

**ALGORITHMS IN AI & DATA SCIENCE 1 (AKIDS 1)**

# Expert Systems

Prof. Dr. Goran Glavaš

# Content

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- Knowledge-Based AI
- Expert Systems
- Inference

Based on the materials from Prof. Dr. Jan Šnajder:

<https://www.fer.unizg.hr/download/repository/AI-2022-08-ExpertSystems.pdf>

# Motivation: An Intelligent Agent

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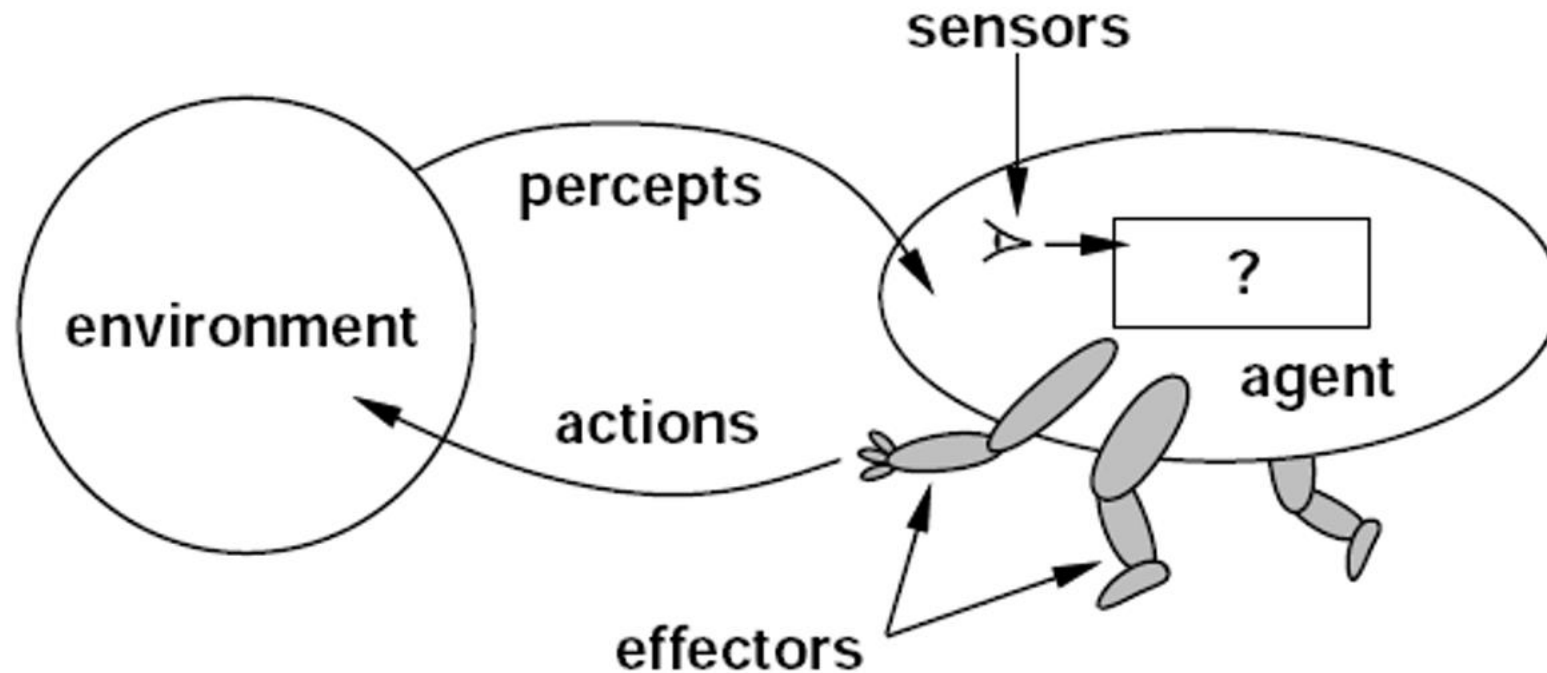


