Mustafa Jarrar: Lecture Notes Inference Methods in First Order Logic Birzeit University, 2022



Artificial Intelligence

## Inference Methods in First Order Logic

Chapter 9 (& extra Material)

Mustafa Jarrar

Birzeit University



# Watch this lecture and download the slides



Course Page: <u>http://www.jarrar.info/courses/AI</u> More Online Courses at: <u>http://www.jarrar.info</u>

Note: Most material adapted and improved from [1]

Mustafa Jarrar: Lecture Notes Inference Methods in First Order Logic Birzeit University, 2022

### Artificial Intelligence Inference Methods in First Order Logic

In this lecture:

Part 1: Motivation

Part 2: Reducing first-order to propositional inference

Part 3: Unification

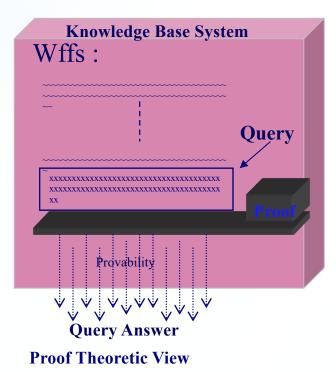
Part 4: Generalized Modus Ponens

Part 5: Forward chaining

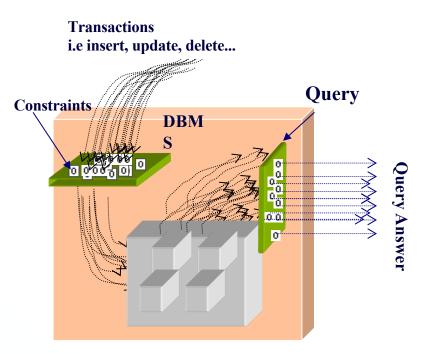
Part 6: Backward chaining

Part 7: Resolution

#### **Motivation: Knowledge Bases vs. Databases**



The KB is a set of formulae and the query evaluation is to prove that the result is provable.



#### **Model Theoretic View**

Evaluating the truth formula for each tuple in the table "Publish"

Mustafa Jarrar: Lecture Notes Inference Methods in First Order Logic Birzeit University, 2022

### Artificial Intelligence Inference Methods in First Order Logic

In this lecture:

Part 1: Motivation



Part 3: Unification

Part 4: Generalized Modus Ponens

Part 5: Forward chaining

Part 6: Backward chaining

Part 7: Resolution

#### **Inference in First-Order Logic**

We may inference in FOL by mapping FOL sentences into propositions, and apply the inference methods of propositional logic.

This mapping is called **propositionalization**.

Thus, Inference in first-order logic can be achieved using:

- Inference rules
- Forward chaining
- Backward chaining
- Resolution
  - Unification
  - Proofs
  - Clausal form
  - Resolution as search

#### **Universal Instantiation (UI)**

Every instantiation of a universally quantified sentence is entailed by it:

 $\forall v \alpha$ 

Subst({v/g},  $\alpha$ )

for any variable *v* and ground term *g* 

• Example:

 $\forall x \ King(x) \land Greedy(x) \Rightarrow Evil(x)$ King(John) Greedy(John)

 $King(John) \land Greedy(John) \Rightarrow Evil(John)$  $King(Richard) \land Greedy(Richard) \Rightarrow Evil(Richard)$ 

#### **Existential Instantiation (EI)**

**Example**:

For any sentence  $\alpha$ , variable  $\nu$ , and constant symbol k that does not appear elsewhere in the knowledge base:  $\exists \nu \alpha$ 

 $\exists x \operatorname{Crown}(x) \land \operatorname{OnHead}(x, \operatorname{John})$   $\Box \operatorname{Crown}(C_1) \land \operatorname{OnHead}(C_1, \operatorname{John})$ 

provided  $C_1$  is a new constant symbol, called a Skolem constant.

- The variable symbol can be replaced by any ground term, i.e., any constant symbol or function symbol applied to ground terms only.
- In other words, we don't want to accidentally draw other inferences about it by introducing the constant.
- Convenient to use this to reason about the unknown object, rather than constantly manipulating the existential quantifier.

#### **Reduction to Propositional Inference**

#### Suppose the KB contains just the following:

 $\forall x \operatorname{King}(x) \land \operatorname{Greedy}(x) \Longrightarrow \operatorname{Evil}(x)$ King(John) Greedy(John) Brother(Richard,John)

Instantiating the universal sentence in all possible ways, we have: King(John) ∧ Greedy(John) ⇒ Evil(John) King(Richard) ∧ Greedy(Richard) ⇒ Evil(Richard) King(John) Greedy(John) Brother(Richard,John)

The new KB is propositionalized: proposition symbols are

King(John), Greedy(John), Evil(John), King(Richard), etc.

Every FOL KB can be propositionalized so as to preserve entailment

(A ground sentence is entailed by new KB iff entailed by original KB)

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)))

#### **Reduction contd.**

Theorem: Herbrand (1930). If a sentence  $\alpha$  is entailed by an FOL KB, it is entailed by a finite subset of the propositionalized KB

Idea: For n = 0 to  $\infty$  do

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

Problem: works if α is entailed, loops if α is not entailed. Godel's Completeness Theorem says that FOL entailment is only semidecidable:

- If a sentence is **true** given a set of axioms, there is a procedure that will determine this.
- If the sentence is **false**, then there is no guarantee that a procedure will ever determine this—i.e., it **may never halt**.

