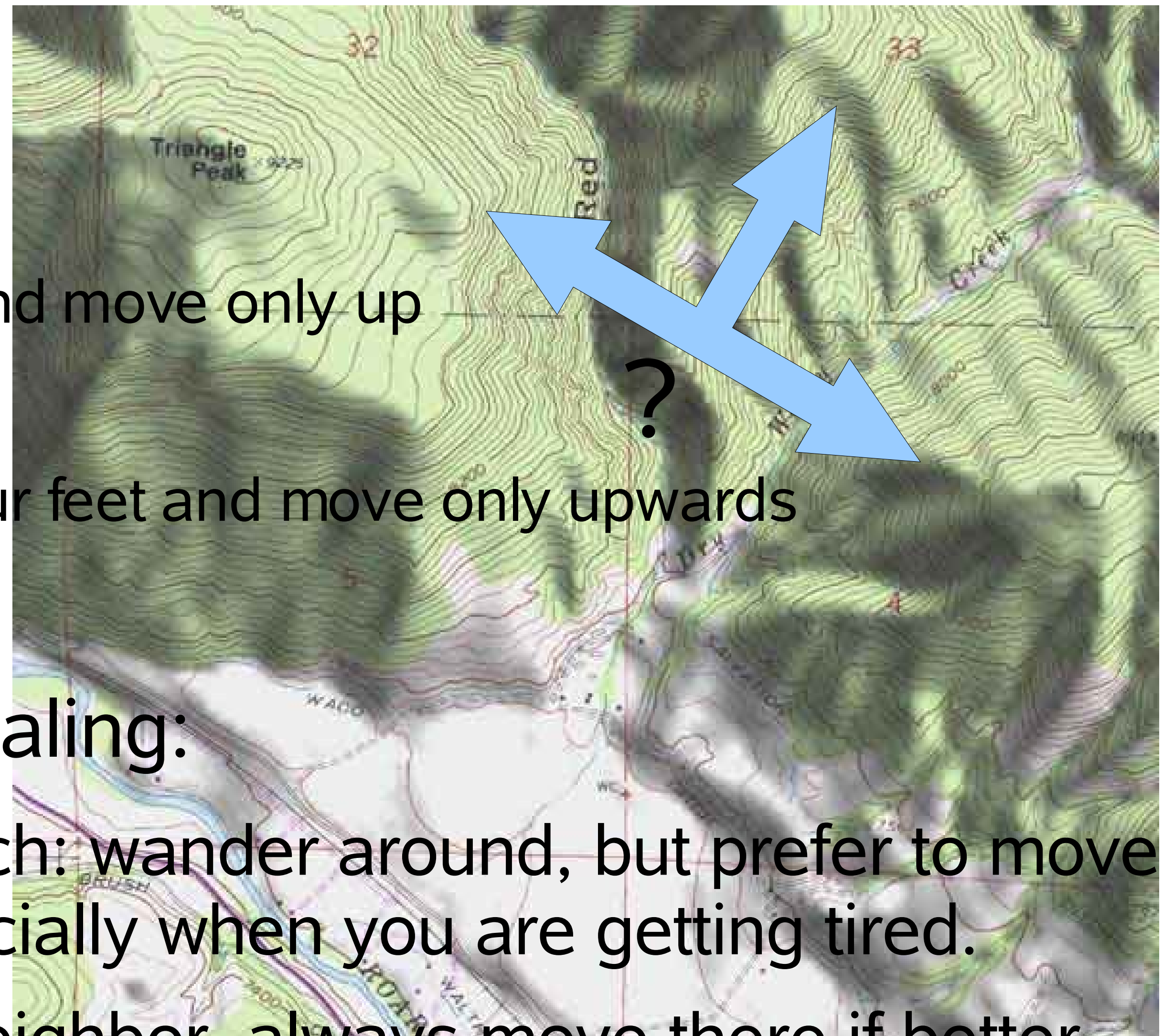
Some ideas on Evolutionary Algorithms

randomized search, or optimization, algorithms,
with evolution-inspired heuristics

Sometimes useful for...

