Ant Colony Optimization with Castes

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Content

1) Ant Algorithms

2) ACO & Applications

3) ACO with Subsolutions

4) ACO with Castes

5) Continuous ACO

1) ANT ALGORITHMS

Clustering *(ACA, ATTA, ACLUSTER, DataBots, Cellular Ants,...)*

Combinatorial Optimization *(ACO, MMAS, AS, ...)*

Continuous and mixed-variable optimization *(ACO*, DACO, AACA, BACA, ...)*

Classification Rules Extraction *(Ant-Miner)*

Feature Extraction

Robotics

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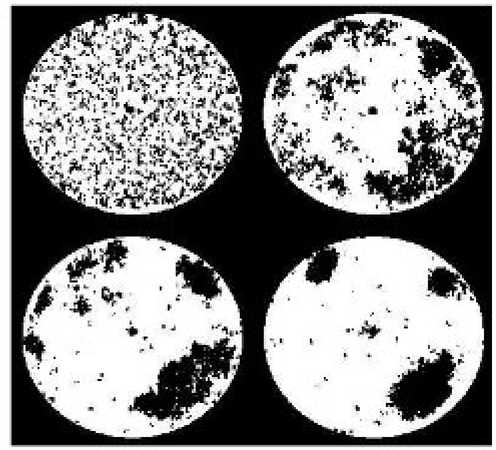
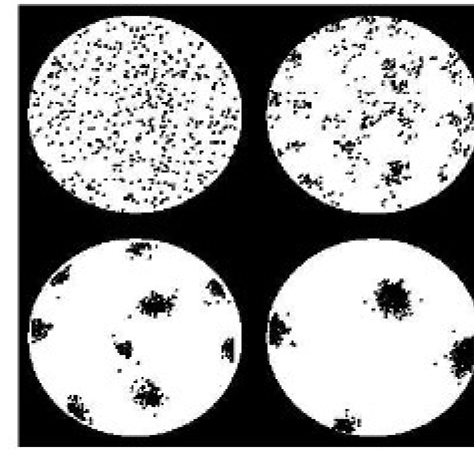
Clustering

Real and simulated ant clustering



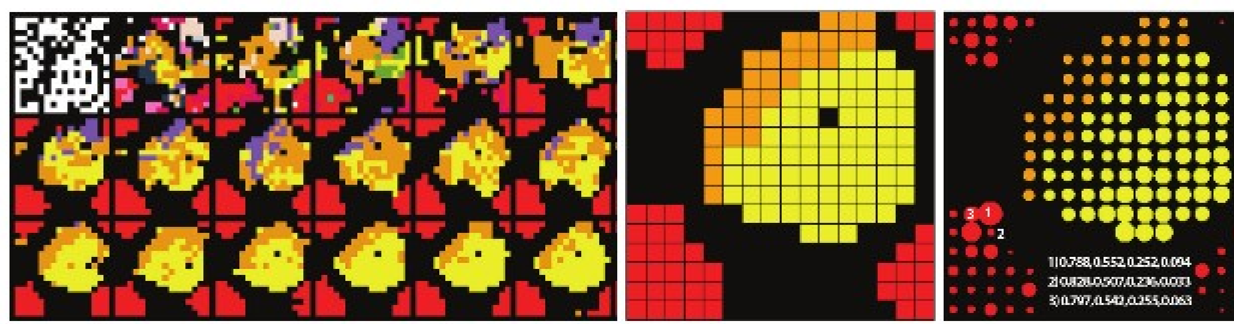


http://code.ulb.ac.be

Cellular ants

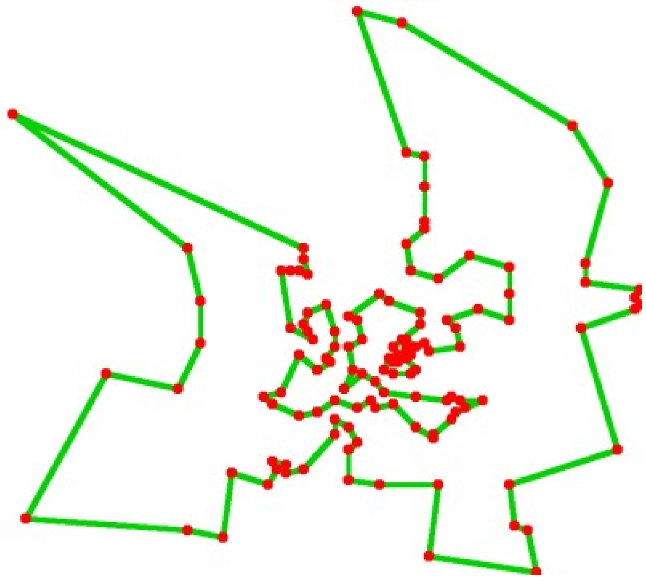
Color and shape negotiations

automatic number of classes, similarity



Moere et al. (2006)

Combinatorial Optimization

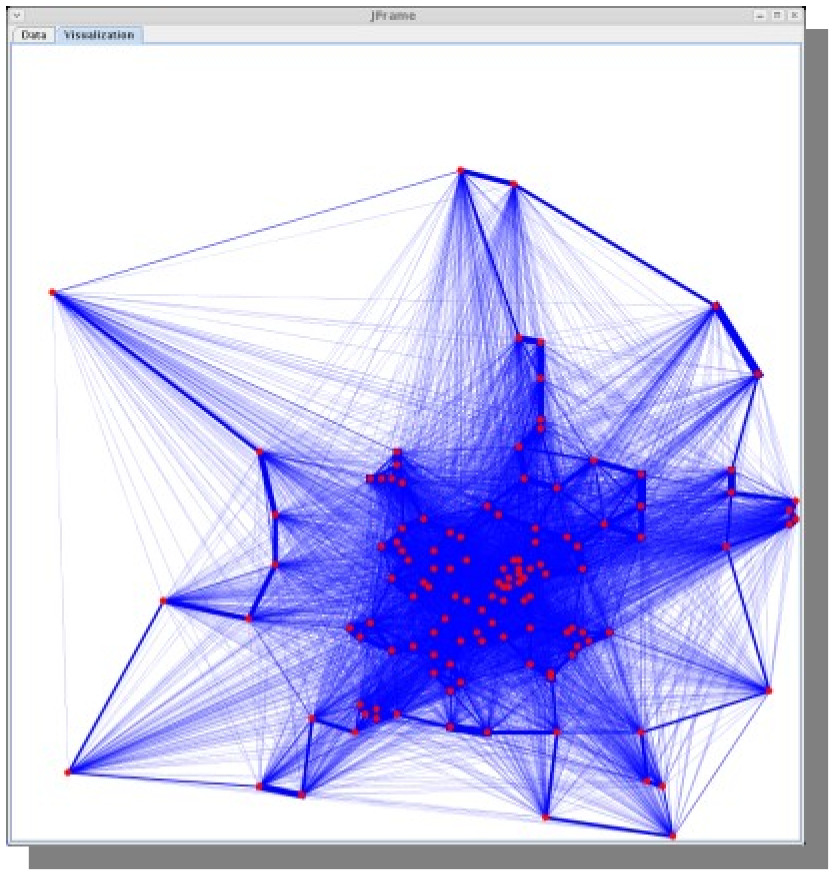


Bruce G. Marcot

TSP, VRP, Quadratic assignment, Job-shop sheduling, Sequential ordering, Graph coloring, Bin packing, Shortest common subsequence, ...

+ dynamic problems like Network Routing or Network Flows

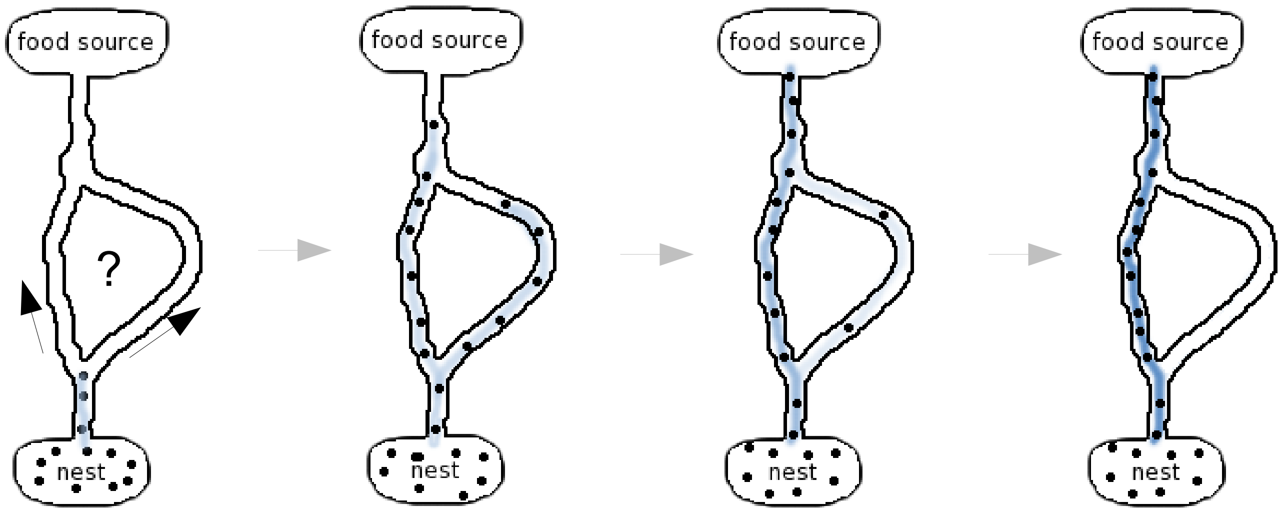
2) ANT COLONY OPTIMIZATION



ACO (Dorigo)

Ant Colony Optimization metaheuristic

- parallel stochastic search
- probability guided by pheromone
- updated by feedback and evaporation

