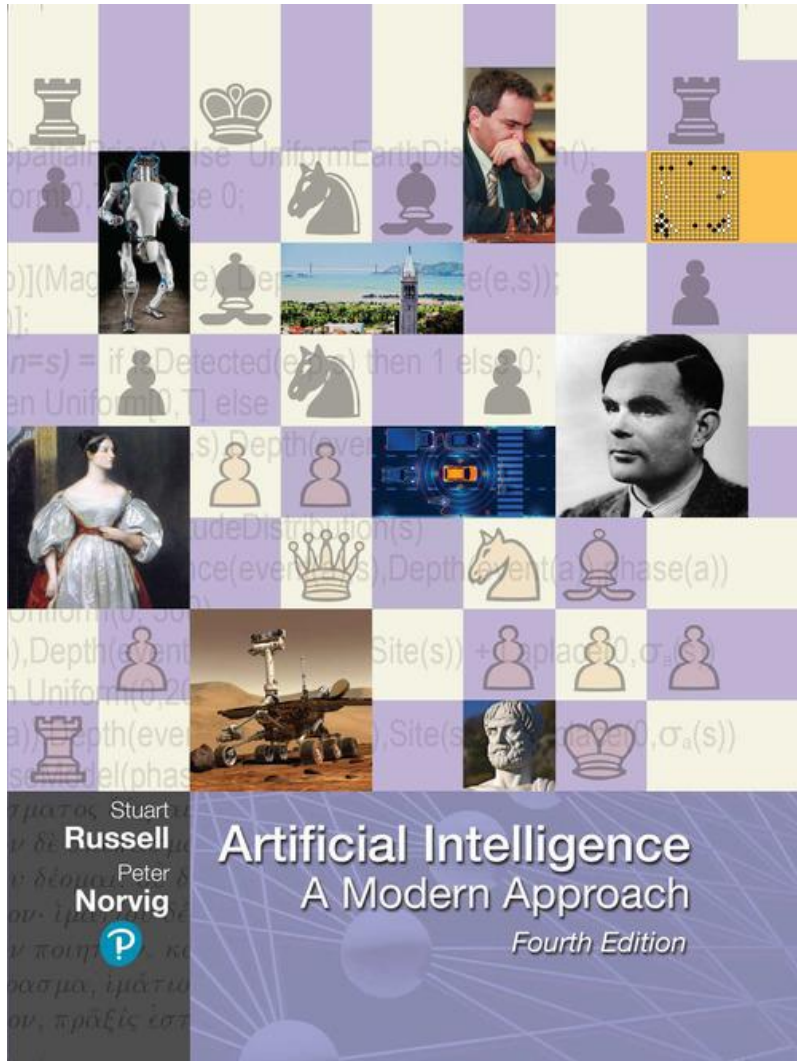


Artificial Intelligence Fundamentals

2024-2025



“The greatest progress that the human race has made lies in learning how to make correct inferences.”

- Friedrich Nietzsche

AIMA Chapter 9

Inference in first-order logic

Outline

- ◆ Reducing first-order inference to propositional inference
- ◆ Unification
- ◆ Generalized Modus Ponens
- ◆ Forward and backward chaining
- ◆ Logic programming
- ◆ Resolution
- ◆ Real-world Knowledge Bases

Universal instantiation (UI)

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

$$\frac{\forall v \ a}{\text{Subst}(\{v/g\}, a)}$$

for any variable v and ground term g

E.g., $\forall x \ King(x) \wedge Greedy(x) \Rightarrow Evil(x)$ yields

$$King(John) \wedge Greedy(John) \Rightarrow Evil(John)$$

$$King(Richard) \wedge Greedy(Richard) \Rightarrow Evil(Richard)$$

$$King(Father(John)) \wedge Greedy(Father(John)) \Rightarrow Evil(Father(John))$$

.

Existential instantiation (EI)

For any sentence a , variable v , and constant symbol k that does not appear elsewhere in the knowledge base:

$$\frac{\exists v \ a}{\text{Subst}(\{v/k\}, a)}$$

E.g., $\exists x \ \text{Crown}(x) \wedge \text{OnHead}(x, \text{John})$ yields

$$\text{Crown}(C_1) \wedge \text{OnHead}(C_1, \text{John})$$

provided C_1 is a new constant symbol, called a **Skolem constant**

Another example: from $\exists x \ d(x^y)/dy = x^y$ we obtain

$$d(e^y)/dy = e^y$$

provided e is a new constant symbol

Existential instantiation contd.

UI can be applied several times to **add** new sentences;
the new KB is logically equivalent to the old

EI can be applied once to **replace** the existential sentence;
the new KB is **not** equivalent to the old,
but is satisfiable iff the old KB was satisfiable

Reduction to propositional inference

Suppose the KB contains just the following:

$\forall x \text{ King}(x) \wedge \text{Greedy}(x) \Rightarrow \text{Evil}(x)$

$\text{King}(\text{John})$

$\text{Greedy}(\text{John})$

$\text{Brother}(\text{Richard}, \text{John})$

Instantiating the universal sentence in **all possible** ways, we have

$\text{King}(\text{John}) \wedge \text{Greedy}(\text{John}) \Rightarrow \text{Evil}(\text{John})$

$\text{King}(\text{Richard}) \wedge \text{Greedy}(\text{Richard}) \Rightarrow \text{Evil}(\text{Richard})$

$\text{King}(\text{John})$

$\text{Greedy}(\text{John})$

$\text{Brother}(\text{Richard}, \text{John})$

The new KB is **propositionalized**: proposition symbols are

$\text{King}(\text{John}), \text{Greedy}(\text{John}), \text{Evil}(\text{John}), \text{King}(\text{Richard})$ 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 a 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 a is entailed by this KB

Problem: works if a is entailed, loops if a 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

$\forall x \text{ King}(x) \wedge \text{Greedy}(x) \Rightarrow \text{Evil}(x)$

$\text{King}(\text{John})$

$\forall y \text{ Greedy}(y)$

$\text{Brother}(\text{Richard}, \text{John})$

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

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

With function symbols, it gets much much worse!

Unification

We can get the inference immediately if we can find a substitution θ such that $King(x)$ and $Greedy(x)$ match $King(John)$ and $Greedy(y)$

$\theta = \{x/John, y/John\}$ works

$Unify(a, \beta) = \theta$ if $a\theta = \beta\theta$

p	q	θ
$Knows(John, x)$	$Knows(John, Jane)$	
$Knows(John, x)$	$Knows(y, OJ)$	
$Knows(John, x)$	$Knows(y, M other(y))$	
$Knows(John, x)$	$Knows(x, OJ)$	

Unification

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$\theta = \{x/John, y/John\}$ works

$Unify(a, \beta) = \theta$ if $a\theta = \beta\theta$

p	q	θ
$Knows(John, x)$	$Knows(John, Jane)$	$\{x/Jane\}$
$Knows(John, x)$	$Knows(y, OJ)$	
$Knows(John, x)$	$Knows(y, Mother(y))$	
$Knows(John, x)$	$Knows(x, OJ)$	

Unification

We can get the inference immediately if we can find a substitution θ such that $King(x)$ and $Greedy(x)$ match $King(John)$ and $Greedy(y)$

$\theta = \{x/John, y/John\}$ works

$Unify(a, \beta) = \theta$ if $a\theta = \beta\theta$

p	q	θ
$Knows(John, x)$	$Knows(John, Jane)$	$\{x/Jane\}$
$Knows(John, x)$	$Knows(y, OJ)$	$\{x/OJ, y/John\}$
$Knows(John, x)$	$Knows(y, Other(y))$	
$Knows(John, x)$	$Knows(x, OJ)$	

Unification

We can get the inference immediately if we can find a substitution θ such that $King(x)$ and $Greedy(x)$ match $King(John)$ and $Greedy(y)$

$\theta = \{x/John, y/John\}$ works

$Unify(a, \beta) = \theta$ if $a\theta = \beta\theta$

p	q	θ
$Knows(John, x)$	$Knows(John, Jane)$	$\{x/Jane\}$
$Knows(John, x)$	$Knows(y, OJ)$	$\{x/OJ, y/John\}$
$Knows(John, x)$	$Knows(y, M other(y))$	$\{y/John, x/M other(John)\}$
$Knows(John, x)$	$Knows(x, OJ)$	

Unification

We can get the inference immediately if we can find a substitution θ such that $King(x)$ and $Greedy(x)$ match $King(John)$ and $Greedy(y)$

$\theta = \{x/John, y/John\}$ works

$Unify(a, \beta) = \theta$ if $a\theta = \beta\theta$

p	q	θ
$Knows(John, x)$	$Knows(John, Jane)$	$\{x/Jane\}$
$Knows(John, x)$	$Knows(y, OJ)$	$\{x/OJ, y/John\}$
$Knows(John, x)$	$Knows(y, M other(y))$	$\{y/John, x/M other(John)\}$
$Knows(John, x)$	$Knows(x, OJ)$	fail

Standardizing apart eliminates overlap of variables, e.g., $Knows(z_{17}, OJ)$

The first algorithm given by Robinson (1965) was rather inefficient; Faster algorithm originated from Martelli, Montanari (1976, 1982)!

