Artificial Intelligence 2, Lecture 1, 20101109

Course introduction and motivation

Biological basis of evolutionary algorithms

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What will you learn? (Aims)

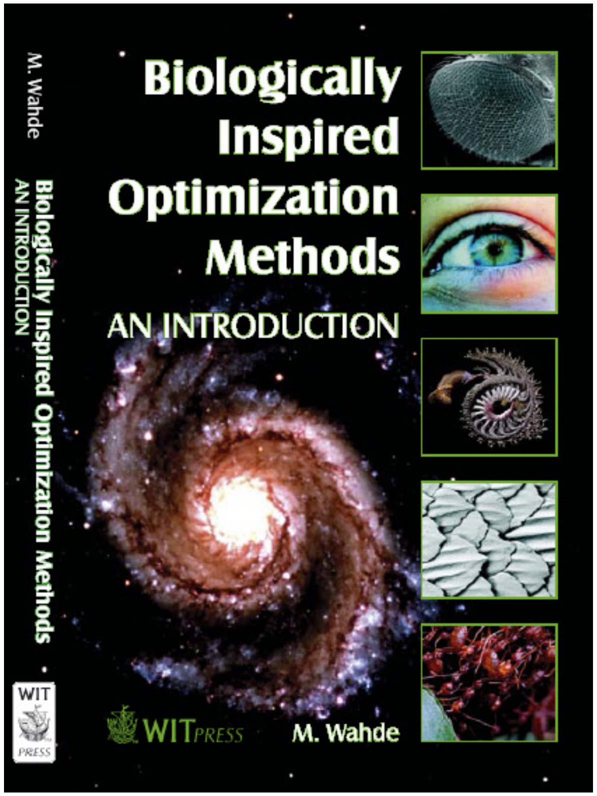
- A brief review of classical optimization methods.
- The basics of several *stochastic optimization methods* (evolutionary algorithms, particle swarm optimization, ant colony optimization).
- The basic biology and physics behind the methods.
- How to *implement* and *apply* the methods, both in simple, straightforward cases and in more complex problems.
- How to select which method to use for a given problem.

Why should you take this course?

- Stochastic optimization algorithms can be used for solving many problems where classical methods are insufficient.
- Stochastic optimization methods are used more and more frequently in industry, particularly in large problems.
- The number of application areas is steadily increasing.
- (Most important!) It is interesting and fun to work with stochastic optimization! ☺

...about the book:

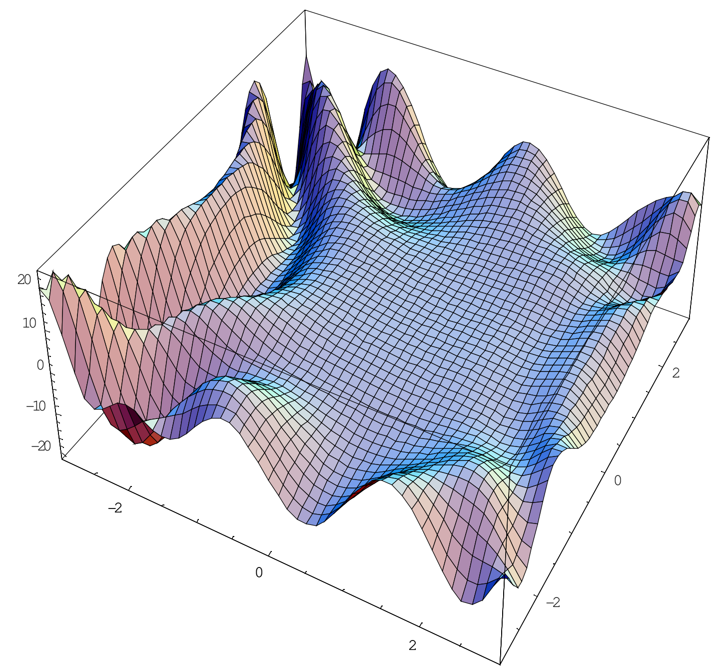
- Available at Chalmers' bookstore (Cremona)
- Unfortunately, it's a bit expensive...
- ..I have negotiated with the publisher to minimize the price that you will have to pay (meaning that I get no income at all from the books sold at Cremona, if that's any comfort.. ☺)
- You may wish to buy the book online.
- Note, however, that Cremona sells the book at a reduced price.



Optimization

- In general, optimization is the problem of finding the (global) minimum (or maximum) of an *objective function*.

- Sometimes (but not always!) the objective function is a specific, well-defined mathematical function, $f = f(x_1,x_2,...)$.



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Optimization methods

- Optimization methods can be divided into two broad categories: *classical (deterministic) optimization methods* and *stochastic optimization methods*.
- Classical optimization methods include, for example, gradient descent (following the steepest slope), Newton's method, penalty methods, lagrange multiplier methods etc.

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Limitations of classical optimization

- Classical methods are less useful in cases with
  - non-differentiable objective functions
  - objective functions whose values can only be obtained as a result of a (lengthy) simulation
  - varying number of variables (as in optimization of neural networks).

- For such problems, *stochastic optimization methods* are more suitable. This course mainly concerns such methods.

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Stochastic optimization methods

- As the name implies, stochastic optimization methods contain an element of stochasticity (randomness).

- Many (but not all) stochastic optimization methods are inspired by biological phenomena.

- Thus, an important subset of stochastic optimization methods are *biologically inspired optimization methods*.

Biologically inspired optimization

- Why would one use inspiration from biological phenomena when defining an optimization method?

- ...Nature is all about *adaptation*, which can be seen as a kind of optimization.

- However, note that, in nature, the target is constantly moving – unlike the case in engineering problems, evolutionary adaptation takes place in a varying fitness landscape (more about this later).

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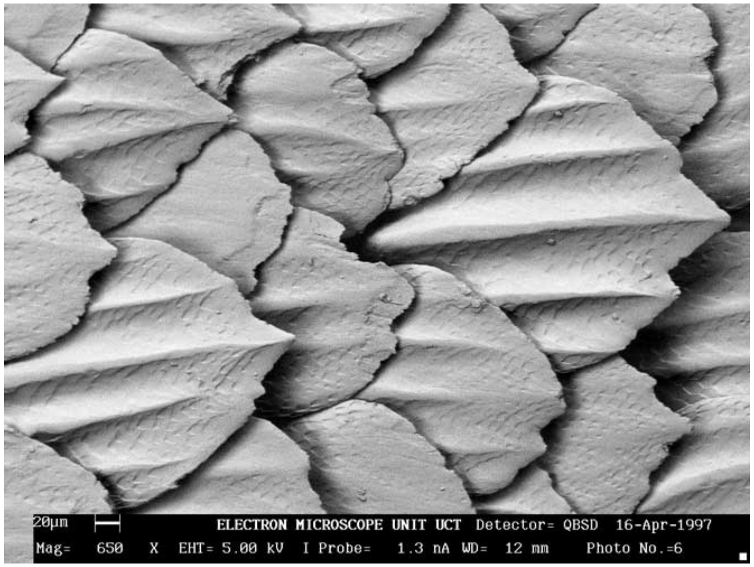
Example 1: Shark skin

- A good example of adaptation (biological optimization).
- The skin of sharks has evolved to allow very fast swimming.



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Example 1: Shark skin

- The rib-like structures affect the interaction between the surface of the shark and the surrounding water, essentially reducing drag.
- Prime example of biological inspiration for engineering concepts: Similar ideas are being applied in order to reduce drag (and noise) of aircraft and other vehicles.
- Shark skin has also inspired the development of the fabric used in swimsuits worn by athletes.

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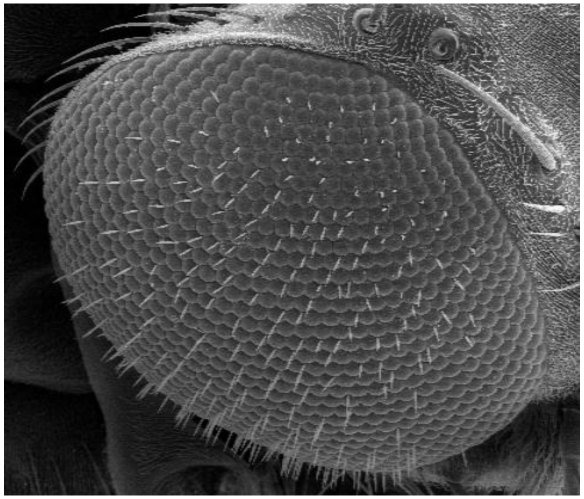
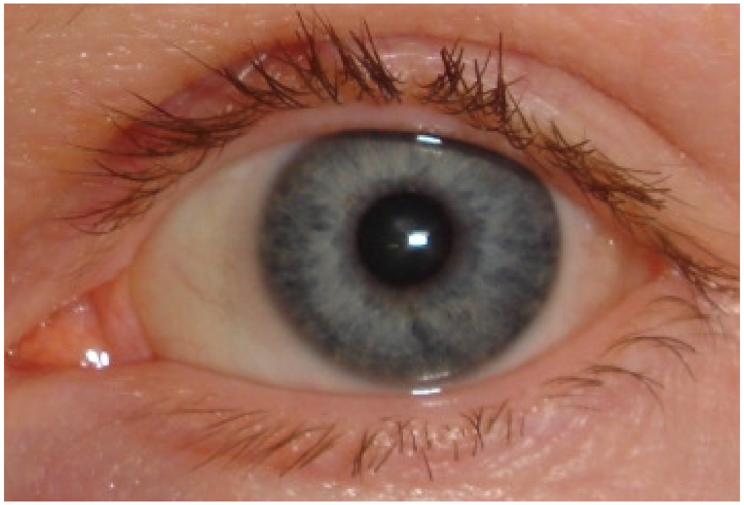
Example 2: Evolution of the eye

- The evolution of eyes is another intersting example.
- Faced with the problem of generating light-gathering devices, evolution has come up with no less than 40 *completely independent* solutions to the problem.





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Example 3: Swarming

- Some species (particularly ants, bees and termites) display very advanced forms of cooperation.
- Specific example: Weaver ants (Oecophylla)

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Example 3: Swarming

- Many organisms (e.g. some bird and fish species) display swarming behavior (for protection against predators, efficient food gathering etc.)

