AI: Representation and Problem Solving



Instructor: Pat Virtue

Slide credits: CMU AI, http://ai.berkeley.edu

Plan

Last Time:

- Propositional logic
- Models and Knowledge Bases
- Satisifiability and Entailment

Today: Logical Agent Algorithms

- Entailment
 - Model checking: Truth table entailment
 - Theorem proving: (Forward chaining), resolution
- Satisfiability: DPLL
- Planning with logic

Plan

Last Time:

- Propositional logic
- Models and Knowledge Bases
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Propositional Logic Vocab

Literal

Atomic sentence: True, False, Symbol, –Symbol

Clause

• Disjunction (OR) of literals: $A \lor B \lor \neg C$

Definite clause

Disjunction (OR) of literals, exactly one is positive

 $\neg A \lor B \lor \neg C$

Horn clause

- Disjunction of literals, at most one is positive
- All definite clauses are Horn clauses

PL: Conjunctive Normal Form (CNF)

Every sentence can be expressed as a conjunction (AND) of clauses Each clause is a disjunction (OR) of literals Each literal is a symbol or a negated symbol • Example: $(\neg A \lor \neg C \lor B) \land (\neg A \lor \neg B \lor C) \land (\chi \checkmark \chi \chi) \land \land$

PL: Conjunctive Normal Form (CNF)

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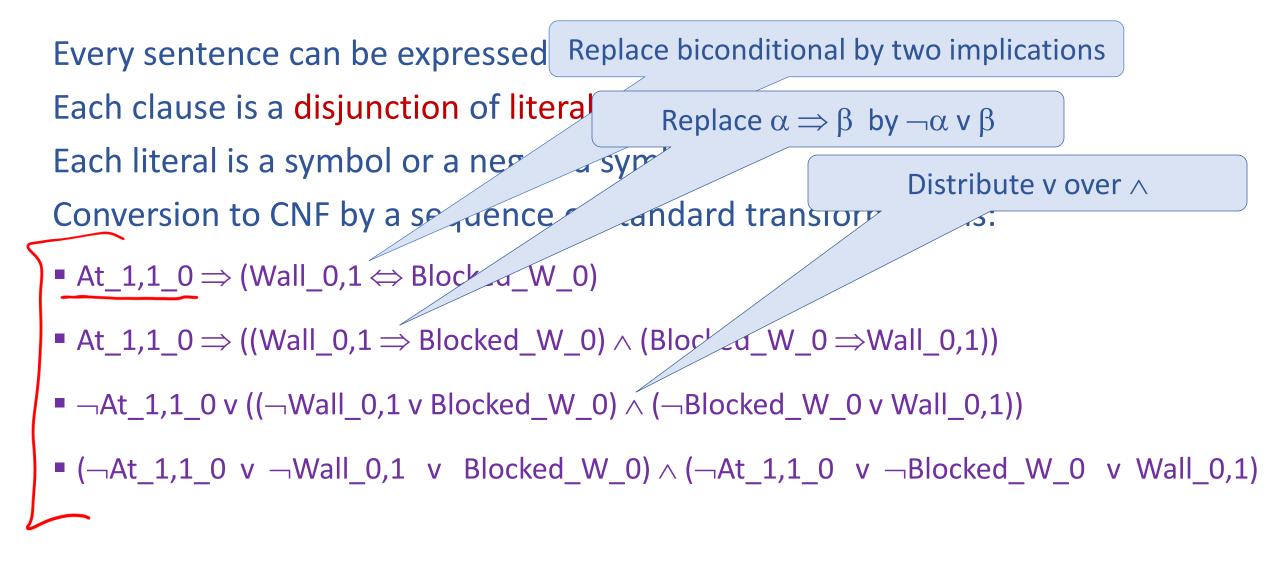
- Each clause is a disjunction of literals
- Each literal is a symbol or a negated symbol

Conversion to CNF by a sequence of standard transformations:

• At_1,1_0 \Rightarrow (Wall_0,1 \Leftrightarrow Blocked_W_0)

- At_1,1_0 \Rightarrow ((Wall_0,1 \Rightarrow Blocked_W_0) \land (Blocked_W_0 \Rightarrow Wall_0,1))
- At_1,1_0 v ((¬Wall_0,1 v Blocked_W_0) ∧ (¬Blocked_W_0 v Wall_0,1))
- (¬At_1,1_0 v ¬Wall_0,1 v Blocked_W_0) ∧ (¬At_1,1_0 v ¬Blocked_W_0 v Wall_0,1)