Image from *Russel & Norving. Artificial Intelligence: A Modern Approach.*

# AI, Knowledge, and Reasoning

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- Humans **know** things and what we know guides how we **do** things
- Human intelligence in big part stems from the ability to **reason** over the internal representations of **knowledge**
  - **Reasoning**: inference of **new knowledge** from existing knowledge

## Knowledge-Based AI

Knowledge-based AI is the body of work in AI that revolves around **knowledge-based agents** which are equipped with two main components: **(1)** the **knowledge base** – a set of „**facts**“, represented in a particular format, and **(2)** the **reasoning engine/mechanism** – an algorithm or set of algorithms that allow for reasoning, i.e., induction of new knowledge from existing knowledge

# Knowledge-Based AI

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- **Knowledge base:** set of „facts” (sometimes called “sentences”, but **not** in a language sense)
  - **Axioms:** facts taken as given and not derived from other facts
- **Facts** represented in a concrete **knowledge representation language**
  - Knowledge-based AI is sometimes also called **symbolic AI**
  - The KR language has a **vocabulary** – set of atomic elements of knowledge, typically some kind of **entities** and **relations** between them
- **Reasoning mechanism:** a set of rules or operations that **induce new facts** from the existing KB
  - Or check if some proposed facts are **consistent with KB**, that is, can be induced from the KB facts

# Symbolism vs. Connectionism

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- Traditional knowledge-based systems represent **symbolic AI**

**Knowledge** about the external world can be **represented with symbols**. **Inference** amounts to **symbol manipulation**. **Intelligent behavior** amounts to **inference**.

Symbolic AI / Symbolism

- Symbolism is contrasted by **connectionism**

**Mental states** and **behavior** emerges from the **interaction of a large number of interconnected and simple processing units**. An **artificial neural network** is a typical example of the connectionist approach to AI.

Connectionist AI / Connectionism

# Symbolism vs. Connectionism

- **Symbolic AI** is **discrete** and inherently (human) **interpretable**
  - **Knowledge:** given as a KB
  - **Inference:** formal symbolic (**rule-based**) reasoning over KB
- **Connectionist (neural) AI** is **continuous** and (mostly) **not** human interpretable
  - **Knowledge:** learned from (large amounts of) raw data
  - **Inference:** **computation** in a continuous representation space

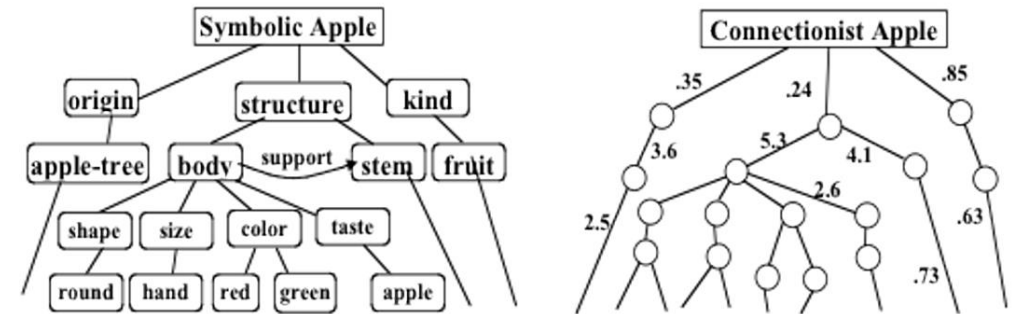


Image from: Minsky, M. (1990). Logical vs. Analogical or Symbolic vs. Connectionist or Neat vs. Scruffy. Artificial Intelligence at MIT. Expanding Frontiers, Patrick H. Winston (Ed.).

# Some Knowledge Formalisms

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- **Propositional logic**
- **Predicate Logic**  
(aka **First-Order Logic**)
- Temporal Logic
- Description Logic  
(basis of modern ontologies and knowledge graphs)
- Fuzzy Logic
- Modal Logic
- Epistemic Logic
- ...



