CS3243: Introduction to Artificial Intelligence

Semester 2, 2020

Logical Agents

AIMA Chapter 7

Knowledge-Based Agents

- Until now trying to find an optimal solution via search.
- No real model of what the agent knows.
- This class: represent agent domain knowledge using logical formulas.

Knowledge Base (KB)

Inference Engine

Domain-independent algorithms

Domain-specific content

- Knowledge base = set of sentences in a formal language
- Declarative approach to building an agent (or other system):
 - TELL it what it needs to know
- Then it can Ask itself what to do answers should follow from the KB
- Agents can be viewed at the knowledge level
 i.e., specify knowledge and goals, regardless of implementation
- Or at the implementation level
 - i.e., data structures in KB and algorithms that manipulate them

What is the best action at time t?

What did I perceive at time t?

What happened? function KB-

 $\Gamma(percep)$

urns an action

persistent: K

knowled

nter, in ally 0, indicating time

What have I done?

Tell(KB, Make-Percept-Sentence(percept, t))

 $action \leftarrow Ask(KB, \dot{M}AKE-ACTION-QUERY(t))$

Tell(KB, Make-Action-Sentence(action, t))

 $t \leftarrow t + 1$

return action

The agent must be able to:

- Represent states, actions, etc.
- Incorporate new percepts
- Update internal world representations
- Deduce hidden world properties, and deduce actions

Wumpus World

SS SSS S Stendt S PIT Breeze -– Breeze PIT \$5.555 Stench \$ - Breeze / Breeze / ∕ Breeze -PIT START

Performance Measure?

Environment?

Actuators?

Sensors?

1

4

2

3

4

Performance measure

- gold +1000, death
 1000
- -1 per action, -10 for using the arrow

Actuators

- Turn left/right, Forward
- Shoot: kills wumpus if facing it; uses up the only arrow
- Grab: picks up gold if in same square
- Climb: get out of cave if in [1,1]

Environment

- 4×4 grid of rooms
- agent, wumpus, gold, pits

Sensors

- Squares adjacent to wumpus are smelly
- Squares adjacent to pit are breezy
- Glitter iff gold is in the same square
- Gets bumped if agent walks into a wall
- Hears scream if wumpus killed

Properties of Wumpus World

Fully Observable?	No – only local perception
Deterministic?	Yes
Episodic?	No – sequential actions
Static?	Yes – nothing moves
Discrete?	Yes
Single-Agent?	Yes

Agent's view

1,4	2,4	3,4	4,4
1,3	2,3	3,3	4,3
1,2 OK	² , ² P ?	3,2	4,2
vA OK	BA OK	3,1 P ?	4,1

 \mathbf{A} = Agent

 \mathbf{B} = Breeze

G = Glitter, Gold

OK = Safe Square

 \mathbf{P} = Pit

S = Stench

V = Visited

W = Wumpus

4	SS SSSS Stench S		Breeze	PIT
3		Breeze	PIT	Breeze
2	\$5555 \$Stench\$		Breeze	
1	START	Breeze	Ē	Breeze

3

Agent's view

	1,4	2,4	3,4	4,4
No Breez		2,3	3,3	4,3
No Stench	S A OK	P? OK	3,2	4,2
at [2,1]	vA OK	B OK	3,1 P ?	4,1

 \mathbf{A} = Agent

 \mathbf{B} = Breeze

G = Glitter, Gold

OK = Safe Square

 \mathbf{P} = Pit

S = Stench

V = Visited

W = Wumpus

4	SS SSSS Stench S		Breeze	PIT
3		Breeze	PİT	Breeze /
2	\$5555 \$Stench\$		Breeze	
1	START	Breeze	Ē	Breeze

Agent's view

1,4	2,4	3,4	4,4
1, 3 W !	2,3 A OK	3,3	4,3
S	2,2	3,2	4,2
OK	OK	OK	
V	B V	3,1	4,1
OK	OK	P !	