PL: Conjunctive Normal Form (CNF)



Logical Agent Vocab

Model

Complete assignment of symbols to True/False

Sentence

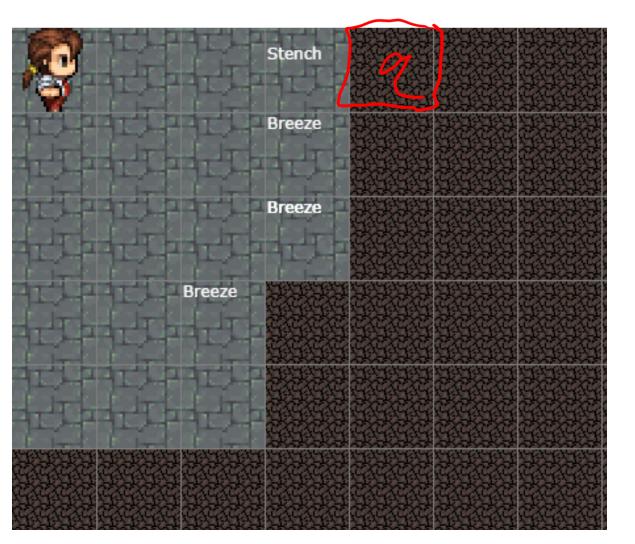
- Logical statement
- Composition of logic symbols and operators

KB

 Collection of sentences representing facts and rules we know about the world

Query 2 Sentence we want to know if it is *provably* True, *provably* False, or *unsure*.

Provably True, Provably False, or Unsure



http://thiagodnf.github.io/wumpus-world-simulator/

Logical Agent Vocab

 \rightarrow Entailment & BInput: sentence1, sentence2



- Each model that satisfies sentence1 must also satisfy sentence2
- If I know 1 holds, then I know 2 holds
- (ASK), TT-ENTAILS, FC-ENTAILS, RESOLUTION-ENTAILS

->> Satisfy

- possible Input: model, sentence $\rightarrow \mathcal{T} \circ \mathcal{F}$
- Is this sentence true in this model?
- Does this model satisfy this sentence
- Does this particular state of the world work?'
- PL-TRUE

Logical Agent Vocab

Satisfiable

Input: sentence KB

-> model

- Can find at least one model that satisfies this sentence
 - (We often want to know what that model is)
- "Is it possible to make this sentence true?"
- DPLL CSP

Valid

- Input: sentence
- sentence is true in all possible models



Outline

Logical Agent Algorithms Vocab

- PL_TRUE
- Entailment
- Model checking: Truth table entailment

CSP

- Theorem proving:
- (Forward chaining), resolution
- Satisfiability: DPLL
- Planning with logic

Propositional Logic

Check if sentence is true in given model In other words, does the model *satisfy* the sentence?

function PL-TRUE?(α , model) returns true or false

But are models and propositional logic sentences α represented?

 $^{1}\times + \vee$

 $\alpha = A \Lambda (B V \neg C)$

Propositional Logic

Check if sentence is true in given model In other words, does the model *satisfy* the sentence?

 $\alpha = A \Lambda (B V \neg C)$

function PL-TRUE?(α ,model) returns true or false if α is a symbol then return Lookup(α , model) if Op(α) = \neg then return **not**(PL-TRUE?(Arg1(α),model)) if Op(α) = \wedge then return **and**(PL-TRUE?(Arg1(α),model), PL-TRUE?(Arg2(α),model))

etc.

(Sometimes called "recursion over syntax")

Outline

Logical Agent Algorithms

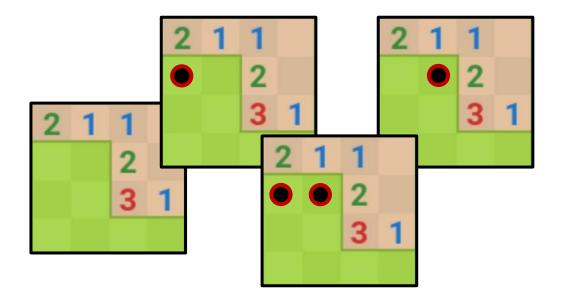
- Vocab
- → PL_TRUE
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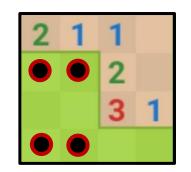
Inference: Proofs

