

TDT4136 Introduction to Artificial Intelligence

Lecture 10 - Knowledge Representation (chap 10)

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Broader outline

Lecture 1: Introduction to AI

Lecture 2: Intelligent agents

Lecture 3: Uninformed Search

Lecture 4: Informed Search

Lecture 5: Logical Agents

Lecture 6: First Order Logic

Lecture 7: Inference in First order Logic

Lecture 8: Adversarial Search

Lecture 9: Constraint Satisfaction Problems

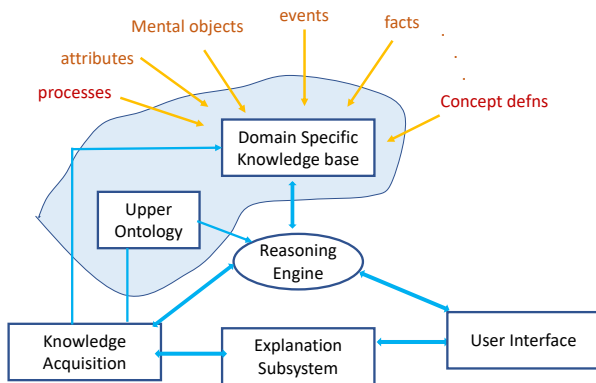
Lecture 10: Multiagent Systems and Game Theory

Lecture 11: Planning

Lecture 12: Knowledge Representation + AI and Ethics

Lecture 13: Summary

Knowledge-based systems



"Knowledge is knowing that a tomato is a fruit, wisdom is not putting it in a fruit salad."

Miles Kington

Knowledge acquisition is the part of the job of Knowledge engineer.

Knowledge engineer:

- decides the content and organization of the knowledge required for the domain specific KB
- acquires this knowledge into the KB

Knowledge acquisition techniques:

- Traditional: working together with human experts - manual work
- Recent: from data bases, text and data - information extraction and knowledge discovery.

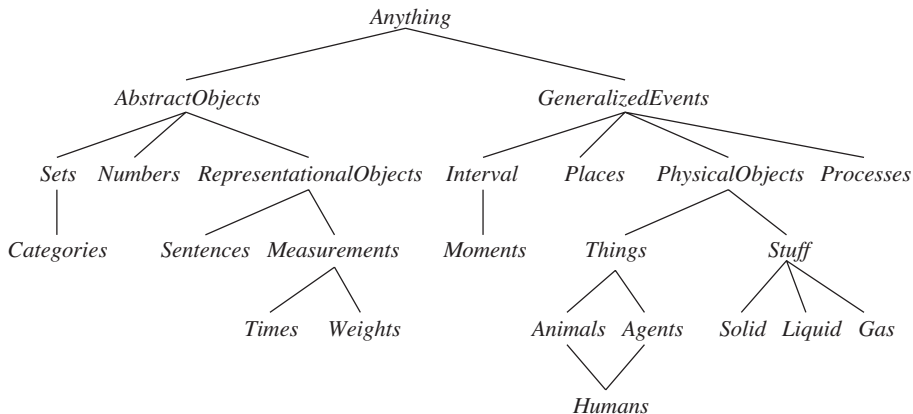
How to create more general and flexible representations

- Concepts like actions, time, physical objects, beliefs
- Operates on a bigger scale than knowledge engineering

Define general framework of concepts

- Upper ontology

The upper ontology of the world



Difference with special-purpose ontologies

A general-purpose ontology should be applicable in more or less any special-purpose domain

- Add domain-specific axioms

In any sufficiently demanding domain different areas of knowledge need to be unified

- Reasoning and problems solving could involve several areas simultaneously

What do we need to express?

- Categories, measures, composite objects, time, space, change, events, processes, physical objects, substances, mental objects, beliefs

IBM Watson : Example of the power of knowledge

https://www.youtube.com/watch?v=_Xcmh1LQB9I

Main requirements for KR languages:

- Expressive power
- Inferential adequacy
- Modifiability
- Readability

Typical KR languages:

- Logic
- Semantic networks
- Frames
- Description Logic
- Production Rules

Categories and objects

Knowledge representation requires the organisation of objects into categories

- Interaction at the level of the objects
- Reasoning at the level of categories

For example, Category-subcategory relationship

- defines a taxonomy
- enables Reasoning through **Inheritance**

Example: All instances of Food are edible, Fruits is a subclass of Food, and Apples is a subclass of Fruit, then an apple is edible

Categories play a role in the **predictions** about objects

- Based on **perceived properties** : An object that is orange colour, spherical with 10 cm diameter and smells. Can this be edible?
- In KB: Orange is a fruit. All fruits are edible. Orange category has the same properties that the perceived object has.
- Predict: It can be eaten

Limitations of logic representations

- Exceptions. Elephants are grey. But Eli, which is an elephant, is blue. Possible to represent in logic?
- Uncertainty, e.g. tomatoes can be red, green or yellow

We will use however FOL to discuss content and organization of knowledge. FOL can easily state facts about categories.