**Truth Tabling** is not complete for FOL because truth table size may be infinite.

**Natural Deduction** is complete for FOL but is not practical because the "branching factor" in the search is too large (so we would have to potentially try every inference rule in every possible way using the set of known sentences).

Generalized Modus Ponens is not complete for FOL.

Generalized Modus Ponens is complete for KBs containing only Horn clauses.

#### **Problems with Propositionalization**

Propositionalization seems to generate lots of irrelevant sentences.

E.g., from:  $\forall x \text{ King}(x) \land \text{Greedy}(x) \Rightarrow \text{Evil}(x)$  King(John)  $\forall y \text{ Greedy}(y)$ Brother(Richard, John)

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.

#### **Problems with Propositionalization**

```
Given this KB:

King(x) \wedge Greedy(x) \Longrightarrow Evil(x)

King(John)

Greedy(John)
```

How do we really know that Evil(John)?

- We find x that is a King and Greedy, if so then x is Evil.
- That is, we need to a substitution {x/John}

But Given this KB:

 $\forall x \operatorname{King}(x) \land \operatorname{Greedy}(x) \Longrightarrow \operatorname{Evil}(x)$ King(John)  $\forall y \operatorname{Greedy}(y)$ 

How do we really know that Evil(John)?

– That is, we need to the substitutions {x/John, y,John}, but how?

Mustafa Jarrar: Lecture Notes Inference Methods in First Order Logic Birzeit University, 2022

### Artificial Intelligence Inference Methods in First Order Logic

In this lecture:

Part 1: Motivation

**Part 2:** Reducing first-order to propositional inference

Part 3: Unification

Part 4: Generalized Modus Ponens

Part 5: Forward chaining

Part 6: Backward chaining

Part 7: Resolution

#### Unification

We can get the inference immediately if we can find a substitution  $\theta$  such that *King(x)* and *Greedy(x)* match *King(John)* and *Greedy(y)*  $\theta = \{x/John, y/John\}$ 

This is called **Unification**, a "pattern-matching" procedure:

- Takes two atomic sentences, called literals, as input
- Returns "Failure" if they do not match and a substitution list,  $\theta$ , if they do

Unify(P,Q) =  $\theta$  if  $P\theta = Q\theta$ 

- That is, unify(p,q) = θ means subst(θ, p) = subst(θ, q) for two atomic sentences, p and q
- **θ** is called the **Most General Unifier** (MGU)
- All variables in the given two literals are implicitly universally quantified.
- To make literals match, replace (universally quantified) variables by terms

#### **Unification Example**

Unify  $(p,q) = \theta$  where Subst $(\theta,p) =$  Subset $(\theta,q)$ 

P	Q	θ
Knows(John,x)		/s(John,Jane)
Knows(John,x)		/s(y,Bill)
Knows(John,x)	Know	/s(y,Mother(y))
Knows(John,x)	Know	/s(x,Elizabeth)

#### **Unification Example**

Unify  $(p,q) = \theta$  where Subst $(\theta,p) =$  Subset $(\theta,q)$ 

P	Q	θ	
Knows(John,x) Knows(John,x) Knows(John,x) Knows(John,x)	Knows() Knows()	John,Jane) /,Bill) /,Mother(y)) ‹,Elizabeth)	{x/Jane}

#### **Unification Example**

Unify  $(p,q) = \theta$  where Subst $(\theta,p) =$  Subset $(\theta,q)$ 

P	Q $\theta$	
Knows(John,x) Knows(John,x) Knows(John,x) Knows(John,x)	Knows(John,Jane) Knows(y,Bill) Knows(y,Mother(y)) Knows(x,Elizabeth)	{x/Jane} {x/Bill,y/John}

P	Q $\theta$	
Knows(John,x) Knows(John,x) Knows(John,x) Knows(John,x)	Knows(John,Jane) Knows(y,Bill) Knows(y,Mother(y)) Knows(x,Elizabeth)	{x/Jane} {x/Bill,y/John} {y/John,x/Mother(John)}

P	Q Ø	
Knows(John,x)	Knows(John,Jane)	{x/Jane}
Knows(John,x)	Knows(y,Bill)	{x/Bill,y/John}
Knows(John,x)	Knows(y,Mother(y))	{y/John,x/Mother(John)}
Knows(John,x)	Knows(x,Elizabeth)	fail

- The last unification failed because x cannot take on the values John and Elizabeth at the same time.
- Because it happens that both sentences use the same variable name.
- Solution: rename x in Knows(x,Elizabeth) into Knows(z<sub>17</sub>,Elizabeth), without changing its meaning. (this is called standardizing apart)

P	Q $\theta$	
Knows(John,x)	Knows(John,Jane)	{x/Jane}
Knows(John,x)	Knows(y,Bill)	{x/Bill,y/John}
Knows(John,x)	Knows(y,Mother(y))	{y/John,x/Mother(John)}
Knows(John,x)	Knows(z <sub>17</sub> ,Elizabeth)	{x/Elizabeth, z <sub>17</sub> /John}

- The last unification failed because x cannot take on the values John and Elizabeth at the same time.
- Because it happens that both sentences use the same variable name.
- Solution: rename x in Knows(x,Elizabeth) into Knows(z<sub>17</sub>,Elizabeth), without changing its meaning. (this is called standardizing apart)