Generalized Modus Ponens (GMP)

$$\frac{p_1^!, p_2^!, \dots, p_n^!, (p_1 \wedge p_2 \wedge \dots \wedge p_n \Rightarrow q)}{q\theta}$$

where $p_i^! \theta = p_i \theta$ for all i

$p_1^!$ is <i>King(John)</i>	p_1 is <i>King(x)</i>
$p_2^!$ is <i>Greedy(y)</i>	p_2 is <i>Greedy(x)</i>
θ is $\{x/\text{John}, y/\text{John}\}$	q is <i>Evil(x)</i>
$q\theta$ is <i>Evil(John)</i>	

GMP used with KB of definite clauses (**exactly** one positive literal)

All variables assumed universally quantified

Soundness of GMP

Need to show that

$$p_1^!, \dots, p_n^!, (p_1 \wedge \dots \wedge p_n \Rightarrow q) \models q\theta$$

provided that $p_i^! \theta = p_i \theta$ for all i

Lemma: For any definite clause p , we have $p \models p\theta$ by UI

1. $(p_1 \wedge \dots \wedge p_n \Rightarrow q) \models (p_1 \wedge \dots \wedge p_n \Rightarrow q)\theta = (p_1\theta \wedge \dots \wedge p_n\theta \Rightarrow q\theta)$
2. $p_1^!, \dots, p_n^! \models p_1^! \wedge \dots \wedge p_n^! \models p_1^!\theta \wedge \dots \wedge p_n^!\theta$
3. From 1 and 2, $q\theta$ follows by ordinary Modus Ponens

Example knowledge base

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:

Example knowledge base contd.

... it is a crime for an American to sell weapons to hostile nations:

American(x) ∧ Weapon(y) ∧ Sells(x, y, z) ∧ Hostile(z) ⇒ Criminal(x)

Nono ... has some missiles

Example knowledge base contd.

... it is a crime for an American to sell weapons to hostile nations:

$American(x) \wedge Weapon(y) \wedge Sells(x, y, z) \wedge Hostile(z) \Rightarrow Criminal(x)$

Nono ... has some missiles, i.e., $\exists x Owns(Nono, x) \wedge Missile(x)$:

$Owns(Nono, M_1)$ and $Missile(M_1)$

... all of its missiles were sold to it by Colonel West

Example knowledge base contd.

... it is a crime for an American to sell weapons to hostile nations:

$$\text{American}(x) \wedge \text{Weapon}(y) \wedge \text{Sells}(x, y, z) \wedge \text{Hostile}(z) \Rightarrow \text{Criminal}(x)$$

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

$$\text{Owns}(\text{Nono}, M_1) \text{ and } \text{Missile}(M_1)$$

... all of its missiles were sold to it by Colonel West

$$\forall x \text{ Missile}(x) \wedge \text{Owns}(\text{Nono}, x) \Rightarrow \text{Sells}(\text{West}, x, \text{Nono})$$

Missiles are weapons:

Example knowledge base contd.

... it is a crime for an American to sell weapons to hostile nations:

$$\text{American}(x) \wedge \text{Weapon}(y) \wedge \text{Sells}(x, y, z) \wedge \text{Hostile}(z) \Rightarrow \text{Criminal}(x)$$

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

$$\text{Owns}(\text{Nono}, M_1) \text{ and } \text{Missile}(M_1)$$

... all of its missiles were sold to it by Colonel West

$$\forall x \text{ Missile}(x) \wedge \text{Owns}(\text{Nono}, x) \Rightarrow \text{Sells}(\text{West}, x, \text{Nono})$$

Missiles are weapons:

$$\text{Missile}(x) \Rightarrow \text{Weapon}(x)$$

An enemy of America counts as “hostile”:

Example knowledge base contd.

... it is a crime for an American to sell weapons to hostile nations:

$$\text{American}(x) \wedge \text{Weapon}(y) \wedge \text{Sells}(x, y, z) \wedge \text{Hostile}(z) \Rightarrow \text{Criminal}(x)$$

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

$$\text{Owns}(\text{Nono}, M_1) \text{ and } \text{Missile}(M_1)$$

... all of its missiles were sold to it by Colonel West

$$\forall x \text{ Missile}(x) \wedge \text{Owns}(\text{Nono}, x) \Rightarrow \text{Sells}(\text{West}, x, \text{Nono})$$

Missiles are weapons:

$$\text{Missile}(x) \Rightarrow \text{Weapon}(x)$$

An enemy of America counts as “hostile”:

$$\text{Enemy}(x, \text{America}) \Rightarrow \text{Hostile}(x)$$

West, who is American ...

$$\text{American}(\text{West})$$

The country Nono, an enemy of America ...

$$\text{Enemy}(\text{Nono}, \text{America})$$

Forward chaining algorithm

```
function FOL-FC-Ask( $KB, a$ ) returns a substitution or false
  repeat until new is empty
     $new \leftarrow \{ \}$ 
    for each sentence  $r$  in  $KB$  do
       $(p_1 \wedge \dots \wedge p_n \Rightarrow q) \leftarrow \text{Standardize-Apart}(r)$ 
      for each  $\theta$  such that  $(p_1 \wedge \dots \wedge p_n)\theta = (p_1^1 \wedge \dots \wedge p_n^1)\theta$ 
        for some  $p_1^1, \dots, p_n^1$  in  $KB$ 
           $q^1 \leftarrow \text{Subst}(\theta, q)$ 
          if  $q^1$  is not a renaming of a sentence already in  $KB$  or new then do
            add  $q^1$  to new
             $\varphi \leftarrow \text{Unify}(q^1, a)$ 
            if  $\varphi$  is not fail then return  $\varphi$ 
    add new to  $KB$ 
  return false
```

Forward chaining proof

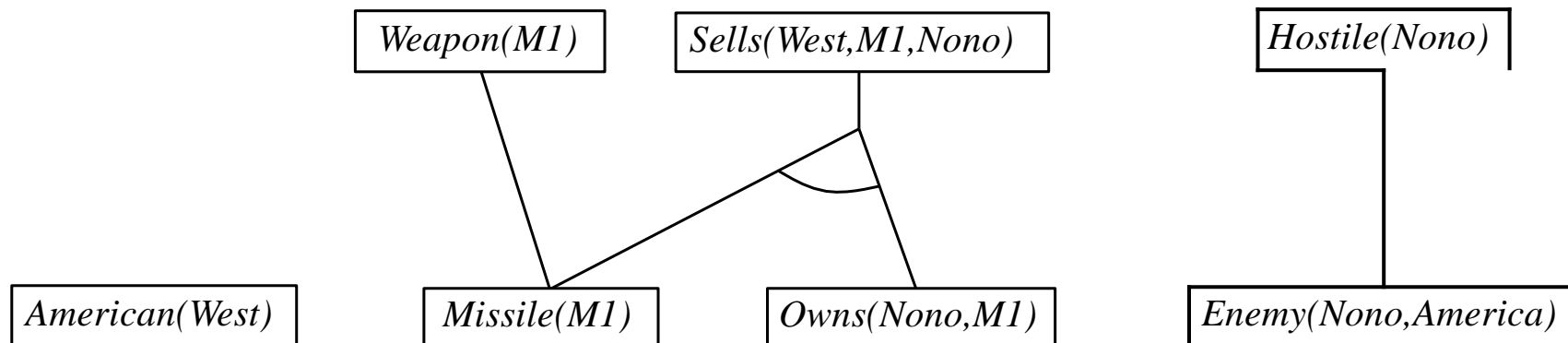
American(West)

Missile(M1)