Image from: <https://sites.psu.edu/orenadamrcl/2012/09/30/rcl-4-logic-reduced/>



# Example: Propositional Logic

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- **Symbols** of the propositional logic
  - Propositional variables (vocabulary, atomic formulae):  $V = \{A, B, C, \dots\}$ 
    - Each  $(A, B, \dots)$  denotes one **knowledge fact**. For example,  $A = \text{„penguins are birds“}$
  - Logical operators (or connectives)
    - Negation ( $\neg$ ), disjunction (OR,  $\vee$ ), conjunction (AND,  $\wedge$ )
    - Implication ( $\rightarrow$ ), equivalence ( $\leftrightarrow$ )
  - Logical (Boolean) constants **True** and **False**
  - Parentheses ( „(“ and „)“)
- **Knowledge (KB) consists of formulae**
  - Each variable is a **formula**
  - If  $F$  is a formula, then  $\neg F$  is also a formula
  - If  $F$  and  $G$  are formulas, then  $F \vee G, F \wedge G, F \rightarrow G, F \leftrightarrow G$  are also formulae

# Example: Propositional Logic

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- **Reasoning:** Based on the semantics of the logic operators
  - Infer if a formula is True ( $\top$ ) or False ( $\perp$ ) from the truth values of atoms
  - Need **semantics** of the propositional logic

$F$	$G$	$\neg F$	$F \wedge G$	$F \vee G$	$F \rightarrow G$	$F \leftrightarrow G$
$\perp$	$\perp$	$\top$	$\perp$	$\perp$	$\top$	$\top$
$\perp$	$\top$	$\top$	$\perp$	$\top$	$\top$	$\perp$
$\top$	$\perp$	$\perp$	$\perp$	$\top$	$\perp$	$\perp$
$\top$	$\top$	$\perp$	$\top$	$\top$	$\top$	$\top$

- **New knowledge: logical consequence**
  - Formula  $G$  is a **logical (semantic) consequence** of formulae  $F_1, \dots, F_n$  if and only if every interpretation that satisfies  $F_1 \wedge \dots \wedge F_n$  also satisfies  $G$ .
  - In other words, if  $F_1 \wedge \dots \wedge F_n \rightarrow G$  is **True** for every interpretation

# Example: Propositional Logic

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## Knowledge:

- **Atoms:**  $P$  = „Rain falls”;  $Q$  = „Cleaners hose the road”;  $R$  = „The road is wet”
- **Formulas (KB):**
  - $(P \vee Q) \rightarrow R$  („If rain falls or cleaners hose, the road becomes wet”)
  - $R$  („road is wet”)
  - $\neg P$  („the rain didn't fall”)
- **Logical inference:**
  - $((P \vee Q) \rightarrow R) \wedge R \wedge \neg P \rightarrow Q?$

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# Expert Systems

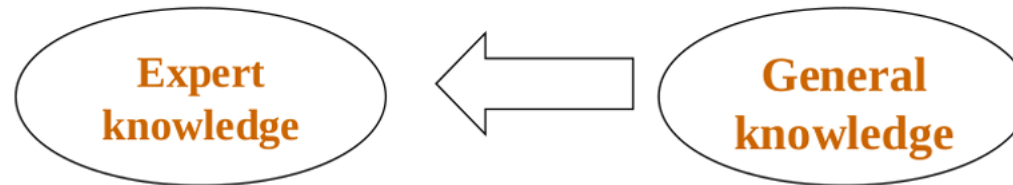
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- A symbolic AI paradigm for **knowledge representation** and **reasoning**
- Very popular in the **80s** – originated from the idea that the majority of human knowledge can be represented in the form of **if-then rules**
  - „If patient’s temperature is above 38°C, medications that lower the body temperature should be administered”
  - „If the traffic light is red, then stop”
- First practically successful „**AI technology**”: machines giving an impression of „**analyzing and thinking**”

# General vs. Expert Knowledge

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- Obviously, it is **impossible** to come up with exhaustive **if-then rules** for all domains of human activity and knowledge
- **Impossible** to encode **general knowledge** with **if-then rules**



