COMPUTATIONAL INTELLIGENCE

September 2014 – November 2014

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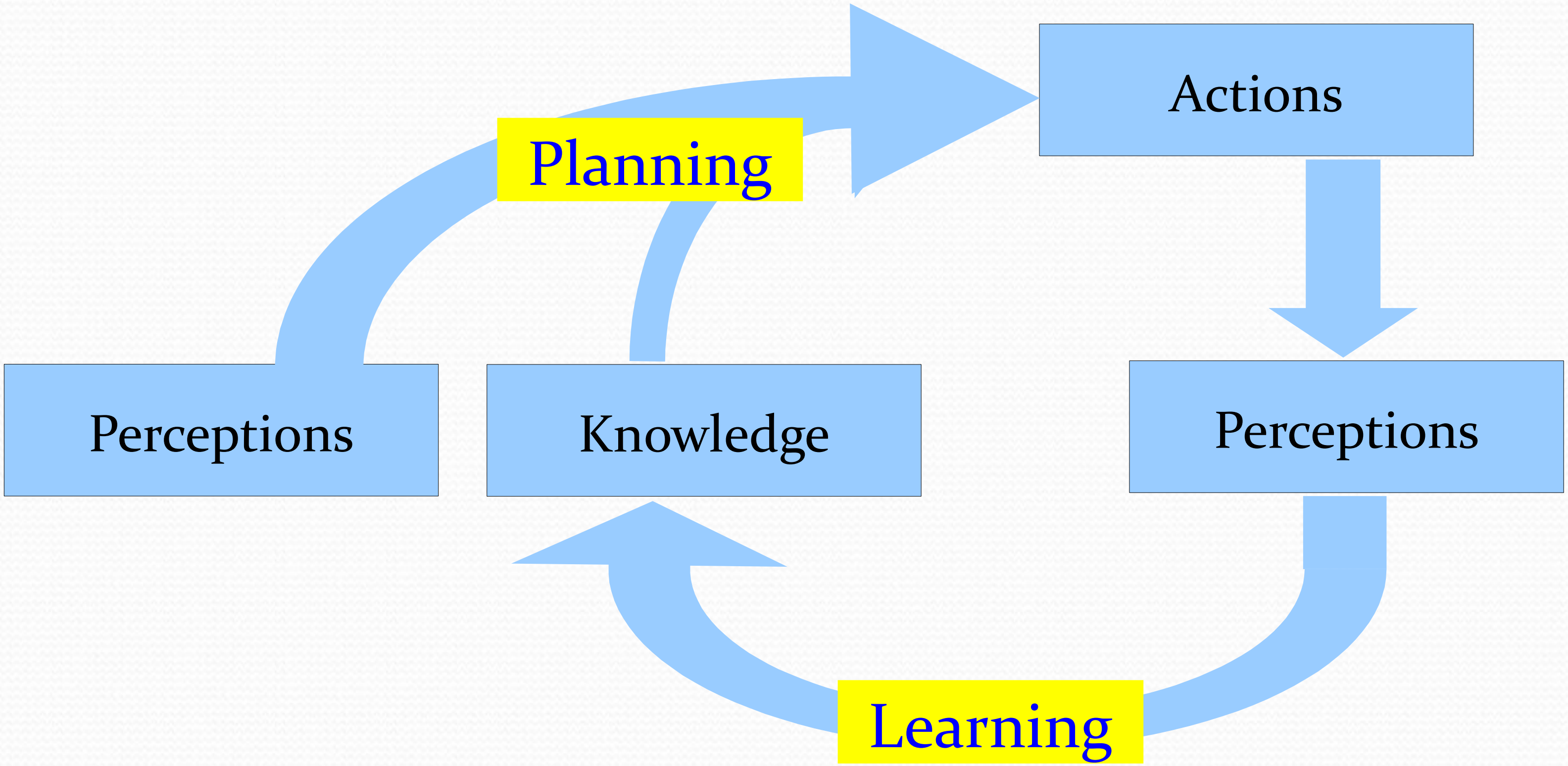
Artificial Intelligence

- Aims to develop intelligent agents that perceive their environment and take actions that maximize their chances of success
- Requires solving several challenges:
  - Knowledge representation:
    how does an agent represent its knowledge and perceptions?
  - Reasoning, planning:
    how does an agent deduce an action based on its perceptions and its knowledge?
  - Learning:
    how does an agent update its knowledge based on its perceptions?

