

# Artificial Intelligence

# 6. First Order Logic Inference

Lars Schmidt-Thieme

Information Systems and Machine Learning Lab (ISMLL)
Institute of Economics and Information Systems
& Institute of Computer Science
University of Hildesheim
http://www.ismll.uni-hildesheim.de

Lars Schmidt-Thieme, Information Systems and Machine Learning Lab (ISMLL), University of Hildesheim, Germany, Course on Artificial Intelligence, summer term 2007

Artificial Intelligence



- 1. Unification
- 2. Forward Chaining
- 3. Backward Chaining
- 4. Resolution

### "Compound Expressions"



Formulas and function terms sometimes are described as **compound expressions**.

For a compound formula, its operator and its arguments is defined:

```
\begin{array}{ll} \operatorname{op}(P(t_1,\ldots,t_n)) := P & \operatorname{args}(P(t_1,\ldots,t_n)) := (t_1,\ldots,t_n) \\ \operatorname{op}(f(t_1,\ldots,t_n)) := f & \operatorname{args}(f(t_1,\ldots,t_n)) := (t_1,\ldots,t_n) \\ \operatorname{op}(\neg\phi) := \neg & \operatorname{args}(\neg\phi) := (\phi) \\ \operatorname{op}(\phi\oplus\psi) := \oplus & \operatorname{args}(\phi\oplus\psi) := (\phi,\psi), \quad \oplus \in \{\land,\lor,\to,\leftrightarrow\} \\ \operatorname{op}(\exists x\phi) := \exists & \operatorname{args}(\exists x\phi) := (x,\phi) \\ \end{array}
```

Atomic terms, i.e., constants and variables, are not considered compound expressions.

Lars Schmidt-Thieme, Information Systems and Machine Learning Lab (ISMLL), University of Hildesheim, Germany, Course on Artificial Intelligence, summer term 2007

1/20

#### Artificial Intelligence / 1. Unification

# Unification / Algorithm



```
i unify(x, y, \theta):
 2 if \theta = failure
      return failure
 4 elsif x = y
         return \theta
6 elsif is-variable(x)
         return unify-var(x, y, \theta)
8 elsif is-variable(y)
         return unify-var(y, x, \theta)
10 elsif is-compound(x) and is-compound(y)
         return unify(args(x), args(y), unify(op(x), op(y), \theta))
12 elsif is-list(x) and is-list(y)
         return unify((x_2,\ldots,x_n),(y_2,\ldots,y_n), unify(x_1,y_1,\theta))
13
14 else
         return failure
15
16 fi
17
18 unify-var(var, x, \theta):
19 if \theta(var) \neq \emptyset
     return unify (\theta(var), x, \theta)
21 elsif \theta(x) \neq \emptyset
         return unify(var, \theta(x), \theta)
23 elsif occurs (var, x)
         return failure
24
25 else
         return \theta \cup \{var \mapsto x\}
```

# Unification / Example



```
\begin{aligned} & \mathsf{unify}(\mathsf{Knows}(\mathsf{John},x),\mathsf{Knows}(y,\mathsf{Mother}(y)),\emptyset) \\ &= \mathsf{unify}((\mathsf{John},x),(y,\mathsf{Mother}(y)),\mathsf{unify}(\mathsf{Knows},\mathsf{Knows},\emptyset)) \\ &= \mathsf{unify}((\mathsf{John},x),(y,\mathsf{Mother}(y)),\emptyset) \\ &= \mathsf{unify}((x),(\mathsf{Mother}(y)),\mathsf{unify}(\mathsf{John},y,\emptyset)) \\ &= \mathsf{unify}((x),(\mathsf{Mother}(y)),\{y/\mathsf{John}\}) \\ &= \mathsf{unify-var}(x,\mathsf{Mother}(y),\{y/\mathsf{John}\}) \\ &= \{y/\mathsf{John},x/\mathsf{Mother}(y)\} \end{aligned}
```

Lars Schmidt-Thieme, Information Systems and Machine Learning Lab (ISMLL), University of Hildesheim, Germany, Course on Artificial Intelligence, summer term 2007