- **Solution**: narrow down the scope to a specific domain
  - For example: medicine, finances, chess, ...
- Expert systems do **not** tackle **general problem solving**

# Expert systems = Intellectual Cloning

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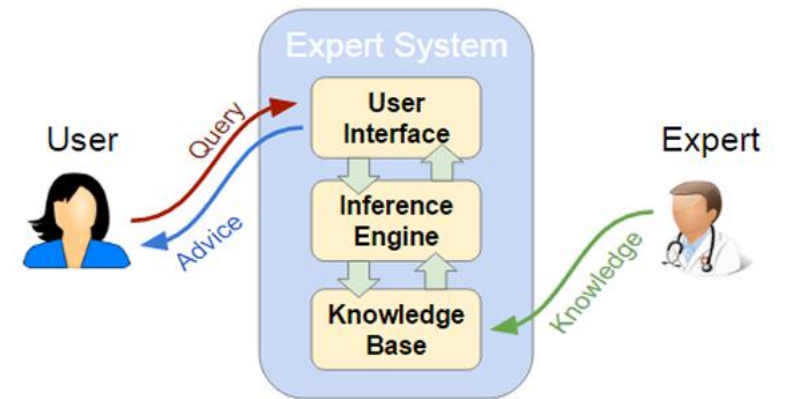
- The overall intent behind **expert systems** is that of **intellectual cloning**
- Find people that have a **reasoning skill** that is **important** and **rare**
  - Expert medical diagnostician
  - Expert business analyst
- **Analyze / extract** their knowledge and reasoning and try to **embody them in a program**
  - In case of **Expert Systems**: as **if-then rules**



# Knowledge base vs. Inference Engine

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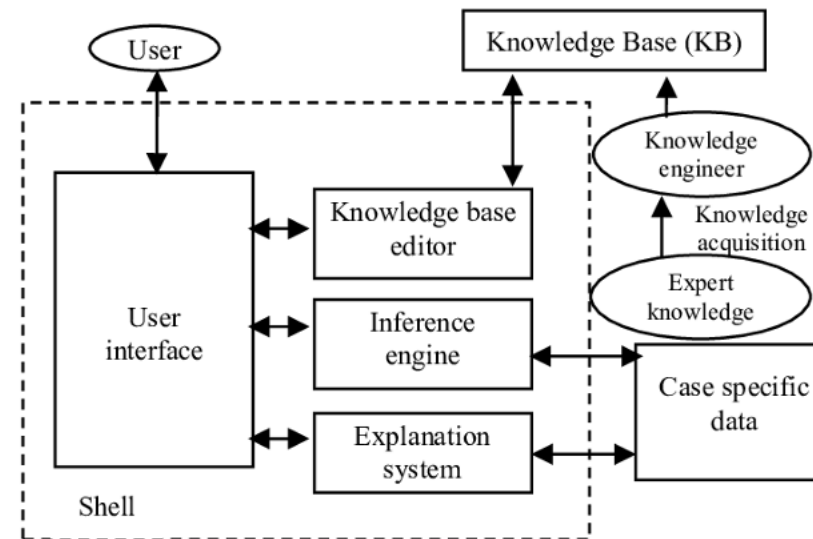
- Different **expert systems** have differing representation technologies, but all have **two main architectural properties**
1. Distinction between **inference engine** and **knowledge base**
    - IE retrieves rules from the KB
  2. Use of **declarative style representations**
    - Rules are data structures with their own **semantics**, rather than part of the code implementing the inference engine





# Expert Systems shell

- **Inference engine** is decoupled from the **knowledge base** → the idea is that IE can operate on any KB that is „plugged in”
- **Expert system shell**: a **tool** for building expert systems
  - Inference engine
  - Knowledge base editor
  - User interface
  - Explanation module



# If-then rules

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- Knowledge in ES is represented by the so-called **production rules**
  - Essentially **if-then rules**
  - **If** [condition/state/premise/antecedent]  
**then** [action/conclusion/consequent]
- It's quite reminiscent of **implication** in logic ( $A \rightarrow B$ ), but there are two key differences
  - In logic, **implication** is a **formula** and as such has a **truth value**
  - The consequent in implication ( $B$  in  $A \rightarrow B$ ) is also a formula, whereas the **consequent** in **if-then rules** of an ES are **actions**
    - Asserting **new facts** but also
    - **Deleting** facts, executing code, printing on screen, ...