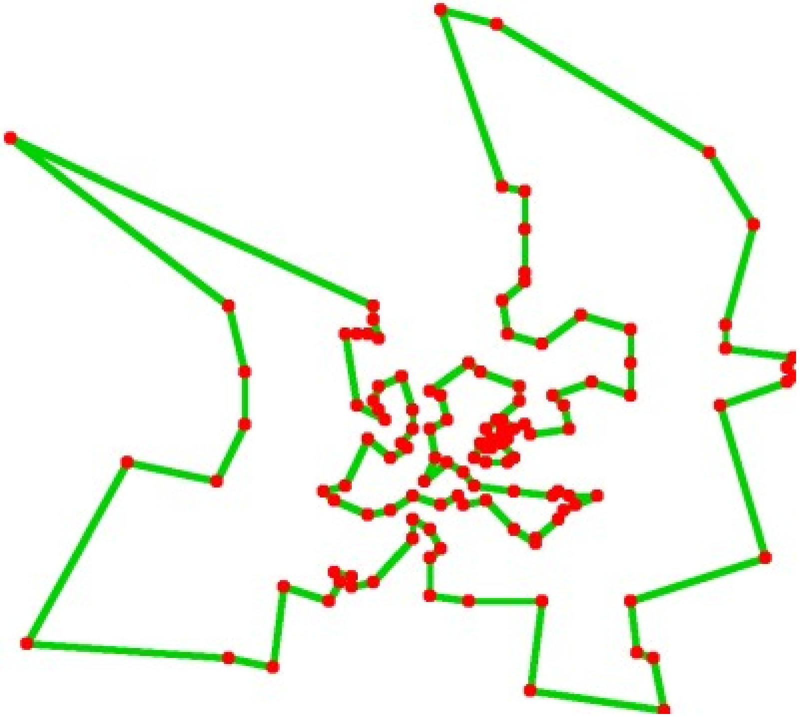


TSP

Travelling Salesman Problem

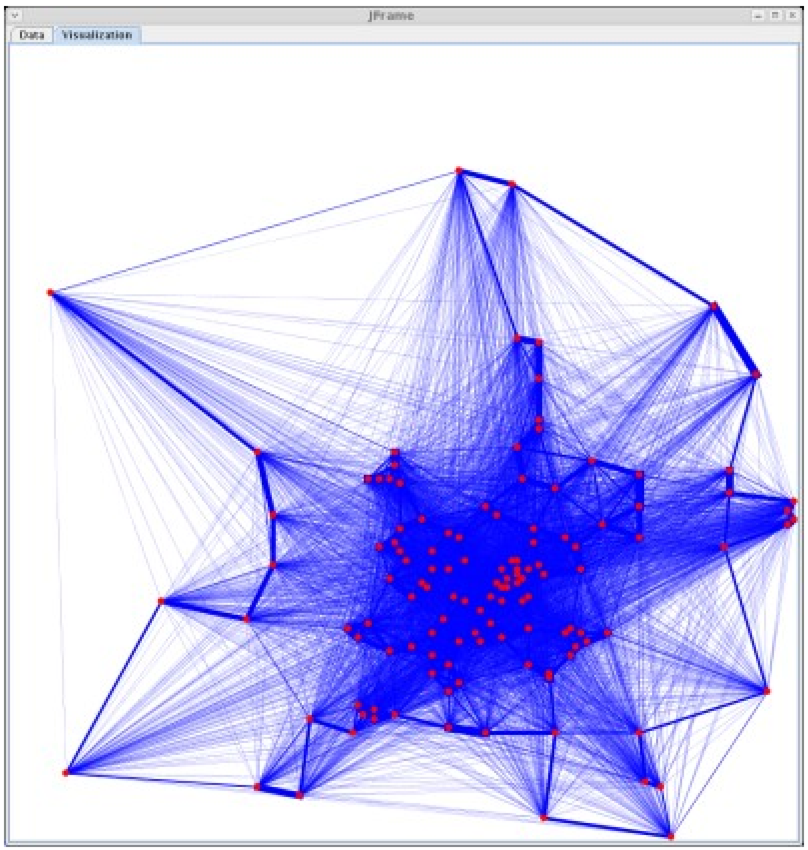
– the shortest closed simple path through given cities

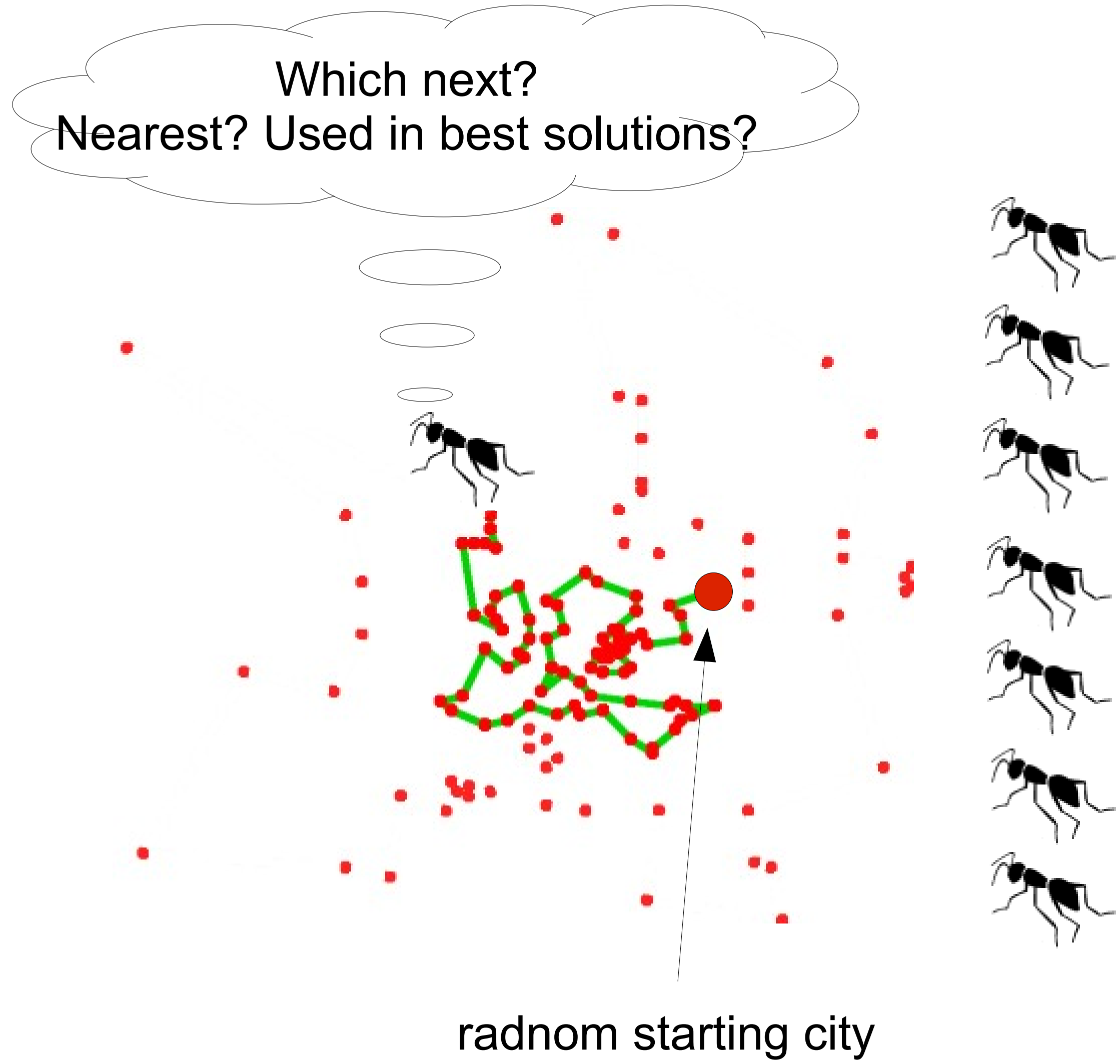
– NP-complete



ACO - path construction

Pheromone map





Max-Min Ant System (MMAS)

Probability of choosing path from city i to city j

$$p_{ij}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{j \in allowed} [\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}} & \text{if } j \in allowed \\ 0 & \text{otherwise} \end{cases}$$

pheromone level
memory

distance^{-1}
heuristic

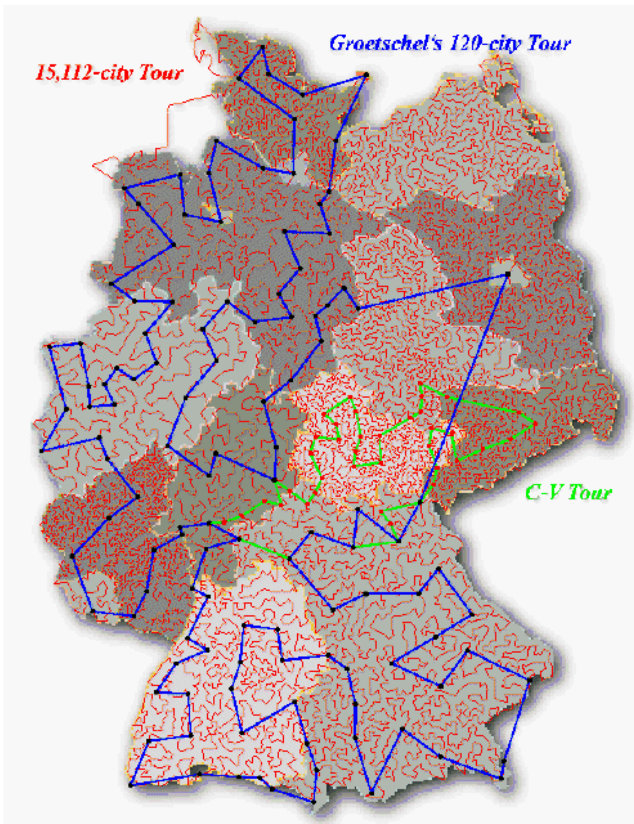
Update by best solution & evaporation

$$\tau_{ij}(t+1) = \rho \cdot \tau_{ij}(t) + \Delta\tau_{ij}(t)$$

depends on inclusion in best tour

Logistics, Circuit Boards

Travelling Salesman, Vehicle Routing, ...



http://www.tsp.gatech.edu

Circuit Boards Drilling (Laser)

http://www.stevenagecircuits.co.uk

Phylogenetic trees

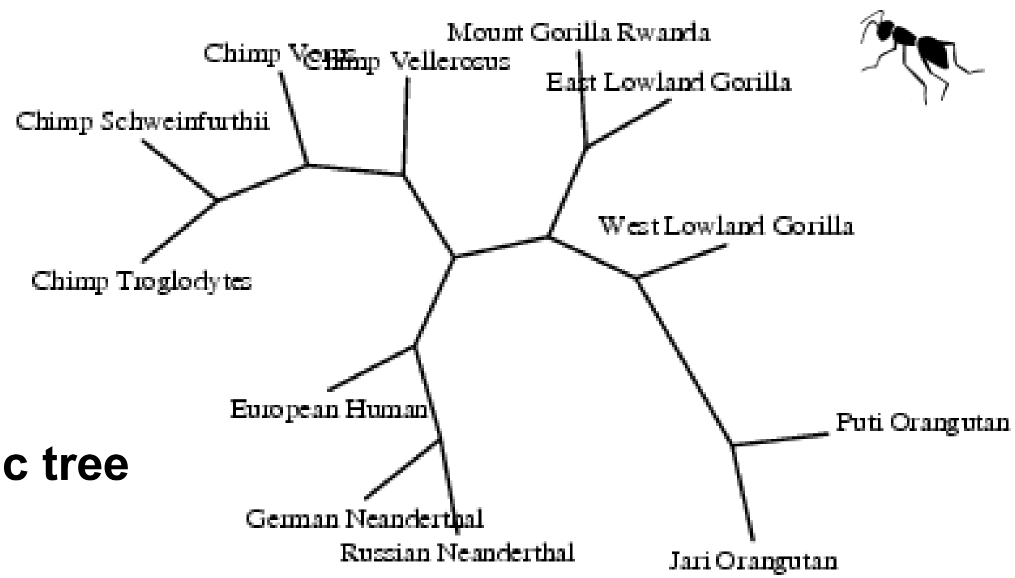
DNA

ACTCGTATCGTGTATGTGCTA ...
CACGACAGGTCTTGCTACATT ...
GGGCTCGCATACATTACTATA ...

