

Artificial Intelligence

4. Propositional Logic

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Artificial Intelligence



- 1. Syntax
- 2. Semantics
- 3. Formal Proofs
- 4. Normal Forms
- 5. Resolution
- 6. Propositional Horn Formulas
- 7. Entailment by Model Checking
- 8. A Silly Example

What is propositional logic?



In propositional logic, atomic formulas are propositions, i.e., assertions such as

A := "'Aristotle is dead."'

B := "'Hildesheim is on the Rhine."'

C := "'Logic is fun."'

Atomic formulas are denoted by capital letters A, B, C, etc.

Each atomic formula is assigned a truth value: true (1) or false (0). (In fuzzy logic truth values can be degrees between 0 and 1.)

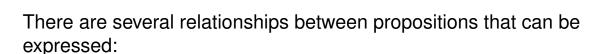
"'Propositional logic is not the study of truth, but of the relationship between the truth of one statement and that of another"' (Hedman 2004).

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Artificial Intelligence / 1. Syntax

What is propositional logic?



word	symbol	example		terminus technicus
not	\neg	not A	$\neg A$	negation
and	\wedge	A and B	$A \wedge B$	conjunction
or	\vee	$A ext{ or } B$	$A \vee B$	disjunction
implies	\rightarrow	A implies B		implication
if and only if	\longleftrightarrow	A if and only if B	$A \leftrightarrow B$	biconditional

What is propositional logic?



The natural language words may have slightly different meanings.

Example:

 $A \wedge B$ and $B \wedge A$ should always have the same meaning.

But the sentences

She became sick and she went to the doctor.

and

She went to the doctor and she became sick.

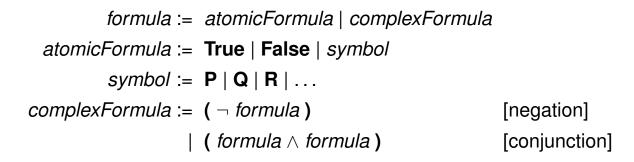
have different meanings.

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Artificial Intelligence / 1. Syntax

Syntax



[positive literal] the same as atomicFormula.

[negative literal] ¬ P where P is an atomic formula.

Formulas also are called sentences or propositions.

Syntax



Let S be a set of atomic formulas.

 $\mathcal{F}(\mathcal{S})$ denotes the set of formulas over $\mathcal{S},$ i.e., the smallest set

- that contains \mathcal{S} : $\mathcal{S} \subseteq \mathcal{F}$,
- is closed under \neg : for all $F \in \mathcal{F}$, also $\neg F \in \mathcal{F}$, and
- is closed under \land : for all $F, G \in \mathcal{F}$, also $F \land G \in \mathcal{F}$.

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Artificial Intelligence / 1. Syntax

Syntax / Abbreviations



Some additional operators are introduced as abbreviations of some complex formulas:

$$\begin{array}{ll} A \vee B := & \neg(\neg A \wedge \neg B) \\ \\ A \to B := & \neg A \vee B \\ \\ A \leftrightarrow B := & (A \to B) \wedge (B \to A) \\ \\ = \neg(\neg \neg A \wedge \neg B) \wedge \neg(\neg \neg B \wedge \neg A) \end{array}$$

Syntax / Bracket Simplification (1/2)



The formal syntax makes extensive use of brackets to make grouping unambiguous:

$$(((\neg P) \lor (Q \land R)) \Rightarrow S)$$

With the usual precedence rules

from highest to lowest: \neg , \wedge , \vee , \Rightarrow , \Leftrightarrow

many brackets can be droppend and formulas be simplified:

$$\neg P \lor Q \land R \Rightarrow S$$

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Artificial Intelligence / 1. Syntax

Syntax / Bracket Simplification (2/2)



Chaining of the same operator still is ambiguous on syntactic level.

The formulas

$$P \wedge Q \wedge R$$
 and $P \vee Q \vee R$ and $P \Leftrightarrow Q \Leftrightarrow R$

can safely be used as the semantics (see below) of both possible groupings

$$(P \wedge Q) \wedge R$$
 and $P \wedge (Q \wedge R)$

is the same.

But

$$P\Rightarrow Q\Rightarrow R$$

is not allowed because the semantics depends on the grouping.

Subformulas



Subformulas of a formula F are substrings that are formulas (if all parentheses are present).

But beware if you omit parentheses! $(A \wedge B \text{ is a substring of } \neg A \wedge B, \text{ but not a subformula!})$

Subformulas also can be recursively defined by

$$\mathsf{subformula}(F) := \left\{ \begin{array}{ll} \{F\}, & \text{if } F \text{ is atomic} \\ \{\neg G\} \cup \mathsf{subformula}(G), & \text{if } F = \neg G \\ \{G \land H\} \cup \mathsf{subformula}(G) \cup \mathsf{subformula}(H), & \text{if } F = G \land H \end{array} \right.$$

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Assignments



Let S be a set of atomic formulas.

A function $\mathcal{A}:\mathcal{S}\to\{0,1\}$ is called an **assignment of** \mathcal{S} or a **model of** \mathcal{S} .

Assignments of complex formulas are defined in terms of assignments of their subformulas:

$$\mathcal{A}(\neg F) := 1 - \mathcal{A}(F)$$
$$\mathcal{A}(F \land G) := \mathcal{A}(F)\mathcal{A}(G)$$

These functions usually are presented as truth tables:

$$\begin{array}{c|c} F & \neg F \\ \hline 0 & 1 \\ 1 & 0 \end{array}$$

F	G	$F \wedge G$
0	0	0
0	1	0
1	0	0
_1	1	1

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Artificial Intelligence / 2. Semantics

Assignments



This way, assignments are extended from $\mathcal{A}:\mathcal{S}\to\{0,1\}$ unambiguously to

$$\mathcal{A}: \mathcal{F}(\mathcal{S}) \to \{0,1\}$$

Assignments can even be extended to some formulas not in $\mathcal{F}(\mathcal{S})$, but say in $\mathcal{F}(\mathcal{S} \cup \mathcal{S}')$ with some additional atomic formulas \mathcal{S}' :

Let
$$F \in \mathcal{F}(\mathcal{S} \cup \mathcal{S}')$$
.

If for every extension of \mathcal{A} to $\mathcal{S} \cup \mathcal{S}'$ — i.e., every assignment \mathcal{A}' of $\mathcal{S} \cup \mathcal{S}'$ with $\mathcal{A}'|_{\mathcal{S}} = \mathcal{A}$ — $\mathcal{A}'(F)$ has the same value, then $\mathcal{A}(F) := \mathcal{A}'(F)$.

Assignments



Example:

Let $S := \{A, B\}$

and A(A) := 1 and A(B) := 0 an assignment on S.