Р	Q $\theta$	
Knows(John,x)	Knows(John,Jane)	{x/Jane}
Knows(John,x)	Knows(y,Bill)	{x/Bill,y/John}
Knows(John,x)	Knows(y,Mother(y))	{y/John,x/Mother(John)}
Knows(John,x)	Knows(z <sub>17</sub> ,Elizabeth)	{x/Elizabeth, z <sub>17</sub> /John}

P	Q	θ				
Knows(John,x) Knows(John,x) Knows(John,x) Knows(John,x)	Knows Knows	s(John,Jane) s(y,Bill) s(y,Mother(y)) s(z <sub>17</sub> ,Elizabeth)	{x/ {y/.	{x/Jane} {x/Bill,y/John} {y/John,x/Mother(John)} {x/Elizabeth, z <sub>17</sub> /John} ??		
In the last case, we have two answers: θ= {y/John,x/z}, or θ= {y/John,x/John, z/John}				This first unification is more general, as it places fewer restrictions on the values of the variables.		

Suppose we have a query Knows(John,x), we need to unify Knows(John,x) with all sentences in KD.

P	Q	θ		
Knows(John,x) Knows(John,x) Knows(John,x) Knows(John,x)	Knows( Knows(	John,Jane) y,Bill) y,Mother(y)) z <sub>17</sub> ,Elizabeth)	{x/ {y/, {x/	Jane} Bill,y/John} John,x/Mother(John)} Elizabeth, z <sub>17</sub> /John} John,x/z}
In the last case	, we have t	two answers:		For every unifiable pair of

 $\theta = \{y/John, x/z\}, or$  $\theta = \{y/John, x/John, z/John\}$  For every unifiable pair of expressions, there is a **Most General Unifier** MGU

#### **Another Example**

#### Example:

- parents(x, father(x), mother(Bill))
- parents(Bill, father(Bill), y)
- {x/Bill, y/mother(Bill)}

Example:

- parents(x, father(x), mother(Bill))
- parents(Bill, father(y), z)
- {x/Bill, y/Bill, z/mother(Bill)}

Example:

- parents(x, father(x), mother(Jane))
- parents(Bill, father(y), mother(y))
- Failure

Mustafa Jarrar: Lecture Notes Inference Methods in First Order Logic Birzeit University, 2022

### Artificial Intelligence Inference Methods in First Order Logic

In this lecture:

- Part 1: Motivation
- **Part 2:** Reducing first-order to propositional inference
- Part 3: Unification



- Part 5: Forward chaining
- Part 6: Backward chaining
- Part 7: Resolution

#### **Generalized Modus Ponens (GMP)**

- A first-order inference rule, to find substitutions easily.
- Apply modus ponens reasoning to generalized rules.
- Combines And-Introduction, Universal-Elimination, and Modus Ponens . Example: {P(c), Q(c),  $\forall x(P(x) \land Q(x)) \Rightarrow R(x)$ } derive R(c)
- General case: Given
  - Atomic sentences  $P_1, P_2, ..., P_n$
  - Implication sentence  $(Q_1 \land Q_2 \land ... \land Q_n) \Rightarrow R$ 
    - $Q_1, ..., Q_n$  and R are atomic sentences
  - **Substitution** subst( $\theta$ ,  $P_i$ ) = subst( $\theta$ ,  $Q_i$ ) (for *i*=1,...,*n*)
  - **Derive new sentence:** subst( $\theta$ , *R*)
- Substitutions
  - subst( $\theta,\,\alpha)$  denotes the result of applying a set of substitutions defined by  $\theta$  to the sentence  $\alpha$
  - A substitution list  $\theta$  = { $v_1/t_1$ ,  $v_2/t_2$ , ...,  $v_n/t_n$ } means to replace all occurrences of variable symbol  $v_i$  by term  $t_i$
  - Substitutions are made in left-to-right order in the list

#### **Generalized Modus Ponens (GMP)**

A first-order inference rule, to find substitutions easily.

$$\frac{P_1, P_2, \dots, P_n, \quad (Q_1 \land Q_2 \land \dots \land Q_n \Longrightarrow R)}{\text{Subst} (R, \theta)} \quad \text{where } P_i \theta = Q_i \theta \text{ for all } i$$

King(John), Greedy(y),(King(x), Greedy(x)  $\Rightarrow$  Evil(x))Subst(Evil(x), {x/John, y/John})

- GMP used with KB of definite clauses (exactly one positive literal).
- All variables assumed universally quantified.

