Training neural networks using swarm intelligence

Swarm intelligence

- deals with natural and artificial systems composed of many individuals
- coordinate using decentralized control and self-organization
- focuses on the collective behaviors that result from the local interactions of the individuals with each other and with their environment
- colonies of ants and termites, schools of fish, flocks of birds, herds of land animals

Properties of swarm system

- composed of many individuals, that are relatively homogeneous (identical or they belong to a few typologies)
- interactions are based on simple behavioral rules that exploit only local information that the individuals exchange directly or via the environment
- overall behavior of the system results from the interactions, that is, the group behavior self-organizes

Properties of swarm system

- scalability – system can maintain its function while increasing its size without the need to redefine the way its parts interact
- parallel action – individuals composing the swarm can perform different actions in different places at the same time
- fault tolerance – failing individual can be easily dismissed and substituted by another one that is fully functioning

Taxonomy

- two dominant sub-fields:
- Ant Colony Optimization
  – inspired by stigmergy and foraging behavior of ants
- Particle Swarm Optimization
  – inspired by flocking, schooling and herding
- like evolutionary computation they are adaptive strategies and typically applied to search and optimization domains

Optimization

- optimization problem $P \rightarrow$ triple (S, Ω, f)
- S is the search space defined over a finite set of decision variables X_i, $i = 1, \ldots, n$
- Ω is a set of constraints among the variables
- $f : S \rightarrow R^+$ is objective function that assigns a positive cost value to each solution of S
- goal – find a solution $s \in S$ such that:

$f(s) \leq f(s), \forall s \in S$ (f minimization)

$f(s) \geq f(s), \forall s \in S$ (f maximization)

Ant Colony Optimization (ACO)

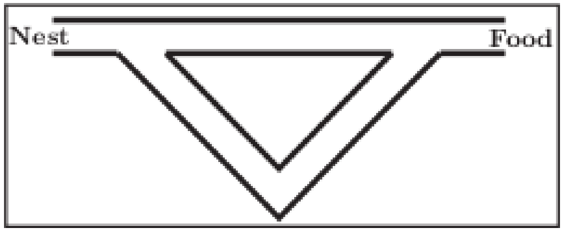
- one of the first techniques for approximate optimization inspired by swarm intelligence

  (M. Dorigo, early 1990s)
- based on foraging behavior of ant colonies
- core of behavior is indirect communication between the ants by means of chemical pheromone trails
- this enables them to find short paths between their nest and food sources

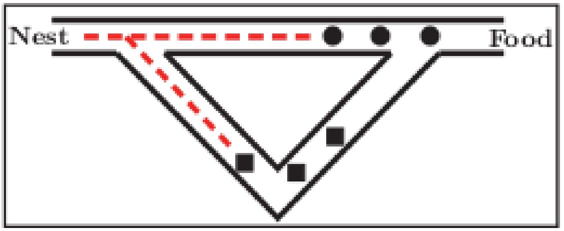
ACO metaphor

- ants initially wander randomly around their environment
- once food is located an ant will begin laying down pheromone in the environment
- numerous trips between the food and the colony are performed (pheromone laying)
- pheromone decays in environment, so that older paths are less likely to be followed
- a positive feedback process routes more and more ants to productive paths

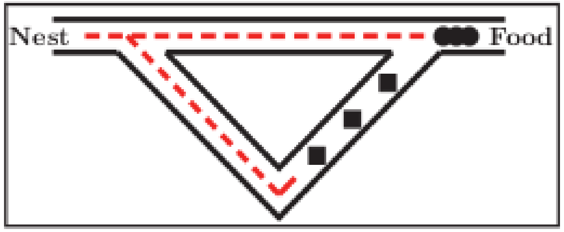
ACO illustration



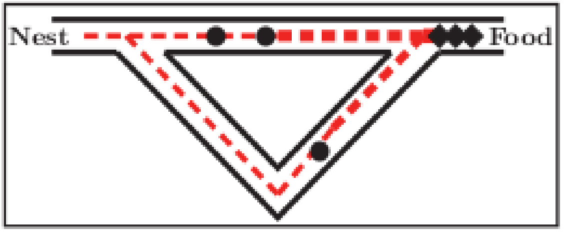
(a) All ants are in the nest. There is no pheromone in the environment



(b) The foraging starts. In probability, 50% of the ants take the short path (see the circles), and 50% take the long path to the food source (see the rhombs)



(c) The ants that have taken the short path have arrived earlier at the food source. Therefore, when returning, the probability that they again take the short path is higher



(d) The pheromone trail on the short path receives, in probability, a stronger reinforcement, and the probability of taking this path grows. Finally, due to the evaporation of the pheromone on the long path, the whole colony will, in probability, use the short path

Bees Algorithm (BA)

- Dervis Karaboga, 2005
- inspired by the foraging behavior of honey bees
- honey bees collect nectar from flower patches as a food source for the hive
- in multiple directions simultaneously from vast areas around their hive (more than 10km)
- performs a kind of neighborhood search combined with random search