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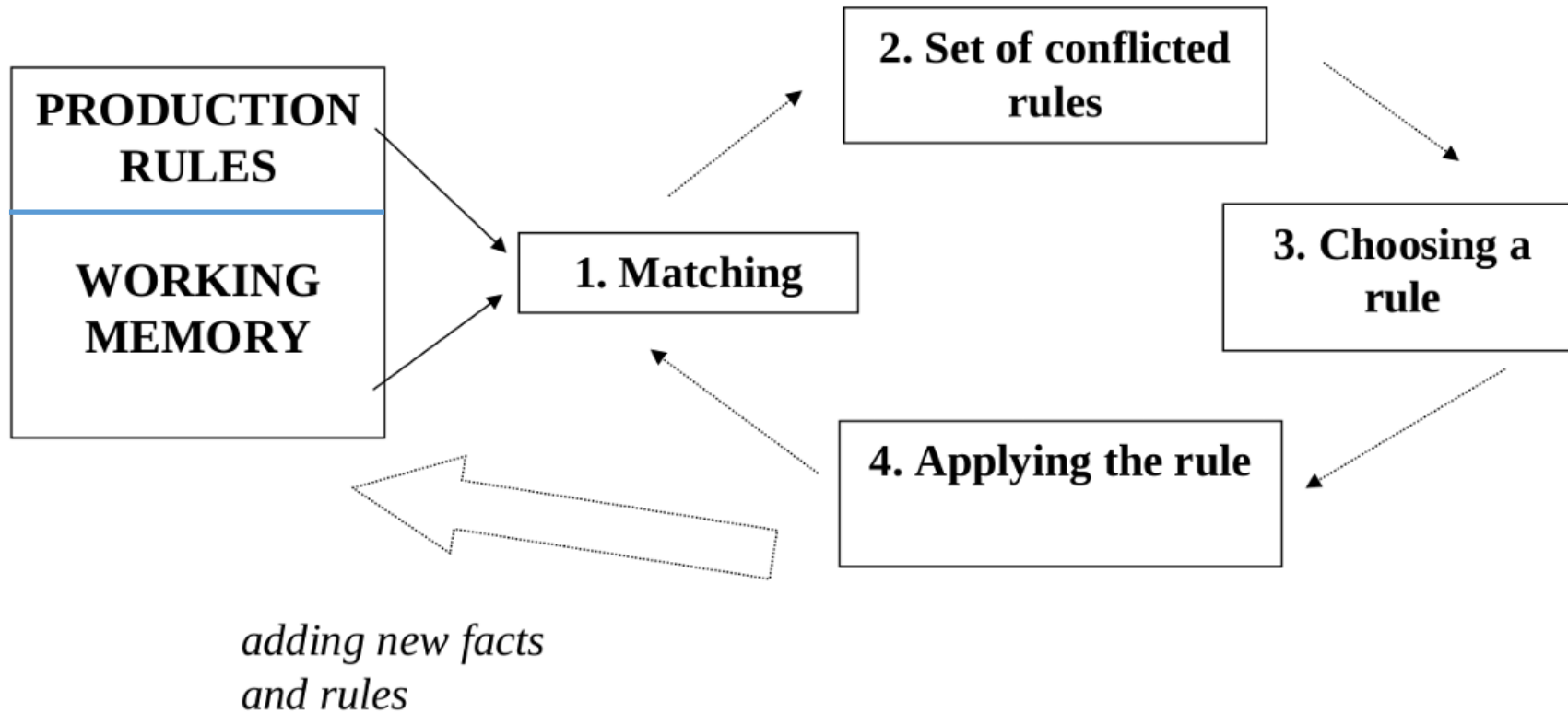
# Inference Components