 \mathbf{A} = Agent

 \mathbf{B} = Breeze

G = Glitter, Gold

OK = Safe Square

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W = Wumpus

4	SS SSSS Stendt		Breeze	PIT
3		Breeze	PIT	Breeze /
2	\$5555 Stench		Breeze	
1	START	Breeze	Ē	Breeze

2

3

4

Agent's view

1,4	2,4	3,4	4,4
1,3 W !	SBG OK	3,3	4,3
S V OK	V OK	3,2 OK	4,2
V OK	B V OK	3,1 P !	4,1

 \mathbf{A} = Agent

 \mathbf{B} = Breeze

G = Glitter, Gold

OK = Safe Square

 \mathbf{P} = Pit

S = Stench

V = Visited

W = Wumpus

4	SS SSSS Signati		Breeze	ЫŢ
3	المراجعة الم	Breeze	PIT	Breeze
2	SS SSS S Stench S		Breeze	
1	START	Breeze	Ē	Breeze

4

Logic in General

- Logic: formal language for KR, infer conclusions
- Syntax: defines the sentences in the language
- Semantics: define the "meaning" of sentences;
 - i.e., define truth of a sentence in a world
- E.g., language of arithmetic
 - $x + 2 \ge y$ is a sentence; x2y + > is not a sentence
 - $x + 2 \ge y$ is true in a world where x = 7, y = 1
 - $x + 2 \ge y$ is false in a world where x = 0, y = 6

Entailment

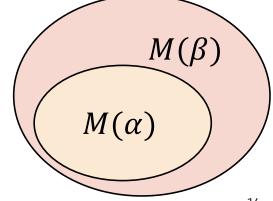
Modeling: m models α if α is true under m. For example, what are models for the following?

$$\alpha = (q \in \mathbb{Z}_+) \land (\forall n, m \in \mathbb{Z}_+: q = nm \Rightarrow n \lor m = 1)$$

- We let $M(\alpha)$ be the set of all models for α
- Entailment means that one thing follows from another:

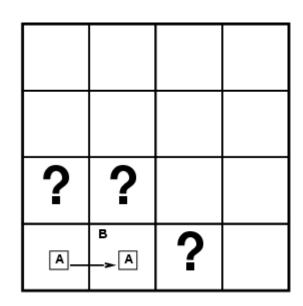
$$\alpha \models \beta$$
 or equivalently $M(\alpha) \subseteq M(\beta)$

For example: $\alpha = (q \text{ is prime}) \text{ entails}$ $\beta = (q \text{ is odd}) \lor (q = 2).$

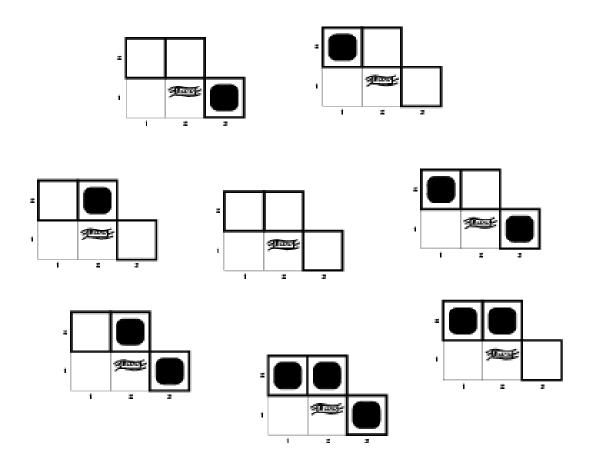


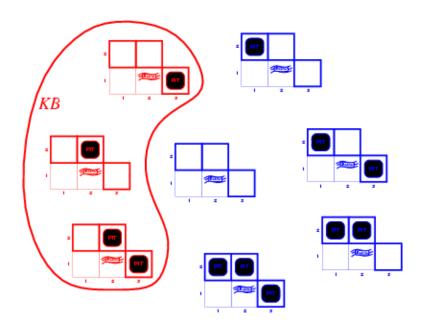
Entailment in the Wumpus World

- Situation after detecting nothing in [1,1], moving right, breeze in [2,1]
- Consider possible models for KB assuming only pits

