

Towards Synthesizing Artificial Neural Networks that Exhibit Cooperative Intelligent Behavior: Some Open Issues in Artificial Life

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[Overview]

- Introduction
- AI vs AL Approach to Cognition
- Animal Intelligence
- Synthesizing Animal Intelligence via Evolution and Learning

[Introduction]

- **Focus:** Understanding the nature of intelligence from an AL perspective, the evolution of complex nervous systems to support cooperative behavior.
- **Main Interest:**
 - Role of ANNs in supporting cognitive process
 - Role of communication in survival strategies

AI vs AL Approach to Cognition

Artificial Intelligence (AI)

- Focus on Individual
- Cognition as operations of logic independent of perception
- Starts with human-level cognition
- Top-down approach: engineer complex systems
- Direct specification of cognitive architectures
- Human-level mental tasks

Artificial Life (AL)

- Focus on group or population
- Cognition as operation of nervous systems integrated with sensory/motor experiences.
- Starts with animal-level cognition
- Bottom-up approach: rely on evolution, development and learning
- Indirect specification
- Survivability in complex environments is the overriding task

[AL Modeling Approach]

Involves specification of below components:

- ***Environments:*** Parameters of the simulated worlds where behaviors may evolve or develop.
- ***Processes of Genetic expression:*** Artificial organisms capability of evolving or developing behaviorally.
- ***Learning and Development:*** Methods under genetic control for modifying or growing the nervous system of artificial animals during their lifetime.
- ***Evolution:*** Recombination and mutation of parental genomes during mating to produce variation in the offspring.

An alternative to engineering complex systems but has issues.

Common Behavior in Animals

- ***Social Grouping*** - useful for protection and enhance cooperation.
- ***Specialization of Labor*** - soldier, queen, drone, forager and nest builder.
- ***Food Finding, Preparation and Storage*** – ants following pheromone trails, wild cats plucking the feathers, wolves dig up holes to drop meat.
- ***Symbiotic behavior*** – Egyptian plover bird ‘cleans’ crocodile’s mouth.
- ***Dominance, Combat and Territoriality*** – kangaroo’s boxing.
- ***Mate Selection and Mating*** – courtship of Australian bower birds.

[Common Behavior in Animals]

- ***Nesting*** – bees, ants, birds.
- ***Parenting*** – sheep require 20 min. licking and cleaning their babies to create memory trace.
- ***Predation Strategies*** – bears scooping fish, lions hunt cooperatively.
- ***Predator avoidance and Defense*** – fleeing to trees, water or burrows. Mobbing. Attacking when cornered.
- ***Disassembling Behavior*** – remaining immobile when mauled.
- ***Primitive tool use and Culture*** – using sticks, rocks or other natural object for food preparation or nest maintenance.
- ***Other Complex Behaviors*** – migration, navigation etc.

Cooperation via Communication

- Cooperation requires communication which can be visual, tactile, acoustic or olfactory means.
- Communication need not be “intentional” and may occur both within and across species.
 - Insect Communication – via chemicals, tactile motions and visual displays.
 - Avian Communication – acoustic and visual
 - Mammalian Communication – wide variety of forms
 - Primate Communication – acoustic and visual
 - Cross-Species Communication – predator prey interactions.

[Development and Learning]

- Behaviors are the result of complex interactions between genetic and developmental factors.
- Although genetic effects are more noticeable and tend to dominate lower life forms, there is strong evidence that nearly all animals are capable of learning (e.g. bees learn the color and odor of certain flowers)

[Related Research]

- More realistic modeling techniques are possible as a result of great increase in computational power with lower cost. Some examples of simulated environments:
 - Evolution/Learning of Food Discrimination
 - Evolution of Foraging and Trail Laying
 - Evolution of Communication
 - Evolution of Predation and Predator Avoidance
 - Toward the Synthesis of Protohuman Intelligence

Evolution/Learning of Food Discrimination

- [Todd and Miller] An aquatic environment with two patches of “plant material” in each there are 2 distinct set of plants: food and poison. The color of food and poison is opposite in two patches. Smell is same for each type of plant in both patches.
- A creature born in one patch stays in that patch for its lifetime however, its offspring might born in any patch.
- Creatures classify if the floating particles are food or poison according to its color or smell.
- Although smell is a consistent distinction between the plant types, it is not to be trusted due to turbulence.

