Weakness: Expensive.



Local search: Given a full assignment for a formula Γ , flip the truth values of variables until satisfying Γ .

Strength: Can quickly find solutions for hard formulas.

Weakness: Cannot prove unsatisfiability.



SAT Solver Paradigms Overview

DPLL: Aims at finding a small search-tree by selecting effective splitting variables (e.g. via looking ahead).

Strength: Effective on small, hard formulas.

Weakness: Expensive.



Local search: Given a full assignment for a formula Γ , flip the truth values of variables until satisfying Γ .

Strength: Can quickly find solutions for hard formulas.

Weakness: Cannot prove unsatisfiability.



Conflict-driven clause learning (CDCL): Makes fast decisions and converts conflicts into learned clauses.

Strength: Effective on large, “easy” formulas.

Weakness: Hard to parallelize.



Davis Putnam Logemann Loveland [DP60,DLL62]

Recursive procedure that in each recursive call:

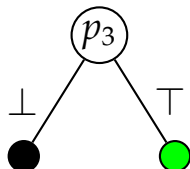
- ▶ Simplifies the formula (using unit propagation)
- ▶ Splits the formula into two subformulas
 - ▶ Variable selection heuristics (which variable to split on)
 - ▶ Direction heuristics (which subformula to explore first)

DPLL: Example

$$\Gamma_{\text{DPLL}} := (p_1 \vee p_2 \vee \neg p_3) \wedge (\neg p_1 \vee p_2 \vee p_3) \wedge \\ (\neg p_1 \vee \neg p_2 \vee p_3) \wedge (p_1 \vee p_3) \wedge (\neg p_1 \vee \neg p_3)$$

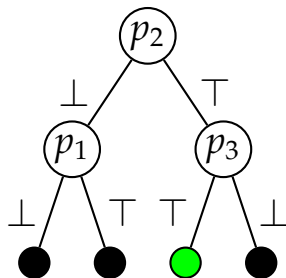
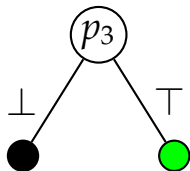
DPLL: Example

$$\Gamma_{\text{DPLL}} := (p_1 \vee p_2 \vee \neg p_3) \wedge (\neg p_1 \vee p_2 \vee p_3) \wedge (\neg p_1 \vee \neg p_2 \vee p_3) \wedge (p_1 \vee p_3) \wedge (\neg p_1 \vee \neg p_3)$$



DPLL: Example

$$\Gamma_{\text{DPLL}} := (p_1 \vee p_2 \vee \neg p_3) \wedge (\neg p_1 \vee p_2 \vee p_3) \wedge (\neg p_1 \vee \neg p_2 \vee p_3) \wedge (p_1 \vee p_3) \wedge (\neg p_1 \vee \neg p_3)$$



DPLL: Slightly Harder Example

Construct a DPLL tree for:

$$\begin{aligned} & (p \vee q \vee \neg r) \wedge (\neg p \vee \neg q \vee r) \wedge \\ & (q \vee r \vee \neg s) \wedge (\neg q \vee \neg r \vee s) \wedge \\ & (p \vee r \vee s) \wedge (\neg p \vee \neg r \vee \neg s) \wedge \\ & (\neg p \vee q \vee s) \end{aligned}$$

What is a good heuristic?

DPLL: Slightly Harder Example

Construct a DPLL tree for:

$$\begin{aligned} & (p \vee q \vee \neg r) \wedge (\neg p \vee \neg q \vee r) \wedge \\ & (q \vee r \vee \neg s) \wedge (\neg q \vee \neg r \vee s) \wedge \\ & (p \vee r \vee s) \wedge (\neg p \vee \neg r \vee \neg s) \wedge \\ & (\neg p \vee q \vee s) \end{aligned}$$

What is a good heuristic?