Artificial Intelligence



Computational Intelligence

- Computational intelligence traditionally studies a subset of three AI techniques:
  - Knowledge representation:
    fuzzy logic & fuzzy set theory
  - Reasoning, planning:
    Evolutionary (genetic) algorithms
  - Learning:
    Neural networks

Knowledge representation: Fuzzy logic

- **Goal:**
  represent "fuzzy" knowledge of an agent

- Traditional logic can be used to represent crisp rules:

  if *A is true* then do *B*

  Boolean in → Boolean out

- Fuzzy logic represents fuzzy rules:

  if *A is true to a high degree / A is likely* then try to make *B true to a high degree /* make *B likely*

  Number in → Number out

Fuzzy logic is less sensitive to errors / noise

Knowledge representation: Fuzzy logic

- Used to build control systems

> if *A is warm to a high degree* then *B should be turned down to a high degree*

- Used to calculate the overall quality (fitness) of a (hypothetical) situation

> if *A is high* then *customer* is *likely good*
> if *B is high* then *customer* is *likely good*
> if *C is high* and *B is not high* then customer is *likely good*
>
> how good would the situation be in which *A* and *C* are high, and *B* is low?

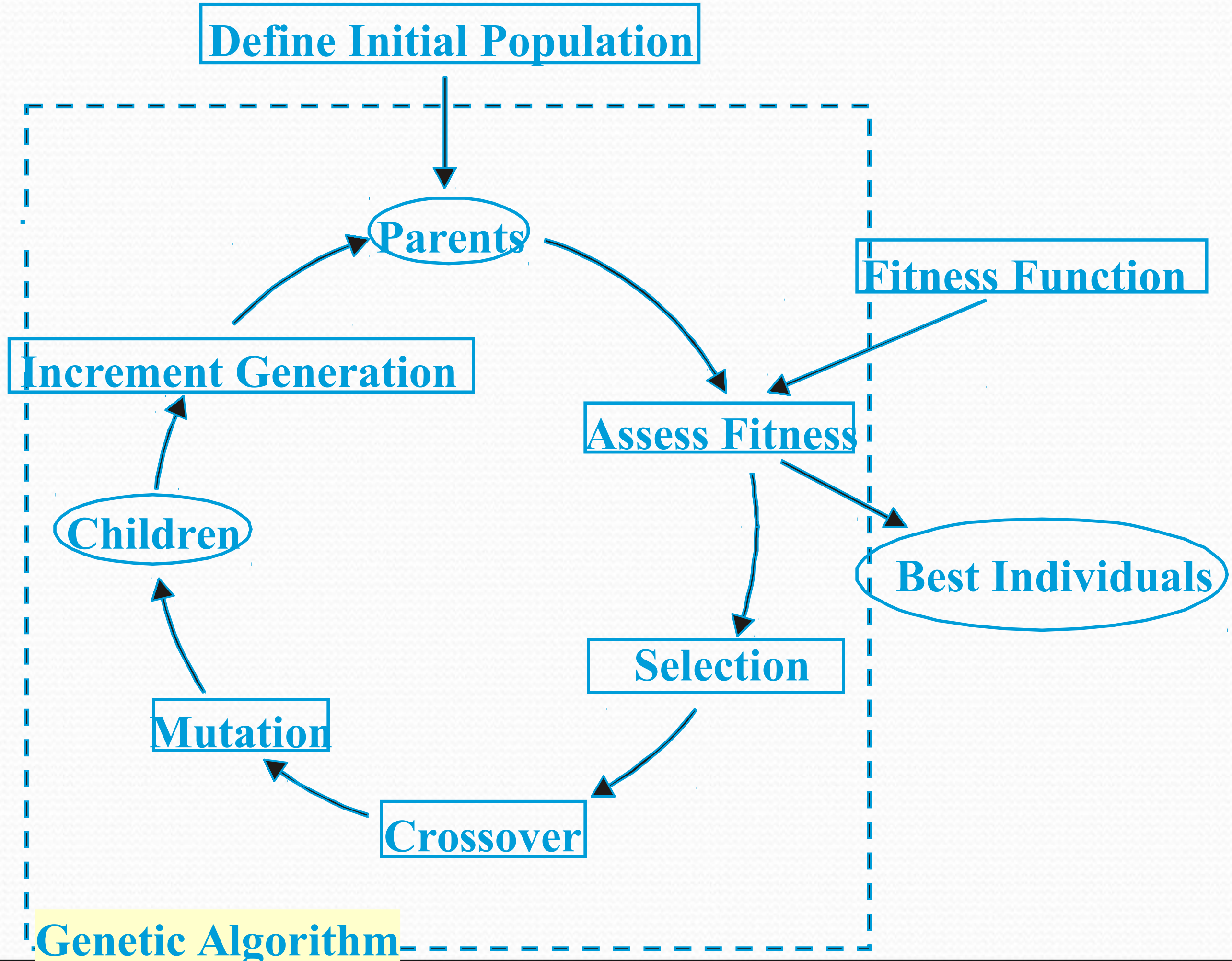
- ***Research challenges: how to interpret fuzzy rules? What are sensible strategies for calculating an output, given inputs? How to make the intuition formal?***