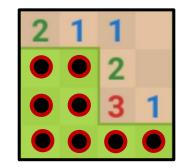
A proof is a *demonstration* of entailment between α and β

Method 1: model-checking

- For every possible world, if α is true make sure that is β true too
- OK for propositional logic (finitely many worlds); not easy for first-order logic





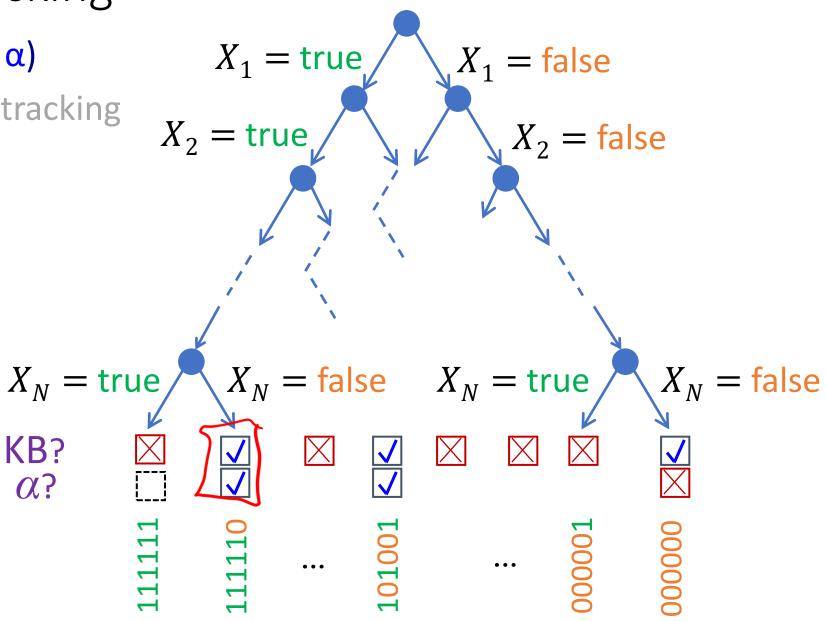


function TT-ENTAILS?(KB, α) Returns true or false

function TT-ENTAILS?(KB, α)

Same recursion as backtracking

 α ?



function TT-ENTAILS?(KB, α) Returns true or false
return TT-CHECK-ALL(KB, α, symbols(KB) U symbols(α), {})

function TT-CHECK-ALL(KB, α, symbols, model) Returns true or false

Recursively check to make sure all models

 \longrightarrow that satisfy the KB also satisfy α

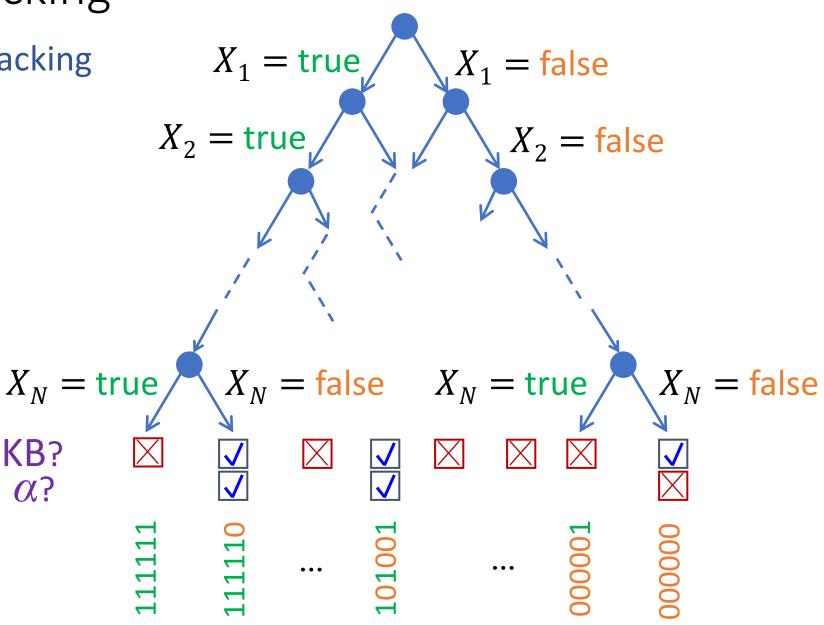
function TT-CHECK-ALL(KB, α , symbols, model) Returns true or false if empty?(symbols) then if PL-TRUE?(KB, model) then return PL-TRUE?(α, model) else return true else $X_i \leftarrow \text{first(symbols)}$ rest \leftarrow rest(symbols) return and (TT-CHECK-ALL(KB, α , rest, model $\cup \{X_i = \text{true}\}$) TT-CHECK-ALL(KB, α , rest, model $\cup \{X_i = \text{false}\}$)

Same recursion as backtracking $O(2^N)$ time, linear space

KB?

