

Overview

Forward-Chaining RBES

- Overview
- Example
- Triggering
- Rete Network

Backward-Chaining RBES

Examples

Forward-Chaining RBES

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Overview

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Backward-Chaining RBES

Examples

- Control cycle:
 - Find rules whose antecedents are true: *triggered* rules
 - Select one: *conflict resolution*
 - *Fire* the rule to take some action
- Continue forever or until some goal is achieved
- Used for synthesis, often, or process control

Example: Winston's "Bagger" Program

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Backward-Chaining RBES

Examples

- Toy forward chainer – domain = bagging groceries
- Steps in this process:
 1. Check what customer has and suggest additions
 2. Bag large items, putting large bottles in first
 3. Bag medium items, putting frozen food in freezer bags
 4. Bag small items wherever there is room
- Working memory:
 - Needs to have information about:
 - items already bagged
 - unbagged items
 - which step (context) we're in

Example: Winston's "Bagger" Program

Conflict resolution strategies – possibilities:

- specificity ordering:
 - if two rules conflict and one is more specific than the other, use it
 - Rule 1 is more specific than Rule 2 if Rule 1's antecedent literals are a superset of Rule 2's (assuming conjunction)
- rule ordering – implicit in rule base (unless using a rete net)
- data ordering – look at some data first (rete does this, sort of)
- size of antecedent – prefer rules with larger antecedent, since it's likely to be more specific
- recency – least/most recently used (depending on needs of designer)
- context-limiting

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Example: Winston's "Bagger" Program

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Backward-Chaining RBES

Examples

- Rules in form of IF-THEN pairs

- Examples:

```
R1: if  step = check-order &  
      exists bag of chips &  
      not exists soft drink bottle  
    then add bottle of pepsi to order
```

```
R2: if  step = check-order  
    then step = bag-large-items
```

```
R3: if step = bag-large-items &  
      exists large item to be bagged &  
      exists large bottle to be bagged &  
      exists bag with < 6 large items  
    then put bottle in bag
```

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Backward-Chaining RBES

Examples

Example: Winston's "Bagger" Program

- Initial state:

Step: check-order

Bagged: nil

Unbagged: bread, Glop brand cheese, granola,
ice cream

- World info:

Object	Size	Container	Frozen?
bread	M	bag	nil
Glop	S	jar	nil
granola	L	box	nil
ice cream	M	box	t
Pepsi	L	bottle	nil
potato chips	M	bag	nil

Finding Triggered Rules

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Backward-Chaining RBES

Examples

- Possibly very time-consuming
- Observations:
 - Rules often share LHS elements (literals)
 - Rules don't usually change over short term
 - When WM changes: usually only a few changes per cycle
- Forgy: build a *rete network* based on the rules
- Rete records state of WM, rules in network – update on change

Rete Network

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Backward-Chaining RBES

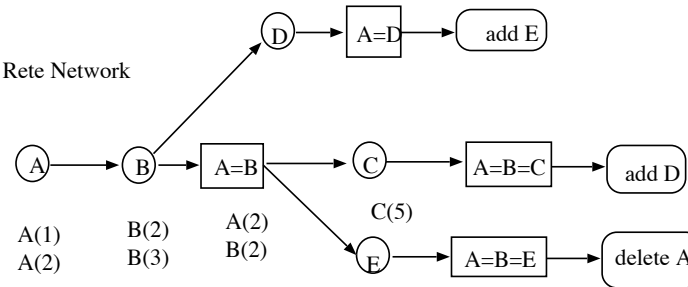
Examples

Rule base:

- 1) $A(x) \& B(x) \& C(x) \implies D(x)$
- 2) $A(x) \& B(y) \& D(x) \implies E(x)$
- 3) $A(x) \& B(x) \& E(x) \implies \text{not } A(x)$

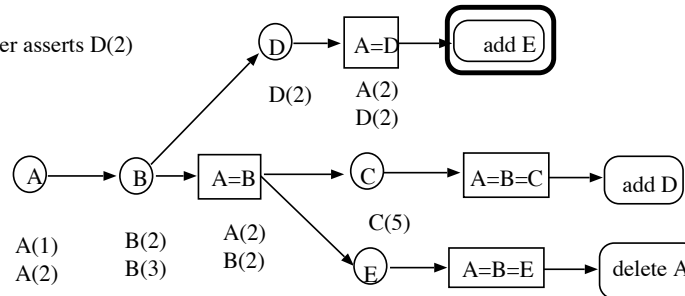
Initial WM: A(1), A(2), B(2), B(3), C(5)

Initial Rete Network



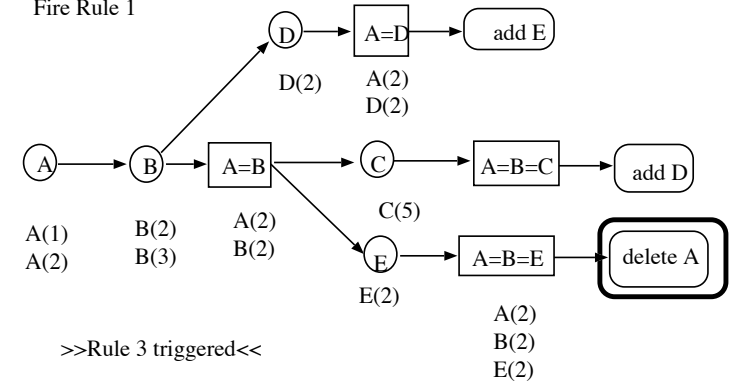
>>Nothing triggered<<

User asserts D(2)



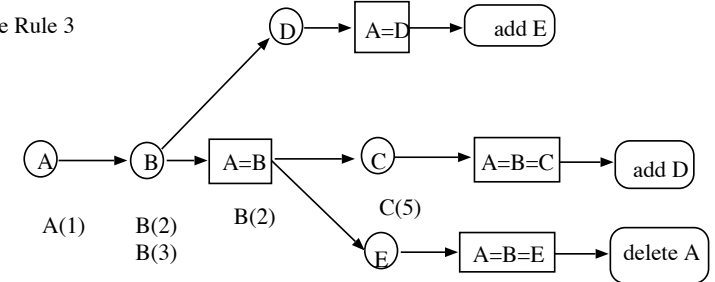
>>Rule 1 triggered

Fire Rule 1



>>Rule 3 triggered<<

Fire Rule 3



>>Nothing triggered<<

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Backward-Chaining RBES

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- How Does It Work?
- Example
- Uncertainty
- Certainty Factors

Examples

Backward-Chaining RBES

Backward-Chaining RBES

Overview

Forward-Chaining RBES

Backward-Chaining RBES

● Overview

- How Does It Work?
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Examples

- Synthesis: pick a solution
- Analysis: gather evidence, form best hypothesis – e.g., medical diagnosis
- Work backward from goal: focus question–asking on relevant facts, tests
- Need uncertainty management
- Follow all (relevant) lines of reasoning: no conflict resolution

How Does It Work?