#### Artificial Intelligence



- 1. Unification
- 2. Forward Chaining
- 3. Backward Chaining
- 4. Resolution

#### Generalized Modus Ponens



premise	conclusion	name
$F \vdash F, \mathcal{F} \vdash F \to G$	$\mathcal{F} \vdash G$	$\rightarrow$ -elimination / modus ponens
$\mathcal{F} \vdash F$	$\mathcal{F} \vdash F\theta$	universial instantiation
$F \vdash F, \mathcal{F} \vdash F' \to G, F\theta = F'\theta$	$\mathcal{F} \vdash G\theta$	generalized modus ponens

#### Lemma 1. Generalized modus ponens is sound.

#### Proof.

1. $\mathcal{F} \vdash F$	[assumption]
2. $\mathcal{F} \vdash F\theta$	[universal instantiation applied to 1]
3. $\mathcal{F} \vdash F' \to G$	[assumption]
4. $\mathcal{F} \vdash F'\theta \to G\theta$	[universal instantiation applied to 3]
5. $\mathcal{F} \vdash G\theta$	[ $\rightarrow$ -elemination applied to 2,4]

Lars Schmidt-Thieme, Information Systems and Machine Learning Lab (ISMLL), University of Hildesheim, Germany, Course on Artificial Intelligence, summer term 2007

#### 4/20

#### Artificial Intelligence / 2. Forward Chaining

# Generalized Modus Ponens / Example



Let the knowledge base  $\mathcal{F}$  be

$$\mathsf{King}(x) \wedge \mathsf{Greedy}(x) \to \mathsf{Evil}(x)$$
  
 $\mathsf{King}(\mathsf{John})$   
 $\mathsf{Greedy}(y)$ 

Now use

$$F := \mathsf{King}(\mathsf{John}) \land \mathsf{Greedy}(y)$$
  
 $F' := \mathsf{King}(x) \land \mathsf{Greedy}(x)$   
 $G := \mathsf{Evil}(x)$ 

then for

$$\theta := \{x/\mathsf{John}, y/\mathsf{John}\}$$

we have

$$F\theta = \text{King(John)} \land \text{Greedy(John)} = F'\theta$$

and thus we can derive

$$G\theta = \text{Evil}(\text{John})$$

#### **Forward Chaining**



Definitions for **conjunctive normal forms** (CNF), **Horn clauses** and **Horn formulas** are the same as in propositional logic. Here, atoms are formulas

$$P(t_1, t_2, \ldots, t_n)$$

where P is a predicate symbol and  $t_i$  are any terms (including variables).

A Horn clause C is called **definite** it it contains exactly one positive literal, i.e., implications of type

$$(\bigvee_{i=1}^{n} \neg L_i) \equiv (\bigwedge_{i=1}^{n} L_i \rightarrow \mathsf{false})$$

are not possible.

If the knowledge base consists of **Horn clauses** only, then generalized modus ponens can be used just like modus ponens to infer statements iteratively by forward chaining.

Lars Schmidt-Thieme, Information Systems and Machine Learning Lab (ISMLL), University of Hildesheim, Germany, Course on Artificial Intelligence, summer term 2007

Artificial Intelligence / 2. Forward Chaining

#### Example

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 (2/4)



The law says that it is a crime for an American to sell weapons to hostile nations.

 $\forall \mathsf{American}(x) \land \mathsf{Weapon}(y) \land \mathsf{Hostile}(z) \land \mathsf{Sell}(x,y,z) \rightarrow \mathsf{Criminal}(x)$ 

The country Nono,

Country(Nono)

an enemy of America,

Enemy(Nono, America)

has some missiles,

 $\exists x \mathsf{Missile}(x) \land \mathsf{Owns}(\mathsf{Nono}, x)$ 

and all of its missiles were sold to it by Colonel West,

 $\forall x \mathsf{Missile}(x) \land \mathsf{Owns}(\mathsf{Nono}, x) \rightarrow \mathsf{Sell}(\mathsf{West}, x, \mathsf{Nono})$ 

who is American.

American(West)

Lars Schmidt-Thieme, Information Systems and Machine Learning Lab (ISMLL), University of Hildesheim, Germany, Course on Artificial Intelligence, summer term 2007

8/20

Artificial Intelligence / 2. Forward Chaining

Example (3/4)



Additional background knowledge: Missiles are weapons.