Then

$$\mathcal{A}(A \land B) = 0$$

$$\mathcal{A}(A \lor B) = 1$$

$$\mathcal{A}(A \land (C \lor \neg C)) = 1$$

$$\mathcal{A}(A \land C \land \neg C) = 0$$

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Artificial Intelligence / 2. Semantics

Validity, Satisfiability, Contradiction

If A(F) = 1, we say

- -F holds under assignment \mathcal{A} or
- $-\mathcal{A}$ models F

and write

$$\mathcal{A} \models F$$

A formula F is called

valid / a tautology, written $\models F$

if it holds under every assignment.

satisfiable

if it holds under some assignment.

unsatisfiable / a contradiction

if it holds under no assignment.

Examples:

 $C \vee \neg C$ is valid.

 $C \wedge \neg C$ is unsatisfiable.

Decision problems



Given a formula $F \in \mathcal{F}(S)$, decide if

- -F is valid?
- -F is satisfiable?

Simple algorithm:

enumerate all possible assignments A of S and compute A(F).

if A(F) = 1 for all A, F is valid.

if A(F) = 1 for at least one A, F is satisfiable.

otherwise F is unsatisfiable.

If F has n different atomic subformulas, the runtime complexity of exhaustive enumeration is $O(2^n)$.

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Artificial Intelligence / 2. Semantics

Consequence / Entailment



Let $F, G \in \mathcal{F}(\mathcal{S})$ be two formulas.

G is said to be a consequence of F or F to entail G

$$F \models G$$

if for every assignment A under which F holds, also G holds, i.e., if $A \models F$, then $A \models G$.

Lemma 1. $F \models G$ if and only if $\models F \rightarrow G$

Proof.

$$\not \models F \to G \text{, i.e., there exists an assignment } \mathcal{A} \text{ with } \mathcal{A}(F \to G) = 0 \\ \Leftrightarrow 1 = \mathcal{A}(\neg(F \to G)) = \mathcal{A}(\neg(\neg F \lor G)) = \mathcal{A}(F \land \neg G) \\ \Leftrightarrow \mathcal{A}(F) = 1 \text{ and } \mathcal{A}(\neg G) = 1, \\ \text{i.e., } \mathcal{A} \models F \text{ but not } \mathcal{A} \models G, \\ \text{i.e., } F \not \models G.$$

Equivalence



Let $F, G \in \mathcal{F}(\mathcal{S})$ be two formulas. G is said to be **equivalent to** F

$$F \equiv G$$

if G is a consequence of F and F is a consequence of G.

Examples:

$$\begin{array}{ll} F \wedge (G \vee H) \ \equiv (F \wedge G) \vee (F \wedge H) \ \ \mbox{[distributivity rule]} \\ F \vee (G \wedge H) \ \equiv (F \vee G) \wedge (F \vee H) \ \ \mbox{[distributivity rule]} \\ \neg (F \wedge G) \ \ \equiv \neg F \vee \neg G \ \ \ \mbox{[DeMorgan's rule]} \\ \neg (F \vee G) \ \ \equiv \neg F \wedge \neg G \ \ \ \mbox{[DeMorgan's rule]} \end{array}$$

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Artificial Intelligence / 2. Semantics

Consequences / Entailment of Theories



Let $\mathcal{F} \subseteq \mathcal{F}(\mathcal{S})$ be a set of formulas (also called a **theory** or a **knowledge base**).

An assignment \mathcal{A} models \mathcal{F}

$$\mathcal{A} \models \mathcal{F}$$

if it models every $F \in \mathcal{F}$.

A formula $G \in \mathcal{F}(\mathcal{S})$ is said to be a consequence of theory \mathcal{F} or a theory \mathcal{F} to entail G

$$\mathcal{F} \models G$$

if every assignment \mathcal{A} that models \mathcal{F} , also models G, i.e., if $\mathcal{A} \models \mathcal{F}$, then $\mathcal{A} \models G$.

If
$$\mathcal{F} = \{F_1, F_2, \dots, F_n\}$$
 is finite, then
$$\mathcal{A} \models \{F_1, F_2, \dots, F_n\} \Leftrightarrow \mathcal{A} \models F_1 \land F_2 \land \dots \land F_n$$

The Consequence Problem



Given two formulas F and G, decide if G is a consequence of F: $F \models G$?

Given a theory \mathcal{F} and a formula G, decide if G is a consequence of \mathcal{F} : $\mathcal{F} \models G$?

The problem for finite theories can be reduced to the problem for a single formula via conjunction.

But as for the other problems, exhaustive enumeration is $O(2^n)$ in the number n of atomic formulas.

But what to do if \mathcal{F} is infinite?

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Example (1/2)



Example:

Let

$$\mathcal{F} := \{A, A \to B, B \to C, C \to D, D \to E, E \to F, F \to G\}$$

and say we want to decide if $\mathcal F$ entails $F\vee G$?

There are $2^7 = 128$ different assignments for $S = \{A, B, \dots, G\}$ that would have to be checked separately.

assignment ${\cal A}$	theory ${\mathcal F}$		
A B C D E F G	$ A \to B B \to C C \to D D \to E E \to F F \to G $	$F \vee G$	
0 0 0 0 0 0 0	0 1 1 1 1 1	0	
0 0 0 0 0 0 1		1	
:	i :	:	
1 0 0 0 0 0 0	$egin{array}{cccccccccccccccccccccccccccccccccccc$	0	
i	: ·	:	
1 1 1 1 1 1 0	$egin{array}{cccccccccccccccccccccccccccccccccccc$	1	
1 1 1 1 1 1 1		1	

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Artificial Intelligence / 3. Formal Proofs

Example (2/2)



Example:

Let

$$\mathcal{F}:=\{A,A\to B,B\to C,C\to D,D\to E,E\to F,F\to G\}$$

and say we want to decide if \mathcal{F} entails $F \vee G$?

On the other hand, we could derive $F \vee G$ from the formulas $\mathcal F$ step by step via

$$A, A \rightarrow B$$
 therefore B

$$B, B \rightarrow C$$
 therefore C

$$C, C \rightarrow D$$
 therefore D

$$D, D \rightarrow E$$
 therefore E

$$E, E \rightarrow F$$
 therefore F

F therefore
$$F \vee G$$

Proofs



Let \mathcal{F} be a set of formulas and G be a formula.

 $\mathcal{F} \vdash G$ denotes that formula G can be derived from formulas \mathcal{F} .

A **proof system** consists of a set of **derivation rules** r that state which derivations follow from which other derivations (parametrized by variables for subformulas).

A **proof for** $\mathcal{F} \models G$ is a sequence of derivations

$$\mathcal{F}_1 \vdash G_1$$

$$\mathcal{F}_2 \vdash G_2$$

$$\vdots$$

$$\mathcal{F}_n \vdash G_n$$

such that each derivation follows from earlier derivations by some rule.

