Spider Monkey optimization

December 20th, 2021

Evolutionary Computing

Cuevas Olvera
Ian Axel

Martínez Coronel
Brayan Yosafat

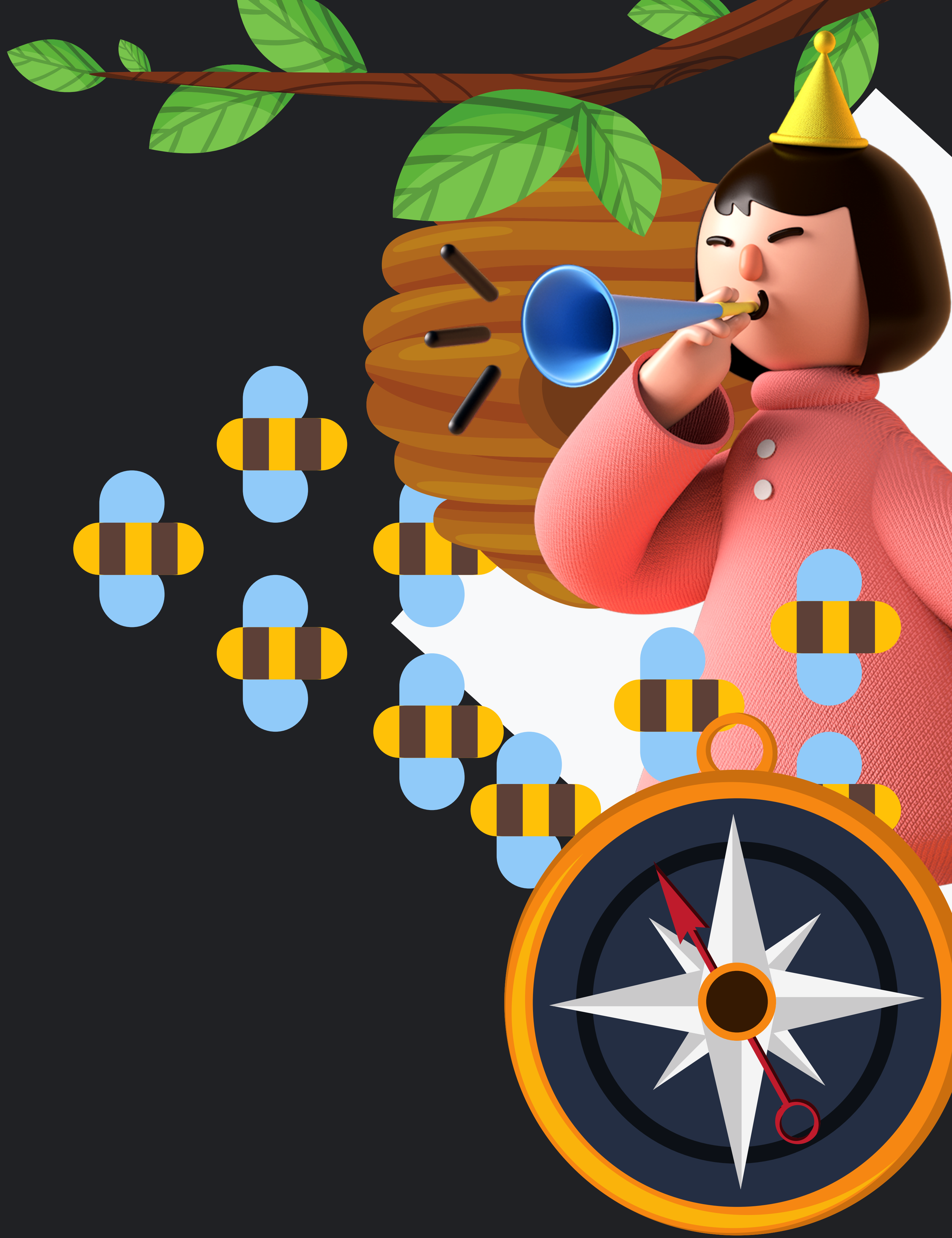
Ortega Estrada
Ismael

Ramírez Olvera
Guillermo

Itinerary

- Swarms in optimizations
- Spider Monkey societies
- Algorithms
- Results

Swarms



- Origin of Swarms
- Swarm Intelligence
- Self-Organization
- Division of Labour

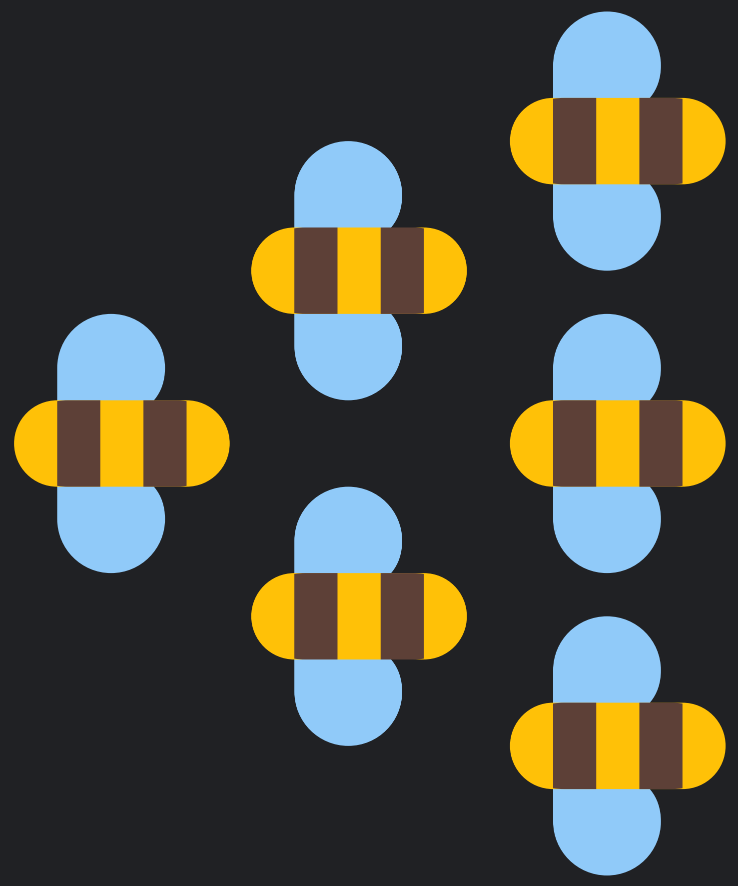
Swarm

An accumulation of creatures (such as ants, fish, birds, termites or honey bees) which behave collectively.