Biologically inspired optimization

- Several different optimization methods have been developed, based on biological phenomena:
  - Evolutionary algorithms (inspired by evolution)
  - Ant colony optimization (inspired by cooperative behavior)
  - Particle swarm optimization (inspired by swarming)

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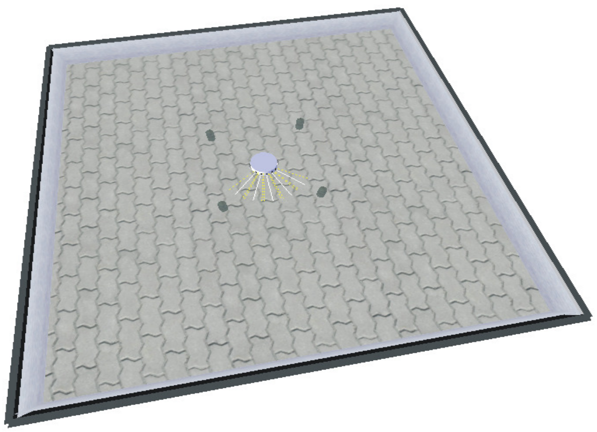
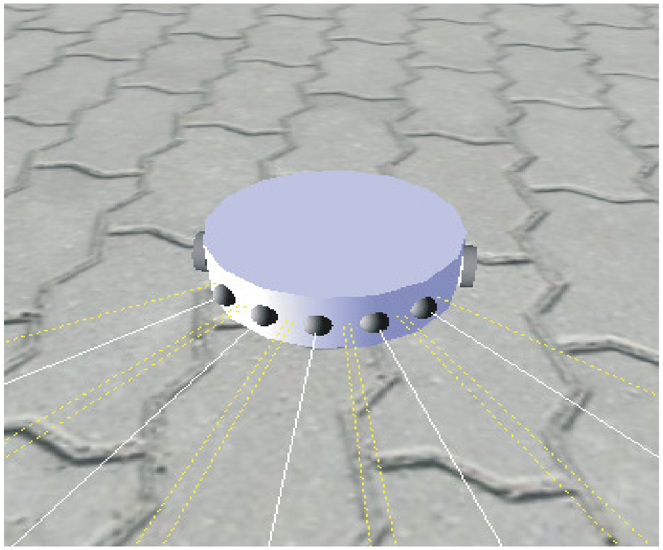
Simple example: robot behavior

- Stochastic optimization methods can be used for the optimization of robot behaviors.
- Simple example: Evolution of a cleaning behavior:





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Simple example: robot behavior

- The robot is required to move the small objects out to the edge of the arena.
- The brain of the robot consists of a sequence of *IF-THEN-ELSE rules*, using sensory readings as inputs.
- Only the final situation (at the end of an evaluation) is used as feedback to the optimization algorithm: (an evolutionary algorithm).

$$F = \sum_{j=1}^{n_o} \left(x_j^2(T) + y_j^2(T) \right),$$

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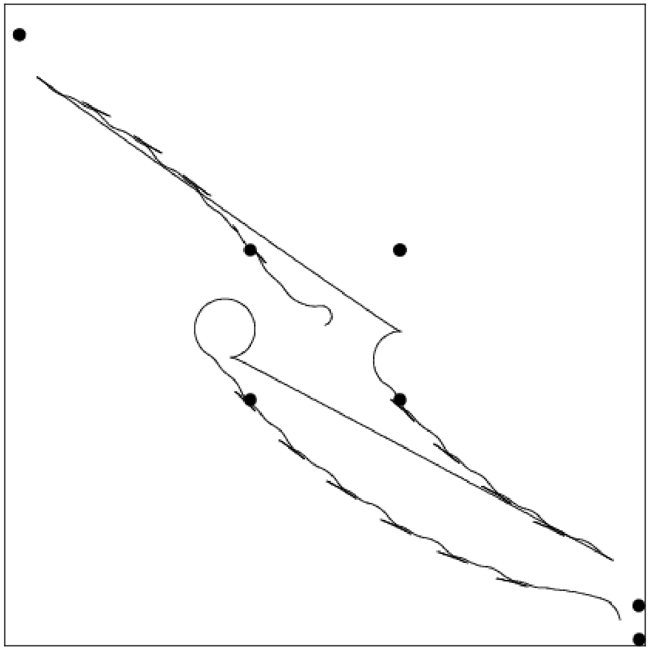
Simple example: robot behavior

- The population of robots gradually evolves the capability to clean the arena, passing through several stages along the way.



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Brief introduction to EAs

- Evolutionary algorithms = EAs.
- Based on darwinian evolution, which is a process involving *gradual*, *hereditary* changes of biological organisms, over long periods of time.
- Basic biological concepts: **Population**, **fitness**, **selection**, **mutation**.
- Individuals that are well adapted to their environment have a high probability of generating offspring.

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Brief introduction to EAs

- Random changes to the *genotype*, (mutations) sometimes leading to large changes of the *phenotype.*
- Mutations provide new material for evolution to work with.
- Note that, while mutations are random, *selection* is not.

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Basic mode of operation of EAs

- In an EA, a **population** of candidate solutions (to the problem at hand) is formed (random initialization)
- Each **individual** in the population is evaluated and assigned a **fitness score** based on its performance.
- New individuals are formed through the processes of **selection**, **crossover**, and **mutation**.
- The new individuals form the second **generation**, which is evaluated in the same way as the first generation etc.
- The process is repeated until a satisfactory solution has been found to the problem at hand.

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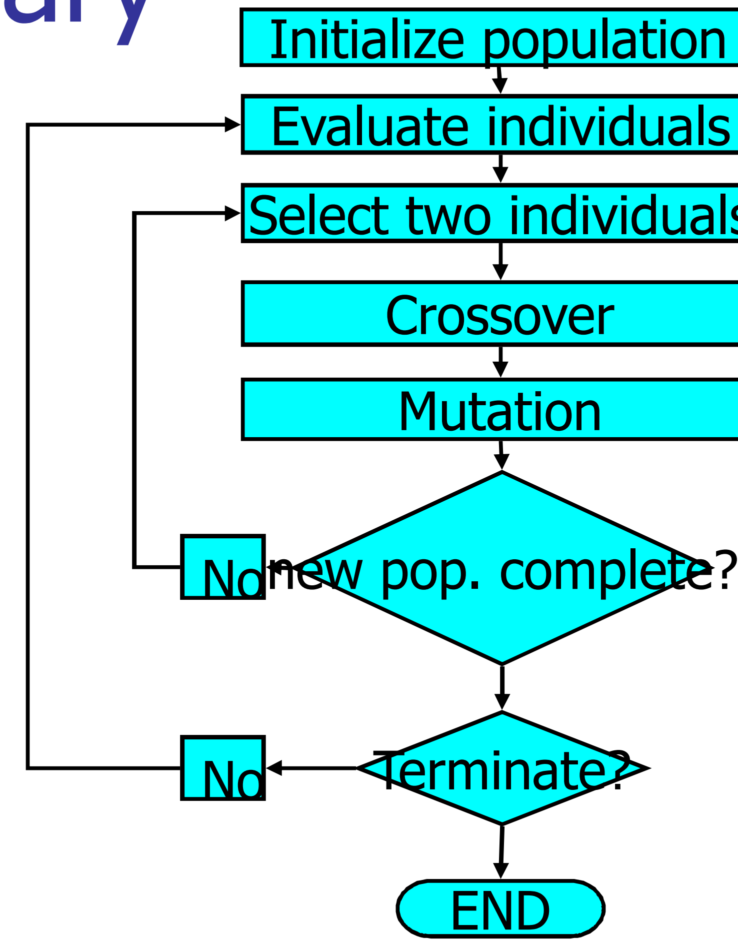
Summary



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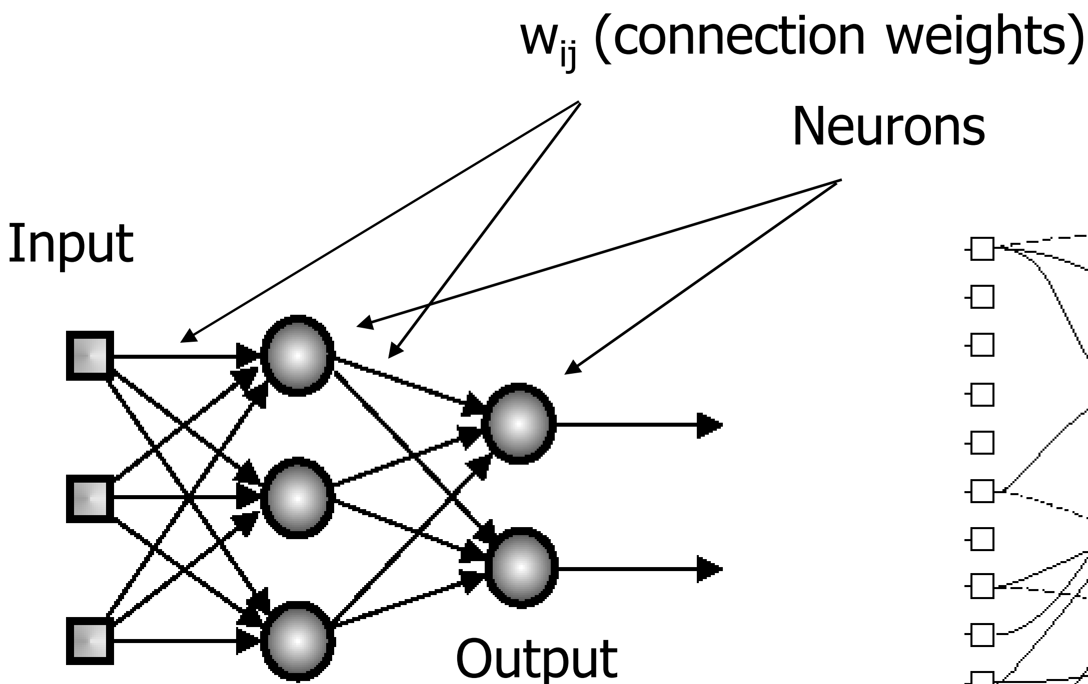
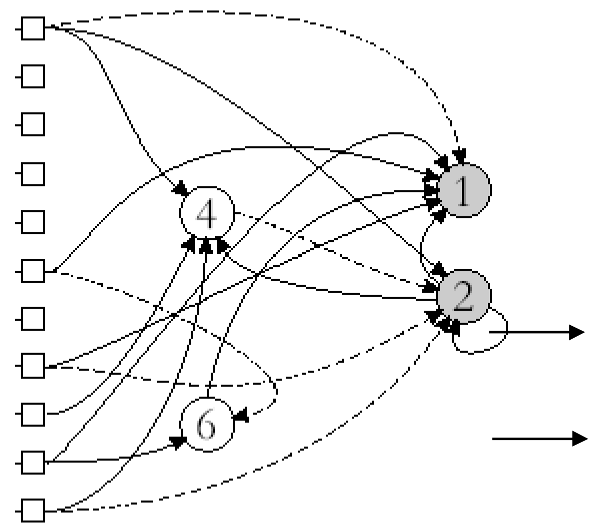
Brief introduction to artificial neural networks (ANNs)

- Based on the properties of the brain.
- Consist of a large number of simple computational elements (neurons) that are connected and together can perform complex calculations.
- The human brain consists of around 10^{11} neurons, and 10^{15} connections between the neurons.
- In ANNs, the computation is determined by the architecture of the network as well as the values of the connection weights connecting different neurons to each other.

Typical ANNs:



Feedforward neural network (FFNN)



Recurrent neural network (RNN)

The computation in an ANN is integrated with its structure.

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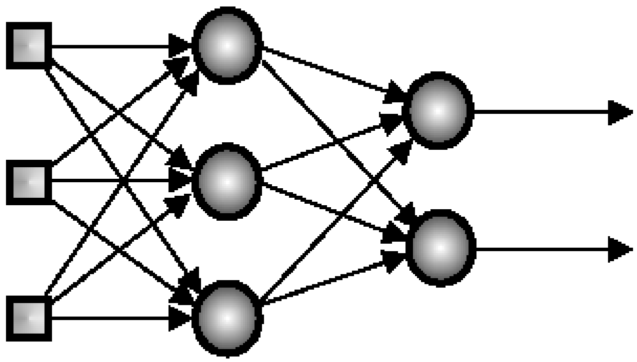
Training ANNs



- Information is stored in the connection weights.
- The procedure of setting the weights in an ANN is referred to as **training**.
- Several methods for training exist, e.g. the **delta rule** (for one-layer networks), **backpropagation** (for multi-layer networks) and **EAs** (for any type of network).

Properties of neural networks

- **Graceful degradation**: Some neurons can be removed without significant alteration of the (distributed) computation performed by the network.

- **Generalization**: A network trained on a given data set is often able to generalize, in the sense that it can provide adequate output for new (previously unseen) input data.

