### Logical Inference and Reasoning Agents

**Foundations of Artificial Intelligence** 

## **Resolution Rule of Inference**

- Resolution provides a complete rule of inference for first order predicate calculus
  - if used in conjunction with a refutation proof procedure (proof by contradiction)
  - requires that formulas be written in clausal form

#### Refutation procedure

- to prove that  $KB \models \alpha$ , show that  $KB \land \neg \alpha$  is unsatisfiable
- i.e., assume the contrary of  $\alpha$ , and arrive at a contradiction
- KB and  $\neg \alpha$ , must be in CNF (conjunction of clauses)
- each step in the refutation procedure involves applying resolution to two clauses, in order to get a new clause



• inference continues until the empty clause  $\square$  is derived (a contradiction)

### **Resolution Rule of Inference**

Basic Propositional Version:



• Full First-Order Version:

$$\frac{(p_1 \lor \ldots \lor p_j \lor \ldots \lor p_m), (q_1 \lor \ldots \lor q_k \lor \ldots \lor q_n)}{(p_1 \lor \ldots \lor p_{j-1} \lor p_{j+1} \lor \ldots \lor p_m \lor q_1 \lor \ldots \lor q_{k-1} \lor q_{k+1} \lor \ldots \lor q_n)\sigma}$$

provided that  $p_i$  and  $\neg q_k$  are *unifiable* via a *substitution*  $\sigma$ 



with substitution  $\sigma = \{x/bob\}$ 

### **Conjunctive Normal Form - Revisited**

• Literal = possibly negated atomic sentence

• e.g.,  $\neg rich(x)$ , or unhappy(bob), etc.

- Clause = disjunction of literals
  - e.g.,  $\neg rich(x) \lor unhappy(x)$
- The *KB* is a conjunction of clauses
- Any first-order logic *KB* can be converted into CNF:
  - 1. Replace  $P \Rightarrow Q$  with  $\neg P \lor Q$
  - ▶ 2. Move inward the negation symbol, e.g.,  $\neg \forall x P$  becomes  $\exists x \neg P$
  - ▶ 3. Standardize variables apart, e.g.,  $\forall x P \lor \exists x Q$  becomes  $\forall x P \lor \exists y Q$
  - ▶ 4. Move quantifiers left in order, e.g.,  $\forall x P \lor \exists y Q$  becomes  $\forall x \exists y (P \lor Q)$
  - ▶ 5. Eliminate ∃ by Skolemization (see later slide)
  - 6. Drop universal quantifiers (we'll assume they are implicit)
  - 7. Distribute  $\land$  over  $\lor$ , e.g.,  $(P \land Q) \lor R$  becomes  $(P \lor Q) \land (P \lor R)$
  - 8. Split conjunctions (into a set of clauses) and rename variables

## **Conversion to CNF - Example 1**

- Original sentence  $(A \land B \Rightarrow C) \lor (D \land \neg G)$
- Eliminate  $\Rightarrow$ :  $(\neg (A \land B) \lor C) \lor (D \land \neg G)$
- Move in negation:  $\neg A \lor \neg B \lor C \lor (D \land \neg G)$
- **Distribute**  $\land$  **over**  $\lor$ :  $(\neg A \lor \neg B \lor C \lor D) \land (\neg A \lor \neg B \lor C \lor \neg G)$
- Split conjunction



## **Skolemization**

• The rules for Skolemization is essentially the same as those we described for quantifier inference rules

- if ∃ does not occur within the scope of a ∀, then drop ∃, and replace all occurrence of the existentially quantified variable with a new constant symbol (called the Skolem constant)
- e.g.,  $\exists x P(x)$  becomes  $P(\hat{a})$ , where  $\hat{a}$  is a new constant symbol
- if ∃ is within the scope of any ∀, then drop ∃, and replace the associated variable with a Skolem function (a new function symbol), whose arguments are the universally quantified variables
- e.g.,  $\forall x \forall y \exists z P(x, y, z)$  becomes  $\forall x \forall y P(x, y, sk(x, y))$
- e.g.,  $\forall x \ person(x) \Rightarrow \exists y \ heart(y) \land has(x,y)$ becomes  $\forall x \ person(x) \Rightarrow heart(sk(x)) \land has(x, sk(x))$

