Logical Agents

Reading: Russell's Chapter 7

Environments

To design an agent we must specify its task environment.

PEAS description of the task environment:

- Performance
- Environment
- Actuators
- Sensors

Wumpus world PEAS description

Performance measure

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

Environment

Squares adjacent to wumpus are smelly

Squares adjacent to pit are breezy

Glitter iff gold is in the same square

Shooting kills wumpus if you are facing it

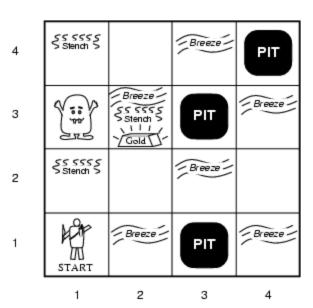
Shooting uses up the only arrow

Grabbing picks up gold if in same square

Releasing drops the gold in same square

Sensors: Stench, Breeze, Glitter, Bump, Scream

Actuators: Left turn, Right turn, Forward, Grab, Release, Shoot



Wumpus world characterization

<u>Fully Observable</u> No – only local perception

Deterministic Yes – outcomes exactly specified

Episodic No – sequential at the level of actions

Static Yes – Wumpus and Pits do not move

Discrete Yes

Single-agent? Yes – Wumpus is essentially a natural feature

A = Agent

B = Breeze

G = Glitter, Gold

OK = Safe square

P = Pit

S = Stench

V = Visited

ок		
OK A	ОК	

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В [OK A		
[OK A	ОК	

```
A = Agent
```

B = Breeze

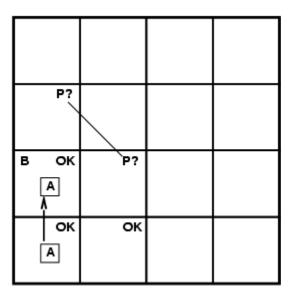
G = Glitter, Gold

OK = Safe square

P = Pit

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V = Visited



A = Agent

B = Breeze

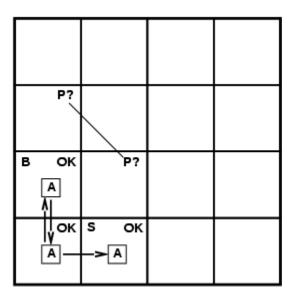
G = Glitter, Gold

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V = Visited



A = Agent

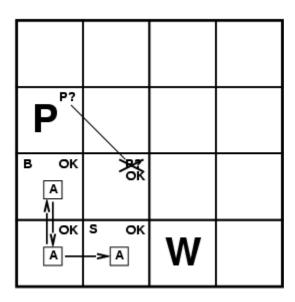
B = Breeze

G = Glitter, Gold OK = Safe square

P = Pit

S = Stench

V = Visited



A = Agent

B = Breeze

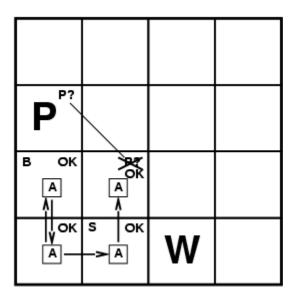
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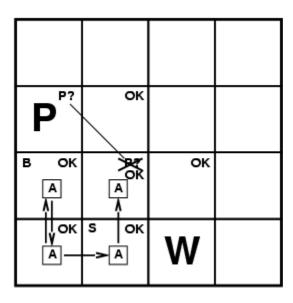
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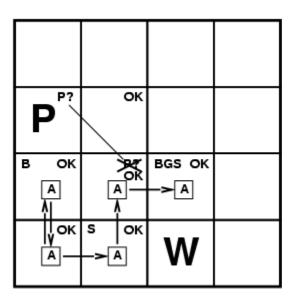
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Logic

- When we have too many states, we want a convenient way of dealing with sets of states.
- The sentence "It's raining" stands for all the states of the world in which it is raining.
- Logic provides a way of manipulating big collections of sets by manipulating short descriptions instead.

Logic

Logics are formal languages for representing information such that conclusions can be drawn

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., the language of arithmetic

```
x+2 \ge y is a sentence; x2+y > \{\} is not a sentence

x+2 \ge y is true iff the number x+2 is no less than the number y

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
```

Propositional logic: Syntax

Propositional logic is the simplest logic – illustrates basic ideas

The proposition symbols P_1 , P_2 etc are sentences

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)

If S_1 and S_2 are sentences, $S_1 \vee S_2$ is a sentence (disjunction)

If S_1 and S_2 are sentences, $S_1 \Rightarrow S_2$ is a sentence (implication)

If S_1 and S_2 are sentences, $S_1 \Leftrightarrow S_2$ is a sentence (biconditional)