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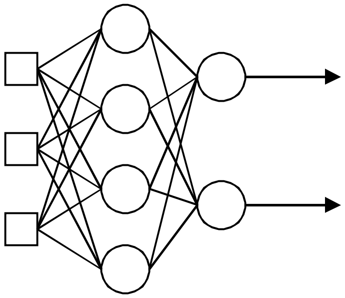
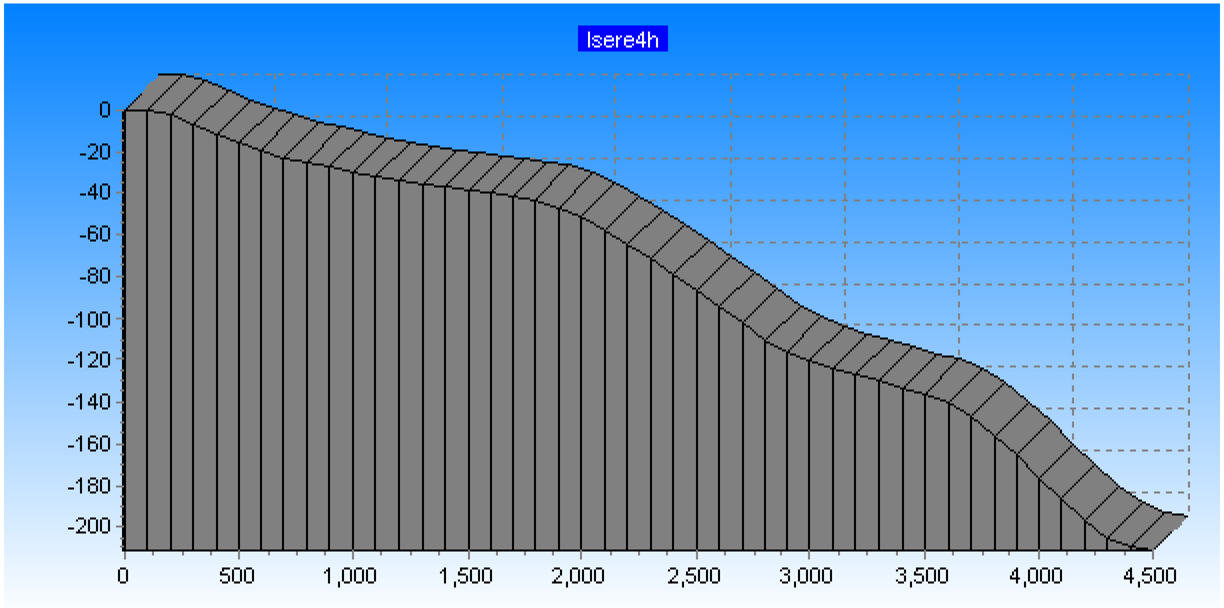
Application example 1

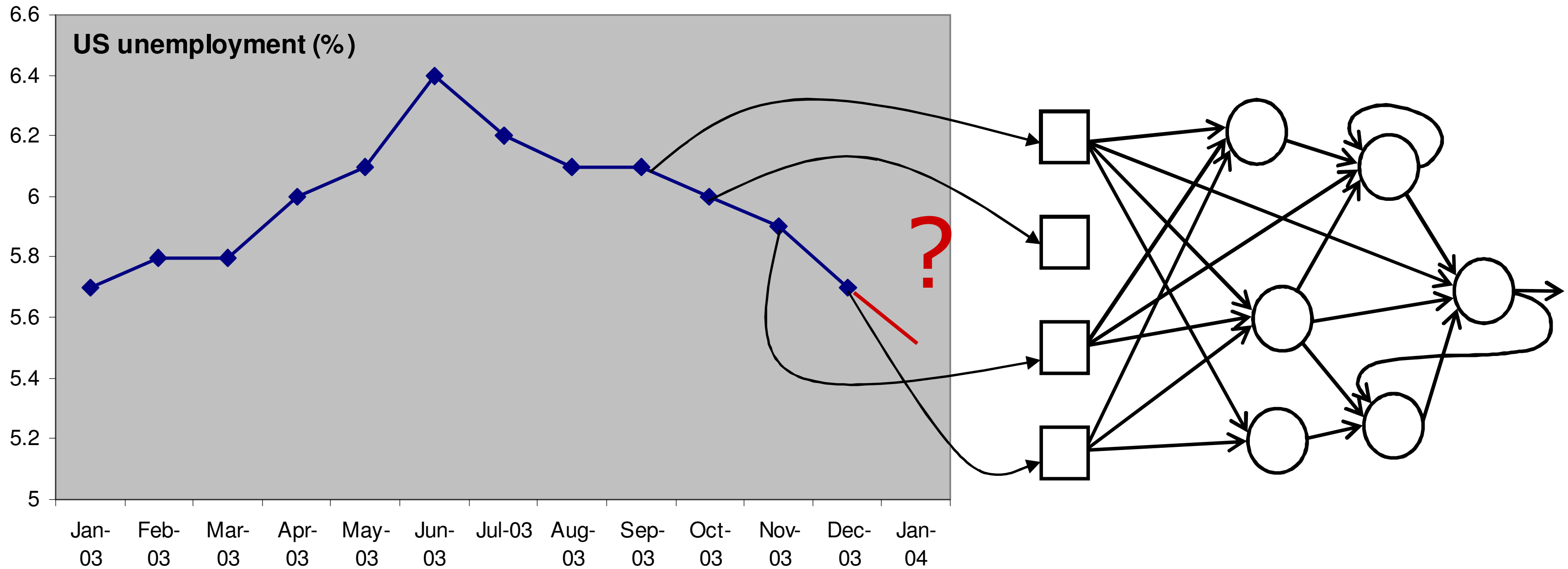
- **Optimization of braking systems in trucks** (using EAs and ANNs)





Application example 2

- **Prediction of time series:** The task is to make a prediction of the next value in a data set. Typical applications: finance, macroeconomics, meteorology etc.



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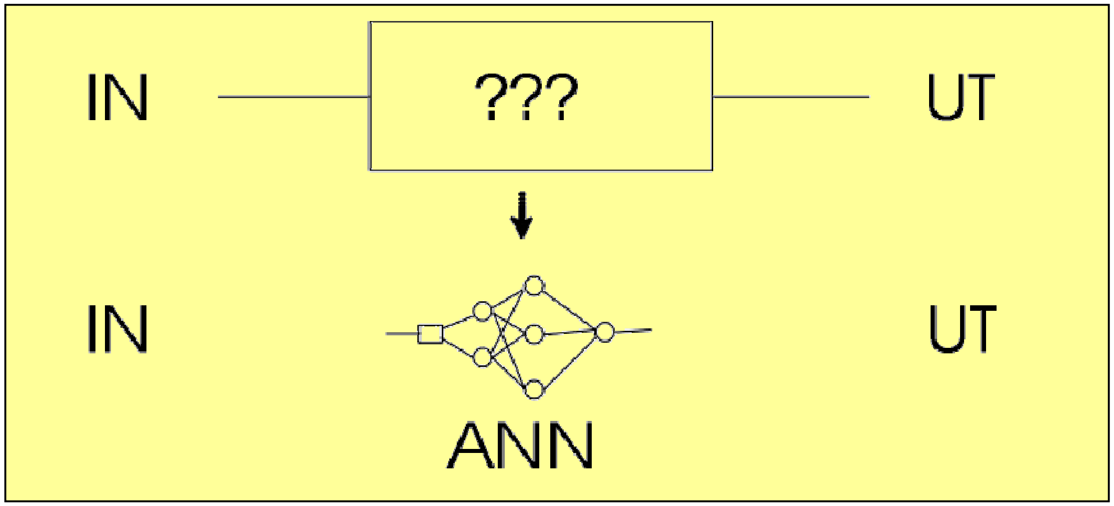
Application example 3

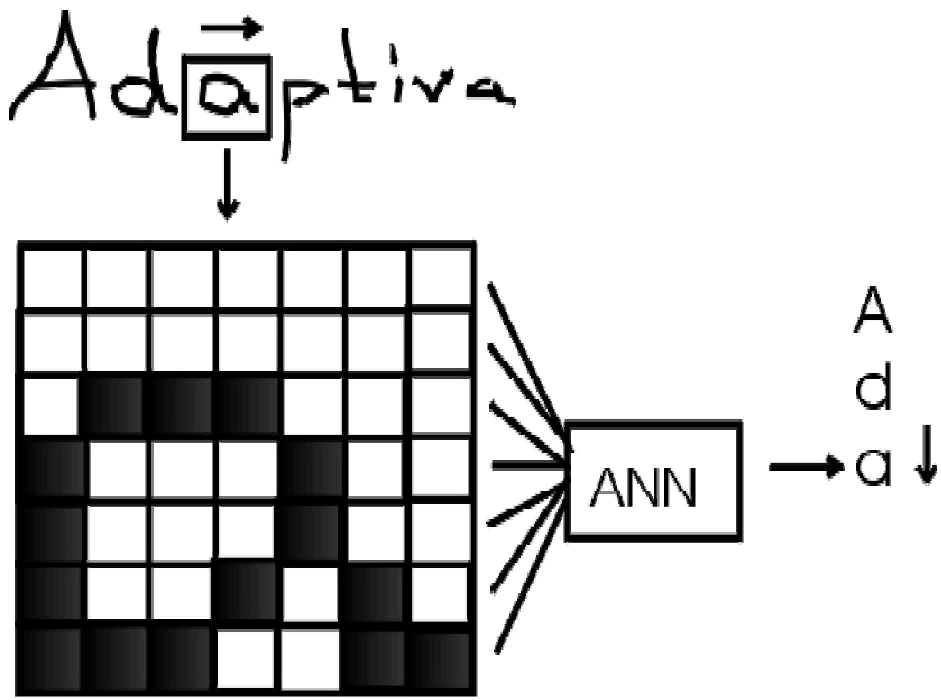
- **System identification** (model-free) of e.g. mechanical systems



- ANNs are often used in cases where it is difficult to find an analytical model.

Application example 4

- Image recognition



Brief introduction to ACO

- Ant colony optimization = ACO.
- Ants are capable of remarkably efficient discovery of short paths during foraging. How do they achieve this?
- Note that ants (1) are (almost) blind, (2) have no explicit leaders
- Method: Ants deposit a trail of (volatile) *pheromones* (a chemical substance) as they move. When choosing a path, ants tend to move in the direction of highest pheromone concentration.

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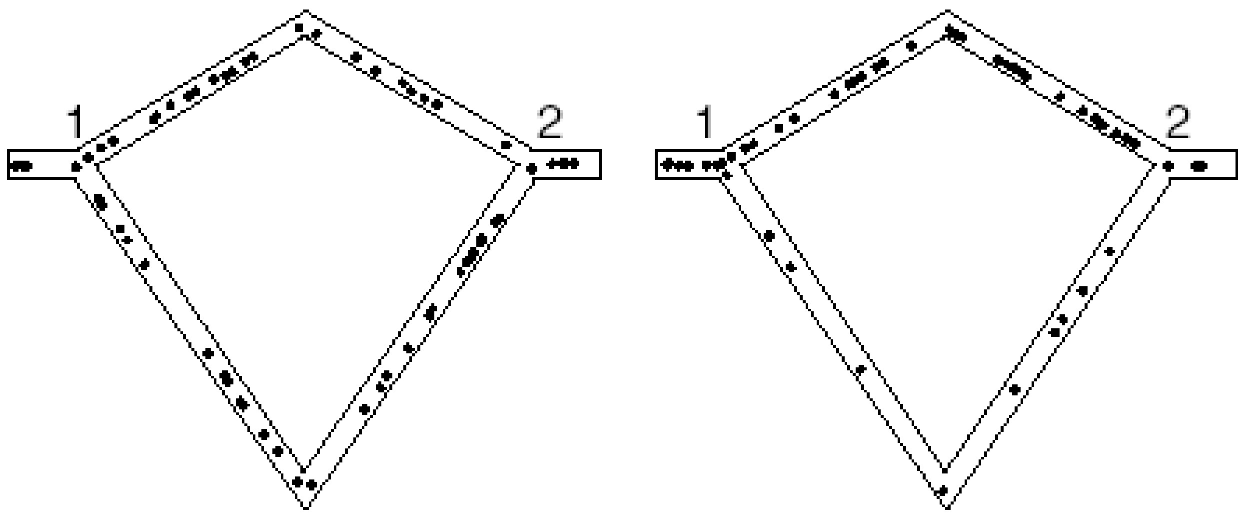
Experiment

- By laying artificial pheromones, the ants soon discover the shortest path:



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Brief introduction to ACO

- The behavior of the ants is an *emergent property* of the ant colony as a whole.
- In ACO, the same principles are used: Artificial ants deposit artificial pheromones, while attempting to find the shortest path in a graph.
- Many problems can be mapped to the problem of finding short paths. The most straightforward example is the travelling salesman problem (TSP).