1	2	3	4	5	6	7	8	9	10	11	12		
0.00	3.48	8.06	31.52	32.07	19.71	19.17	17.40	24.75	24.42	28.81	18.16	German_Neanderthal	1
	0.00	7.32	31.16	31.04	18.62	18.07	16.87	22.22	21.48	28.62	16.67	Russian_Neanderthal	2
		0.00	29.00	29.88	17.07	17.42	18.32	21.68	20.63	25.61	18.18	European_Human	3
			0.00	0.58	31.93	31.12	31.12	32.73	33.09	35.02	29.82	Puti_Orangutan	4
				0.00	32.53	31.72	31.72	33.83	34.20	35.82	30.06	Jari_Orangutan	5
					0.00	5.90	11.80	21.80	21.43	29.06	11.31	Chimp_Troglodytes	6
						0.00	10.06	20.38	20.75	29.17	8.66	Chimp_Schweinfurthii	7
							0.00	23.02	21.89	28.41	8.66	Chimp_Verus	8
								0.00	5.08	15.99	16.57	Mountain_Gorilla_Rwanda	9
									0.00	15.45	16.57	Eastern_Lowland_Gorilla	10
										0.00	22.55	Western_Lowland_Gorilla	11
											0.00	Chimp_Vellerosus	12

Similarity matrix

ACO on TSP



Phylogenetic tree

3) ACO WITH SUBSOLUTIONS

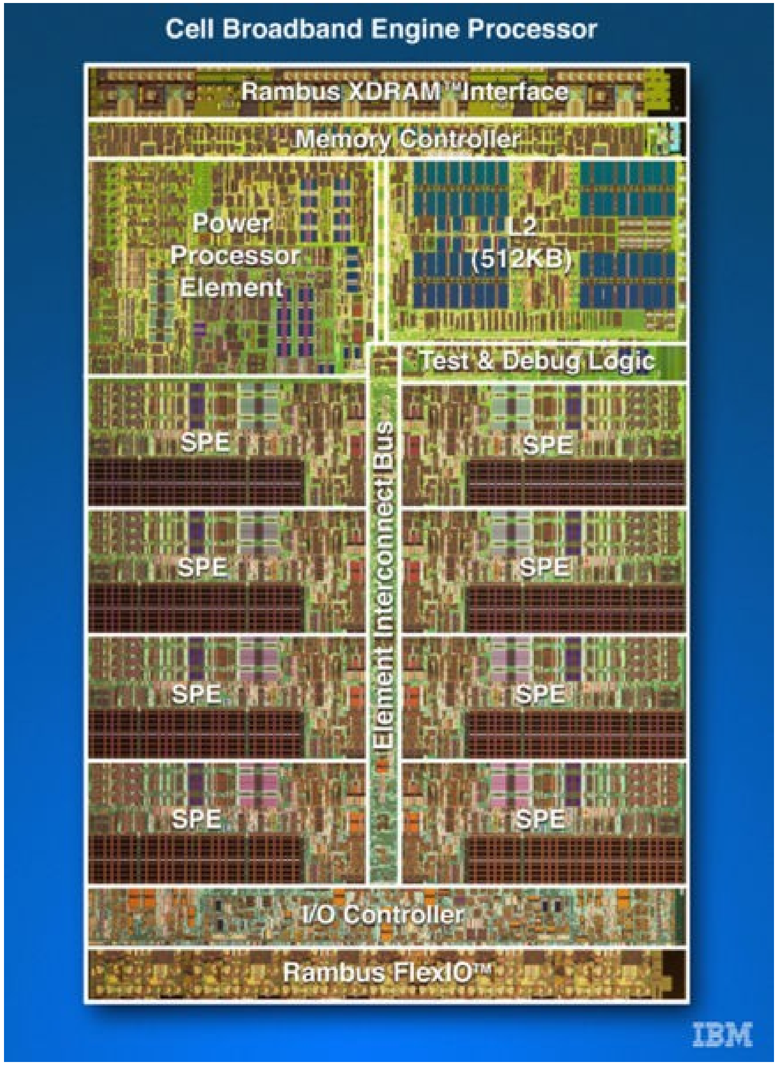
Parallelization on Cell

Cell Broadband Engine

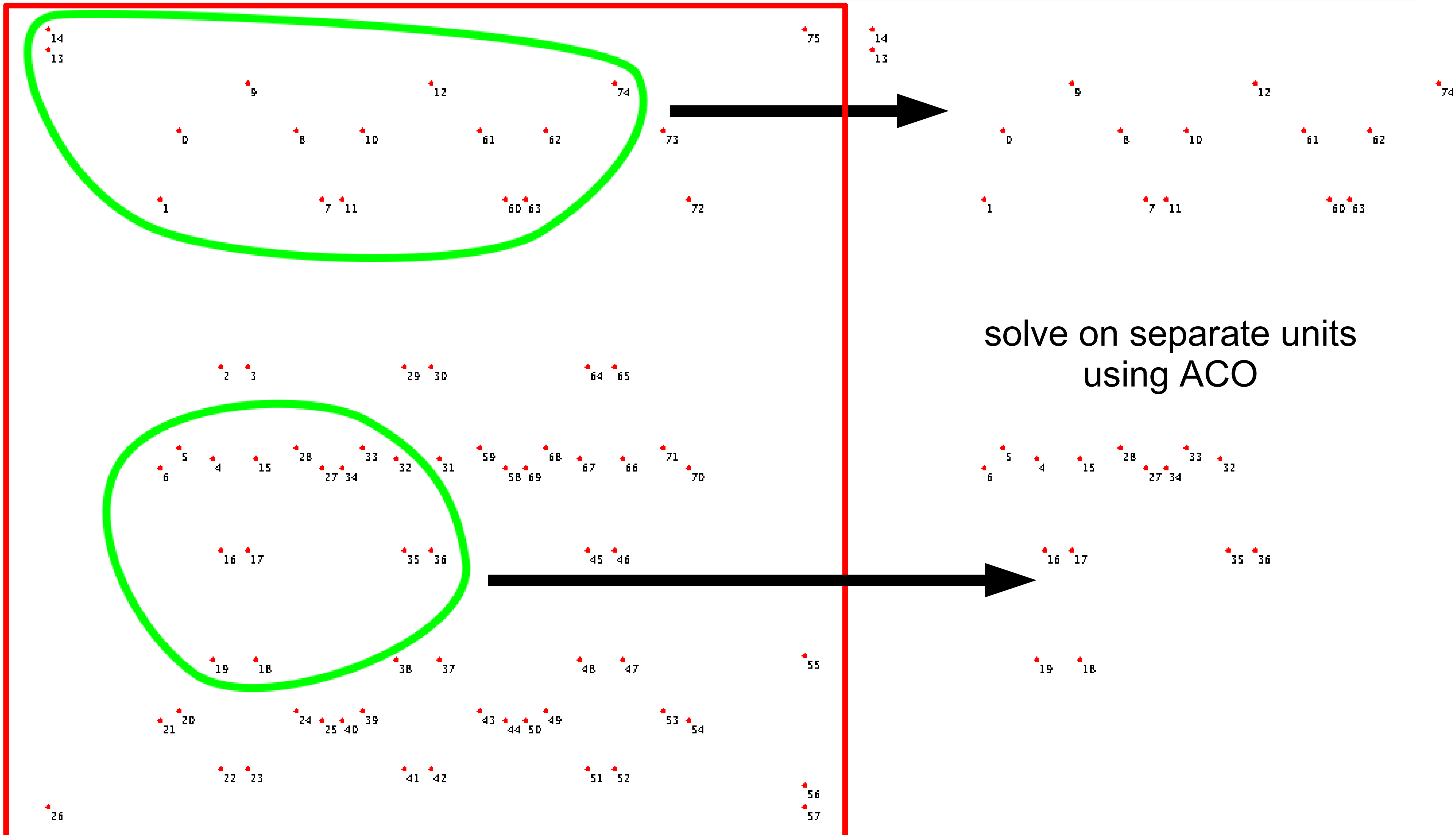
Processor

1 x PPE

8 x SPE

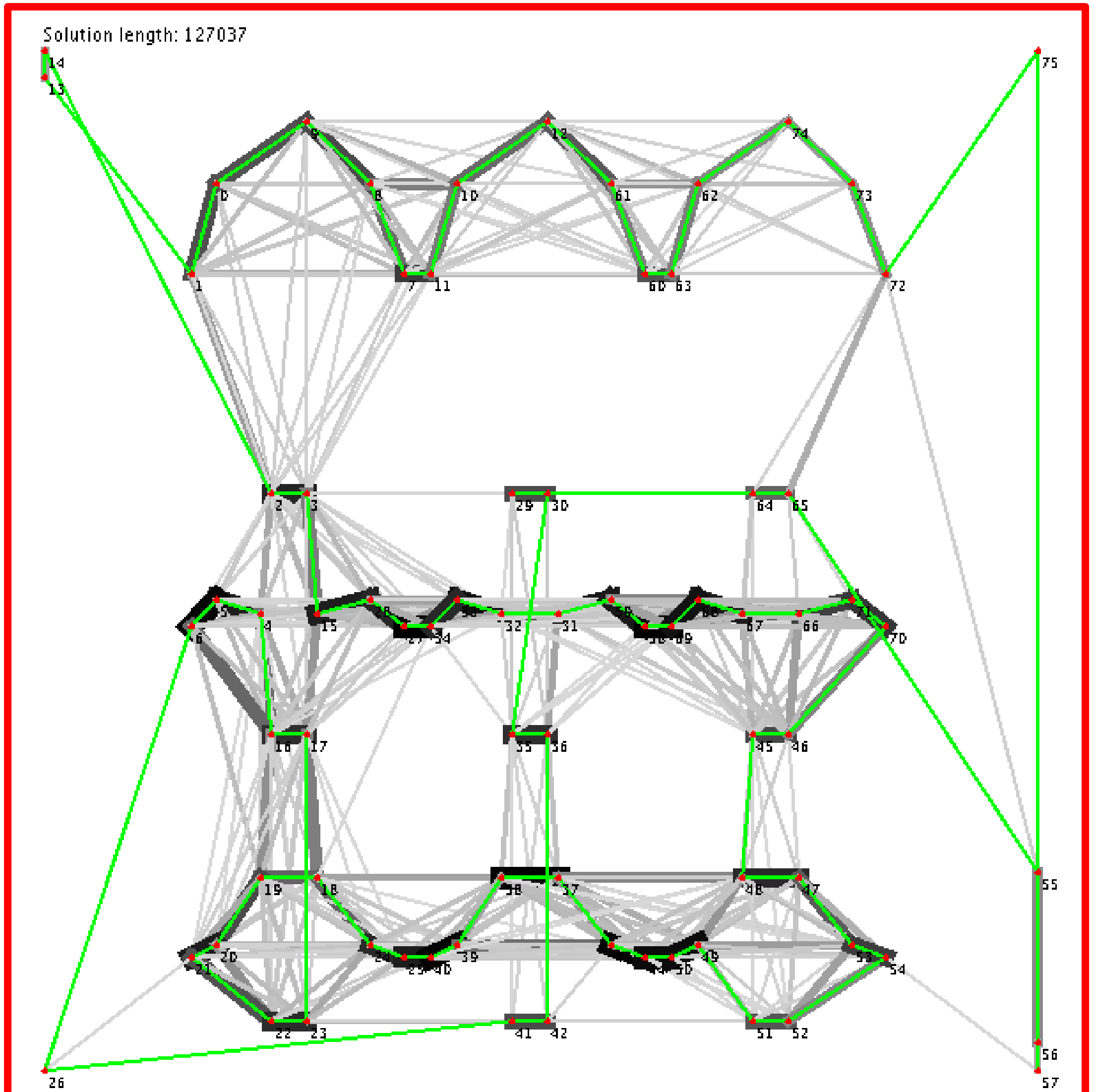


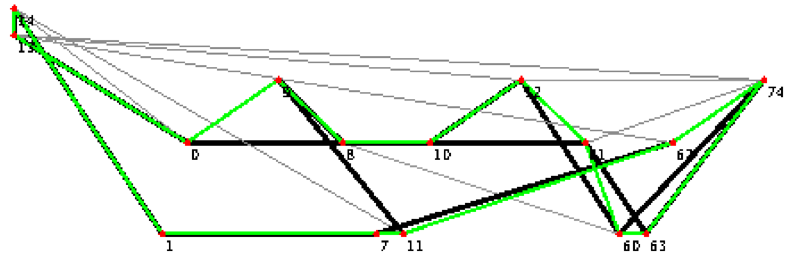
Step 1: Select Subsets of Cities



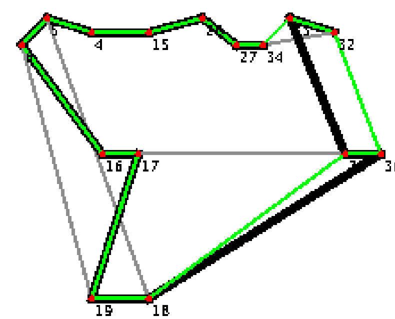
solve on separate units using ACO

Step 2: Solve & Return Pheromone

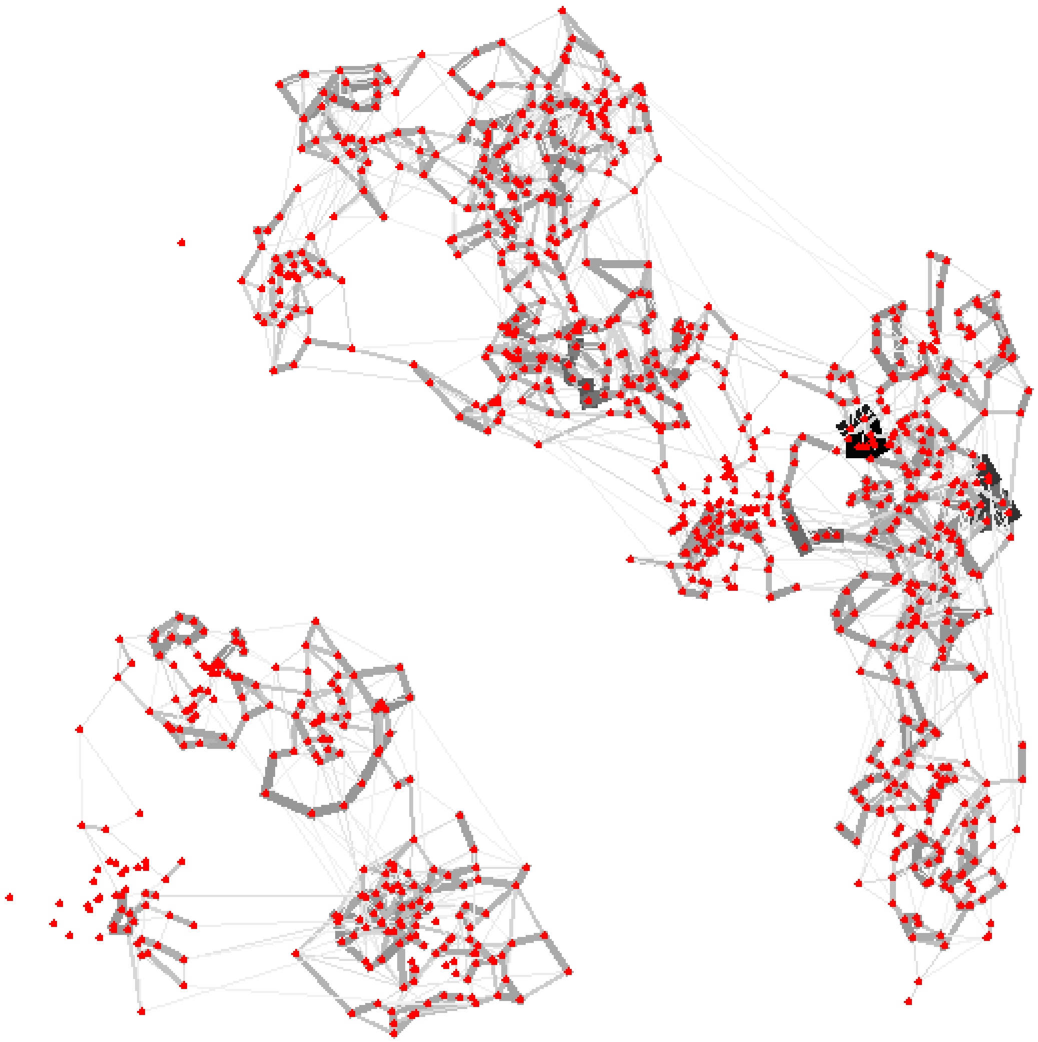




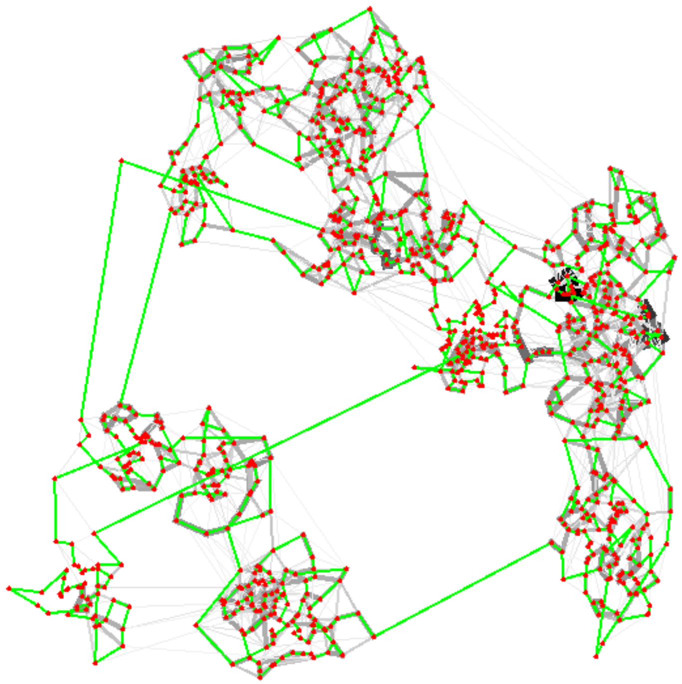
merge pheromone matrices



Pheromone Map for 1000 Cities



with one solution:

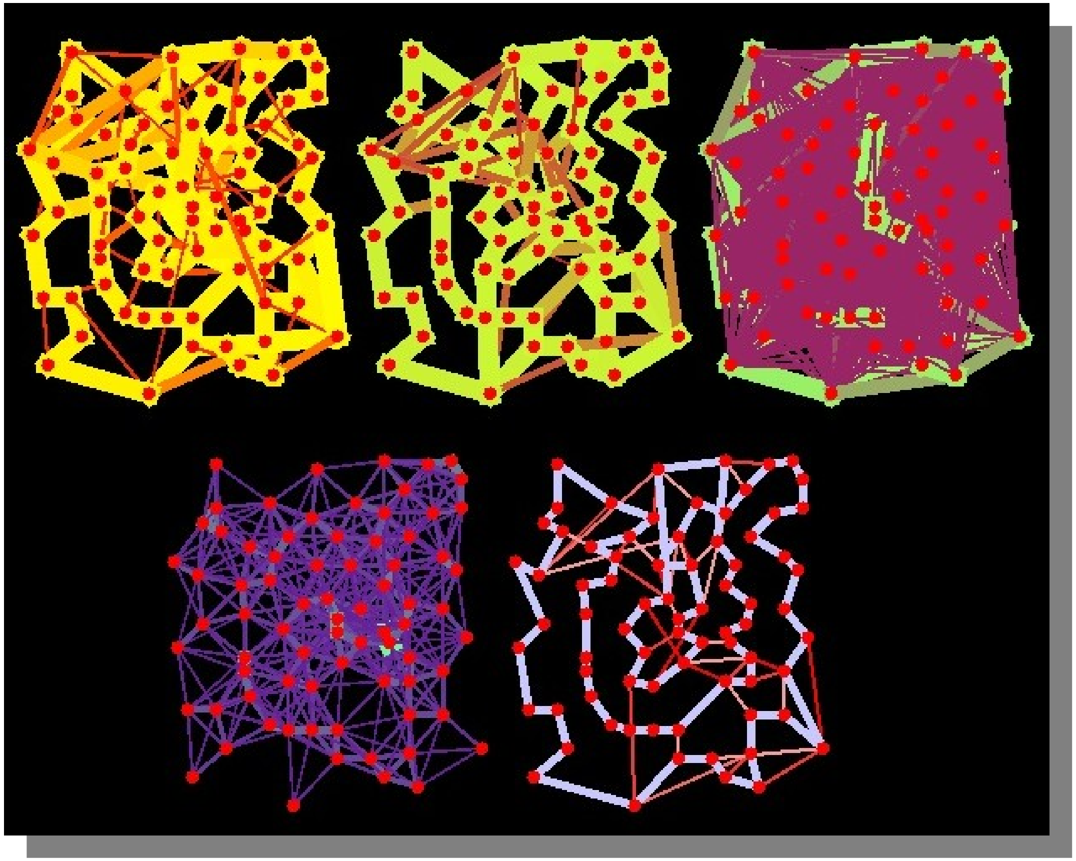


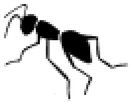
Results

Dataset	eil51	pr76	rat99
Greedy solution	482	130921	1437
Optimal solution	426	108159	1211
ACO+subsolutions	449	118644	1318
% above optimum	5.4	9.7	8.8

Dataset	kroA100	lin105	bier127
Greedy solution	24698	16935	128726
Optimal solution	21282	14379	118282
ACO+subsolutions	22922	15262	125809
% above optimum	7.7	6.1	6.4

4) ACO WITH CASTES





Problem with Optimal Parameters

Probability of choosing path from city i to city j

$$p_{ij}(t) = \begin{cases} \frac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{j \in allowed} \underbrace{[\tau_{ij}(t)]^{\alpha}}_{\text{pheromone level}} \cdot \underbrace{[\eta_{ij}]^{\beta}}_{\text{distance}^{-1}}} & \text{if } j \in allowed \\ 0 & \text{otherwise} \end{cases}$$

We can search for optimal parameters (problem dependent)

Adapt parameters

OR

ACO+C: Ant Castes

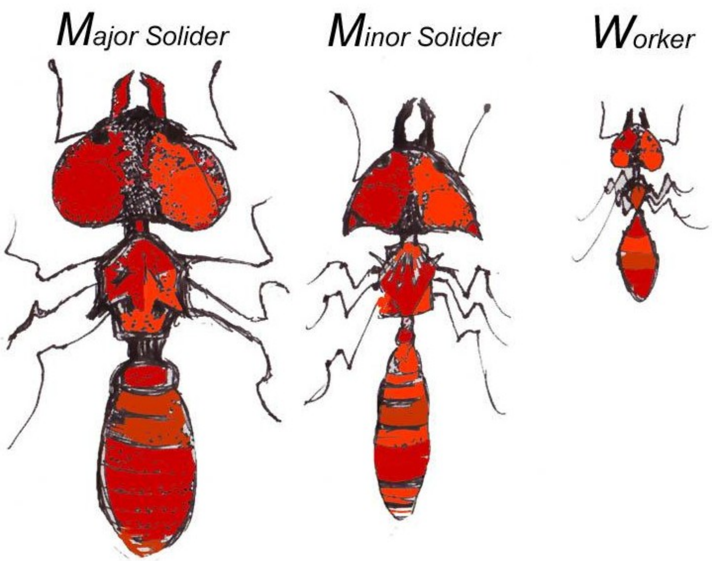
Specialization of ants -> castes

different behaviour

(workers, explorers, ...)

several kinds of pheromone

(attractive vs. repulsive)



Example: MMAS+C

Castes with different parameters α_l, β_l

Probability of choosing city for *l*-th caste

$$p_{ij}^{l}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha_l} \cdot [\eta_{ij}]^{\beta_l}}{\sum_{j \in allowed} [\tau_{ij}(t)]^{\alpha_l} \cdot [\eta_{ij}]^{\beta_l}} & \text{if } j \in allowed \\ 0 & \text{otherwise} \end{cases}$$

