COMPUTATIONAL INTELLIGENCE

September 2012 – November 2012

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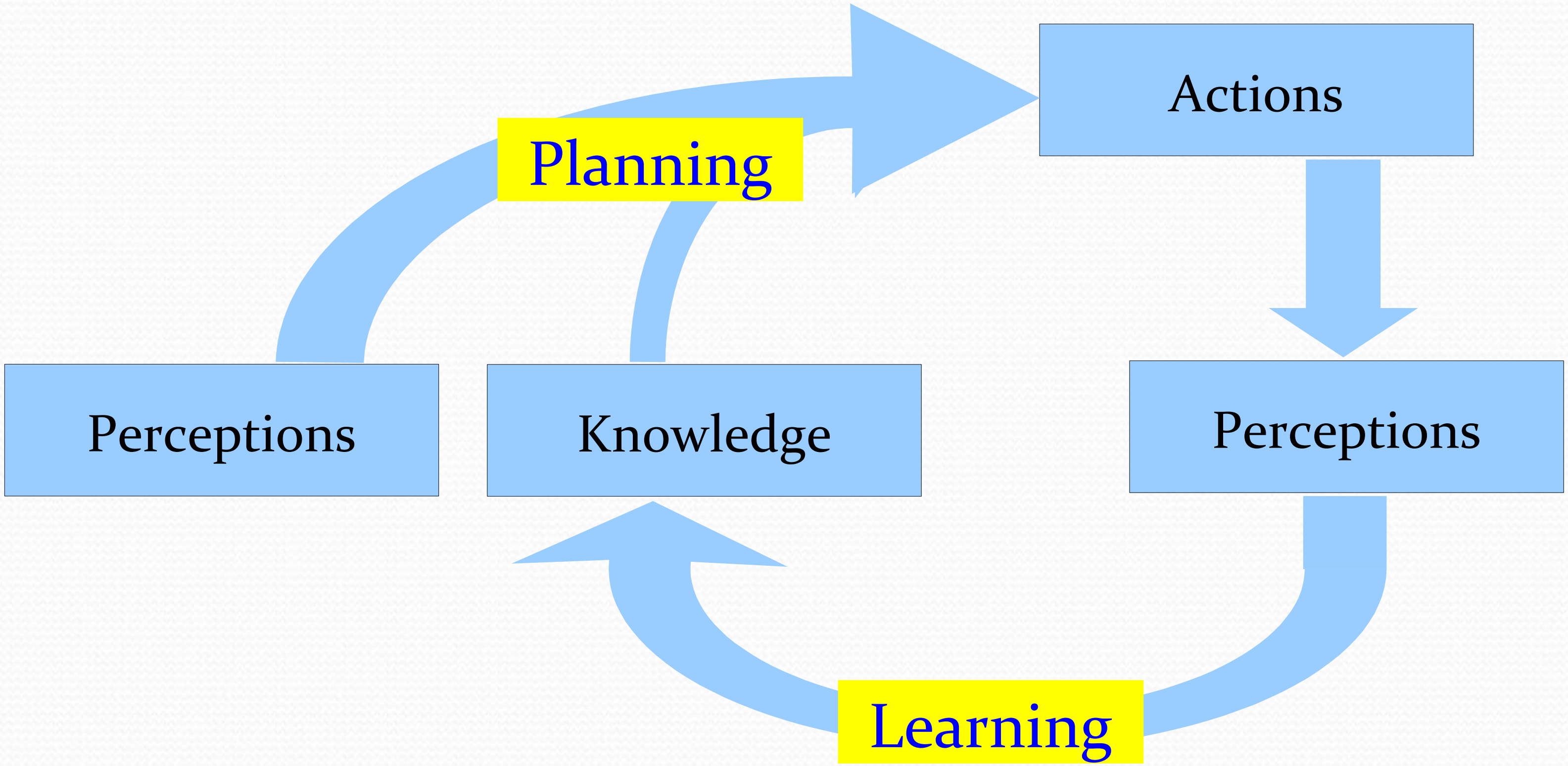
Artificial Intelligence

- 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?
  - 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 likely* then *outcome* is *likely good*
if *B is likely* then *outcome* is *likely good*
if *C is likely* and *B is not likely* then outcome is *likely good*

how good would the situation be in which *A* and *C* are true, and *B* is false?