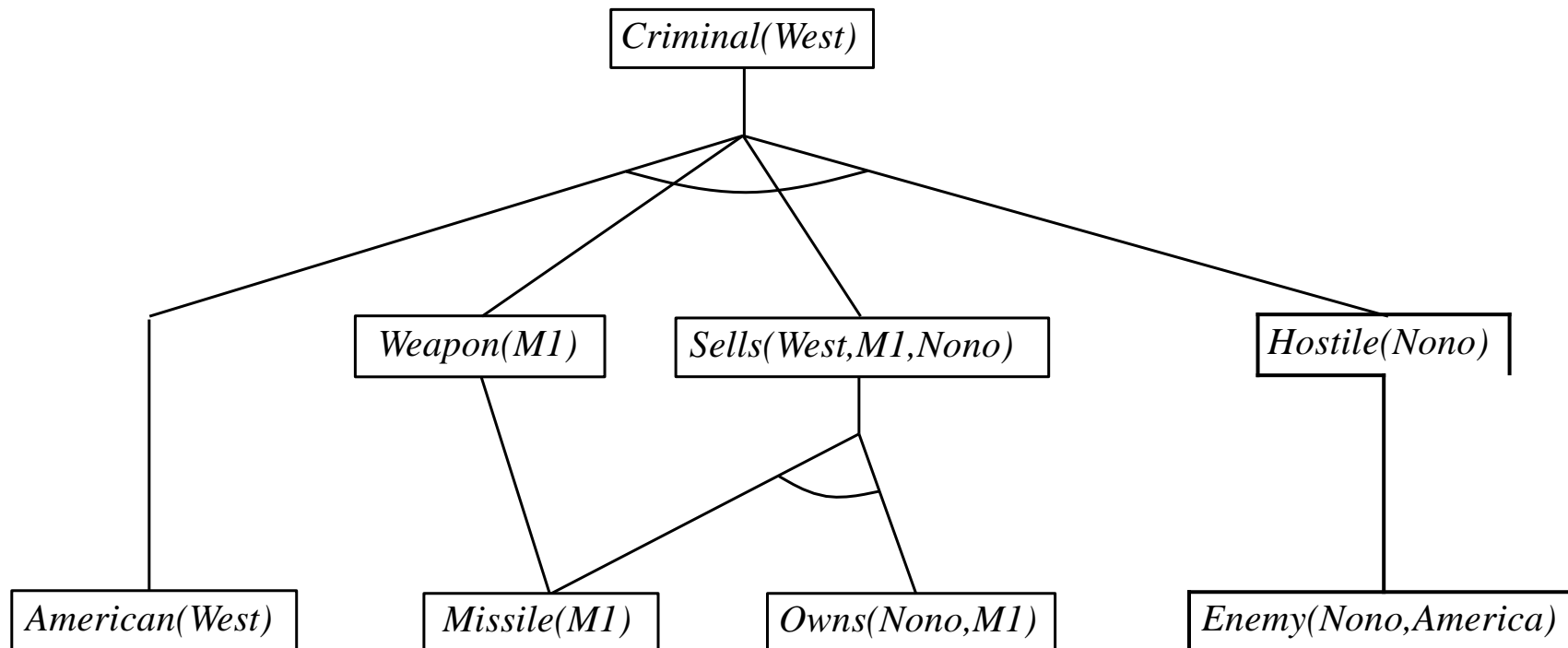
Owns(Nono,M1)

Enemy(Nono,America)

Forward chaining proof



Forward chaining proof



Properties of forward chaining

Sound and complete for first-order definite clauses
(proof similar to propositional proof)

Datalog = first-order definite clauses + **no functions** (e.g., crime KB)

FC terminates for Datalog in poly iterations: at most $p \cdot n^k$ literals

May not terminate in general if a is not entailed

This is unavoidable: entailment with definite clauses is semidecidable

Efficiency of forward chaining

Simple observation: no need to match a rule on iteration k
if a premise wasn't added on iteration $k - 1$

⇒ match each rule whose premise contains a newly added literal

Matching itself can be expensive

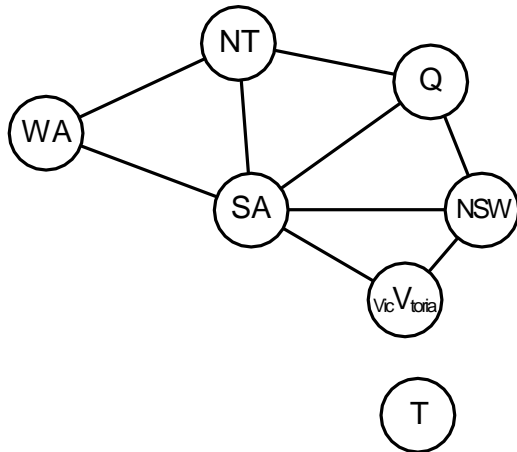
Database indexing allows $O(1)$ retrieval of known facts

e.g., query $Missile(x)$ retrieves $Missile(M_1)$

Matching conjunctive premises against known facts is NP-hard

Forward chaining is widely used in deductive databases

Hard matching example



$Diff(wa, nt) \wedge Diff(wa, sa) \wedge$
 $Diff(nt, q) \wedge Diff(nt, sa) \wedge$
 $Diff(q, nsw) \wedge Diff(q, sa) \wedge$
 $Diff(nsw, v) \wedge Diff(nsw, sa) \wedge$
 $Diff(v, sa) \Rightarrow Colorable()$

$Diff(Red, Blue) \quad Diff(Red, Green)$
 $Diff(Green, Red) \quad Diff(Green, Blue)$
 $Diff(Blue, Red) \quad Diff(Blue, Green)$

Colorable() is inferred iff the CSP has a solution

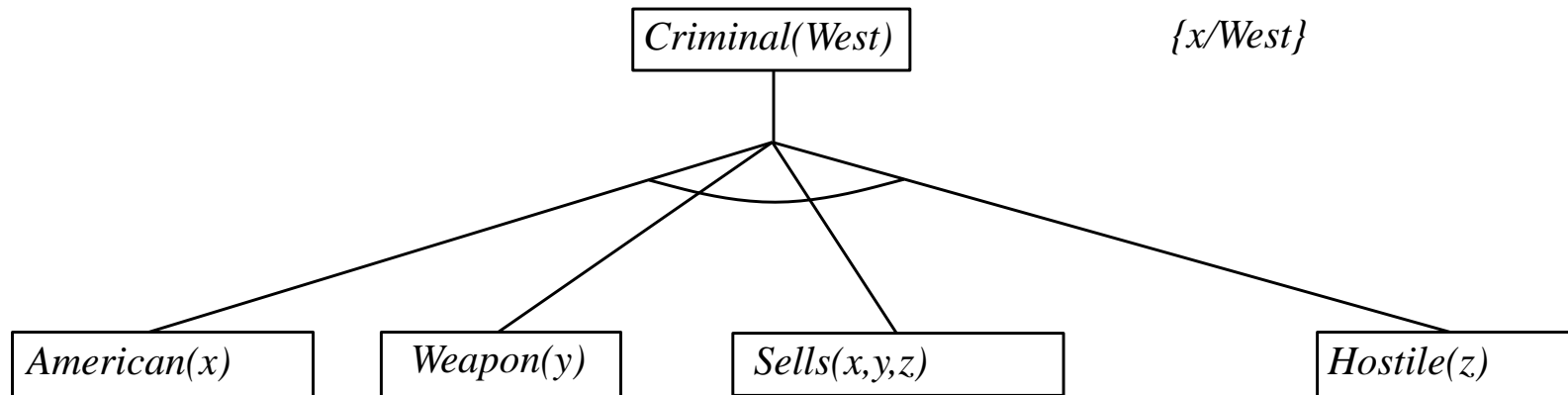
Backward chaining algorithm

```
function FOL-BC-Ask( $KB, goals, \theta$ ) returns a set of substitutions
  inputs:  $KB$ , a knowledge base
            $goals$ , a list of conjuncts forming a query ( $\theta$  already applied)
            $\theta$ , the current substitution, initially the empty substitution  $\{ \}$ 
  local variables:  $answers$ , a set of substitutions, initially empty
  if  $goals$  is empty then return  $\{ \theta \}$ 
   $q^1 \leftarrow \text{Subst}(\theta, \text{First}(goals))$ 
  for each sentence  $r$  in  $KB$ 
    where  $\text{Standardize-Apart}(r) = (p_1 \wedge \dots \wedge p_n \Rightarrow q)$ 
    and  $\theta \leftarrow \text{Unify}(q, q^1)$  succeeds
     $new\_goals \leftarrow [p_1, \dots, p_n | \text{Rest}(goals)]$ 
     $answers \leftarrow \text{FOL-BC-Ask}(KB, new\_goals, \text{Compose}(\theta, \theta)) \cup answers$ 
  return  $answers$ 
```