Evolution of Foraging and Trail Laying

[Collins]

- A series of experiments, AntFarm I through V were carried out hoping to observe foraging and trail laying behavior in ants.
- First trail laying behavior were un-antlike, mostly in circular motion.
- In later stages of experiment antlike exploration evolved but pheromone release was did not until it is forced for certain generations.

Evolution of Communication

- Werner and Dyer experiment: In a grid environment male and female members try to mate where females are immobile and males are blind.
- Whenever a male is in 5X5 grid sensory area, females signal to direct the male.
- As a result of the experiment females evolved to produce correct signals for directions while males coevolved to interpret the signals.

Evolution of Predation and Predator Avoidance

- Werner and Dyer experiment: 2D grid environment where multiple species (*biots*) inhabit. Environment contains physical objects (trees, holes, plants etc.)
- Biots produce involuntary smell to distinguish its species and sound relative to their speed. They can also make voluntary sounds for communication.
- Whenever two biots of same species and different gender meets in same grid they mate.
- In one of the results prey learned to run away from the predator and predator learned to chase. Also prey evolved to form herds to protect from its predator.

Toward the Synthesis of Protohuman Intelligence

- Still too early to discuss synthesis of protohuman forms of intelligence via AL techniques since even complex animal behaviors not yet been engineered, evolved or designed.
- It may be possible to engineer sophisticated ANNs that are capable of aspects of human thinking and placed in an environment where they can undergo evolution.

Evolving Neural Networks

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[Outline]

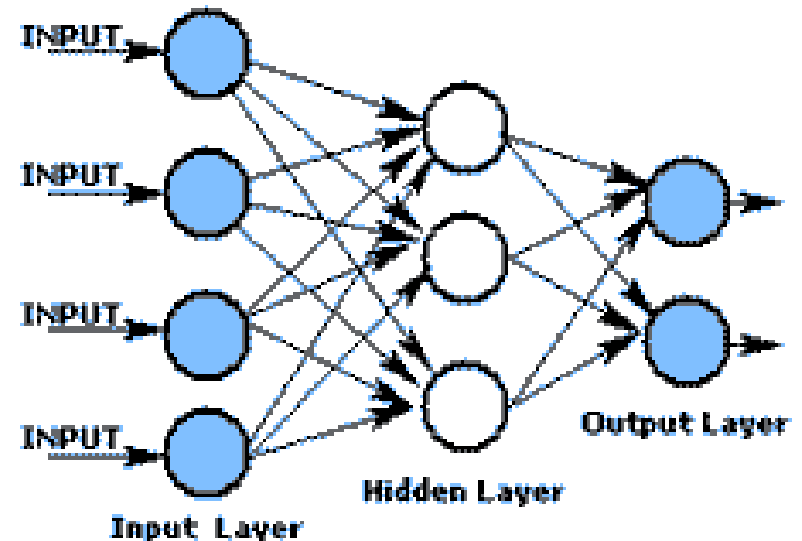
- Neural Networks
- Evolutionary Programming
- Experiments with Evolutionary Networks
 - XOR Problem
 - Gasoline Blending Problem
- Conclusion / Discussion

[Artificial Neural Networks]

- ***Parallel processing*** structures that provide the capability to perform various ***pattern recognition*** tasks.
- Their architecture is modeled after the brain.
- Topologies can be constructed to generate arbitrarily complex decision regions hence they are well suited for use as ***detectors*** and ***classifiers***.

