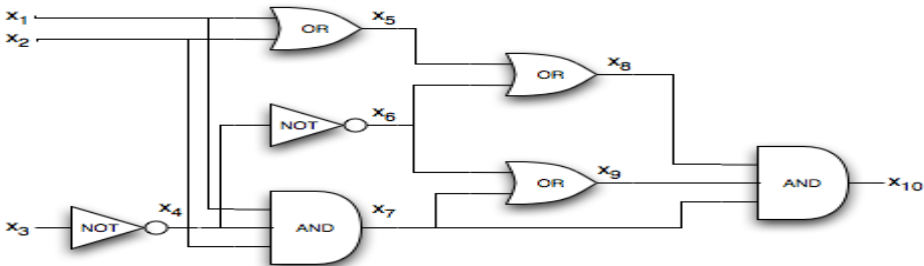


# Practical SAT Solving

Lecture 3

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INSTITUTE FOR THEORETICAL COMPUTER SCIENCE



- You get homework points for doing homework and showing up with them on the exercises
- You will have the possibility to collect at least 100 points during the semester (plus a lot more bonus points)
- You must collect at least 50 points to pass the exercises and be allowed to participate in the oral exam.
- Extra homework points improve your grade:
  - $\geq 70$  points improves grade by 0.3
  - $\geq 90$  points improves grade by 0.7
  - $\geq 110$  points improves grade by 1.0

# Lecture Outline

- Planning as Satisfiability
- Random Formulas

## Informal Definition

Planning is the process of finding a plan, i.e., a sequence of actions that changes the state of the world from some initial state to a desired (goal) state.

## Examples

- Delivering some packages
- Building a submarine
- Robot motion planning
- Fulfilling a scientific goal by an autonomous space probe

# Trucking Example



## ■ Initial State

- There is a truck and a package in city A
- There is a package in city B

## ■ Goal

- There are two packages in city C

## ■ Possible Actions

- (Un)loading packages from/on the truck, driving between cities

## Planning Problem Definition

A planning problem instance is  $\Pi$  is a tuple  $(\mathcal{X}, \mathcal{A}, s_I, s_G)$  where

- $\mathcal{X}$  is a set of multivalued variables with finite domains.
  - each variable  $x \in \mathcal{X}$  has a finite possible set of values  $dom(x)$
- $\mathcal{A}$  is a set actions. Each action  $a \in \mathcal{A}$  is a tuple  $(pre(a), eff(a))$ 
  - $pre(a)$  is a set of preconditions of action  $a$
  - $eff(a)$  is a set of effects of action  $a$
  - both are sets of equalities of the form  $x = v$  where  $x \in \mathcal{X}$  and  $v \in dom(x)$
- $s_I$  is the initial state, it is a **full** assignment of the variables in  $\mathcal{X}$
- $s_G$  is the set of goal conditions, it is a set of equalities (same as  $pre(a)$  and  $eff(a)$ )

## World State

A state is full assignment of the variables in  $\mathcal{X}$  (each variable  $x \in \mathcal{X}$  has exactly one value assigned from its domain  $dom(x)$ ). A state can be represented as a set of equalities.

The initial state  $s_I$  is a state. A state  $s$  is a goal state if  $s_G \subseteq s$

## Applicable Actions

An action  $a \in \mathcal{A}$  is applicable in the state  $s$  if  $pre(a) \subseteq s$

## Applying an Action

When an action  $a \in \mathcal{A}$  is applied in the state  $s$  it changes to the state  $s'$  such that  $eff(a) \subseteq s'$  and the difference between  $s$  and  $s'$  is minimal (only variables used in  $eff(a)$  are changed).

## A Plan

A plan for  $P$  for a planning problem  $\Pi = (\mathcal{X}, \mathcal{A}, s_I, s_G)$  is sequence of actions  $a_1, a_2, \dots, a_n$  such that

- $\forall i a_i \in \mathcal{A}$
- let  $s_1 = s_I$  and  $s_{i+1} = \text{apply}(s_i, a_i)$
- $a_i$  is applicable in  $s_i$
- $s_G \subseteq s_{n+1}$

If  $P = \{a_1, a_2, \dots, a_n\}$  then  $n$  is the length of the plan  $P$ .