Bonabeau defines Swarm Intelligence as '*any attemp to design algorithms or distributed problem-solving devices inspired by the collective behaviour of social insect colonies and other animal societies*'.

Swarm Intelligence

Is a meta-heuristic approach with nature inspired techniques for optimization: social creatures use their learning to solve complex tasks.



Researchers have studied several species for solving complex problems from nonlinear, nonconvex to combinatorial, some of them are: Ant Colony, Particle Swarm, Bacterial Foreaging and Artificial Bee Colony.

Swarm Intelligence

The authors of the Spider Monkey Optimization say that we get a Intelligent Swarm with these sufficient and neccesary conditions:

Self-Organization

Division of labour

Self Organization

This enables two levels of response, low-level (from individuals) and global level, so they don't need and authority and forcing them to planning.

In practice, this creates patterns in both levels, the global is made by all locals, as Bonabeau defined it, the info for doing so come from 4 sources:

Self Organization

1. Positive feedback: from the output of the system, promote structutes and diversity aiming (as a society) to a new stable state.
2. Negative feedback: compensates the effect of positive feedback and helps to stabilize the collective pattern.
3. Fluctuations: random changes in the systems, this is crucial if we want to discover new structures or solutions
4. Other interactions: the way individuals learn

Division of labour

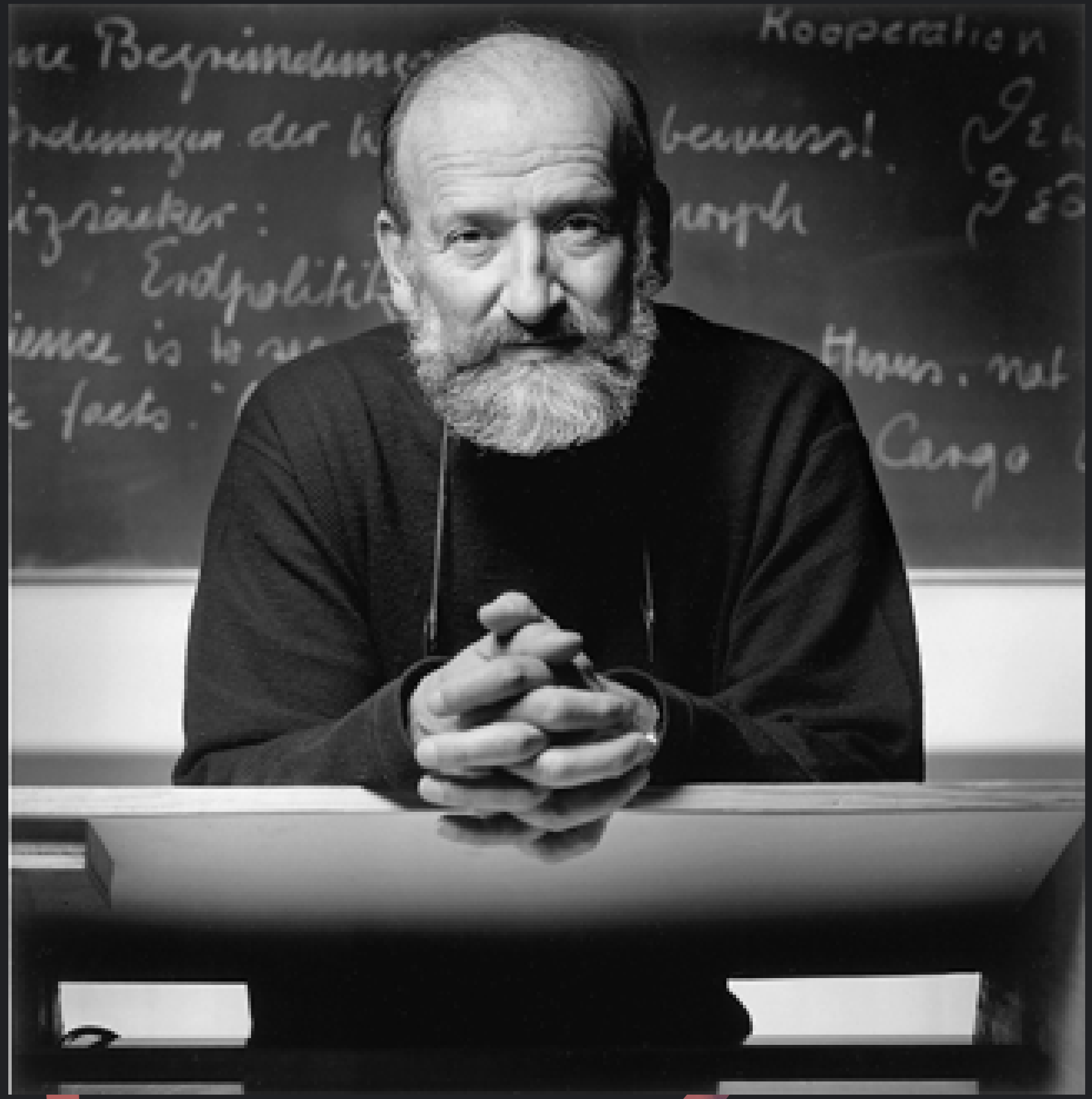
Cooperative labour in specific task or roles. This shows a better performance when tasks are done by specialized individuals, this lead to "independent" groups, and allows paralelism.

