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THE ROLE OF COMPETITION IN SOCIAL GROUPS

the case study of Ant Colonies
and its applications

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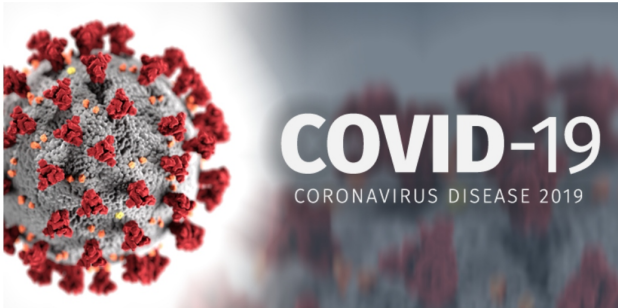
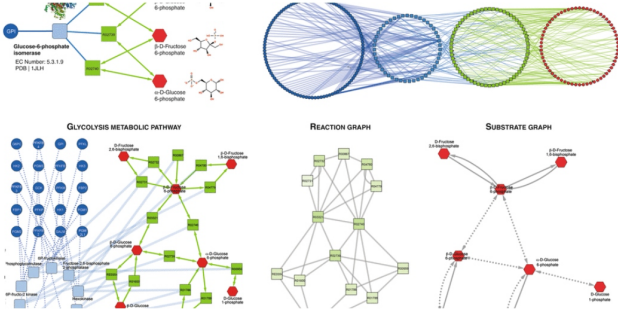
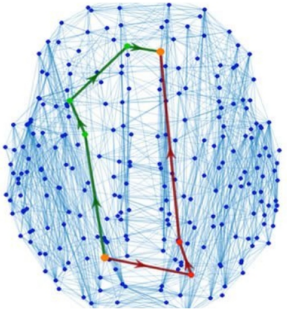
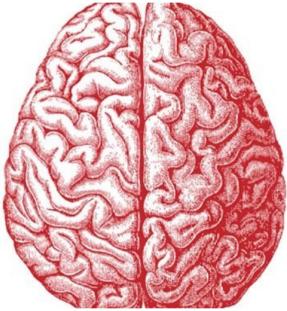
TALK OUTLINE

- **INTRODUCTION**
- **STATE OF ART**
 - Networks
 - Collective behaviour
 - Ant Colony Optimization
 - Swarm intelligence
- **THE MODEL**
 - Optimization strategies
 - A Game Theory approach
 - Crowd Evacuation Modelling
- **CONCLUSIONS AND FUTURE AIMS**



INTRODUCTION

Looking at the world we live in we can notice that we are surrounded by a multitude of systems that seem different but have something in common.