A cheap and reasonably effective heuristic is MOMS:
Maximum Occurrence in clauses of Minimum Size

DPLL: Pseudocode

DPLL (τ, Γ)

- 1: $\tau' := \text{Simplify}(\tau, \Gamma)$
- 2: **if** $\llbracket \Gamma \rrbracket_{\tau'} = \top$ **then return** satisfiable
- 3: **if** $\llbracket \Gamma \rrbracket_{\tau'} = \perp$ **then return** unsatisfiable
- 4: $l_{\text{decision}} := \text{Decide}(\tau', \Gamma)$
- 5: **if** (DPLL($\tau' \cup l_{\text{decision}} := \top, \Gamma$) = satisfiable) **then**
- 6: **return** satisfiable
- 7: **return** DPLL($\tau' \cup l_{\text{decision}} := \perp, \Gamma$)

DPLL: Demo in Lean

```
-- textbook: dpllSat
partial def dpllSatAux (τ : PropAssignment) (φ : CnfForm) : Option (PropAssignment × CnfForm) :=
  if φ.hasEmpty then none
  else match pickSplit? φ with
    -- No variables left to split on, we found a solution.
    | none => some (τ, φ)
    -- Split on `x`.
    -- `<|>` is the "or else" operator which tries one action, and if that failed tries the other.
    | some x => goWithNew x τ φ <|> goWithNew (-x) τ φ

where
  /-- Assigns `x` to true and continues out DPLL. -/
  goWithNew (x : Lit) (τ : PropAssignment) (φ : CnfForm) : Option (PropAssignment × CnfForm) :=
    let (τ', φ') := propagateWithNew x τ φ
    dpllSatAux τ' φ'

/-- Solve `φ` using DPLL. Return a satisfying assignment if found, otherwise `none`. -/
def dpllSat (φ : CnfForm) : Option PropAssignment :=
  let (τ, φ) := propagateUnits [] φ
  (dpllSatAux τ φ).map fun (τ, _) => τ
-- end textbook: dpllSat
```


DPLL: Look-aheads

DPLL with selection of (effective) decision variables by **look-aheads** on variables

DPLL: Look-aheads

DPLL with selection of (effective) decision variables by **look-aheads** on variables

Look-ahead:

- ▶ Assign a variable to a truth value

DPLL: Look-aheads

DPLL with selection of (effective) decision variables by **look-aheads** on variables

Look-ahead:

- ▶ Assign a variable to a truth value
- ▶ Simplify the formula

DPLL: Look-aheads

DPLL with selection of (effective) decision variables by **look-aheads** on variables

Look-ahead:

- ▶ Assign a variable to a truth value
- ▶ Simplify the formula
- ▶ Measure the reduction

DPLL: Look-aheads

DPLL with selection of (effective) decision variables by **look-aheads** on variables

Look-ahead:

- ▶ Assign a variable to a truth value
- ▶ Simplify the formula
- ▶ Measure the reduction
- ▶ Learn if possible

DPLL: Look-aheads

DPLL with selection of (effective) decision variables by **look-aheads** on variables

Look-ahead:

- ▶ Assign a variable to a truth value
- ▶ Simplify the formula
- ▶ Measure the reduction
- ▶ Learn if possible
- ▶ Backtrack

DPLL: Look-ahead Reduction Heuristics

- ▶ Number of satisfied clauses

DPLL: Look-ahead Reduction Heuristics

- ▶ Number of satisfied clauses
- ▶ Number of implied variables

DPLL: Look-ahead Reduction Heuristics

- ▶ Number of satisfied clauses
- ▶ Number of implied variables
- ▶ New (reduced, not satisfied) clauses
 - ▶ Smaller clauses more important
 - ▶ Weights based on occurrences