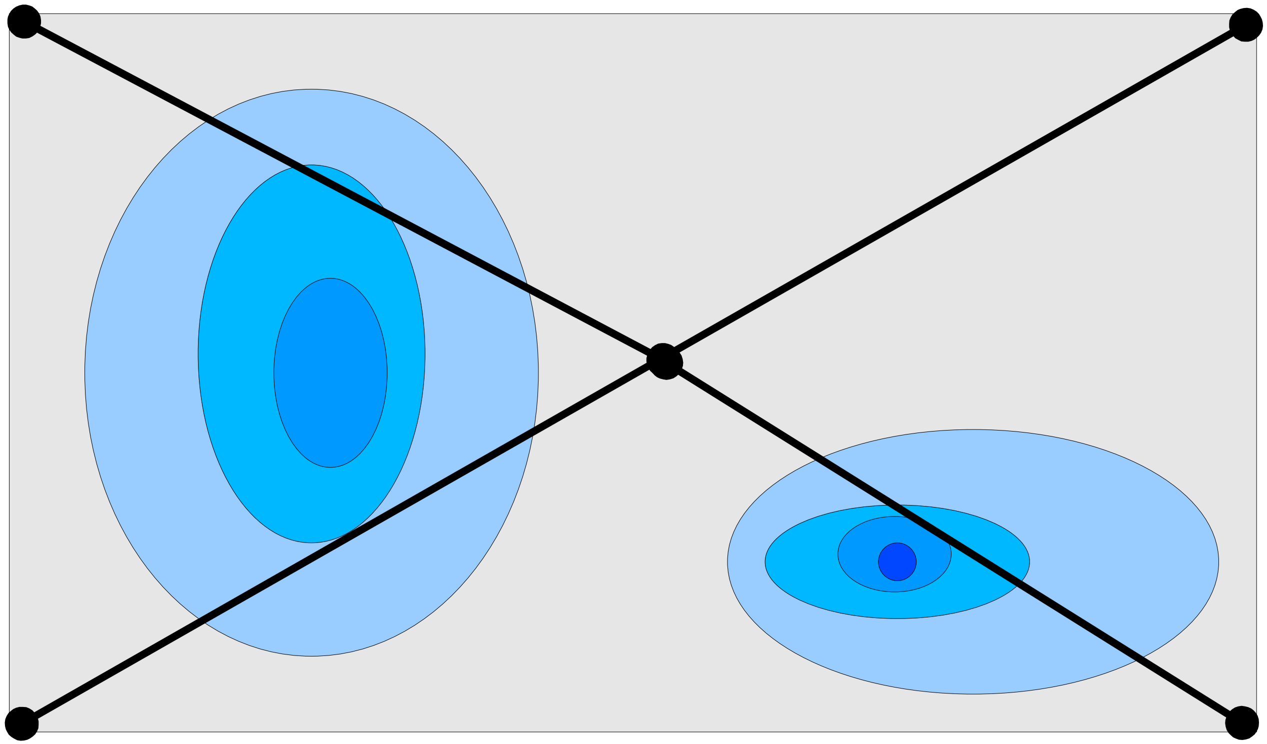
- global optimization: finding the best solution ever
- multimodal optimization, exploring the search space: finding many alternative solutions / localizing many optima
- finding sufficient solutions (not necessarily optimal) of hard problems
- optimizing objects with continuous, discrete and structural components

What is global optimization?



- Greedy search:
  - hill climbing
    - look around and move only up
  - gradient based
    - look under your feet and move only upwards
- doesn't work.
- Simulated annealing:
  - Hiker's approach: wander around, but prefer to move upwards, especially when you are getting tired.
  - Pick random neighbor, always move there if better, and sometimes also if a bit worse.

How to „map” the search space?