First-order logic and categories

An object is a member of a category

$BB_{12} \in \textit{Basketballs}$

$\text{Member}(\text{BB12}, \text{Basketballs})$

A category is a subclass of another category

$\textit{Basketballs} \subset \textit{Balls}$

$\text{Subcategory}(\text{Basketballs}, \text{Balls})$ ¹

All members of a category have some properties

$(x \in \textit{Basketballs}) \Rightarrow \textit{Spherical}(x)$

All members of a category can be recognized by some properties

$\textit{Orange}(x) \wedge \textit{Round}(x) \wedge \textit{Diameter}(x) = 9.5'' \wedge x \in \textit{Balls} \Rightarrow x \in \textit{Basketballs}$

¹We use subcategory, subclass, and subset interchangeably

Relations between categories

Disjoint: Two or more categories are disjoint if they have no members in common

Disjoint(*{Animals, Vegetables}*)

Exhaustive Decomposition: A set of categories *s* constitutes an exhaustive decomposition of a category *c* if all members of the set *c* are covered by categories in *s*

ExhaustiveDecomposition(*{Americans, Canadians, Mexicans}*, *NorthAmerican*)

Partition: A disjoint exhaustive decomposition is a partition

Partition(*{Archaea*², *Bacteria, Eukarya*³}, *LivingThings*)

²Archaeobacteria are primitive, single-celled microorganisms that are prokaryotes with no cell nucleus

³The Eukarya Domain includes the Animal, Plant, Fungus, and Protist Kingdoms

Many categories have no clear-cut definitions (chair, bush, book)

Tomatoes: sometimes green, red, yellow, black. Mostly round and mostly red.

One solution: category *Typical(Tomatoes)*

$$x \in \textit{Typical}(\textit{Tomatoes}) \Rightarrow \textit{Red}(x) \wedge \textit{Spherical}(x)$$

We can write down useful facts about categories without providing exact definitions

Physical composition

One object may be part of another

PartOf(Bucharest, Romania)

PartOf(Romania, EasternEurope)

PartOf(EasternEurope, Europe)

PartOf(Europe, Earth)

The *PartOf* predicate is transitive reflexive and transitive

PartOf(x, x)

$\text{PartOf}(x, y) \wedge \text{PartOf}(y, z) \Rightarrow \text{PartOf}(x, z)$

So we can infer that *PartOf(Bucharest, Earth)*

Composite objects are often characterized by structural relations among parts

Addresses what happens **during** the action,

Example: $At(Knut, NTNU)$

refers to the fact of Knut being at NTNU, but does not say whether it is true.

For this we need the predicate T :

$$T(At(Knut, NTNU), t)$$

Time intervals

Represented as an interval $i = (start, end)$

$T(f, t)$ f is true at time t

$Happens(e, i)$ e happens over the time interval i

$Initiates(e, f, t)$ e causes f to start to hold at time t

$Terminates(e, f, t)$ e causes f to cease to hold at time t

$Clipped(f, i)$ f ceases to be true at some point during interval i

$Restored(f, i)$ f becomes true sometime during interval i

Mental events and objects

- So far, knowledge based agents can have beliefs and deduce new beliefs
- What about **knowledge about** beliefs? What about knowledge about the inference process?
- Requires a model of the **mental objects** in someones head and the processes that manipulate these objects
- **Relationships** between agents and mental objects:
 - believes,
 - knows,
 - wants,
 - ...
- Example: *Believes(Lois, Flies(Superman))* with *Flies(Superman)* being a candidate for a **mental object**
- An agent can now reason about the beliefs of agents

intrinsic and Extrinsic properties

- Stuff versus things, e.g butter versus elephant
- count nouns versus mass nouns in linguistic
- an instance of stuff continues to be stuff when divided but not things
- instances of stuff have intrinsic properties that belong to the substance, e.g., butter has property *melting point*
- instances of thing have extrinsic properties, e.g., weight.

Developed by Ross Quillian, as “a psychological model of associative memory” (1968).

Associationist theories define the meaning of an object in terms of a network of associations with other objects in a domain or a knowledge base.