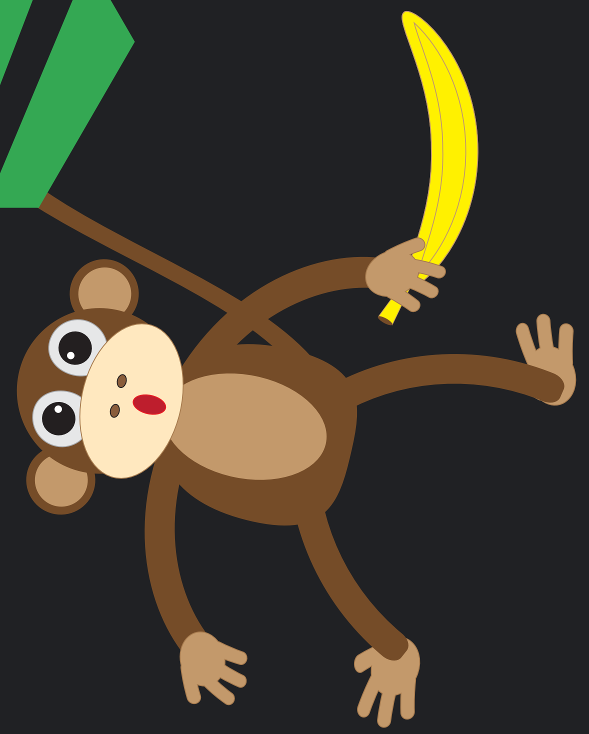
Simultaneosly working by specialized individuals is believed to be more efficient that sequential task performance by unspecialized individuals.

Monkeys

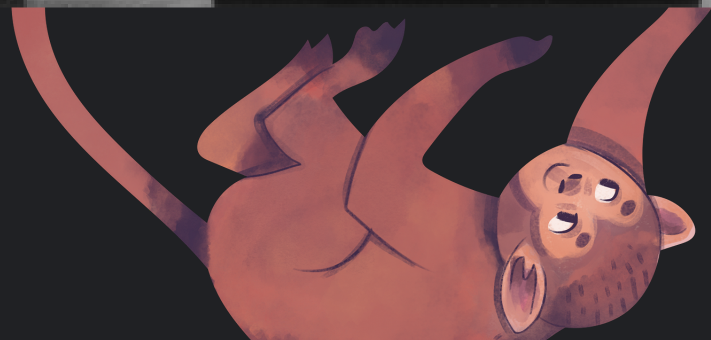
- Fission-fusion Swarm
- Organization and behavior
- Communication