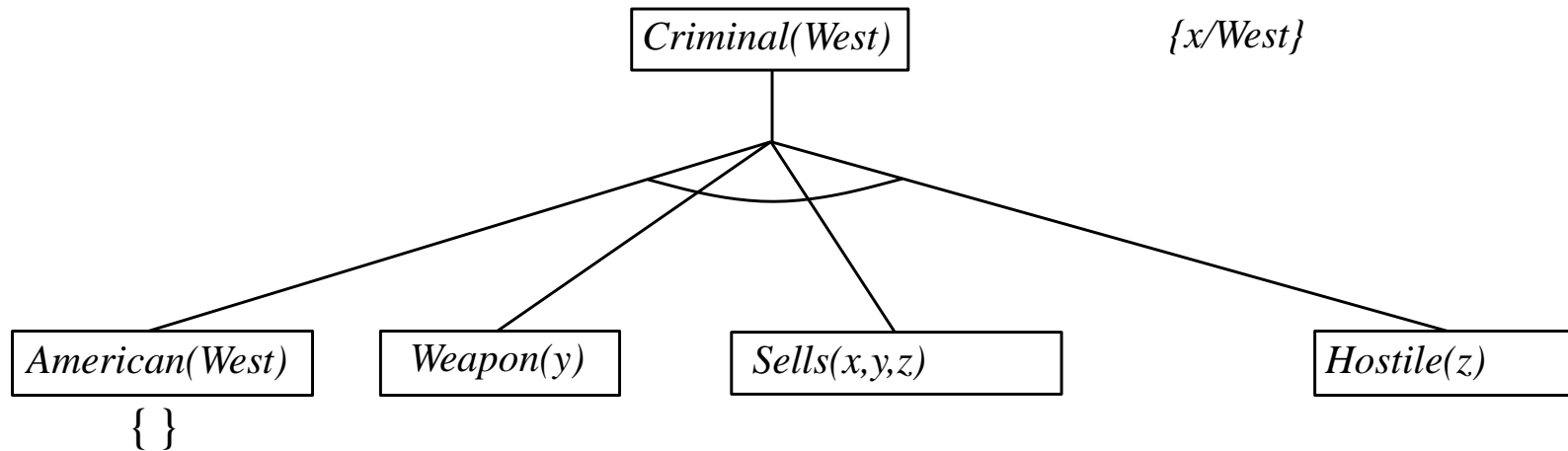
Backward chaining example

Criminal(West)