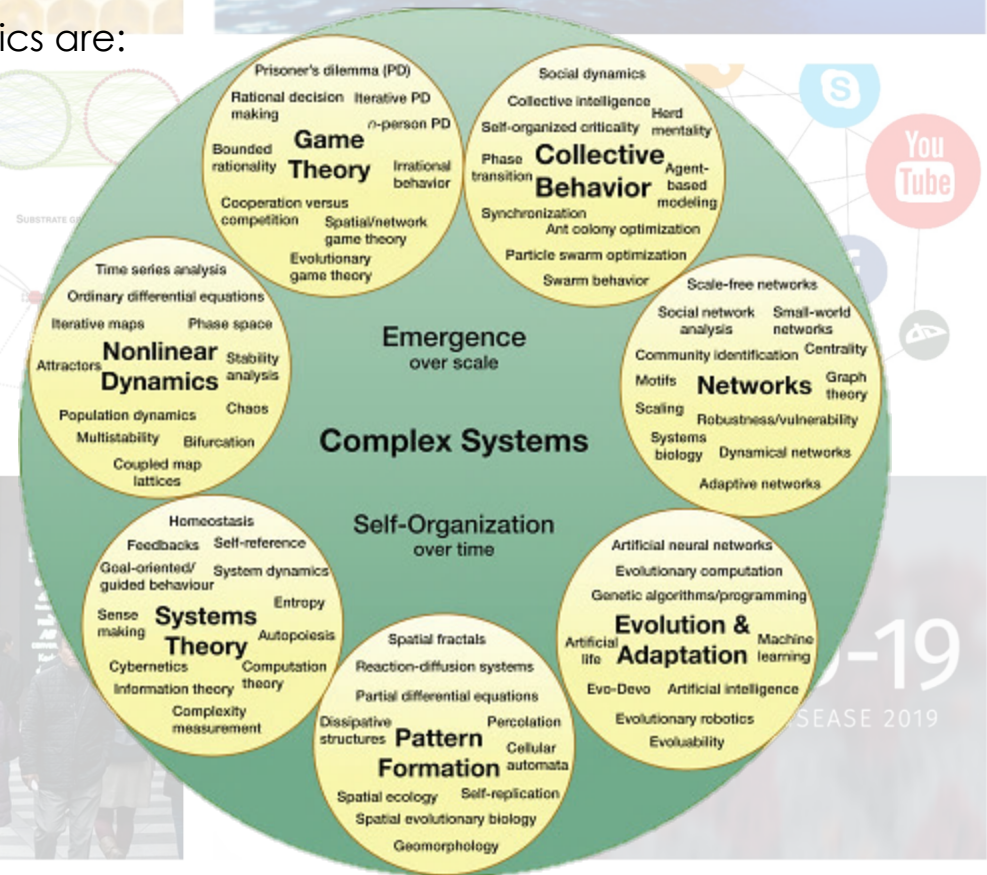
INTRODUCTION

What these systems have in common?

Is difficult to **extrapolate models** and **understand their evolution** over time due to dependencies, relationships, or other types of interactions between their parts or between the entire system and the environment.

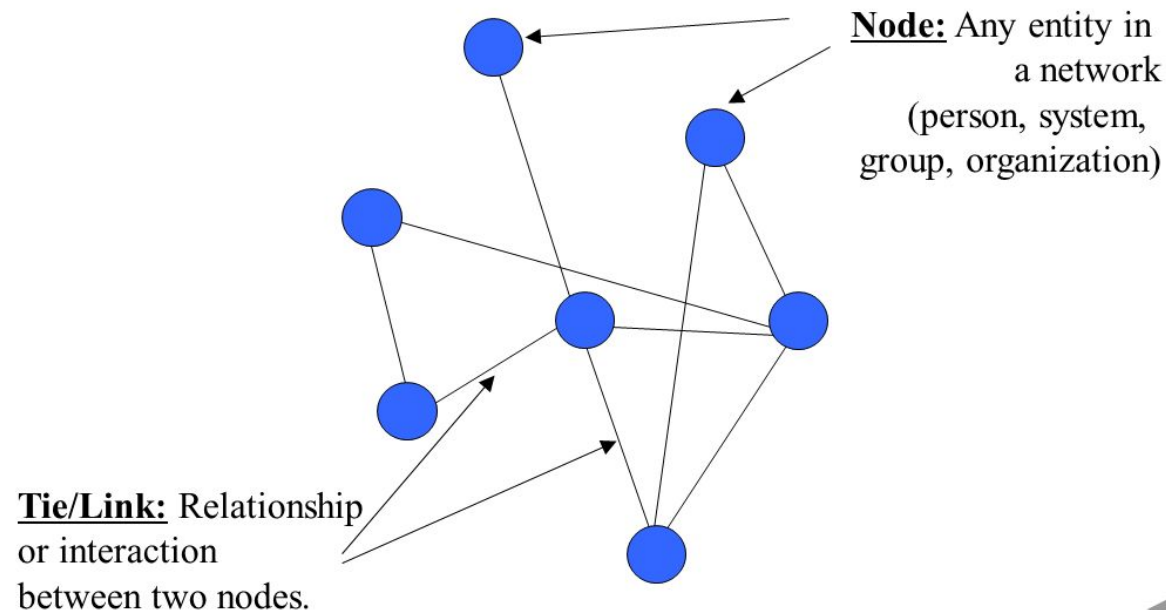
This kind of systems are called **complex systems** and their main characteristics are:

- **Interaction:** they are composed of many elements that interact with each other;
- **Nonlinearity:** such interactions are non linear and may lead to unexpected behaviour;
- **Self-organization:** complex systems can react and adapt to different events;
- **Co-evolution:** they interact with the environment and evolve in response to its changes;
- **Emergent behaviour:** the global behaviour is not predictable by looking at single interactions;
- **Decentralized control:** there is no one who makes decisions or coordinates the movement.