Fission-fusion society

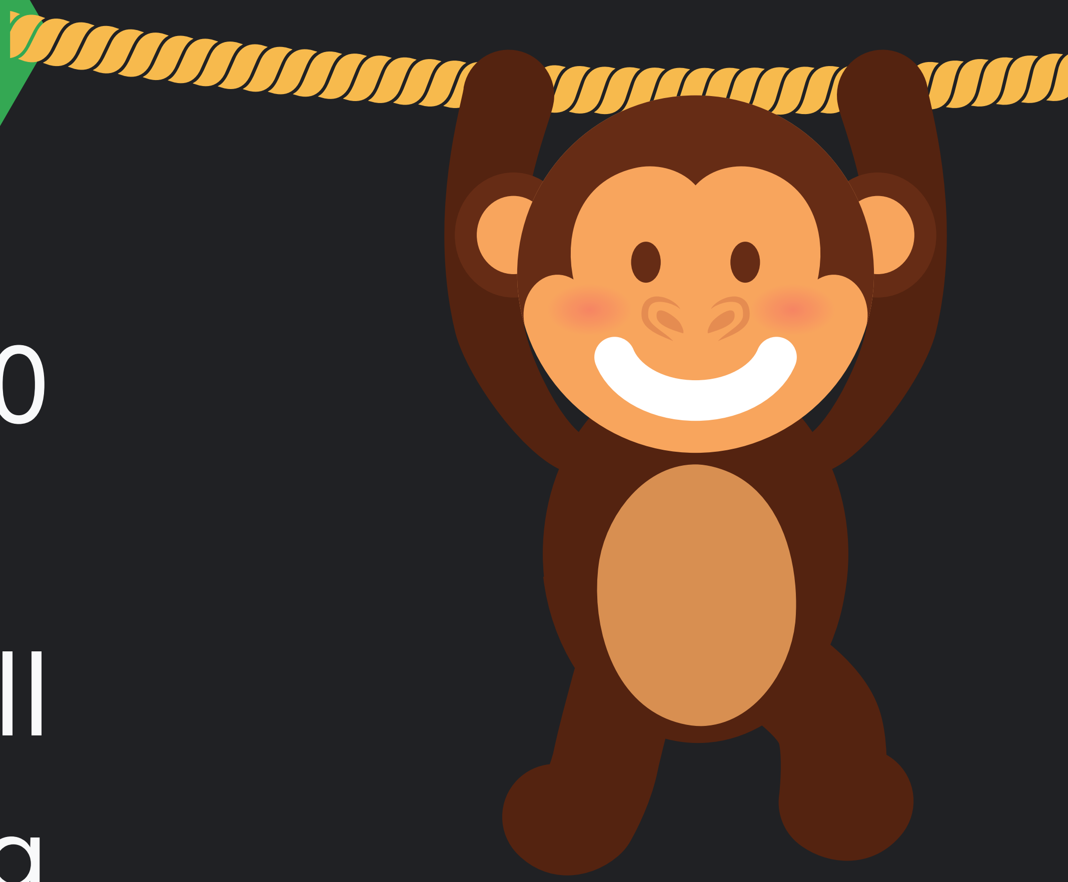




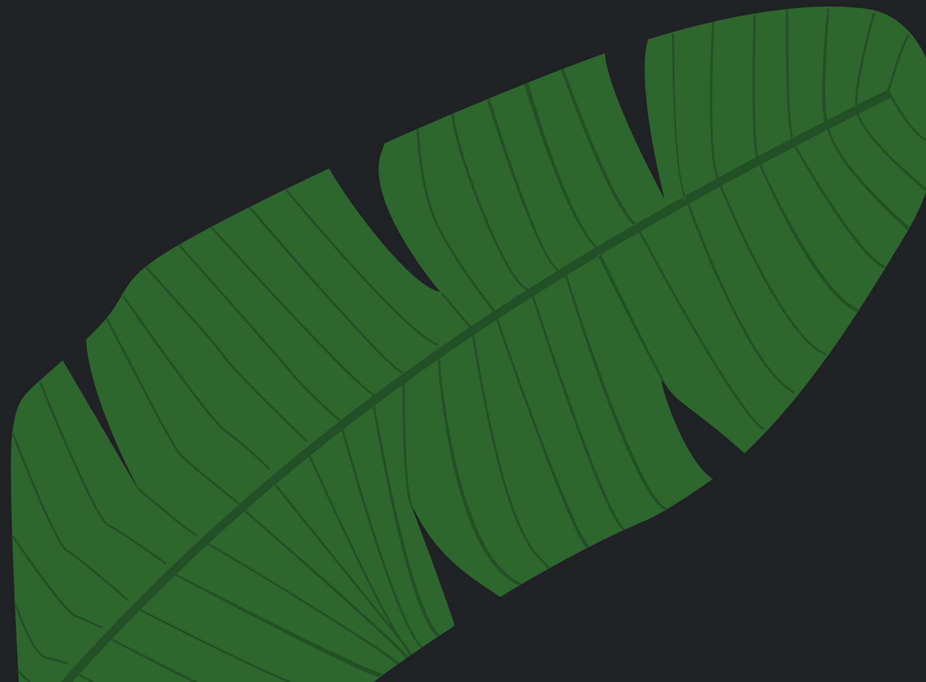
- *The change in composition*
- *Subgroup size*
- *Dispersion of different groups*



Social Organization and Behavior



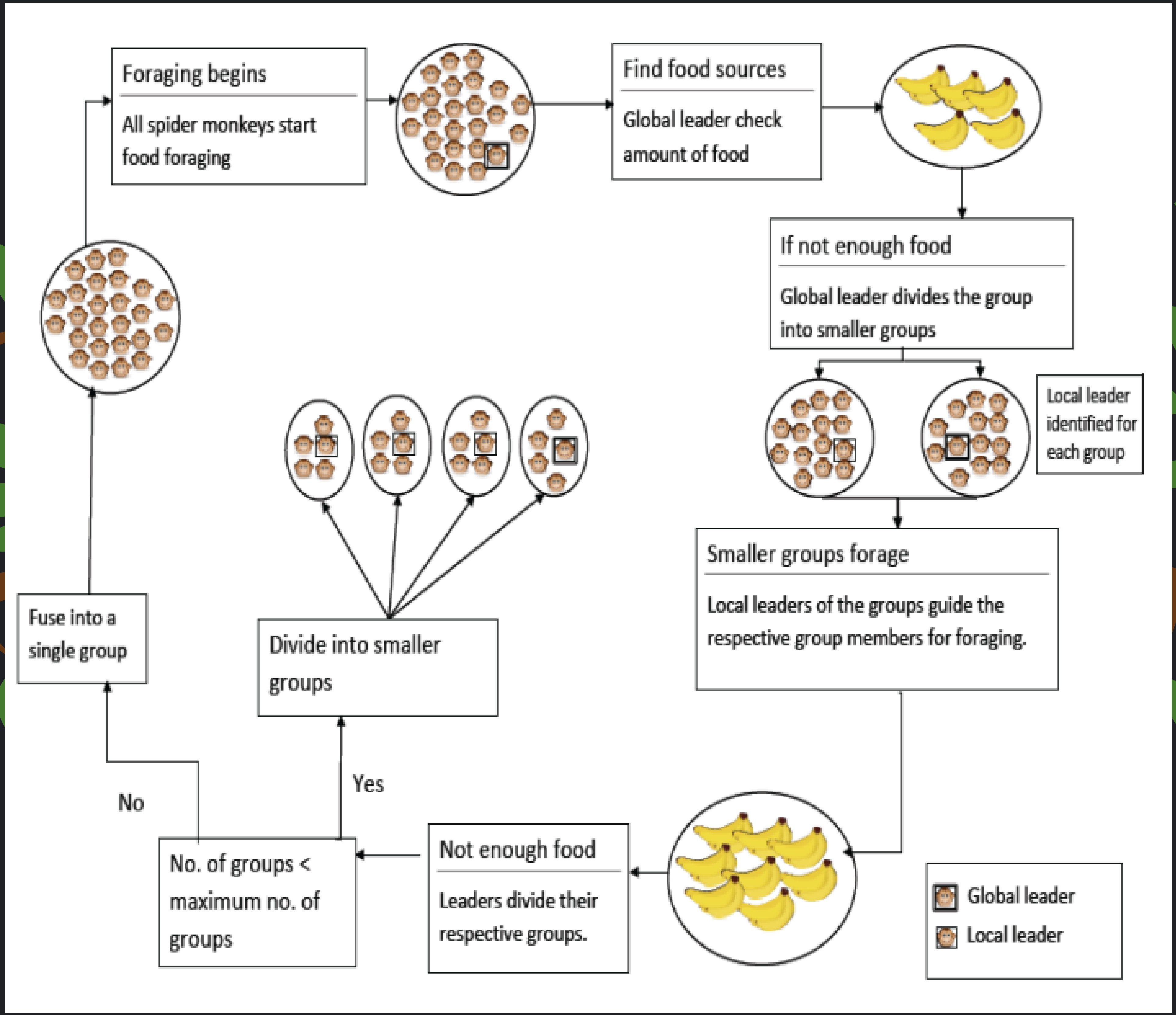
1. Spider monkeys live in a group of about 40-50 individuals.
2. All individuals in this community forage in small groups by going off in different directions during the day and everybody share the foraging experience in the night at their habitat.
3. The lead female spider monkey decides the forage route.