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- **Working memory** – part of the knowledge base that:
  - Stores **facts** (i) added by the user before inference or (ii) **new facts** derived during inference
  - Does not store them permanently (akin to **short-term memory** in humans)
- **Inference engine** – a control mechanism carrying out the following:
  - **Matching** – facts from the **working memory** need to be matched against the **left-hand side** (LHS or condition) of the **if-then rules**
  - **Conflict resolution** – if the working memory matches the LHS of **more than one rule**, need to **select** one of the rules based on some criteria
  - **Rule application** (aka „**rule firing**”) – executing the action specified by the **right-hand side** of the rule whose LHS was matched

# Inference cycle

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# Inference in Rule-Based Systems

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- Establish a **reasoning chain** which is a **sequence of conclusions** that link the starting condition to the solution of the problem
  - The reasoning procedure is called **chaining**
- **Forward chaining**
  - **Starting with known data** and advancing toward a conclusion
  - **To use:** when there is a **small amount of data** and a **large space of possible solutions**
- **Backward chaining**
  - **Choosing a possible conclusion** (hypothesis) and **trying to prove** that it is valid by finding valid evidence
  - **To use:** Not too many possible conclusions, the amount of **known data is large**
- **Bidirectional inference**
  - Combines forward and backward chaining

# Factorization –Variables and Values

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- **If-then rules** in ES will operate on a set of **variables**, each with a **domain**
  - Similar like in Discrete Optimization and Constraint Satisfaction
- The variables and their domains can be referred to as **ontology** of the expert system
  - $O = X_1, X_2, \dots, X_n,$   
 $X_1 \in D_1, X_2 \in D_2, \dots, X_n \in D_n$
  - **Rules format**
    - **If**  $X_i == x_i$  **and**  $X_j == x_j$  **and** ... **and**  $X_k == x_k$  **then**  $X_m = x_m$

# Example

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- **Knowledge base** for determining type of **fruit**
- **Ontology (variables and possible values):**
  - **Shape:** elongated | circular | rounded
  - **Surface:** smooth | coarse
  - **Color:** green | yellow | brown-yellow | red | blue | orange
  - **No. seeds:** 0 | 1 | >1
  - **Seed type:** multiple | bony
  - **Diameter:** <10cm | >10cm
  - **Fruit type:** vine | tree
  - **Fruit:** banana | watermelon | cantaloupe | apple | apricot | cherry | peach | plum | orange





# Example

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- Knowledge base for determining type of fruit
- If-then rules
  - $R_1$ : **IF** Shape = elongated & Color = green | yellow **THEN** Fruit = banana
  - $R_2$ : **IF** Shape = circular | rounded & Diameter = >10cm **THEN** Fruit Type = vine
  - $R_3$ : **IF** Shape = circular & Diameter = <10cm **THEN** Fruit Type = tree
  - $R_4$ : **IF** No. Seeds = 1 **THEN** Seed Type = bony
  - $R_5$ : **IF** No. Seeds = >1 **THEN** Seed Type = multiple
  - $R_6$ : **IF** Fruit type = vine & Color = green **THEN** Fruit = watermelon
  - $R_7$ : **IF** Fruit type = vine & Color = yellow & Surface = smooth **THEN** Fruit = melon

# Example

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- $R_8$ : **IF** Fruit type = vine & Color = brown-yellow & Surface = course  
**THEN** Fruit = cantaloupe
- $R_9$ : **IF** Fruit type = tree & Color = orange & Seed Type = bony  
**THEN** Fruit = apricot
- $R_{10}$ : **IF** Fruit type = tree & Color = orange & Seed Type = multiple  
**THEN** Fruit = orange
- $R_{11}$ : **IF** Fruit type = tree & Color = red & Seed Type = bony  
**THEN** Fruit = cherry
- $R_{12}$ : **IF** Fruit type = tree & Color = orange & Seed Type = bony  
**THEN** Fruit = peach
- $R_{13}$ : **IF** Fruit type = tree & Color = yellow | green & Seed Type = multiple  
**THEN** Fruit = apple
- $R_{14}$ : **IF** Fruit type = tree & Color = blue & Seed Type = bony  
**THEN** Fruit = plum