Overview

Forward-Chaining RBES

Backward-Chaining RBES

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Examples

- Sort of like a backward-chaining theorem prover
- Want to conclude something about x :
 - Is x in WM? Then conclude something from that.
 - Are there rules that conclude something about x ? Then for each rule:
 - Try to conclude something about each antecedent (*backchain*).
 - If that's possible, fire the rule, giving some evidence for x .
 - Combine evidence for and against x .

Example: Zoo World

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Examples

- Goal: `id(Animal1,?x)`
- Initial state 1:
`color(Animal1,tawny),`
`eye-direction(Animal1,forward),`
`teeth-shape(Animal1,pointed),`
`eats(Animal1,meat),`
`hair(Animal1), dark-spots(Animal1)`
- Initial state 2:
`color(Animal1,tawny),`
`eye-direction(Animal1,forward),`
`teeth-shape(Animal1,pointed),`
`eats(Animal1,meat),`
`hair(Animal1)`

Uncertainty Handling

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Examples

- Obvious way: probability theory
- Need some way to assess belief, given some evidence

Uncertainty Handling

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Examples

- Obvious way: probability theory
- Need some way to assess belief, given some evidence
- Bayes' rule:

$$P(H \mid E) = \frac{P(E \mid H) \cdot P(H)}{P(E)}$$

where $P(E) = P(E \mid H) \cdot P(H) + P(E \mid \neg H) \cdot P(\neg H)$

Uncertainty Handling

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- Example:
 - H: Joey has lung cancer
 - E: Joey smokes

$$P(lung-Ca \mid smoking) = \frac{P(smoking \mid lung-Ca) \cdot P(lung-Ca)}{P(smoking)}$$

Uncertainty Handling

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Examples

- General form:

$$P(H_i | E) = \frac{P(E | H_i) \cdot P(H_i)}{\sum P(E | H_j) \cdot P(H_j)}$$

- And with some prior evidence E and a new observation e :

$$P(H | e, E) = P(H | e) \cdot \frac{P(E | e, H)}{P(E | e)}$$

Problems with Bayesian approach

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Examples

- There are problems with Bayesian probability for expert systems (in dispute recently)
- Probabilities may be difficult to obtain
 - $P(E)$, $P(H)$, $P(E|H)$ may be hard to get in general – for example, where E = cough, or H = AIDS
 - empirical evidence suggests that people are not very good at estimating probabilities [Tversky & Kahneman, e.g.]
- Size of set of probabilities needed $O(2^n)$
 - Even if we could obtain them – requires too much space
 - ...and too much time to use, and compute

Problems with Bayesian approach

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Examples

- In the general case, we're interested in

$$P(H \mid E_1 \wedge E_2 \wedge \dots \wedge E_n)$$

which is completely impractical to get

- Also assumes that $P(H_1), P(H_2), \dots$ are disjoint probability distributions, that is, that H_i are independent and that they cover the set of all hypotheses!
- *Bayesian nets* address many of these problems in a different formalism

A Kludge: Certainty Factors

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Examples

- Approximation to probability theory
- MYCIN (e.g.): $CF[H, E] = MB[H, E] - MD[H, E]$
- Since rule only supports/denies one fact: need only one number to give CF for H given E
- One CF per literal, one per rule

Combining Certainty Factors

Overview

Forward-Chaining RBES

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Examples

- Formally, when two rules give evidence about same literal:

$$MB[H, s_1 \wedge s_2] = 0 \text{ if } MD = 1,$$

$$MB[H, s_1] + MB[H, s_2] \cdot (1 - MB[H, s_1])$$

- Similarly for MD
- Simple update function!

Example

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Examples

- Rule A: If x then s_1
- Rule B: If y then s_2
- Rule C: If s_1 then H
- Rule D: If s_2 then H
- suppose $MB[H, s_1] = 0.3, MD = 0 \Rightarrow CF = 0.3$
- now rule B fires, giving $MB[H, s_2]$ as, say, 0.2:

$$MB[H, s_1 \wedge s_2] = 0.3 + 0.2 \cdot 0.7 = 0.44$$

$$MD = 0$$

$$CF = 0.44$$

Certainty Factors

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Examples

- How to compute $CF(A \wedge B)$ for rule antecedents?

$$MB[H_1 \wedge H_2, E] = \min(MB[H_1, E], MB[H_2, E])$$

and for $CF(A \vee B)$:

$$MB[H_1 \wedge H_2, E] = \max(MB[H_1, E], MB[H_2, E])$$

Certainty Factors

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Examples

- How to update certainty based on rule firing?
 - Two things to consider: MB/MD in antecedents (computed as above) and the CF of the rule:

$$MB[H, S] = MB'[H, S] \cdot \max(0, CF[S, E])$$

where $MB'[H, S]$ is how much you'd believe S if E were completely believed (i.e., the rule CF), and $CF[S, E]$ is the certainty you have in S given all the evidence.

- Essentially: you multiply the CF of the rule times the CF of the evidence

Certainty Factors

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Examples

- More recently (1986), it's been found that CFs aren't in conflict with basic probability theory
- Why, then, do they work and Bayesian techniques seem not to?