 α ?

Can we do better?



Inference: Proofs

A proof is a *demonstration* of entailment between α and β Method 1: *model-checking*

- For every possible world, if α is true make sure that is β true too
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Method 2: theorem-proving

- Search for a sequence of proof steps (applications of *inference rules*) leading from α to β
- E.g., from $P \land (P \Rightarrow Q)$, infer Q by *Modus Ponens*

Properties

• Sound algorithm: everything it claims to prove is in fact entailed

------> Complete algorithm: every sentence that is entailed can be proved

Simple Theorem Proving: Forward Chaining

Forward chaining applies Modus Ponens to generate new facts:

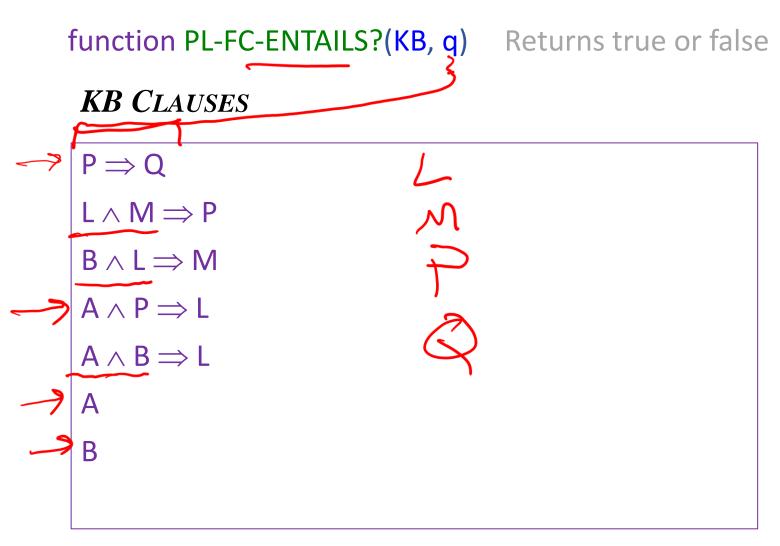
• Given $X_1 \wedge X_2 \wedge \dots \times X_n \Rightarrow Y \text{ and } X_1, X_2, \dots, X_n$

Infer Y

 $L = \mathbb{R}$

Forward chaining keeps applying this rule, adding new facts, until nothing more can be added

Forward Chaining Algorithm



KBF2

Properties

Forward Chaining is:

- Sound and complete for definite-clause KBs
- Complexity: linear time ③

Resolution is another theorem-proving algorithm that is:

- Sound and complete for any PL KBs!
- Complexity: exponential time ⊗

Vocab Reminder

Literal

- Atomic sentence:
 - T, F, Symbol, ¬Symbol

Clause

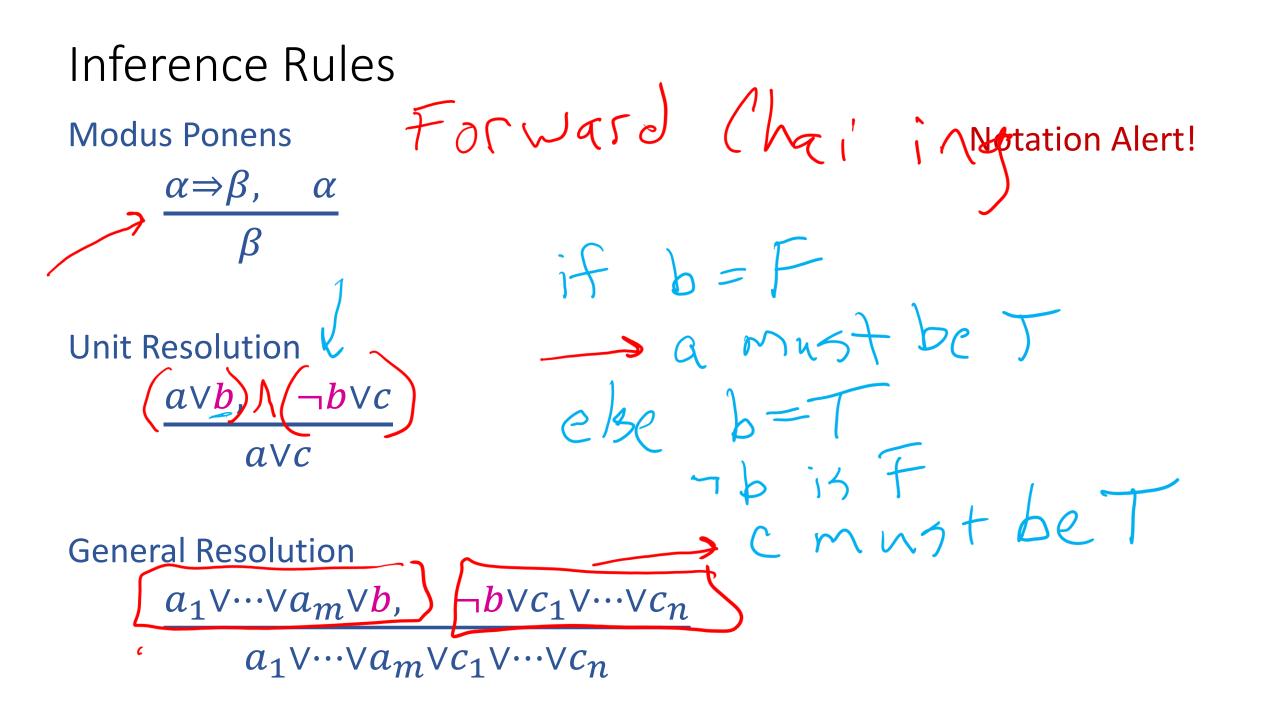
• Disjunction of literals: $A \lor B \lor \neg C$

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Resolution

Algorithm Overview

function PL-RESOLUTION?(KB, α) returns true or false

We want to prove that KB entails α

In other words, we want to prove that we cannot satisfy (KB and **not** α)

XB FX

SAT (KBA 70)-1No

- 1. Start with a set of CNF clauses, including the KB as well as $\neg \alpha$
- 2. Keep resolving pairs of clauses until
- \rightarrow A. You resolve the empty clause

Contradiction found!

KB $\land \neg \alpha$ cannot be satisfied

Return true, KB entails α

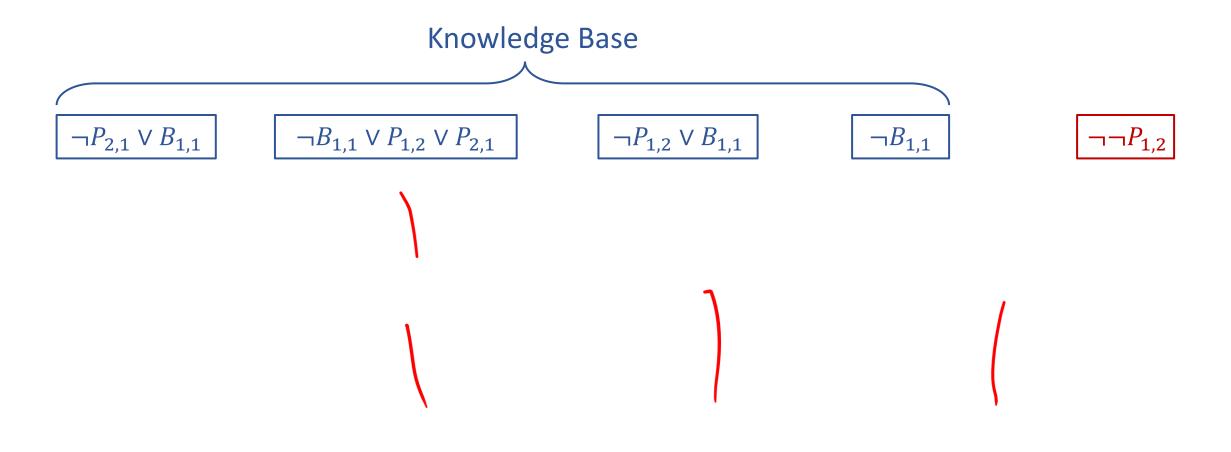
B. No new clauses added

Return false, KB does not entail α

Resolution

Example trying to prove $\neg P_{1,2}$

General Resolution $\frac{a_1 \vee \cdots \vee a_m \vee b}{a_1 \vee \cdots \vee a_m \vee c_1 \vee \cdots \vee c_n}$