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Artificial Intelligence / 3. Formal Proofs

Example (1/2)



Let the proof system consist of just three rules:

premise	conclusion	name
$F \in \mathcal{F}$	$\mathcal{F} \vdash F$	assumption
$\mathcal{F} \vdash F$	$\mathcal{F} \vdash F \vee G$	∨-introduction
$\mathcal{F} \vdash F, \mathcal{F} \vdash F \to G$	$\mathcal{F} \vdash G$	$\rightarrow \text{-elimination}$

Example (2/2)



The we can proof $F \vee G$ from

$$\mathcal{F} := \{A, A \to B, B \to C, C \to D, D \to E, E \to F, F \to G\}$$

by

- 1. $\mathcal{F} \vdash A$ [assumption]
- 2. $\mathcal{F} \vdash A \rightarrow B$ [assumption]
- 3. $\mathcal{F} \vdash B$ [\rightarrow -elimination applied to 1,2]
- 4. $\mathcal{F} \vdash B \rightarrow C$ [assumption]
- 5. $\mathcal{F} \vdash C$ [\rightarrow -elimination applied to 3,4]
- 6. $\mathcal{F} \vdash C \rightarrow D$ [assumption]
- 7. $\mathcal{F} \vdash D$ [\rightarrow -elimination applied to 5,6]
- 8. $\mathcal{F} \vdash D \rightarrow E$ [assumption]
- 9. $\mathcal{F} \vdash E$ [\rightarrow -elimination applied to 7,8]
- 10. $\mathcal{F} \vdash E \rightarrow F$ [assumption]
- 11. $\mathcal{F} \vdash F$ [\rightarrow -elimination applied to 9,10]
- 12. $\mathcal{F} \vdash F \lor G$ [\lor -introduction applied to 11]

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Artificial Intelligence / 3. Formal Proofs

Basic rules for derivation



premise	conclusion	name
$G \in \mathcal{F}$	$\mathcal{F} \vdash G$	assumption
$\mathcal{F} \vdash G, \mathcal{F} \subseteq \mathcal{F}'$	$\mathcal{F}' \vdash G$	monotonicity
$\mathcal{F} \vdash \neg \neg G$	$\mathcal{F} \vdash G$	double negation
$\overline{\mathcal{F} \vdash F, \mathcal{F} \vdash G}$	$\mathcal{F} \vdash F \land G$	∧-introduction
$\mathcal{F} \vdash F \land G$	$\mathcal{F} \vdash F$	\wedge -elimination
$\mathcal{F} \vdash F \land G$	$\mathcal{F} \vdash G \land F$	∴-symmetry
$F \vdash F$	$\mathcal{F} \vdash F \lor G$	∨-introduction
$\mathcal{F} \vdash F \land G$,		
$\mathcal{F} \cup \{F\} \vdash H, \mathcal{F} \cup \{G\} \vdash H$	$\mathcal{F} \vdash H$	∨-elimination
$\mathcal{F} \vdash F \lor G$	$\mathcal{F} \vdash G \lor F$	∨-symmetry
$\overline{\mathcal{F} \cup \{F\} \vdash G}$	$\mathcal{F} \vdash F \to G$	→ -introduction
$\mathcal{F} \vdash F, \mathcal{F} \vdash F \to G$	$\mathcal{F} \vdash G$	ightarrow -elimination
$F \vdash F$	$\mathcal{F} \vdash (F)$	()-introduction
$\mathcal{F} \vdash (F)$	$\mathcal{F} \vdash F$	()-elimination
$\mathcal{F} \vdash ((F \land G) \land H)$	$\mathcal{F} \vdash F \land G \land H$	\land -parentheses rule
$\mathcal{F} \vdash ((F \lor G) \lor H)$	$\mathcal{F} \vdash F \lor G \lor H$	∨-parentheses rule

More rules



Additionally one needs rules for definitions of \vee , \rightarrow and \leftrightarrow :

rule			name
$F \vdash F \lor G$	if and only if	$\mathcal{F} \vdash \neg (\neg F \land \neg G)$	∨-definition
$\mathcal{F} \vdash F \to G$	if and only if	$\mathcal{F} \vdash \neg F \lor G$	\rightarrow -definition
$\mathcal{F} \vdash F \leftrightarrow G$	if and only if	$\mathcal{F} \vdash F \to G, \mathcal{F} \vdash G \to F$	→-definition

More rules can be derived from these rules.

E.g.,

premise	conclusion	name
none	$\mathcal{F} \vdash \neg G \lor G$	tautology rule

proof:

- 1. $\mathcal{F} \cup \{G\} \vdash G$ [assumption]
- 2. $\mathcal{F} \vdash G \xrightarrow{\cdot} G \quad [\rightarrow$ -introduction applied to 1]
- 3. $\mathcal{F} \vdash \neg G \lor G$ [\lor -definition applied to 2]

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Artificial Intelligence / 3. Formal Proofs

More rules



premise	conclusion	name
none	$\mathcal{F} \vdash \neg G \lor G$	tautology rule

Soundness



A proof system is called **sound** if $\mathcal{F} \vdash G$, then $\mathcal{F} \models G$.

Lemma 2. The proof system outlined in this section is sound.

Proof. Show for each rule, that for its conclusion $\mathcal{F} \vdash G$: $\mathcal{F} \models G$.

∧-elimination:

F	G	$F \wedge G$	$F \wedge G \to F$
0	0	0	1
0	1	0	1
1	0	0	1
1	1	1	1

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Artificial Intelligence / 3. Formal Proofs

Completeness



A proof system is called **complete** if $\mathcal{F} \models G$, then $\mathcal{F} \vdash G$.

Lemma 3. The proof system outlined in this section is complete.

Proof. See Hedmann 2004, p. 47.



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Artificial Intelligence / 4. Normal Forms

Definition Normal Forms



Formulas

$$F = \bigwedge_{i=1}^{n} \bigvee_{j=1}^{m_i} L_{i,j}$$

where $L_{i,j}$ is a literal (i.e., either an atom or the negation of an atom) are called **conjunctive normal form** (**CNF**).

Formulas

$$F = \bigvee_{i=1}^{n} \bigwedge_{j=1}^{m_i} L_{i,j}$$

where $L_{i,j}$ is a literal (i.e., either an atom or the negation of an atom) are called **disjunctive normal form** (**DNF**).

Here we write

$$\bigwedge_{i=1}^{n} F_i := F_1 \wedge F_2 \wedge \ldots \wedge F_n, \quad \bigvee_{i=1}^{n} F_i := F_1 \vee F_2 \vee \ldots \vee F_n$$

Definition Normal Forms / Examples



Examples:

$$(A \vee B) \wedge (C \vee D) \wedge (\neg A \vee \neg B \vee \neg D) \text{ is in CNF}$$

$$(\neg A \wedge B) \vee C \vee (B \wedge \neg C \wedge D) \text{ is in DNF}$$

$$(A \vee B) \wedge ((A \wedge C) \vee (B \wedge D)) \text{ is neither}$$

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Artificial Intelligence / 4. Normal Forms

Existence of CNF and DNF Equivalents



Lemma 4. Each formula is equivalent to a formula in CNF as well as to a formula in DNF.