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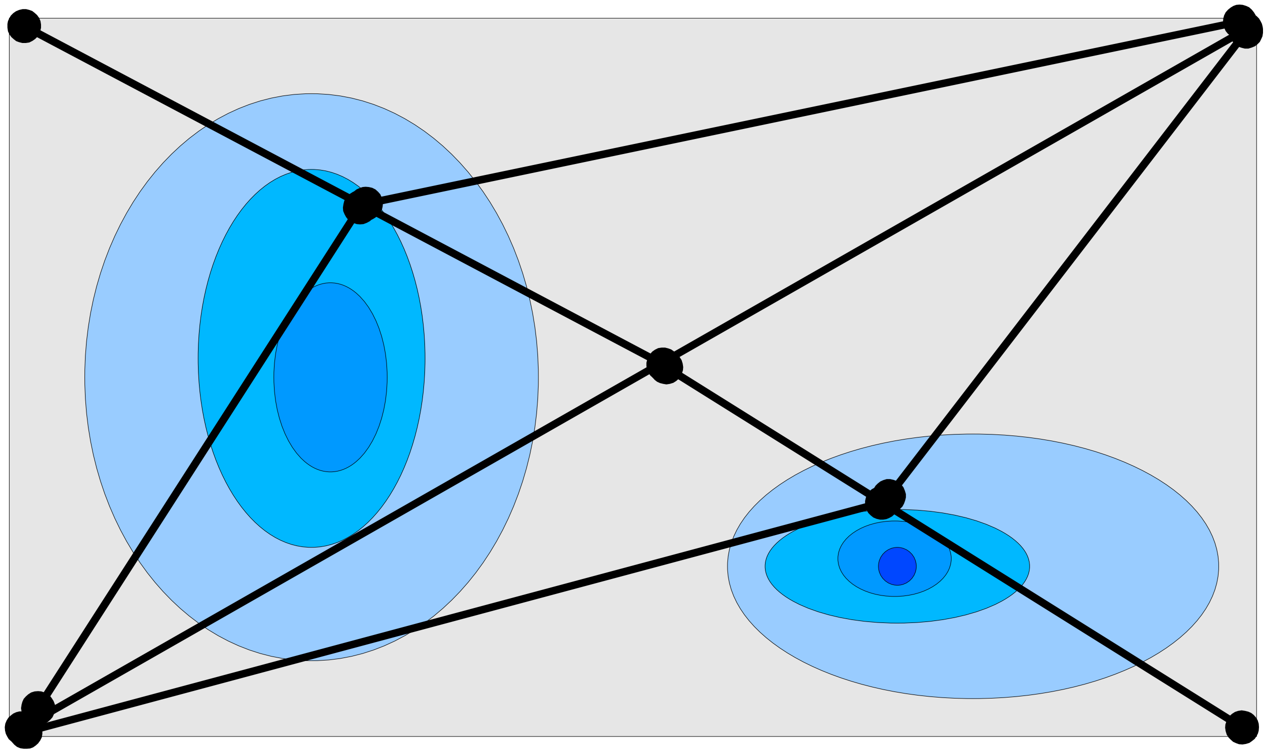