Social Organization and Behavior

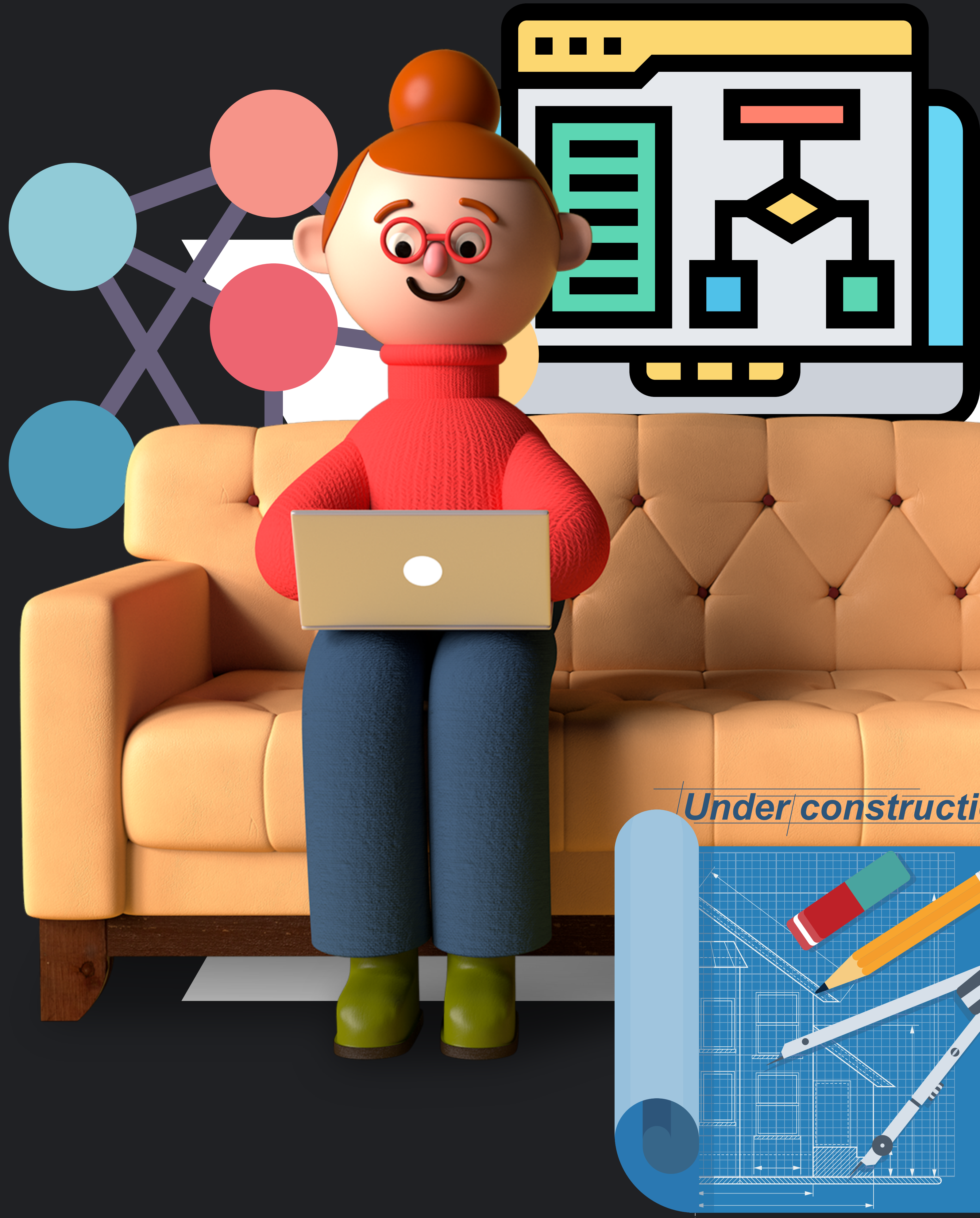
1. If the leader does not find sufficient food then she divides the group into smaller groups and these groups forage, separately.
2. Individuals of the society might not be noticed closer at one place because of their mutual tolerance among each other. When they come into contact their gestures reflect that they are actually part of a large group.

Comunication



Algorithm

- Key ideas and hyperparameters
- Leader Phases
- Learning Phases
- Decision Phases



Key ideas

- The group is around 40-50 individuals, uses FFSS (fission-fusion social structure).
- A female acts as a global leader, if she is not able to get enough food, she divides the groups (from 3 to 8 members each sub-group).
- The algorithm just uses FFSS of Spider Monkeys

Key ideas

- Sub-groups have a female leader too, she takes decisions and make plans each day (local leader)

- All members can communicate between them, in reality they use postures or sounds.

- The algorithm follow 4 steps: evaluating distance, update positions, local leaders update best position of their sub-group, global leader update best position.

Hyperparameters

There are two hyperparameters, LocalLeaderLimit and GlobalLeaderLimit, both are used for avoiding stagnation (if a local/global leader doesn't update herself in a specified number of times the group is re-directed to a different direction).

With these ideas, this aims to have self-organization and division of labour for obtaining 'food'.