Proof. Let F be the formula and proof by induction: if F is atomic, it clearly is CNF as well as DNF. if $F = \neg G$, then let $G \equiv \bigwedge_i \bigvee_j L_{i,j}$ by induction.

$$F = \neg G \equiv \neg \bigwedge_{i} \bigvee_{j} L_{i,j} \equiv \bigvee_{i} \bigwedge_{j} \neg L_{i,j} \equiv \bigvee_{i} \bigwedge_{j} L'_{i,j}$$

where $L'_{i,j} := \neg A$ if $L_{i,j} = A$ is atomic and $L'_{i,j} := A$ if $L_{i,j} = \neg A$ is the negation of an atom, i.e., F is equivalent to a DNF. Similar for CNF.

if $F = G \wedge H$, then F obviously is equivalent to a CNF.

To show that F is also equivalent to a DNF, let $G \equiv \bigvee_i L_i$ and $H \equiv \bigvee_j M_j$ be DNFs, respectively. Then

$$F = G \wedge H \equiv (\bigvee_{i} L_{i}) \wedge (\bigvee_{j} M_{j}) \equiv \bigvee_{i} \bigvee_{j} (L_{i} \wedge M_{j})$$

is in DNF.

CNF/DNF algorithm



- i cnf(formula F):
- ² Replace all subformulas $(G \leftrightarrow H)$ of F by $((\neg G \lor H) \land (\neg H \lor G))$
- ${\it 3}$ Replace all subformulas $(G \to H)$ of F by $(\neg G \lor H)$
- 5 Move ¬ inwards:
- 6 Replace all subformulas $\neg (G \land H)$ of F by $(\neg G \lor \neg H)$
- 7 Replace all subformulas $\neg (G \lor H)$ of F by $(\neg G \land \neg H)$
- 8 Replace all subformulas $\neg\neg G$ of F by G
- 10 Apply the ∨ -distributivity rule:
- 11 Replace all subformulas $G \vee (H \wedge I)$ of F by $(G \vee H) \wedge (G \vee I)$
- 12 Replace all subformulas $(H \wedge I) \vee G$ of F by $(H \vee G) \wedge (I \vee G)$
- 13 return F

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Artificial Intelligence / 4. Normal Forms

CNF/DNF algorithm / Example



$$F = (A \lor B) \to (\neg B \land A)$$

$$\equiv \neg (A \lor B) \lor (\neg B \land A)$$

$$\equiv (\neg A \land \neg B) \lor (\neg B \land A)$$

$$\equiv ((\neg A \land \neg B) \lor \neg B) \land ((\neg A \land \neg B) \lor A)$$

$$\equiv ((\neg A \lor \neg B) \land (\neg B \lor \neg B)) \land ((\neg A \lor A) \land (\neg B \lor A))$$

$$\equiv (\neg A \lor \neg B) \land (\neg B \lor \neg B) \land (\neg A \lor A) \land (\neg B \lor A)$$

$$\equiv (\neg A \lor \neg B) \land \neg B \land (\neg B \lor A)$$

$$\equiv \neg B$$



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Artificial Intelligence / 5. Resolution

Clauses



A formula

$$\bigvee_{i=1}^{n} L_i$$

where L_i are literals is called **clause**.

Obviously, each CNF is a conjunction of clauses and determined up to equivalence by its set of clauses

$$\mathsf{clauses}(F) := \{\bigvee_{j=1}^{m_i} L_{i,j} \,|\, i=1,\ldots,n\}$$

Clauses are often written as sets of literals:

$$\bigvee_{i=1}^{n} L_i \leadsto \{L_1, L_2, \dots, L_n\}$$

Resolvents



Let F and G be two clauses (described by sets of literals) with $A \in F$ and $\neg A \in G$. Then the clause

$$(F \setminus \{A\}) \cup (G \setminus \{\neg A\})$$

is called a resolvent of F and G.

Example:

Let

$$F := \{A, \neg B, C\}, \quad G := \{B, \neg C, D\}$$

then a resolvent of F and G is

$$(\{A, \neg B, C\} \setminus \{C\}) \cup (\{B, \neg C, D\} \setminus \{\neg C\}) = \{A, \neg B, B, D\}$$

Resolvents are not unique, e.g., another resolvent of F and G is

$$(\{A, \neg B, C\} \setminus \{\neg B\}) \cup (\{B, \neg C, D\} \setminus \{B\}) = \{A, C, \neg C, D\}$$

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Artificial Intelligence / 5. Resolution

Resolvents can be derived



Lemma 5. Resolvents can be derived.

More detailed: let F and G be two clauses and R a resolvent of F and G, then

$$\{F,G\} \vdash R$$

Resolvents can be derived



Proof. Let

$$F = F' \lor A$$
, $G = G' \lor \neg A$, $R = F' \lor G'$

Then

- 1. $\{F' \lor A, G' \lor \neg A\}$ $\vdash F' \lor A$ assumption
- 2. $\{F' \lor A, G' \lor \neg A, \neg A\} \vdash F' \lor A$ monotonicity applied to 1
- 3. $\{F' \lor A, G' \lor \neg A, \neg A\}$ $\vdash \neg A$ assumption 4. $\{F' \lor A, G' \lor \neg A, \neg A\}$ $\vdash F'$ \lor -elimination applied to 2 and 35. $\{F' \lor A, G' \lor \neg A, \neg A\}$ $\vdash F' \lor G'$ \lor -introduction applied to 4
- 6. $\{F' \lor A, G' \lor \neg A\} \vdash G' \lor \neg A$ assumption
- 7. $\{F' \lor A, G' \lor \neg A, \neg \neg A\} \vdash G' \lor \neg A$ monotonicity applied to 6
- 8. $\{F' \lor A, G' \lor \neg A, \neg \neg A\} \vdash \neg \neg A$ assumption
- 9. $\{F' \lor A, G' \lor \neg A, \neg \neg A\} \vdash G' \lor$ -elimination applied to 7 and 8
- 10. $\{F' \lor A, G' \lor \neg A, \neg \neg A\} \vdash G' \lor F' \lor \text{-introduction applied to } 9$
- 11. $\{F' \lor A, G' \lor \neg A, \neg \neg A\} \vdash F' \lor G' \lor \text{-symmetry applied to } 10$
- 12. $\{F' \lor A, G' \lor \neg A\}$ $\vdash F' \lor G'$ proof by cases applied to 5 and 11

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Artificial Intelligence / 5. Resolution

Resolution Proof System



Let F be a CNF. We define

 $Res^0(F) := clauses(F)$

 $\mathsf{Res}^i(F) := \mathsf{Res}^{i-1}(F)$

 $\cup \{R \mid R \text{ is a resolvent of two clauses } C, D \in \mathsf{Res}^{i-1}(F)\}$

As there are only finite many clauses of a finite set of atoms, for some i we have

$$\mathsf{Res}^i(F) = \mathsf{Res}^{i-1}(F)$$

and call this $Res^*(F)$.