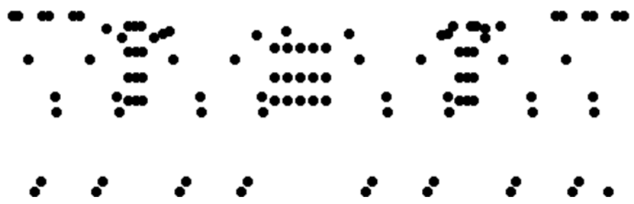
Different beaviour for each caste

Data

8 TSP, 3 Assymetric TSP from TSPLIB

Real cities, drilling problems:

eil101.tsp



lin105.tsp

pr107.tsp

MMAS vs. MMAS+C

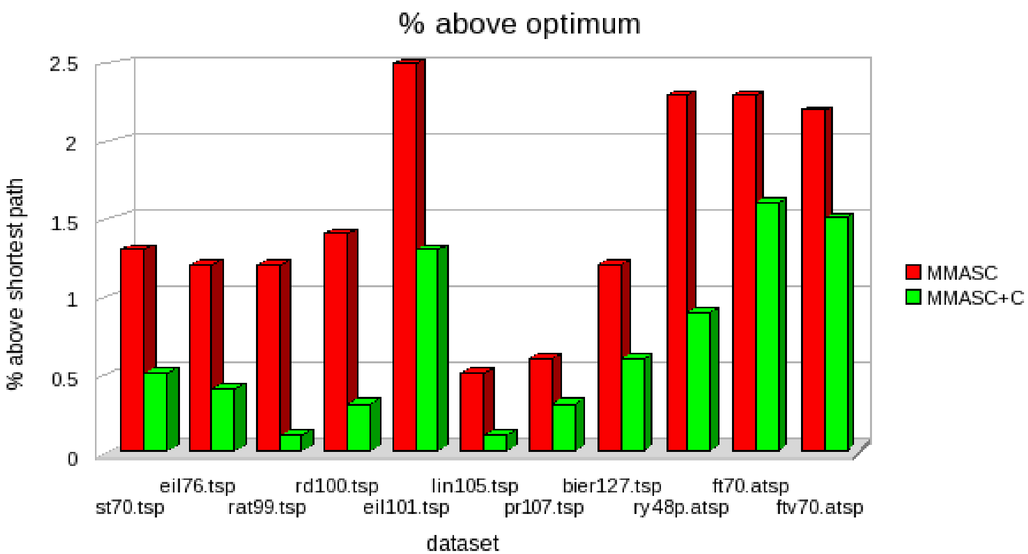
caste	1
α	1.0
β	1.0

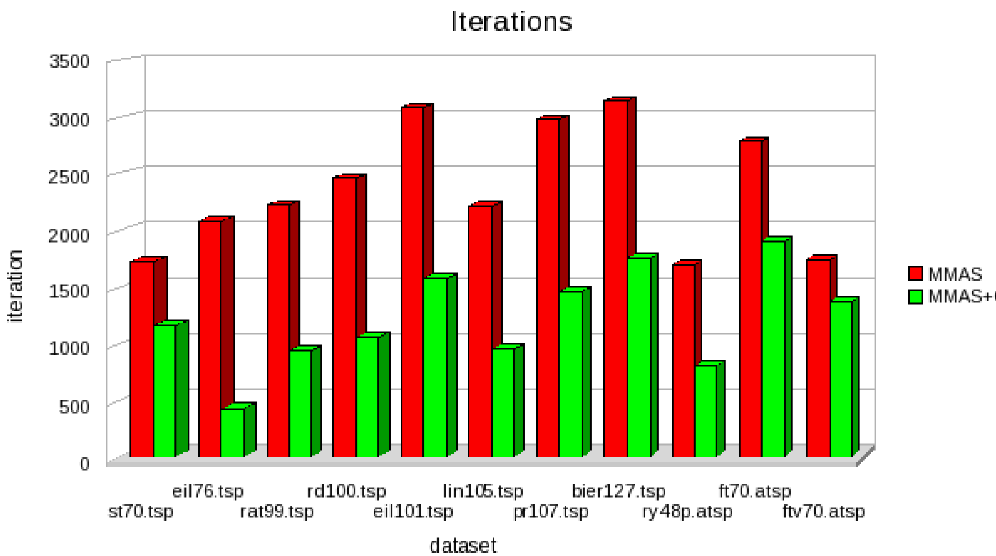
MMAS

caste	0	1	2	3	4	5	6	7	8	9
α	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
β	9.0	8.0	7.0	6.0	5.0	4.0	3.0	2.0	1.0	-1.0

MMAS+C (10 castes)

Averages from 30 runs, lower = better:

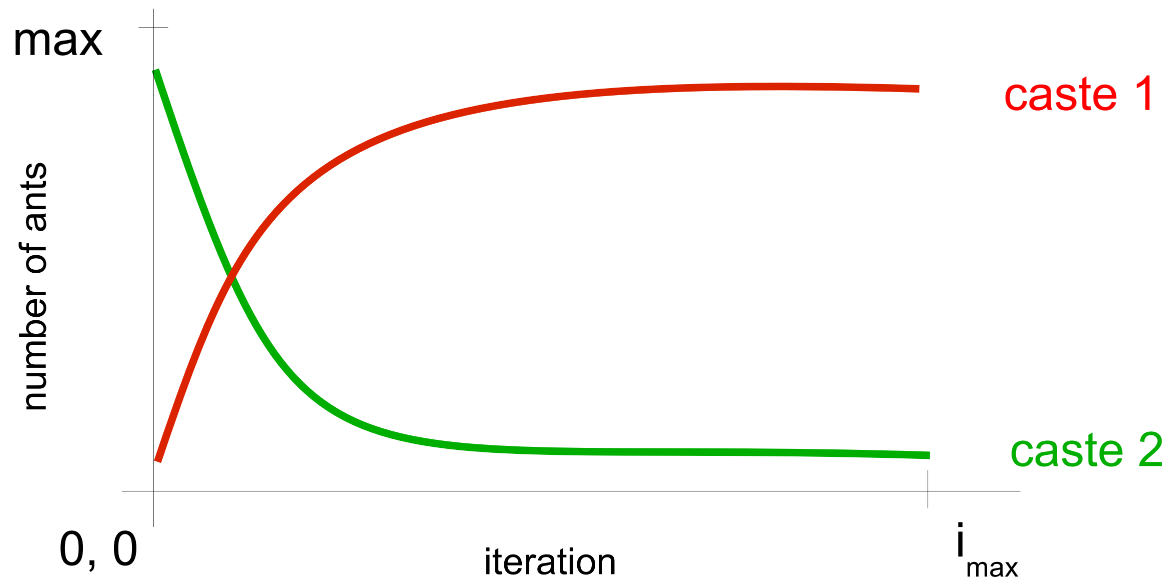




Adaptive castes

Dynamic number of ants in castes

Depends on number of improvements

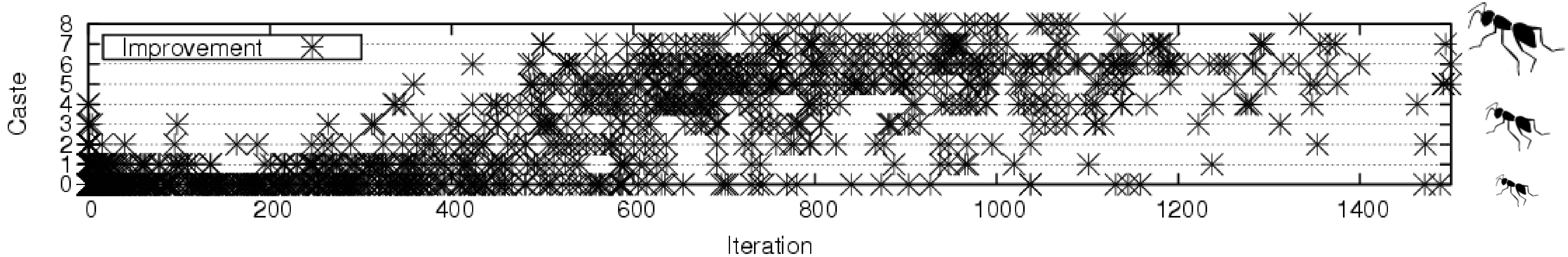


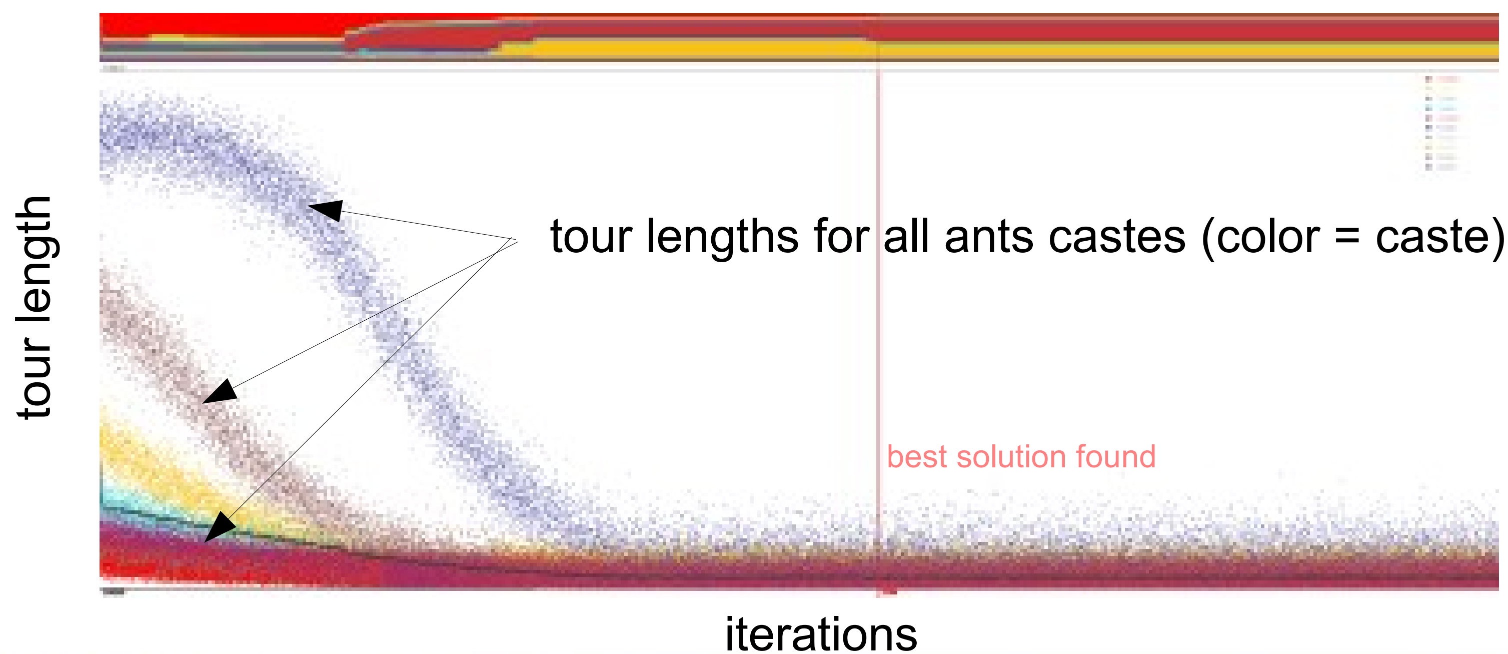
Improvement not significant (larger problems?)

Dynamics

<- strong nearest distance heuristric

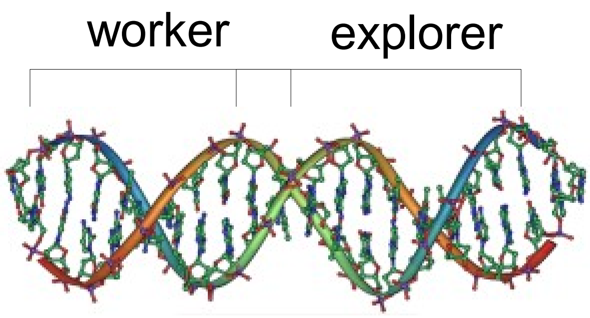
pheromone based local search ->





GA castes design

Genetic algorithm improving "queens"



Improvement not significant

Algorithm is robust or

Results too close to optimum -> larger problems?