#### **Soundness of GMP**

Need to show that

$$P_1, \ldots, P_n, (Q_1 \land \ldots \land Q_n \Longrightarrow Q) \models R \theta$$

provided that  $Pi \theta = Qi \theta$  for all *i* 

Lemma: For any sentence Q, we have  $Q \models Q \theta$  by UI  $(P_1 \land \ldots \land P_n \Rightarrow \mathsf{R}) \models (P_1 \land \ldots \land P_n \Rightarrow \mathsf{R}) \theta = (P_1 \theta \land \ldots \land P_n \theta \Rightarrow \mathsf{R} \theta)$ 

 $Q_1 \setminus ..., \lor P_n \models Q_1 \land ... \land Q_n \models P_1 \theta \land ... \land Q_n \theta$ From 1 and 2, R  $\theta$  follows by ordinary Modus Ponens



Mustafa Jarrar: Lecture Notes Inference Methods in First Order Logic Birzeit University, 2022

### Artificial Intelligence Inference Methods in First Order Logic

In this lecture:

- Part 1: Motivation
- Part 2: Reducing first-order to propositional inference
- Part 3: Unification
- Part 4: Generalized Modus Ponens
  - Part 5: Forward chaining
- Part 6: Backward chaining
- Part 7: Resolution

Proofs start with the given axioms/premises in KB, deriving new sentences using GMP until the goal/query sentence is derived

This defines a **forward-chaining** inference procedure because it moves "forward" from the KB to the goal

Natural deduction using GMP is **complete** for KBs containing **only Horn clauses** 

The law says that it is a crime for an American to sell weapons to hostile nations. The country Nono, an enemy of America, has some missiles, and all of its missiles were sold to it by Colonel West, who is American.

Prove that Col. West is a criminal

#### Example Knowledge Base contd.

... it is a crime for an American to sell weapons to hostile nations:  $American(x) \land Weapon(y) \land Sells(x,y,z) \land Hostile(z) \Rightarrow Criminal(x)$ 

```
Nono ... has some missiles, i.e., \exists x \text{ Owns}(\text{Nono},x) \land \text{Missile}(x):

Owns(Nono,M_1) \land Missile(M_1)
```

... all of its missiles were sold to it by Colonel West *Missile(x)* ∧ *Owns(Nono,x)* ⇒ *Sells(West,x,Nono)* 

Missiles are weapons:  $Missile(x) \Rightarrow Weapon(x)$ 

An enemy of America counts as "hostile":  $Enemy(x, America) \Rightarrow Hostile(x)$ 

West, who is American ...