Certainty Factors

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Examples

- More recently (1986), it's been found that CFs aren't in conflict with basic probability theory
- Why, then, do they work and Bayesian techniques seem not to?
 - Heuristics
 - They assume rule independence – conditional probabilities are 0
 - The knowledge engineer has to ensure this
 - Leads to compound antecedents, but...
 - ...makes it tractable and modular
- Many recent expert systems are based on *Bayesian networks*

Example Expert Systems

Overview

Forward-Chaining
RBES

Backward-Chaining
RBES

Examples

- DENDRAL
- R1/XCON [J. McDermott] – DEC
- MYCIN, EMYCIN, ONCOCIN, PUFF, VM, CENTAUR, MDX, MDX2,...
- Blackboard systems

Topic: Structured knowledge representation

Symbolic Reasoning

Symbolic reasoning

Knowledge representation

First-order logic

Theorem proving

Rule-based reasoning

Structured knowledge representation

Local DL example: Orca

Structured Knowledge Representations

Structured KRep

- Overview
- Ontological Commitment
- Pros and cons
- Kinds of Structured Representation

Frames

Semantic Networks

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Description Logics

- Problem with logic and rules:
 - No real structure
 - Representation doesn't reflect patterns—structure—in world
- Need a knowledge representation that is *structured*

Ontological Commitment

Structured KRep

- Overview
- **Ontological Commitment**
- Pros and cons
- Kinds of Structured Representation

Frames

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Description Logics

- Ontological commitment for structured representations:
 - World consists of objects
 - Objects have properties
 - Relations exist between objects
- I.e., pretty much same as FOPC...

Ontological Commitment

Structured KRep

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Frames

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Description Logics

- Ontological commitment for structured representations:
 - World consists of objects
 - Objects have properties
 - Relations exist between objects
- I.e., pretty much same as FOPC...
- ...difference is *structure* of representation

Advantages and Disadvantages

Structured KRep

- Overview
- Ontological Commitment
- **Pros and cons**
- Kinds of Structured Representation

Frames

Semantic Networks

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Description Logics

- Reflects structure of the world
- Groups knowledge together:
 - Easier access
 - Easy to establish salient features
 - Conceptually easier for many people
- But managing relationships is not easy

Frames

Structured KRep

Frames

- Overview

- Inheritance
- Representation
- Example
- Proc. attachment
- Other info
- Examples

Semantic Networks

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Description Logics

- Frames are one kind of structured representation
- Originally: used to describe visual scenes [Minsky]
- Frames are *slot-filler* representations:
 - *Slots* of frame: name attributes or relations
 - *Filler* of slot contains its value
- Since frames can fill slots \Rightarrow interconnected *frame system*
- Frame rely heavily on *isa* relationships \Rightarrow isa hierarchies

Caveats for Object-Oriented Programmers

Overview

Knowledge Representation

Isa Hierarchies

- Overview
- Isa \neq OOP
- Example
- Which nodes?
- Tangled ISA Hierarchies
- Other Hierarchies

- ISA hierarchies are not copied from C++, Java, Python...
- OOP: inheritance partly (mainly?) to share function, abstraction – ISA: class–subclass relationship is semantic, not for convenience
- Create classes that “make sense”
- Make sure ISA reflects a subclass/class relationship

Let's Create an Animal Hierarchy

Overview

Knowledge Representation

Isa Hierarchies

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- Which nodes?
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Animals to include:

dog	cat	monkey	elephant	guppie
catfish	parrot	robin	Muffet	Clyde

Let's Create an Animal Hierarchy

Overview

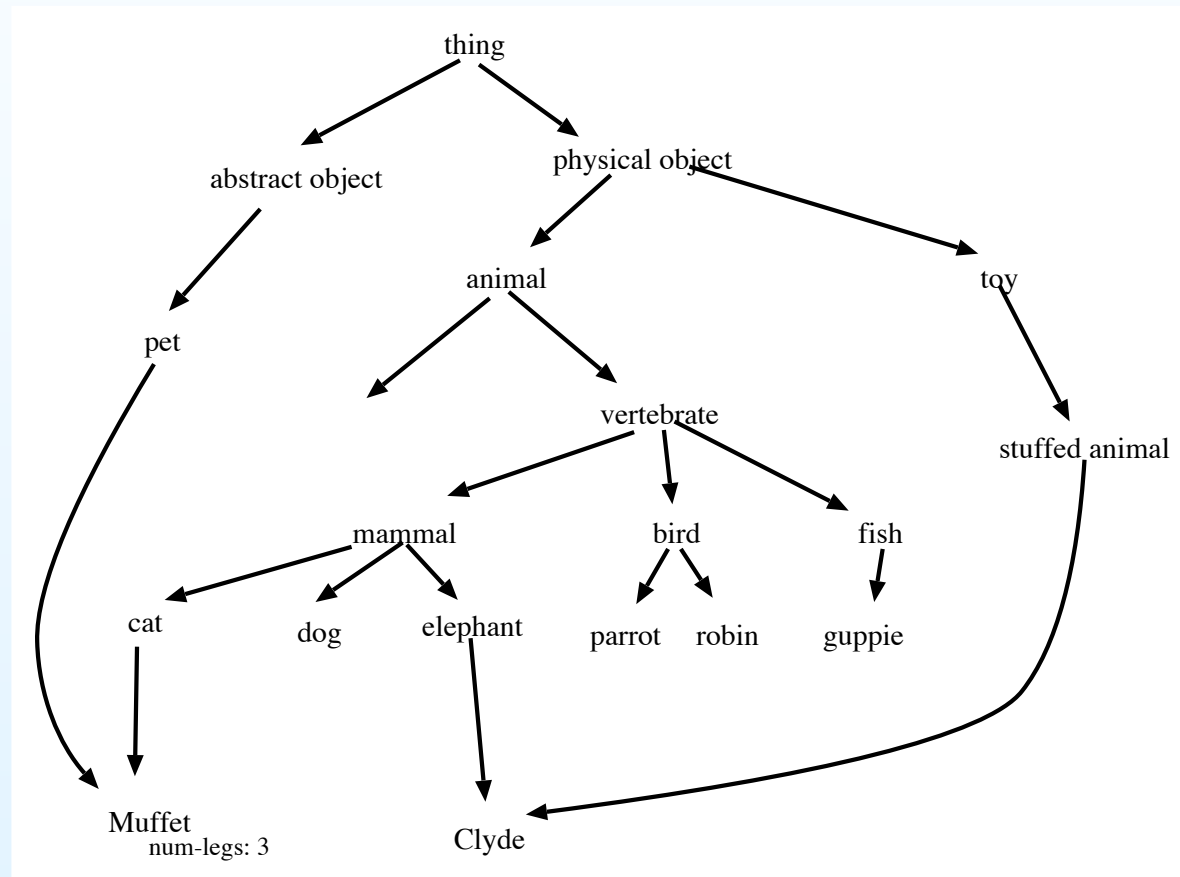
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Let's Create an Animal Hierarchy