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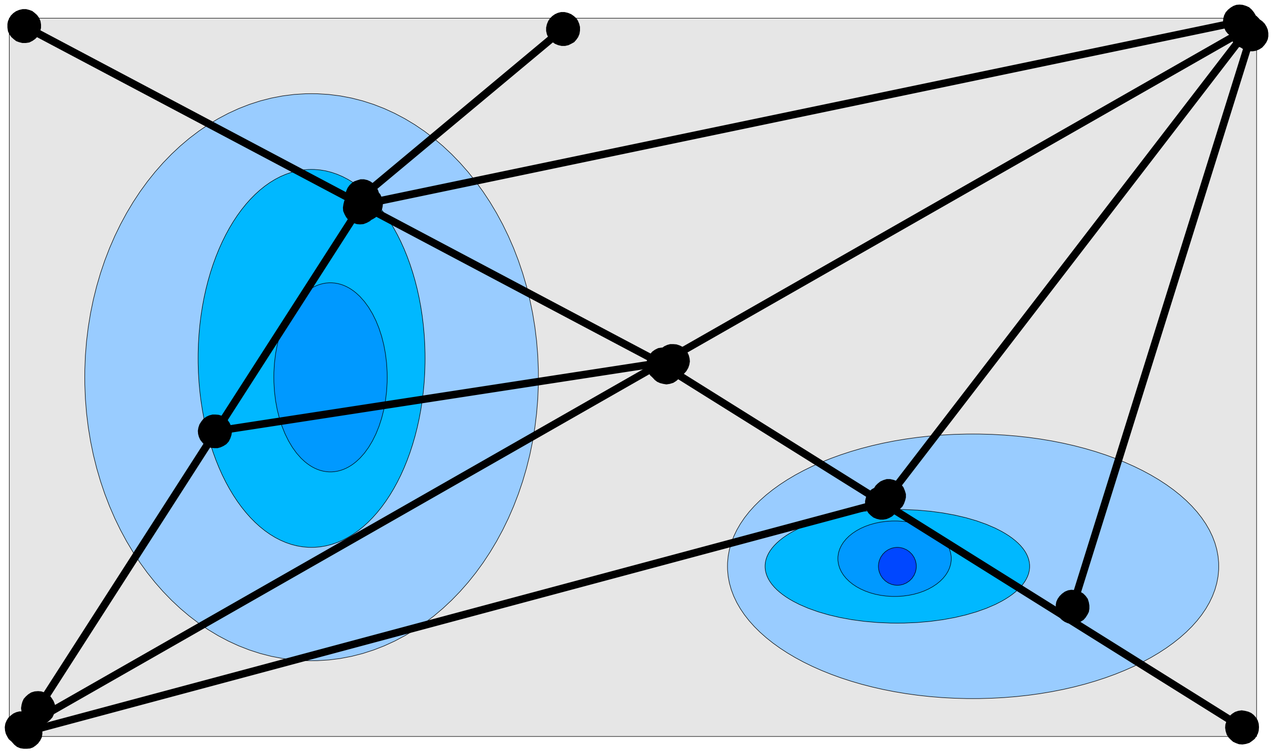

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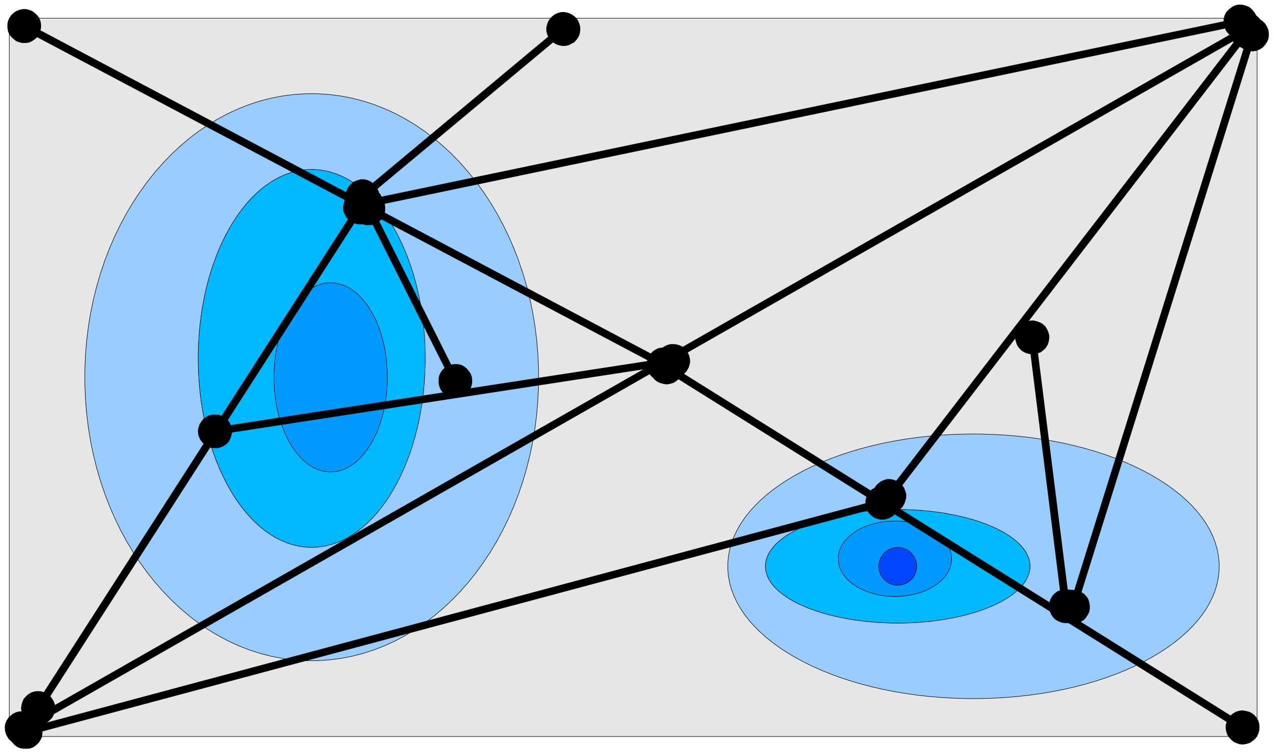