 $\forall x \mathsf{Missile}(x) \to \mathsf{Weapon}(x)$ 

Enemies of America are hostile.

 $\forall x \mathsf{Enemy}(x, \mathsf{America}) \to \mathsf{Hostile}(x)$ 

Prove that Col. West is a criminal

Criminal(West)?

#### Example (4/4)



The knowledge base can be simplified by

- existential instantiation and
- omitting universal quantifiers
   (as all free variables are universally quantified anyway)

```
American(x) \land \mathsf{Weapon}(y) \land \mathsf{Hostile}(z) \land \mathsf{Sell}(x,y,z) \to \mathsf{Criminal}(x)
Country(Nono)
Enemy(Nono, America)
Missile(M_1) \land \mathsf{Owns}(\mathsf{Nono}, M_1)
Missile(x) \land \mathsf{Owns}(\mathsf{Nono}, x) \to \mathsf{Sell}(\mathsf{West}, x, \mathsf{Nono})
American(West)
Missile(x) \to \mathsf{Weapon}(x)
Enemy(x, \mathsf{America}) \to \mathsf{Hostile}(x)
```

→ This knowledge base consists of definite Horn clauses only!

Lars Schmidt-Thieme, Information Systems and Machine Learning Lab (ISMLL), University of Hildesheim, Germany, Course on Artificial Intelligence, summer term 2007

Artificial Intelligence / 2. Forward Chaining

# A Sind Charles

10/20

# Forward Chaining

```
i entails-fc(FOL definite horn formula F, query atom Q):
 _2 \mathcal{C} := \emptyset
 s \ \mathcal{C}' := \operatorname{clauses}(F)
     while C' \neq \emptyset do
                   \mathcal{C} := \mathcal{C} \cup \mathcal{C}'
                   \mathcal{C}' := \emptyset
                   \operatorname{for} C \in \mathcal{C} \operatorname{\underline{do}}
                           C' := \operatorname{standardize-apart}(C)
                           for atoms A_1, A_2, \ldots, A_n \in \mathcal{C} and \theta with body (C')\theta = (A_1 \wedge A_2 \wedge \ldots \wedge A_n)\theta do
                                   H := \text{head}(C')\theta
10
                                   \underline{\mathbf{if}}\ H \not\in \mathcal{C} and H \not\in \mathcal{C}'
                                        \mathcal{C}' := \mathcal{C}' \cup \{H\}
12
                                        \underline{\mathbf{if}} \ \mathrm{unify}(H,Q) \ \underline{\mathbf{return}} \ \mathrm{true} \ \underline{\mathbf{fi}}
13
                           \underline{o}\mathbf{d}
15
                   od
17 od
18 return false
```

# Forward Chaining / Example



American(West)

Missile(M1)

Owns(Nono,M1)

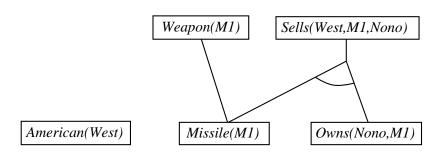
Enemy(Nono,America)

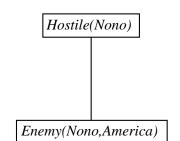
Lars Schmidt-Thieme, Information Systems and Machine Learning Lab (ISMLL), University of Hildesheim, Germany, Course on Artificial Intelligence, summer term 2007

11/20

#### Artificial Intelligence / 2. Forward Chaining

# Forward Chaining / Example

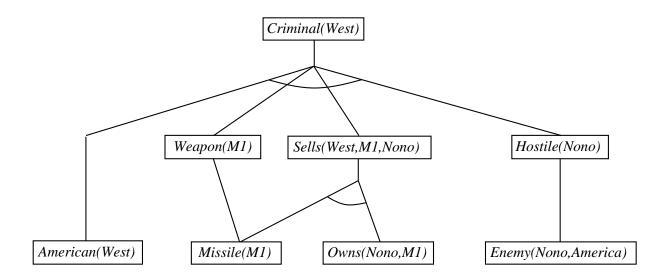




Lars Schmidt-Thieme, Information Systems and Machine Learning Lab (ISMLL), University of Hildesheim, Germany, Course on Artificial Intelligence, summer term 2007