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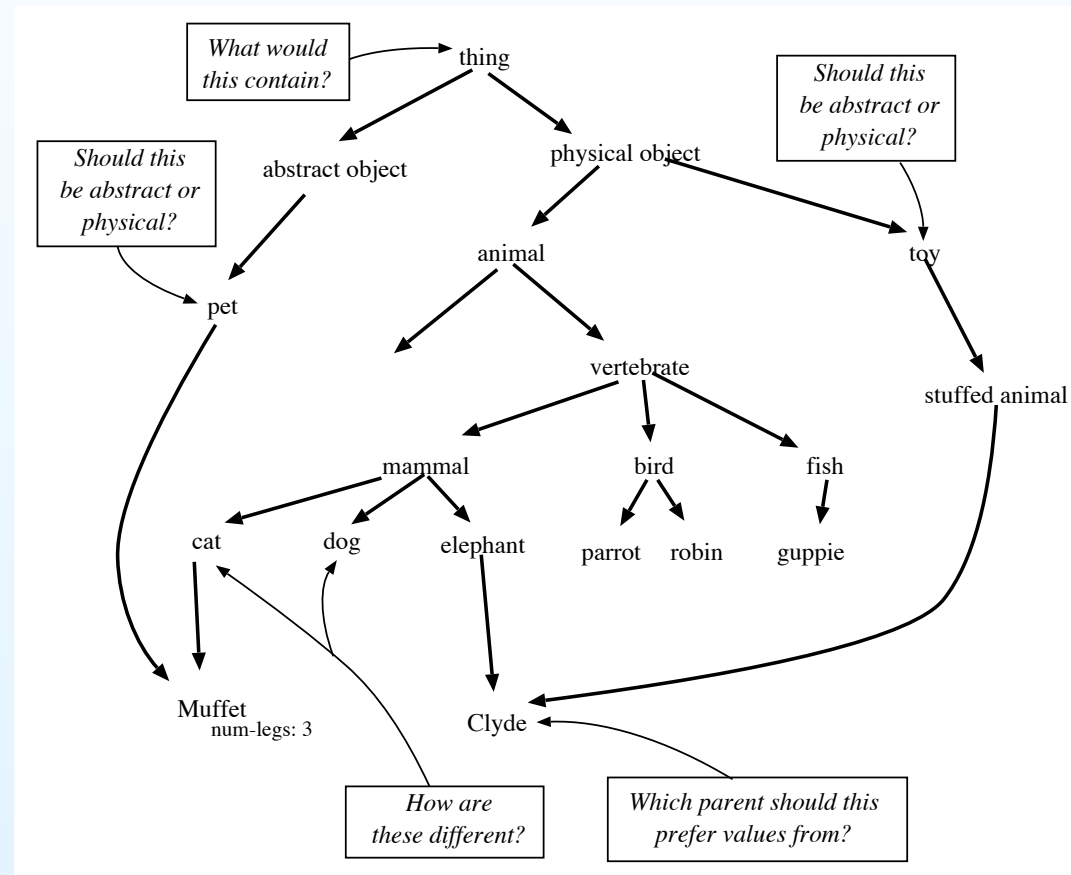
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Deciding on the Nodes

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- Instances must have their own nodes
 - cannot inherit from an instance
 - no default information is stored
- Prototypes or Classes?
 - A prototype describes some typical member of a group
 - Classes partition the knowledge base – may have more than one partitioning
 - *is-covered-by*: the set of classes that form a partitioning
 - *mutually-disjoint-with*: the relationship between classes in a partitioning

Deciding on the Nodes

Overview

Knowledge Representation

Isa Hierarchies

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- The right types
 - group things by significant properties
 - properties identified with types should be unlikely to change
 - existing taxonomies, *basic level categories* can help

Tangled ISA Hierarchies

Overview

Knowledge Representation

Isa Hierarchies

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- Example
- Which nodes?
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- Other Hierarchies

- The problem: An entity is a member of more than one type or class and need to get information about the entity from the correct parent
- Possible solutions:
 - if there are no conflicting slots, take information from wherever it resides
 - weight parents for the slots
 - inferential distance

Tangled ISA Hierarchies: Inferential distance

Overview

Knowledge Representation

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- NEVER want to count links

Tangled ISA Hierarchies: Inferer

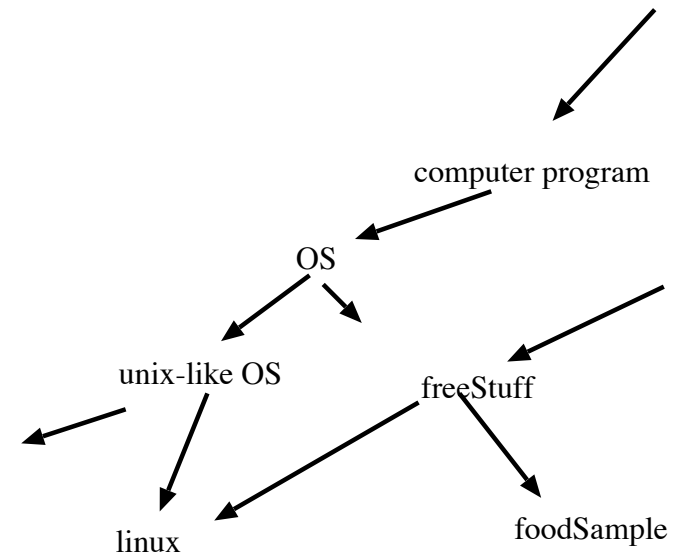
Overview

Knowledge Representation

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- NEVER want to count links
- $class_2$ is further than $class_3$ from $class_1$ if there is a path through $class_3$ to $class_2$
- only a partial order
- conflicts are unresolved if the classes are not related



Linux is more like a computer program, or samples of sausage at Hannaford's?

Other Hierarchies

Overview

Knowledge Representation

Isa Hierarchies

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- Partonomic hierarchy
- Can make your own
 - must be transitive and anti-symmetric
 - must inherit relation
 - can inherit other features

Inheritance in Frames

Structured KRep

Frames

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Semantic Networks

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Description Logics

- Frames make use of inheritance through the *isa* links
- Slots are inherited:
 - Helps determine which slots (attributes, relations) the frame has
 - A kind of default knowledge
- Fillers are inherited, too

Representing Knowledge with Frames

Structured KRep

Frames

- Overview
- Inheritance
- **Representation**
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Semantic Networks

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Description Logics

- Frames can be used to represent abstract as well as physical “objects”
- Frames as classes of objects: e.g., HUMANS
- Frames as prototypes of objects: e.g., HUMAN
- Frames as *instances* of a class/exemplar of a prototype: e.g., ROY, HUMAN001, etc.
- *isa*: sub-type or instance-of link?