*American(West)* The country Nono, an enemy of America ... *Enemy(Nono,America)* 

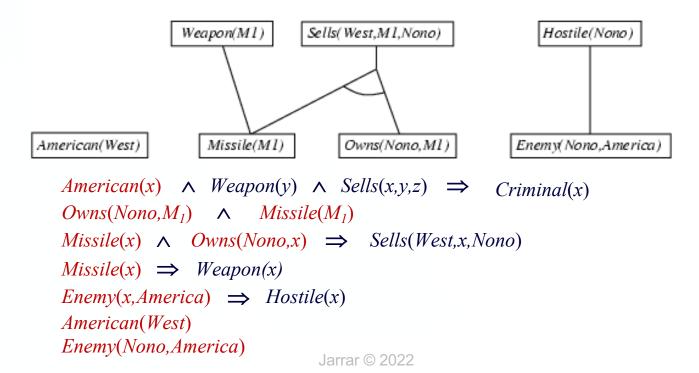
#### **Forward Chaining Proof**

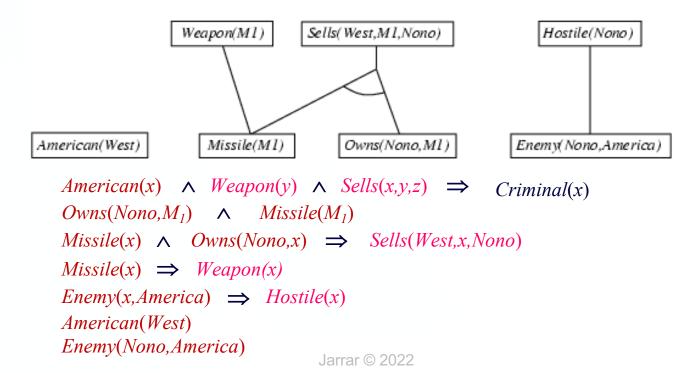


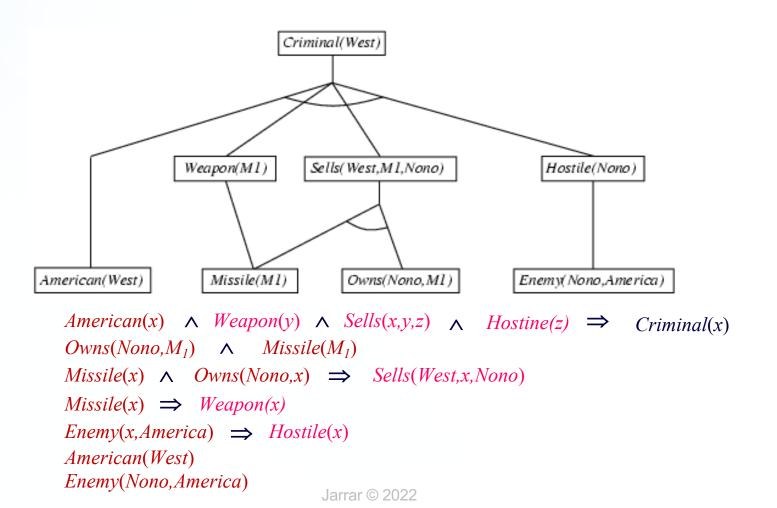
35

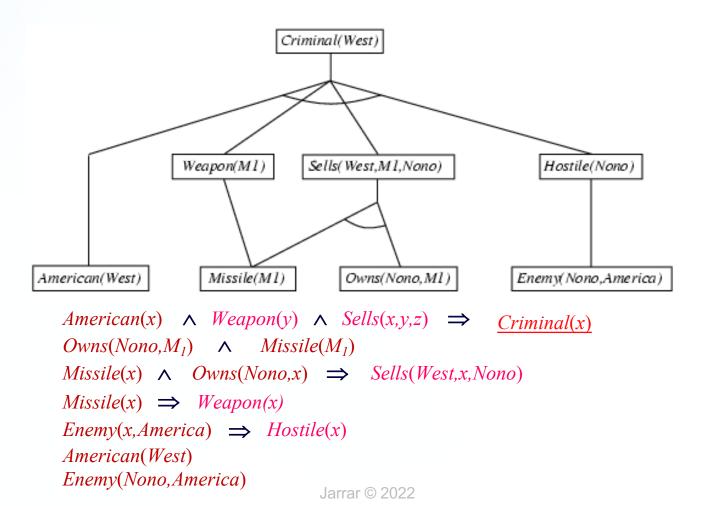
#### **Forward Chaining Proof**











(40)

# **Properties of Forward Chaining**

Sound and complete for first-order definite clauses.

Datalog = first-order definite clauses + no functions FC terminates for Datalog in finite number of iterations.

May not terminate in general if  $\alpha$  is not entailed.

This is unavoidable: entailment with definite clauses is semidecidable.

# **Efficiency of Forward Chaining**

Incremental forward chaining: no need to match a rule on iteration k if a premise wasn't added on iteration k-1

 $\Rightarrow$  Match each rule whose premise contains a newly added positive literal.

Matching itself can be expensive: Database indexing allows O(1) retrieval of known facts e.g., query *Missile(x)* retrieves *Missile(M<sub>1</sub>)* 

Forward chaining is widely used in deductive databases.

Mustafa Jarrar: Lecture Notes Inference Methods in First Order Logic Birzeit University, 2022

# Artificial Intelligence Inference Methods in First Order Logic

In this lecture:

- Part 1: Motivation
- □ Part 2: Reducing first-order to propositional inference

Part 3: Unification

Part 4: Generalized Modus Ponens

Part 5: Forward chaining

Part 6: Backward chaining

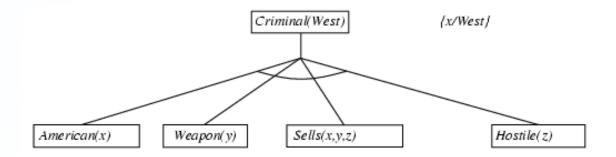
Part 7: Resolution

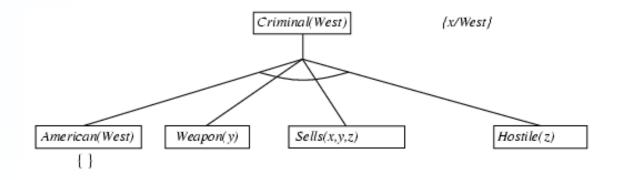
# **Backward Chaining**

Proofs start with the goal query, find implications that would allow you to prove it, and then prove each of the antecedents in the implication, continuing to work "backwards" until you arrive at the axioms, which we know are true.

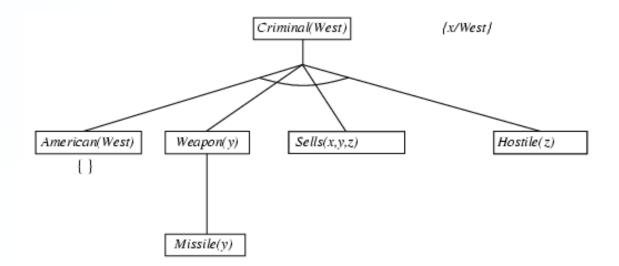
Backward-chaining deduction using GMP is **complete** for KBs containing **only Horn clauses.** 

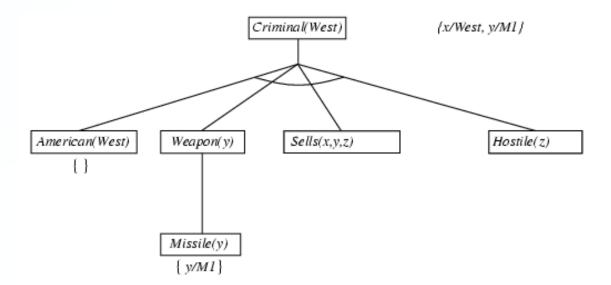
Criminal(West)