## **Conversion to CNF - Example 2**

**Convert:**  $\forall x [(\forall y \ p(x,y)) \Rightarrow \neg(\forall y (q(x,y) \Rightarrow r(x,y)))]$ 

- (1)  $\forall x [\neg(\forall y \ p(x,y)) \lor \neg(\forall y (\neg q(x,y) \lor r(x,y)))]$
- (2)  $\forall x [(\exists y \neg p(x, y)) \lor (\exists y (q(x, y) \land \neg r(x, y)))]$
- (3)  $\forall x [(\exists y \neg p(x, y)) \lor (\exists z (q(x, z) \land \neg r(x, z)))]$
- (4)  $\forall x \exists y \exists z [\neg p(x,y) \lor (q(x,z) \land \neg r(x,z))]$
- (5)  $\forall x [\neg p(x, sk_1(x)) \lor (q(x, sk_2(x)) \land \neg r(x, sk_2(x)))]$
- (6)  $\neg p(x, sk_1(x)) \lor (q(x, sk_2(x)) \land \neg r(x, sk_2(x)))$
- (7)  $[\neg p(x, sk_1(x)) \lor q(x, sk_2(x))] \land [\neg p(x, sk_1(x)) \lor \neg r(x, sk_2(x))]$
- (8)  $\{\neg p(x, sk_1(x)) \lor q(x, sk_2(x)), \neg p(w, sk_1(w)) \lor \neg r(w, sk_2(w))\}$





### **Refutation Procedure - Example 2**

$$\mathbf{KB} = \begin{cases} 1. \quad father(john, mary) \\ 2. \quad mother(sue, john) \\ 3. \quad father(bob, john) \\ 4. \quad \forall x \forall y [(father(x, y) \lor mother(x, y)) \Rightarrow parent(x, y)] \\ 5. \quad \forall x \forall y [\exists z (parent(x, z) \land parent(z, y)) \Rightarrow grand(x, y)] \end{cases}$$

Converting 4 to CNF:

4.  $(\neg father(x, y) \lor parent(x, y)) \land (\neg mother(x, y) \lor parent(x, y))$ 

Converting 5 to CNF:

5.  $\forall x \forall y [\neg \exists z (parent(x,z) \land parent(z,y)) \lor grand(x,y)]$   $\equiv \forall x \forall y \forall z [\neg (parent(x,z) \land parent(z,y)) \lor grand(x,y)]$  $\equiv \neg parent(x,z) \lor \neg parent(z,y) \lor grand(x,y)$ 

### **Refutation Procedure - Example 2 (cont.)**



Here is the final KB in clausal form:

A digression: what if we wanted to add a clause saying that there is someone who is neither the father nor the mother of *john*:

$$\exists x [\neg father(x, john) \land \neg mother(x, john)]$$

In clausal form:

 $\{\neg father(\hat{a}, john), \neg mother(\hat{a}, john)\}$ 

Next we want to prove each of the following using resolution refutation:

grand(sue,mary)(sue is a grandparent of mary) $\exists x \ parent(x, john)$ (there is someone who is john's parent)

### **Refutation Procedure - Example 2 (cont.)**

To prove, we must first negate the goal and transform into clausal form:

$$\neg \exists x \ parent(x, john) \longrightarrow \forall x \neg parent(x, john) \longrightarrow \neg parent(x, john)$$

The refutation (proof by contradiction):



Note that the proof is *constructive*: we end up with an *answer* x = bob

### **Refutation Procedure - Example 2 (cont.)**

Now, let's prove that *sue* is the grandparent of *mary*:



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## **Substitutions and Unification**

# • A *substitution* is a set of *bindings* of the form *v* = *t*, where *v* is a variable and *t* is a term

- If *P* is an expression and  $\sigma$  is a substitution, then application of  $\sigma$  to *P*, denoted by  $(P)\sigma$ , is the result of *simultaneously* replacing each variable *x* in *P* with a term *t*, where x = t is in  $\sigma$
- E.g., P = likes(sue, z), and σ = {w = john, z = mother\_of(john)} then (P)σ = likes(sue, mother\_of(john))
- E.g.,  $P = likes(father_of(w), z)$ , and  $\sigma = \{w = john, z = mother_of(x)\}$ then  $(P)\sigma = likes(father_of(john), mother_of(x))$
- E.g., P = likes(father\_of(z), z), and σ = {z = mother\_of(john)} then (P)σ = likes(father\_of(mother\_of(john)), mother\_of(john))