General Resolution Resolution $a_1 \vee \cdots \vee a_m \vee b$, $\neg b \vee c_1 \vee \cdots \vee c_n$ $a_1 \vee \cdots \vee a_m \vee c_1 \vee \cdots \vee c_n$ Example trying to prove $\neg P_{1,2}$ Knowledge Base $\neg B_{1,1}$ *P*_{1,2} $\neg P_{2,1} \lor B_{1,1}$ $\neg B_{1,1} \lor P_{1,2} \lor P_{2,1}$ $\neg P_{1,2} \lor B_{1,1}$ $\neg P_{1,2}$ ' $\neg B_{1,1} \lor P_{1,2} \lor B_{1,1} | | P_{1,2} \lor P_{2,1} \lor \neg P_{2,1} | | \neg B_{1,1} \lor P_{2,1} \lor B_{1,1} | | P_{1,2} \lor P_{2,1} \lor \neg P_{1,2}$ $\neg P_{2,1}$

Resolution

function PL-RESOLUTION?(KB, α) returns true or false clauses \leftarrow the set of clauses in the CNF representation of KB $\wedge \neg \alpha$ new \leftarrow { } loop do for each pair of clauses C_i , C_j in clauses do resolvents \leftarrow PL-RESOLVE (C_i, C_i) if resolvents contains the empty clause then return true $new \leftarrow new \cup resolvants$ if new \subseteq clauses then return false clauses \leftarrow clauses \cup new

Properties

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- Sound and complete for definite-clause KBs
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Resolution is another theorem-proving algorithm that is:

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<u>Vocab Reminder</u> Literal

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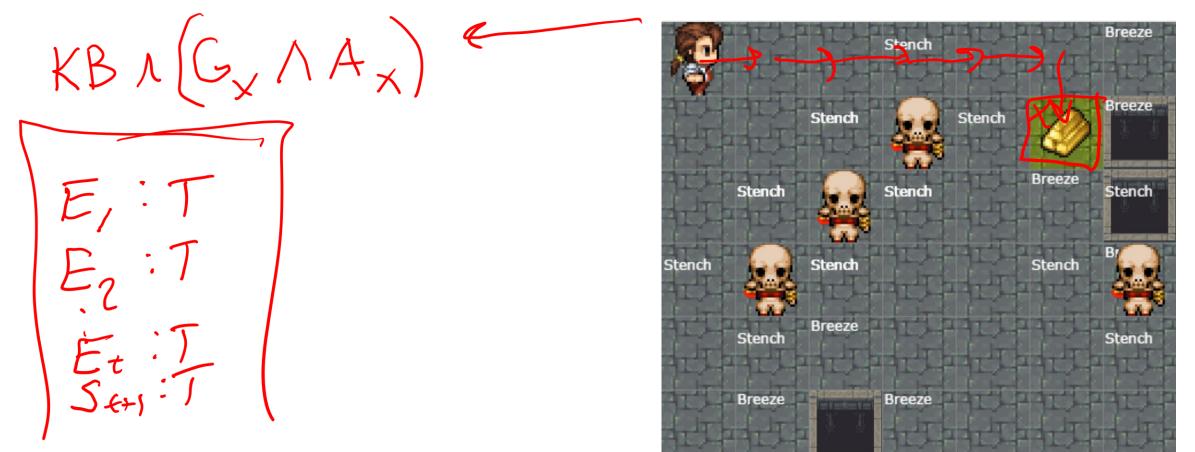
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Satisfiability and Entailment

A sentence is *satisfiable* if it is true in at least one world (e.g. CSPs!)



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Satisfiability and Entailment

A sentence is *satisfiable* if it is true in at least one world (cf CSPs!)

Suppose we have a hyper-efficient SAT solver; how can we use it to test entailment?