Demo: Configuration

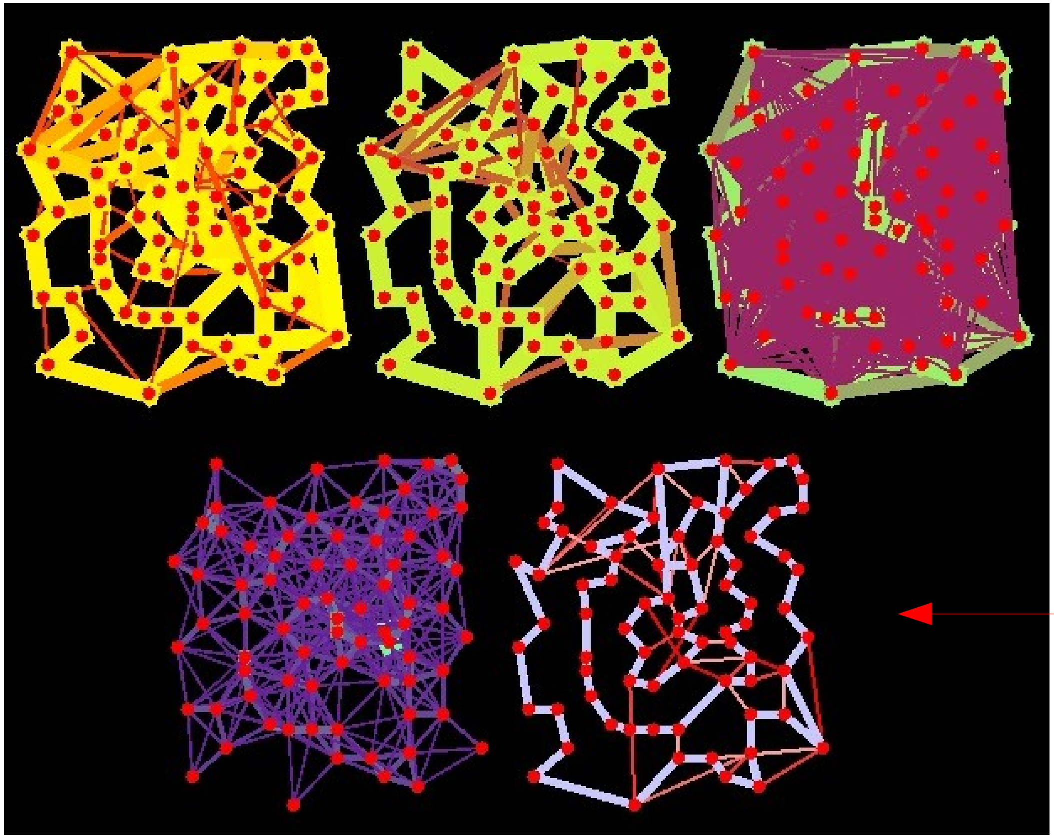
```
# castes:
#id  weight greedyprob beta  attractpheromone[]       repulsepheromone[]      laypheromone[]
  0  1.0    0.1        4.0   2.0 0.0 0.0 1.0 0.0      0.0 0.0 0.0 0.0 0.0     1.0  0.05 0.0  0.0 0.0
  1  1.0    0.1        10.0  0.0 2.0 0.0 1.0 0.0      0.0 0.0 0.0 0.0 0.0     0.0  1.0  0.0  0.0 0.0
2 2  1.0    0.1        4.0   2.0 2.0 2.0 1.0 0.0      0.0 0.0 0.0 0.0 0.0     0.05 0.05 0.5  0.0 0.0
  3  1.0    0.1        1.0   2.0 2.0 2.0 1.0 0.0      0.0 0.0 0.0 0.0 0.0     0.05 0.05 0.5  0.0 0.0
  4  1.0    0.0        0.0   2.0 2.0 2.0 2.0 0.0      0.0 0.0 0.0 0.0 0.0     0.05 0.05 0.05 0.0 0.0
                                 1                                                      2

# pheromones
# id evaporation
  0  0.05
  1  0.01
  2  0.025
  3  NN
  4  0.8
```

caste 2 is attracted to the pheromone 1 by exponent 2.0

and lays most substance to the pheromone 2

Demo: Visualization



3 standard pheromones

solutions for all pheromones

(thicker lines = best solution)

static "greedy" pheromone

... demonstration

Improvemets

Limited neighborhood

Restarts (pheromone reinitialization)

Hybridization (k-OPT, Lin-Kernighan)

but

random + restarts + LK = are the ants necessary?

experiments needed

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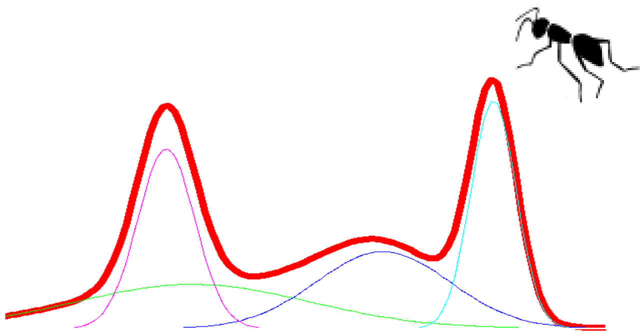
Comparison with other methods

- Reported to perform better than GA and SA on TSP, but results depend strongly on parameters, lot of experiments only on e.g. 3 small datasets
- Comparison with standard methods
  - e.g. Concorde (http://www.tsp.gatech.edu/concorde/)
  - comparison not available
  - results of Concorde seems to be unreachable
  - biggest problem: 526280881 celestial objects
  - found path that is proved to be within 0.796% of the cost of an optimal tour (using decomposition)

5) CONTINUOUS ACO

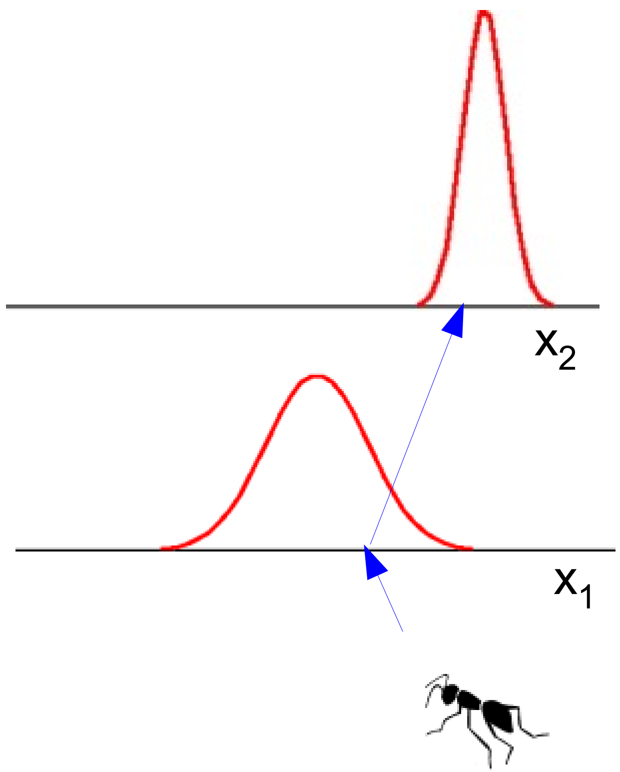


Direct Application of ACO

DACO *(Min Kong, Peng Tian 2006)*

n variables x_i with normal distribution

$$N(\mu_i, \sigma_i), i \in \{1, \cdots, n\}$$

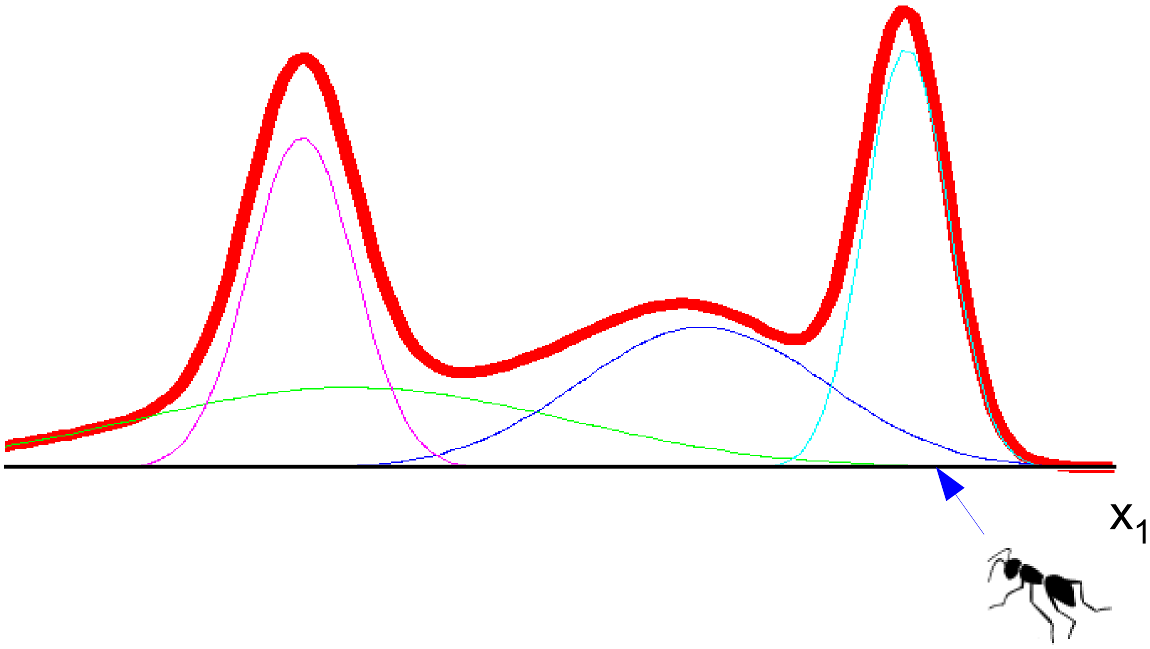


Updates by global best solution **x**:

$$\boldsymbol{\mu}(t) = (1 - \rho)\,\boldsymbol{\mu}(t - 1) + \rho\mathbf{x}$$
$$\boldsymbol{\sigma}(t) = (1 - \rho)\,\boldsymbol{\sigma}(t - 1) + \rho|\mathbf{x} - \boldsymbol{\mu}(t - 1)|$$

Extended ACO

ACO* *(Socha 2004)*



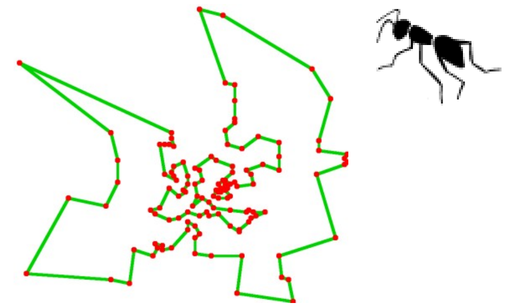
complex
pheromone
distribution

Gaussian kernel PDF

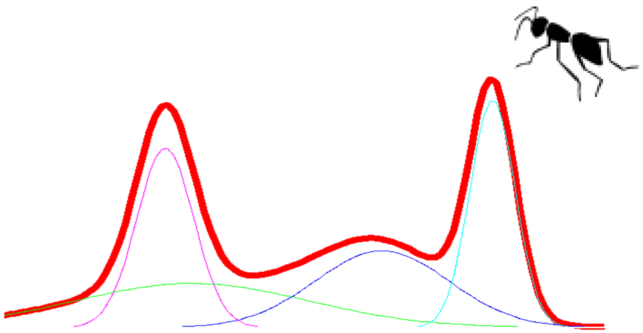
$$G_i(z) = \sum_{j=1}^{k} \omega_j \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu_j)^2}{2\sigma_j{}^2}}$$

Ants & Neural Networks

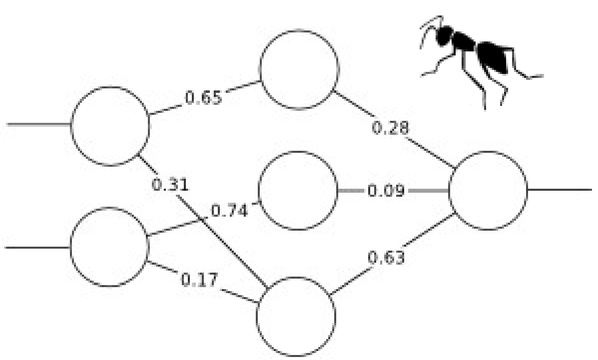
Ant Colony Optimization for combinatorial optimization (TSP)...