### **Substitutions and Unification**

• Let P and Q be two expressions, and  $\sigma a$  substitution. Then  $\sigma$  is a *unifier* of P and Q, if  $(P)\sigma = (Q)\sigma$ 

In the above definition, "=" means syntactic equality only

E.g., P = likes(john, z), and Q = likes(w, mother\_of(john)) then σ = {w = john, z = mother\_of(john)} is a unifier of P and Q

• E.g., 
$$E_1 = p(x, f(y))$$
, and  $E_2 = p(g(z), w)$   
then  $\sigma_1 = \{ x = g(a), y = b, z = a, w = f(b) \}$   
 $\sigma_2 = \{ x = g(a), z = a, w = f(y) \}$   
 $\sigma_3 = \{ x = g(z), w = f(y) \}$ 

are all unifiers for the two expressions. What's the difference?

In the above example, σ<sub>2</sub> is more general than σ<sub>1</sub>, since by applying some other substitution (in this case {y = b}) to elements of σ<sub>2</sub>, we can obtain σ<sub>1</sub>. We say that σ<sub>1</sub> is an *instance* of σ<sub>2</sub>. Note that σ<sub>3</sub> is in fact the *most general unifier* (*mgu*) of E<sub>1</sub> and E<sub>2</sub>: all instances of σ<sub>3</sub> are unifiers, and any substitution that is more general than σ<sub>3</sub> is not a unifier of E<sub>1</sub> and E<sub>2</sub> (e.g., σ<sub>4</sub> = { x = v, w = f(y) } is more general than σ<sub>3</sub>, but is not a unifier.

### **Substitutions and Unification**

• Expressions may not be unifiable

E.g., 
$$E_1 = p(x, y)$$
, and  $E_2 = q(x, y)$   
 $E_1 = p(a, y)$ , and  $E_2 = p(f(x), y)$   
 $E_1 = p(x, f(y))$ , and  $E_2 = p(g(z), g(w))$   
 $E_1 = p(x, f(x))$ , and  $E_2 = p(y, y)$  (why are these not unifiable?)

• How about p(x) and p(f(x))?

- the "occur check" problem: when unifying two expressions, need to check to make sure that a variable of one expression, does not occur in the other expression.
- Another Example (find the mgu of  $E_1$  and  $E_2$ )

 $E_1 = p(f(x, g(x, y), h(z, y))) \qquad E_2 = p(z, h(f(u, v), f(a, b)))$ 

- how about  $\sigma_1 = \{ z = f(x, g(x,y)), z = f(u, v), y = f(a, b) \}$ not good: don't know which binding for *z* to apply
- how about  $\sigma_2 = \{ z = f(x, g(x,y)), u = x, v = g(x, y), y = f(a, b) \}$ not good: is not a unifier

$$\mathsf{mgu}(E_1, E_2) = \{ z = f(x, g(x, f(a, b))), u = x, v = g(x, f(a, b)), y = f(a, b) \}$$

### **Forward and Backward Chaining**

#### Generalized Modus Ponens

$$rac{p_1,p_2,...,p_n}{q heta}, \quad rac{q_1\wedge q_2\wedge \ldots \wedge q_n \Rightarrow q}{q heta}$$

where  $\theta$  is a substitution that unifies  $p_i$  and  $q_i$  for all *i*, i.e.,  $(p_i)\theta = (q_i)\theta$ .

- GMP is complete for Horn knowledge bases
- Recall: a Horn knowledge base is one in which all sentences are of the form

• 
$$p_1 \wedge p_2 \wedge \ldots \wedge p_n \Rightarrow q$$
 OR

- $p_1 \wedge p_2 \wedge \ldots \wedge p_n$
- In other words, all sentence are in the form of an implication rule with zero or one predicate on the right-hand-side (sentences with zero predicates on the rhs are sometimes referred to as "facts").
- For such knowledge bases, we can apply GMP in a forward or a backward direction.

### **Forward and Backward Chaining**

#### Forward Chaining

- Start with KB, infer new consequences using inference rule(s), add new consequences to KB, continue this process (possibly until a goal is reached)
- In a knowledge-based agent this amounts to repeated application of the TELL operation
- May generate many irrelevant conclusions, so not usually suitable for solving for a specific goal
- Useful for building a knowledge base incrementally as new facts come in
- Usually, the forward chaining procedure is triggered when a new fact is added to the knowledge base
  - In this case, FC will try to generate all consequences of the new fact (based on existing facts) and adds those which are note already in the KB.