- Suppose $\alpha \models \beta$
- Then $\alpha \Rightarrow \beta$ is true in all worlds

KBA79

- Hence $\neg(\alpha \Rightarrow \beta)$ is false in all worlds
- Hence $\alpha \wedge \neg \beta$ is false in all worlds, i.e., unsatisfiable

So, add the negated conclusion to what you know, test for (un)satisfiability; also known as reductio ad absurdum

Efficient SAT solvers operate on *conjunctive normal form*

Efficient SAT solvers

DPLL (Davis-Putnam-Logemann-Loveland) is the core of modern solvers

Essentially a backtracking search over models with some extras:

- Early termination: stop if
 - all clauses are satisfied; e.g., $(A \lor B) \land (A \lor \neg C)$ is satisfied by $\{A=true\}$
 - any clause is falsified; e.g., $(A \lor B) \land (A \lor \neg C)$ is satisfied by $\{A=false, B=false\}$
- Pure literals: if all occurrences of a symbol in as-yet-unsatisfied clauses have the same sign, then give the symbol that value
 - E.g., A is pure and positive in $(A \lor B) \land (A \lor \neg C) \land (C \lor \neg B)$ so set it to true
- Unit clauses: if a clause is left with a single literal, set symbol to satisfy clause
 - E.g., if A=false, $(A \lor B) \land (A \lor \neg C)$ becomes $(false \lor B) \land (false \lor \neg C)$, i.e. $(B) \land (\neg C)$
 - Satisfying the unit clauses often leads to further propagation, new unit clauses, etc.

DPLL algorithm

function DPLL(clauses, symbols, model) returns true or false if every clause in clauses is true in model then return true if some clause in clauses is false in model then return false

P, value ← FIND-PURE-SYMBOL(symbols, clauses, model) if P is non-null then return DPLL(clauses, symbols–P, modelU{P=value})

P, value ← FIND-UNIT-CLAUSE(clauses, model) if P is non-null then return DPLL(clauses, symbols–P, modelU{P=value})

P ← First(symbols) rest ← Rest(symbols)

Outline

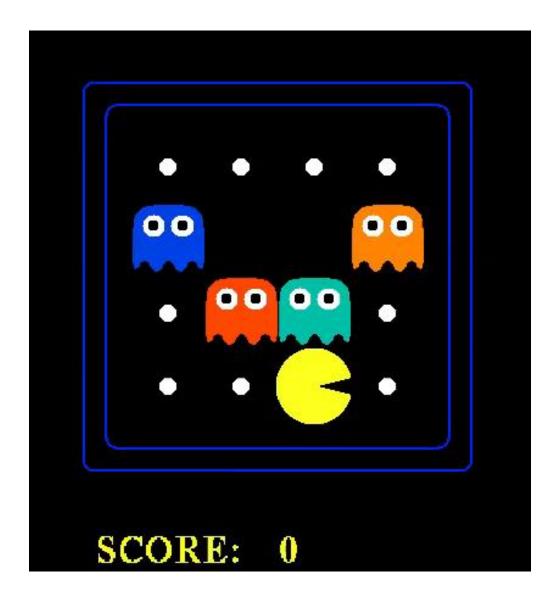
Logical Agent Algorithms

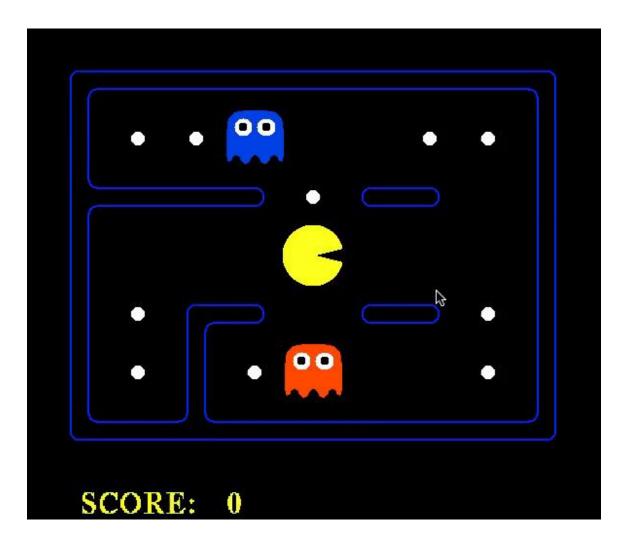
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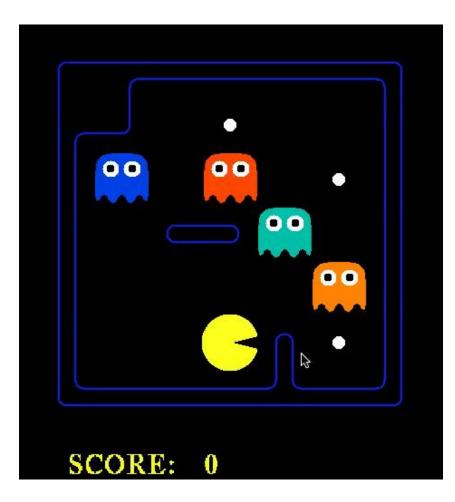
Planning as Satisfiability