Entailment

Entailment means that one thing follows from another:

$$KB \models \alpha$$

Knowledge base KB entails sentence α if and only if α is true in all worlds where KB is true

E.g., the KB containing "the Giants won" and "the Reds won" entails "Either the Giants won or the Reds won"

E.g., x+y = 4 entails 4 = x+y

Entailment is a relationship between sentences (i.e., syntax) that is based on semantics

Semantics

Meaning of a sentence is truth value {t, f}

Interpretation is an assignment of truth values to the propositional variables

 $\models_i \alpha$ [Sentence α is **t** in interpretation i]

 $\not\models_i \alpha$ [Sentence α is \mathbf{f} in interpretation i]

Semantic Rules

```
| true | for all i | false | for all i | the sentence false has truth value f in all interpret. |
```

```
\models_{i} \neg \alpha if and only if \not\models_{i} \alpha

\models_{i} \alpha \land \beta if and only if \not\models_{i} \alpha and \not\models_{i} \beta [conjunction]

\models_{i} \alpha \lor \beta if and only if \not\models_{i} \alpha or \not\models_{i} \beta [disjunction]

\models_{i} P iff i(P) = \mathbf{t}
```

Models

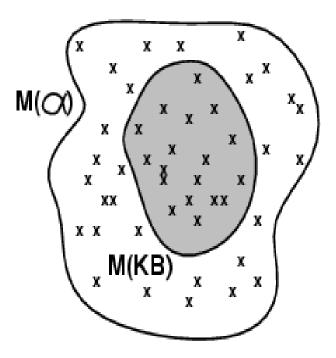
Logicians typically think in terms of models

We say m is a model of a sentence α if α is true in m

 $M(\alpha)$ is the set of all models of α

Then KB $\models \alpha$ iff $M(KB) \subseteq M(\alpha)$

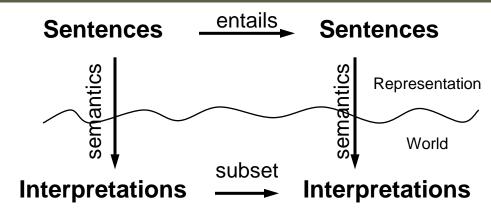
E.g. KB = Giants won and Reds won $\alpha = Giants$ won



Models and Entailment

An interpretation i is a model of a sentence α iff $\models_i \alpha$

A set of sentences KB entails α iff every model of KB is also a model of α



Deduction Theorem:

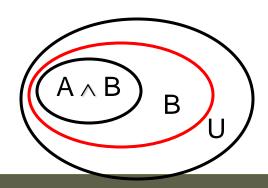
$$KB \models \alpha \text{ iff } \models KB \Rightarrow \alpha$$

KB entails a if and only if (KB $\Rightarrow a$) is valid

$$A \wedge B \models B$$

$$KB = A \wedge B$$

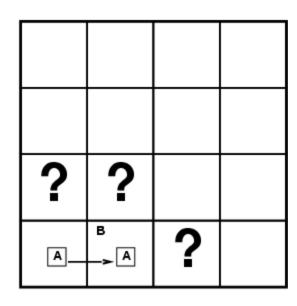
 $a = B$



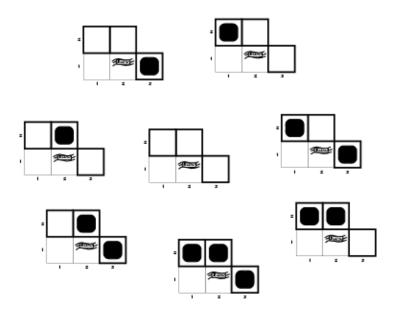
Entailment in the wumpus world

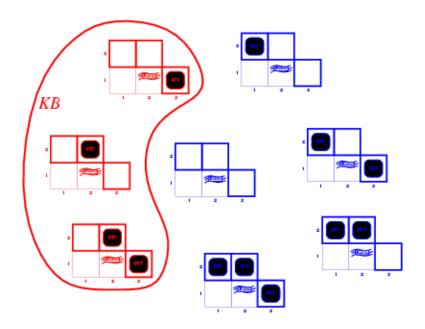
Situation after detecting nothing in [1,1], moving right, breeze in [2,1]