The clauses in $Res^*(F)$ can be derived by just two rules:

premise	conclusio	n name
1. C is a clause of F	$F \vdash C$	[assumption]
2. $F \vdash C, F \vdash D, R$ is a resolvent of C ,	$D F \vdash R$	[resolution]

Soundness & Completeness



The resolution proof system claims for a CNF *F*:

F is unsatisfiable $\iff \emptyset \in \mathsf{Res}^*(F)$

Lemma 6. Resolution is sound and complete.

Proof.

sound: as resolution can be proved.

complete: not so obvious to see; see Hedmann 2004, p. 42. □

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Artificial Intelligence / 5. Resolution

Entailment by Resolvents / Algorithm



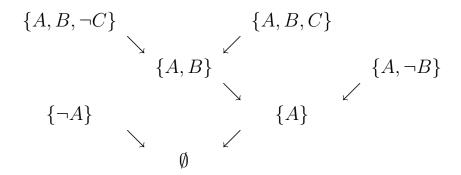
```
\begin{array}{ll} \textit{1} \;\; \text{entails}(\text{formula}\;F, \text{query formula}\;Q):\\ \textit{2}\;\; \mathcal{C} := \emptyset\\ \textit{3}\;\; \mathcal{C}' := \text{clauses}(\text{cnf}(F \land \neg Q))\\ \textit{4}\;\; & \underline{\text{while}}\;\mathcal{C}' \neq \emptyset \; \underline{\text{do}}\\ \textit{5}\;\; & \mathcal{C} := \mathcal{C} \cup \mathcal{C}'\\ \textit{6}\;\; & \mathcal{C}' := \emptyset\\ \textit{7}\;\; & \underline{\text{for}}\;C, D \in \mathcal{C}\; \underline{\text{do}}\\ \textit{8}\;\; & \mathcal{R} := \{R \mid R \text{ is a resolvent of } C, D\}\\ \textit{9}\;\; & \underline{\text{if}}\;\emptyset \in \mathcal{R}\; \underline{\text{return}} \; \text{true}\; \underline{\text{fi}}\\ \textit{10}\;\; & \mathcal{C}' := \mathcal{C}' \cup \mathcal{R}\\ \textit{11}\;\; & \underline{\text{od}}\\ \textit{12}\;\; \underline{\text{od}}\\ \textit{13}\;\; \underline{\text{return}}\; \text{false} \end{array}
```

Entailment by Resolvents / Example



Is the following formula satisfiable?

$$F := (A \lor B \lor \neg C) \land \neg A \land (A \lor B \lor C) \land (A \lor \neg B)$$



Therefore, F is unsatisfiable.

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Artificial Intelligence

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Horn Formulas



A CNF F is called **Horn formula** if each conjunction contains at most one positive literal, i.e.

$$F = \bigwedge_{i=1}^{n} \bigvee_{j=1}^{m_i} L_{i,j}$$

where $L_{i,j}$ are literals and for each i there is at most one j with $L_{i,j}$ positive.

Example:

$$A \wedge (\neg A \vee \neg B \vee C) \wedge (\neg B \vee C) \wedge (\neg B \vee D) \wedge (\neg C \vee \neg D) \text{ is Horn } A \vee B \text{ is not Horn}$$

Different from CNF, not every formula has an equivalent Horn formula.

Example: $A \vee B$

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Artificial Intelligence / 6. Propositional Horn Formulas

Basic Horn Formulas



A formula

$$\bigvee_{i=1}^{n} L_i$$

where L_i are literals and at most one is positive, is called **Horn** clause or **Basic Horn formula**.

Obviously, each Horn formula is a conjunction of Horn clauses and determined up to equivalence by its sets of clauses

$$\mathsf{clauses}(F) := \{\bigvee_{j=1}^{m_i} L_{i,j} \,|\, i=1,\ldots,n\}$$

Example:

 $A \wedge (\neg A \vee \neg B \vee C) \wedge (\neg B \vee C) \wedge (\neg B \vee D) \wedge (\neg C \vee \neg D) \text{ is Horn, but not basic Horn} \\ (\neg A \vee \neg B \vee C) \text{ is basic Horn}$

Basic Horn Formulas as Implications



Basic Horn formulas can be written as implications of atoms/positive literals:

$$(\bigvee_{i=1}^{n} \neg L_{i} \lor M) \equiv (\bigwedge_{i=1}^{n} L_{i} \to M)$$
$$(\bigvee_{i=1}^{n} \neg L_{i}) \equiv (\bigwedge_{i=1}^{n} L_{i} \to \mathsf{false})$$
$$M \equiv (\mathsf{true} \to M)$$

where L_i and M are positive literals.

Example:

$$\begin{array}{l} A \wedge (\neg A \vee \neg B \vee C) \wedge (\neg B \vee C) \wedge (\neg B \vee D) \wedge (\neg C \vee \neg D) \\ \equiv (\mathsf{true} \to A) \wedge (A \wedge B \to C) \wedge (B \to C) \wedge (B \to D) \wedge (C \wedge D \to \mathsf{false}) \end{array}$$

For an implication $L \to M$, we write

$$\begin{array}{l} \mathsf{body}(L \to M) := & L \\ \mathsf{head}(L \to M) := & M \end{array}$$

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Artificial Intelligence / 6. Propositional Horn Formulas

Entailment for Horn Formulas



The entailment problem for Horn formulas can be solved efficiently, in linear time in the number of clauses.

Idea: build assignment incrementally using clauses for inference:

- 1. all atoms that occur in clauses without premise are assigned true,
- 2. for all clauses where all premises are already assigned true, assign also the head true.
- 3. once the query atom is assigned true, terminate and return true.
- 4. if there are no more clauses with all premises assigned true, terminate and return true.

Satisfiability:

Horn formulas without a clauses with head false always are satisfiable. Horn formulas with some clauses with head false are unsatisfiable, if the atom false is entailed.

Entailment for Horn Formulas / Example



Is the following Horn formula satisfiable?

$$(\mathsf{true} \to A) \land (A \land B \to C) \land (C \to D) \land (C \land D \to \mathsf{false}) \land (\mathsf{true} \to B)$$

Can we entail the query atom false?

As there are clauses true $\to A$ and true $\to B$, we assign A and B to true.

As now all premises of $A \wedge B \to C$ are true, we assign C to true.