Given a hyper-efficient SAT solver, can we use it to make plans?

Yes, for fully observable, deterministic case: planning problem is solvable iff there is some satisfying assignment for actions etc.







Planning as Satisfiability

Given a hyper-efficient SAT solver, can we use it to make plans? Yes, for fully observable, deterministic case: planning problem is $rac{1}{2}$ solvable iff there is some satisfying assignment for actions etc.

For T = 1 to infinity, set up the KB as follows and run SAT solver: Initial state, domain constraints Transition model sentences up to time T For T = 1 to infinity, set up the KB as follows and run SAT solver: $P_{11,0}$ $P_{11,$

- Goal is true at time T
- Precondition axioms: At $1,1_0 \land N_0 \Rightarrow \neg Wall 1,2$ etc.

P=40=T P11.0=T North=T'

• Action exclusion axioms: $\neg(N_0 \land W_0) \land \neg(N_0 \land S_0) \land ...$ etc.

Initial State

The agent may know its initial location:

At_1,1_0

•

Or, it may not:

At_1,1_0 v At_1,2_0 v At_1,3_0 v ... v At_3,3_0

We also need a *domain constraint* – cannot be in two places at once!

- ¬(At_1,1_0 ∧ At_1,2_0) ∧ ¬(At_1,1_0 ∧ At_1,3_0) ∧ ...
- ¬(At_1,1_1 ∧ At_1,2_1) ∧ ¬(At_1,1_1 ∧ At_1,3_1) ∧ ...

Fluents and Effect Axioms

A *fluent* is a state variable that changes over time

How does each *state variable* or *fluent* at each time gets its value?

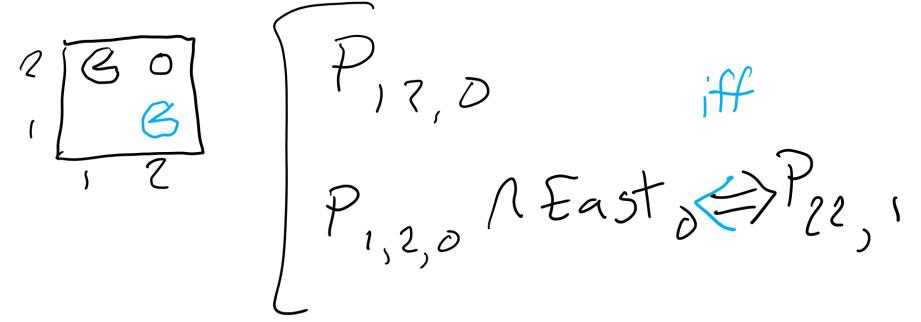
Fluents for PL Pacman are Pacman_x,y_t , e.g., Pacman _3,3_17 Made $P_{1,2,0} \land East_{0} \Longrightarrow P_{22,1}$ $T \land F = T$

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Fluents and Successor-state Axioms

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A state variable gets its value according to a successor-state axiom • $X_t \Leftrightarrow [X_{t-1} \land \neg (\text{some action}_{t-1} \text{ made it false})] \lor [\neg X_{t-1} \land (\text{some action}_{t-1} \text{ made it true})]$ $P_{22,1} \qquad P_{22,0} \qquad (more P) \lor P_{22,0} \land (more P) \lor P_{22,0} \land (more P)]$

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For Pacman location:

■ Pacman _3,3_17 ⇔ [Pacman _3,3_16 ∧ ¬((¬Wall_3,4 ∧ N_16) v (¬Wall_4,3 ∧ E_16) v ...)]

v [¬ Pacman _3,3_16 ^ ((Pacman _3,2_16 ^ ¬Wall_3,3 ^ N_16) v

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