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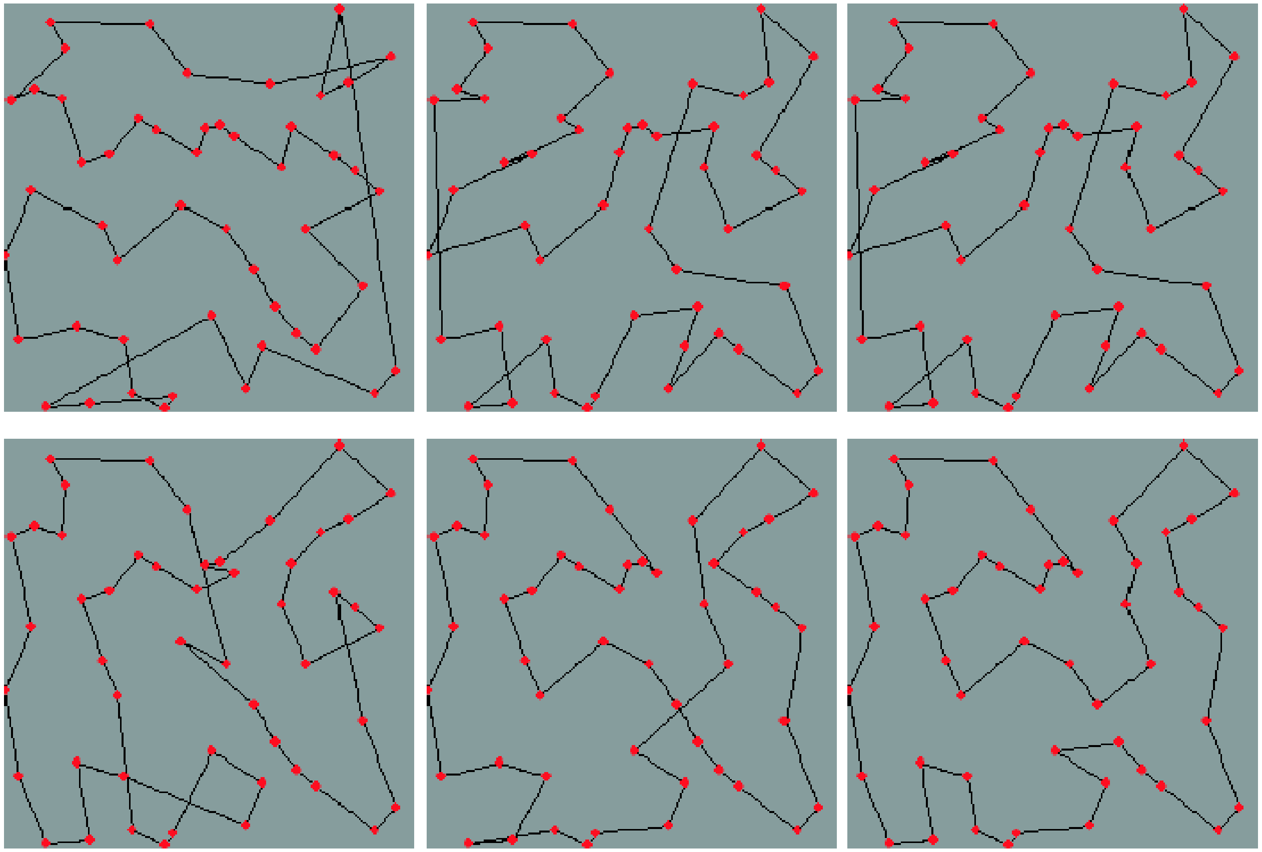
Brief introduction to ACO



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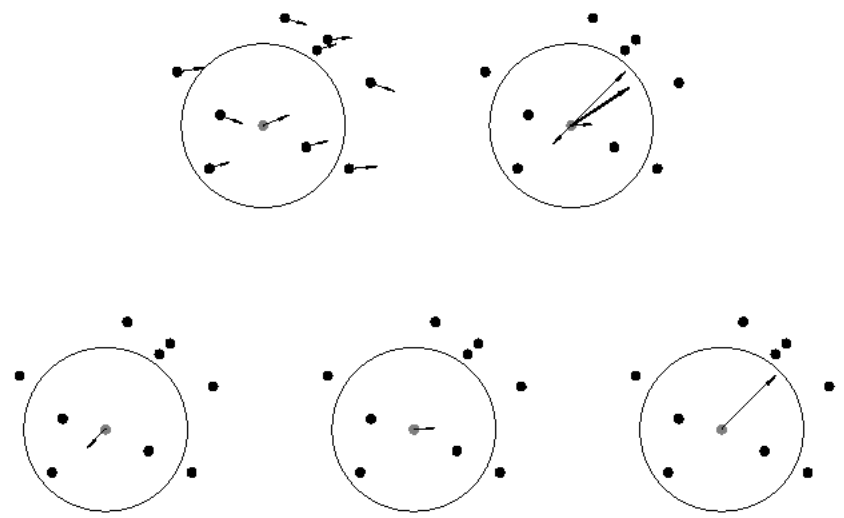
Brief introduction to PSO

- Particle swarm optimization = PSO
- Based on swarming behavior
- The *Boids* model: (that inspired the development of PSO)
- The movement of artificial bird-like objects (boids) is determined by three steers: *cohesion*, *alignment* and *separation*.



Brief introduction to PSO

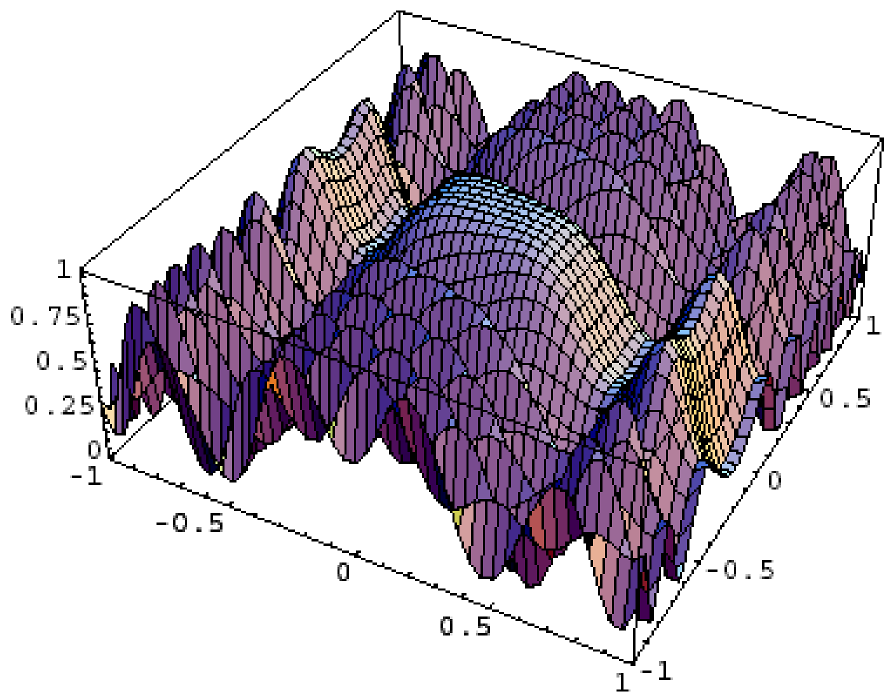
- PSO is based on the same principles: A population of particles move in the *n*-dimensional search space.
- The velocities of the *particles* in the swarm are updated according to

$$v_{ij} \leftarrow v_{ij} + c_1 q \left(\frac{x_{ij}^{\mathrm{pb}} - x_{ij}}{\Delta t} \right) + c_2 r \left(\frac{x_j^{\mathrm{sb}} - x_{ij}}{\Delta t} \right), \; j = 1, \ldots, n,$$

- ...where x_{ij}^{pb} is the best position (best value of the objective function) obtained by particle i and x_i^{sb} is the best position obtained by any particle in the swarm

Applications of stochastic opt.

- Function optimization: (particularly in problems involving many local optima)

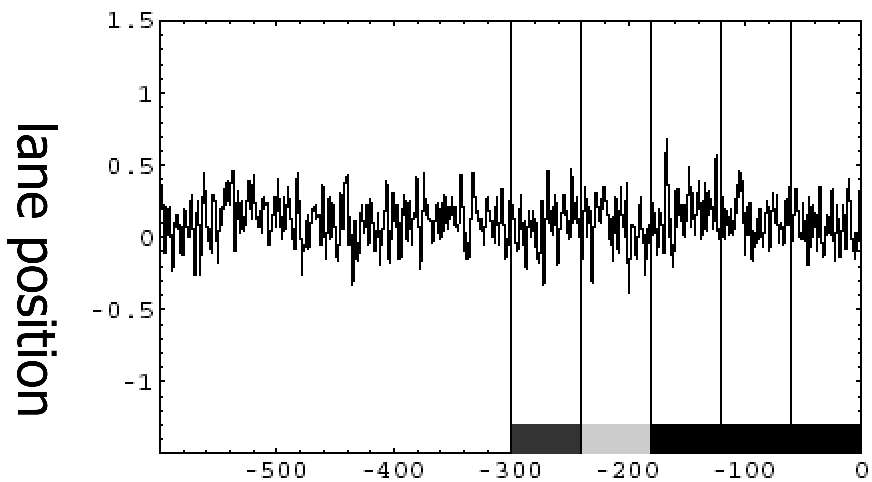


Applications of stochastic opt.

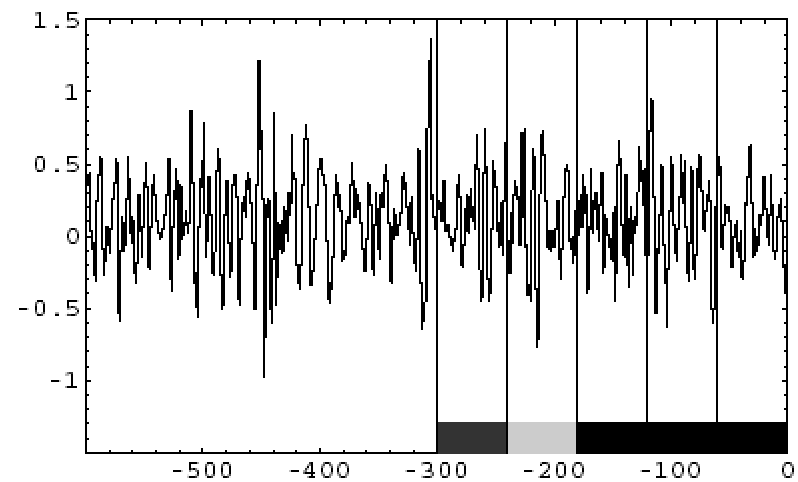
- Scheduling (e.g. airline crews)

Applications of stochastic opt.