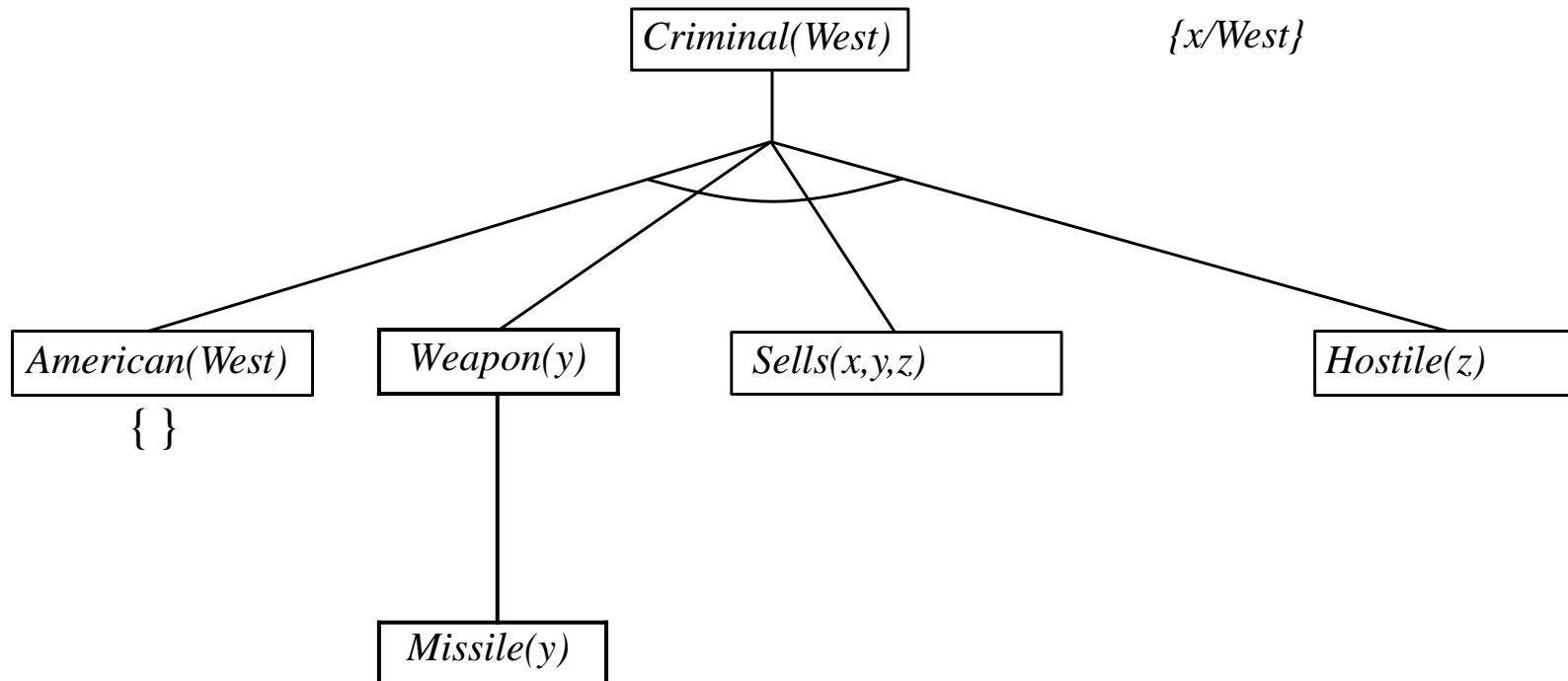
Backward chaining example



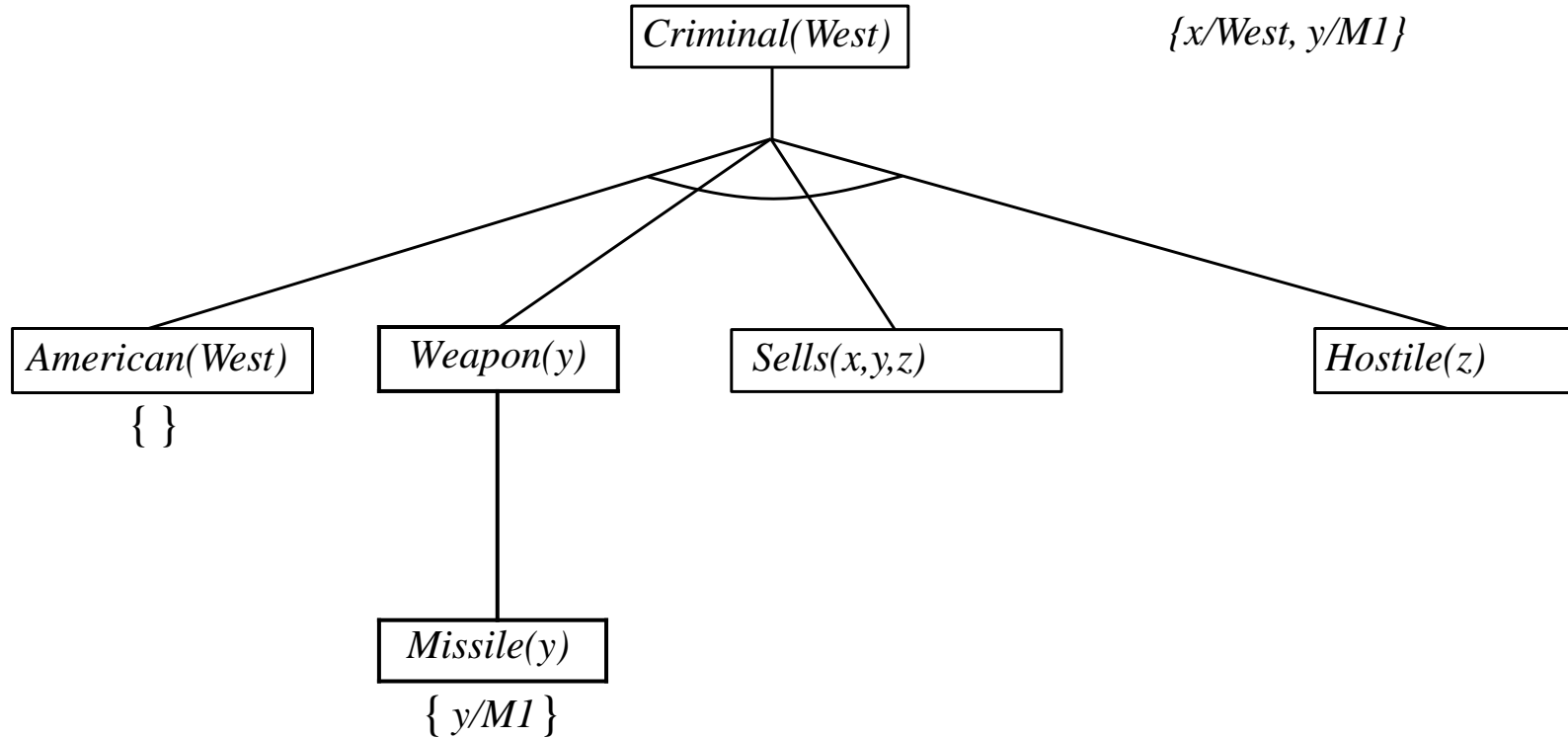
Backward chaining example



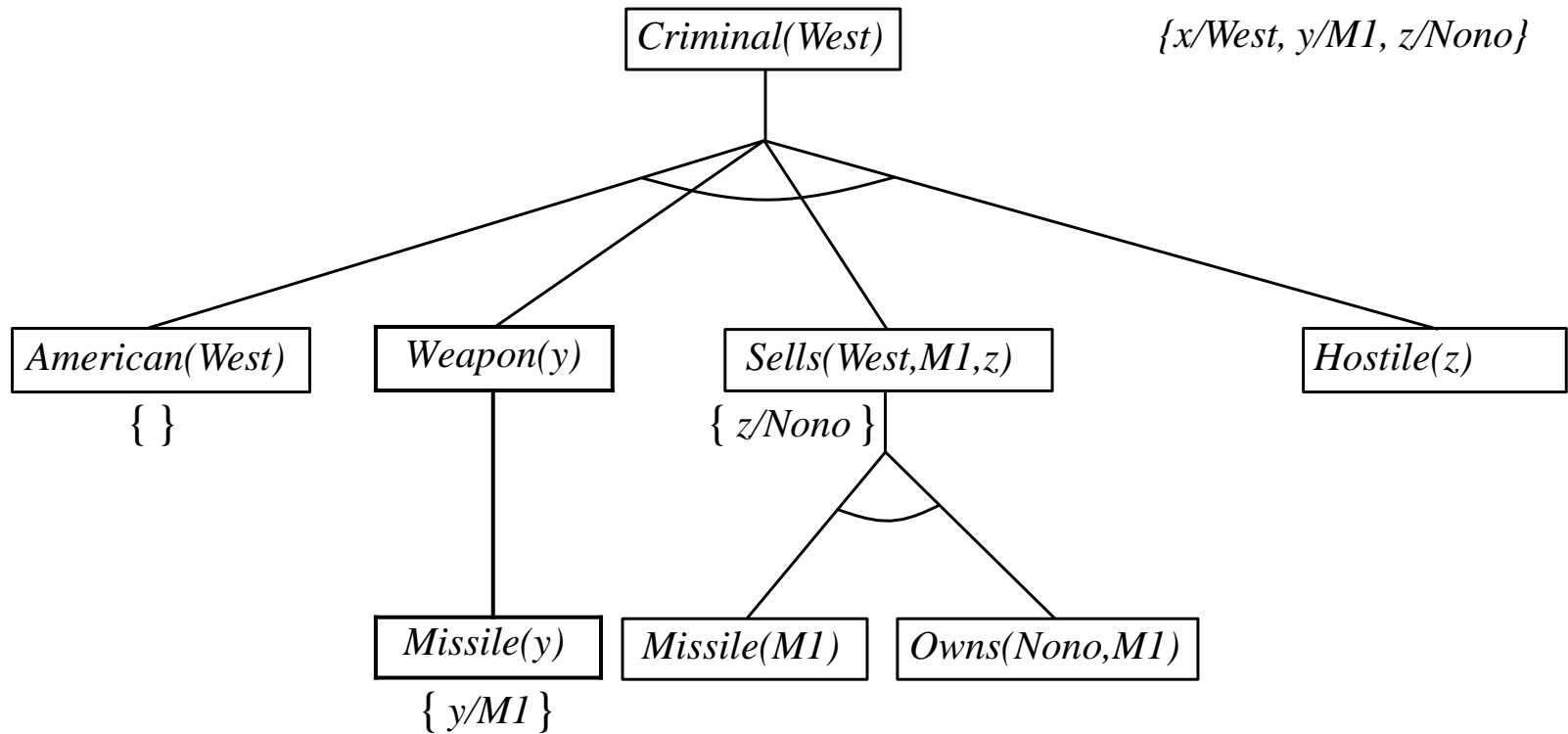
Backward chaining example



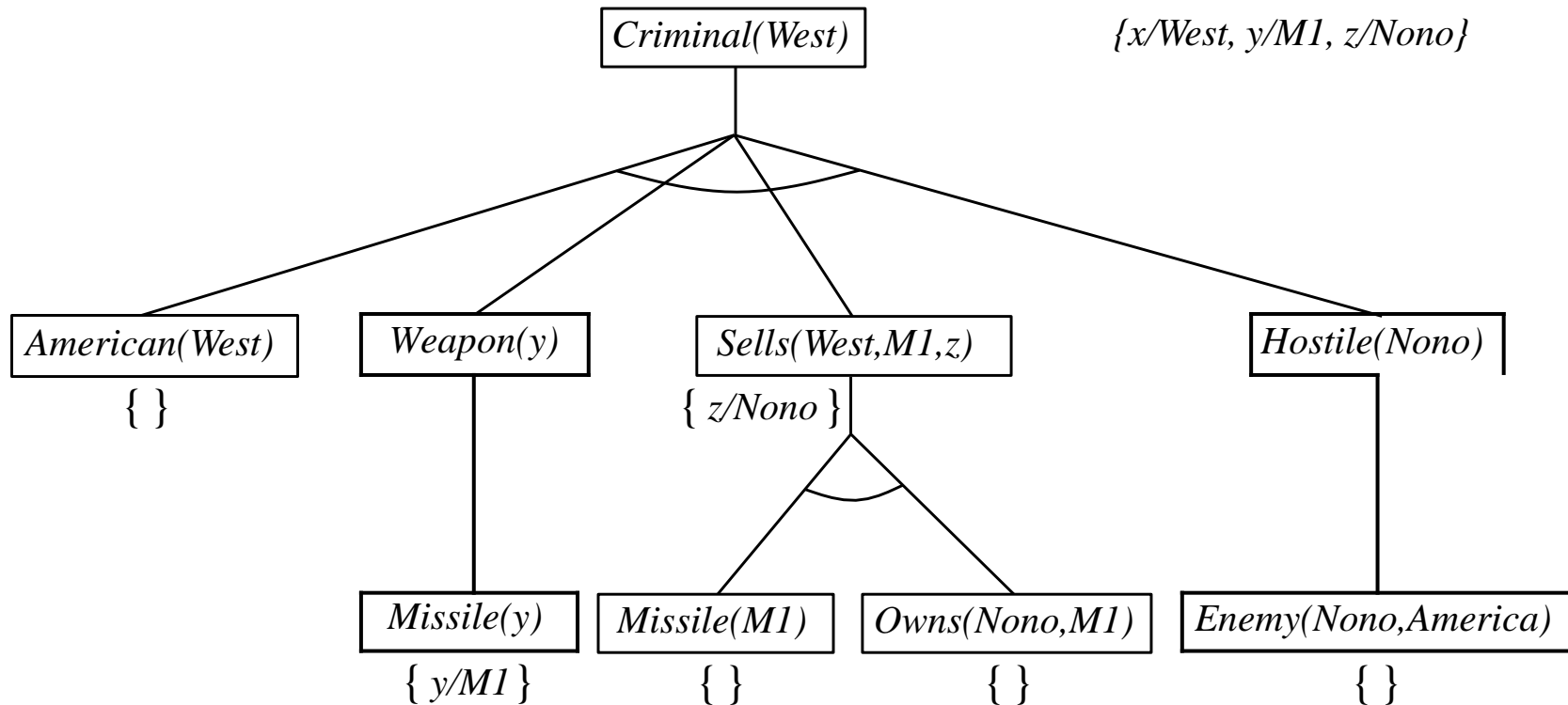
Backward chaining example



Backward chaining example



Backward chaining example



Properties of backward chaining

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

Incomplete due to infinite loops

⇒ fix by checking current goal against every goal on stack

Inefficient due to repeated subgoals (both success and failure)

⇒ fix using caching of previous results (extra space!)