STATE OF ART – NETWORKS

A complex system is usually composed of many components and their interactions. Such a system can be represented by a network where nodes represent the components and links represent their interactions. They are studied in Network Science, that considers the system as a network, whose nodes are the elements of the system and the links are the relations between them. A **network** is defined by a pair $G(E, V)$ where $V = \{v_1, v_2, \dots, v_p\}$ is the set of **vertices** (the elements of the system) and $E = \{e_i\} \subseteq \mathbb{N} \times \mathbb{N}$ the set of **arcs** (the relations between the elements of the system), with $i = 1, 2, \dots, n$ and $e_i = \{v_l, v_m\}$ any pair of nodes.

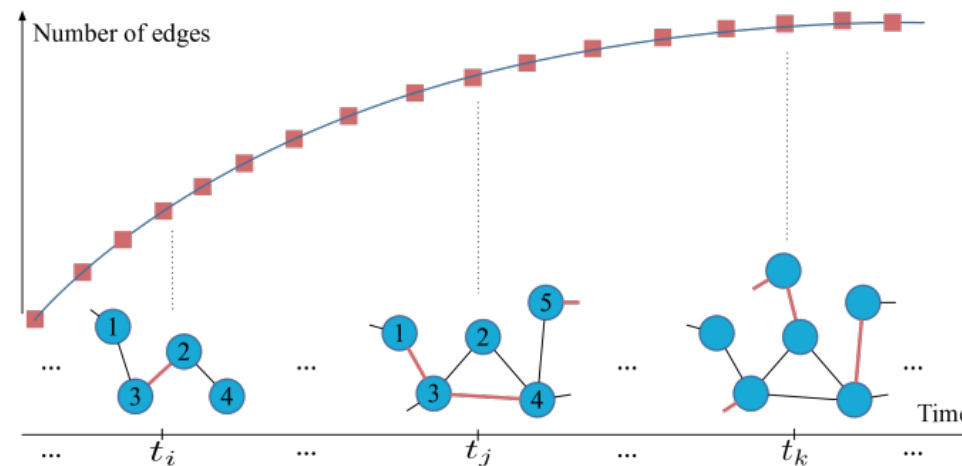
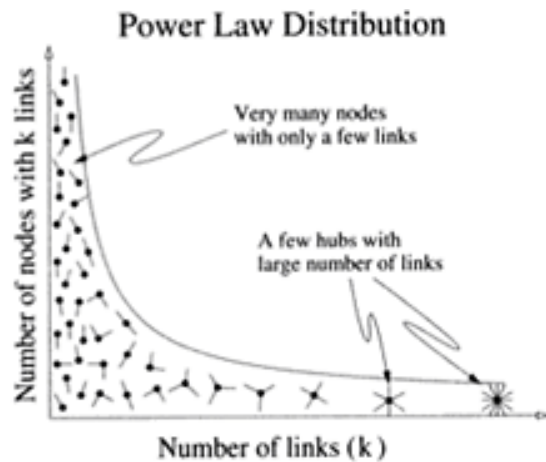


STATE OF ART – NETWORKS

Network of real systems have **non-trivial topological characteristics**:

- Power-law degree distribution.
- High clustering coefficient.
- Evolve over time.

Dynamic Networks are defined by $G(E, V)$ where $V = \{v, t_s, t_v\}$ with v generic node, t_s and t_v the instant in which a node appears and the instant in which it disappears ($t_s \leq t_v$). $E = \{u, v, t_s, t_e\}$ is a set with $u, v \in V$ two generic nodes and t_s and t_e the instant in which a link appears between them and the instant in which the same link disappears ($t_s \leq t_e$). Nodes can appear or disappear and the links damaged or repaired. The state of the network changes over time¹.