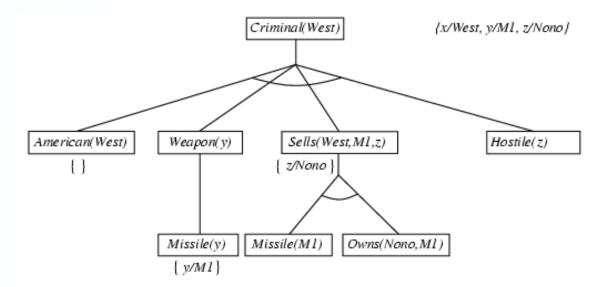


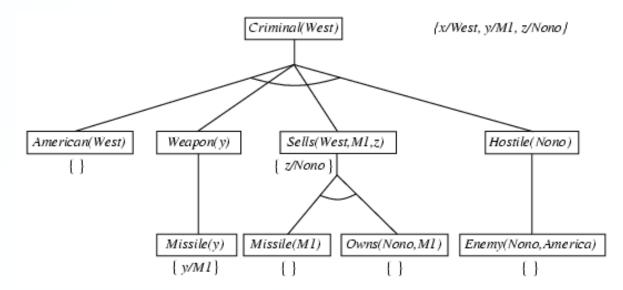






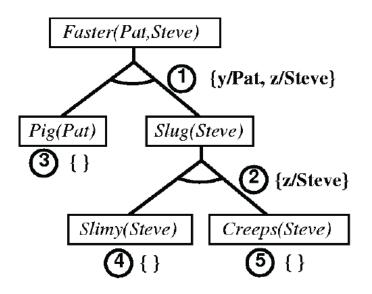






# **One More Backward Chaining Example**

- 1.  $Pig(y) \land Slug(z) \Longrightarrow Faster (y, z)$
- 2. Slimy(a)  $\land$  Creeps(a)  $\Rightarrow$  Slug(a)
- 3. Pig(Pat)
- 4. Slimy(Steve)
- 5. Creeps(Steve)



# **Properties of Backward Chaining**

Depth-first recursive proof search: space is linear in size of proof.

Incomplete due to infinite loops

 $\Rightarrow$  fix by checking current goal against every goal on stack.

Inefficient due to repeated subgoals (both success and failure).  $\Rightarrow$  fix using caching of previous results (extra space)

Widely used for logic programming.

# Forward vs. Backward Chaining

# FC is data-driven

- Automatic, unconscious processing
- E.g., object recognition, routine decisions
- May do lots of work that is irrelevant to the goal
- More efficient when you want to compute all conclusions.

# BC is goal-driven, better for problem-solving

- Where are my keys? How do I get to my next class?
- Complexity of BC can be much less than linear in the size of the KB
- More efficient when you want one or a few decisions.

# **Logic Programming**

- Algorithm = Logic + Control
- A backward chain reasoning theorem-prover applied to declarative sentences in the form of implications:

If  $B_1$  and ... and  $B_n$  then H

• Implications are treated as goal-reduction procedures:

to show/solve H, show/solve  $B_1$  and ... and  $B_n$ .

where implication would be interpreted as a solution of problem H given solutions of  $B_1 \dots B_n$ .

- Find a solution is a proof search, which done Depth-first backward chaining.
- Because automated proof search is generally infeasible, logic programming relies on the programmer to ensure that inferences are generated efficiently. Also by restricting the underlying logic to a "well-behaved" fragment such as Horn clauses or Hereditary Harrop formulas.

# Logic Programming: Prolog

Developed by Alain Colmerauer(Marseille) and Robert Kowalski(Edinburgh) in 1972.

Program = set of clauses of the form

 $P(x)_1 \wedge \ldots \wedge p(x_n) \Rightarrow head$ written as

head :-  $P(x_1)$ , ...,  $P(x_n)$ .

#### For example:

```
criminal(X) :- american(X), weapon(Y), sells(X,Y,Z), hostile(Z).
```

Closed-world assumption ("negation as failure").

- alive(X) :- not dead(X).
- alive(joe) succeeds if dead(joe) fails.

# Logic Programming: Prolog

```
mother(Nuha, Sara).
father(Ali, Sara).
father(Ali, Dina).
father(Said, Ali).
sibling(X, Y) :- parent(Z, X), parent(Z, Y).
parent (X, Y) :- father(X, Y).
parent(X, Y) :- mother (X, Y).
```

?- sibling(Sara, Dina).Yes

?- father(Father, Child). // enumerates all valid answers

Mustafa Jarrar: Lecture Notes Inference Methods in First Order Logic Birzeit University, 2022

# Artificial Intelligence Inference Methods in First Order Logic

In this lecture:

- Part 1: Motivation
- □ Part 2: Reducing first-order to propositional inference
- Part 3: Unification
- Part 4: Generalized Modus Ponens
- Part 5: Forward chaining
- Part 6: Backward chaining
  - Part 7: Resolution

#### **Resolution in FOL**

Recall: We saw that the propositional resolution is a refutationly **complete** inference procedure **for Propositional Logic**.

Here, we extend resolution to FOL.

First we need to covert sentences in to CNF, for example:

 $\forall x \operatorname{American}(x) \land \operatorname{Weapon}(y) \land \operatorname{Sells}(x,y,z) \land \operatorname{Hostile}(z) \Rightarrow \operatorname{Criminal}(x)$ 

becomes

 $\neg$  American(x)  $\lor \neg$  Weapon(y)  $\lor \neg$  Sells(x,y,z)  $\lor \neg$  Hostile(z)  $\lor$  Criminal(x)

Every sentence of first-order logic can be converted into **inferentially equivalent** CNF sentence.

The procedure for conversion to CNF is similar to the propositional case.