Representing Knowledge with Frames

Structured KRep

Frames

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Semantic Networks

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Description Logics

How would you represent each of the following?

- Car
- Police car
- A particular police car, say Car54

Representing Knowledge with Frames

Structured KRep

Frames

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Semantic Networks

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Description Logics

How would you represent each of the following?

- Car
- Police car
- A particular police car, say Car54
- Water
- River or lake

Other Information Associated with Slots

Structured KRep

Frames

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Semantic Networks

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Description Logics

- *constraints*: range or type of values that must fill slots
- *defining values*: all members of the type must have this value
- *special inheritance*: inherit from some other frame or hierarchy than the *isa* hierarchy

Examples

Structured KRep

Frames

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Semantic Networks

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Description Logics

```
(defframe living-thing (^natural-object)
  (living? t)
  (density ^moderate)
  (physical-state ^solid)
  (substance ^protoplasm)
  (status ^nominal-health))
```


Examples

Structured KRep

Frames

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Semantic Networks

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Description Logics

```
(defframe orca (^planner ^mobile-agent)
  (mission - (default (^mission)))
  (plan - (default (^intention-structure)))
  (location @(vehicle location))
  (heading @(vehicle heading))
  (depth @(vehicle depth))
  (altitude @(vehicle altitude))
  (velocity @(motion velocity))
  (acceleration @(motion acceleration))
  (motion @(vehicle motion))
  (vehicle - (default (^EAVE)))
  (equipment @(vehicle mission-package))
  (communication-system @(vehicle communication-system))
  (communication - (default (^set))))
```


Semantic Networks

Structured KRep

Frames

Semantic Networks

● Overview

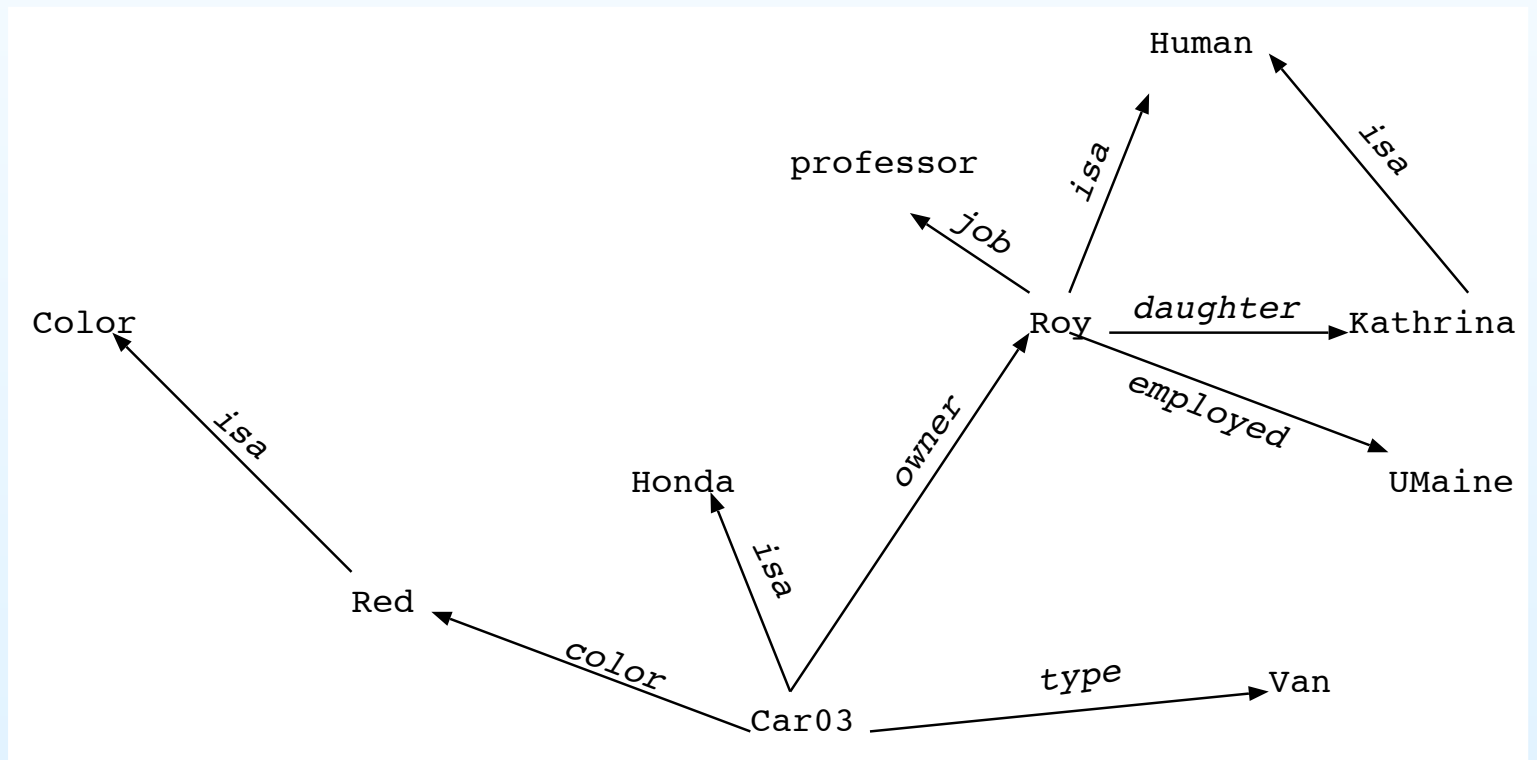
● Vs. frames

CD

Cyc

Description Logics

- A semantic network is a set of nodes and arcs:
 - Nodes = concepts
 - Arcs = relationships or attributes
- Example