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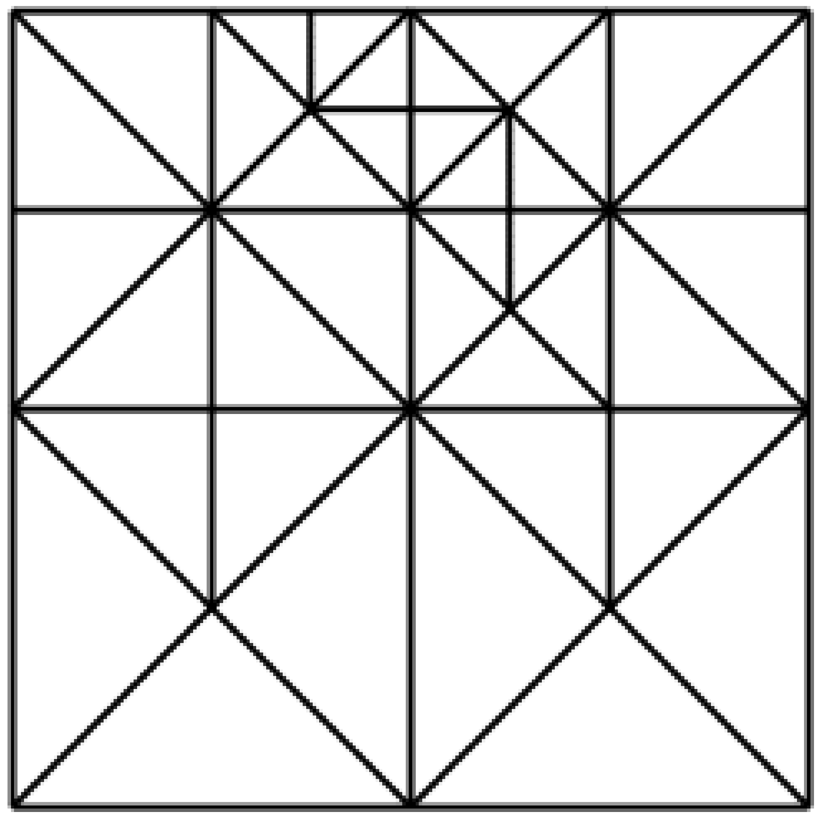


fig. 3: Adaptive triangulation

How to „map” the search space?

- A triangle or polygon estimates the fitness of its area by the mean of fitness at its vertices.
- Select the figure with high fitness (or sometimes with big volume), divide a triangle by adding a vertex on the edge with biggest fitness difference, divide a polygon by a diagonal joining two vertices each between vertices differing in fitness.
- When running short on memory, remove an edge with low fitness or low difference in fitness between figures it separates.

How to „map” the search space?

- This algorithm I've developed yesterday sounds promising, but is somewhat complicated... what is its maximal simplification?
- Keep just the points, and select an edge with high fitness to divide!
- This is a form of „phenotype recombination”.

How to „map” the search space?

- Random moving of a point to a close neighbor as in simulated annealing is „mutation”.
- Recombination and mutation are the basic operators of evolutionary algorithms (EAs).
- We can look at the population processed by an EA as an implicit adaptive map of the fitness in the search space.
- Or as a randomized hypothesis (prob. distribution) of where the true optimum is.
  - This hypothesis is updated with each generation of the EA.