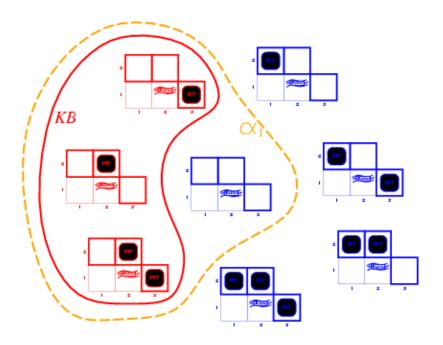


3 Boolean choices ⇒8 possible models

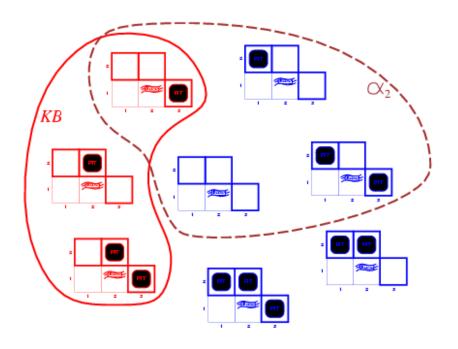




KB = wumpus-world rules + percepts



- KB = wumpus-world rules + percepts
- α_1 = "[1,2] is safe", $KB \models \alpha_1$, proved by model checking
- The agent can infer that [1,2] is safe



- KB = wumpus-world rules + percepts
- α_2 = "[2,2] is safe", $KB \not\models \alpha_2$
- The agent cannot infer that [2,2] is safe (or unsafe)!

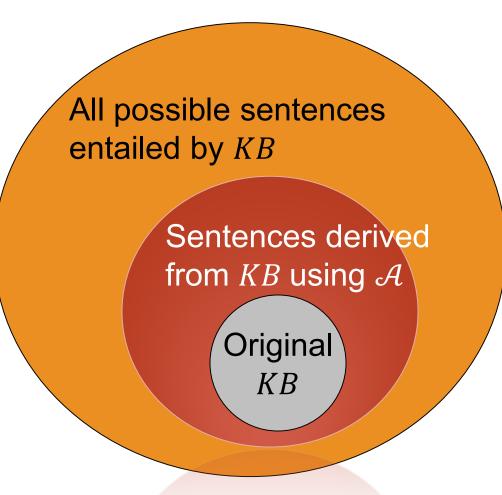
Inference algorithm: is a sentence α is derived from KB?

- Define $KB \vdash_{\mathcal{A}} \alpha$ to be "sentence α is derived from KB by inference algorithm \mathcal{A} "
 - \mathcal{A} is **sound** if $KB \vdash_{\mathcal{A}} \alpha$ implies $KB \vDash \alpha$. "don't infer nonsense"
 - \mathcal{A} is **complete** if $KB \models \alpha$, implies $KB \vdash_{\mathcal{A}} \alpha$. "If it's implied, it can be inferred"

Is an inference algorithm complete and sound?

Completeness: \mathcal{A} is complete if whenever $KB \models \alpha$, it is also true that $KB \vdash_{\mathcal{A}} \alpha$

- An incomplete inference algorithm cannot reach all possible conclusions
- Equivalent to completeness in search (chapter 3)



Propositional Logic: Syntax

- A simple logic illustrates basic ideas
- Defines allowable sentences
- Sentences are represented by symbols e.g. S_1, S_2
- Logical connectives for constructing complex sentences from simpler ones:
 - If S is a sentence, $\neg S$ is a sentence (negation)
 - If S_1 and S_2 are sentences:
 - $S_1 \wedge S_2$ is a sentence (conjunction)
 - $S_1 \vee S_2$ is a sentence (disjunction)
 - $S_1 \Rightarrow S_2$ is a sentence (implication)
 - $S_1 \Leftrightarrow S_2$ is a sentence (biconditional)

Propositional Logic: Semantics

A model is then just a truth assignment to the basic variables.