Semantic networks and frames

Structured KRep

Frames

Semantic Networks

• Overview

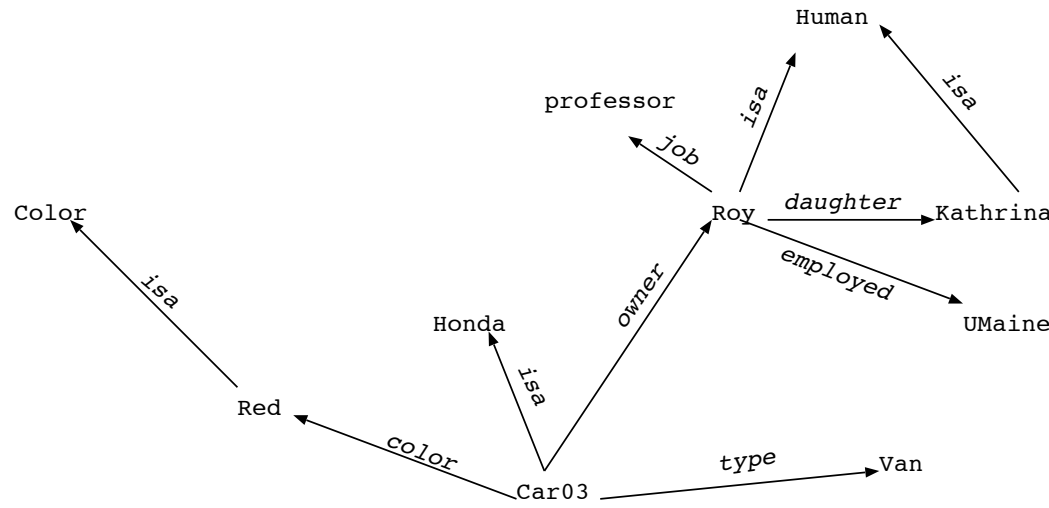
• Vs. frames

CD

Cyc

Description Logics

- Semantic nets and frames are very similar
- Can view frames as portions of semantic nets



Car03:
 isa: Honda
 type: Van
 color: Red
 owner: Roy

Red:
 isa: Color
 ...

Roy:
 isa: Human
 daughter: Kathrina
 job: Professor
 employed: UMaine

Kathrina:
 isa: Human
 ...

Semantic networks and frames

Structured KRep

Frames

Semantic Networks

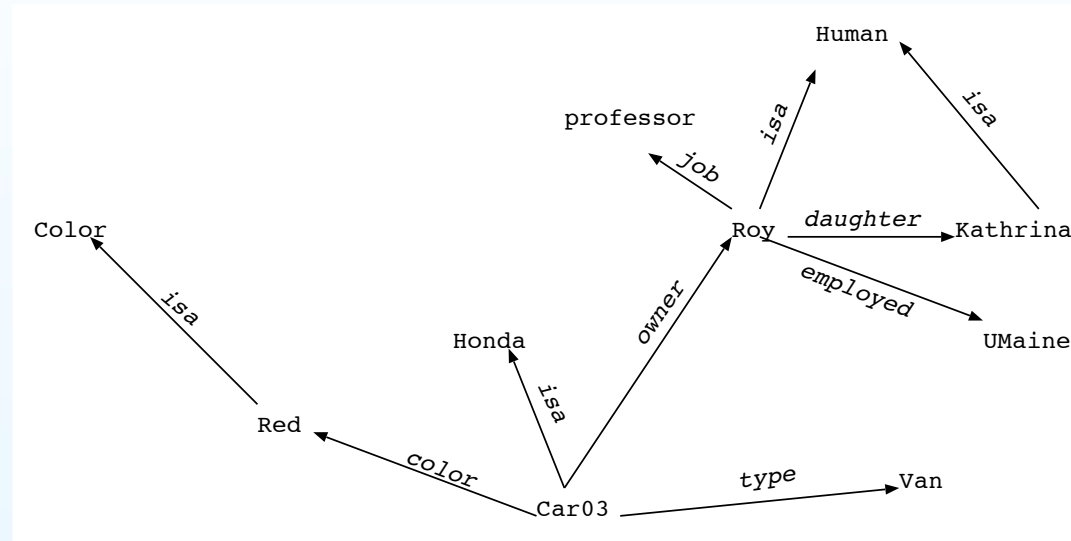
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Description Logics

- Semantic nets and frames are very similar
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Car03:
isa: Honda
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color: Red
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Red:
isa: Color
...

Roy:
isa: Human
daughter: Kathrina
job: Professor
employed: UMaine

Kathrina:
isa: Human
...

- Hard to do procedural attachment in semantic net

Why CYC?

Structured KRep

Frames

Semantic Networks

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Cyc

- Overview
- Why?
- Representation
- Kn. acquisition
- CYCL
- Extensions
- Ontology
- Upper ontology

Description Logics

- Try to overcome *brittleness* of expert systems, other AI programs
- Test many/all existing knowledge representation techniques to see if they scale up
- Provide a shared commonsense knowledge base for smaller, special-purpose programs
- Study what commonsense knowledge *is*

CYCL

Structured KRep

Frames

Semantic Networks

CD

Cyc

- Overview
- Why?
- Representation
- Kn. acquisition
- **CYCL**
- Extensions
- Ontology
- Upper ontology

Description Logics

- CYC's representation language is CYCL
- Standard extensions to frame programs:
 - tangled hierarchies
 - slots as objects/frames
 - inheritance via other slots (*transfers-through*) slot

```
frame color
  isa: slot
  transfers-through: top-level-part-of
frame car01:
  color: red
frame car-door01:
  top-level-part-of: car01
```

- mutually-disjoint with
- distinction between *instance* and *isa*

CYCL-specific extensions

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Semantic Networks

CD

Cyc

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Description Logics

- Additional inheritance mechanisms
- Constraint language

Me:

```
likes:  
constraints (beerConstraint)
```

beerConstraint:

```
slotConstrained: (likes)  
slotValueSubsumes:  
  (TheSetOf X (Person allInstances)  
   (And (likes-to-drink X beer)  
        (Not (ThereExists Y (Drinks allInstances)  
                  (And (Equal Y sissyDrink)  
                        (likes-to-drink X Y))))))  
propagateDirection: forward
```

Mike:

```
likes-to-drink: (beer)
```


Description logics

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Frames

Semantic Networks

CD

Cyc

Description Logics

- Tbox and Abox
- Examples
- Counting
- Inference in DL
- Different DLs
- CLASSIC
- Uses

- Logic:
 - very general, good semantics, but:
 - cumbersome
 - intractable, not decidable
- Frames and semantic nets (“network representations”):
 - specialized reasoning, intuitive, but:
 - semantics lacking/inconsistent
- Brachman’s KL-ONE system: attempted to add rigor to network representations
- Gave rise to what is now called *description logics*

Basics

Structured KRep

Frames

Semantic Networks

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- Concerned with concepts and roles
- Concepts correspond to sets of individuals
- Primitive concepts:
 - e.g., Car, Human, etc.
 - equivalent to: $\text{Car}(x)$, etc., in FOL