- Classification-related problems, for example detection of sleepiness in car drivers based on time series of driving behavior:



Alert driver



sleepy driver

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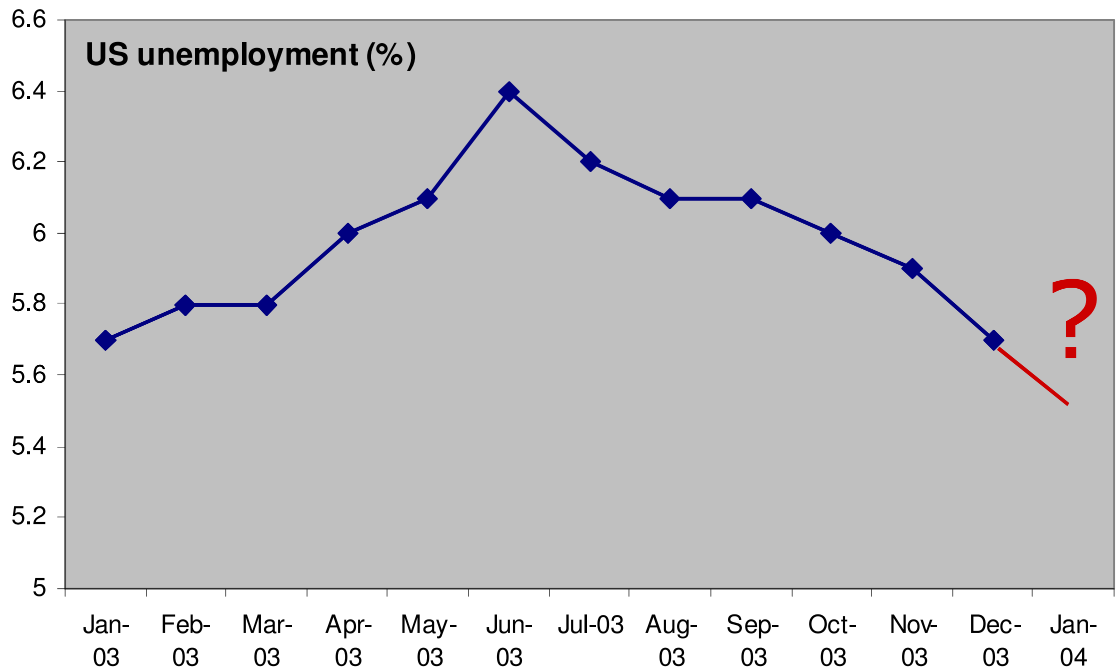
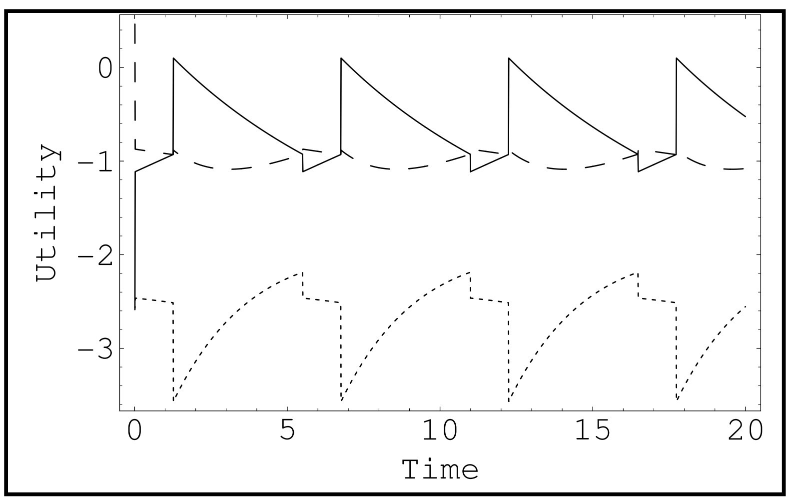
Applications of stochastic opt.

- Time series prediction: Applications in meteorology, seismology, epidemiology, finance, macroeconomics etc.



Applications of stochastic opt.

- Various problems concerning autonomous robots, e.g. behavior selection and decision-making.



Practical details

- There are two teachers: Mattias Wahde (MW) and Krister Wolff (KW)
- The course web page can be found at http://www.am.chalmers.se/~wolff/AI2/CoursePage.html
- Check the web page ***OFTEN***. There may be updates.

Practical details (schedule)

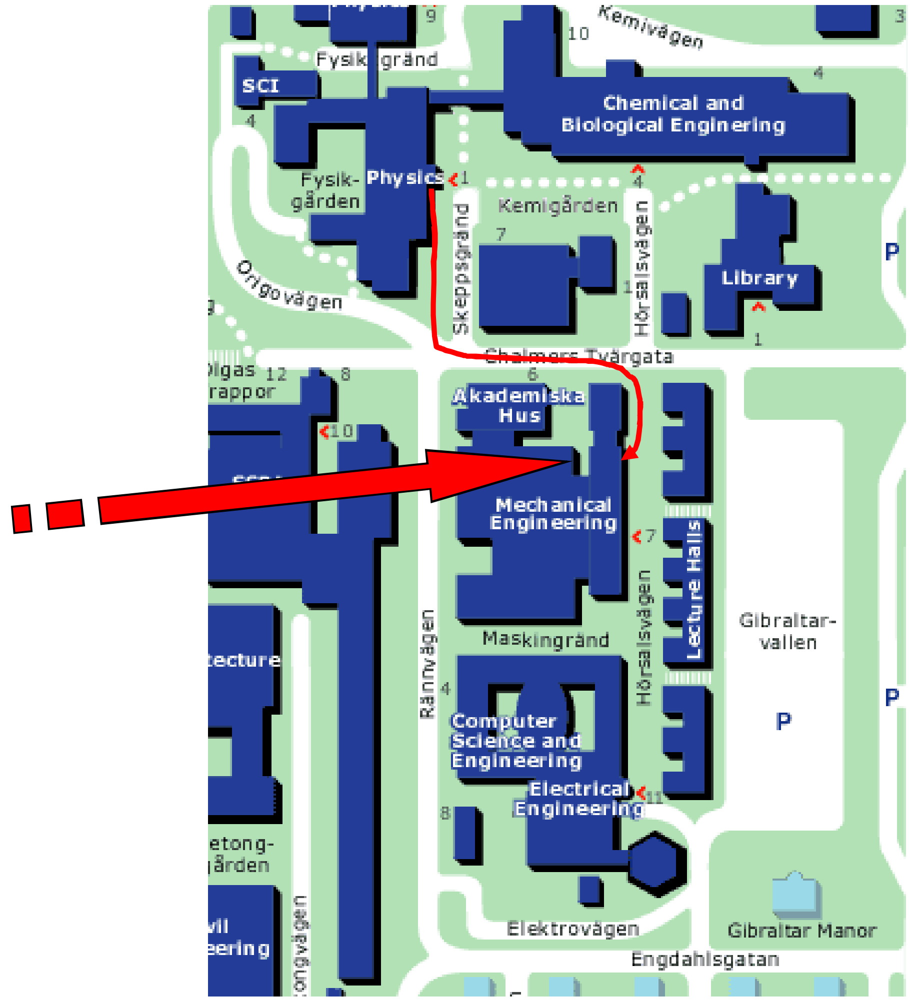
Date	Time	Room	Lecturer	Contents
20101109	13.00-15.00	Svea213	MW	Course introduction, biological basis of evolutionary algorithms (EAs)
20101111	13.00-15.00	Svea118	MW	Basics of EAs
20101116	13.00-15.00	Svea219	MW	Properties of EAs, I
20101118	13.00-15.00	Svea118	MW	Properties of EAs, II
20101123	13.00-15.00	Svea219	KW	Linear genetic programming (LGP)
20101125	13.00-15.00	Svea118	KW	Applications of EAs
20101130	13.00-15.00	Svea213	KW	Introduction to artificial neural networks (ANNs)
20101202	13.00-15.00	Svea118	KW	Ant colony optimization (ACO)
20101207	13.00-15.00	Svea213	KW	Particle swarm optimization (PSO)
20101209	13.00-15.00	Svea118	MW	Algorithm performance comparison, course summary

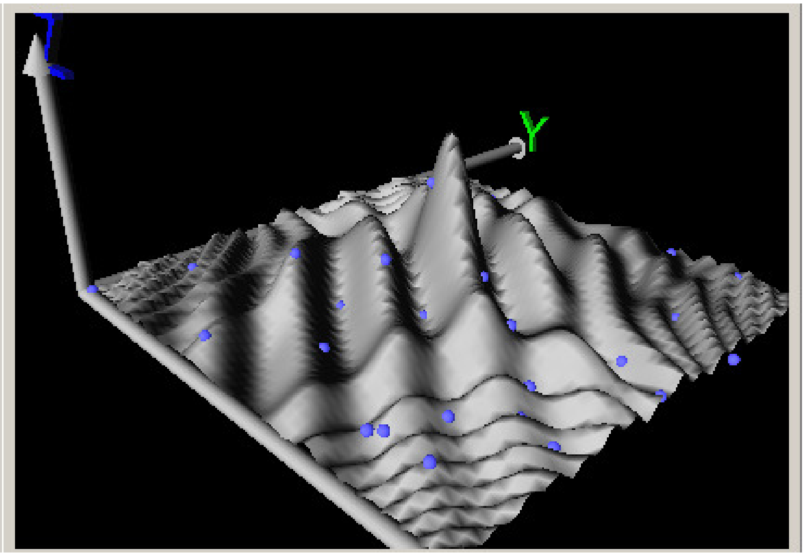
Practical details

- Examination:
  - Home problems (maximum 25p)
  - Exam (maximum 25p)
- The exam will take place on December 16, 2010, 08.30-12.30.
- Note: You need at least 10p *on the exam* to pass the course!

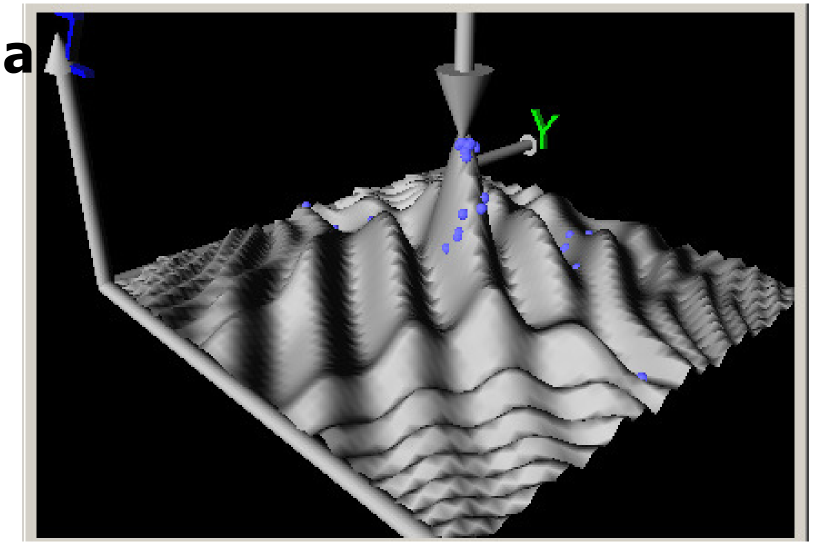
Office location

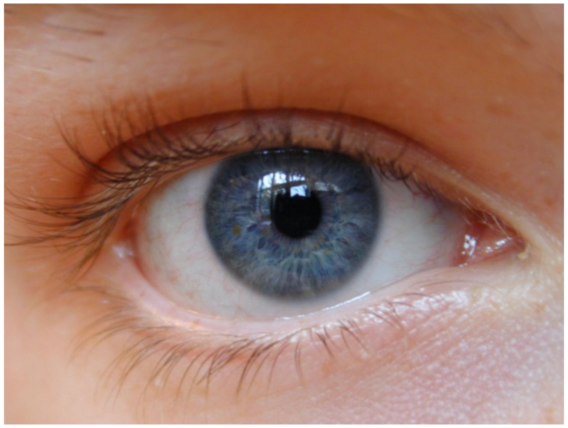
- Mechanical engineering building (nya M-huset), 1st floor.
- Enter near Café Bulten, follow the blue signs to ”Applied Mechanics” (Tillämpad mekanik)
- Dial my extension (3727) or Krister’s (3625) at the door.