If a model has *n* variables, how many truth assignments are there?

All other sentences' truth value is derived according to logical rules.

$$x_1 = T; x_2 = F; x_3 = T$$

$$(x_1 \land \neg x_2) \Rightarrow \neg (x_3 \lor (\neg x_1 \land x_2)) = ?$$

Knowledge Base for Wumpus World

- P_{ij} = True \Leftrightarrow there is a pit in [i, j].
- $B_{ij} = \text{True} \Leftrightarrow \text{there is breeze in } [i, j]$
- Rules:
 - $R_1: \neg P_{1,1}$
 - R_4 : $\neg B_{1,1}$
 - $R_5: P_{2,1}$

KB is true iff $\bigwedge_{k=1,\ldots,5} R_k$ is true

- "Pits cause breezes in adjacent squares"
 - $R_2: B_{1,1} \Leftrightarrow (P_{1,2} \vee P_{2,1})$
 - $R_3: B_{2,1} \Leftrightarrow (P_{1,1} \vee P_{2,2} \vee P_{3,1})$

Inference

- Given a knowledge base, infer something nonobvious about the world.
- Mimic logical human reasoning
- After exploring 3 squares, we have some understanding of the Wumpus world
- Inference ⇒ Deriving knowledge out of percepts

Given KB and α , we want to know if $KB \vdash \alpha$

Truth Table for Inference

Is $lpha_1$ true $arphi$	vheneve	r ,1	$P_{1,2}$	$P_{2,1}$	$P_{2,2}$	$P_{3,1}$	KB	α_1
KB is	true?	se	false	false	false	false	false	true
fal.	$se \mid false$	false	false	false	false	true	false	true
:	:	:	:	:	:	:	:	:
fal.	se true	false	false	false	false	false	false	true
fal.	se true	false	false	false	false	true	\underline{true}	\underline{true}
fal.	se $true$	false	false	false	true	false	\underline{true}	\underline{true}
fal.	se true	false	false	false	true	true	\underline{true}	\underline{true}
fal.	se true	false	false	true	false	false	false	true
:	:	:	:	:	:	:	:	:
tru	e true	true	true	true	true	true	false	false

 $R_1: \neg P_{1.1}$

 $\alpha_1 = \neg P_{1,2}$

 R_4 : $\neg B_{1,1}$ Does KB entail α_1 ?

 $R_5: B_{2,1}$

Can we infer that [1,2] is safe from pits?

Inference by Truth-Table Enumeration

- Depth-first enumeration of all models is sound and complete
- For n symbols, time complexity is $\mathcal{O}(2^n)$, space complexity is $\mathcal{O}(n)$

```
inputs: KB, the knowledge base, a sentence in propositional logic
           \alpha, the query, a sentence in propositional logic
  symbols \leftarrow a list of the proposition symbols in K\!B and \alpha
  return TT-CHECK-ALL(KB, \alpha, symbols, \{\})
function TT-CHECK-ALL(KB, \alpha, symbols, model) returns true or false
  if EMPTY?(symbols) then
      if PL-True?(KB, model) then return PL-True?(\alpha, model)
      else return true // when KB is false, always return true
  else do
      P \leftarrow FIRST(symbols)
      rest \leftarrow REST(symbols)
      return (TT-CHECK-ALL(KB, \alpha, rest, model \cup \{P = true\})
              and
              TT-CHECK-ALL(KB, \alpha, rest, model \cup \{P = false \}))
```

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

Check all possible truth assignments

Validity and Satisfiability

A sentence is valid if it is true in all models,

e.g.,
$$True$$
, $A \square A$, $A \Rightarrow A$, $(A \land (A \Rightarrow B)) \Rightarrow B$