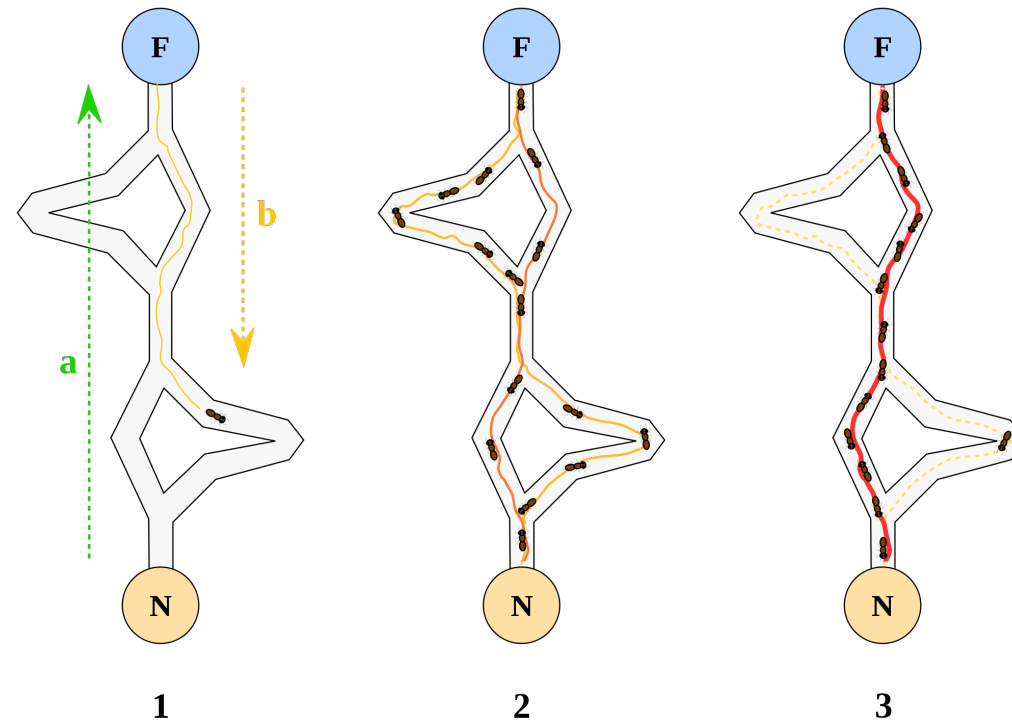


STATE OF ART – COLLECTIVE BEHAVIOUR

Collective behaviour is a form of social behaviour involving the coordinated behaviour of large groups of similar individuals as well as emergent properties of these groups. This can include the costs and benefits of group membership, the transfer of information across the group, the group decision-making process, and group locomotion and synchronization.

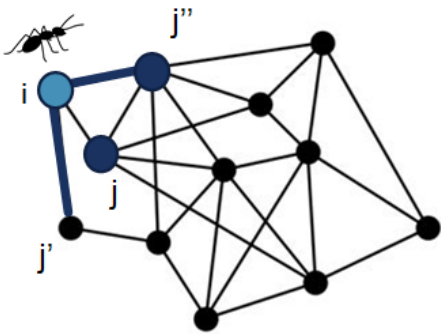
The use of the term has been expanded to include reference to humans, cells, social animals, insects, and many others.

The ants' behaviour is the best example in nature of complex systems that manifest a collective behaviour. They can find the shortest path between their ant hill and a source of food, and communicate it to the others through chemical signals released along the path, called pheromones. This kind of indirect cooperation of the ants is called *stigmergy* and it has been successfully applied to solve many kinds of optimization problems such as the Travelling Salesman's Problem (TSP), vehicle routing, and others.



STATE OF ART – ANT COLONY OPTIMIZATION

The Ant Colony Optimization is an algorithm proposed by **Marco Dorigo**² in 1990 that is inspired by the behaviour of ants. They can identify the **shortest path** between a food source and their anthill and communicate it to the others through chemical signals called pheromones. The environment is represented as a graph $G = (V, E)$ where V is the set of nodes and E the set of arcs. It belongs to the **Swarm Intelligence** class.