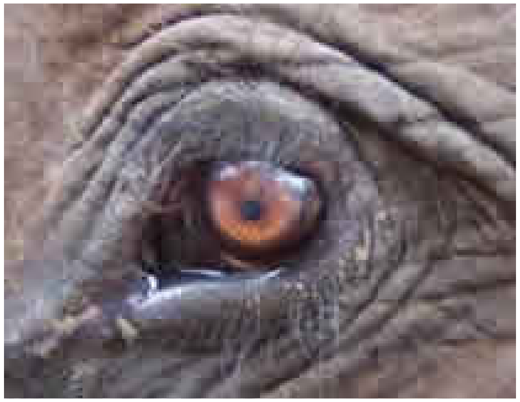


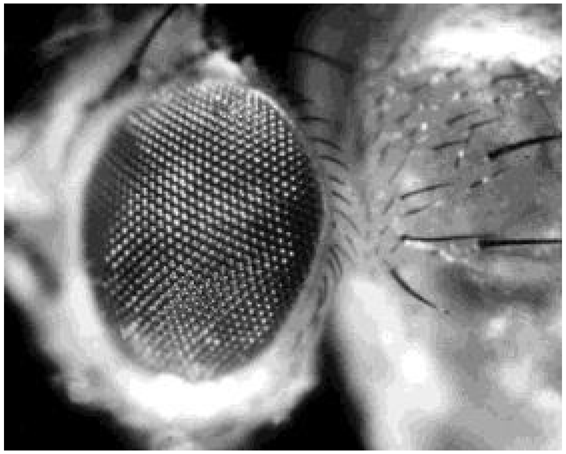


EAs are good at avoiding local optima!

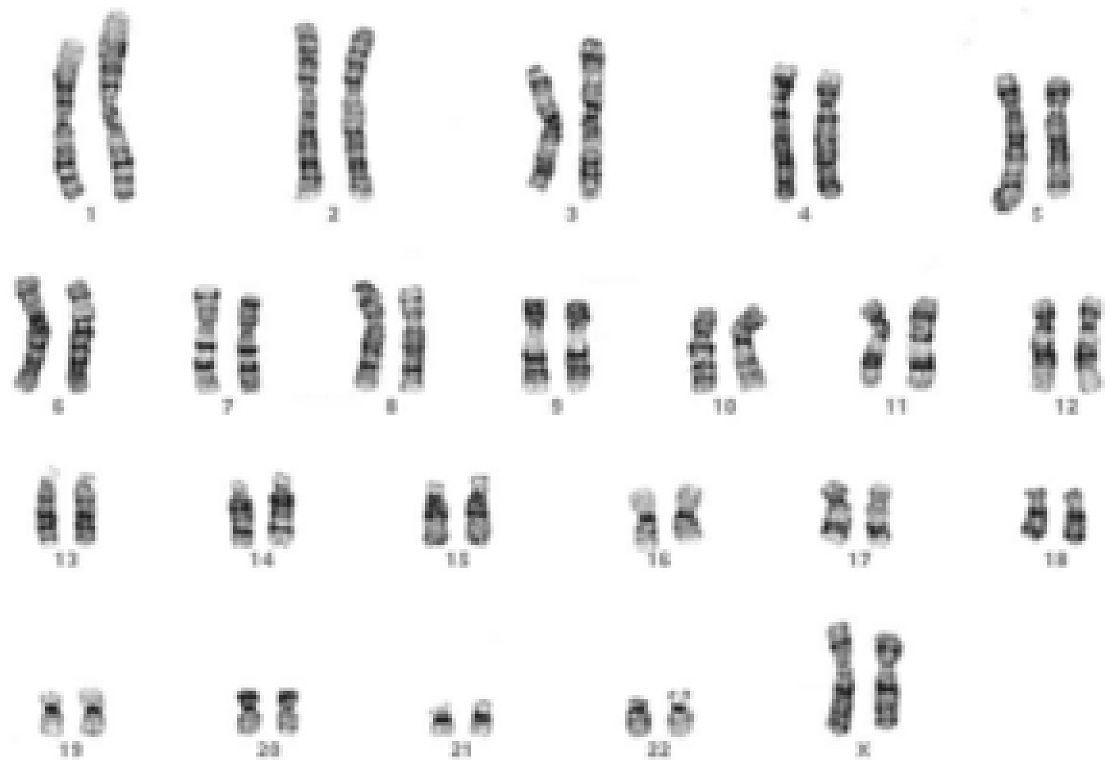








”Liger”



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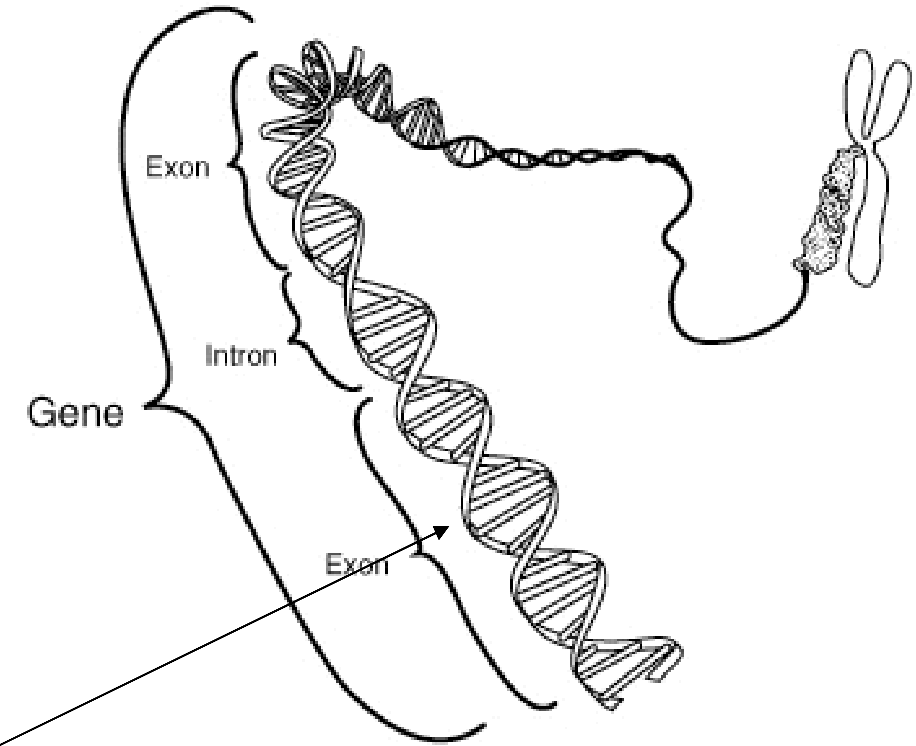

Sequence of base pairs:

...A-C-C-T-C-G-G-T-C-A-G...
| | | | | | | | | | |
...T-G-G-A-G-C-C-A-G-T-C...

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Chromosome numbers in selected species

Fruit fly	8
Cat	38
Human	46
Ape	48
Horse	64
Dog	78
Carp	104

Number of genes in selected species

Bacterium	500-6,000
Yeast	6,000
Fruit fly	13,600
Human	~25,000

(However, there are many species (e.g. some fish) with more genes than humans)

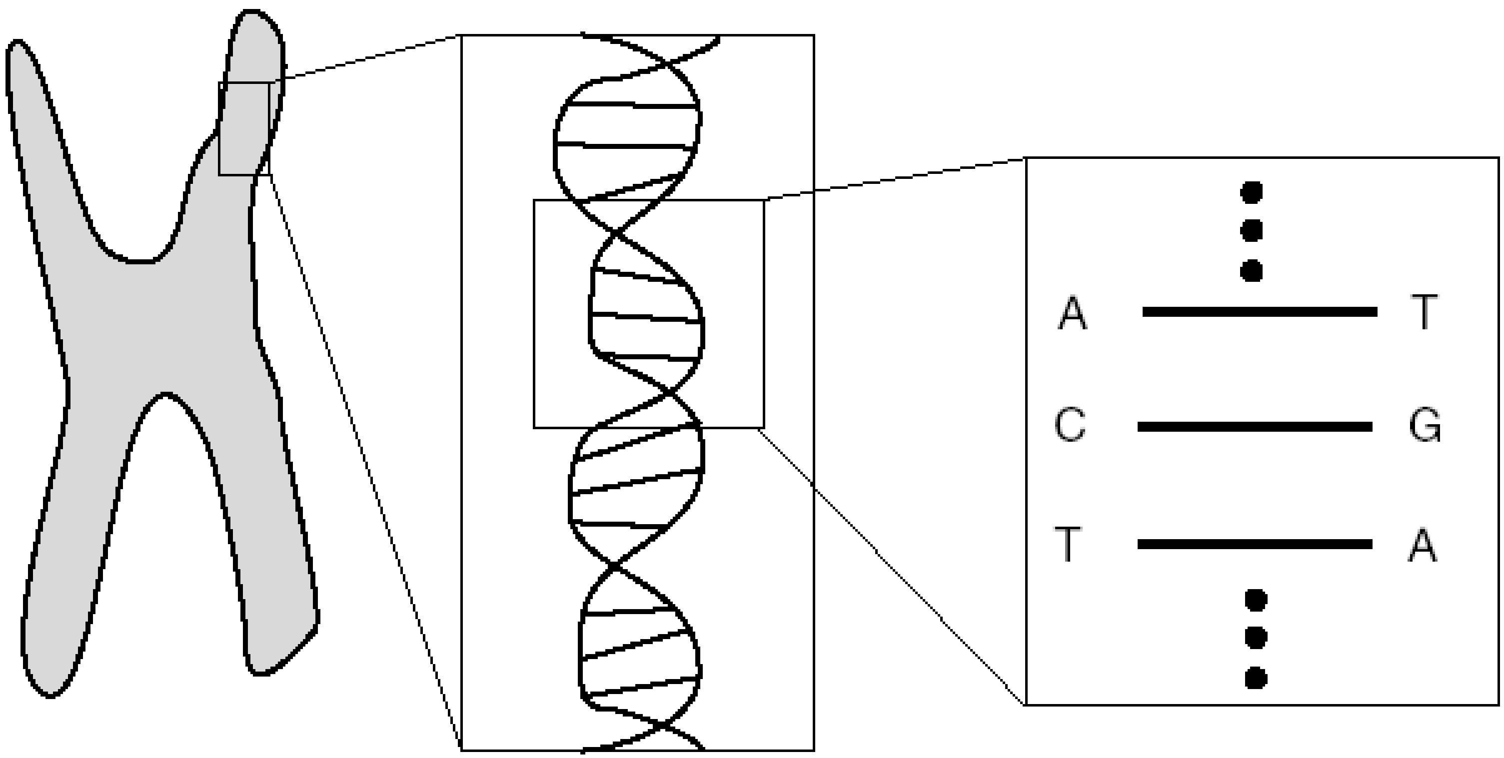
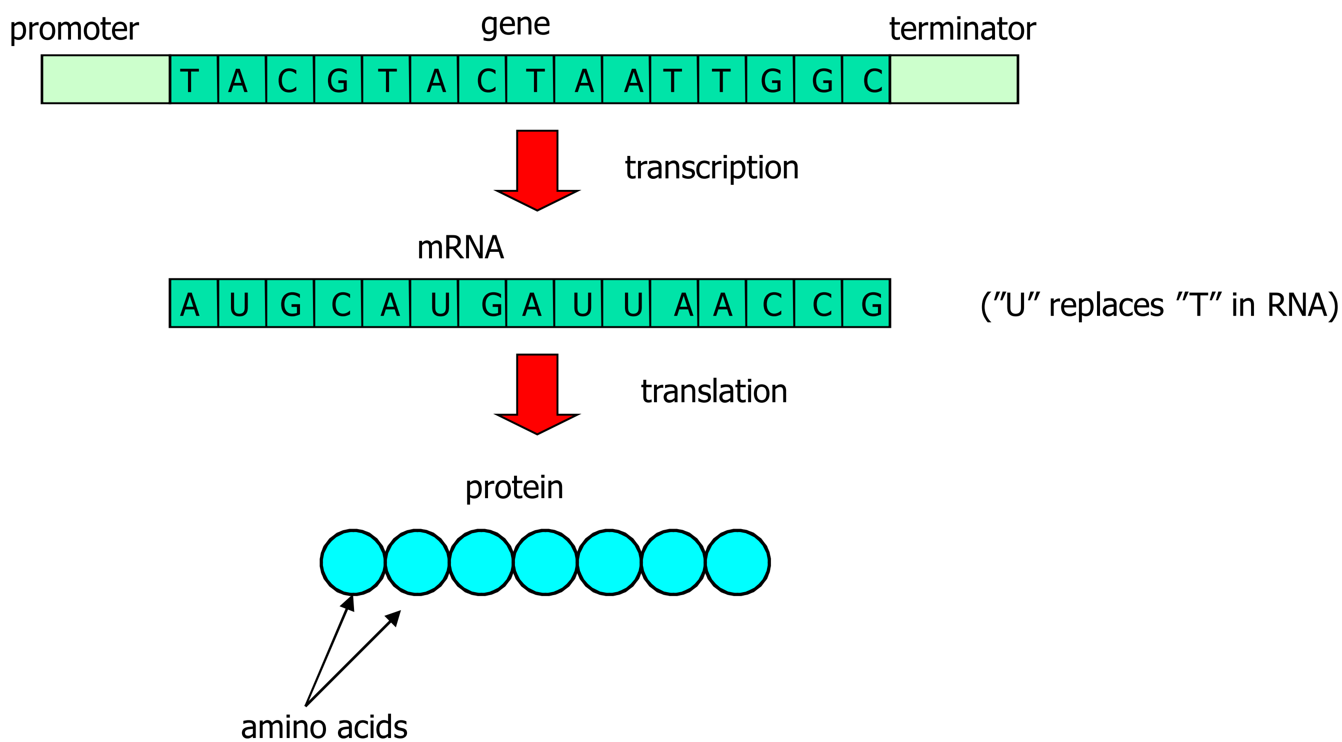