Planning / optimization: Evolutionary Algorithms

- **Goal of an evolutionary algorithm:**
  to find a plan that optimizes a given fitness function
  - the fitness could be defined by means of fuzzy logic, but does not have to be
- **Example:**
  the traveling salesman problem
  - **Given** a number of cities, distances between the cities
  - **Find** an order in which to visit the cities such that the total distance traveled is minimized

Evolutionary Algorithms

- **Method:** evolve populations of solutions by mimicking evolution in nature



Nature-inspired optimization

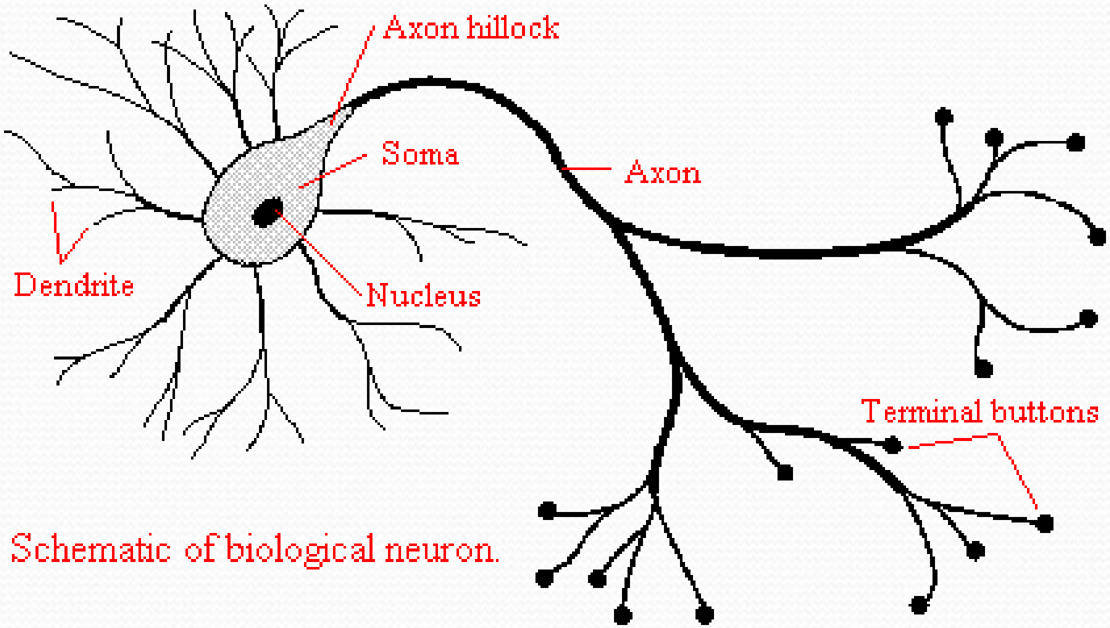
- Evolutionary algorithms
- Particle swarm optimization
- Artificial ants