Selfish Gene

- A pattern is a relation between a piece of information and particular objects, its „instances”.
- The information is „genotype”, and the instance is „phenotype”.
- Patterns at „time t+1” are the patterns that managed to put themselves there from „time t”. They „are fit”.
- Patterns „with individuality” are short enough so that they are seldom disrupted. To „be fit”, they often perform some function. Called **genes**.

Evolution and Modularity

- We would like to select for meaningful genes rather than individuals, because the pool of competing individuals is enormous, and for a gene (i.e. feature type), the pool of competing **alleles** (i.e. feature values) is relatively small.
- When the problem is modular (decomposable into features), and genes match to features, EAs with recombination search for alleles in parallel. When genes don't match to features, recombination is just a large-scale mutation.
- Example of a modular problem: TSP.

Evolution and Modularity

- Location of a city en route (i.e. first, or fifth, city) is not a good feature, it doesn't tell anything about the path.
- Edges are better features. But perhaps angles (corners, triples of cities) are even better?
- With a good set of features, it is often very difficult to design a good recombination operator, which should:
  - preserve features of parents, shouldn't introduce features not present in parents
  - allow to balance features from both parents, shouldn't force most features to come from the same parent

Evolution and Modularity

- The above conditions often cannot be met exactly (i.e. for TSP): see „Forma Analysis” by Nicholas J. Radcliffe.
- When recombination tends not to disrupt groups of related genes, it can give exponential speed-up compared to mutation only (and thus to non-EA search strategies).
  - This has been shown for Traveling Salesman Probl.
- Therefore, related genes should lay close in the genome. There are techniques to let this linkage evolve. A recent powerful one is „Bayesian Optimisation Algorithm”.

Genetic Programming (GP) and Modularity

- GP takes programs as the genotype. This sounds as a powerful idea: programs are the „ultimate representation” for solutions.
- But the original GP falls completely short on the issues we discussed so far (genes, recombination, linkage).
- Fortunately, there has been much progress:
  - NeuroEvolution of Augmenting Topologies (NEAT) [1]
  - Meta-Optimizing Semantic Evolutionary Search (MOSES) [2]
- These approaches learn new genes incrementally.

EAs in other mechanisms

- EAs are usually separate tools in a toolbox, but sometimes they are parts of other tools.
- One such tool is also biology inspired: Artificial Immunological Systems (AISs).
  - AISs use fuzzy matching of antibodies to detect pathogens.
  - AISs use *negative selection*, which eliminates detrimential antibodies (detecting organism own cells) in the early phase, and *positive selection* to increase affinity to detected pathogens.
- The other one I want to talk about are Learning Classifier Systems.

Learning Classifier Systems [3]