Basics

Structured KRep

Frames

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CD

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 - equivalent to: $\text{Car}(x)$, etc., in FOL
- Roles:
 - Like slots in frames
 - E.g., hasChildren

Basics

Structured KRep

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CD

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- Concerned with concepts and roles
- Concepts correspond to sets of individuals
- Primitive concepts:
 - e.g., Car, Human, etc.
 - equivalent to: $\text{Car}(x)$, etc., in FOL
- Roles:
 - Like slots in frames
 - E.g., hasChildren
- Complex (compound) concepts:
 - Built by composition from other concepts and roles
 - Often *intersection of concepts* (\sqcap) as operator
 - Different composition operators \Rightarrow different logics

Tbox and Abox

Structured KRep

Frames

Semantic Networks

CD

Cyc

Description Logics

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- Knowledge in a DL system divided into two “boxes”
- *Tbox* (terminological box):
 - definitions – the ontology, i.e.
 - consists of concepts – e.g., Human
 - relatively static across problems

Tbox and Abox

Structured KRep

Frames

Semantic Networks

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Cyc

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- Knowledge in a DL system divided into two “boxes”
- *Tbox* (terminological box):
 - definitions – the ontology, i.e.
 - consists of concepts – e.g., Human
 - relatively static across problems
- *Abox* (assertion box):
 - facts about current problem
 - instances of concepts – e.g., Human(Roy)
 - dynamic across, even within problems

Tbox Examples

- Woman:

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Frames

Semantic Networks

CDCyc

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Tbox Examples

Structured KRep

Frames

Semantic Networks

CD

Cyc

Description Logics

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- Woman:

Woman \equiv Person \sqcap Female

Tbox Examples

Structured KRep

Frames

Semantic Networks

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Cyc

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- Woman:

Woman \equiv Person \sqcap Female

- Parent:

Tbox Examples

Structured KRep

Frames

Semantic Networks

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Cyc

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- Woman:

Woman \equiv Person \sqcap Female

- Parent:

$$\text{Parent} \equiv \text{Person} \sqcap \exists \text{hasChild}.\text{Person}$$

Tbox Examples

Structured KRep

Frames

Semantic Networks

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- Woman:

Woman \equiv Person \sqcap Female

- Parent:

$$\text{Parent} \equiv \text{Person} \sqcap \exists \text{hasChild}.\text{Person}$$

- Mother:

Tbox Examples

Structured KRep

Frames

Semantic Networks

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- Woman:

$\text{Woman} \equiv \text{Person} \sqcap \text{Female}$

- Parent:

$\text{Parent} \equiv \text{Person} \sqcap \exists \text{hasChild}.\text{Person}$

- Mother:

$\text{Mother} \equiv \text{Parent} \sqcap \text{Woman}$

Tbox Examples

Structured KRep

Frames

Semantic Networks

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- Uses

- Woman:

Woman \equiv Person \sqcap Female

- Parent:

$$\text{Parent} \equiv \text{Person} \sqcap \exists \text{hasChild}.\text{Person}$$

- Mother:

Mother \equiv Parent \sqcap Woman

- Students who take COS 470:

Tbox Examples

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Frames

Semantic Networks

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Cyc

Description Logics

- Tbox and Abox
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- Different DLs
- CLASSIC
- Uses

- Woman:

Woman \equiv Person \sqcap Female

- Parent:

$$\text{Parent} \equiv \text{Person} \sqcap \exists \text{hasChild}.\text{Person}$$

- Mother:

Mother \equiv Parent \sqcap Woman

- Students who take COS 470:

Student $\sqcap \exists \text{classSchedule} . (\exists \text{contains} . \text{COS470})$

Abox Examples

- Joe is Harry's son:

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Semantic Networks

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Abox Examples

Structured KRep

Frames

Semantic Networks

CD

Cyc

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- Joe is Harry's son:

$$hasSon(Harry, Joe)$$

Abox Examples

Structured KRep

Frames

Semantic Networks

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- Joe is Harry's son:

$$hasSon(Harry, Joe)$$

- Roy is a professor:

Abox Examples

Structured KRep

Frames

Semantic Networks

CD

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- Joe is Harry's son:

$$hasSon(Harry, Joe)$$

- Roy is a professor:

Professor (Roy)

Abox Examples

Structured KRep

Frames

Semantic Networks

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Cyc

Description Logics

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- Joe is Harry's son:

$$hasSon(Harry, Joe)$$

- Roy is a professor:

Professor (Roy)

$$\text{Person}(\text{Roy}) \sqcap \text{hasRole}(\text{Roy}, \text{Professor})$$

Abox Examples

Structured KRep

Frames

Semantic Networks

CD

Cyc

Description Logics

- Tbox and Abox

- **Examples**

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- Different DLs

- CLASSIC

- Uses

- Joe is Harry's son:

hasSon(Harry, Joe)

- Roy is a professor:

Professor(Roy)

Person(Roy) \sqcap hasRole(Roy, Professor)

(Person \sqcap \exists hasRole.Professor)(Roy)

Counting

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Cyc

Description Logics

- Tbox and Abox
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- Some logics can count, too
- E.g.: “A mother with two female and at least one male children”:

Counting

Structured KRep

Frames

Semantic Networks

CD

Cyc

Description Logics

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- Different DLs
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- Some logics can count, too
- E.g.: “A mother with two female and at least one male children”:

$$\text{Mother} \sqcap = 2(\text{hasChild.Female}) \sqcap \geq 1(\text{hasChild.Male})$$

Inference in DL

Structured KRep

Frames

Semantic Networks

CD

Cyc

Description Logics

- Tbox and Abox
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- Counting
- Inference in DL
- Different DLs
- CLASSIC
- Uses

- Reasoning in DL systems occurs in context of Tbox and Abox
- Tbox reasoning: *subsumption*

- Is concept $A \sqsubseteq$ concept B ?
- E.g.:

Mother \equiv Person \sqcap Female $\sqcap \exists$ hasChild.Person

Parent \equiv Person $\sqcap \exists$ hasChild.Person

Mother \sqsubseteq Parent

- Can be much more complicated and indirect
- Abox reasoning: *classification*
 - Is A an instance of concept B ?
- Often other kinds of reasoning, too