Proportional transition rule

$$p_{ij}^k(t) = \begin{cases} \frac{\tau_{ij}(t)^\alpha \cdot \eta_{ij}^\beta}{\sum_{l \in J_i^k} \tau_{il}(t)^\alpha \cdot \eta_{il}^\beta} & \text{if } j \in J_i^k \\ 0 & \text{if } j \notin J_i^k \end{cases}$$

- τ_{ij} pheromone intensity the path (i,j) ,
- α parameter that controls the importance of τ_{ij} ,
- η_{ij} visibility of the node j ,
- β parameter that controls the importance η_{ij} ,
- J_i^k set of possible movements of the ant.

Reinforcement rule

$$\Delta\tau_{ij}^k(t) = \begin{cases} \frac{Q}{L^k(t)} & \text{if } (i,j) \in T^k(t) \\ 0 & \text{if } (i,j) \notin T^k(t) \end{cases}$$

- L^k length of the path,
- T^k total path made by the ant
- Q parameter.

Global updating rule

$$\tau_{ij}(t+1) = (1 - \rho) \tau_{ij}(t) + \sum_{k=1}^m \Delta\tau_{ij}^k(t)$$

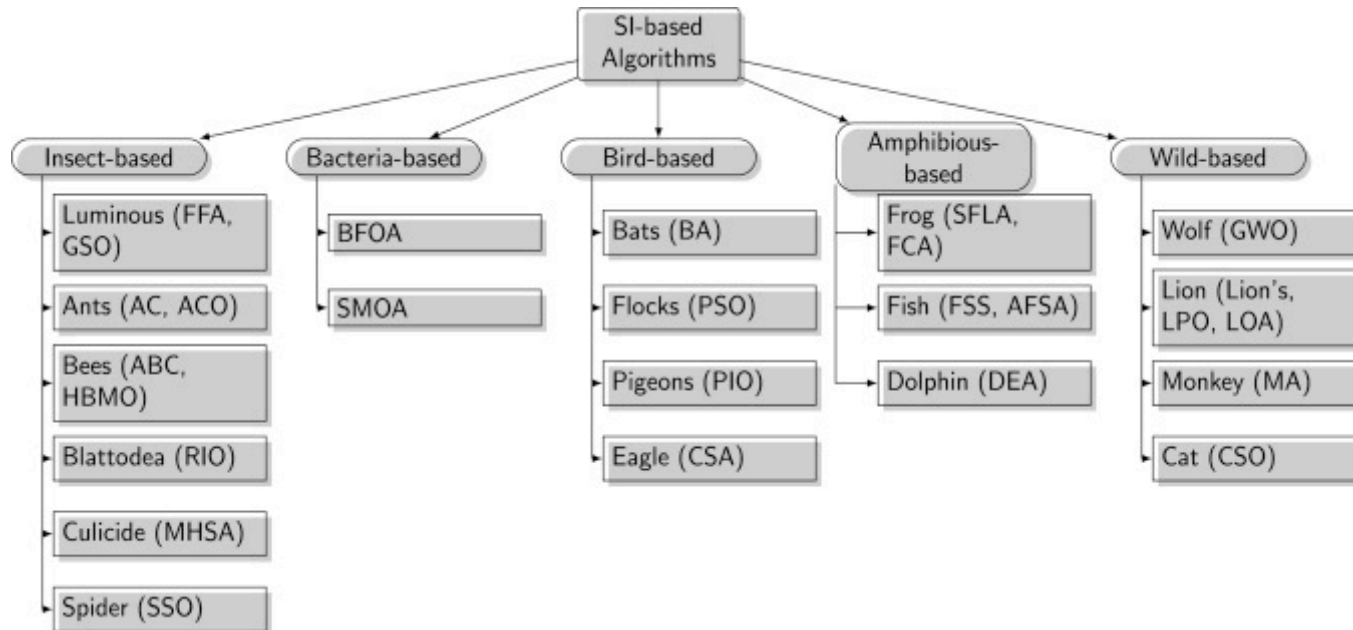
- τ_{ij} pheromone intensity on the path (i,j) ,
- $0 < \rho < 1$ pheromone evaporation rate,
- $\Delta\tau_{ij}^k$ deposited pheromone,
- m number of ants.