# **Conversion to CNF**

- The procedure for conversion to CNF is similar to the positional case.
- For example: "Everyone who loves all animals is loved by someone", or  $\forall x [\forall y Animal(y) \Rightarrow Loves(x,y)] \Rightarrow [\exists y Loves(y,x)]$

#### **Step 1 Eliminate Implications**

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

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

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

# **Conversion to CNF contd.**

Step 2. Move – inwards:

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

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

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

**Step 4. Skolemize**: a more general form of existential instantiation. Each existential variable is replaced by a Skolem function of the enclosing universally quantified variables:

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

Step 5. Drop universal quantifiers:

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

Step 6. Distribute  $\lor$  over  $\land$  :

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

# **Resolution in FOL**

The inference rule (FOL version):

 $\frac{l_1 \vee \cdots \vee l_k, \qquad m_1 \vee \cdots \vee m_n}{(l_1 \vee \cdots \vee l_{i-1} \vee l_{i+1} \vee \cdots \vee l_k \vee m_1 \vee \cdots \vee m_{j-1} \vee m_{j+1} \vee \cdots \vee m_n) \theta}$ 

where  $\text{Unify}(l_i, \neg m_j) = \theta$ .

The two clauses are assumed to be standardized apart so that they share no variables.

Apply resolution steps to  $CNF(KB \land \neg \alpha)$ .

Let's extend the previous example, and apply the resolution: Everyone who loves all animals is loved by someone. Anyone who kills an animal is loved by no one. Ali loves all animals. Either Ali or Kais killed the cat, who is an animal and its is named Foxi. Did Kais killed the cat?

# **Resolution in FOL (Example)**

Let's extend the previous example, and apply the resolution:

Everyone who loves all animals is loved by someone.

Anyone who kills an animal is loved by no one.

Ali loves all animals.

Either Ali or Kais killed the cat, who is an animal and its is named Foxi.

Did Kais killed the cat?

In FOL:

A. 
$$\forall x [\forall y Animal(y) \Rightarrow Loves(x,y)] \Rightarrow [\exists y Loves(y,x)]$$

B.  $\forall x,y,z \ [Animal(x) \Rightarrow Kills(y,x)] \Rightarrow \neg Loves(z,y)$ 

- C.  $\forall x \text{ Animal}(x) \Rightarrow \text{Loves}(\text{Ali},x)$
- D. Kills (Ali,Foxi) v Kills(Kais, Foxi)
- E. Cat(Foxi)
- F.  $\forall x \operatorname{Cat}(x) \Rightarrow \operatorname{Animal}(x)$
- ¬G. ¬Kills(Kais,Foxi)

# **Resolution in FOL (Example)**

- A.  $\forall x \ [\forall y \ Animal(y) \Rightarrow Loves(x,y)] \Rightarrow [\exists y \ Loves(y,x)]$
- B.  $\forall x,y,z \ [Animal(x) \Rightarrow Kills(y,x)] \Rightarrow \neg Loves(z,y)$
- C.  $\forall x \operatorname{Animal}(x) \Rightarrow \operatorname{Loves}(\operatorname{Ali},x)$
- D. Kills (Ali,Foxi) v Kills(Kais, Foxi)
- E. Cat(Foxi)
- F.  $\forall x \operatorname{Cat}(x) \Rightarrow \operatorname{Animal}(x)$
- ¬G. ¬Kills(Kais,Foxi)

After applying the CNF, we obtain:

- A1. Animal(F(x))  $\lor$  Loves(G(x),x)
- A2.  $\neg Loves(x,F(x)) \lor Loves(G(x),x)$
- B1. Animal(x)  $\lor$   $\neg$ Loves(z,y)
- B2.  $\neg$ Kills(y,x)  $\lor \neg$ Loves(z,y)
- C.  $\neg$ Animal(x)  $\lor$  Loves(Ali,x)
- D. Kills(Ali,Foxi) v Kills(Kais, Foxi)
- E. Cat(Foxi)
- F.  $\neg Cat(x) \lor Animal(x)$
- ¬G. ¬Kills(Kais,Foxi)

# **Resolution in FOL (Example)**

A1	Animal( $F(x)$ ) $\lor$ Loves( $G(x),x$ )		
A2	$\neg$ Loves(x, F(x)) $\lor$ Loves(G(x), x)		
B1	Animal(x) $\lor \neg$ Loves(z,y)		
B2	$\neg$ Kills(y,x) $\lor \neg$ Loves(z,y)		
С	$\neg$ Animal(x) $\lor$ Loves(Ali, x)		
D	Kills(Ali, Foxi) v Kills(Kais, Foxi)		
Е	Cat(Foxi)		
F	$\neg Cat(x) \lor Animal(x)$		
G	–Kills(Kais, Foxi)		
н	Animal (Foxi)	E,F	{x/Foxi}
I	Kills(Ali, Foxi)	D,G	{}
J	$\neg$ Animal(F(Ali)) $\lor$ Loves(G(Ali), Ali)	A2,C	{x/Ali, F(x)/x}
K	Loves(G(Ali), Ali)	J,A1	{F(x)/F(Ali), X/Ali}
L	¬Kills(Ali,x)	B2, K	z/G(Ali), y/Ali
М	Kills(Kais, Foxi)	D,L	{x/Foxi}
Ν	· ·	M,G	

The law says that it is a crime for an American to sell weapons to hostile nations. The country Nono, an enemy of America, has some missiles, and all of its missiles were sold to it by Colonel West, who is American.