Consider possible models for KB assuming only pits

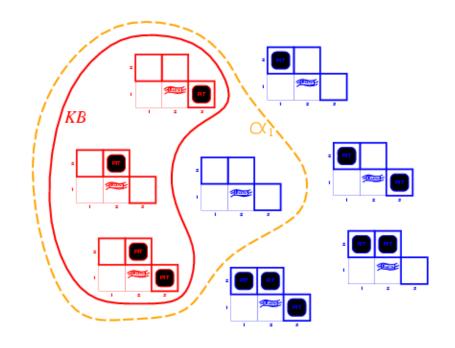


3 Boolean choices ⇒ 8 possible models

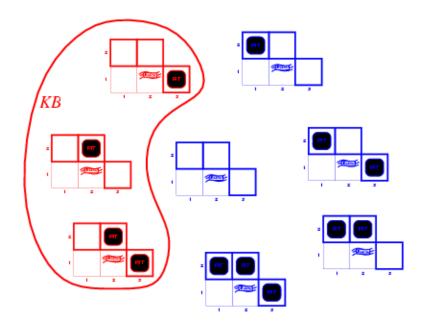




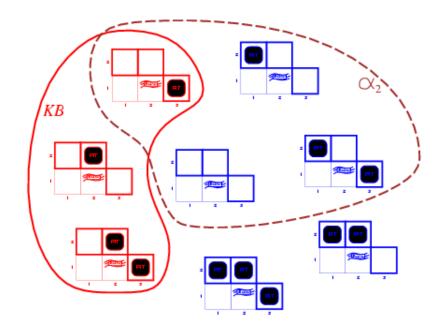
KB = wumpus-world rules + observations



KB = wumpus-world rules + observations α_1 = "[1,2] is safe", $KB \models \alpha_1$, proved by model checking



KB = wumpus-world rules + observations



KB = wumpus-world rules + observations α_2 = "[2,2] is safe", $KB \not\models \alpha_2$

Truth tables for connectives

P	Q	$\neg P$	$P \wedge Q$	$P \lor Q$	$P \Rightarrow Q$	$P \Leftrightarrow Q$
false	false	true	false	false	true	true
false	true	true	false	true	true	false
true	false	false	false	true	false	false
true	true	false	true	true	true	true

Wumpus world sentences

```
Let P_{i,j} be true if there is a pit in [i, j].
Let B_{i,j} be true if there is a breeze in [i, j].
```

Let KB include the following 5 rules:

```
R1: \neg P_{1,1}
R2: B_{1,1} \Leftrightarrow (P_{1,2} \lor P_{2,1})
R3: B_{2,1} \Leftrightarrow (P_{1,1} \lor P_{2,2} \lor P_{3,1})
```

R4: $\neg B_{1,1}$

R5: B_{2.1}

and $\alpha_1 = "[1,2]$ is safe"

Truth tables for inference

$B_{1,1}$	$B_{2,1}$	$P_{1,1}$	$P_{1,2}$	$P_{2,1}$	$P_{2,2}$	$P_{3,1}$	KB	α_1
false	true							
false	false	false	false	false	false	true	false	true
:	:	:	:	:	:	:	:	:
false	true	false	false	false	false	false	false	true
false	true	false	false	false	false	true	\underline{true}	\underline{true}
false	true	false	false	false	true	false	\underline{true}	\underline{true}
false	true	false	false	false	true	true	\underline{true}	\underline{true}
false	true	false	false	true	false	false	false	true
:	:	:	:	:	:	:	:	:
true	false	false						

Inference by enumeration

Depth-first enumeration of all models is sound and complete

```
function TT-Entails?(KB, \alpha) returns true or false
symbols \leftarrow \text{a list of the proposition symbols in } KB \text{ and } \alpha
\text{return TT-Check-All}(KB, \alpha, symbols, [])
function TT-Check-All}(KB, \alpha, symbols, model) returns true or false
\text{if Empty?}(symbols) \text{ then}
\text{if PL-True?}(KB, model) \text{ then return PL-True?}(\alpha, model)
\text{else return } true
\text{else do}
P \leftarrow \text{First}(symbols); rest \leftarrow \text{Rest}(symbols)
\text{return TT-Check-All}(KB, \alpha, rest, \text{Extend}(P, true, model) \text{ and}
\text{TT-Check-All}(KB, \alpha, rest, \text{Extend}(P, false, model)
```