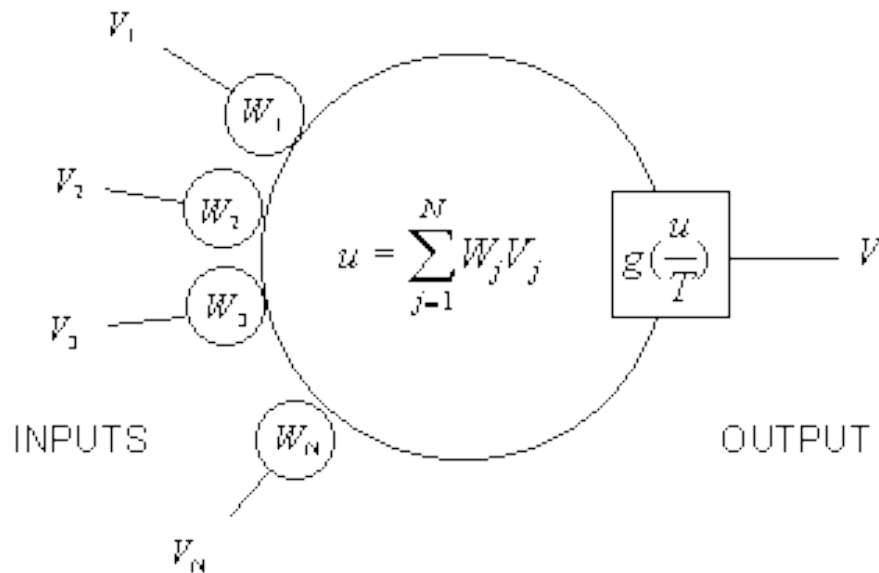
Artificial Neural Networks

- Consists of multiple units called **Artificial Neurons** or **nodes**.
- Each node is part of one of 3 types of hierarchically ordered layers: Input, Hidden and Output layers.
- In each layer input is processed and passed to the next layer for further processing.



Artificial Neuron (Node)

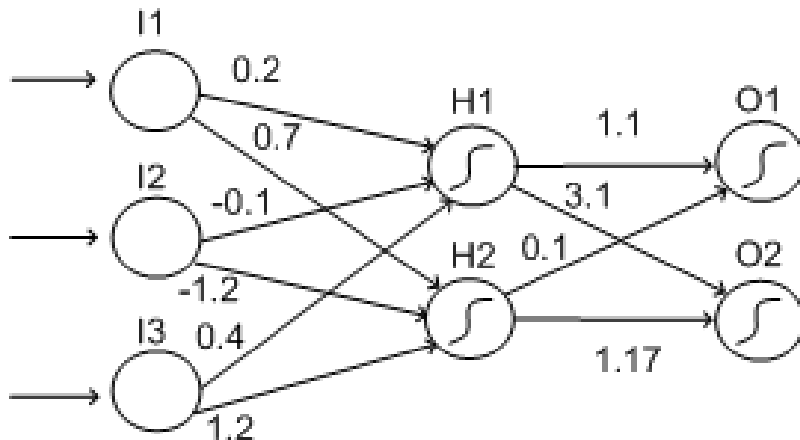
- Receives one or more inputs, **sums these according to their weights and produces an output** after passing the sum through the **activation function**.



- The weight of inputs are modified to match the desired output. Therefore capable of **learning**.

Multi-layer Neural Networks

- A network is **trained** over a set of samples by adjusting the weights of interconnections using **back propagation**.



- A trained network is then used to classify future inputs according to their similarity with the training sample.

[Why Artificial Neural Networks]

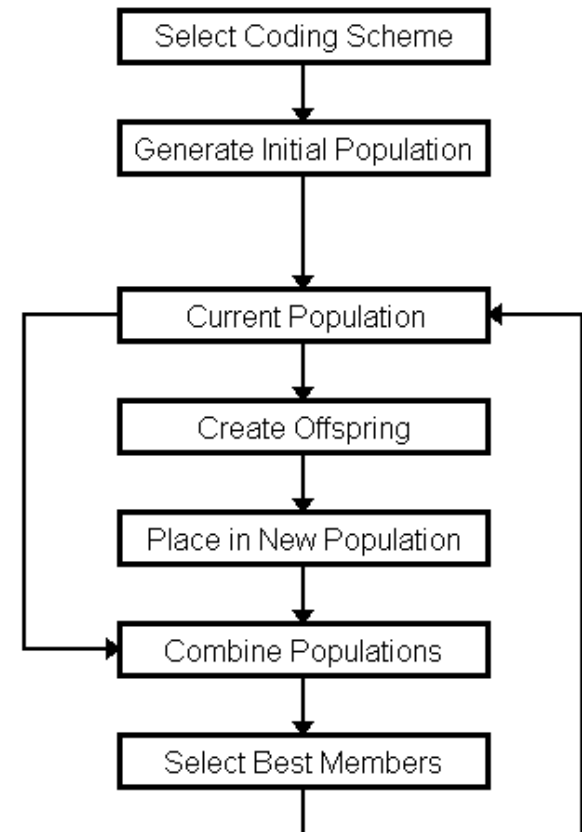
- ANNs do not require any assumptions on underlying statistics of the environment like classic pattern recognition algorithms.
- ANNs are can effectively address a broad class of problems.
- ANNs have an intrinsic fault tolerance: Network can perform well in overall even if some neurons may fail.