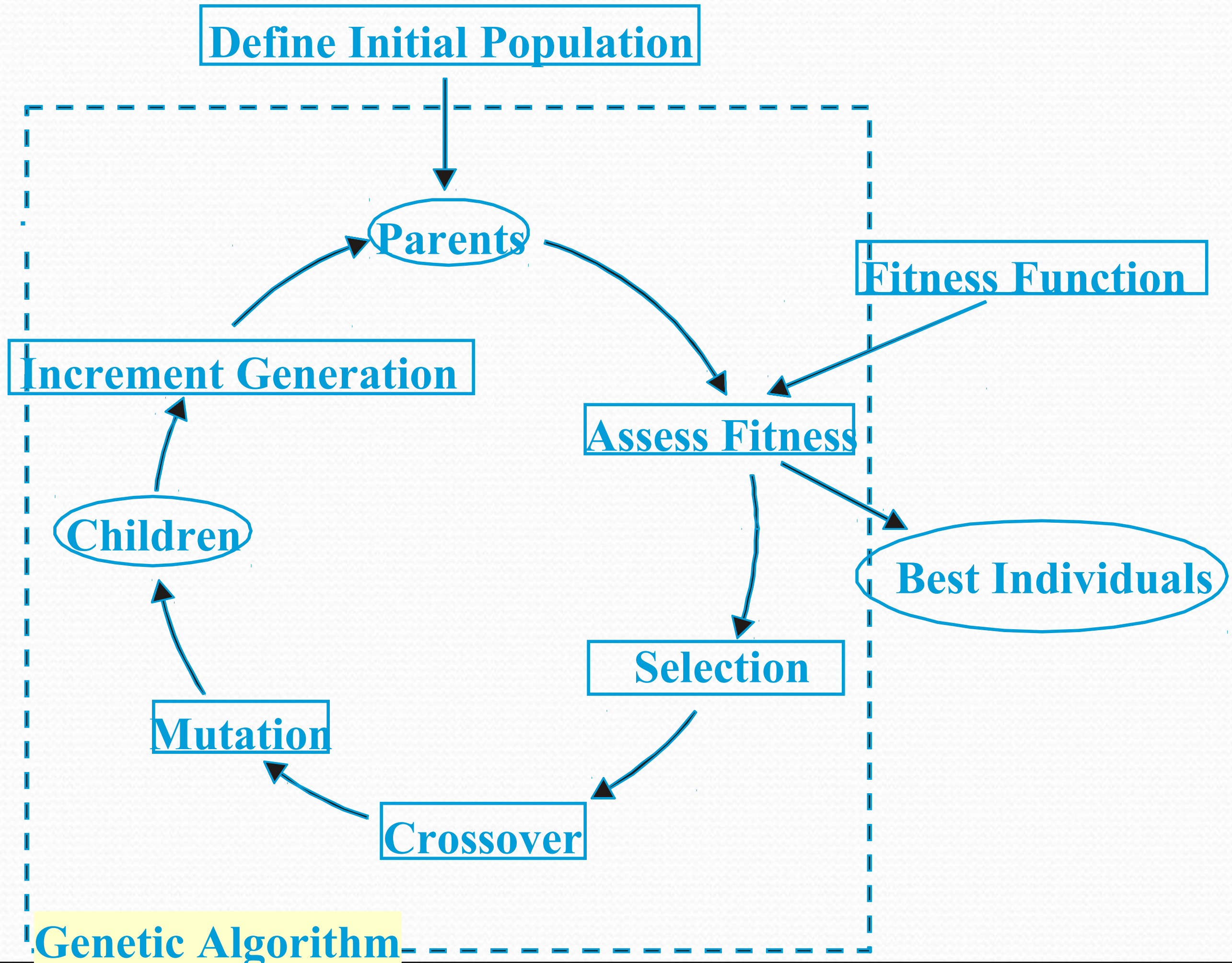
- ***Research challenges: how to interpret fuzzy rules? What are sensible strategies for calculating an output, given inputs?***