Phases

SMO process consists of six phases:

- Local Leader phase
- Global Leader phase
- Local Leader Learning phase
- Global Leader Learning phase
- Local Leader Decision phase
- Global Leader Decision phase

Initialization of the Population

SMO generates a uniformly distributed population of N spider monkeys where each monkey is a D-dimensional vector, where D is the number of variables in the optimization.

Each spider monkey SM corresponds to the potential solution of the problem. Each SM is initialized as follows.

$$SM_{ij} = SM_{minj} + U(0,1) \times (SM_{maxj} - SM_{minj})$$

Where "minj" and "maxj" are bounds bounds of each SM in jth direction, and U is a uniformly distributed random number in the range [0,1]

Local Leader Phase (LLP)

In this phase, SM modify its current position based on the information of the local leader experience as well as local group memers experience, a new fitness value of so obtained is calculated and if it is higher than the older, them SM updtates its position with the new one.

$$SMnew_{ij} = SM_{ij} + U(0,1) \times (LL_{kj} - SM_{ij}) + U(-1,1) \times (SM_{rj} - SM_{ij})$$

Local Leader Phase (LLP)

Algorithm 1 Position update process in Local Leader Phase:

for each member $SM_i \in k^{th}$ group **do**
  for each $j \in \{1, ..., D\}$ **do**
    if $U(0,1) \geq pr$ **then**
      $SMnew_{ij} = SM_{ij} + U(0,1) \times (LL_{kj} - SM_{ij}) + U(-1,1) \times (SM_{rj} - SM_{ij})$
    else
      $SMnew_{ij} = SM_{ij}$
    end if
  end for
end for

Global Leader Phase (GLP)

All de SM update their position using experience of Global Leader and local groups member's experience:

$$SMnew_{ij} = SM_{ij} + U(0,1) \times (GL_j - SM_{ij}) + U(-1,1) \times (SM_{rj} - SM_{ij})$$

The position of the SMi is updated based on da probability which is calculated as follows

$$prob_i = \frac{fitness_i}{\sum_{i=1}^{N} fitness_i}$$

Global Leader Phase (GLP)

Algorithm 2 Position update process in Global Leader Phase (GLP) :

$count = 0$;
while $count < group\ size$ **do**
  for each member $SM_i \in$ group **do**
    if $U(0,1) < prob_i$ **then**
      $count = count + 1$.
      Randomly select $j \in \{1 \ldots D\}$.
      Randomly select $SM_r \in$ group s.t. $r \neq i$.
      $SMnew_{ij} = SM_{ij} + U(0,1) \times (GL_j - SM_{ij}) + U(-1,1) \times (SM_{rj} - SM_{ij})$.
    end if
  end for
end while

Global Leader Learning (GLL)

The position of the global leader is updated by applying the greedy selection in the population, the position of the SM having best fitness in the population is selected as the updated position of the global leader.

Local Leader Learning (LLL)

The position of the local leader is updated by applying the greedy selection in that group, the position of the SM having best fitness in that group is selected as the updated position of the local leader.

Local Leader Decision (LLD)

If any LL position is not updated up to the LocalLeaderLimiter, then all the members of that group update their positions either by random initialization of by using information from GL and LL.

$$SMnew_{ij} = SM_{ij} + U(0,1) \times (GL_j - SM_{ij}) + U(0,1) \times (SM_{ij} - LL_{kj});$$

Local Leader Decision (LLD)

Algorithm 3 Local Leader Decision Phase:

if $LocalLimitCount > LocalLeaderLimit$ **then**
    $LocalLimitCount = 0.$
    for each $j \in \{1...D\}$ **do**
        if $U(0,1) \geq pr$ **then**
            $SMnew_{ij} = SM_{minj} + U(0,1) \times (SM_{maxj} - SM_{minj})$
        else
            $SMnew_{ij} = SM_{ij} + U(0,1) \times (GL_j - SM_{ij}) + U(0,1) \times (SM_{ij} - LL_{kj})$
        end if
    end for
end if

Global Leader Decision (GLD)

The position of global leader is monitored and if it is not updated up to predetermined number of iterations (GlobalLeaderLimiter), then the global leader divides de population into smaller groups. It is divided into two groups, then three and so on till it reaches the maximum number of groups.

Global Leader Decision (GLD)

Algorithm 4 Global Leader Decision Phase:

if $GlobalLimitCount > GlobalLeaderLimit$ **then**
    $GlobalLimitCount = 0$
    if Number of groups $< MG$ **then**
        Divide the population into groups.
    else
        Combine all the groups to make a single group.
    end if
    Update Local Leaders position.
end if

Algorithm 5 Spider Monkey Optimization (SMO) Algorithm:

1. Initialize Population, $LocalLeaderLimit$, $GlobalLeaderLimit$, pr.
2. Calculate fitness (i.e. the distance of individuals from food sources).
3. Select global leader and local leaders by applying greedy selection (see section 3.1.4 3.1.5,).

while (Termination criteria is not satisfied) **do**

(i) For finding the objective (Food Source), generate the new positions for all the group members by using self experience, local leader experience and group members experience using algorithm (1).

(ii) Apply the greedy selection process for all the group members based on their fitness;

(iii) Calculate the probability $prob_i$ for all the group members using equation (4).

(iv) Produce new positions for the all the group members, selected by $prob_i$, by using self experience, global leader experience and group members experiences using algorithm (2).

(v) Update the position of local and global leaders, by applying the greedy selection process on all the groups (see section 3.1.4, 3.1.5).

(vi) If any Local group leader is not updating her position after a specified number of times ($LocalLeaderLimit$) then re-direct all members of that particular group for foraging by algorithm (3)

(vii) If Global Leader is not updating her position for a specified number of times ($GlobalLeaderLimit$) then she divides the group into smaller groups by algorithm (4), but minimum size of each group should be 4.

end while

Results

- Comparisons
- Conclusions

Comparison

Which is the best?