[Problems with ANNs]

- Back propagation uses a ***gradient search*** in order to minimize the error between actual and target outputs which does not guarantee to find the global minimum. Solutions for local minimum:
 - Avoid the problem and restart with a random set of weights
 - Perturb the weights and continue training
 - Some methods are successful at overcoming local optima but require large execution times.
 - Evolutionary Programming

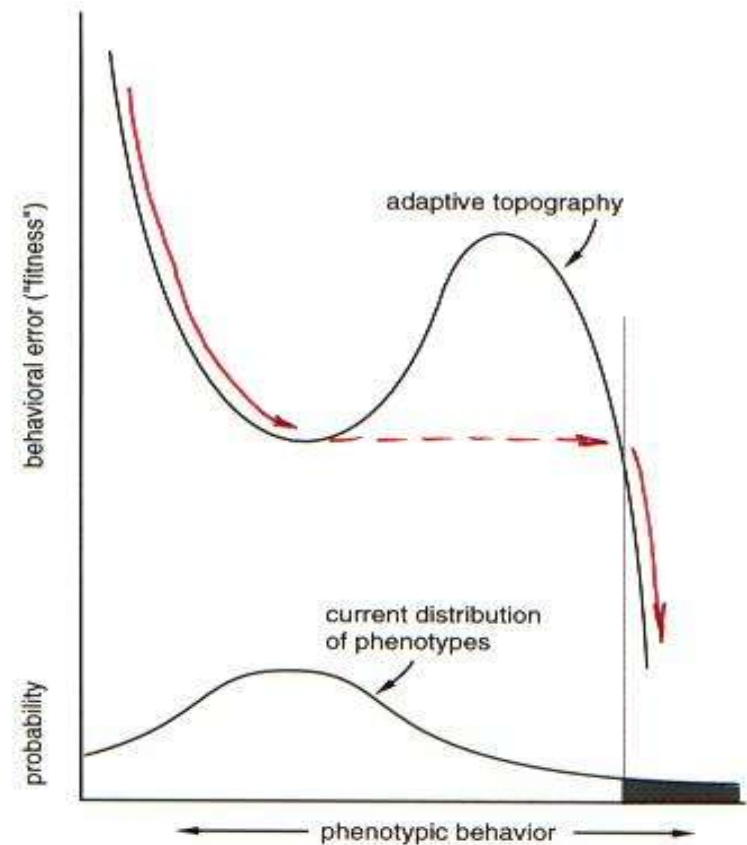
Evolutionary Programming

- An original population of “machines” are measured by their ability to predict next event w.r.t. a payoff function.
- Offspring are created through random mutation of “parents”.
- Offspring are scored on their predictive ability as their parents.
- Machines that are most suitable for the task at hand are probabilistically selected to become new parents.
- An actual prediction is made and surviving machines become parents of the next generation.



[Adaptive Topography]

- Wright introduced the concept (1932) which describes the ***fitness of the organisms***.
- It is the mapping of genotypes to their respective phenotypes. Each peak in the curve represent an optimized phenotype.
- Adaptive topography is subject to change w.r.t. the environment.



Applying Evolutionary Programming to train ANNs

- ***Adaptive topography*** is applied to minimize the error while evolution is proceeding.
- Mutation and selection is ***performed on the weights and bias terms*** of the network rather than the state machines.
- At each generation a population of vectors whose components are the weight and bias terms is maintained.
- Each vector has a corresponding error score. The ***ones with the smallest error score are selected*** to become parents of next generation.

[An Example]

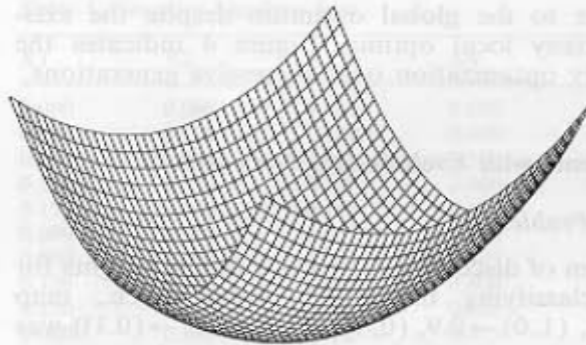


Fig. 1. $F(x, y) = x^2 + 2y^2 - 0.3 \cos(3\pi x) - 0.4 \cos(4\pi y) + 0.7$. $x, y \in [-50, 50]$