### **Forward and Backward Chaining**

#### Backward Chaining

- Start with goal to be proved, apply modus ponens in a backward manner to obtain premises, then try to solve for premises until known facts (already in KB) are reached
- This is useful for solving for a particular goal
- In a knowledge-based agent this amounts to applications of the ASK operation
- The proofs can be viewed as an "AND/OR" tree
  - Root is the goal to be proved
  - For each node, its children are the subgoals that must be proved in order to prove the goal at the current node
  - If the goal is conjunctive (i.e., the premise of rule is a conjunction), then each conjunct is represented as a child and the node is marked as an "AND node" in this case, both subgoals have to be proved
  - If the goal can be proved using alternative facts in KB, each alternate subgoal is represented as a child and the node is marked as an "OR node" in this case, only one of the subgoals need to be proved



### **Proof Tree for Backward Chaining**



### **Backward Chaining: Blocks World**



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### **Example: Using Resolution in Blocks World**



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## A Knowledge-Based Agent for Blocks World

- Scenario: our agent is a robot that needs to be able to move blocks on top of other blocks (if they are "clear") or onto the floor.
- Full axiomatization of the problem requires two types of axioms:
  - A set of axioms (facts) describing the current state of the world (this includes "definitions" of predicates such as on, above, clear, etc)
  - A set of axioms that describe the effect of our actions
    - in this case, there is one action: "move(x, y)"
    - need axioms that tell us what happens to blocks when they are moved
    - Important: in the real implementation of the agent a predicate such as "move(x, y)" is associated with a specific action of the robot which is triggered when the subgoal involving the "move" predicate succeeds.

## **Agent for Blocks World**

( )

-

success

success

 $(\mathbf{n})$ 

....



E A D C B	onFloor(C)clear(A)onFloor(B)clear(E)on(A,C) $on(x,y) \Rightarrow above(x,y)$ on(D,B) $on(x,z) \land above(z,y) \Rightarrow a$	bove $(x,y)$
	$\sim$ on(y,x) => clear(x) Need this to tell be "clear." It als	us what it means for a block to so tells us how to clear a block.
	$clear(x) \land clear(y) \land move(x,y) \Longrightarrow on(x,y)$ $clear(x) \land move(x,Floor) \Longrightarrow onFloor(x)$ $on(x,y) \land clear(x) \land move(x,Floor) \Longrightarrow clean$ $\cdots$	r(y) How actions affect our world
How do we get E to be on top of A?	on(E,A) x = E y = A clear(E) clear(A) move(E,A)	Note that "move" predicate is assumed to always succeed, and is associated with some real operation.

## **Agent for Blocks World**



## **Efficient Control of Reasoning**

• We have seen that during proofs (using resolution or Modus Ponens, etc.), there are different choices we can make at each step

#### • Consider: $house(h, p) \wedge rich(p) \Rightarrow big(h)$

- if we want to find *h* for which *big*(*h*) is true, we can do it in two ways
  - 1. find a rich person *p*, and hope that *h* will turn-out to be *p*'s house
  - 2. first show *h* is a house owned by *p*, then try to show that *p* is rich
- usually 2nd approach is more likely to yield a solution; first approach is often too random, but this is not always the case
- Prolog always takes the left-most subgoal to resolve with a clause in KB
- we can always order conjuncts on the left: "ordered resolution"

#### • Limitations (of controlling the search)

- control info. is static (2nd subgoal is deferred and we can't change this during the search)
- control information is provided by user (in form of axioms, ordering, etc.); we want the computer to do this

## **Types of Control Strategies**

Fundamental question is when to make the control decision: 3 possibilities

- ▶ 1. when the knowledge base is constructed (compile-time or static control)
- 2. during the search (run-time or dynamic control)
- 3. when the query appears (hybrid approach)

#### Trade-offs

- static is more efficient, but less flexible (less intelligent), since we don't need to figure it out as the interpreter is running
- dynamic is more flexible, but less efficient and harder to implement
- hybrid approach may work well if we make the right choice on which part should be static and which part dynamic

## **Using Statistical Properties of the KB**

- In hybrid approach, ordering of subgoals may depend on statistical properties of the KB
- Example:

 $related(x, y) \land loves(x, y) \Rightarrow family-oriented(x)$ 

- now suppose:
  - john has a small family and loves some of them
  - mary has a large family, but only loves her cat
- which ordering to use for queries: family-oriented(john) and family-oriented(mary)?
- For john
  - begin by enumerating relatives and then check to see if he loves any of them
- For mary
  - better to notice that she only loves her cat, and then check to see that they are not related