Widely used (without much improvements!) for [logic programming](#)

Logic programming

Sound bite: computation as inference on logical KBs

Logic programming

1. Identify problem
2. Assemble information
3. Tea break
4. Encode information in KB
5. Encode problem instance as facts
6. Ask queries
7. Find false facts

Ordinary programming

- Identify problem
- Assemble information
- Figure out solution
- Program solution
- Encode problem instance as data
- Apply program to data
- Debug procedural errors

Should be easier to debug *Capital(NewYork, US)* than $x := x + 2$!

Prolog systems

Basis: backward chaining with Horn clauses + bells & whistles

Widely used in Europe, Japan (basis of 5th Generation project)

Program = set of clauses = $\text{head} :- \text{literal}_1, \dots, \text{literal}_n.$

e.g. $\text{criminal}(X) :- \text{american}(X), \text{weapon}(Y), \text{sells}(X, Y, Z), \text{hostile}(Z).$

Efficient unification by open coding

Efficient retrieval of matching clauses by direct linking Depth-first,
left-to-right backward chaining

Built-in predicates for arithmetic etc., e.g., $X \text{ is } Y * Z + 3$

Closed-world assumption (“negation as failure”) e.g., given
 $\text{alive}(X) :- \text{not dead}(X).$

$\text{alive}(\text{joe})$ succeeds if $\text{dead}(\text{joe})$ fails

Prolog examples

Depth-first search from a start state X:

% Define edges of the graph

edge(a, b).

edge(a, c).

edge(b, d).

edge(c, e).

edge(e, f).

% DFS: Check if there is a path from Start to Goal

dfs(Start, Goal) :- edge(Start, Goal).

% Base case: Direct connection

dfs(Goal, Goal).

% Base case: Found the goal.

dfs(Start, Goal) :-

edge(Start, NextNode),

% Recursive case: Find a connected node

dfs(NextNode, Goal).

% Continue searching from the next node

?- dfs(a, f). will return true

Prolog examples

Appending two lists to produce a third:

```
append([],Y,Y).
```

```
append([X|L],Y,[X|Z]) :- append(L,Y,Z).
```

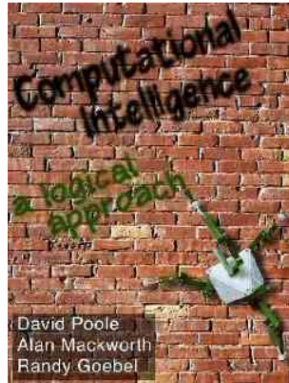
```
query:    append(A,B,[1,2]) ?
```

```
answers:  A=[]      B=[1,2]
```

```
          A=[1]     B=[2]
```

```
          A=[1,2]   B=[]
```

Can you implement a Neural Network in Prolog?



Computational Intelligence


A Logical Approach

[David Poole](#)
[Alan Mackworth](#)
[Randy Goebel](#)

Published by [Oxford University Press](#), New York.

Computational Intelligence: A Logical Approach is a textbook on artificial intelligence. It was published in January 1998.

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Resolution: brief summary

Full first-order version:

$$\frac{p_1 \vee \cdots \vee p_k, \quad m_1 \vee \cdots \vee m_n}{(p_1 \vee \cdots \vee p_{i-1} \vee p_{i+1} \vee \cdots \vee p_k \vee m_1 \vee \cdots \vee m_{j-1} \vee m_{j+1} \vee \cdots \vee m_n)\theta}$$

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

example,

$$\frac{\neg \text{Rich}(x) \vee \text{Unhappy}(x) \quad \text{Rich}(\text{Ken})}{\text{Unhappy}(\text{Ken})}$$

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

Apply resolution steps to $\text{CNF}(KB \wedge \neg a)$; complete for FOL

Conversion to CNF

Everyone who loves all animals is loved by someone:

$$\forall x [\forall y \text{ Animal}(y) \Rightarrow \text{Loves}(x, y)] \Rightarrow [\exists y \text{ Loves}(y, x)]$$

1. Eliminate biconditionals and implications

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

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

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

$$\forall x [\exists y \neg \neg \text{Animal}(y) \wedge \neg \text{Loves}(x, y)] \vee [\exists y \text{ Loves}(y, x)]$$

$$\forall x [\exists y \text{ Animal}(y) \wedge \neg \text{Loves}(x, y)] \vee [\exists y \text{ Loves}(y, x)]$$

Conversion to CNF contd.

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

$$\forall x [\exists y \text{ Animal}(y) \wedge \neg \text{Loves}(x, y)] \vee [\exists z \text{ Loves}(z, x)]$$

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

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

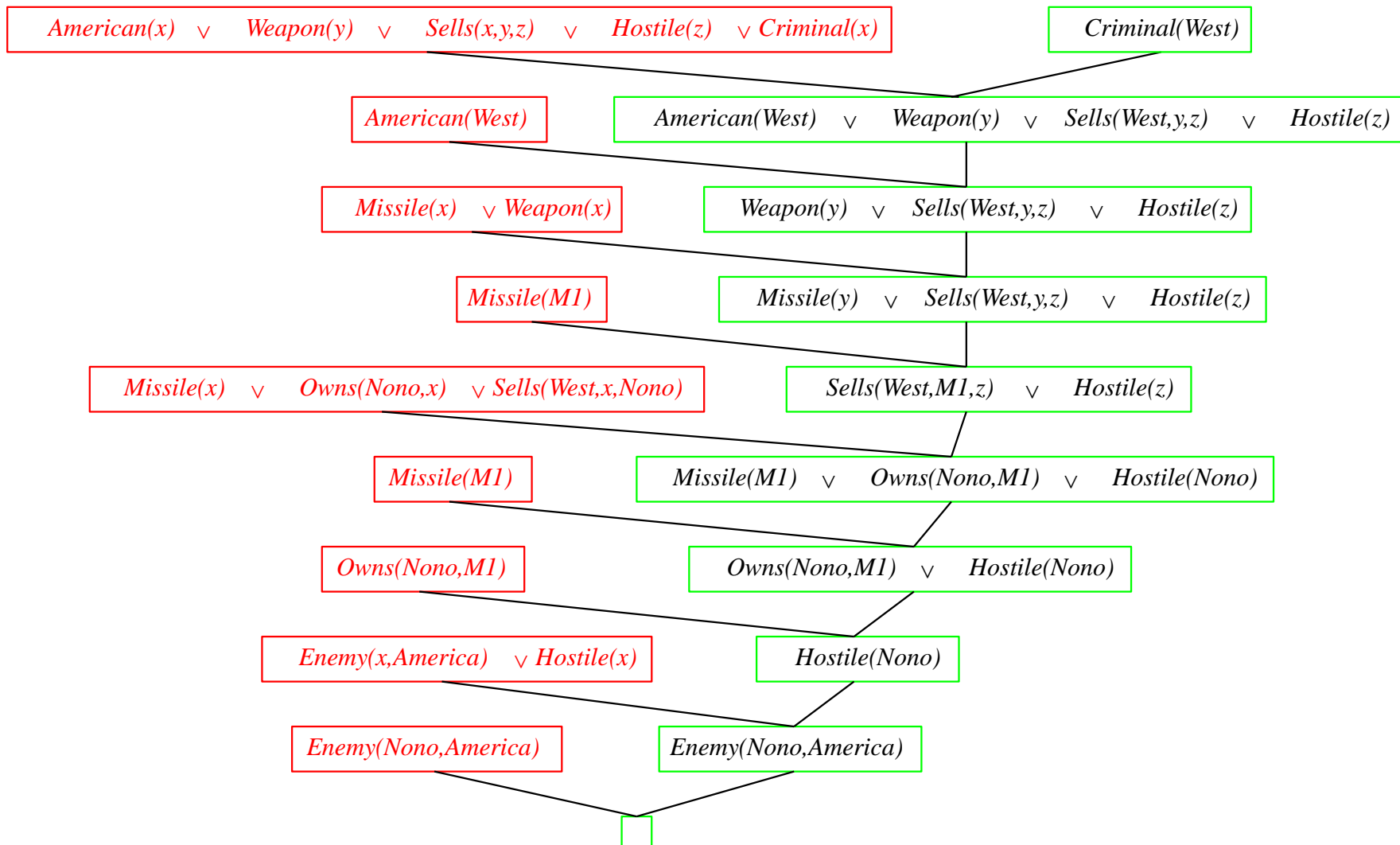
5. Drop universal quantifiers:

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

6. Distribute \wedge over \vee :

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

Resolution proof: definite clauses



Real-world KBs: The CYC project

Cyc is a long-term AI project that aims to assemble a **comprehensive ontology** and **knowledge base** that spans the basic concepts and rules about how the world works.