# Forward Chaining: Example

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- **Input (known) data:**
  - Diameter = 2cm (<10cm), Shape: circular, No. seeds: 1, Color: red
- **Conflict resolution:** take the rule with smaller number

Step	Working memory	Conflicting rules	Rule that fires
0	Diameter = <10cm Shape = circular No. seeds = 1 Color = red	R3, R4	R3 (smaller number)
1	+ Fruit Type = tree	<del>R3</del> , R4	R4
2	+ Seed Type = bony	<del>R3</del> , <del>R4</del> , R11	R11
3	+ Fruit = cherry	<del>R3</del> , <del>R4</del> , <del>R11</del>	<b>DONE</b>

# Backward Chaining

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- Starts with a **desired goal** (hypothesis) and determines whether the existing facts support proving the goal
- Start with an **empty list of facts**, the **goal variable** is given
  - We start from all rules that assign a **value** to the **goal variable**, and check what is on the LHS
  - If on LHS we have a variable for which we don't have the value yet either, we try to infer it → look for all rules with that variable on LHS, etc.
- **Last in first out** principle of trying to figure out values for variables
  - **Q:** Which data structure do we need then?

# Backward Chaining: Steps

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**Step 1.** Put the **goal variable** onto the (empty) stack

**Step 2.** Top of stack always the variable for which we need to find the value. Find all rules with the **variable from the stack top** on **RHS**

- If no rule has the stack-top variable on the RHS, **ask the user**

**Step 3.** For each such rule:

- 3a.** If LHS satisfied (all variables have correct values in WM),
- **apply** the rule (place the RHS variable and value into WM)
  - **remove** the current goal from the stack,
  - continue from Step 2

# Backward Chaining: Steps

---

**Step 1.** Put the **goal variable** onto the (empty) stack

**Step 2.** Top of stack always the variable for which we need to find the value. Find all rules with the **variable from the stack top** on **RHS**

- If no rule has the stack-top variable on the RHS, **ask the user**

**Step 3.** For each such rule:

**3b.** If LHS not satisfied because of different value of some variable compared to WM, do not apply the rule

**3c.** If LHS not satisfied because the value of some variable is not in WM at all, then add that variable to the stack

# Backward Chaining: Example

- Our fruit example → the goal variable is **fruit**

Step	Stack	Working memory	Conflicting rules	Action
0	Fruit		R1, R6, R8, R9, R10, R11, R12, R13, R14	<b>Shape</b> (LHS of R1) not in WM and not on RHS of any rule, <b>ask user</b>
1	Fruit	<b>Shape</b> = circular	R6, R8, R9, R10, R11, R12, R13, R14	<b>Fruit Type</b> (LHS of R6) not in WM but exists on RHS of rules, <b>add to stack</b>
2	Fruit Type Fruit	<b>Shape</b> = circular	R2, R3 ( <b>Fruit Type</b> on RHS)	<b>Diameter</b> (LHS of R2) not in WM and not on RHS of any rule, <b>ask user</b>
3	Fruit Type Fruit	<b>Shape</b> = circular <b>Diameter</b> = <10cm	R3	LHS of R3 is satisfied (all variables with correct values in WM), add RHS to WM and pop the stack