An optimal plan is a plan of shortest length.



# Trucking Example



- variables: Truck Location  $T$ ,  $dom(T) = \{A, B, C\}$ , Package Locations  $P_1$  and  $P_2$ ,  $dom(P_1) = dom(P_2) = \{A, B, C, T\}$
- Initial state:  $\{T = A, P_1 = A, P_2 = B\}$
- Goal:  $\{P_1 = C, P_2 = C\}$
- Actions:  $load(P_i, L) = (\{T = L, P_i = L\}, \{P_i = T\})$   
 $unload(P_i, L) = (\{T = L, P_i = T\}, \{P_i = L\})$   
 $drive(L_1, L_2) = (\{T = L_1\}, \{T = L_2\})$  where  $i \in \{1, 2\}$  and  $L, L_1, L_2 \in \{A, B, C\}$

# Trucking Example



## World State

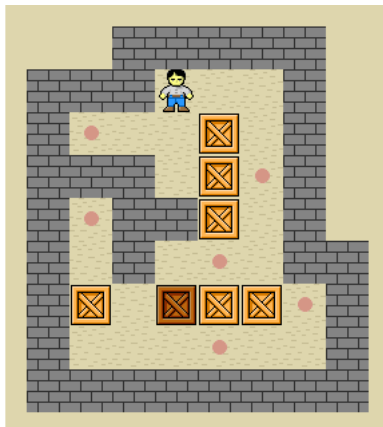
- $T = A, P_1 = A, P_2 = B$
- $T = A, P_1 = T, P_2 = B$
- $T = B, P_1 = T, P_2 = B$
- $T = B, P_1 = T, P_2 = T$
- $T = C, P_1 = T, P_2 = T$
- $T = C, P_1 = C, P_2 = C$

## The Plan

- $load(P_1, A)$
- $drive(A, B)$
- $load(P_2, B)$
- $drive(B, C)$
- $unload(P_1, C), unload(P_2, C)$

# Sokoban Example

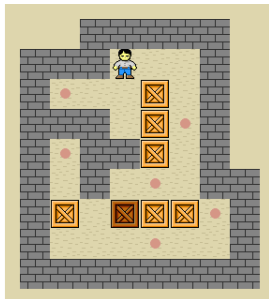
- Initial State
  - There is a worker and a bunch of boxes
- Goal
  - All the boxes must in goal positions
- Possible Actions
  - moving with the worker
  - pushing boxes
- Forbidden
  - to pull boxes
  - move through walls or boxes



<http://wki.pe/Sokoban>

# Encoding Sokoban

- Variables – For each location we have variable, the domain is WORKER, BOX, EMPTY
- Initial State – assign values based on the picture
- Goal – goal position variables have value BOX
- Actions – move and push for each possible location
- $push(L_1, L_2, L_3) = (\{L_1 = W, L_2 = B, L_3 = E\}, \{L_1 = E, L_2 = W, L_3 = B\})$
- $move(L_1, L_2) = (\{L_1 = W, L_2 = E\}, \{L_1 = E, L_2 = W\})$



# Encoding Planning into CNF

Is that even possible?

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- We cannot encode the existence of a plan in general
- But we can encode the existence of plan up to some length

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## SATPLAN Algorithm

- INPUT: a planning problem  $\Pi$
- OUTPUT: a plan  $P$

**for**  $m := 1, 2, \dots$  **do**

$F = \text{encodePlanExists}(\Pi, m)$

**if**  $\text{solver.isSat}(F)$  **then**

**return**  $\text{extractPlan}(\Pi, m, \text{solver.solution})$

## The Task

Given a planning problem instance  $\Pi = (\mathcal{X}, \mathcal{A}, s_I, s_G)$  and  $k \in \mathbb{N}$  construct a CNF formula  $F$  such that  $F$  is satisfiable if and only if there is plan of length  $k$  for  $\Pi$ .