The project began in July 1984 as the flagship project of the 400-person Microelectronics and Computer Technology Corporation (MCC), a research consortium started by two dozen large United States based corporations *"to counter a then ominous Japanese effort in AI, the so-called "fifth-generation" project."*

Hoping to capture *common sense knowledge*, Cyc focuses on implicit knowledge that other AI platforms may take for granted.

Cyc enables semantic reasoners to perform human-like reasoning and be **less "brittle"** when confronted with novel situations.

Douglas Lenat began the project in July 1984 at MCC, where he was Principal Scientist 1984–1994, and then, since January 1995, has been under active development by the **Cycorp company**, where he was the CEO and recently died (2023).

The CYC project



[Douglas Lenat: Cyc and the Quest to Solve Common Sense Reasoning in AI | Lex Fridman Podcast #221 - YouTube](#)

The CYC project (Some details)

Within a few years of the launch of the Cyc project it became clear that even representing simple knowledge (e.g. a typical news story or advertisement, etc.) would require more than the expressive power of full first-order logic

By 1989,[6] CycL (the custom representation language of the CYC project) had expanded in expressive power to **higher-order logic** (HOL).

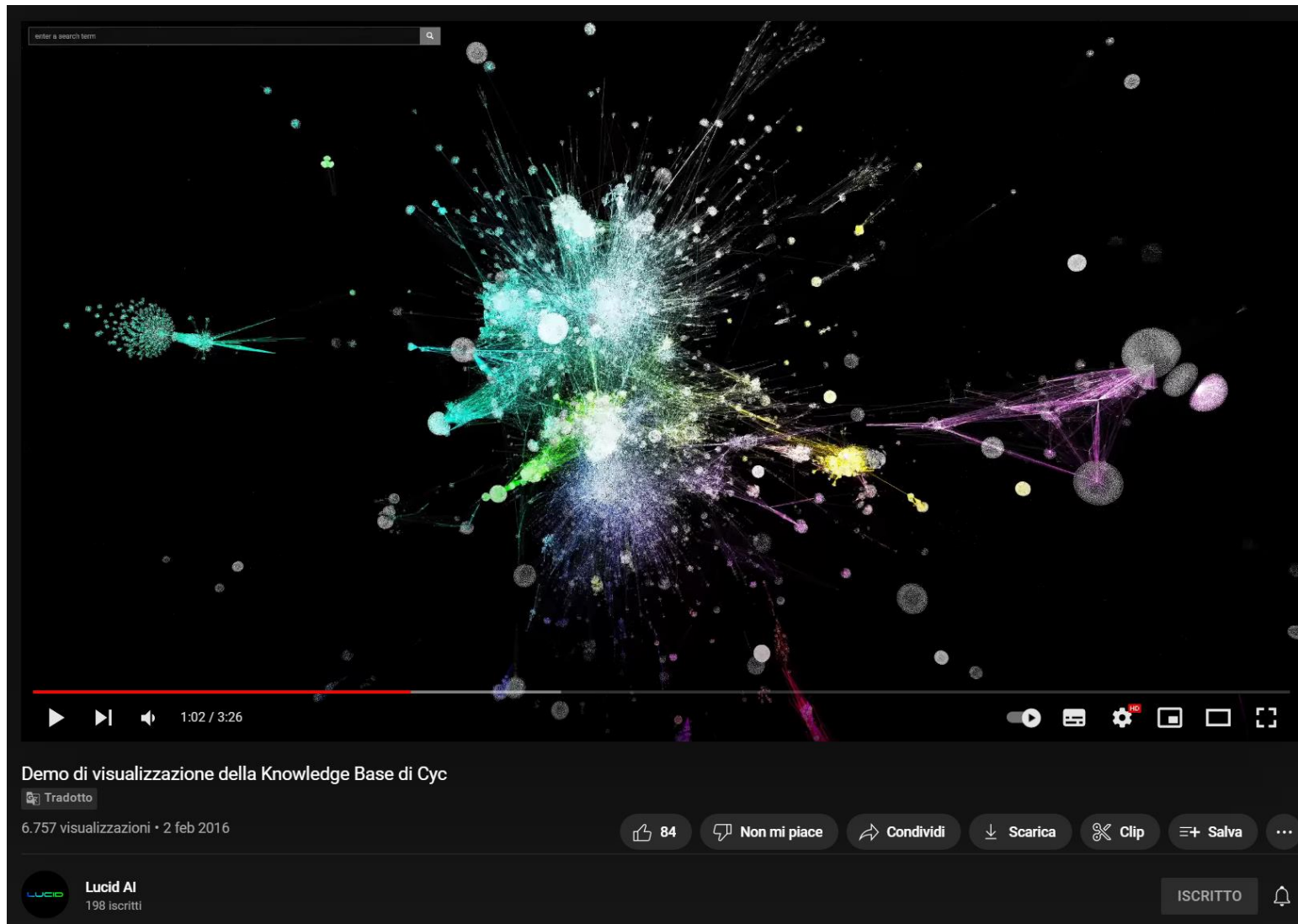
The Cyc **inference engine** design separates the epistemological problem (what content should be in the Cyc KB) from the heuristic problem (how Cyc could efficiently infer arguments hundreds of steps deep, in a sea of tens of millions of axioms).

To do the former, the **CycL language** and well-understood logical inference might suffice.

For the latter, Cyc used a **community-of-agents architecture**, where **specialized reasoning modules** can be used to attack different sub-problems.

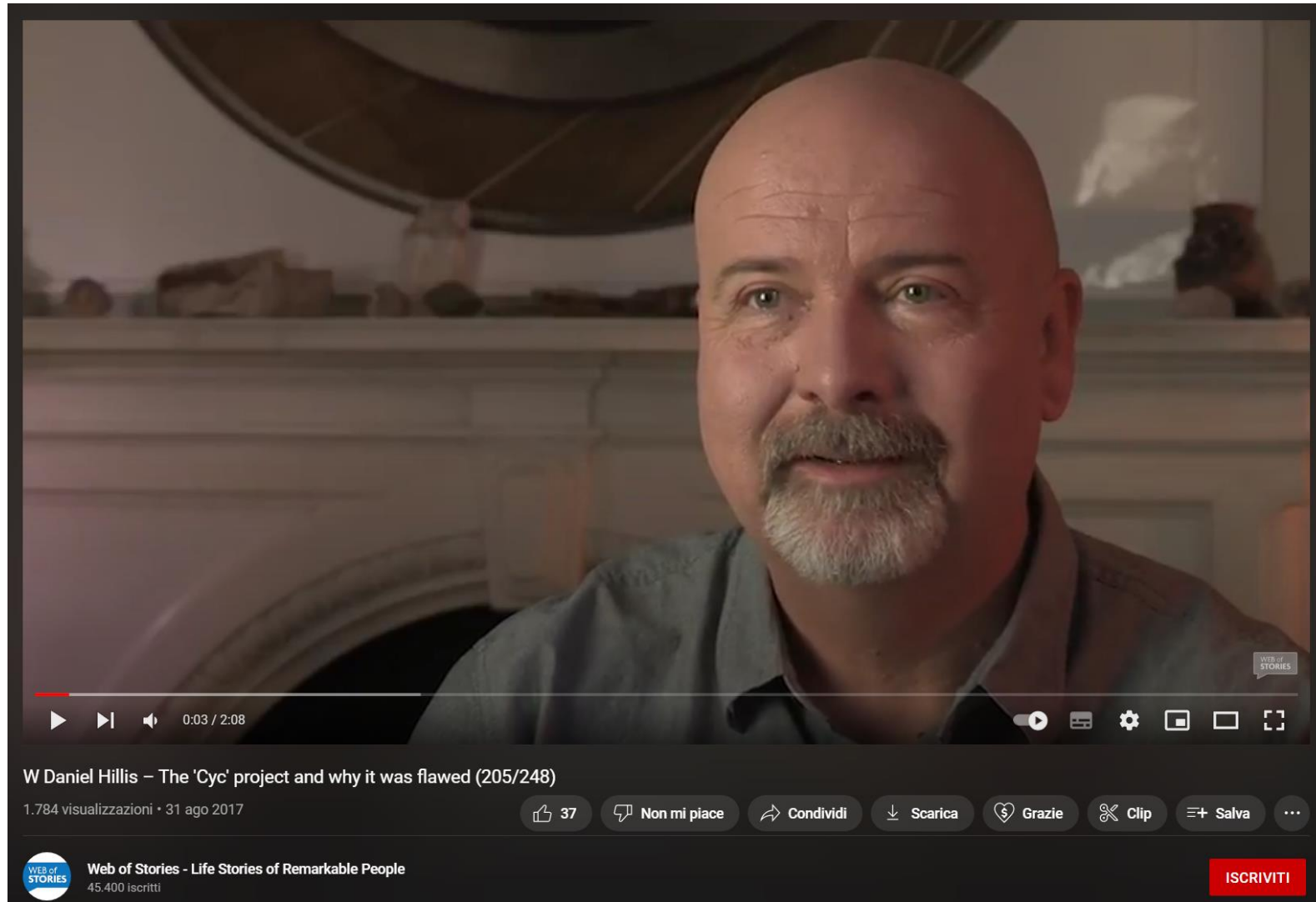
By 1994 there were 20 such **heuristic level (HL)** modules;[8] as of 2017 there are over **1,050 HL modules**. **Common-sense rules and assertions** grew to about 1 million in 1994, and as of 2017 is about 24.5 million.