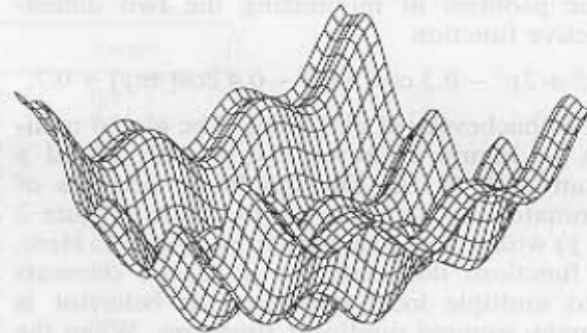
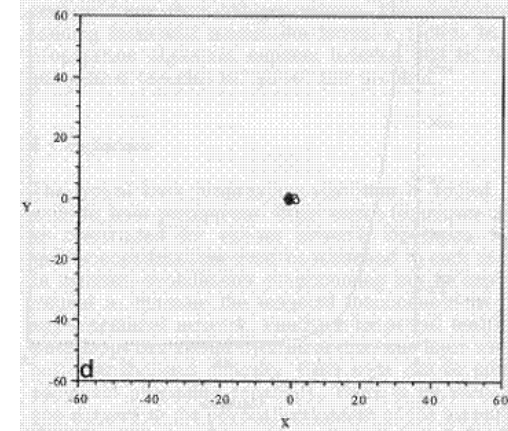
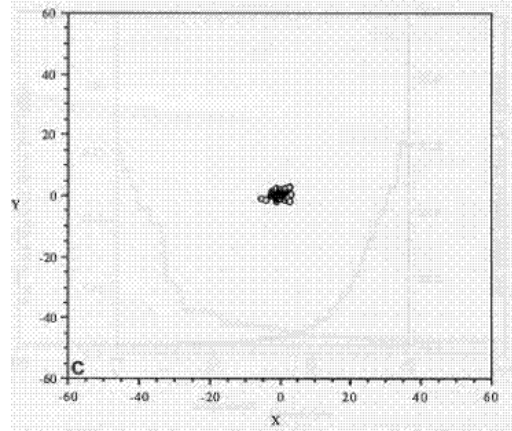
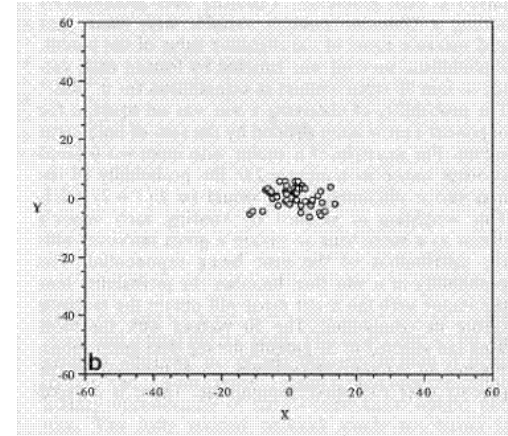
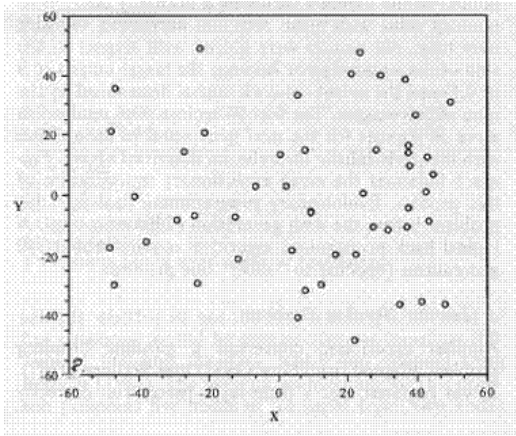


Fig. 2. $F(x, y) = x^2 + 2y^2 - 0.3 \cos(3\pi x) - 0.4 \cos(4\pi y) + 0.7$. $x, y \in [-1, 1]$