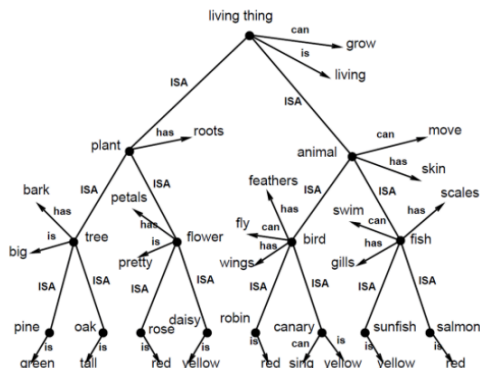
Quillian experimented with human subjects:

The structure of the networks was devised from laboratory testing of human response times to questions such as ‘Is a canary a bird?’, “Can a canary sing?”, “Is a canary yellow?”, or “Can a canary fly?”

Quillian experiments

Experiment: E.g., “Can a canary fly?” needed longer response time than “Can a canary sing?”.

Quillian: humans organize knowledge hierarchically and store information at its most abstract level



- reduces the size of the knowledge base; prevents update inconsistencies

Logic vs semantic networks

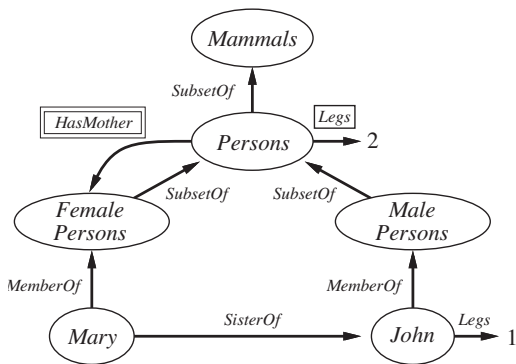
Main idea: Knowledge is not a large collection of small pieces of knowledge but larger pieces that are highly interconnected. The meaning of a concept emerges from how it is connected to other concepts

Efficient algorithms for category membership inference using inheritance reasoning

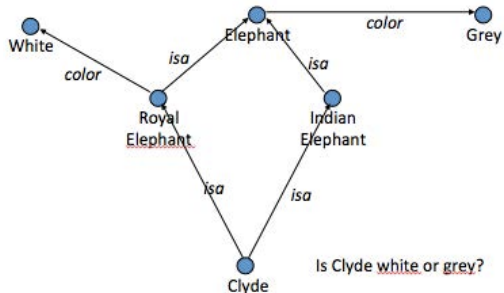
- Female persons inherit all properties from person
- Similar to object-oriented programming

Inference of **inverse links**, e.g. *SisterOf* vs. *HasSister*

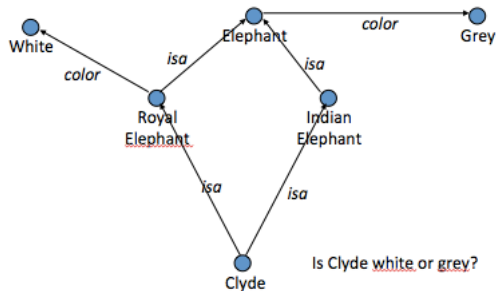
Semantic network example



Multiple inheritance



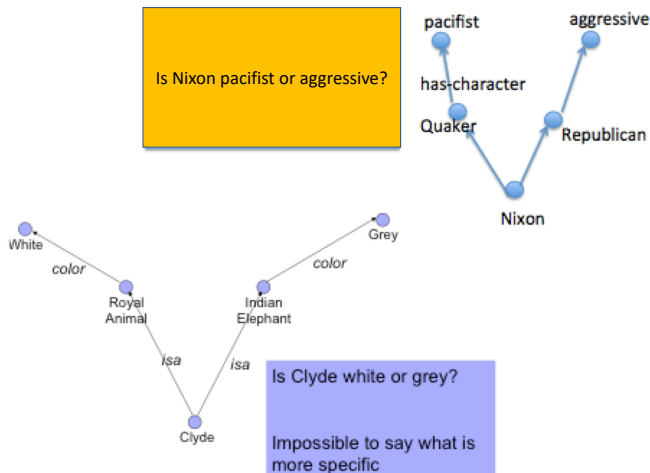
Multiple inheritance - cont



Is Clyde white or grey?

White – Royal Elephant is more specific than Elephant.

Multiple inheritance - cont



Use model preference. E.g., religious belief may be given preference over political beliefs.

Frame-based representations - example

A Frame consists of a number of slots.