Validity is connected to entailment via the Deduction Theorem:

$$KB \models \alpha \text{ iff } (KB \Rightarrow \alpha) \text{ is valid}$$

A sentence is satisfiable if it is true in some model e.g., $A \lor B$, C

A sentence is unsatisfiable if it is true in no models e.g., $A \land \neg A$

Satisfiability is connected to entailment via the following:

 $KB \models \alpha$ if and only if $(KB \land \neg \alpha)$ is unsatisfiable

Proof Methods

Applying inference rules (aka theorem proving)

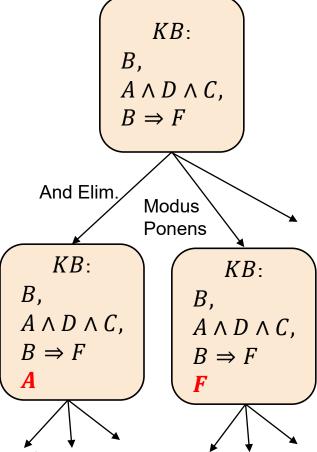
- Generation of new sentences from old
- Proof = sequential application of inference rules
- Inference rules are actions in a search algorithm
- Proof can be more efficient: ignores irrelevant propositions
- Transformation of sentences into a normal form

Model checking

- Truth table enumeration (time complexity exponential in n)
- Improved backtracking, e.g. DPLL
- local search in model space (sound but incomplete), e.g. min-conflicts-like hill-climbing algorithm

Applying Inference Rules

- Equivalent to a search problem
 - States: KBs (initial state is initial KB)
 - Actions: Inference rules
 - Transition: add sentence to current KB
 - Goal: KB contains sentence to prove
- Examples of inference rules
 - And-Elimination (A.E.): $a \land b \models a$
 - Modus Ponens (M.P.): $a \land (a \Rightarrow b) \models b$
 - Logical Equivalences: $(a \lor b) \models \neg(\neg a \land \neg b)$



Resolution for Conjunctive Normal Form (CNF)

- conjunction of "disjunctions of literals" (clauses)
- E.g., $(x_1 \lor \neg x_2) \land (x_2 \lor x_3 \lor \neg x_4)$
- Resolution: if a literal x appears in C_1 and its negation $\neg x$ appears in C_2 , it can be deleted:

$$\frac{(x_1 \vee \cdots \vee x_m \vee x) \wedge (y_1 \vee \cdots \vee y_k \vee \neg x)}{(x_1 \vee \cdots \vee x_m \vee y_1 \vee \cdots \vee y_k)}$$

(delete duplicate variables as necessary)

Resolution is sound and complete for propositional logic

Conversion to CNF: the Rules

- **1.** Convert $\alpha \Leftrightarrow \beta$ to $(\alpha \Rightarrow \beta) \land (\beta \Rightarrow \alpha)$
- **2.** Convert $\alpha \Rightarrow \beta$ to $\neg \alpha \lor \beta$
- 3. Move ¬ inwards using De Morgan and double negation
 - **1.** Convert $\neg(\alpha \lor \beta)$ to $\neg\alpha \land \neg\beta$
 - **2.** Convert $\neg(\alpha \land \beta)$ to $\neg \alpha \lor \neg \beta$
 - 3. Convert $\neg(\neg \alpha)$ to α
- **4.** Convert $(\alpha \lor (\beta \land \gamma))$ to $(\alpha \lor \beta) \land (\alpha \lor \gamma)$

Resolution Algorithm

```
function PL-RESOLUTION(KB, \alpha) returns true or false
  inputs: KB, the knowledge base, a sentence in propositional logic
           \alpha, the query, a sentence in propositional logic
  clauses \leftarrow the set of clauses in the CNF representation of KB \land \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_j)
          if resolvents contains the empty clause then return true
           new \leftarrow new \cup resolvents
                                                          What does an
      if new \subseteq clauses then return false
                                                          empty clause
       clauses \leftarrow clauses \cup new
                                                              imply??
```