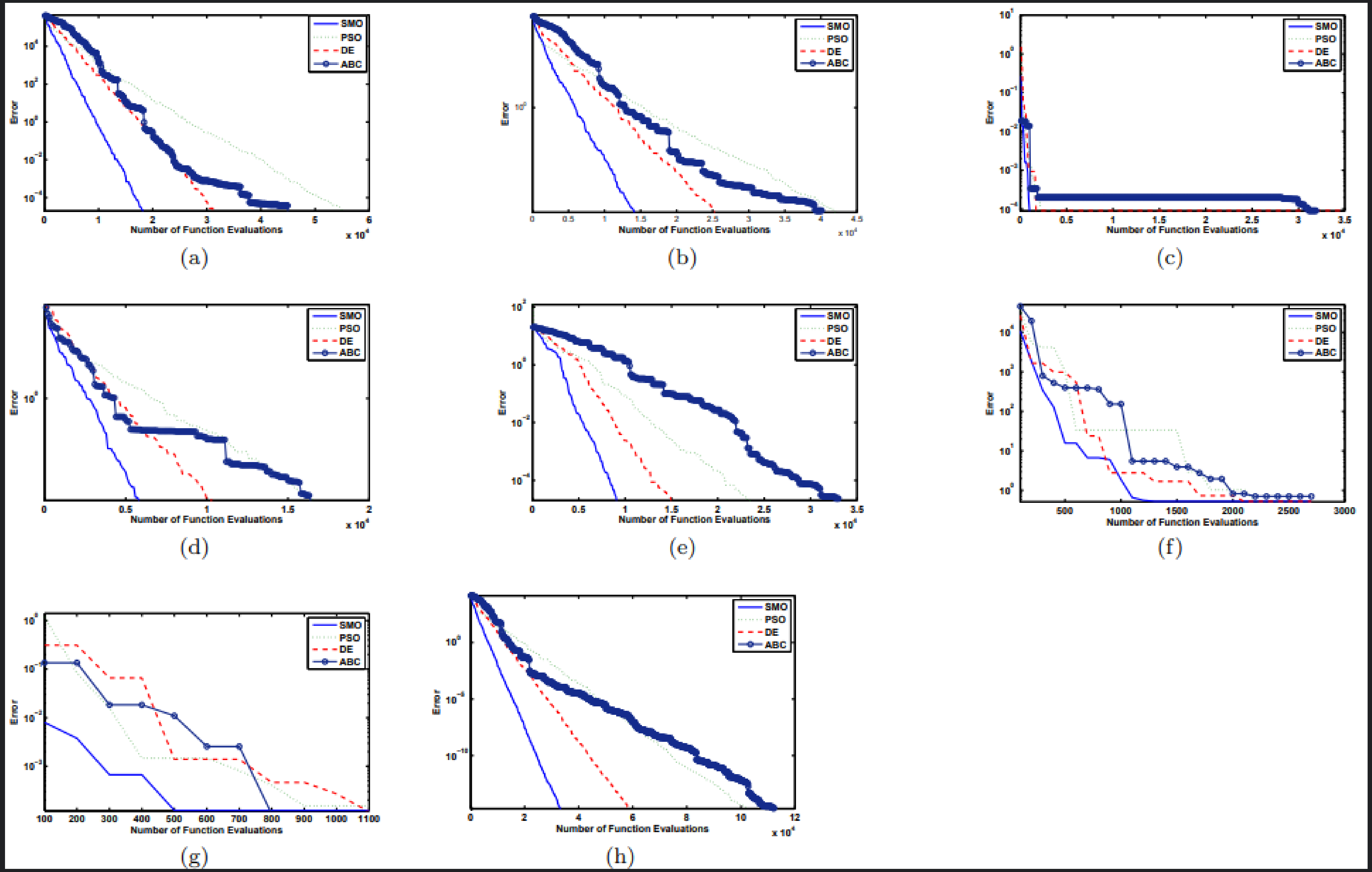
Comparison

The table shows that most of the time SMO outperforms in terms of reliability, efficiency and accuracy.

The Test Functions are found in the paper "Spider Monkey Optimization Algorithm for Numerical Optimization".

Test Function	Algorithm	ME	SD	AFE	SR
f_1	SMO	5.24E-06	3.57E-06	58578.22	100
	PSO	3.51E-01	3.10E-01	197777.5	2
	DE	5.21E-02	4.97E-02	177211.5	17
	ABC	4.51E-06	3.61E-06	44076	100
f_2	SMO	1.00E-06	0.00E+00	16897.82	100
	PSO	1.00E-06	0.00E+00	38102	100
	DE	3.00E-01	5.24E-01	38547.5	88
	ABC	1.00E-06	0.00E+00	20047	100
f_3	SMO	8.77E-06	1.31E-06	16648.83	100
	PSO	2.09E-03	1.45E-02	36645.5	98
	DE	8.55E-06	1.24E-06	20572.5	100
	ABC	7.53E-06	2.24E-06	37194	100
f_4	SMO	2.29E-04	1.54E-03	17539.9	98
	PSO	7.79E-04	2.81E-03	48651	93
	DE	5.57E-04	2.39E-03	30088.5	95
	ABC	7.83E-06	2.19E-06	41435	100
f_5	SMO	8.88E-06	9.53E-07	15323.22	100
	PSO	9.33E-06	5.73E-07	44406.5	100
	DE	8.89E-06	1.37E-06	27901.5	100
	ABC	8.48E-06	1.81E-06	44961	100
f_6	SMO	4.81E-06	2.58E-06	1569.15	100
	PSO	4.22E-06	2.67E-06	2762	100
	DE	4.72E-06	1.13E-06	1849	100
	ABC	7.81E-06	2.42E-06	31948.76	100
f_7	SMO	1.21E-04	1.56E-04	44133.41	96
	PSO	8.51E-06	1.83E-06	48767	100
	DE	4.20E-04	2.02E-03	70633	67
	ABC	1.50E-04	7.87E-05	2.0E+05	0