A slot consists of a variable (a property) which has a value.

dog

isa : animal

has-part : tail

has-part : legs

no-of-legs : 4

characteristic : barks

instance : fido

instance : bert

fido

isa : dog

characteristic :
fat

characteristic :
ugly

fido inherits
from 'dog'

Frame-based representations - example

room

isa : section-of-building

has-part : floor

has-part : wall

has-part : floor

*has-part : window

has-part : door

*no-of-doors : 1

no-of-walls : 4

storage-room

isa : room

has-part : no-window

no-of-doors : 2

here **storage-room**
inherits from room, but
overrides the default
values of
has-part : window and
no-of-doors : 1

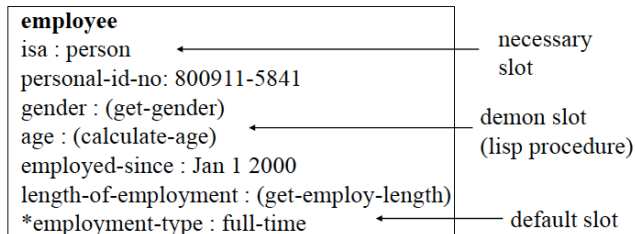
Frame-based representations

- Semantic networks where nodes have structure
- Frame with a number of slots (age, height, ...)
- Each slot stores specific item of information – attribute-value or slot-filler pairs
- When agent faces a new situation - Slots can be filled in (value may be another frame)
- Filling in may trigger actions
- May trigger retrieval of other frames
- Inheritance of properties between frames
- Very similar to objects in OOP

Frame-based representations - example

Logic and semantic networks are declarative knowledge representation languages.

Frame-based languages are also mainly declarative but can also represent procedural knowledge through **demons**



FOL is monotonic which is limiting - the set of entailed sentences can only increase.

If $KB \models \alpha$ then $KB \wedge \beta \models \alpha$

Nonmonotonic logic, e.g.,:

- Circumscription
- Default logic

Circumscription

- Introduced by McCarthy: "A bird will fly if it is not abnormal."
- McCarty introduces an *ab* predicate into the default reasoning rule:
 - $(\forall x)[(bird(x) \wedge \neg ab(x)) \rightarrow flies(x)]$
 - If there is no proof given by the logic that $ab(x)$, we can "circumscribe" the *ab* predicate and assume that it is not true.
- Given the premises
 - $(\forall x)[penguin(x) \rightarrow \neg flies(x)]$
 - $(\forall x)[penguin(x) \rightarrow bird(x)]$
 - $bird(Tweety)$
- If we add $penguin(Tweety)$ to the premises, then we can infer $ab(Tweet)$ by rewriting the default sentence like this:
 $(\forall x)bird(x) \wedge \neg flies(x) \rightarrow ab(x)$

- If we add *penguin(Tweety)* to the premises, then we can infer *ab(Tweety)* by rewriting the default sentence like this:

$$\begin{aligned} & (\forall x)[(bird(x) \wedge \neg ab(x)) \rightarrow flies(x)] \\ \equiv & (\forall x)[\neg(bird(x) \wedge \neg ab(x)) \vee flies(x)]_{(IE)} \\ \equiv & (\forall x)[(\neg bird(x) \vee ab(x)) \vee flies(x)]_{(DeMorgan)} \\ \equiv & (\forall x)[\neg bird(x) \vee ab(x) \vee flies(x)]_{(associativity\ of\ disjunction)} \\ \equiv & (\forall x)[\neg bird(x) \vee flies(x) \vee ab(x)]_{(commutativity\ of\ disjunction)} \\ \equiv & (\forall x)[\neg(bird(x) \wedge \neg flies(x)) \vee ab(x)]_{(DeMorgan)} \\ \equiv & (\forall x)[(bird(x) \wedge \neg flies(x)) \rightarrow ab(x)]_{(Introd\ of\ implication)} \end{aligned}$$

Default rules that produce contingent conclusions.

Example: $\text{Bird}(x) : \text{Flies}(x) \setminus \text{Flies}(x)$

means "If $\text{Bird}(x)$ is true and $\text{Flies}(x)$ is consistent with KB then $\text{Flies}(x)$ can be concluded by default

A default rule has 3 components:

- Prerequisite (P),
- Justification (J),
- Conclusion(C)

$P: J_1, \dots, J_n \setminus C$

If P and J_1, \dots, J_n cannot be proven false, then the conclusion can be drawn.

Many of the inferences have default status rather than being absolutely certain

- Inferred facts can be wrong and need to be retracted = **belief revision**
- Assume knowledge base contains sentence P and we want to execute $Tell(KB, \neg P)$
- To avoid contradiction: $Retract(KB, P)$
- But what about sentences inferred from P ?

Truth maintenance systems are designed to handle these complications