Logical equivalence

Two sentences are logically equivalent iff true in same models: $\alpha \equiv \beta$ iff $\alpha \models \beta$ and $\beta \models \alpha$ $(\alpha \wedge \beta) \equiv (\beta \wedge \alpha)$ commutativity of \wedge $(\alpha \vee \beta) \equiv (\beta \vee \alpha)$ commutativity of \vee $((\alpha \land \beta) \land \gamma) \equiv (\alpha \land (\beta \land \gamma))$ associativity of \land $((\alpha \vee \beta) \vee \gamma) \equiv (\alpha \vee (\beta \vee \gamma))$ associativity of \vee $\neg(\neg\alpha) \equiv \alpha$ double-negation elimination $(\alpha \Rightarrow \beta) \equiv (\neg \beta \Rightarrow \neg \alpha)$ contraposition $(\alpha \Rightarrow \beta) \equiv (\neg \alpha \lor \beta)$ implication elimination $(\alpha \Leftrightarrow \beta) \equiv ((\alpha \Rightarrow \beta) \land (\beta \Rightarrow \alpha))$ biconditional elimination $\neg(\alpha \land \beta) \equiv (\neg \alpha \lor \neg \beta)$ de Morgan $\neg(\alpha \lor \beta) \equiv (\neg \alpha \land \neg \beta)$ de Morgan $(\alpha \wedge (\beta \vee \gamma)) \equiv ((\alpha \wedge \beta) \vee (\alpha \wedge \gamma))$ distributivity of \wedge over \vee $(\alpha \vee (\beta \wedge \gamma)) \equiv ((\alpha \vee \beta) \wedge (\alpha \vee \gamma))$ distributivity of \vee over \wedge

Validity and satisfiability

A sentence is valid if it is true in all models, e.g., *True*, $A \lor \neg A$, $A \Rightarrow A$, $(A \land (A \Rightarrow B)) \Rightarrow B$

Validity is connected to the inference via: $KB \models \alpha$ if and only if $(KB \Rightarrow \alpha)$ is valid

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

A sentence is unsatisfiable if it is true in no models e.g., A ^ ¬ A

Satisfiability is connected to the inference via: $KB \models \alpha$ if and only if $(KB \land \neg \alpha)$ is unsatisfiable

Rules of Inference

Rules of Inference

Double Negaton (- -)

$$\begin{array}{c}
P \Rightarrow Q \\
P \\
\hline
\therefore Q
\end{array}$$

Modus Ponens (-⇒)

Reductio Ad Absurdum (+-)

Conditional Proof $(+ \Rightarrow)$

Proof methods

Proof methods divide into (roughly) two kinds:

Application of inference rules

Legitimate (sound) generation of new sentences from old

Proof = a sequence of inference rule applications

Can use inference rules as operators in a standard search algorithm

Typically require transformation of sentences into a normal form

Model checking

truth table enumeration (always exponential in *n*)

improved backtracking, e.g., Davis--Putnam-Logemann-Loveland (DPLL)

heuristic search in model space (sound but incomplete) e.g., hill-climbing like algorithms

Resolution

Conjunctive Normal Form (CNF)

conjunction of disjunctions of literals clauses

E.g.,
$$(A \lor \neg B) \land (B \lor \neg C \lor \neg D)$$

Resolution inference rule (for CNF):

$$I_1 \vee \ldots \vee I_k$$

$$m_1 \vee ... \vee m_n$$

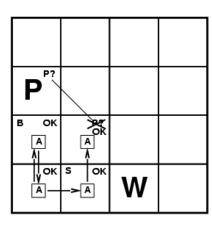
$$\underline{l_1 \vee ... \vee l_{i-1} \vee l_{i+1} \vee ... \vee l_k \vee m_1 \vee ... \vee m_{j-1} \vee m_{j+1} \vee ... \vee m_n}$$

where I_i and m_i are complementary literals.

E.g.,
$$P_{1,3} \vee P_{2,2}$$
, $\neg P_{2,2}$

$$P_{1,3}$$

Resolution is sound and complete for propositional logic



Conversion to CNF

$$B_{1,1} \Leftrightarrow (P_{1,2} \vee P_{2,1})$$

1. Eliminate \Leftrightarrow , replacing $\alpha \Leftrightarrow \beta$ with $(\alpha \Rightarrow \beta) \land (\beta \Rightarrow \alpha)$.

$$(\mathsf{B}_{1.1} \Rightarrow (\mathsf{P}_{1.2} \vee \mathsf{P}_{2.1})) \wedge ((\mathsf{P}_{1.2} \vee \mathsf{P}_{2.1}) \Rightarrow \mathsf{B}_{1.1})$$

2. Eliminate \Rightarrow , replacing $\alpha \Rightarrow \beta$ with $\neg \alpha \lor \beta$.

$$(\neg B_{1,1} \lor P_{1,2} \lor P_{2,1}) \land (\neg (P_{1,2} \lor P_{2,1}) \lor B_{1,1})$$

3. Move \neg inwards using de Morgan's rules and double-negation:

$$(\neg B_{1,1} \lor P_{1,2} \lor P_{2,1}) \land ((\neg P_{1,2} \land \neg P_{2,1}) \lor B_{1,1})$$

4. Apply distributivity law (∧ over ∨) and flatten:

$$(\neg B_{1,1} \lor P_{1,2} \lor P_{2,1}) \land (\neg P_{1,2} \lor B_{1,1}) \land (\neg P_{2,1} \lor B_{1,1})$$