Convergence Characteristics



Statistical Analysis

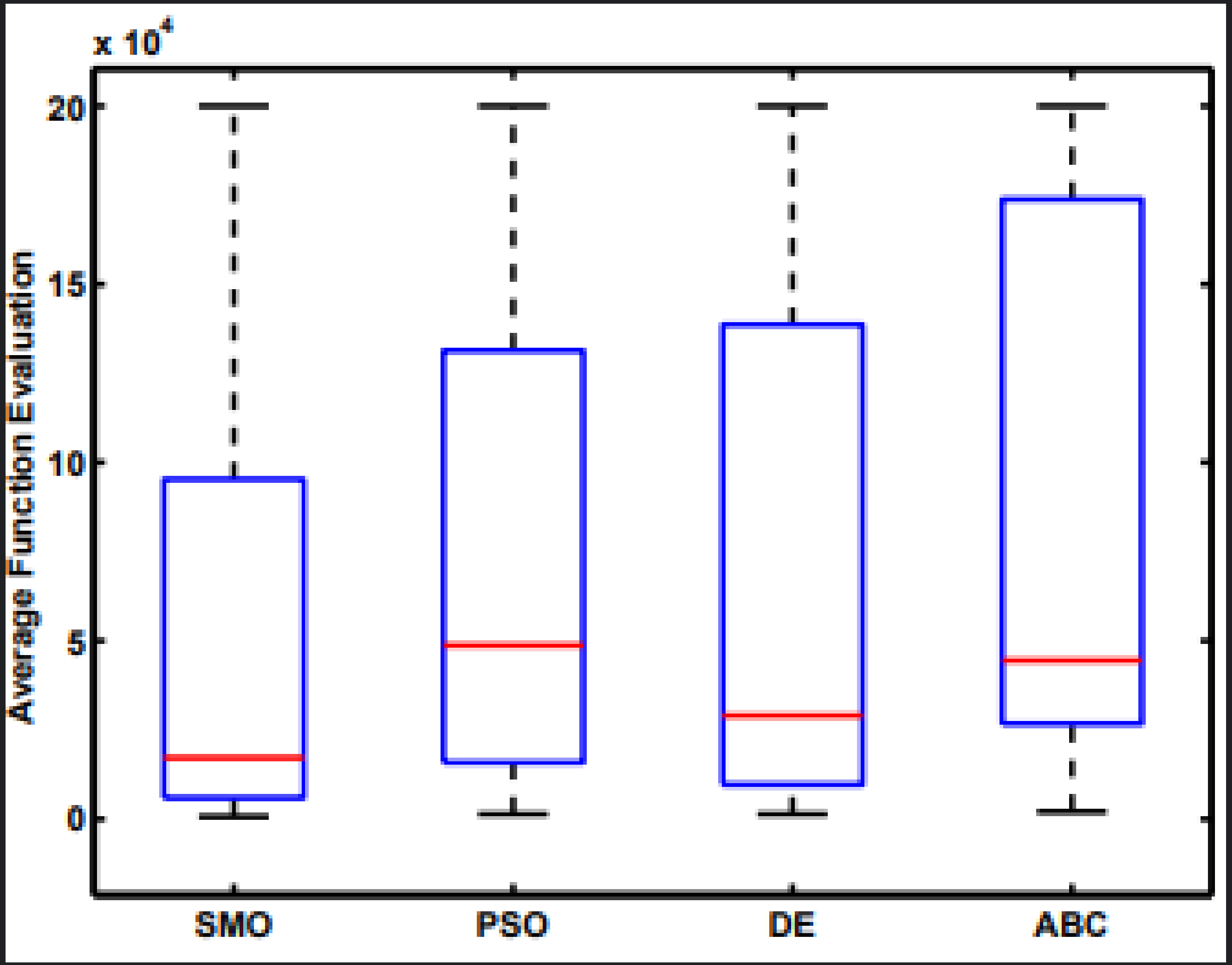
The t-test is quite popular among researchers in the field of evolutionary computation.

Test Problem	Students t test with SMO			Test Problem	Students t test with SMO		
	PSO	DE	ABC		PSO	DE	ABC
f_1	+	+	-	f_{14}	+	+	+
f_2	+	+	+	f_{15}	+	+	+
f_3	+	+	+	f_{16}	-	-	+
f_4	+	+	+	f_{17}	+	+	+
f_5	+	+	+	f_{18}	+	+	+
f_6	+	+	+	f_{19}	+	+	+
f_7	-	+	+	f_{20}	+	+	+
f_8	+	-	-	f_{21}	+	+	-
f_9	+	+	-	f_{22}	-	-	+
f_{10}	+	+	+	f_{23}	+	+	+
f_{11}	=	=	=	f_{24}	-	+	+
f_{12}	=	=	=	f_{25}	-	-	+
f_{13}	+	+	-				

Statistical Analysis

The empirical distribution of data is efficiently represented graphically by the boxplot analysis tool.

SMO is the best of all strategies.



Conclusion

The algorithm proves to be very flexible in the category of swarm intelligence based algorithms.

Generally, in the solution search process, exploration and exploitation capabilities contradict each other.

Therefore to obtain better performance on the problems of optimization, the two capabilities should be well balanced.

Conclusion

It has been shown that, for most of the problems the reliability (due to success rate), efficiency (due to average number of function evaluations) and accuracy (due to mean objective function value) of SMO algorithm is higher than that of ABC, PSO and DE.

References

Videos about the SMO (three parts):
https://youtu.be/8noex_neNcA
https://youtu.be/hiuZnzF712s
https://youtu.be/LQVfPzES2xE

Original Paper (there are 2 versions of the paper, the one with the Python code is easier to read):
https://smo.scrs.in/

Thank you for your attention