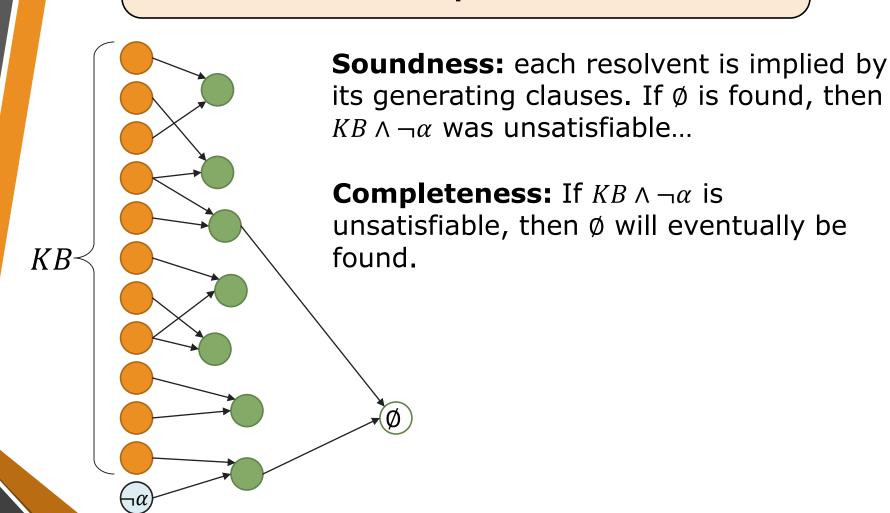
Proof by contradiction: show that $KB \land \neg \alpha$ is unsatisfiable

The resolution algorithm summary: repeatedly resolve two clauses from the list of clauses, and add the the result to list of clauses.

Keep on doing this until the empty clause is found.

Why is Resolution for CNF Sound and Complete?

Why is Resolution for CNF Sound and Complete?



Resolution Example

•
$$KB = (B_{1,1} \Leftrightarrow (P_{1,2} \vee P_{2,1})) \wedge (\neg B_{1,1})$$

$$\bullet \alpha = \neg P_{1,2}$$

Prove that $KB \to \alpha$ via proof by contradiction, i.e. assume that $KB \land \neg \alpha$ holds and resolve to contradiction.

Forward and Backward Chaining

- Horn Form (restricted)
 - KB = conjunction of Horn clauses
 - Horn clause = definite clause or goal clause
 - Definite clause : $\bigwedge_j \alpha_j \Rightarrow \beta$
 - Goal clause : $\bigwedge_{i} \alpha_{i} \Rightarrow False$
 - e.g., $C \land (B \Rightarrow A) \land (C \land D \Rightarrow B)$
- Inference with Horn clauses: forward chaining or backward chaining algorithms. Easy to interpret, run in linear time
- Inference is Modus Ponens (for Horn Form): sound for Horn KB

$$\frac{\alpha_1, \dots, \alpha_k; \Lambda_j \, \alpha_j \Rightarrow \beta}{\beta}$$

Forward Chaining (FC)

• Idea: Fire any rule whose premise is satisfied in the *KB*, add its conclusion to the *KB*, repeat until query is found

KB of horn clauses

$$P \Rightarrow Q$$

$$L \land M \Rightarrow P$$

$$B \land L \Rightarrow M$$

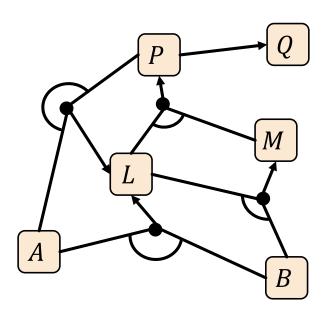
$$A \land P \Rightarrow L$$

$$A \land B \Rightarrow L$$

$$A$$

$$B$$

AND-OR graph



Forward Chaining (FC) Algorithm

- For every rule c, let count(c) be the number of symbols in c's premise.
- For every symbol s, let inferred(s) be initially False
- Let agenda be a queue of symbols (initially containing all symbols known to be true.
- While agenda ≠ Ø:
 - pop a symbol p from agenda; if it is q we're done
 - Set inferred(p) = True
 - For each clause $c \in KB$ such that p is in the premise of c, decrement count(c). If count(c) = 0, add c's conclusion to agenda.