All are
robust optimization algorithms:
if the fitness function changes, solutions usually adapt relatively easily

- **Research challenge: which algorithm finds a good solution as quickly as possible?**

Learning: Neural Networks

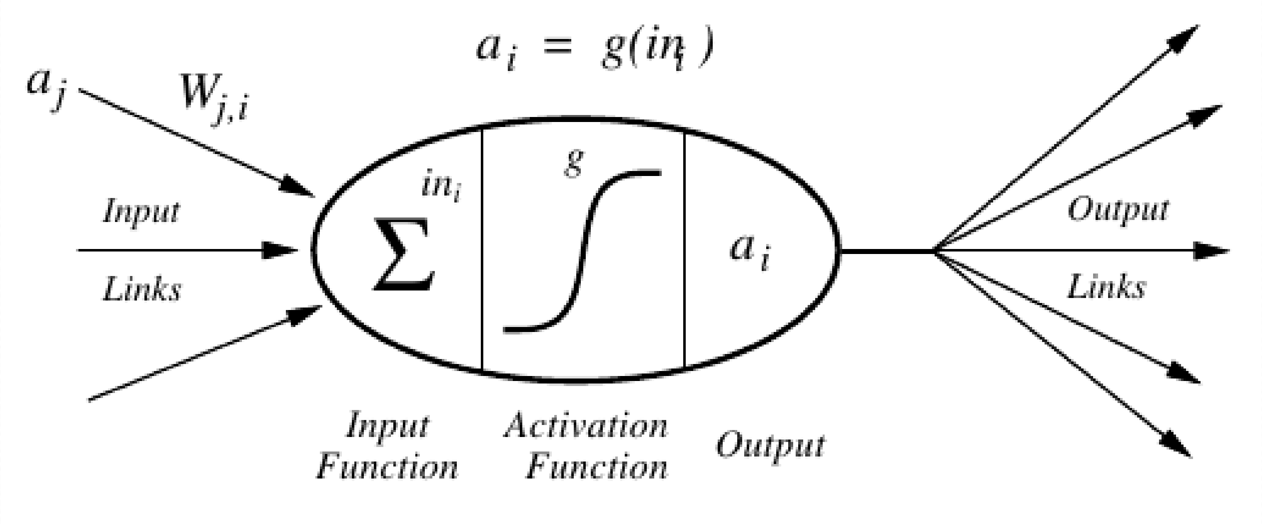
- Inspired by biological nervous systems



Schematic of biological neuron.

Learning: Neural Networks

- Artificial neuron



(Neuron/Unit)

- Also a neural network represents knowledge, and is often used used to transform input to output

Learning: Neural Networks

- Different types of neural networks:
  - feed-forward neural networks
  - self-organizing maps
  - recurrent networks
  - radial basis function networks
  - fuzzy-neural networks

Research challenge: how to learn a neural network? What is a good architecture for a neural network?

Computational Intelligence

- Knowledge representation:
  fuzzy logic & fuzzy set theory

→ You haven't followed a basic course on logic

- Reasoning, planning:
  Evolutionary (genetic) algorithms
- Learning:
  Neural networks

→ Basis already discussed in course artificial intelligence

→ - Also in course on data mining
- Advanced topics require strong mathematics

Computational Intelligence

- Knowledge representation & planning:
  traditional logic, SAT solvers, constraint programming
- Knowledge representation:
  fuzzy logic & fuzzy set theory
- Reasoning, planning:
  Evolutionary (genetic) algorithms
- ~~Learning:
  Neural networks~~

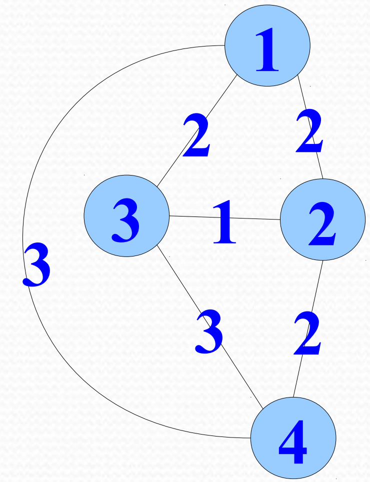
Central Theme

- Artificial intelligence inspired methods for
  - Knowledge representation:
    - Logic
    - Fuzzy logic
  - Optimization & planning:
    - SAT solving
    - Constraint programming
    - Local search
    - Evolutionary algorithms