As now all premises of $C \to D$ are true, we assign D to true.

As now all premises of $C \wedge D \rightarrow$ false are true, we entail the query atom false.

Therefore, the formula is not satisfiable.

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Artificial Intelligence / 6. Propositional Horn Formulas

And/Or Graphs



Horn clauses:

$$P \Longrightarrow Q$$

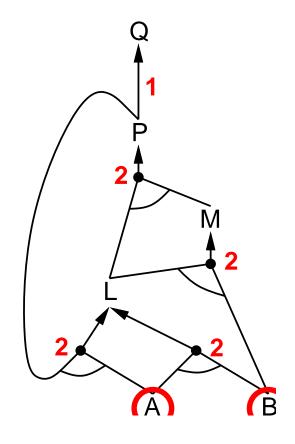
$$L \land M \Longrightarrow P$$

$$B \land L \Longrightarrow M$$

$$A \land P \Longrightarrow L$$

$$A \land B \Longrightarrow L$$

$$A$$



Entailment for Horn Formulas / Algorithm



```
i entail(horn formula F, query atom Q):
 _2 \mathcal{S} := atoms(F)
 \mathcal{A}(A) := \text{false},
                               \forall A \in \mathcal{S}
 4 \mathcal{C} := \operatorname{clauses}(F)
 5 p(C) := number of premises in body(C), \forall C \in \mathcal{C}
 6 \mathcal{H} := \{ \text{head}(C) \mid C \in \mathcal{C} : \text{body}(C) = \emptyset \}
 <sup>7</sup> while \mathcal{H} \neq \emptyset do
              A := \text{remove-element}(\mathcal{H})
              if A = Q return true fi
              \underline{\mathbf{if}} \, \mathcal{A}(A) = \text{false}
10
                  \mathcal{A}(A) := \text{true}
                  for C \in \mathcal{C} : A occurs in body(C) do
12
                        p(C) := p(C) - 1
                        \underline{\mathbf{if}}(p(C)=0)
                           append(\mathcal{H}, head(C))
                  od
              fi
20 return false
```

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Artificial Intelligence / 6. Propositional Horn Formulas

Entailment for Horn Formulas / Soundness & Completeness



Lemma 7. The inference algorithm for Horn formulas is sound and complete.

Proof.

sound, i.e., every derived atom is entailed: in each step only modus ponens / →-elimination rule applied.

complete, i.e., every entailed atom will be derived: \mathcal{A} is an assignment for F, i.e., each clause holds: assume $L_1 \wedge L_2 \wedge \ldots \wedge L_n \to M$ is clause that does not hold. Then $\mathcal{A}(L_i) = \text{true}$ and $\mathcal{A}(M) = \text{false}$. But in this case M would have been assigned true, so there cannot be a clause that does not hold.

As A is an assignment that models F, any atom not assigned true in A is not entailed by F. And all the atoms assigned true by A will be derived.



- 1. Syntax
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Artificial Intelligence / 7. Entailment by Model Checking

Entailment, Satisfiability, Existence of Models



Entailment of a query formula Q by a given formula F can also be computed by **model checking**, i.e.,

computing a model/assignment that models F but not Q $(F \land \neg Q \text{ is satisfiable})$ then F does not entail Q.

show that there is no model that models F but not Q $(F \wedge \neg Q \text{ is not satisfiable})$

then F entails Q.

Approaches



Different approaches:

incremental model building / complete enumeration compute all assignments and check each individually.

incremental model building / use inference where possible use inference in some easy to check situations, otherwise enumerate all possible assignments.

local search

start with a complete random assignment, update the truth value of some variables in each step to make less clauses false.

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Artificial Intelligence / 7. Entailment by Model Checking

Use inference where possible / Early stopping



Transform the formula to check for satisfiability to CNF.

A clause is true, if a single of its literal is true. The formula is true, if each clause is true.

Example:

$$(A \lor \neg B \lor C) \land (\neg B \lor \neg C \lor D) \land (A \land D)$$

Assume partial assignment: A(B) = false, A(D) = true.

Then each clause is already true, so we do not have to complete the assignment but can stop here.

Use inference where possible / early stopping



A clause is false, if all of its literals are false. The formula is false, if one of its clauses is false.

Example:

$$(A \lor \neg B \lor C) \land (\neg B \lor \neg C \lor D) \land (A \land D)$$

Assume partial assignment: A(A) = false, A(D) = false.

The last clause is false, so this partial assignment cannot be completed to a model.

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Artificial Intelligence / 7. Entailment by Model Checking

Use inference where possible / pure symbols



If of some symbol A, only positive (or only negative) literals occur, then the symbol safely can be assigned true (or false). Such symbols are called **pure**.

Example:

$$(A \vee \neg B \vee C) \wedge (\neg B \vee \neg C \vee D) \wedge (A \wedge D)$$

Assume empty assignment: $A = \emptyset$.

A is pure as it appears only in positive form.

B is pure as it appears only in negative form.

D is pure as it appears only in positive form.

 \rightsquigarrow it is safe to assign $\mathcal{A}(A) = \text{true}$, $\mathcal{A}(B) = \text{false}$ and $\mathcal{A}(D) = \text{true}$.

Use inference where possible / unit clauses



If some clause consists only of a single literal not yet assigned to false, then the respective symbol safely can be assigned true (or false).

Such symbolsclauses called unit clauses.

Example:

$$(A \vee \neg B \vee C) \wedge (\neg B \vee \neg C \vee D) \wedge (A \wedge D)$$

Assume partial assignment: A(A) = false, A(C) = false.

The first clause consists only of the literal $\neg B$ not yet assigned to false.

$$\rightsquigarrow \mathcal{A}(B) = \mathsf{false}.$$

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Artificial Intelligence / 7. Entailment by Model Checking

Davis-Putnam Algorithm



Model checking using

early stopping

(true if one literal of each clause is true, false if all literals of one clause are false)

pure symbols

(occurs only as positive or only as negative literal)

unit clauses

(contains only one literal not yet assigned to false)

is called **Davis-Putnam Algorithm** or **DPLL** (after its inventors Martin Davis, Hilary Putnam (1960) and Davis, Logemann and Loveland (1962)).