Prove that Col. West is a criminal

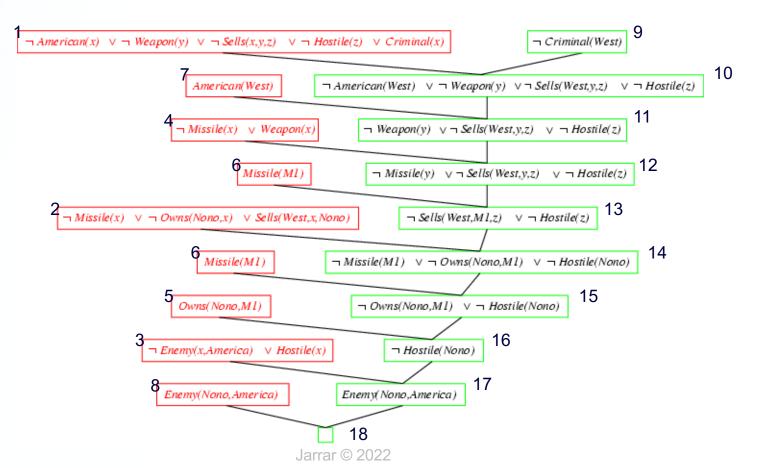
Assume this is represented in FOL (and in CNF):

```
\neg \operatorname{American}(x) \lor \neg \operatorname{Weapon}(y) \lor \neg \operatorname{Sells}(x,y,z) \lor \neg \operatorname{Hostile}(z) \lor \operatorname{Criminal}(x) \\ \neg \operatorname{Missile}(x) \lor \neg \operatorname{Owns}(\operatorname{Nono}, x) \lor \operatorname{Sells}(\operatorname{West}, x, \operatorname{Nano}) \\ \neg \operatorname{Enemy}(x, \operatorname{America}) \lor \operatorname{Hostile}(x) \\ \neg \operatorname{Missile}(x) \lor \operatorname{Weapon}(x) \\ \operatorname{Owns}(\operatorname{Nono}, \operatorname{M1}) \\ \operatorname{Missile}(\operatorname{M1}) \\ \operatorname{American}(\operatorname{West}) \\ \operatorname{Enemy}(\operatorname{Nano}, \operatorname{America}) \\ \neg \operatorname{Criminal}(\operatorname{West})
```

1	$\neg$ American(x) $\lor \neg$ Weapon(y) $\lor \neg$ Sells(x,y,z) $\lor \neg$ Hostile(z) $\lor$ Criminal(x)	
2	¬Missile(x) ∨ ¬Owns(Nono,x) ∨ Sells(West,x,Nano)	
3	¬Enemy(x,America) ∨ Hostile(x)	
4	$\neg$ Missile(x) $\lor$ Weapon(x)	
5	Owns(Nono,M <sub>1</sub> )	
6	Missile(M <sub>1</sub> )	
7	American(West)	
8	Enemy(Nano,America)	
9	⊸Criminal (West)	
10		
11		
12		
13		
14		
15		
16		
17		
18		

1	$\neg$ American(x) $\lor \neg$ Weapon(y) $\lor \neg$ Sells(x,y,z) $\lor \neg$ Hostile(z) $\lor$ Criminal(x)		
2	¬Missile(x) ∨ ¬Owns(Nono,x) ∨ Sells(West,x,Nano)		
3	¬Enemy(x,America) ∨ Hostile(x)		
4	$\neg$ Missile(x) $\lor$ Weapon(x)		
5	Owns(Nono,M <sub>1</sub> )		
6	Missile(M <sub>1</sub> )		
7	American(West)		
8	Enemy(Nano,America)		
9	¬Criminal (West)		
10	$\neg$ American(West) $\lor \neg$ Weapon(y) $\lor \neg$ Sells(West,y,z) $\lor \neg$ Hostile(z)	1,9	{x/West}
11	$\neg$ Weapon(y) $\lor \neg$ Sells(West,y,z) $\lor \neg$ Hostile(z)	7,10	{x/West}
12	$\negMissile(y) \lor \negSells(West, y, z) \lor \negHostile(z)$	4,11	{x/y}
13	$\neg$ Sells(West,M <sub>1</sub> ,z) $\lor \neg$ Hostile(z)	6,12	{y/M <sub>1</sub> }
14	$\neg Missile(M_1) \lor \neg Owns(Nono, M_1) \lor \neg Hostile(Nano)$	2,13	{x/M <sub>1</sub> , z/Nano}
15	$\neg$ Owns(Nono, M <sub>1</sub> ) $\lor \neg$ Hostile(Nano)	6,14	8
16	-Hostile(Nano)	5,15	8
17	–Enemy(Nano,America)	3,16	{x/Nano}
18		8,17	8

#### Another representation (as Tree)



## **Summary**

- Instantiating quantifiers is typically very slow.
- Unification is much more efficient than Instantiating quantifiers.
- **Generalized Modus Ponens** = Modus Ponens + unification, which is then used in forward/backward chaining.
- Generalized Modus Ponens is complete but semidecidable.
- Forward chaining is complete, and used in deductive databases, and Datalogs with polynomial time.
- **Backward chaining** is complete, used in logic programming, suffers from redundant inference and infinite loops.

Jarrar © 2022

- Generalized Resolution is refutation complete for sentences with CNF.
- There are **no decidable** inference methods for FOL.
- The exam will evaluate: What\How\Why (for all above)
- Next Lecture: Description logics are decidable logics.



#### References

 S. Russell and P. Norvig: Artificial Intelligence: A Modern Approach Prentice Hall, 2003, Second Edition
 Paula Matuszek: Lecture Notes on Artificial Intelligence <u>http://www.csc.villanova.edu/~matuszek/fall2008/Logic.ppt</u>