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

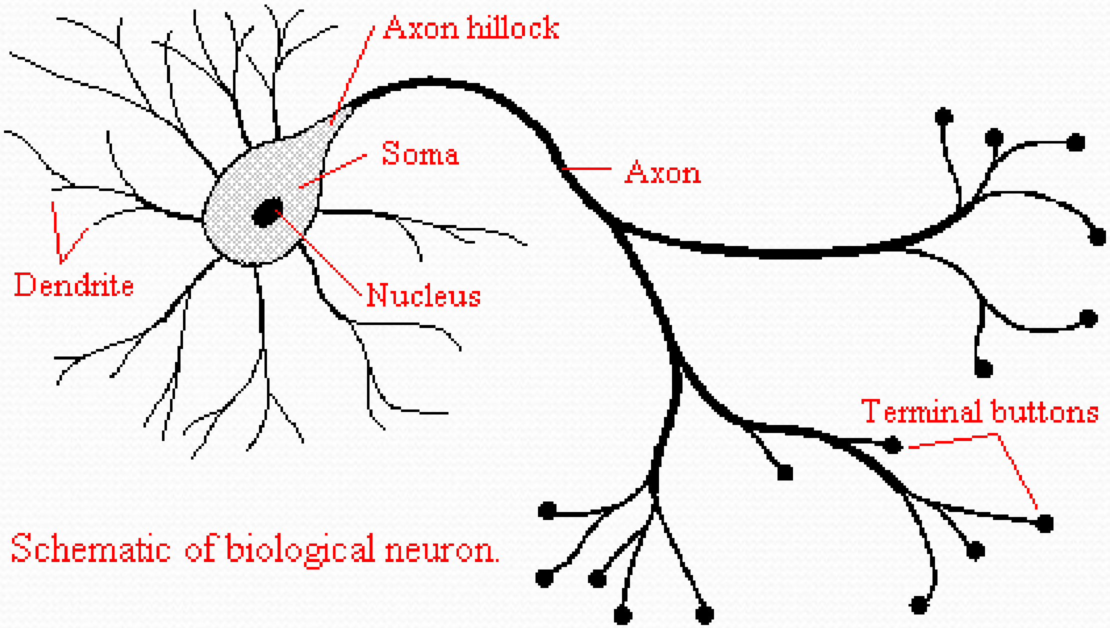
- Evolutionary algorithms
- Particle swarm optimization
- Artificial ants

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

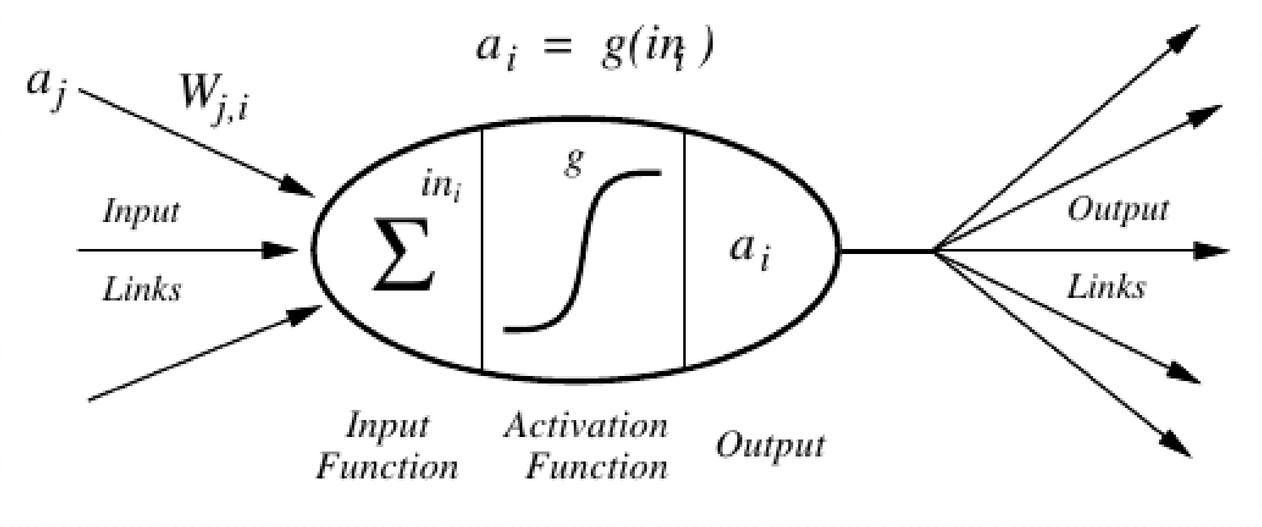
- Inspired by biological nervous systems