Davis-Putnam Algorithm



```
I entails-dpll(formula F, query formula Q):
  2 \mathcal{C} := \text{clauses}(\text{cnf}(F \land \neg Q))
  \beta \mathcal{A}(A) := \emptyset \quad \forall A \in \mathcal{S}(\mathcal{C})
  4 return not satisfiable-dpll(\mathcal{C}, \mathcal{A})
 6 satisfiable-dpll(set of clauses C, partial assignment A):
  7 \underline{\mathbf{if}} \ \forall C \in \mathcal{C} \exists A \in C : \mathcal{A}(A) = \text{true } \underline{\mathbf{return}} \text{ true } \underline{\mathbf{fi}}
 8 if \exists C \in \mathcal{C} \forall A \in C : \mathcal{A}(A) = \text{false } \underline{\text{return}} \text{ false } \underline{\text{fi}}
10 if \exists A \in \mathcal{A}^{-1}(\emptyset) : \forall C \in \mathcal{C} : A \in C \text{ or } \neg A \notin C
                                                                                                                                                          [pure symbol]
          return satisfiable.dpll(\mathcal{C}, \mathcal{A} \cup \{A \mapsto \mathsf{true}\})
12 <u>elsif</u> \exists A \in \mathcal{A}^{-1}(\emptyset) : \forall C \in \mathcal{C} : \neg A \in C \text{ or } A \notin C
               return satisfiable-dpll(\mathcal{C}, \mathcal{A} \cup \{A \mapsto \text{false}\}\)
14 fi
16 if \exists C \in \mathcal{C}, A \in \mathcal{A}^{-1}(\emptyset) : A \in C \text{ and } \forall B \in C, B \neq A : \mathcal{A}(B) = \text{false}
                                                                                                                                                        [unit clause]
         return satisfiable-dpll(\mathcal{C}, \mathcal{A} \cup \{A \mapsto \mathsf{true}\})
18 elsif \exists C \in \mathcal{C}, AA^{-1}(\emptyset) : \neg A \in C \text{ and } \forall B \in C, B \neq \neg A : A(B) = \text{false}
               return satisfiable-dpll(C, A \cup \{A \mapsto false\})
20 <u>fi</u>
22 A = \operatorname{random}(\mathcal{A}^{-1}(\emptyset))
23 return satisfiable-dpll(\mathcal{C}, \mathcal{A} \cup \{A \mapsto \text{true}\}) | satisfiable-dpll(\mathcal{C}, \mathcal{A} \cup \{A \mapsto \text{false}\})
```

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Artificial Intelligence / 7. Entailment by Model Checking

Local Search: WalkSat

Wersite Tilldeshell

Local search algorithm for deciding satisfiability

- start with a random complete assignment,
- stop when all clauses are satisfied,
- ullet otherwise pick an unsatisfied clause C and
 - either flip the assignment of the symbol that maximizes the number of satisfied clauses (min-conflicts step)

$$A := \operatorname{argmax}_{A \in \mathcal{S}(C)} | \{ C' \in \mathcal{C} \mid \mathcal{A}|_{\mathcal{S} \backslash \{A\}} \cup \{ A \mapsto 1 - \mathcal{A}(A) \} \models C' \} |$$

– or flip a random symbol of ${\cal C}.$

Cannot prove insatisfiability, just indicates that no solution may exist as it could not be computed in time.

WalkSat Algorithm



```
\begin{array}{l} \textit{1} \; \text{satisfiable-walksat}(\text{set of clauses }\mathcal{C}, \text{random walk prob. } p \in [0,1], \text{maxSteps}): \\ \textit{2} \; \mathcal{A} := \text{random assignment of }\mathcal{S}(\mathcal{C}) \\ \textit{3} \; \underbrace{\textbf{for}} \; i := 1 \ldots \text{maxSteps} \; \underline{\textbf{do}} \\ \textit{4} \qquad \underbrace{\textbf{if}} \; \forall C \in \mathcal{C} : \mathcal{A}(C) = \text{true } \underline{\textbf{return}} \; \text{true } \; \underline{\textbf{fi}} \\ \textit{5} \qquad C := \text{random} \{C \in \mathcal{C} \mid \mathcal{A}(C) = \text{false}\} \\ \textit{6} \qquad \underbrace{\textbf{if}} \; \text{random}() > p \\ \textit{7} \qquad A := \operatorname{argmax}_{A \in \mathcal{S}(C)} | \{C' \in \mathcal{C} \mid \mathcal{A}|_{\mathcal{S} \setminus \{A\}} \cup \{A \mapsto 1 - \mathcal{A}(A)\} \models C'\}| \\ \textit{8} \qquad \underbrace{\textbf{else}} \\ \textit{9} \qquad A := \text{random } \mathcal{S}(C) \\ \textit{10} \qquad \underbrace{\textbf{fi}} \\ \textit{11} \qquad \mathcal{A}(A) := 1 - \mathcal{A}(A) \\ \textit{12} \; \underbrace{\textbf{od}} \\ \textit{13} \; \underbrace{\textbf{return}} \; \text{failure} \\ \end{array}
```

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Artificial Intelligence / 7. Entailment by Model Checking

Hard Satisfibility Problems



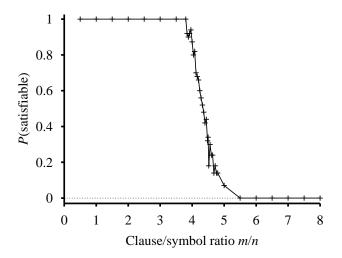
3-CNF: CNF where each clause consists of exactly 3 literals.

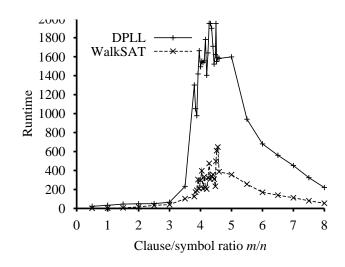
The **satisfiability problem (SAT)** for 3-CNF formulas is called **3-SAT** and still NP-complete.

The more clauses per symbol a SAT problem has, the more models may be ruled out and thus the less likely it is satisfiable.

Hard Satisfibility Problems







Probability of a random 3-CNF with 50 symbols to be satisfiable.

Median runtime of DPLL and WalkSat for 100 random satisfiable 3-CNFs with 50 symbols.

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Artificial Intelligence



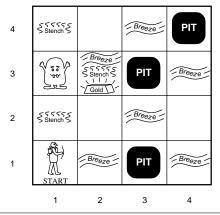
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Wumpus World



Toy example by Gregory Yob (1975), adapted by our textbook.

- -4×4 grid, tiles numbered (1,1) to (4,4),
- the agent starts in (1,1),
- the beast Wumpus sits at a random tile, unknown to the agent,
- a pile of gold sits at another random tile, unknown to the agent,
- some pits are located at random tiles, unknown to the agent.
- if the agent enteres the tile of the Wumpus, he will be eaten,
- if the agent enteres a pit, he will be trapped,



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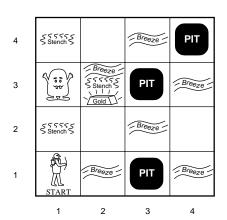
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Artificial Intelligence / 8. A Silly Example

Wumpus World

Toy example by Gregory Yob (1975), adapted by our textbook.

- the agent has a single shot to shoot at a neighboring tile and kill the Wumpus if it is there,
- the agent can pick up the pile of gold if it is at the same tile,
- the agent can move to neighboring tiles,
- the agent perceives a breeze at neighboring tiles of pits,
- the agent perceives stench at neighboring tiles of the Wumpus.