# Forward Chaining / Example





Lars Schmidt-Thieme, Information Systems and Machine Learning Lab (ISMLL), University of Hildesheim, Germany, Course on Artificial Intelligence, summer term 2007

#### Artificial Intelligence



- 1. Unification
- 2. Forward Chaining
- 3. Backward Chaining
- 4. Resolution

#### **Backward Chaining**



Backward chaining works the other way around:

- keep a list of yet unsatisfied atoms Q
  starting with the query atom.
- try to find rules whichs head match atoms in Q (after unification) and replace the atom from Q by the atoms of the body of the matching rule.
- proceed recursively until no more atoms have to be satisfied.

Backward chaining keeps track of the substitution needed during the proof.

Lars Schmidt-Thieme, Information Systems and Machine Learning Lab (ISMLL), University of Hildesheim, Germany, Course on Artificial Intelligence, summer term 2007

12/20

#### Artificial Intelligence / 3. Backward Chaining

# Backward Chaining / Algorithm



```
\begin{array}{l} \textit{l} \ \ \text{entails-bc}(\text{FOL definite horn formula}\ F, \text{query atom}\ Q):\\ \mathbf{2} \ \ \mathbf{return} \ \ \text{entails-bc-goals}(\text{clauses}(F), \{Q\}, \emptyset) \neq \emptyset\\ \mathbf{3} \\ \mathbf{4} \ \ \ \text{entails-bc-goals}(\text{set of FOL definite Horn clauses}\ \mathcal{C}, \text{set of FOL atoms}\ Q, \theta):\\ \mathbf{5} \ \ \mathbf{if}\ Q = \emptyset \ \ \mathbf{return}\ \{\theta\}\ \mathbf{fi}\\ \mathbf{6} \ \Theta := \emptyset\\ \mathbf{7} \ \ \mathbf{for}\ C \in \mathcal{C}\ \mathbf{do}\\ \mathbf{8} \ \ C' := \text{standardize-apart}(C)\\ \mathbf{9} \ \ \theta' := \text{unify}(\text{head}(C'), Q[1]\theta)\\ \mathbf{10} \ \ \ \mathbf{if}\ \theta' \neq \text{failure}\\ \mathbf{11} \ \ \ \Theta := \Theta \cup \text{entails-bc-goals}(\mathcal{C}, \text{atoms}(\text{body}(C')) \cup (Q \setminus \{C\}), \theta \cup \theta')\\ \mathbf{12} \ \ \mathbf{fi}\\ \mathbf{13} \ \ \mathbf{od}\\ \mathbf{14} \ \ \mathbf{return}\ \Theta \end{array}
```



Criminal(West)

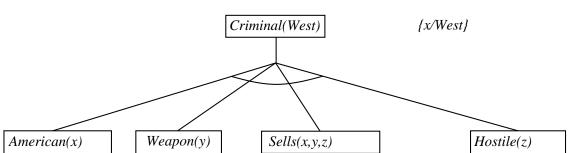
Lars Schmidt-Thieme, Information Systems and Machine Learning Lab (ISMLL), University of Hildesheim, Germany, Course on Artificial Intelligence, summer term 2007

#### 13/20

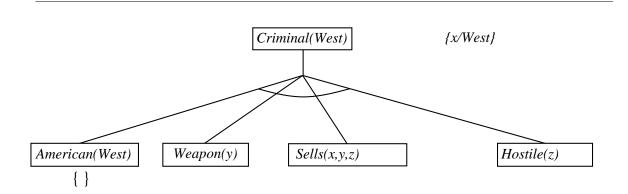
#### Artificial Intelligence / 3. Backward Chaining

# Backward Chaining / Example









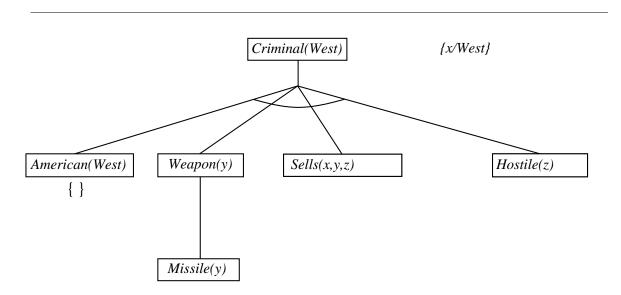
Lars Schmidt-Thieme, Information Systems and Machine Learning Lab (ISMLL), University of Hildesheim, Germany, Course on Artificial Intelligence, summer term 2007