Forward chaining is sound and complete for Horn *KB*

Forward Chaining Example

```
Iteration 1: [A, B]

Iteration 2: [B]

Iteration 3: [] \Rightarrow [L]

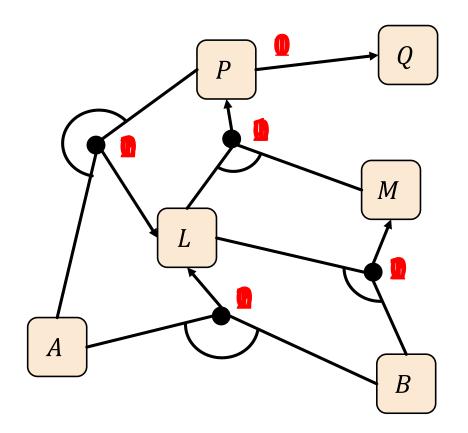
Iteration 4: [] \Rightarrow [M]

Iteration 5: [] \Rightarrow [P]

Iteration 6: [] \Rightarrow [L, Q]

Iteration 7: [Q]
```

Iteration 8: []



Proof of Completeness

FC derives every atomic sentence entailed by Horn *KB*

- 1. Suppose FC reaches a fixed point where no new atomic sentences are derived
- 2. Consider the final state as a model m that assigns true/false to symbols based on the inferred table
- 3. Every clause in the original KB is true in m

$$\alpha_1 \wedge \cdots \wedge \alpha_k \Rightarrow \beta$$

- 4. Hence, m is a model of KB
- 5. If $KB \models q$, then q is true in every model of KB, including m.

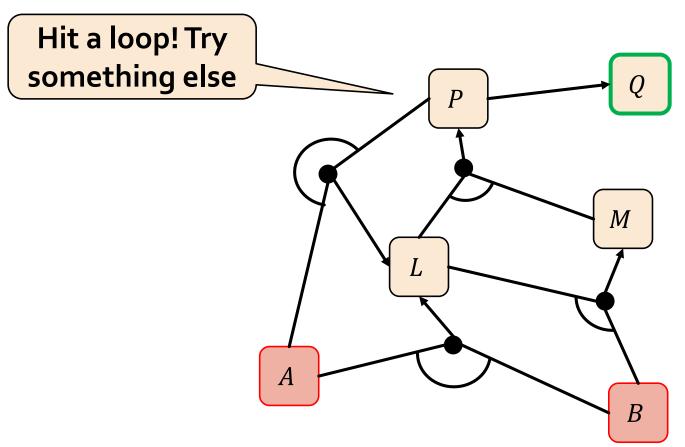
Backward Chaining (BC)

Backtracking depth-first search algorithm

Idea: work backwards from the query q

- To prove q by BC,
 - check if q is known already, or
 - prove by BC the premise of some rule concluding q
- Avoid loops: check if new subgoal is already on the goal stack
- Avoid repeated work: check if new subgoal
 - has already been proven true, or
 - has already failed

Backwards Chaining Example



Forward vs. Backward Chaining

FC = data-driven reasoning

- e.g., object recognition, routine decisions
- May do a lot of work that is irrelevant to the goal

BC = goal-driven reasoning

- e.g., Where are my keys? How do I get into a PhD program?
- Complexity of BC can be sublinear in |KB|.

