A brief history of reasoning

| 450B.C. | Stoics | propositional logic, inference (maybe) |
|---------|--------------|--|
| 322B.C. | Aristotle | "syllogisms" (inference rules), quantifiers |
| 1565 | Cardano | probability theory (propositional logic + uncertainty) |
| 1847 | Boole | propositional logic (again) |
| 1879 | Frege | first-order logic |
| 1922 | Wittgenstein | proof by truth tables |
| 1930 | Gödel | \exists complete algorithm for FOL |
| 1930 | Herbrand | complete algorithm for FOL (reduce to propositional) |
| 1931 | Gödel | $ eg \exists$ complete algorithm for arithmetic |
| 1960 | Davis/Putnam | "practical" algorithm for propositional logic |
| 1965 | Robinson | "practical" algorithm for FOL—resolution |

Resolution

Conjunctive Normal Form (CNF—universal) 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): complete for propositional logic

 $\ell_1 \vee \cdots \vee \ell_k, \qquad m_1 \vee \cdots \vee m_n$ $\overline{\ell_1 \vee \cdots \vee \ell_{i-1} \vee \ell_{i+1} \vee \cdots \vee \ell_k \vee m_1 \vee \cdots \vee m_{j-1} \vee m_{j+1} \vee \cdots \vee m_n}$ where ℓ_i and m_j are complementary literals. E.g., $\frac{P_{1,3} \lor P_{2,2}, \qquad \neg P_{2,2}}{P_{1,3}}$ Ρ

Resolution is sound and complete for propositional logic



Conversion to CNF

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

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

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

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 (\lor over \land) 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 \wedge \neg \alpha unsatisfiable
```

```
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 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