Template of a Constraint Optimization Problem

- **Given:**
  - …
- **Find:**
  - …
- **Such that:**
  - … is **minimal/maximal**
  - … is satisfied

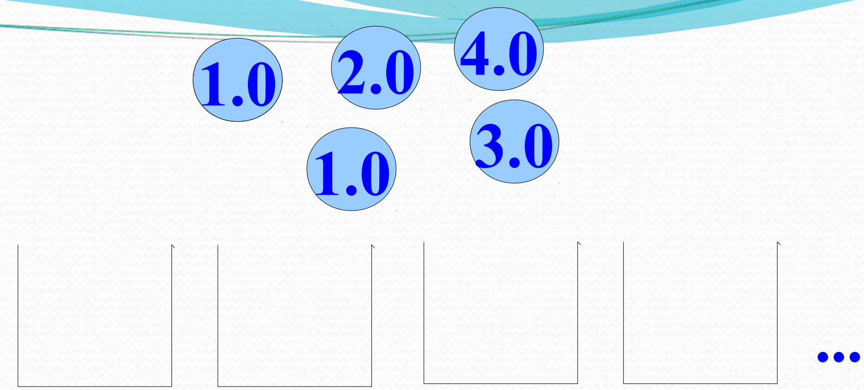
Example 1: Traveling Salesmen



- **Given:**
  - *N* cities
  - *D[i,j]* distances between cities
- **Find:**
  - an assignment *p[i]* for *i=1..N* with *p[i]* in *1..N*, indicating that at step *i* city *p[i]* is visited
- **Such that:**
  - all cities are visited exactly once
  - *D[p[1],p[2]]+D[p[2],p[3]]+…+D[p[n-1],p[n]]+D[p[n],p[1]]* is **minimal**

Optimization

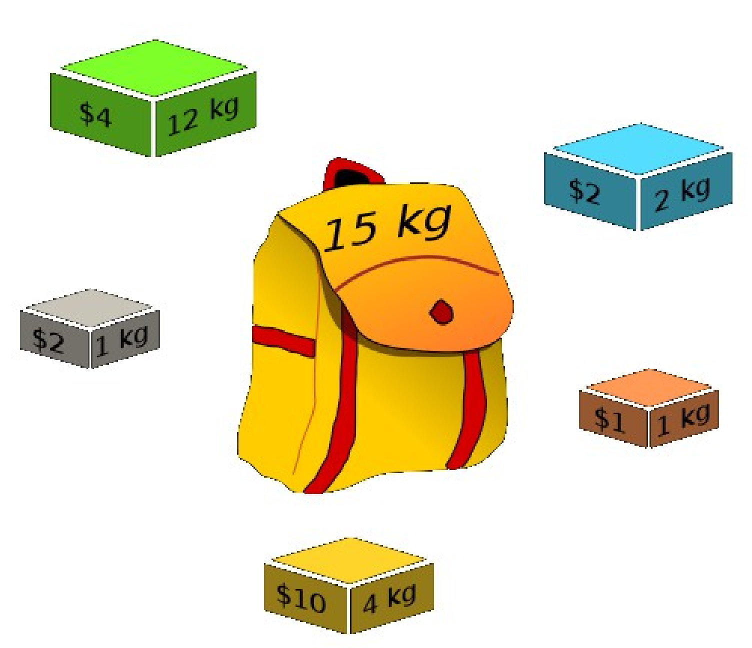
Example 2: Binpacking



Each bin: 4.0

- **Given:**
  - N items with sizes $a_1, \ldots, a_N$
  - A bin size V
- **Find:**
  - an assignment $p[i]$ for $i=1..N$ to positive integers, indicating that item i is put in bin $p[i]$
- **Such that:**
  - $\max_i p[i]$ is **minimal** (number of bins is small)
  - $\sum_{p[i]=j} a_i \leq V$ for all bins j (no more than weight V in each bin)