Resolution algorithm

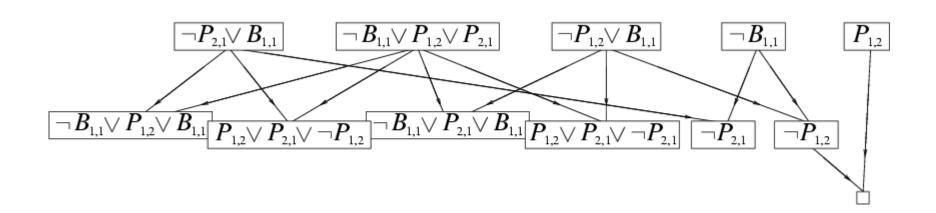
Proof by contradiction, i.e., show $KB \land \neg \alpha$ unsatisfiable

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

Resolution example

$$KB = (B_{1,1} \Leftrightarrow (P_{1,2} \lor P_{2,1})) \land \neg B_{1,1}$$

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



Propositional Resolution - An Example

$$(P \land Q) \Rightarrow R$$

$$(S \vee T) \Rightarrow Q$$

T

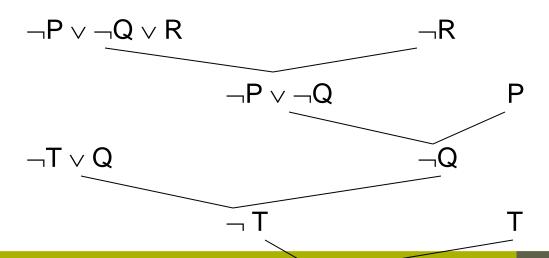
$$P$$
 $\neg P \lor \neg Q \lor R$

$$\neg S \vee Q$$

$$\neg T \vee Q$$

(5)

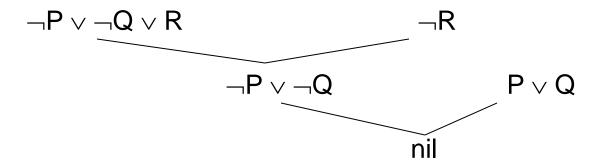
Prove R:



Propositional Resolution – Only Select One Pair to Resolve

$$P \lor Q \qquad (1)$$
$$\neg P \lor \neg Q \lor R \qquad (2)$$

Prove R:



But is R entailed by the two facts we have been given?

Forward and backward chaining

Horn Form (restricted)

KB = conjunction of Horn clauses

```
Horn clause = proposition symbol; or (conjunction of symbols) \Rightarrow symbol E.g., C \land (B \Rightarrow A) \land (C \land D \Rightarrow B)
```

Modus Ponens (for Horn Form): complete for Horn KBs

$$\alpha_1, \ldots, \alpha_n, \qquad \qquad \alpha_1 \wedge \ldots \wedge \alpha_n \Rightarrow \beta$$

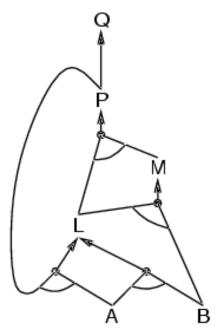
Can be used with forward chaining or backward chaining. These algorithms are very natural and run in linear time

Forward chaining

Idea: fire any rule whose premises are satisfied in the *KB*,

add its conclusion to the KB, until query is found

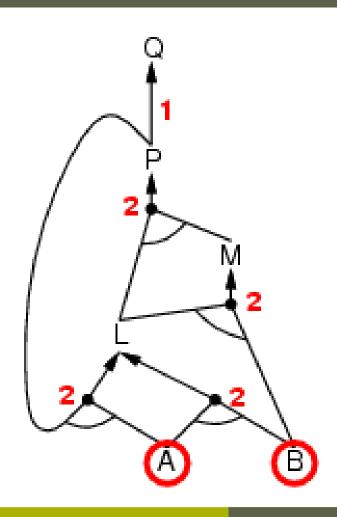
$$P \Rightarrow Q$$
 $L \land M \Rightarrow P$
 $B \land L \Rightarrow M$
 $A \land P \Rightarrow L$
 $A \land B \Rightarrow L$
 A