2. M. Dorigo and L. Gambardella, "Ant colony system: a cooperative learning approach to the traveling salesman problem," IEEE Transactions on Evolutionary Computation, vol. 1, no. 1, pp. 53–66, 1997

STATE OF ART – SWARM INTELLIGENCE

The **swarm intelligence** is defined as the *collective behaviour* of decentralized and self-organized systems in which the group manifests a form of "intelligence" greater than any element of it alone.

- The swarm can solve complex problems that a single individual with simple abilities cannot solve.
- The swarm is made up of several elements that can get lost or damaged without affecting the performance of the entire group.
- Individuals perceive information only locally, perform simple actions, have little or no memory, and do not know what the overall state of the system is or its purpose³.



- **The goal is reached thanks to the cooperation of every member of the group.**
- **Cooperation is the manifestation of emergent behaviour.**
- **There is no one that commands and coordinates the group.**
- **Cooperation is a winning strategy.**

STATE OF ART

Everyday we observe several examples of **cooperative** and **competitive** behaviours in the world around us, at different levels of complexity.

Social insects **cooperate** and work together to find food and other resources



Several agents can **cooperate** at one level



Mammals **compete** one against the other or against elements of the same species



...and **compete** at another



STATE OF ART



COOPERATION

- For the evolution of the species.
- Cooperative Dynamics



COMPETITION

- For the survival of the individual.
- Competitive Dynamics



The evolution and our society are the result of an equilibrium of cooperative and competitive dynamics.

THE MODEL – OPTIMIZATION STRATEGIES

Several studies have been made to investigate **the role of the cooperation** among the CAS⁴. The **role of competition** among these systems is still not so clearly understood. This gap motivated us to present:

an agent-based model to study the effects of two different optimization strategies (cooperative and competitive) implemented through a modified ACO algorithm for solving a dynamic labyrinth.

HOW

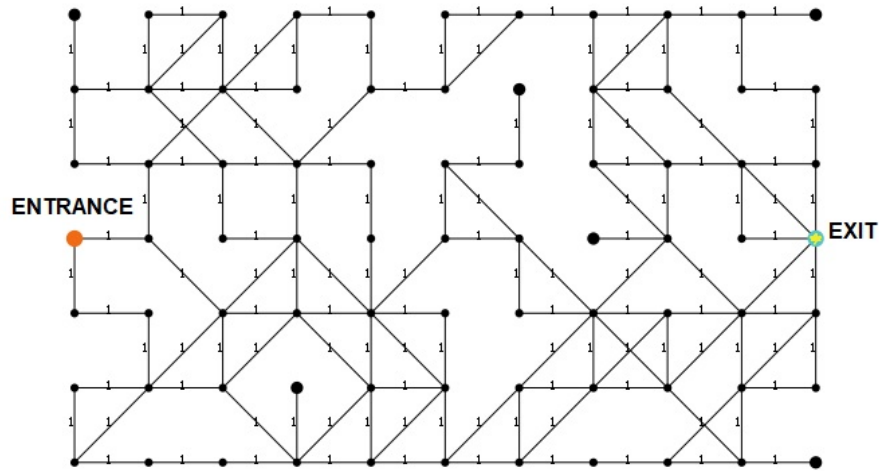
Cooperative and **competitive** ants are put in competition with each other to see if such competition stimulates both, or one of them, to be more efficient.

WHY

Designing efficient algorithms capable to find the shortest route in a dynamic environment is crucial especially in emergency situations (*earthquakes, volcanic eruptions, hurricanes*). In this cases we have little or no information about the state of the system because it changes rapidly from time to time. Classical methodologies have an high computational cost and fail when applied to networks with uncertainty, dynamism and/or incomplete information

THE MODEL – OPTIMIZATION STRATEGIES

The project was implemented using **NetLogo**⁵, an agent-based programming language and an Integrated Development Environment (IDE). We:



The resources can be taken by the ants if and only if they **reach it by the shortest path**. When there are no more resources a new node will be selected as exit, with the same amount of resources on it.