Proof Methods

Applying inference rules (aka theorem proving)

- Generation of new sentences from old
- Proof = sequential application of inference rules
- Inference rules are actions in a search algorithm
- Proof can be more efficient: ignores irrelevant propositions
- Transformation of sentences into a normal form

Model checking

- Truth table enumeration (time complexity exponential in n)
- Improved backtracking, e.g. DPLL
- local search in model space (sound but incomplete), e.g. min-conflicts-like hill-climbing algorithm

Efficient Propositional Model Checking

Two families of efficient algorithms for propositional model checking:

- Complete backtracking search algorithms
 - DPLL algorithm (Davis, Putnam, Logemann, Loveland)
- Incomplete local search algorithms
 - WALKSAT algorithm

These algorithms test a sentence for satisfiability; used for inference.

Recall: Satisfiability is connected to entailment via

 $KB \models \alpha$ if and only if $(KB \land \neg \alpha)$ is unsatisfiable

DPLL Algorithm

How are DPLL and CSP related?

Determine if a given CNF formula $\phi = C_1 \land \dots \land C_m$ is satisfiable Improvements over truth table enumeration:

- 1. Early termination
 - (a) A clause is true iff any literal in it is true.
 - (b) The formula ϕ is false if any clause is false.
- 2. Pure symbol heuristic

Least constraining value

Pure symbol: always appears with the same "sign" in all clauses.

e.g., in $(A \lor \neg B) \land (\neg B \lor \neg C) \land (C \lor A)$, A and B are pure; C is impure.

Make a pure symbol's literal true: Doing this can never make a clause false.

Ignore clauses that are already true in the model constructed so far.

3. Unit clause heuristic

Most constrained variable

Unit clause: only one literal in the clause.

The only literal in a unit clause must be true.

DPLL Algorithm

```
function DPLL-SATISFIABLE?(s) returns true or false
           inputs: s, a sentence in propositional logic
           clauses \leftarrow the set of clauses in the CNF representation of s
           symbols \leftarrow a list of the proposition symbols in s
                                                                                Early
           return DPLL(clauses, symbols, { })
                                                                            Termination
         function DPLL(clauses, symbols, model) returns true or false
                                                                                Try to apply
           if every clause in clauses is true in model then return true
                                                                                 heuristics
           if some clause in clauses is false in model then return false
           P, value \leftarrow \text{FIND-PURE-SYMBOL}(symbols, clauses, model)
           P is non-null then return DPLL(clauses, symbols -P, model \cup \{P=value\})
If it doesn't
              value \leftarrow FIND-UNIT-CLAUSE(clauses, model)
work, brute
              P is non-null then return DPLL(clauses, symbols - P, model \cup \{P=value\})
  force.
                FIRST(symbols); rest \leftarrow REST(symbols)
           return DPLL(clauses, rest, model \cup {P=true}) or
                   DPLL(clauses, rest, model \cup \{P=false\}))
```

WALKSAT Algorithm

- Incomplete, local search algorithm
- Evaluation function: minimize the number of unsatisfied clauses
- Balance between greediness and randomness

WALKSATAlgorithm

CNF formula: $\phi = C_1 \land \cdots \land C_m$

- 1. Start with a random variable assignment $\ell_1 \dots \ell_n$, where $\ell_i \in \{True, False\}$
- 2. If $\vec{\ell}$ satisfies the formula return $\vec{\ell}$.
- 3. Choose a random unsatisfied clause $C_i \in \phi$
- 4. With probability p flip the truth value of a random symbol $x_i \in C_j$; else flip a symbol $x_i \in C_j$ that maximizes number of satisfied clauses in ϕ .
- 5. Repeat steps 2-4 *MaxFlips* times.

Why is WalkSat incomplete?

How are WALKSAT and local search related?

Inference-Based Agents in the Wumpus World

A wumpus-world agent using propositional logic:

64 distinct proposition symbols, 155 sentences

Expressiveness Limitation of Propositional Logic

- KB contains "physics" sentences for every single square
- For every time t and every location [i, j],

$$L_{i,j}^t \wedge FacingEast^t \wedge Forward^t \Rightarrow L_{i+1,j}^t$$

Rapid proliferation of clauses