DPLL: Learning Necessary Assignments

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

DPLL: Learning Necessary Assignments

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

$$\tau = \{p_1 = \top\}$$

DPLL: Learning Necessary Assignments

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

$$\tau = \{p_1 = \top, p_2 = \top\}$$

DPLL: Learning Necessary Assignments

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

$$\tau = \{p_1 = \top, p_2 = \top, p_3 = \top\}$$

DPLL: Learning Necessary Assignments

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

$$\tau = \{p_1 = \top, p_2 = \top, p_3 = \top, p_4 = \top\}$$

DPLL: Learning Necessary Assignments

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

$$\tau = \{p_1 = \top, p_2 = \top, p_3 = \top, p_4 = \top\}$$

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

DPLL: Learning Necessary Assignments

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

$$\tau = \{p_1 = \top, p_2 = \top, p_3 = \top, p_4 = \top\}$$

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

$$\tau = \{p_1 = \perp\}$$

DPLL: Learning Necessary Assignments

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

$$\tau = \{p_1 = \top, p_2 = \top, p_3 = \top, p_4 = \top\}$$

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

$$\tau = \{p_1 = \perp, p_6 = \perp\}$$

DPLL: Learning Necessary Assignments

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

$$\tau = \{p_1 = \top, p_2 = \top, p_3 = \top, p_4 = \top\}$$

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

$$\tau = \{p_1 = \perp, p_6 = \perp, p_3 = \top\}$$

DPLL: Look-ahead Autarky Detection

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

DPLL: Look-ahead Autarky Detection

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

$$\tau = \{p_1 = \top\}$$

DPLL: Look-ahead Autarky Detection

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

$$\tau = \{p_1 = \top, p_2 = \top\}$$

DPLL: Look-ahead Autarky Detection

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

$$\tau = \{p_1 = \top, p_2 = \top, p_3 = \top\}$$

DPLL: Look-ahead Autarky Detection

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

$$\tau = \{p_1 = \top, p_2 = \top, p_3 = \top, p_4 = \top\}$$

DPLL: Look-ahead Autarky Detection

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

$$\tau = \{p_1 = \top, p_2 = \top, p_3 = \top, p_4 = \top\}$$

Γ_{LEARN} satisfiability equivalent to $(p_5 \vee \bar{p}_6)$

DPLL: Look-ahead Autarky Detection

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

$$\tau = \{p_1 = \top, p_2 = \top, p_3 = \top, p_4 = \top\}$$

Γ_{LEARN} satisfiability equivalent to $(p_5 \vee \bar{p}_6)$

Could reduce computational cost on UNSAT

DPLL: Look-ahead 1-Autarky Learning

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

DPLL: Look-ahead 1-Autarky Learning

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

$$\tau = \{p_2 = \perp\}$$

DPLL: Look-ahead 1-Autarky Learning

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

$$\tau = \{p_2 = \perp, p_1 = \perp\}$$

DPLL: Look-ahead 1-Autarky Learning

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

$$\tau = \{p_2 = \perp, p_1 = \perp, p_6 = \perp\}$$

DPLL: Look-ahead 1-Autarky Learning

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

$$\tau = \{p_2 = \perp, p_1 = \perp, p_6 = \perp, p_3 = \top\}$$

DPLL: Look-ahead 1-Autarky Learning

$$\Gamma_{\text{LEARN}} := (\bar{p}_1 \vee \bar{p}_3 \vee p_4) \wedge (\bar{p}_1 \vee \bar{p}_2 \vee p_3) \wedge \\ (\bar{p}_1 \vee p_2) \wedge (p_1 \vee p_3 \vee p_6) \wedge (\bar{p}_1 \vee p_4 \vee \bar{p}_5) \wedge \\ (p_1 \vee \bar{p}_6) \wedge (p_4 \vee p_5 \vee p_6) \wedge (p_5 \vee \bar{p}_6)$$

$$\tau = \{p_2 = \perp, p_1 = \perp, p_6 = \perp, p_3 = \top\}$$

(local) 1-autarky resolvents:

$$(\bar{p}_2 \vee \bar{p}_4) \text{ and } (\bar{p}_2 \vee \bar{p}_5)$$