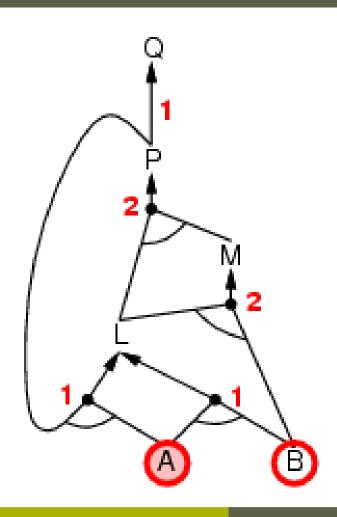


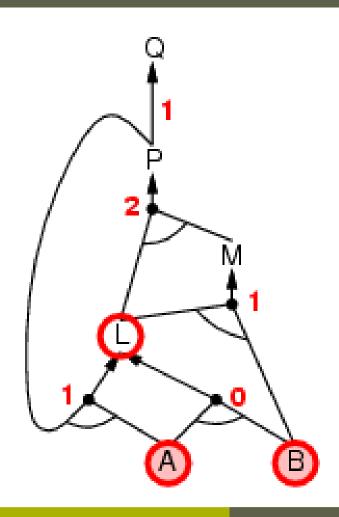
Forward chaining algorithm

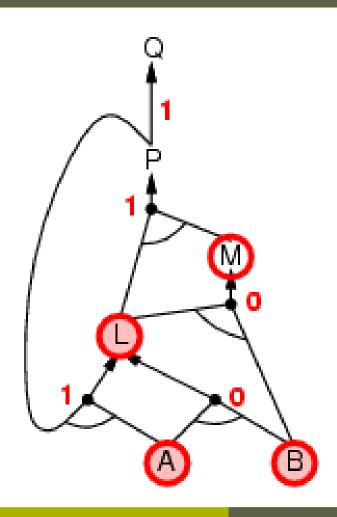
```
function PL-FC-ENTAILS? (KB, q) returns true or false
  local variables: count, a table, indexed by clause, initially the number of premises
                         inferred, a table, indexed by symbol, each entry initially false
                        agenda, a list of symbols, initially the symbols known to be true
   while agenda is not empty do
         p \leftarrow \text{Pop}(agenda)
        unless inferred[p] do
              inferred[p] \leftarrow true
              for each Horn clause c in whose premise p appears do
                   decrement count[c]
                   \mathbf{if} \; \mathit{count}[\mathit{c}] = \mathbf{0} \; \mathbf{then} \; \mathbf{do}
                        if HEAD[c] = q then return true
                        Push(Head[c], agenda)
   return false
```

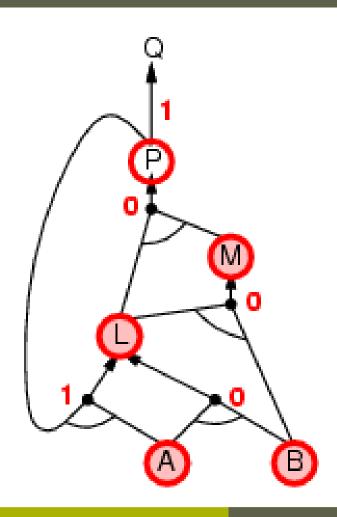
Forward chaining is sound and complete for Horn KB

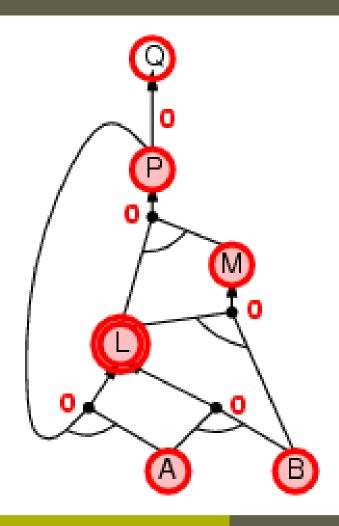


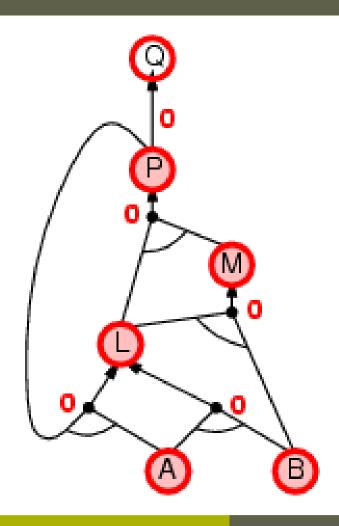


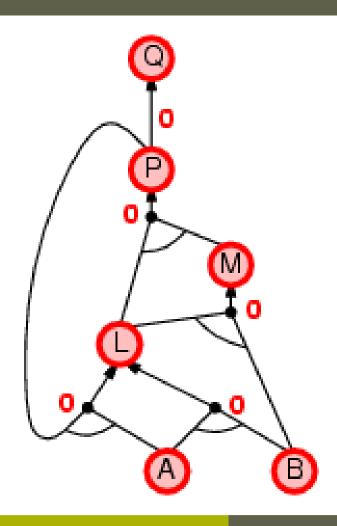












Backward chaining

Idea: work backwards from the query *q*:

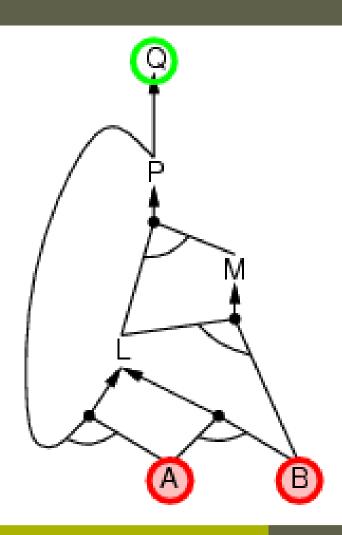
to prove q by BC, check if q is known already, or prove by BC all premises of some rule concluding q

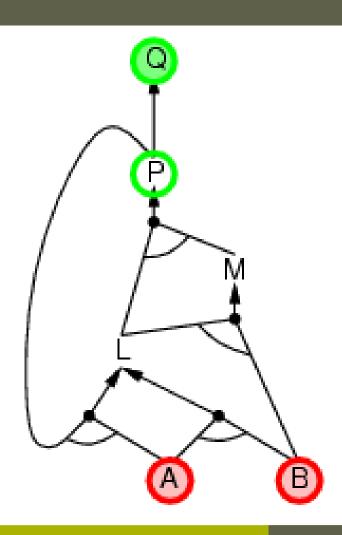
Avoid loops: check if new subgoal is already on the goal stack

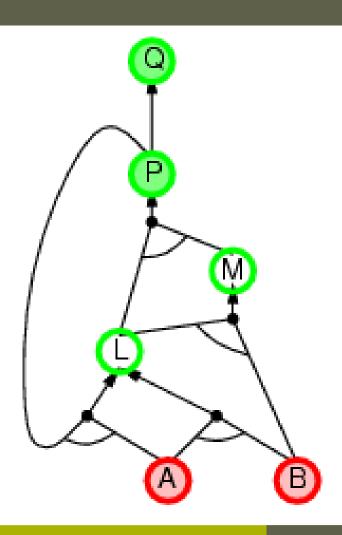
Avoid repeated work: check if new subgoal