Different DLs

Structured KRep

Frames

Semantic Networks

CD

Cyc

Description Logics

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- DL really comprised of a family of logics
- Basic is \mathcal{AL} (ascription language)
- Add other operators, get new languages – e.g., \mathcal{ALU} would be \mathcal{AL} plus union, etc.
- Simple DLs: decidable, (relatively) efficient inferences
- More expressive DLs: give up efficiency, even decidability

Example Implementation: CLASSIC

- The CLASSIC language is an implementation of a DL ($\mathcal{AL}?$)
- Example: a bachelor

Bachelor = And(Unmarried, Adult, Male)

Structured KRep

Frames

Semantic Networks

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Cyc

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Example Implementation: CLASSIC

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Frames

Semantic Networks

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Cyc

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- **CLASSIC**
- Uses

- The CLASSIC language is an implementation of a DL ($\mathcal{AL}?$)
- Example: a bachelor

Bachelor = And(Unmarried, Adult, Male)

- (From R&N) Men with at least three sons who are all unemployed and married to doctors, and at most two daughters who are all professors in physics or math departments:

```
And(Man, AtLeast(3, Son), AtMost(2, Daughter),  
    All(Son, And(Unemployed, Married,  
                 All(Spouse, Doctor))),  
    All(Daughter, And(Professor,  
                     Fills(Department, Physics, Math))))
```


Symbolic
Reasoning

Symbolic
reasoning

Knowledge
representation

First-order logic

Theorem proving

Rule-based
reasoning

Structured
knowledge
representation

Local DL example:
Orca

Topic: Local DL example: Orca

Example Orca DL

Definition=(SOME expectsPresenceOf Salinity)
Certainty=0.401

Definition=(SOME expectsPresenceOf OceanSurface)
Certainty=0.436

Definition=(SOME expectsPresenceOf
 (AND Thruster (SOME hasAdvisedValue ShoreBased)))
Certainty=0.769

Definition=(SOME expectsPresenceOf
 (AND Location
 (SOME hasNumber
 (AND Float
 (D-FILLER hasNumericValue


```

(D-LITERAL 19.115639 (D-BASE-TYPE float)))
(D-FILLER hasUnitOfMeasure
  (D-LITERAL somerandomstring
    (D-BASE-TYPE string))))))
(SOME hasNumber
  (AND Integer
    (D-FILLER hasNumericValue
      (D-LITERAL 31 (D-BASE-TYPE integer)))
    (D-FILLER hasUnitOfMeasure
      (D-LITERAL somerandomstring
        (D-BASE-TYPE string)))))))

```

Certainty=0.482

```

Definition=(SOME expectsPresenceOf
  (AND Survey (SOME hasDegreeExpected Mine)
    (SOME definesGoal ActiveMission)))

```

Certainty=0.125

```

Definition=(SOME expectsPresenceOf
  (AND DetectSubmarine
    (D-FILLER hasEventDescription

```

```
(D-LITERAL somerandomstring
(D-BASE-TYPE
  http://www.w3.org/2001/XMLSchema#string))))
```

Certainty=0.243

```
Definition=(SOME hasFuzzyFeature
  (AND Danger
    (SOME hasFuzzyMembershipFunction
      (AND TrapezoidalFunction
        (SOME hasLocalMaxAt Number)
        (SOME hasLocalMaxAt
          (AND Float
            (D-FILLER hasNumericValue
              (D-LITERAL 24.848389
                (D-BASE-TYPE
                  http://www.w3.org/2001/XMLSchema#float)
              (D-FILLER hasUnitOfMeasure
                (D-LITERAL somerandomstring
                  (D-BASE-TYPE
                    http://www.w3.org/2001/XMLSchema#string)
                (SOME hasLocalMinAt Number)
```

```

(SOME hasLocalMinAt
  (AND Integer
    (D-FILLER hasNumericValue
      (D-LITERAL 5
        (D-BASE-TYPE
          http://www.w3.org/2001/XMLSchema#int
        (D-FILLER hasUnitOfMeasure
          (D-LITERAL somerandomstring
            (D-BASE-TYPE
              http://www.w3.org/2001/XMLSchema#str:

```

Certainty=0.334

```

Definition=(AND (SOME hasActivePeriod EnteringContext)
  (SOME hasOperationalSetting
    (AND SelfDepth (SOME hasAdvisedValue Medium))))

```

Certainty=0.943

```

Definition=(AND
  (SOME definesGoal
    (AND SamplingComplete
      (D-FILLER hasEventDescription

```

```
(D-LITERAL somerandomstring
  (D-BASE-TYPE
    http://www.w3.org/2001/XMLSchema#string))))
(SOME hasCost Medium) (SOME hasDegreeExpected High)
(SOME hasImportance High)
(SOME isAchievedBy (AND Maneuver (SOME hasActor PeerAgent))))
Certainty=0.559
```

```
-----
Definition=(AND
  (SOME respondsWithAction
    (AND CommunicateStatus
      (SOME hasObject
        (AND NavigationComputer
          (SOME hasCost
            (AND SelfBatteryLevel
              (SOME hasStateValue Medium))))))
    (SOME hasActor AdversaryAgent)
    (SOME isSampleTargetOf PeerAgent)))
  (SOME hasImportance Medium)
  (SOME handlesEvent
    (AND SensorFailure
```

```
(D-FILLER hasEventDescription
(D-LITERAL somerandomstring
(D-BASE-TYPE
http://www.w3.org/2001/XMLSchema#string))))))
```

Certainty=0.124

```
Definition=(AND
  (SOME handlesEvent
    (AND PowerFailure
      (SOME hasStateValue
        (AND ThrusterFailure
          (D-FILLER hasEventDescription
            (D-LITERAL somerandomstring
              (D-BASE-TYPE
                http://www.w3.org/2001/XMLSchema#string)))))))
    (SOME hasImportance Low)
    (SOME respondsWithAction
      (AND MaintainPosition (SOME hasActor Agent))))
```

Certainty=0.904

```
Definition=(SOME definesAction
```

```
(AND Thruster
  (SOME hasObject
    (AND PeerAgent (SOME hasNumber Targeted)))
  (SOME hasSpeed AdversaryAgent)))
```

Certainty=0.655

```
Definition=(SOME definesAction
  (AND MaintainPosition
    (SOME hasDirection
      (AND Number (SOME handlesEvent Submarine)))
    (SOME hasSpeed
      (AND Float
        (SOME hasObject
          (AND Navigate
            (SOME hasActor AdversaryAgent))))))
  (SOME definesGoal Thruster)))
```

Certainty=0.117