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?

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~~

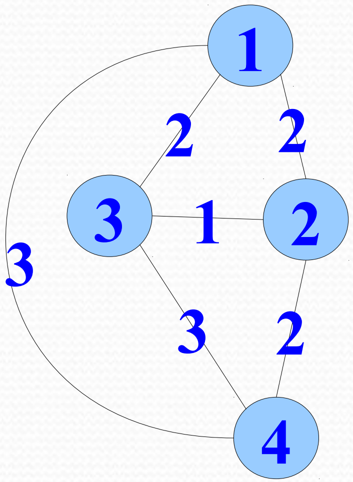
Central Theme

- 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

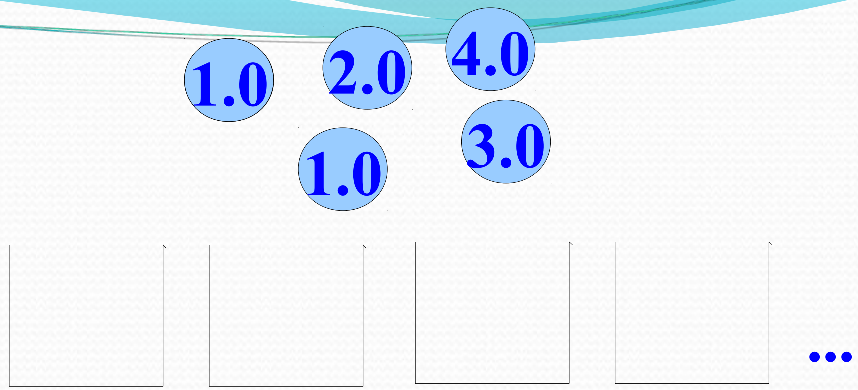
Example 1: Traveling Salesmen



- **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:**
  - *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

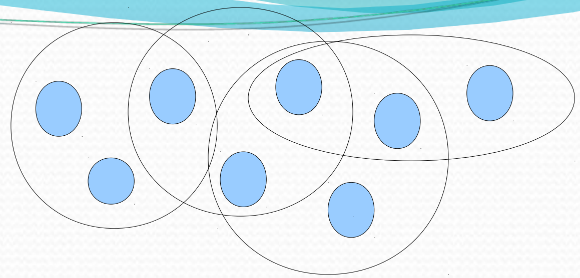
- **Given:**
  - N items with sizes $a_1,\ldots,a_N$, prices $p_1,\ldots,p_N$
  - A maximum weight W
- **Find:**
  - a subset of items I
- **Such that:**
  - $\sum_{i \in I} p_i$ is **maximal** (very valuable knapsack)
  - $\sum_{i \in I} a_i \leq W$ (knapsack with low weight)

Example 3b: Unbounded Knapsack

- **Given:**
  - N possible items with sizes $a_1,\ldots,a_N$, prices $p_1,\ldots,p_N$
  - A weight 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 $\boldsymbol{S}$ of the N given sets, i.e. each set in $\boldsymbol{S}$ 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