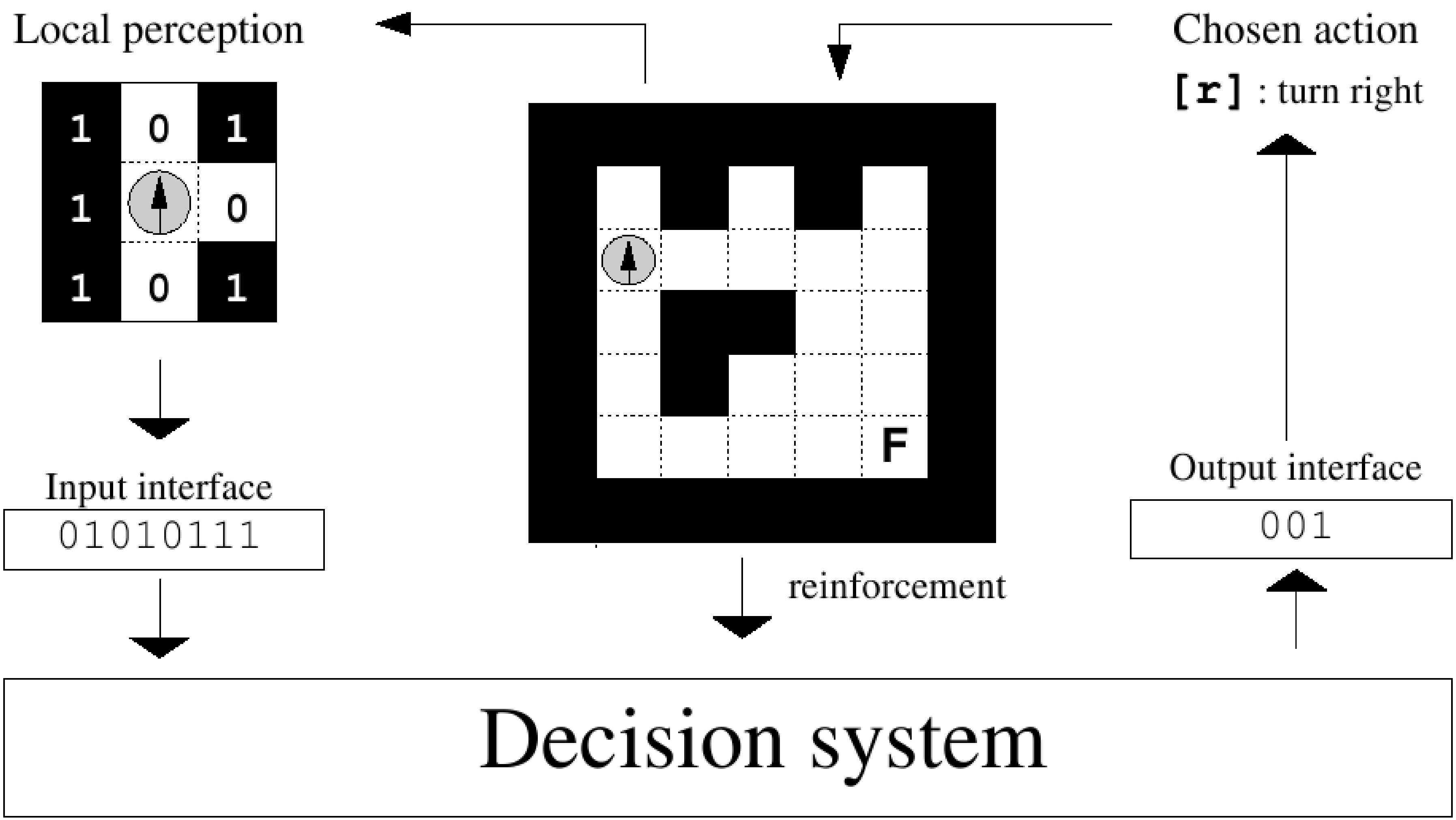
- Abstract Learning Classifier Systems (LCSs) are rule-based systems that automatically build their ruleset using Genetic Algorithm (GA).
- Reinforcement Learning (RL) learns what actions to pick in given states, knowing only the experienced rewards. LCS rules represent state-action(-reward) table in a compact way.
- RL must balance
  - exploration: trying out new actions to see what rewards they give
  - exploitation: following the action with biggest expected rewards (based on experience so far)

Learning Classifier Systems

There are several flavors of LCSs now:

- the „**Pittsburgh approach**” used GA on populations of whole systems; currently (after „Michigan approach”) a single LCS is evolved, using GA inside its learning mechanism
- **strength-based** systems (i.e. ZCS) use the expected reward of a rule (which matches state and produces action) as its fitness
- **accuracy-based** systems (i.e. XCS) represent expected reward in a rule and use accuracy of reward prediction as fitness; GA works only on classifiers matching current situation
- **anticipation-based** systems (ALCSs) don't use condition -> action rules, but condition, action -> effect rules: they build a state transition model; they favor actions bringing more information; often don't use GA but sophisticated specialization and generalization heuristics

Learning Classifier Systems



References and Sources

1. „*Evolving Neural Networks through Augmenting Topologies*”, Kenneth O. Stanley, Risto Miikkulainen, 2002
2. „*Competent Program Evolution*”, Moshe Looks, 2006
3. „*Learning Classifier Systems: A Survey*”, Olivier Sigaud, Stewart W. Wilson, 2007
4. Some pictures I grabbed from the internet.