13/20

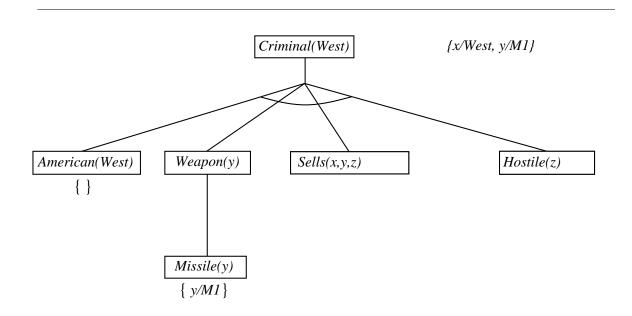
#### Artificial Intelligence / 3. Backward Chaining

# Backward Chaining / Example







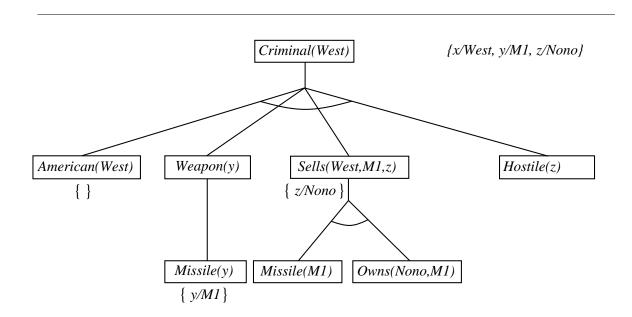


Lars Schmidt-Thieme, Information Systems and Machine Learning Lab (ISMLL), University of Hildesheim, Germany, Course on Artificial Intelligence, summer term 2007

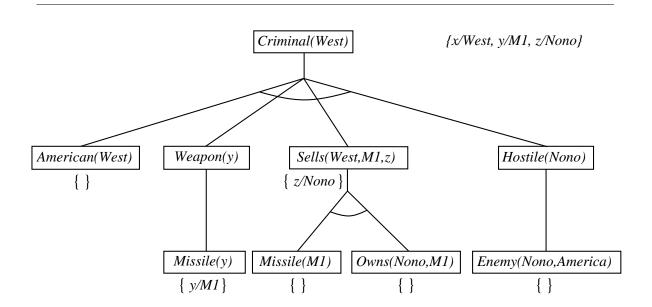
#### Artificial Intelligence / 3. Backward Chaining

# Backward Chaining / Example









Lars Schmidt-Thieme, Information Systems and Machine Learning Lab (ISMLL), University of Hildesheim, Germany, Course on Artificial Intelligence, summer term 2007

13/20

#### Artificial Intelligence / 3. Backward Chaining

# Logic Programming: Prolog



Prolog: logical programming language (PROgrammation en LOGique; Alain Colmerauer and Philippe Roussel, ca. 1972)

Allows knowlegde bases (= programs) consisting of definite Horn clauses.

Uses depth-first, left-to-right backward chaining (with several improvements).

# Example:

```
evil(X):- king(X), greedy(X).
king(john).
greedy(X).
?- evil(john)
```

# Negation as Failure



Prolog allows the usage of negated atoms in rule bodies interpreting them by **negation as failure**:

```
good(X) :- not evil(X)
```

Now the query ?- good (richard) would evaluate to true as the opposite, evil (richard) cannot be proved.

This is also called **closed world assumption**: if a fact is not encoded in the knowledge base and cannot be inferred, then it is considered not to be true.

Negation as failure renders Prolog **non-monotonic**: if one adds formulas to the knowledge base, inferences may become untrue.

Example: add evil (richard) to the knowledge base, now the query ?- good (richard) evaluates to false.

In first order logics we could not derive any conclusions about good (richard).