- **started** with an existing model⁶ originally provided for the possibility of creating different, simple and random labyrinths;
- **fixed** the seed of the random numbers to repeat the simulations under stable conditions (at each run, the same labyrinth is regenerated).
- **created** a network underneath the labyrinth;
- **realized** more complex labyrinths by adding other links between some nodes with at least two first neighbours and other nodes also with at least two first neighbours;
- **entrance**: randomly chosen among edge nodes;
- **exit**: variable and randomly selected among the edge nodes that are not on the same side of the entrance. It is also with a limited amount of resources on it.

5. U. Wilensky, "Netlogo," Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL, 1999. [Online].Available: <http://ccl.northwestern.edu/netlogo/>

6. J.Steiner,"Mazemaker,"2004.[Online].Avail-able:http://ccl.northwestern.edu/netlogo/models/community/maze-maker-2004

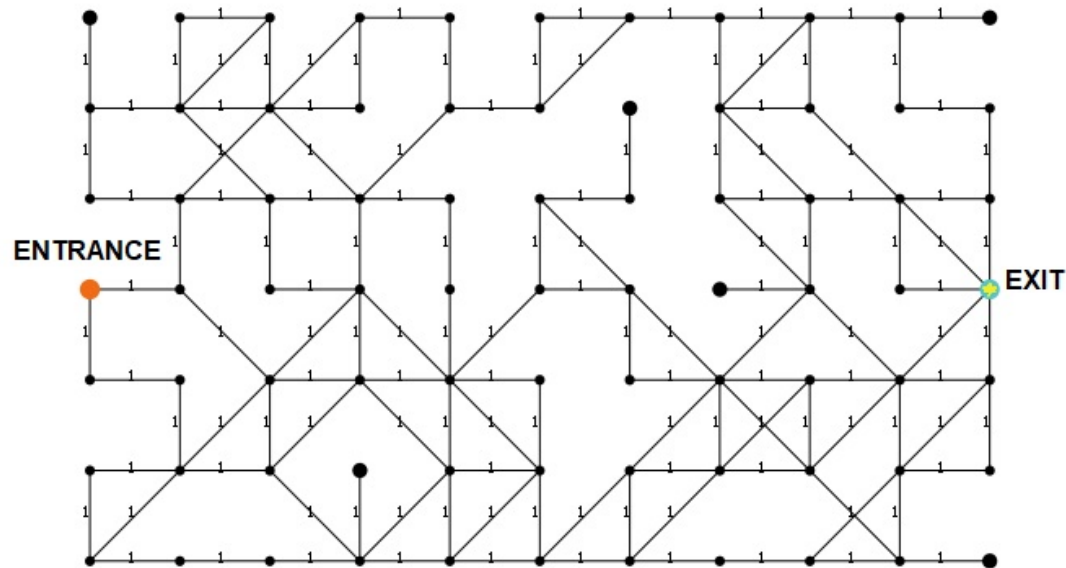
THE MODEL – OPTIMIZATION STRATEGIES

Effects of Different Dynamics in an Ant Colony Optimization Algorithm⁷

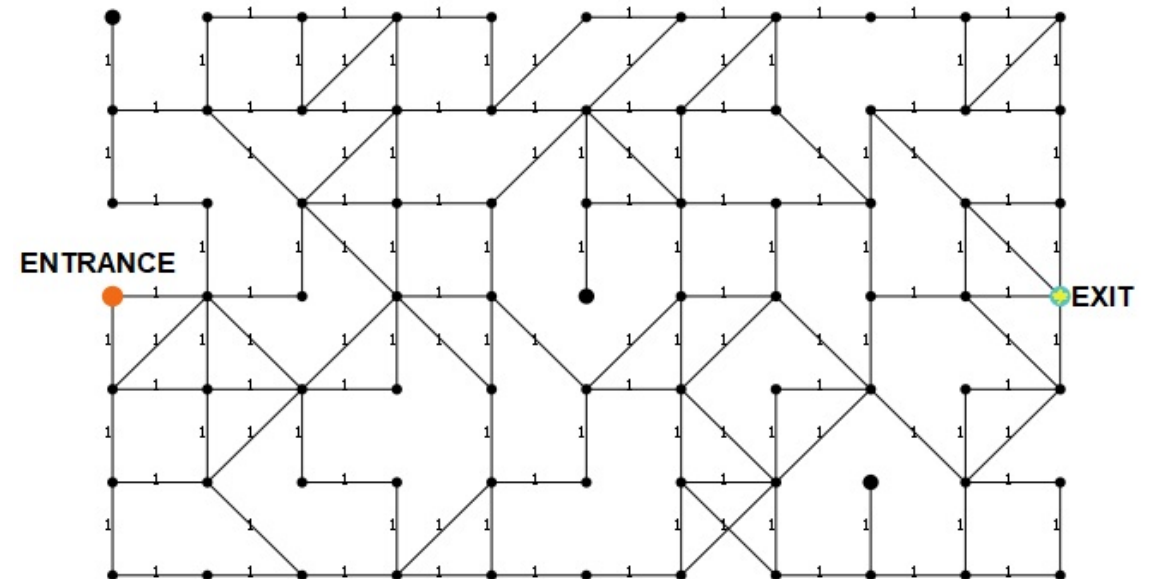
C. Crespi, R. A. Scollo and M. Pavone

We have performed the simulations by using two different labyrinths both with same number of nodes ($|V| = 77$) and links ($|E| = 128$) but different distribution of links. In this instance, the entrance is generated on the left and the exit on the right. We have:

- **called** “A” the labyrinth with a non-uniform distribution of links and “B” the ones with a uniform distribution;



Labyrinth scenario A



Labyrinth scenario B

THE MODEL – OPTIMIZATION STRATEGIES

Effects of Different Dynamics in an Ant Colony Optimization Algorithm⁷

C. Crespi, R. A. Scollo and M. Pavone