if new \subseteq clauses then return false

clauses \leftarrow clauses \cup new
```

Resolution example

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



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:

- 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 v \neg B), (\neg B v \neg C), (C v 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)
if P is non-null then return DPLL(clauses, symbols-P, [P = value|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

Hard satisfiability problems

 Consider random 3-CNF sentences. e.g., (¬D v ¬B v C) ∧ (B v ¬A v ¬C) ∧ (¬C v ¬B v E) ∧ (E v ¬D v B) ∧ (B v E v ¬C)

$$m$$
 = number of clauses
 n = number of symbols

 Hard problems seem to cluster near *m/n* = 4.3 (critical point)

Hard satisfiability problems



Hard satisfiability problems



 Median runtime for 100 satisfiable random 3-CNF sentences, n = 50

Pros and cons of propositional logic

- Sectional logic is declarative: pieces of syntax correspond to facts
- Propositional logic allows partial/disjunctive/negated information (unlike most data structures and databases)
- \bigcirc Propositional logic is **compositional**: meaning of $B_{1,1} \wedge P_{1,2}$ is derived from meaning of $B_{1,1}$ and of $P_{1,2}$
- Meaning in propositional logic is context-independent (unlike natural language, where meaning depends on context)
- Propositional logic has very limited expressive power (unlike natural language)
 E.g., cannot say "pits cause breezes in adjacent squares" except by writing one sentence for each square

First-order logic

Whereas propositional logic assumes world contains **facts**, first-order logic (like natural language) assumes the world contains

. . .

- Objects: people, houses, numbers, theories, Ronald McDonald, colors, baseball games, wars, centuries . . .
- Relations: red, round, bogus, prime, multistoried . . ., brother of, bigger than, inside, part of, has color, occurred after, owns, comes between, . . .
- Functions: father of, best friend, third inning of, one more than, end of

Syntax of FOL: Basic elements

ConstantsKingJohn, 2, UCB, ...PredicatesBrother, >, ...FunctionsSqrt, LeftLegOf, ...Variablesx, y, a, b, ...Connectives $\land \lor \neg \Rightarrow \Leftrightarrow$ Equality=Quantifiers $\forall \exists$

Deducing hidden properties

Properties of locations:

 $\begin{array}{ll} \forall x,t \ At(Agent,x,t) \land Smelt(t) \Rightarrow Smelly(x) \\ \forall x,t \ At(Agent,x,t) \land Breeze(t) \Rightarrow Breezy(x) \end{array}$

Squares are breezy near a pit:

Neither of these is complete—e.g., the causal rule doesn't say whether squares far away from pits can be breezy

Definition for the *Breezy* predicate:

 $\forall y \ Breezy(y) \Leftrightarrow [\exists x \ Pit(x) \land Adjacent(x,y)]$

Knowledge base for the wumpus world

"Perception"

 $\begin{array}{ll} \forall \, b, g, t \; \; Percept([Smell, b, g], t) \; \Rightarrow \; Smelt(t) \\ \forall \, s, b, t \; \; Percept([s, b, Glitter], t) \; \Rightarrow \; AtGold(t) \end{array}$

 $\mathsf{Reflex:} \ \forall t \ AtGold(t) \ \Rightarrow \ Action(Grab, t)$

Reflex with internal state: do we have the gold already? $\forall t \ AtGold(t) \land \neg Holding(Gold, t) \Rightarrow Action(Grab, t)$

Holding(Gold, t) cannot be observed \Rightarrow keeping track of change is essential

Reduction to propositional inference

Suppose the KB contains just the following:

 $\begin{array}{l} \forall x \;\; King(x) \wedge Greedy(x) \; \Rightarrow \; Evil(x) \\ King(John) \\ Greedy(John) \\ Brother(Richard, John) \end{array}$

Instantiating the universal sentence in all possible ways, we have

$$\begin{split} &King(John) \wedge Greedy(John) \Rightarrow Evil(John) \\ &King(Richard) \wedge Greedy(Richard) \Rightarrow Evil(Richard) \\ &King(John) \\ &Greedy(John) \\ &Brother(Richard, John) \end{split}$$

The new KB is propositionalized: proposition symbols are

 $King(John),\ Greedy(John),\ Evil(John), King(Richard)\, {\rm etc.}$

Reduction contd.

Claim: a ground sentence* is entailed by new KB iff entailed by original KB

Claim: every FOL KB can be propositionalized so as to preserve entailment

Idea: propositionalize KB and query, apply resolution, return result

Problem: with function symbols, there are infinitely many ground terms, e.g., Father(Father(Father(John)))

Theorem: Herbrand (1930). If a sentence α is entailed by an FOL KB, it is entailed by a **finite** subset of the propositional KB

Idea: For n = 0 to ∞ do

create a propositional KB by instantiating with depth-n terms see if α is entailed by this KB

Problem: works if α is entailed, loops if α is not entailed

Theorem: Turing (1936), Church (1936), entailment in FOL is semidecidable

Problems with propositionalization

Propositionalization seems to generate lots of irrelevant sentences. E.g., from

 $\begin{array}{l} \forall x \;\; King(x) \wedge Greedy(x) \; \Rightarrow \; Evil(x) \\ King(John) \\ \forall y \;\; Greedy(y) \\ Brother(Richard, John) \end{array}$

it seems obvious that Evil(John), but propositionalization produces lots of facts such as Greedy(Richard) that are irrelevant

With $p \ k$ -ary predicates and n constants, there are $p \cdot n^k$ instantiations

With function symbols, it gets nuch much worse!

Resolution: brief summary

Full first-order version:

 $\frac{\ell_1 \vee \cdots \vee \ell_k, \quad m_1 \vee \cdots \vee m_n}{(\ell_1 \vee \cdots \vee \ell_{i+1} \vee \cdots \vee \ell_k \vee m_1 \vee \cdots \vee m_{j-1} \vee m_{j+1} \vee \cdots \vee m_n)\theta}$

where $\text{UNIFY}(\ell_i, \neg m_j) = \theta$.

For example,

 $\begin{array}{c} \neg Rich(x) \lor Unhappy(x) \\ Rich(Ken) \\ \hline \\ Unhappy(Ken) \end{array}$

with $\theta = \{x/Ken\}$

Apply resolution steps to $CNF(KB \land \neg \alpha)$; complete for FOL

Conversion to CNF

Everyone who loves all animals is loved by someone: $\forall x \ [\forall y \ Animal(y) \Rightarrow Loves(x, y)] \Rightarrow [\exists y \ Loves(y, x)]$

1. Eliminate biconditionals and implications

 $\forall x \ [\neg \forall y \ \neg Animal(y) \lor Loves(x,y)] \lor [\exists y \ Loves(y,x)]$

2. Move \neg inwards: $\neg \forall x, p \equiv \exists x \neg p, \neg \exists x, p \equiv \forall x \neg p$:

 $\begin{array}{l} \forall x \hspace{0.2cm} [\exists y \hspace{0.2cm} \neg (\neg Animal(y) \lor Loves(x,y))] \lor [\exists y \hspace{0.2cm} Loves(y,x)] \\ \forall x \hspace{0.2cm} [\exists y \hspace{0.2cm} \neg \neg Animal(y) \land \neg Loves(x,y)] \lor [\exists y \hspace{0.2cm} Loves(y,x)] \\ \forall x \hspace{0.2cm} [\exists y \hspace{0.2cm} Animal(y) \land \neg Loves(x,y)] \lor [\exists y \hspace{0.2cm} Loves(y,x)] \\ \end{array}$

Conversion to CNF contd.

3. Standardize variables: each quantifier should use a different one

 $\forall x \; [\exists y \; Animal(y) \land \neg Loves(x,y)] \lor [\exists z \; Loves(z,x)]$

 Skolemize: a more general form of existential instantiation. Each existential variable is replaced by a Skolem function of the enclosing universally quantified variables:

 $\forall x \ [Animal(F(x)) \land \neg Loves(x,F(x))] \lor Loves(G(x),x)$

5. Drop universal quantifiers:

 $[Animal(F(x)) \land \neg Loves(x,F(x))] \lor Loves(G(x),x)$

6. Distribute \land over \lor :

 $[Animal(F(x)) \lor Loves(G(x), x)] \land [\neg Loves(x, F(x)) \lor Loves(G(x), x)]$