Lars Schmidt-Thieme, Information Systems and Machine Learning Lab (ISMLL), University of Hildesheim, Germany, Course on Artificial Intelligence, summer term 2007

15/20

Artificial Intelligence / 3. Backward Chaining

#### Prolog / Examples



Appending two lists to produce a third: append(X,Y,Z) encodes that X appended to Y results in Z.



- 1. Unification
- 2. Forward Chaining
- 3. Backward Chaining
- 4. Resolution

Lars Schmidt-Thieme, Information Systems and Machine Learning Lab (ISMLL), University of Hildesheim, Germany, Course on Artificial Intelligence, summer term 2007



#### Artificial Intelligence / 4. Resolution

# **FOL Resolvents**



#### Full first-order version:

$$\frac{\ell_1 \vee \dots \vee \ell_k, \qquad m_1 \vee \dots \vee m_n}{(\ell_1 \vee \dots \vee \ell_{i-1} \vee \ell_{i+1} \vee \dots \vee \ell_k \vee m_1 \vee \dots \vee m_{j-1} \vee m_{j+1} \vee \dots \vee m_n)\theta}$$
 where  $\mathsf{Unify}(\ell_i, \neg m_j) = \theta$ .

For example,

$$\frac{\neg \mathsf{Rich}(x) \lor \mathsf{Unhappy}(x), \quad \mathsf{Rich}(\mathsf{Ken})}{\mathsf{Unhappy}(\mathsf{Ken})}$$

with 
$$\ell_i = \neg \text{Rich}(x)$$
,  $m_j = \text{Rich}(\text{Ken})$  and  $\theta = \{x/\text{Ken}\}$ 

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

#### Conversion to CNF



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

1. Eliminate biconditionals and implications

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

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

$$\begin{split} \forall x [\exists y \neg (\neg \mathsf{Animal}(y) \lor \mathsf{Loves}(x,y))] \lor [\exists y \mathsf{Loves}(y,x)] \\ \forall x [\exists y \neg \neg \mathsf{Animal}(y) \land \neg \mathsf{Loves}(x,y)] \lor [\exists y \mathsf{Loves}(y,x)] \\ \forall x [\exists y \mathsf{Animal}(y) \land \neg \mathsf{Loves}(x,y)] \lor [\exists y \mathsf{Loves}(y,x)] \end{split}$$

Lars Schmidt-Thieme, Information Systems and Machine Learning Lab (ISMLL), University of Hildesheim, Germany, Course on Artificial Intelligence, summer term 2007



#### Artificial Intelligence / 4. Resolution

#### Conversion to CNF



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

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

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

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

5. Drop universal quantifiers:

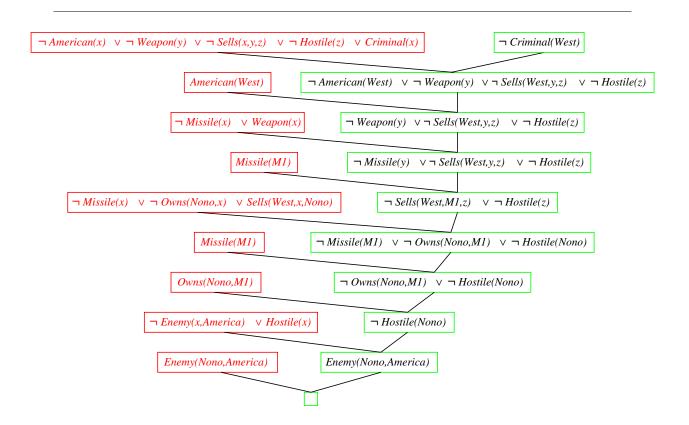
$$[\mathsf{Animal}(F(x)) \land \neg \mathsf{Loves}(x, F(x))] \lor \mathsf{Loves}(G(x), x)$$

6. Distribute ∧ over ∨:

$$[\mathsf{Animal}(F(x)) \vee \mathsf{Loves}(G(x),x)] \wedge [\neg \mathsf{Loves}(x,F(x)) \vee \mathsf{Loves}(G(x),x)]$$

# Resolution / Example





Lars Schmidt-Thieme, Information Systems and Machine Learning Lab (ISMLL), University of Hildesheim, Germany, Course on Artificial Intelligence, summer term 2007

20/20