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We will need two kinds of variables

- Variables to encode the actions:  
 $a_i^t$  for each  $t \in \{1, \dots, k\}$  and  $a_i \in \mathcal{A}$
- Variables to encode the states:  
 $b_{x=v}^t$  for each  $t \in \{1, \dots, k+1\}$ ,  $x \in \mathcal{X}$  and  $v \in \text{dom}(x)$

In total we have  $k|\mathcal{A}| + (k+1) \sum_{x \in \mathcal{X}} \text{dom}(x)$  variables

We will need six kinds of clauses

- The first state is the initial state
- The goal conditions are satisfied in the end
- Each state variable has at least one value
- Each state variable has at most one value
- If an action is applied it must be applicable
- If an action is applied its effects are applied in the next step
- State variables cannot change without an action between steps
- At most one action is used in each step

# Encoding Planning into CNF

The first state is the initial state

$$\begin{aligned} & (b_{x=v}^1) \\ \forall (x = v) \in s_I & \end{aligned} \tag{1}$$

The goal conditions are satisfied in the end

$$\begin{aligned} & (b_{x=v}^{n+1}) \\ \forall (x = v) \in s_G & \end{aligned} \tag{2}$$

Each state variable has at least one value

$$(b_{x=v_1}^t \vee b_{x=v_2}^t \vee \dots \vee b_{x=v_d}^t) \\ \forall x \in X, \text{dom}(x) = \{v_1, v_2, \dots, v_d\}, \forall t \in \{1, \dots, k+1\} \quad (3)$$

Each state variable has at most one value

$$(\neg b_{x=v_i}^t \vee \neg b_{x=v_j}^t) \\ \forall x \in X, v_i \neq v_j, \{v_i, v_j\} \subseteq \text{dom}(x), \forall t \in \{1, \dots, k+1\} \quad (4)$$

If an action is applied it must be applicable

$$\begin{aligned} & (\neg a^t \vee b_{x=v}^t) \\ \forall a \in \mathcal{A}, \forall (x=v) \in \text{pre}(a), \forall t \in \{1, \dots, k\} \end{aligned} \tag{5}$$

If an action is applied its effects are applied in the next step

$$\begin{aligned} & (\neg a^t \vee b_{x=v}^{t+1}) \\ \forall a \in \mathcal{A}, \forall (x=v) \in \text{eff}(a), \forall t \in \{1, \dots, k\} \end{aligned} \tag{6}$$

State variables cannot change without an action between steps

$$(\neg b_{x=v}^{t+1} \vee b_{x=v}^t \vee a_{s_1}^t \vee \dots \vee a_{s_j}^t)$$

$$\forall x \in X, \forall v \in \text{dom}(x), \text{support}(x = v) = \{a_{s_1}, \dots, a_{s_j}\}, \forall t \in \{1, \dots, k\}$$

(7)

By  $\text{support}(x = v) \subseteq \mathcal{A}$  we mean the set of *supporting actions* of the assignment  $x = v$ , i.e., the set of actions that have  $x = v$  as one of their effects.

At most one action is used in each step

$$\begin{aligned} & (\neg a_i^t \vee \neg a_j^t) \\ \forall \{a_i, a_j\} \subseteq \mathcal{A}, a_i \neq a_j \forall t \in \{1, \dots, k\} \end{aligned} \tag{8}$$

## The Task Solved

Given a planning problem instance  $\Pi = (\mathcal{X}, \mathcal{A}, s_I, s_G)$  and  $k \in \mathbb{N}$  a CNF formula  $F$ , which is a conjunction of all the above described clauses is satisfiable if and only if there is plan of length  $k$  for  $\Pi$ .