Example 3: Knapsack



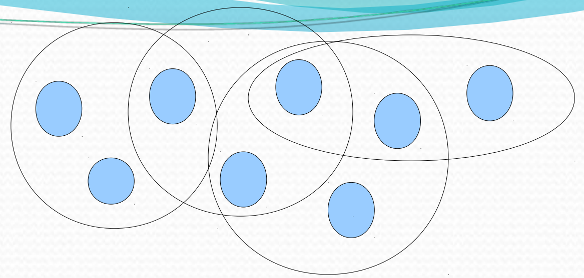
- **Given:**
  - N items with sizes $a_1,\ldots,a_N$, prices $p_1,\ldots,p_N$
  - A maximum weight W
- **Find:**
  - a subset of items I
- **Such that:**
  - $\sum_{i \in I} p_i$ is **maximal** (very valuable knapsack)
  - $\sum_{i \in I} a_i \leq W$ (knapsack with low weight)

Example 3b: Unbounded Knapsack

- **Given:**
  - N possible items with weights $a_1,\ldots,a_N$, prices $p_1,\ldots,p_N$
  - A weight threshold W
- **Find:**
  - an integer $w[i]$ for each item i
- **Such that:**
  - $\sum_{i=1}^{N} w[i]p_i$ is **maximal** (very valuable knapsack)
  - $\sum_{i=1}^{N} w[i]a_i \leq W$ (knapsack with low weight)

Portfolio Optimization

Example 4: Set Cover



- **Given:**
  - *N* sets, each a subset of the universe $U=\{1,2,\ldots,m\}$
- **Find:**
  - A subset ***S*** of the *N* given sets, i.e. each set in ***S*** equals one of the given sets, but not all given sets need to be selected.
- **Such that:**
  - $|\boldsymbol{S}|$ is **minimal** (small subset)
  - $\bigcup_{S \in \mathbf{S}} S = U$ (each element is covered)

How to solve these problems?

- Many such problems are hard
  - "NP hard" → no polynomial algorithm is known
- Two solutions:
  - Exact: require exponential time in the worst case
  - Inexact: polynomial, but may not find the best solutions
- Both types of solutions have been studied in artificial intelligence, algorithms, and operations research

High-Level, Declarative Problem Solving in AI

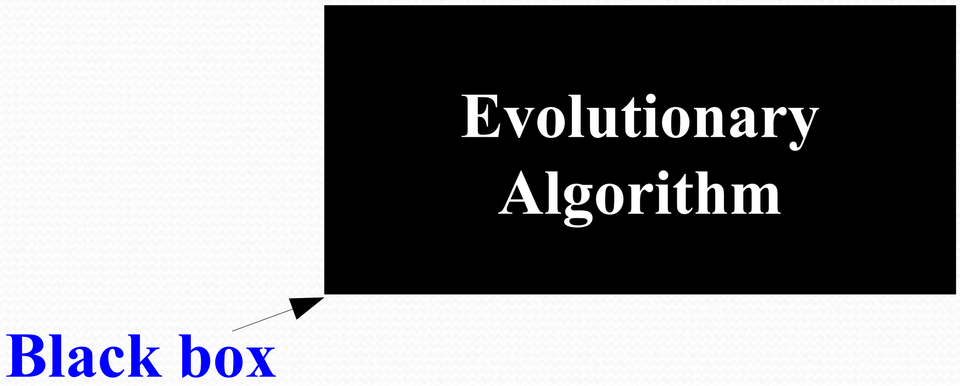
- Distinguishing feature of AI approaches: they aim to be "intelligent" and generic by solving problems (semi-)automatically

- Idea: solve a problem in two stages:
  - 1. Describe the problem in a concise way in a computer language.
  - 2. Run a general algorithm (a "solver" or an "inference engine") on this description to solve the problem.

i.e., the programmer does **not** write an imperative algorithm.