Figure 3.1: *A schematic representation of a chromosome is shown in the left side of the figure. The two blow-ups on the right show the individual base pairs. Note that A is always paired with T, and C is always paired with G.*

Genes are used for making proteins, through the two steps of *transcription* and *translation*:



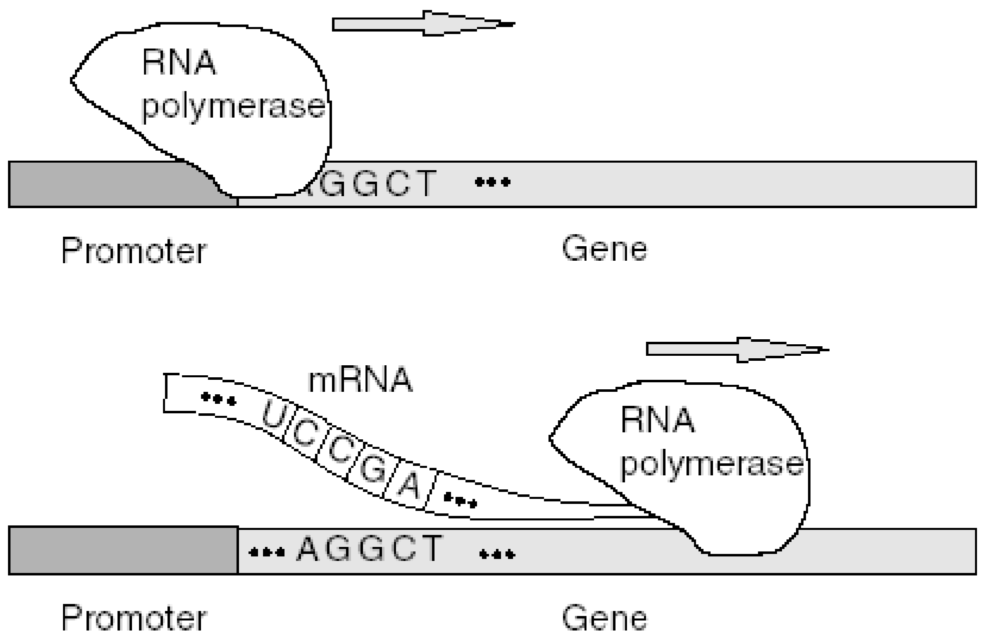
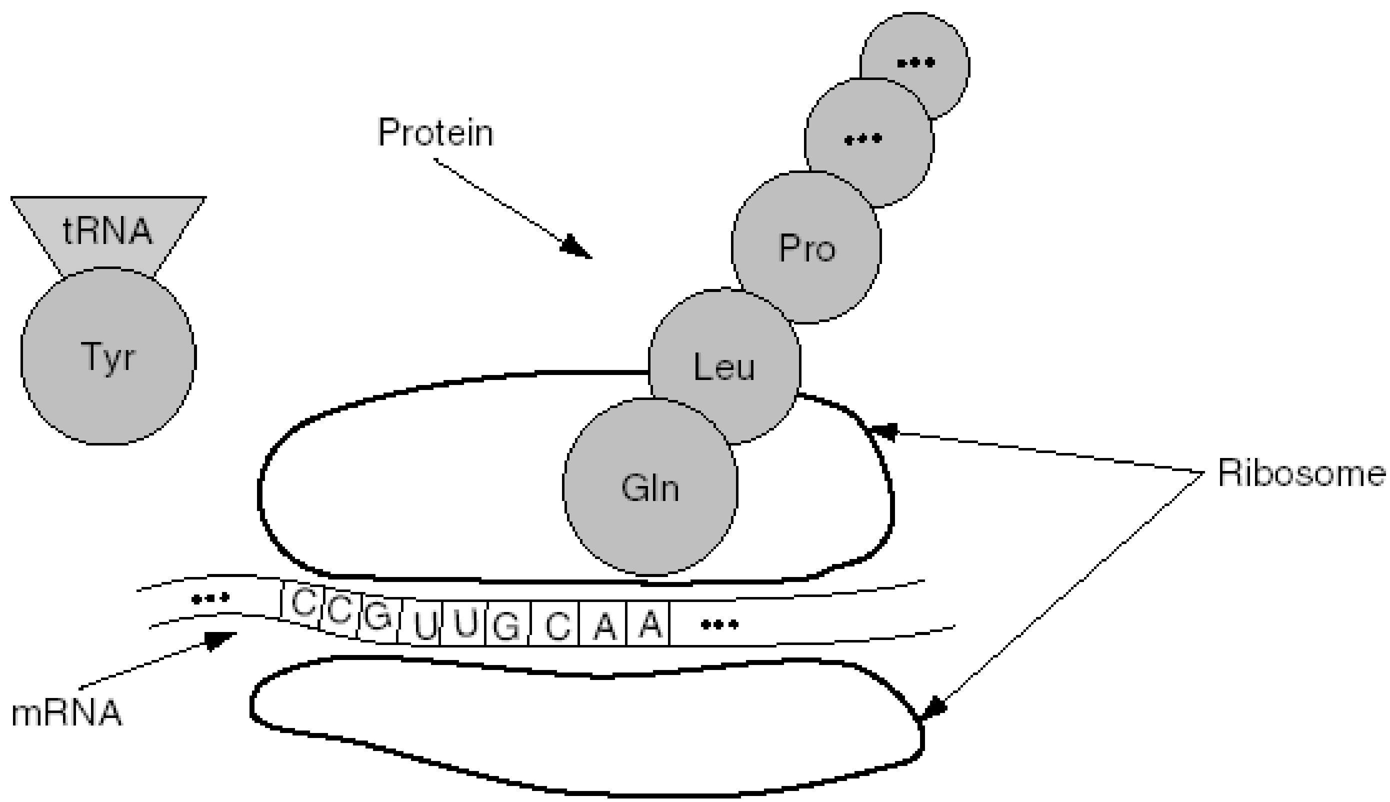
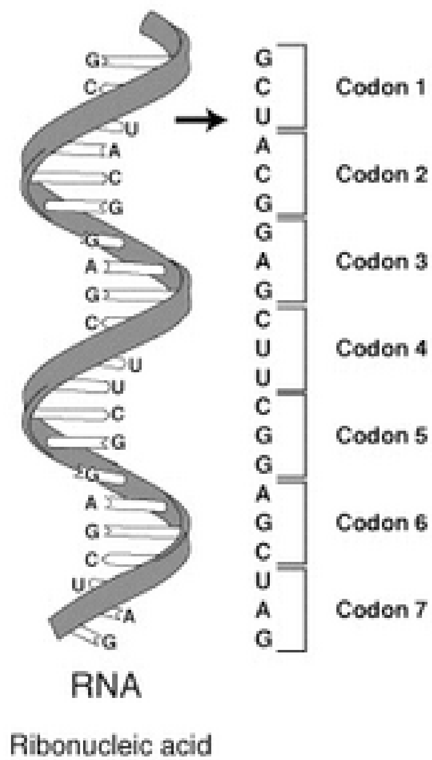


Figure 3.2: *The transcription process. The RNA polymerase binds to a promoter region and then moves along the DNA molecule, generating an mRNA molecule by joining bases available in the cell.*

Translation: (mRNA guiding the formation of proteins)



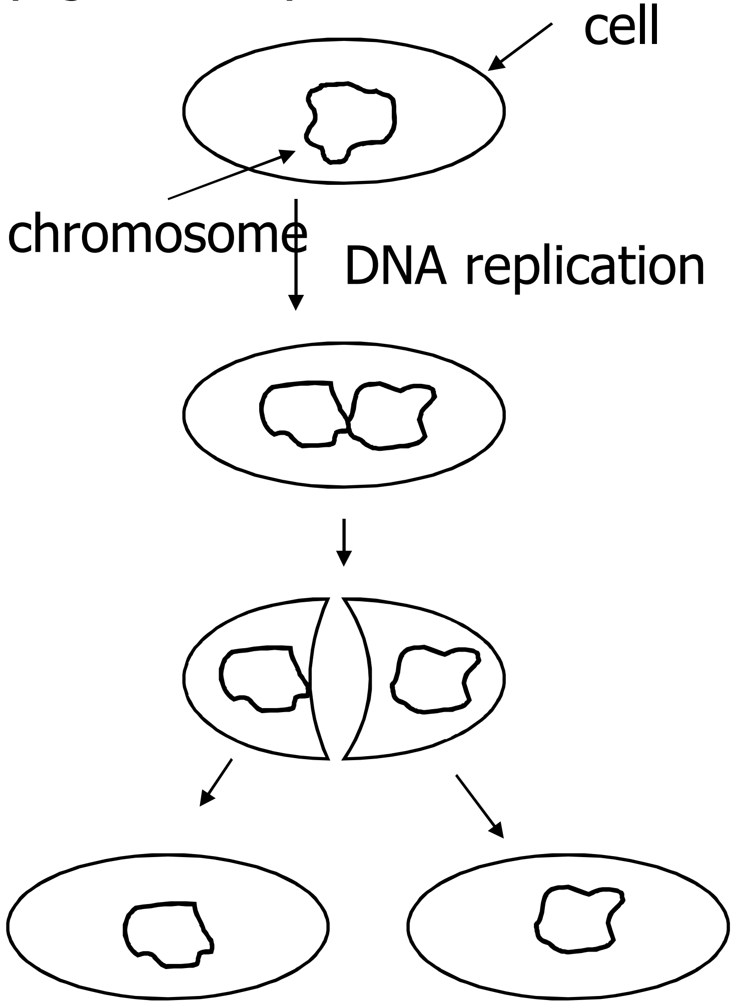


Second Position

First Position	U		C		A		G		Third Position
U	UUU	Phe	UCU	Ser	UAU	Tyr	UGU	Cys	U
	UUC	Phe	UCC	Ser	UAC	Tyr	UGC	Cys	C
	UUA	Leu	UCA	Ser	UAA	*Stop*	UGA	*Stop*	A
	UUG	Leu	UCG	Ser	UAG	*Stop*	UGG	Trp	G
C	CUU	Leu	CCU	Pro	CAU	His	CGU	Arg	U
	CUC	Leu	CCC	Pro	CAC	His	CGC	Arg	C
	CUA	Leu	CCA	Pro	CAA	Gln	CGA	Arg	A
	CUG	Leu	CCG	Pro	CAG	Gln	CGG	Arg	G
A	AUU	Ile	ACU	Thr	AAU	Asn	AGU	Ser	U
	AUC	Ile	ACC	Thr	AAC	Asn	AGC	Ser	C
	AUA	Ile	ACA	Thr	AAA	Lys	AGA	Arg	A
start	AUG	Met	ACG	Thr	AAG	Lys	AGG	Arg	G
G	GUU	Val	GCU	Ala	GAU	Asp	GGU	Gly	U
	GUC	Val	GCC	Ala	GAC	Asp	GGC	Gly	C
	GUA	Val	GCA	Ala	GAA	Glu	GGA	Gly	A
start	GUG	Val	GCG	Ala	GAG	Glu	GGG	Gly	G