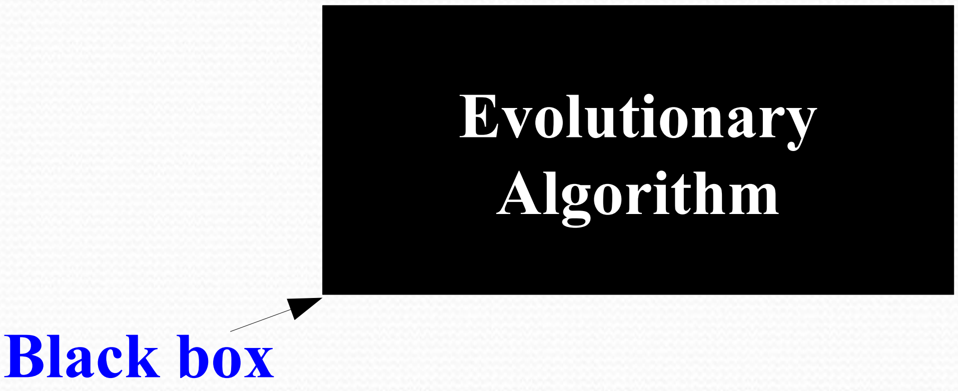
- Distinguishing feature of AI approaches: they aim to be "intelligent" by solving a problem (semi-)automatically

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

i.e., one does **not** write an 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

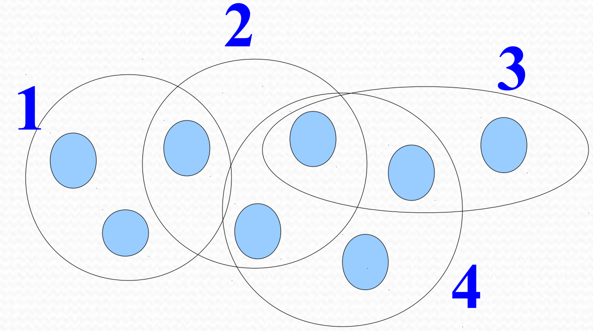


High-Level Declarative Problem Solving in AI

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

0	1	1	0

2^{nd} and 3^{rd} 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

- Reasoning, planning:
  Evolutionary (genetic) algorithms

- ~~Learning:~~
  ~~Neural networks~~

Course overview

- 12 lectures of 2 hours
- 8 practicum sessions → working on exercises

week	Datum	Maandag								Dinsdag								Woensdag								Donderdag								Vrijdag							
nr	Ma	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	3 sep					Opening ac. jaar					CI										CI		pr CI					HCI										Stud ver			
37	10 sep			HCI		DaMi					CI										CI		pr CI					HCI													
38	17 sep			HCI		DaMi					CI										CI		pr CI					HCI													
39	24 sep			HCI		DaMi																						HCI													
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41	8 okt			HCI		DaMi															CI		pr CI					HCI													
42	15 okt			HCI		DaMi															CI		pr CI					HCI													
43	22 okt			HCI		DaMi															CI		pr CI					HCI													
44	29 okt			HCI		DaMi				pr Fin		Fin								Fin			CI					HCI								Fin					
45	5 nov			HCI		DaMi			t Fin	pr Fin		Fin								Fin			pr CI					HCI								Fin					
46	12 nov			HCI		DaMi			t Fin	pr Fin		Fin								Fin			CI					HCI								Fin					
47	19 nov			HCI		DaMi			t Fin	pr Fin		Fin								Fin			pr CI					HCI				Bach				Fin					
48	26 nov			HCI		DaMi			t Fin	pr Fin		Fin								Fin			CI					HCI				Bach				Fin					
49	3 dec			HCI		DaMi			t Fin	pr Fin		Fin								Fin								HCI				Bach				Fin					
50	10 dec			HCI		DaMi			t Fin	pr Fin		Fin								Fin																Fin					
51	17 dec																					T Fin																			

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