# Backward Chaining: Example

Step	Stack	Working memory	Conflicting rules	Action
4	Fruit	Shape = circular Diameter = <10cm Fruit Type = tree	R6, R8, R9, R10, R11, R12, R13, R14	The LHS of R6 is in conflict with WM, proceed to next rule
5	Fruit	Shape = circular Diameter = <10cm Fruit Type = tree	R8, R9, R10, R11, R12, R13, R14	The LHS of R8 is in conflict with WM, proceed to next rule
6	Fruit	Shape = circular Diameter = <10cm Fruit Type = tree	R9, R10, R11, R12, R13, R14	The LHS of R9 has <b>Color</b> which is not in WM, and not in RHS of any rule, ask user
7	Fruit	Shape = circular Diameter = <10cm Fruit Type = tree Color = red	R11	The LHS of R11 has Seed Type which is not in WM but exists in RHS of another rule, push <b>Seed Type</b> to stack



# Backward Chaining: Example

Step	Stack	Working memory	Conflicting rules	Action
8	Seed Type Fruit	Shape = circular Diameter = <10cm Fruit Type = tree Color = red	R4, R5	R4 has <b>No. Seeds</b> on LHS, which we don't have in WM nor do we have any rules with it on RHS, <b>ask user</b>
9	Seed Type Fruit	Shape = circular Diameter = <10cm Fruit Type = tree Color = red No. Seeds = 1	R4, R5	LHS of R4 is satisfied, we add the RHS to WM and pop the stack
10	Fruit	Shape = circular Diameter = <10cm Fruit Type = tree Color = red No. Seeds = 1 Seed Type = bony	R11	LHS of R11 is satisfied, add the RHS ( <b>Fruit = cherry</b> ) to WM and pop the stack → stack will be empty → <b>DONE</b>

# Backward Chaining: Algorithm

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- Let's write the pseudocode for **backward chaining**, using **appropriate data structures** and in a **modular fashion**!
- **Data structures:**
  - **Q:** How to represent the ontology (variables and allowed values for each)?
  - **Q:** How to represent the working memory?
  - **Q:** How would you represent a rule?
- **Ontology** and **rules** are **static**
- **Working memory** changes, but can only grow
  - And we know its maximal size (number of variables) in advance
- A **lot of „reading“** into all three, not much writing
- No similarity or neighbourhood required (*min, max, previous, next, ...*)

# Backward Chaining: Algorithm

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- **Ontology**

- **hash table** of **hash tables**
- **Keys:** variables, **Values:** hash table with allowed values for the variable
- When user provides a value, we need to check if it's allowed for the variable

- **Rule:** has LHS and RHS, assume RHS always has only one variable

- **LHS:** **hash table** (Key: variable, Value: value)
- **RHS:** pair (tuple) – variable, value

- **Working Memory:** **hash table**

```
value_valid(ont, var, val)
    vals = ont[var]
    if val in vals # hashtable lookup
        return True
    else
        return False
```

```
rule_status(rule, wm)
    for var in rule.LHS
        if var not in wm
            return var # not in wm
        elif rule.LHS[var] != wm[var]
            return False # in wm, wrong val
    return True
```

```
apply_rule(rule, wm)
    var = rule.RHS.var
    val = rule.RHS.val
    wm[var] = val
```

# Backward Chaining: Algorithm

```
backward_chain(ont, rules, goal)
    s = [] # empty stack
    s.push(goal)
    wm = {} # empty hash table
    while not s.is_empty()
        goal = s.peek()
        matches = find_rules(rules, goal)
        if len(matches) == 0 # no rule with stack-top variable on RHS
            val = ask_user(goal)
            if value_valid(ont, val, goal)
                wm[goal] = val
            else
                return „error“
        for m in matches
            status = rule_status(m, wm)
            if status == True # LHS satisfied
                apply_rule(m, wm) # RHS added to wm
                s.pop()
                break
            elif status == False # LHS in conflict with wm
                continue
            else # status is a variable not in wm
                s.push(status)
                break
    return wm[goal]
```

```
find_rules(rules, goal)
    matches = []
    for rule in rules
        if rule.RHS.var == goal
            matches.append(rule)
    return matches
```

- Execution **stack**
  - Function `peek` just reads the value from the top, without removing it
- This basic variant of the algorithm is quite **inefficient**
  - **Q:** How would you speed it up?
- **Q:** how would you implement backchaining **without** (an explicit) **stack**?

# Questions?

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