(”U” replaces ”T” in RNA)

Asexual reproduction (e.g. bacteria)



1 0 1 1 1 0 1 0 0 0 1 0 1 1 0 0 0 1 0 0 0 0 0 1 1 0 0 0 1 1 0 1 0 1 1 0 0 | 1 0 1 0 0 0 0 1 0 1 1 0 0 0 1 1 0

0 1 0 1 1 0 1 1 1 0 1 0 1 1 1 0 1 1 0 0 0 1 0 1 0 1 1 0 1 0 0 1 1 0 1 0 1 | 1 1 1 0 0 0 1 0 1 0 0 1 0 1 1 0 1

1 0 1 1 1 0 1 0 0 0 1 0 1 1 0 0 0 1 0 0 0 0 0 1 1 0 0 0 1 1 0 1 0 1 1 0 0 1 1 1 0 0 0 1 0 1 0 0 1 0 1 1 0 1

0 1 0 1 1 0 1 1 1 0 1 0 1 1 1 0 1 1 0 0 0 1 0 1 0 1 1 0 1 0 0 1 1 0 1 0 1 1 0 1 0 0 0 0 1 0 1 1 0 0 0 1 1 0

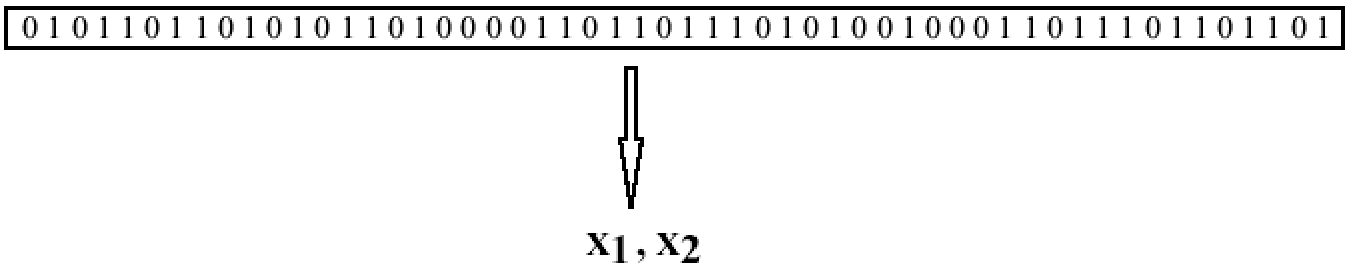
Reproduction (crossover) in EAs. (NOTE! Strongly simplified compared to the biological case!)

0 1 0 1 1 1 0 1 1 1 1 1 0 0 1 0 1 1 0 0 0 0 1 0 0 1 1 0 1 0 0 1 1 0 1 0 1 0 0 0 1 1 1 0 1 0 1 1 0 0 0 1 0 1

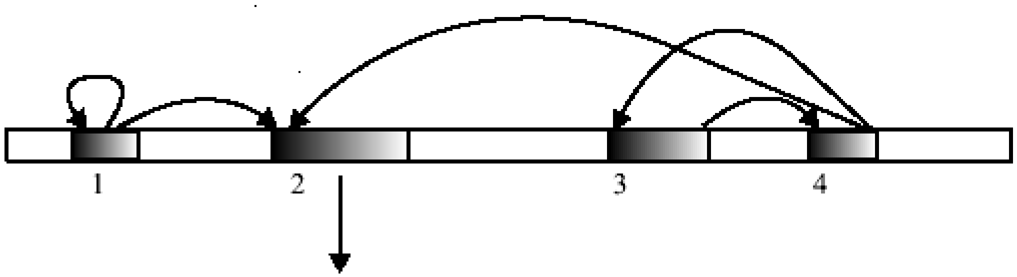
x, y

The decoding procedure in EAs is, in general, strongly simplified!

EA

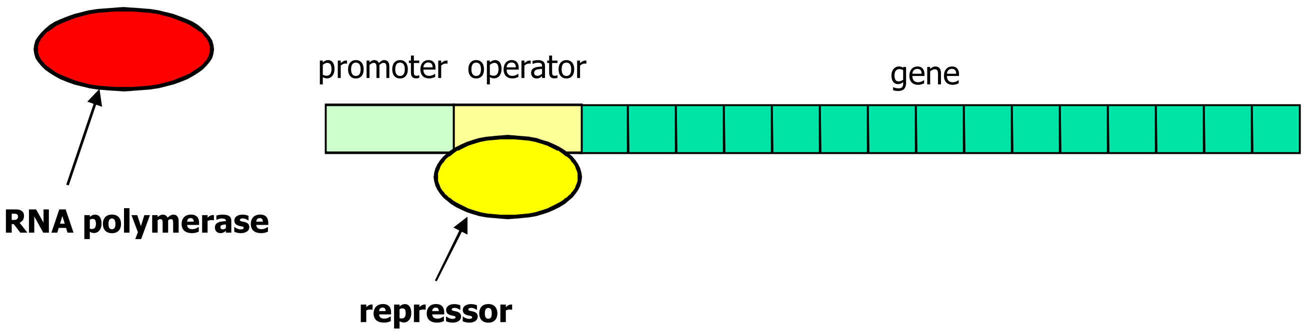

0 1 0 1 1 0 1 1 0 1 0 1 0 1 1 0 1 0 0 0 0 1 1 0 1 1 0 1 1 1 0 1 0 1 0 0 1 0 0 0 1 1 0 1 1 1 0 1 1 0 1 1 0 1
x_1, x_2

Biology

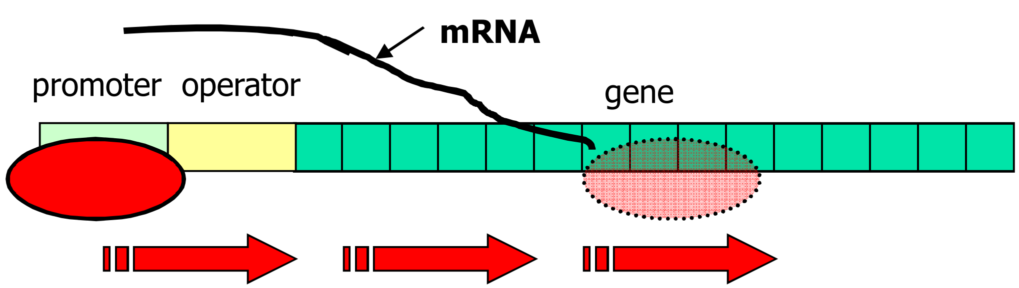

1
2
3
4

Regulatory genes: (transcription factors) genes that regulate the expression of other genes. Example of gene regulation:

Repressor protein (= the product of some other (regulatory) gene) bound to operator site: transcription is prevented



Repressor *not* bound to operator: the RNA polymerase can reach the promoter and proceed with transcription:

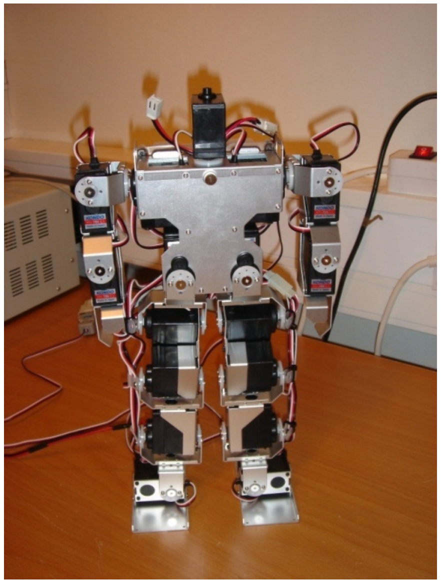


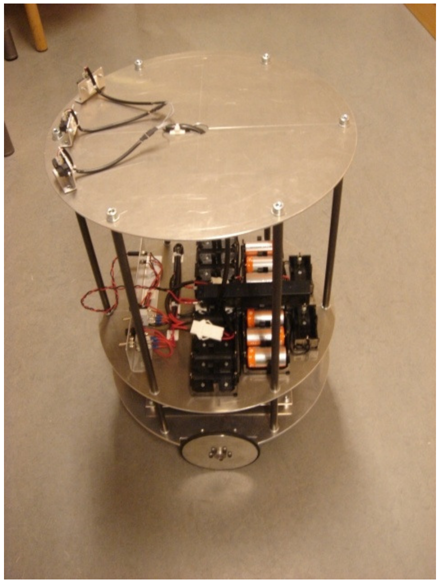
Evolution

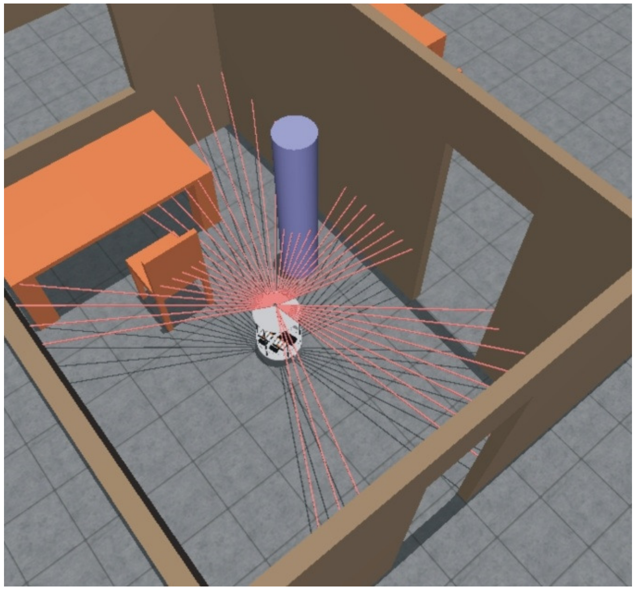
- Acts on **populations** of individuals (of a given species).
- Information is stored in the form of **chromosomes**.
- Each chromosome contains many **genes**.
- Well adapted individuals spread their genetic material (**reproduction**)
- Sexual reproduction: combination of genetic material from two individuals.
- Mutations generate new material for evolution to work with.

Adaptive systems research group

- My research group (Adaptive systems) mainly work with autonomous (freely moving) robots







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e-mail: mattias.wahde@chalmers.se www: www.me.chalmers.se/~mwahde

Adaptive systems research group

- In particular, we are carrying out research regarding decision-making (behavior selection) in autonomous robots.

- We cooperate with groups in Japan (Waseda Univ., Tokyo) and Taiwan (ITRI, Hsinchu).

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