... can be extended for continuous optimization...

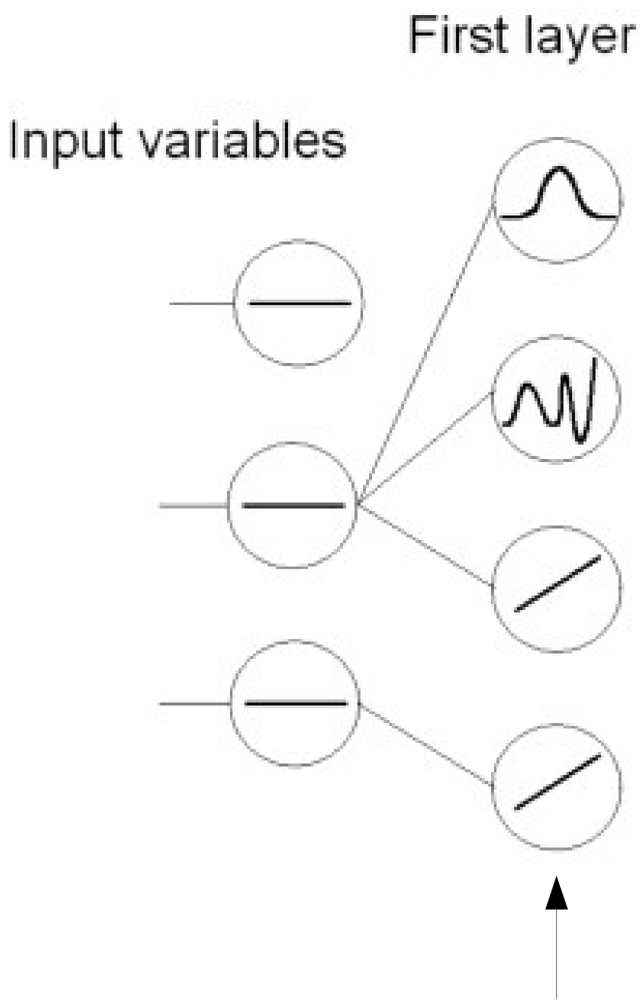


...can optimize NN weights



(Blum, Socha 2005)

GAME (Kordík)