## **Controlling Search at Run-Time**

#### Method 1: Forward Checking

- basic idea: if during the search we commit to a choice that "we know" will lead to dead end, then we backtrack and make another choice
- but, how can we "know" this without solving the problem completely?
- answer: look ahead for a while to make sure that there are potential solutions for other subgoals based on choices made so far

#### • Example: crossword puzzle

when filling-in a word, check ahead to make sure that there are still solutions for any crossing word

#### • Example:

 $mother(m,c) \land lives-at(m,h) \land married(c,s) \land lives-at(s,h) \Rightarrow sad(s)$ 

- i.e., "people are unhappy if they live with their mothers-in-law;" now suppose we want to find someone who is sad
- look-ahead here could be checking info. about all marriages, if this information is explicitly state in the KB
- so, first find a mother and a child; then find out where the mother lives; but what if the child isn't married: no reason to continue; should go back and find another binding for c

## **Controlling Search at Run-Time**

#### Method 2: Cheapest-First Heuristic

good idea to first solve terms for which there are only a few solutions; this choice would simultaneously reduce the size of subsequent search space (harder predicates in the conjuncts are solved before they become impossible, so there is less need for backtracking)

#### • Example: want to find a carpenter whose father is a senator!!!

#### $carpenter(x) \land father(y, x) \land senator(y)$

suppose we have the following statistics about the knowledge base

<u>Conjunct</u>	<u>No. of Sol</u>	utions
<i>carpenter</i> ( <i>x</i> )	10 <sup>5</sup>	
senator(y)	100	
father(y, x)	108	
<pre>father(y, constant)</pre>	1	(a specific person has only one father)
<pre>father(constant, x)</pre>	) 2.3	(people on average have 2.3 children)

- in the above ordering, we have 10<sup>5</sup> choices for carpenters, but once we choose one, then there is one choice for a father, and he is either a senator or not ( search space: 10<sup>5</sup> )
- but, it is easier to enumerate senators first, then consider the term *father*(constant, x); once x has been bound to another constant, it is either a carpenter or it is not (search space: 100 \* 2.3 = 230)

## **Declarative Control of Search**

# • How about giving the system declarative information about the problem itself (i.e., include meta-information in the KB)?

- We can add control rules which would be treated as other (base-level) rules
- Problem: we now have to solve the control problem itself
- When would this be a good idea

#### An Example

- Planning a trip: when to head to the airport?
- We know that flights are scheduled, and we can't control them (this is base-level info.)
- So, control rule: "when planning a trip, plan the flight first"
- Note that we used base-level info. to develop a meta-level control rule

#### • Problem:

- After storing the control rule we have lost the information about its justification
- Suppose we find out that flights are every 30 minutes, but we can only get a ride to airport between 10 and 11 AM; this suggests that we should first plan out trip to airport
- But, since the control rule was stored directly in KB, we can't change the control behavior during the execution

# Principle: if control rules are to be stored, they should be independent of base-level information

### Meta-vs. Base-Level Reasoning Tradeoff

#### The Basic Rule (Computational Principle)

- the time spent at meta-level must be recovered at the base-level by finding a quicker (more optimal) path to the solution
- but, how do we know this without first solving the problem?
  - must somehow determine the "expected" time that will be recovered
- open problem:
  - we know very little about how this "expected" time should be quantified

#### Two Extremes:

- 1. ignore meta-level entirely: take action without worrying about their suitability (shoot from the hip approach), e.g., BFS, DFS
- 2. work compulsively at meta-level: refuse to take *any* action before *proving* it is the right thing to do
- Problem with these is that you can always find cases where either is a bad protocol
  - e.g., we could miss easy exam heuristic in case 1: do problems with most points first

## Meta-Reasoning (Cont.)

#### • The Interleaving Approach

- only specific proposal has been to interleave the two approaches, i.e., merge two computational principles
  - 1. never introspect; 2. introspect compulsively
- shown to give results generally within a factor of two of optimal solution
- this is the "schizophrenic" AI system approach
  - there are adherents to this idea in psychology: "everyone has two opposite personalities that keep each other in check

#### The Human Model

- human problem solvers don't do this kind of interleaving
- usually start by expecting problem to be easy enough to solve directly; as time passes, spend more time on strategies to solve the problem