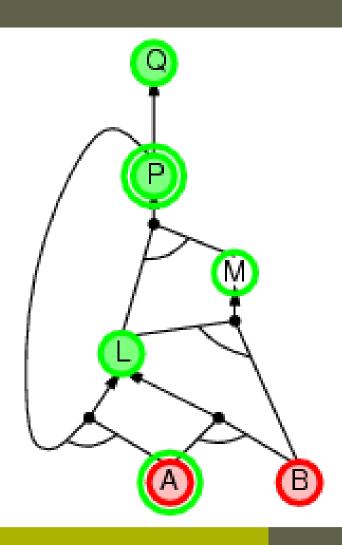
has already been proved true, or

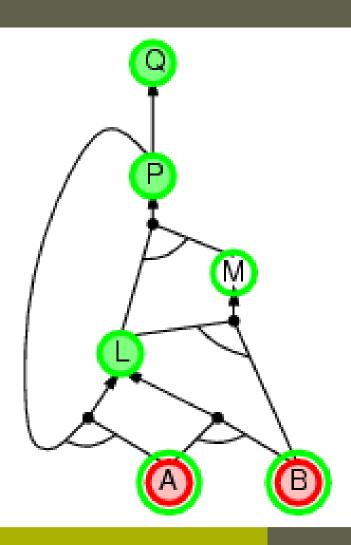
has already failed

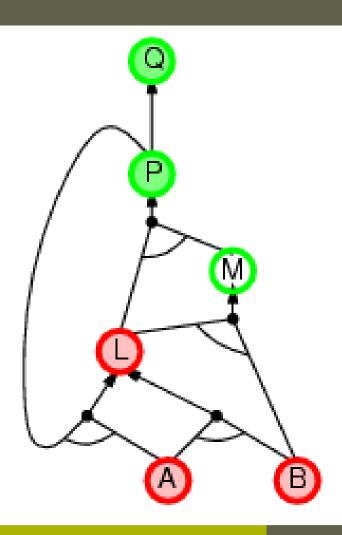


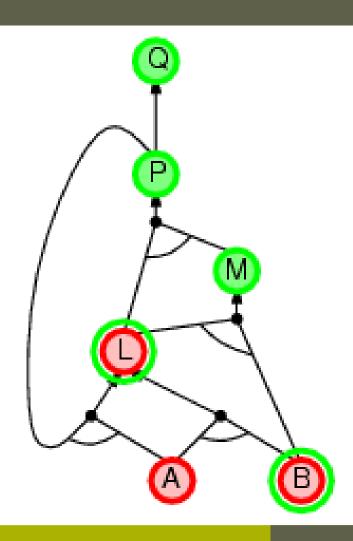


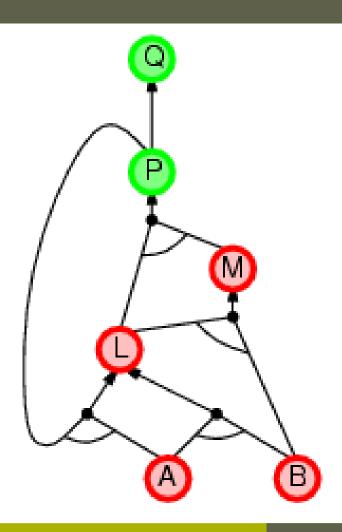


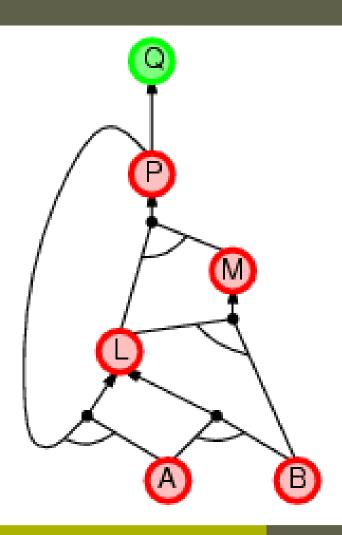


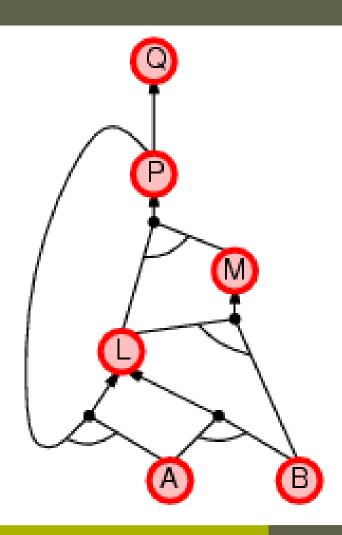












Forward vs. backward chaining

FC is data-driven, automatic, unconscious processing

May do lots of work that is irrelevant to the goal

BC is goal-driven, appropriate for problem-solving

Complexity of BC can be much less than linear in the size of KB

Efficient propositional inference

Two families of efficient algorithms for propositional inference:

Complete backtracking search algorithms

DPLL algorithm (Davis, Putnam, Logemann, Loveland)

Incomplete local search algorithms
WalkSAT algorithm

The DPLL algorithm

Determine if an input propositional logic sentence (in CNF) is satisfiable.

Improvements over truth table enumeration:

1. Early termination

A clause is true if any literal is true. A sentence is false if any clause is false.

2. Pure symbol heuristic

Pure symbol: always appears with the same "sign" in all clauses. e.g., In the three clauses (A $\vee \neg$ B), (\neg B $\vee \neg$ C), (C \vee A), A and B are pure, C is impure. Make a pure symbol literal true.

3. Unit clause heuristic

Unit clause: only one literal in the clause The only literal in a unit clause must be true.

The 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
   return DPLL(clauses, symbols, [])
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 \leftarrow \text{Find-Pure-Symbol}(symbols, clauses, model)
   if P is non-null then return DPLL(clauses, symbols-P, [P = value | model])
   P, value \leftarrow \text{FIND-UNIT-CLAUSE}(clauses, model)
    \textbf{if } P \textbf{ is non-null then return } \mathrm{DPLL}(\mathit{clauses}, \mathit{symbols-}P, [P = \mathit{value}|\mathit{model}]) 
   P \leftarrow \text{First}(symbols); rest \leftarrow \text{Rest}(symbols)
   return DPLL(clauses, rest, [P = true | model]) or
            DPLL(clauses, rest, [P = false | model])
```

The WalkSAT algorithm

Incomplete, local search algorithm

Evaluation function: The min-conflict heuristic of minimizing the number of unsatisfied clauses

Balance between greediness and randomness

The WalkSAT algorithm

```
function WalkSAT(clauses, p, max-flips) returns a satisfying model or failure inputs: clauses, a set of clauses in propositional logic p, the probability of choosing to do a "random walk" move max-flips, number of flips allowed before giving up model \leftarrow a random assignment of true/false to the symbols in clauses for i=1 to max-flips do if model satisfies clauses then return model clause \leftarrow a randomly selected clause from clauses that is false in model with probability p flip the value in model of a randomly selected symbol from clause else flip whichever symbol in clause maximizes the number of satisfied clauses return failure
```