BA Metaphor

- the hive sends out scouts that locate patches of flowers, that then return to the hive
- they inform other bees about the fitness and location of a food source via a waggle dance
- the scout returns to the flower patch with follower bees
- small number of scouts continue to search for new patches, while bees returning from flower patches continue to communicate the quality of the patch

SWIRL

- SWarm Intelligence-based Reinforcement Learning
- neural network can be presented as graph with weights, so that:
  - ACO can be utilized to topology selection (neurons count in layers)
  - PSO can be utilized to weights optimization
- → ACO algorithm allocates training iterations to the PSO algorithm
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SWIRL neural network training

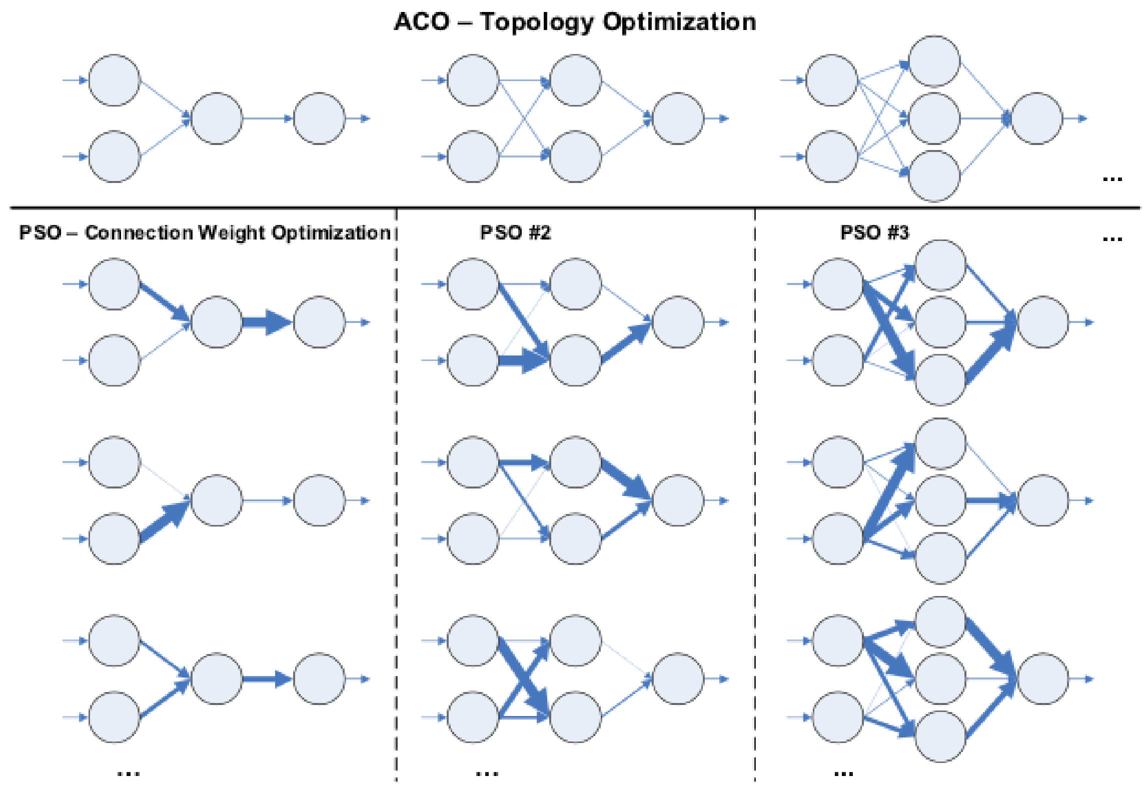

Fig. 1. SWIRL overview. The ACO algorithm is used to select the ANN topology. This is shown as a horizontal list of topologies under consideration at the top of the diagram. A separate instance of the PSO algorithm is used to optimize the connection weights for a particular topology. This is depicted as a vertical list of successive configurations, where the arrow thickness is used to indicate the connection weight.

SWIRL performance

PERFORMANCE COMPARISON OF DIFFERENT ALGORITHMS SOLVING THE DOUBLE POLE BALANCE PROBLEM

Method	Total Evaluations	Generations/Iterations
Evolutionary programming	307200	150
Conventional Neuroevolution	80000	800
SANE	12600	63
ESP	3800	19
NEAT	3600	24
SWIRL	3516	15

Thank you for your attention

Any questions...??

Sources

- Blum, C.; Li, X.: *Swarm Intelligence in Optimization*. 2008, Springer
- Karaboga, D.; Basturk, B.: *A powerful and efficient algorithm for numerical function optimization: artificial bee colony algorithm.* 2007, Springer
- Conforth, M.; Meng, Y.: *Reinforcement learning for neural networks using swarm intelligence*. 2008, IEEE Swarm Intelligence Symposium