High-Level Declarative Problem Solving in AI

- Example search: evolutionary algorithm
  - Step 1:
    - Specify what the individuals in a population look like
    - Specify the quality of an individual (fitness)
  - Step 2: (Ideal situation)
    - Run an existing evolutionary algorithm without modification

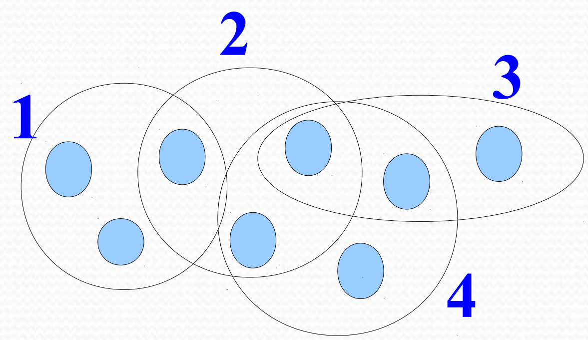


High-Level Declarative Problem Solving in AI

- Example problem: set cover
- Representation of an individual in a bitstring:

0	1	1	0

2nd and 3rd set are selected



- Fitness: (assuming small=very fit)
  - Number of sets selected?
  - Number of sets selected +
    (number of uncovered elements) x *w*

Very large weight

High-Level Declarative Problem Solving in AI

- What about optimal solutions?

- Alternative *general* systems that take a *declarative* input specification and find optimal solutions:

  - Constraint programming

  - SAT solvers

  - ILP solver

High-Level Declarative Problem Solving in AI

- Which programming language to use?
  - C++ ?
  - Java ?
  - Prolog ?
  - Python

Why Python?

- Scripting language with a high level of abstraction
  - Implements features also seen in functional and logic programming
- Well-supported language with many libraries available
- Quickly gaining popularity in the scientific community (Coursera)

Why Python?

	2011	2012		2011	2012
R	45.1%	52.5%	Unix shell	10.4%	14.7%
Python	24.6%	36.1%	C/C++	12.8%	14.3%
SQL	32.3%	32.1%	MATLAB	14.6%	13.1%
Java	24.4%	24.1%	Perl	7.9%	9.0%
SAS	21.2%	19.7%	Hadoop-based	6.1%	6.7%

www.kdnuggets.com

Computational Intelligence

- Basic course in Python
- Knowledge representation & planning:
  traditional logic, SAT solvers, constraint programming
- Knowledge representation:
  fuzzy logic & fuzzy set theory
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- Learning:
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Course overview

- 13 lectures
- Lectures & practicums will often be combined

week	Date	Monday								Tuesday								Wednesday								Thursday								Friday							
nr	Mo	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
36	1 Sep			HCI		opening Ac. Year																						HCI										Inaug. Stud. ver.			
37	8 Sep					DaMi									CI/pr CI							CI		pr CI				HCI													
38	15 Sep			HCI		DaMi									CI/pr CI													HCI													
39	22 Sep			HCI		DaMi									CI/pr CI							CI		pr CI				HCI													
40	29 Sep			HCI		DaMi									CI/pr CI							CI		pr CI				HCI						Relief of Leiden							
41	6 Oct			HCI		DaMi																						HCI													
42	13 Oct			HCI		DaMi									CI/pr CI							CI		pr CI				HCI													
43	20 Oct			HCI		DaMi									CI/pr CI							CI		pr CI				HCI													
44	27 Oct			HCI		DaMi				Fin pr		Fin								Fin			CI/pr CI					HCI								Fin					
45	3 Nov			HCI		DaMi			t Fin	Fin pr		Fin								Fin			CI/pr CI					HCI								Fin					
46	10 Nov			HCI		DaMi			t Fin	Fin pr		Fin								Fin			CI/pr CI					HCI								Fin					
47	17 Nov			HCI		DaMi			t Fin	Fin pr		Fin			Bach					Fin								HCI								Fin					
48	24 Nov			HCI		DaMi			t Fin	Fin pr		Fin								Fin			Cleveringa					HCI								Fin					
49	1 Dec			HCI		DaMi			t Fin	Fin pr		Fin			Bach					Fin								HCI								Fin					
50	8 Dec			HCI		DaMi			t Fin	Fin pr		Fin			Bach					Fin																Fin					
51	15 Dec																	T Fin																							
52	22 Dec					T HCI																																			
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3	12 Jan																					Bach																			
4	19 Jan																																								
5	26 Jan																					Bach																			

- Final mark obtained 70% from a written exam and 30% from practicum assignments