## Optimizations

- Better encoding of at-most-one
- Allowing several actions in each step
- Encoding variable transitions instead of variable values



## Goldbergs Random Formulas – 1979

Generate  $m$  clauses on  $n$  variables such that for each clause  $c$  each variable  $x_i$  is in  $c$  as positive literal with probability  $\frac{1}{3}$ , as a negative literal with probability  $\frac{1}{3}$  and not at all with probability  $\frac{1}{3}$ .

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- Goldberg showed that these instances can be solved in polynomial time (using the DPLL algorithm) and therefore "SAT is easy".
- in 1983 Franco and Paull pointed out, that these instances are so easy that just guessing assignments solves it in  $\mathcal{O}(1)$  expected time

## Uniform Random k-SAT – 1983 Franco and Paull

Uniform random k-SAT formulas are formed by selecting uniformly and independently  $m$  clauses of length  $k$  from the set of all  $2^k \binom{n}{k}$  clauses on a given set of  $n$  variables.

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## Phase Transition Hypothesis

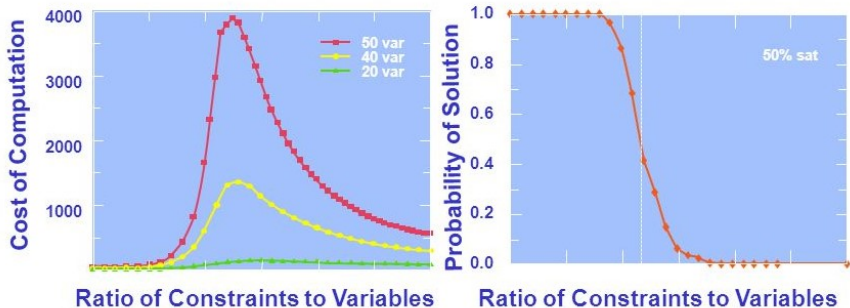
Let  $\alpha = \frac{m}{n}$  be the ratio of clauses and variables of a k-SAT formula. For each  $k$  there exists a constant  $\alpha_k$  such that

- A random k-SAT formula with  $\alpha < \alpha_k$  is satisfiable w.h.p.
- A random k-SAT formula with  $\alpha > \alpha_k$  is unsatisfiable w.h.p.

w.h.p. means "with high probability", the hypothesis is proven only for 2-SAT where  $\alpha_2 = 1$ .

# Phase Transition – 3-SAT

- Selman *et al.* (1994):



- From experiments we deduce that  $\alpha_3$  is around 4.25
- Myth: phase transition is where the hardest formulas are

- How to generate a random satisfiable formula?

- How to generate a random satisfiable formula?
- Hidden Solution Algorithm
  - Take a truth assignment  $\phi$
  - Generate random clauses but only add those that satisfy  $\phi$



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  - Same as previous but with 2 assignments  $\phi$  and  $\bar{\phi}$
- Clause Distribution Control

## CDC Algorithm

- INPUT: a truth assignment  $\phi$  on  $n$  variables
- OUTPUT: a random  $k$ -SAT CNF satisfied by  $\phi$

$F = \emptyset$

**while**  $|F| < r * n$  **do**

$C =$  a random  $k$ -clause on  $n$  variables

$s =$  number of literals in  $C$  satisfied by  $\phi$

$r =$  a random real number  $(0, 1)$

**if**  $s > 0$  and  $p_s > r$  **then**

$F = F \cup \{C\}$

**return**  $F$

$r, p_1, p_2, \dots, p_k$  are parameters of the CDC algorithm

# Choosing CDC parameters $p_i$ and $r$ ?

- Barthel et. al algorithm
  - $0.077 < p_1 < 0.25$
  - $p_2 = (1 - 4p_1)/6$
  - $p_3 = (1 + 2p_1)/6$
  - $r > 4.25$
- Q-Hidden algorithm
  - $p_i = q^i$  for a parameter  $q$
  - $r$  not specified
- Automatic configuration based algorithm
  - use an automatic configuration tool and a solver to optimize  $p_i$  and  $r$  against

# Are you touched by SAT?