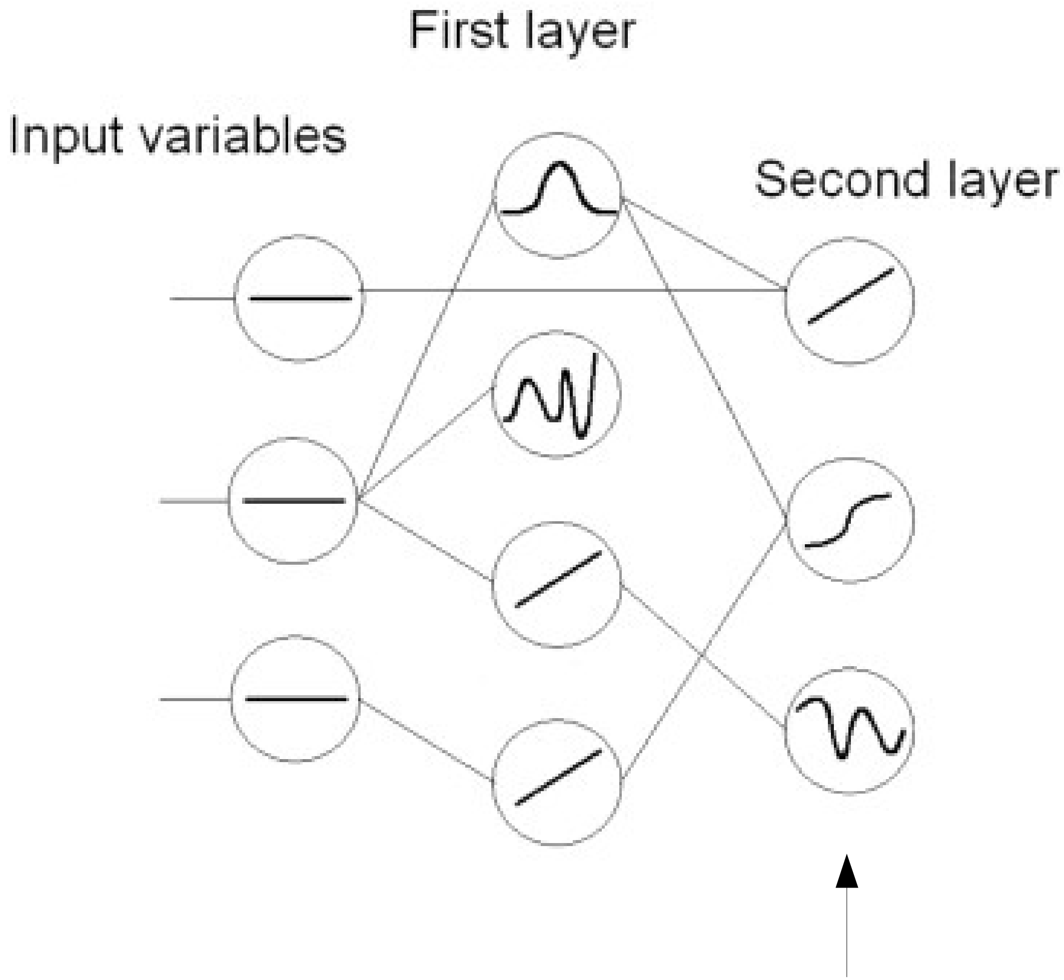


Select:
transfer function,
parameters,
optimization method

for each unit

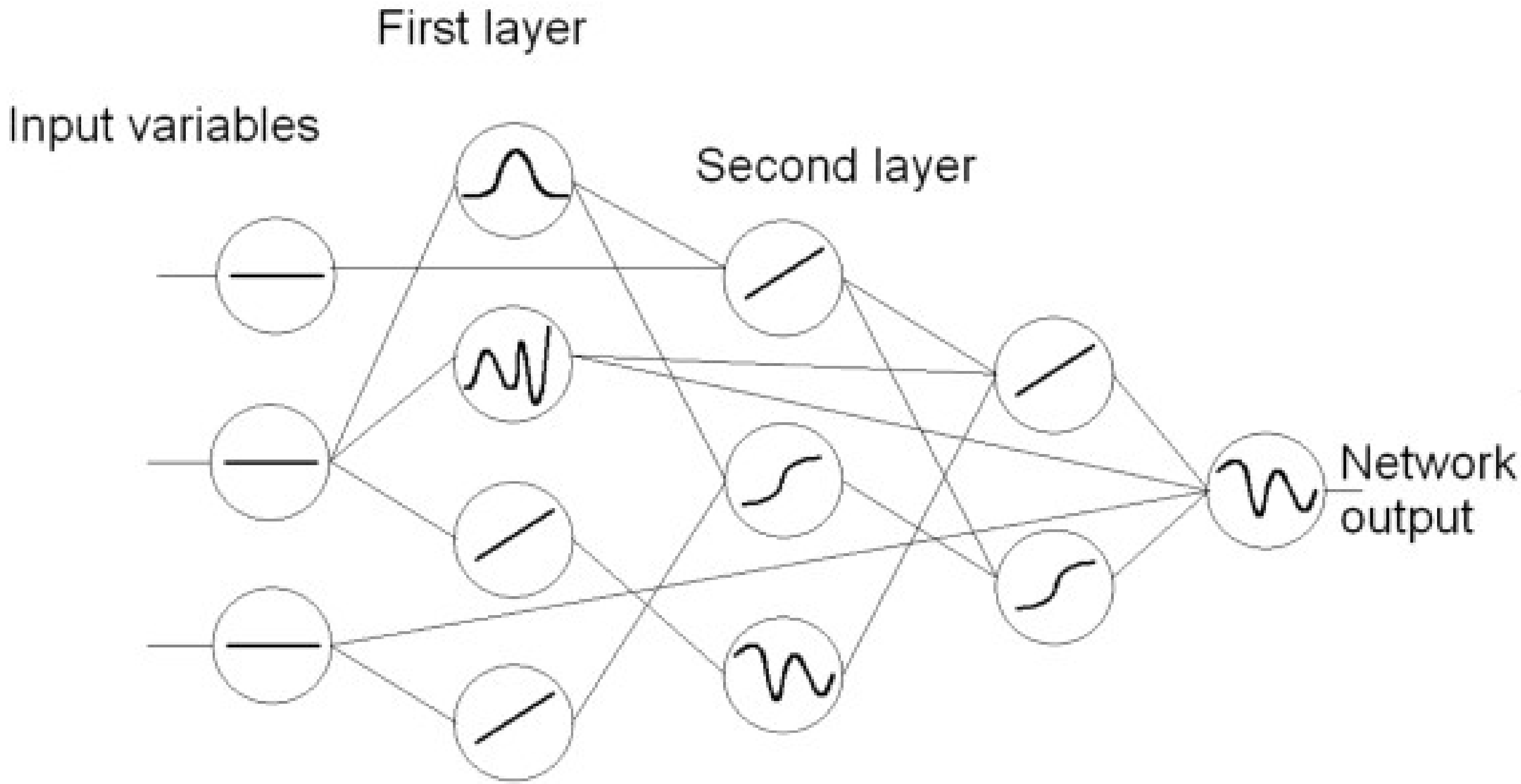
Niching Genetic Algorithm

GAME



Niching Genetic Algorithm

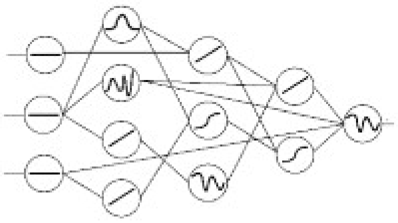
GAME

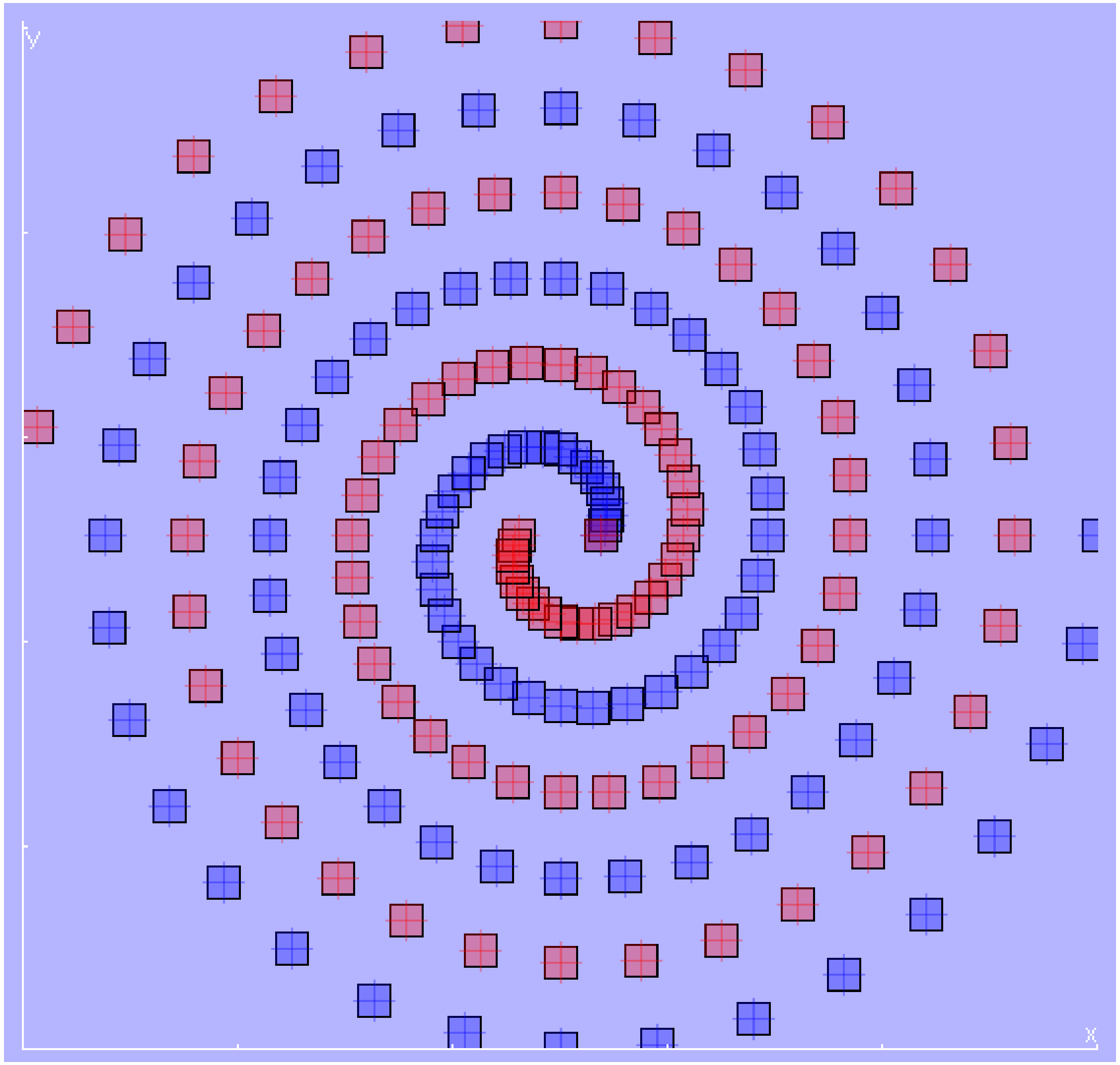


Two spirals dataset

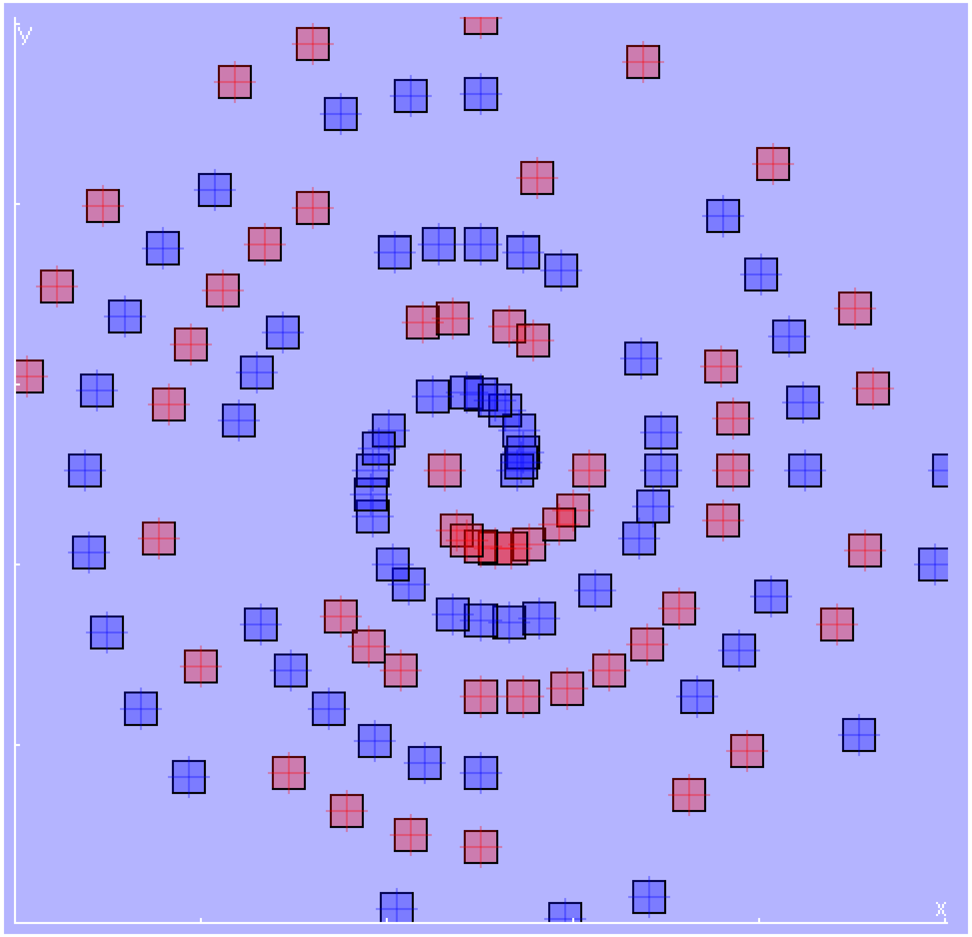
Classification

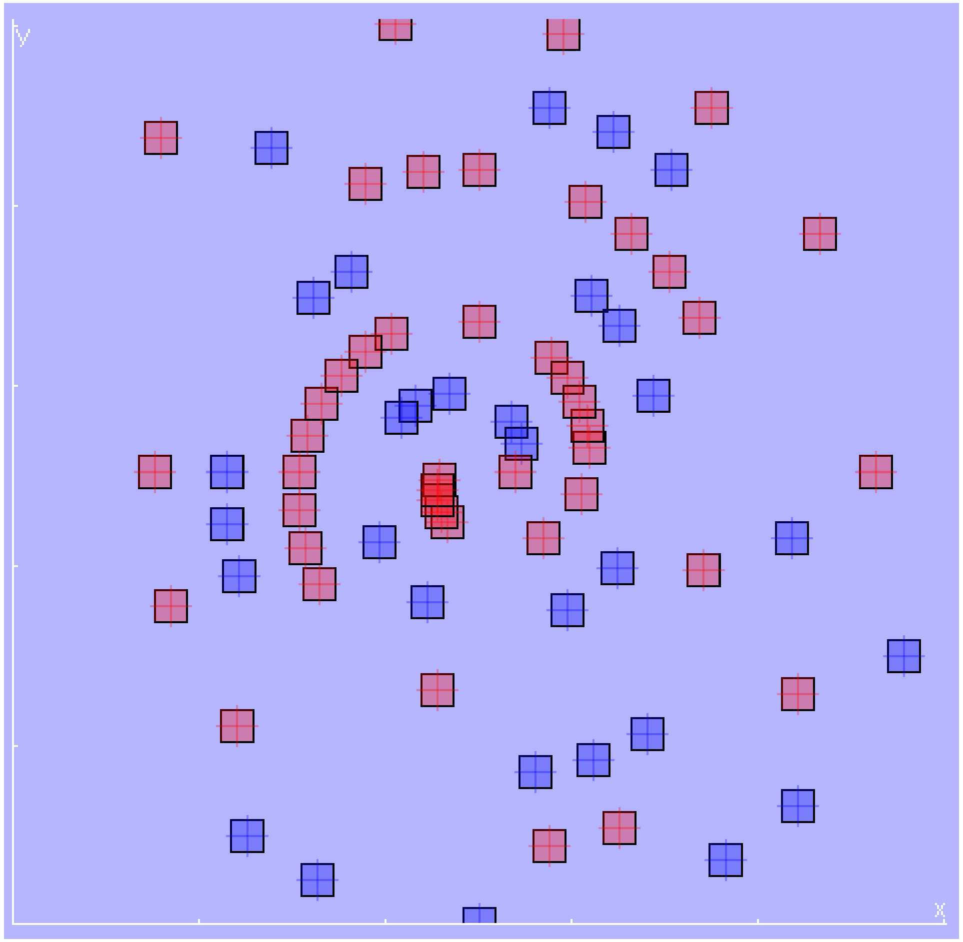
2 classes



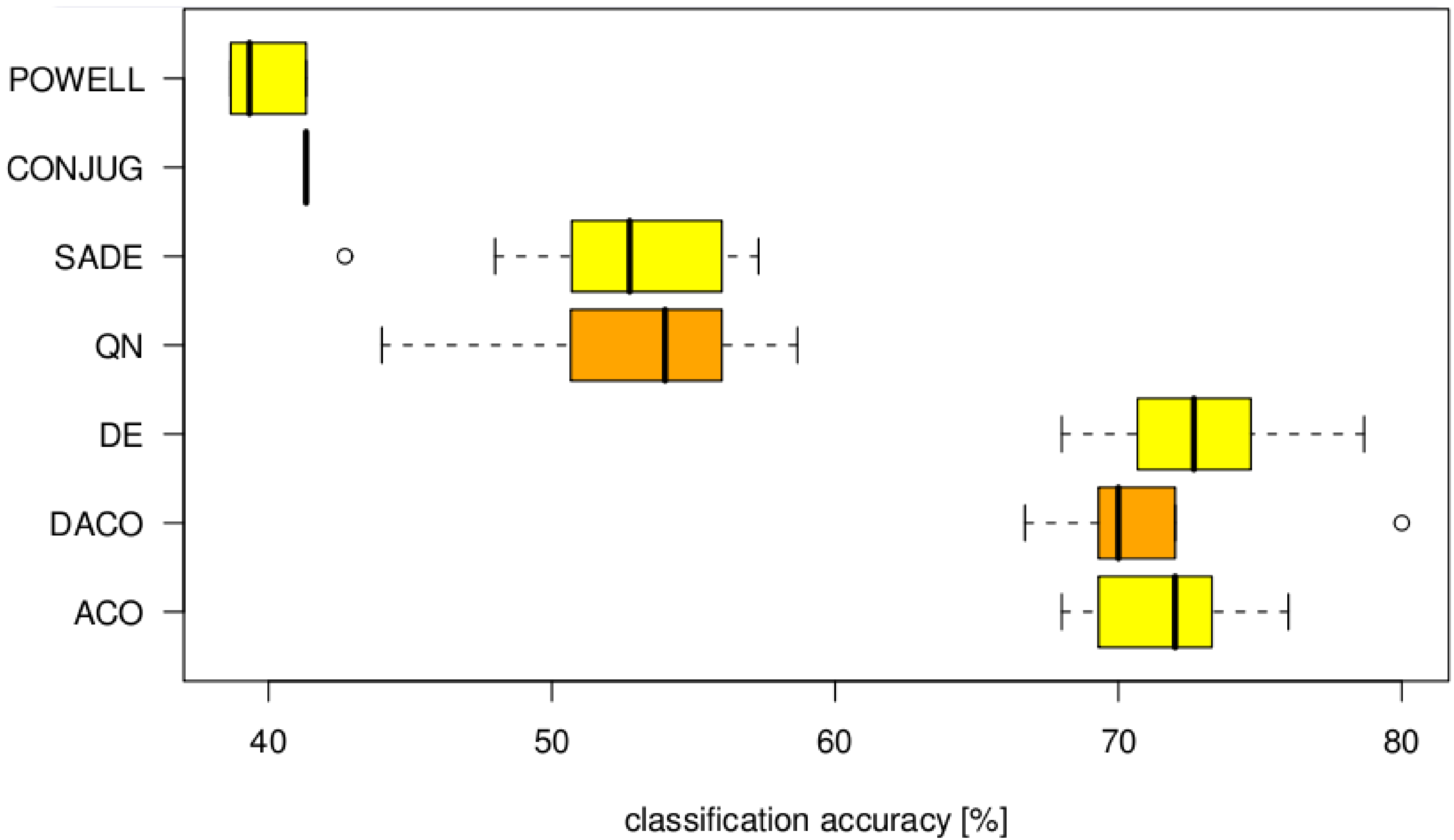


Training and testing set





Results on testing dataset



Thank you