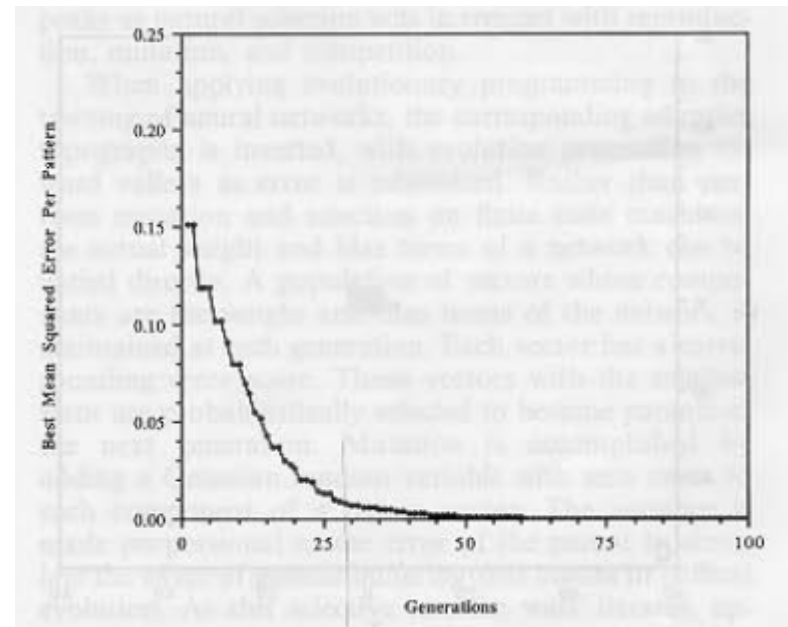
- A set of 50 parent vectors were maintained at each generation to minimize $F(x, y)$.
- For each vector to survive it has to compete 10 other vectors for a win.
- $(\text{opponents error} / (\text{opponents error} + \text{self error}))$

[An Example (cont'd)]



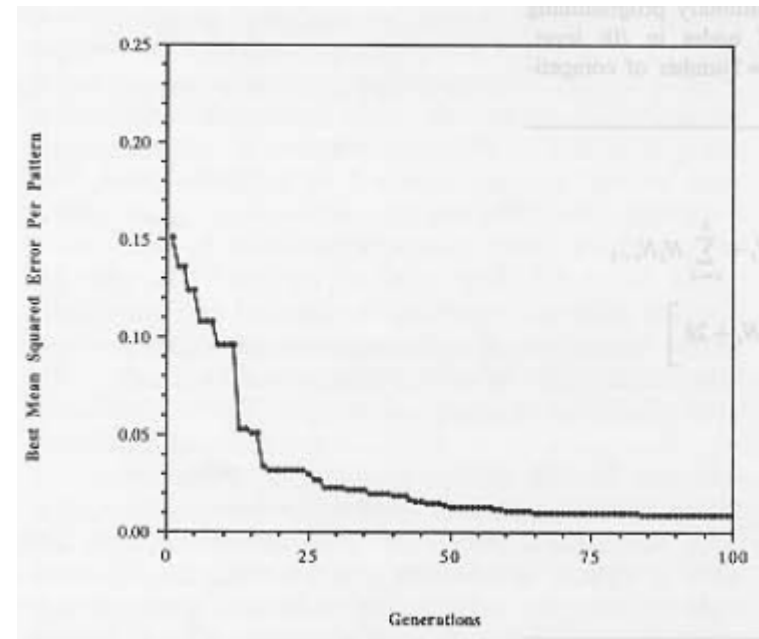
[XOR Problem]

- A multilayer perceptron with 1 hidden layer was used.
- A population of 50 parent vectors were initialized randomly.
- Evolutionary programming solved this problem before 40th generation while back propagation requires 240.



[A Gasoline Blending Problem]

- Identify if octane rating of a blend of 5 chemicals is equal to 100 using a multilayer perceptron with 2 hidden layers.
- Fully trained network made no errors in classification.
- Appropriate set of weights was discovered fewer than 100 generations while back propagation requires 400 to 500 epochs.



[Conclusion]

- Evolutionary programming ***can be implemented to optimize the weighted interconnections of any generalized network***. Back propagation is limited to certain topologies.
- ***Real world pattern classification problems are typically contain multiple optima***. Back propagation guarantees to find local one and needs to be restarted with random points or additional nodes in case of unsatisfactory performance.
- In back propagation, it is ***possible to overdefine*** the network.

[Conclusion]

- Evolutionary programming ***offers a parallel search which can overcome local optima.***
- Although Evolutionary programming is more costly than back propagation per iteration, overall performance is almost the same because evolutionary algorithm requires fewer iterations.