00/00

Physics



64 variables:

 $P_{x,y}$ tile x, y contains a pit $(x, y = 1, \dots, 4)$.

 $W_{x,y}$ tile x,y contains the Wumpus $(x,y=1,\ldots,4)$.

 $B_{x,y}$ tile x, y contains a breeze $(x, y = 1, \dots, 4)$.

 $S_{x,y}$ tile x, y contains stench $(x, y = 1, \dots, 4)$.

start is save: (2 formulas)

$$\neg P_{1,1}, \quad \neg W_{1,1}$$

how breeze arises: (16 formulas)

$$B_{x,y} \leftrightarrow P_{x-1,y} \lor P_{x+1,y} \lor P_{x,y-1} \lor P_{x,y+1}, \quad x, y = 1, \dots, 4$$

how stench arises: (16 formulas)

$$S_{x,y} \leftrightarrow W_{x-1,y} \lor W_{x+1,y} \lor W_{x,y-1} \lor W_{x,y+1}, \quad x, y = 1, \dots, 4$$

there is exactly one Wumpus: (121 formulas)

$$W_{1,1} \lor W_{1,2} \lor \ldots \lor W_{4,4}$$

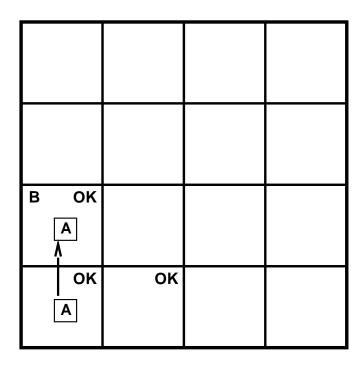
 $\neg W_{x,y} \lor \neg W_{x',y'}, \quad x, y, x', y' = 1, \ldots, 4, x \neq x' \text{ or } y \neq y'$

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Artificial Intelligence / 8. A Silly Example

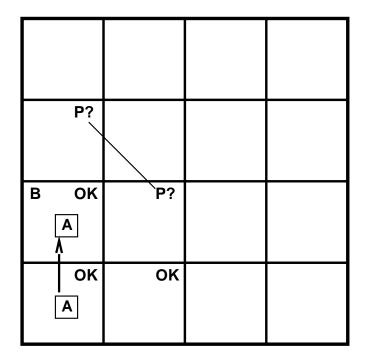
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Explore the Wumpus World

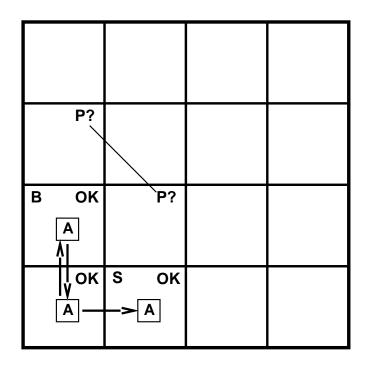




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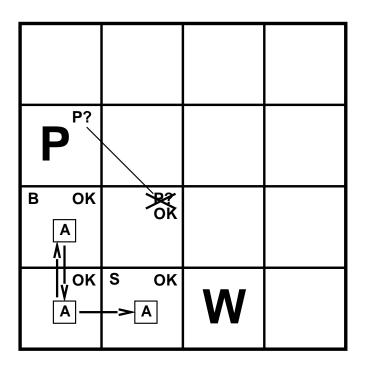
Artificial Intelligence / 8. A Silly Example





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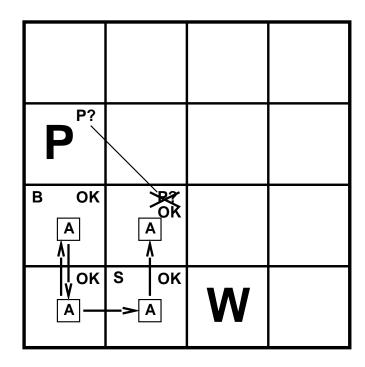




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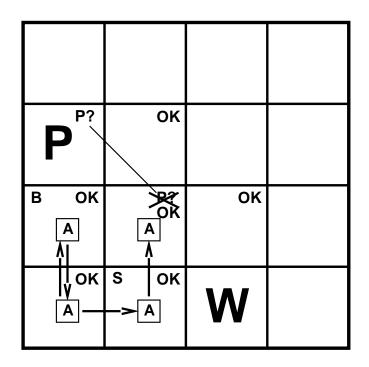
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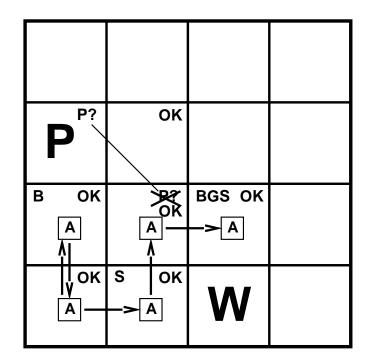




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Wumpus World



Perceptions are **told** / added to the knowledgebase.

Consequences as conditions for actions can then be **asked** from the knowledgebase, e.g.,

• tile x, y is provably safe if

$$\neg W_{x,y} \wedge \neg P_{x,y}$$

is entailed by the knowledgebase.

if there are no provably safe tiles,
 choose among tiles x, y that may or may not be dangerous,
 i.e., where

$$W_{x,y} \vee P_{x,y}$$

is **not** entailed.

Beyond Wumpus World, have a look at General Game Playing (http://games.stanford.edu).

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Artificial Intelligence / 8. A Silly Example

Wumpus World



```
function PL-Wumpus-Agent(percept) returns an action
   inputs: percept, a list, [stench, breeze, glitter]
   static: KB, a knowledge base, initially containing the "physics" of the wumpus world
            x, y, orientation, the agent's position (initially [1,1]) and orientation (initially right)
            visited, an array indicating which squares have been visited, initially false
            action, the agent's most recent action, initially null
            plan, an action sequence, initially empty
   update x, y, orientation, visited based on action
   if stench then Tell(KB, S_{x,y}) else Tell(KB, \neg S_{x,y})
   if breeze then Tell(KB, B_{x,y}) else Tell(KB, \neg B_{x,y})
   if qlitter then action \leftarrow qrab
   else if plan is nonempty then action \leftarrow Pop(plan)
   else if for some fringe square [i,j], ASK(KB, (\neg P_{i,j} \land \neg W_{i,j})) is true or
            for some fringe square [i,j], Ask(KB, (P_{i,j} \vee W_{i,j})) is false then do
        plan \leftarrow A^*-Graph-Search(Route-Problem([x,y], orientation, [i,j], visited))
        action \leftarrow Pop(plan)
   else action \leftarrow a randomly chosen move
   return action
```