The CYC KB Visualization



[Demo di visualizzazione della Knowledge Base di Cyc - YouTube](#)

The CYC Criticism



[W Daniel Hillis – The 'Cyc' project and why it was flawed \(205/248\) - YouTube](#)

The CYC Criticism

The Cyc project has been described as *"one of the most controversial endeavors of the artificial intelligence history"*.

Catherine Havasi, CEO of Luminoso, says that Cyc is the predecessor project to IBM's Watson.

Machine-learning scientist **Pedro Domingos** refers to the project as a *"catastrophic failure"* for several reasons, including the unending amount of data required to produce any viable results and the **inability for Cyc to evolve on its own**.

Further readings: Domingos, Pedro (2015). [*The Master Algorithm: How the Quest for the Ultimate Learning Machine Will Remake Our World*](#). ISBN 978-0465065707.

A Comparative Survey of DBpedia, Freebase, OpenCyc, Wikidata, and YAGO

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Abstract. In recent years, several noteworthy large, crossdomain and openly available knowledge graphs (KGs) have been created. These include DBpedia, Freebase, OpenCyc, Wikidata, and YAGO. Although extensively in use, these KGs have not been subject to an in-depth comparison so far. In this survey, we first define aspects according to which KGs can be analyzed. Next, we analyze and compare the above mentioned KGs along those aspects and finally propose a method for finding the most suitable KG for a given setting.

Keywords: Knowledge Graph, Comparison, DBpedia, Freebase, OpenCyc, Wikidata, YAGO

1. Introduction

The idea of the Semantic Web is that of publishing and querying knowledge on the Web in a semantically structured way. According to Guns [27], the term “Se-

between entities (e.g., *isSpouseOf*) can be represented on the Web.

When it comes to realizing the idea of the Semantic Web, knowledge graphs (KGs) are currently seen as one of the most essential components. We define

<https://www.semantic-web-journal.net/system/files/swj1141.pdf>

Wikidata + SPARQL



WIKIDATA

Main page
Community portal
Project chat
Create a new Item
Recent changes
Random Item
Query Service
Nearby
Help
Donate

Lexicographical data
Create a new Lexeme
Recent changes
Random Lexeme

Tools
What links here
Related changes
Special pages
Permanent link
Page information

In Wikipedia
 Add links

Project page Discussion



Wikidata is turning 10 in October 2022, and the community birthday events all around the world. You can join one of the

Wikidata:SPARQL tutorial

Translate

Other languages: [Bahasa Indonesia](#) [British English](#) [Deutsch](#) [English](#) [Türkçe](#) [català](#) [dansk](#) [українська](#) [հայերեն](#) [العربية](#) [中文](#) [日本語](#)

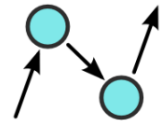
WDQS, the [Wikidata Query Service](#), is a powerful tool to provide insight into Wikidata's content. This guide will teach you how to use it. Before writing your own SPARQL query, look at [{{Item documentation}}](#) or any other [generic SPARQL query template](#).

Contents [hide]

- 1 Before we start
- 2 SPARQL basics
- 3 Our first query
 - 3.1 Autocompletion
- 4 Advanced triple patterns
- 5 Instances and classes
 - 5.1 Property paths
- 6 Qualifiers
- 7 ORDER and LIMIT
 - 7.1 Exercise
 - 7.1.1 Arthur Conan Doyle books
 - 7.1.2 Chemical elements

https://www.wikidata.org/wiki/Wikidata:SPARQL_tutorial

Conceptnet 5



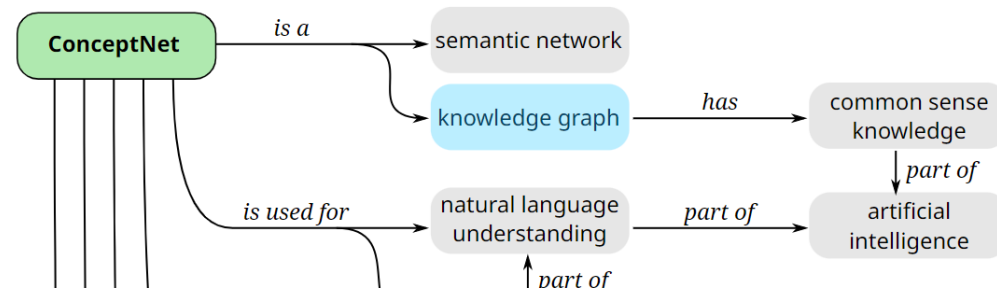
ConceptNet

An open, multilingual knowledge graph

What is ConceptNet?

ConceptNet is a freely-available semantic network, designed to help computers understand the meanings of words that people use.

ConceptNet originated from the crowdsourcing project Open Mind Common Sense, which was launched in 1999 at the MIT Media Lab. It has since grown to include knowledge from other crowdsourced resources, expert-created resources, and games with a purpose.



<https://conceptnet.io>

[API](#) · [commonsense/conceptnet5](#) [Wiki](#) · [GitHub](#)

AIMA notebooks: «logic.ipynb»

Logic

This Jupyter notebook acts as supporting material for topics covered in **Chapter 6 Logical Agents**, **Chapter 7 First-Order Logic** and **Chapter 8 Inference in First-Order Logic** of the book *Artificial Intelligence: A Modern Approach*. We make use of the implementations in the `logic.py` module. See the [intro notebook](#) for instructions.

Let's first import everything from the `logic` module.

```
In [1]: from utils import *
        from logic import *
        from notebook import psource
```

CONTENTS

- Logical sentences
 - Expr
 - PropKB
 - Knowledge-based agents
 - Inference in propositional knowledge base
 - Truth table enumeration
 - Proof by resolution
 - Forward and backward chaining
 - DPLL
 - WalkSAT
 - SATPlan
 - FolKB
 - Inference in first order knowledge base
 - Unification
 - Forward chaining algorithm
 - Backward chaining algorithm

<https://github.com/aimacode/aima-python/blob/master/logic.ipynb>

Summary

- **Unification** identify appropriate substitutions for variables eliminates the instantiation step in first-order proofs, making the process more efficient in many cases
- **Forward chaining** is used in deductive databases, where it can be combined with relational database operations. It is also used in *production systems*
- **Backward chaining** is used in logic programming systems, which employ sophisticated compiler technology to provide very fast inference
- **Prolog**, unlike first-order logic, uses a closed world with the unique names assumption and negation as failure.
- The generalized **resolution** inference rule provides a complete proof system for first order logic, using knowledge bases in conjunctive normal form.
- Some **real-world knowledge bases** are open-access to use!

In the next lecture...

- ◆ Definition of Classical Planning
- ◆ Algorithms for Classical Planning
- ◆ Heuristics for Planning
- ◆ Hierarchical Planning
- ◆ Planning and Acting in Nondeterministic Domains
- ◆ Time, Schedules, and Resources
- ◆ Analysis of Planning Approaches