We have performed the simulations by using two different labyrinths both with same number of nodes ($|V| = 77$) and links ($|E| = 128$) but different distribution of links. We have:

- **used** 100 ants for both type of labyrinths;
- **created** a **cooperation factor** $F \in [0,1]$ to define the proportion of cooperative ants with respect to the colony. Once it is defined, the other ants will act in a competitive way.
- **set** the initial pheromone trail on the links to 1.0;
- **set** the evaporation rate α to 0.1;
- **set** the maximum number of generations to 100;
- **started** the experiments with a cooperation factor value $F = 0.00$ (that define a colony of just competitive ants) and incremented it with steps of 0.05 to the value $F = 1.00$ (that define a colony of just cooperative ants).
- **performed** 100 independent simulations for every value of F .

7. C. Crespi, R. A. Scollo and M. Pavone (2020). "Effects of Different Dynamics in an Ant Colony Optimization Algorithm". In: 7th International Conference on Soft Computing Machine Intelligence (ISCFI), pp. 8–11. DOI: 10.1109/ISCFI51676.2020.9311553.

THE MODEL – OPTIMIZATION STRATEGIES

Effects of Different Dynamics in an Ant Colony Optimization Algorithm⁷

C. Crespi, R. A. Scollo and M. Pavone

Our labyrinth is a graph $G = (V, E)$ where V is the set of nodes and E the set of arcs.

Proportional transition rule

$$p_{ij}^k(t) = \begin{cases} \frac{\tau_{ij}(t)}{\sum_{l \in J_i^k} \tau_{il}(t)} & \text{if } j \in J_i^k \\ 0 & \text{otherwise} \end{cases}$$

- τ_{ij} pheromone intensity the path (i,j) ,
- $0 < \alpha < 1$ pheromone evaporation rate,
- $\Delta\tau_{ij}^k$ deposited pheromone.

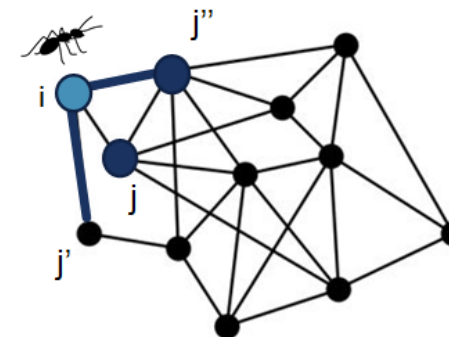
Static reinforcement rule

$$\Delta\tau_{ij}^k = 1.5$$

Global updating rule

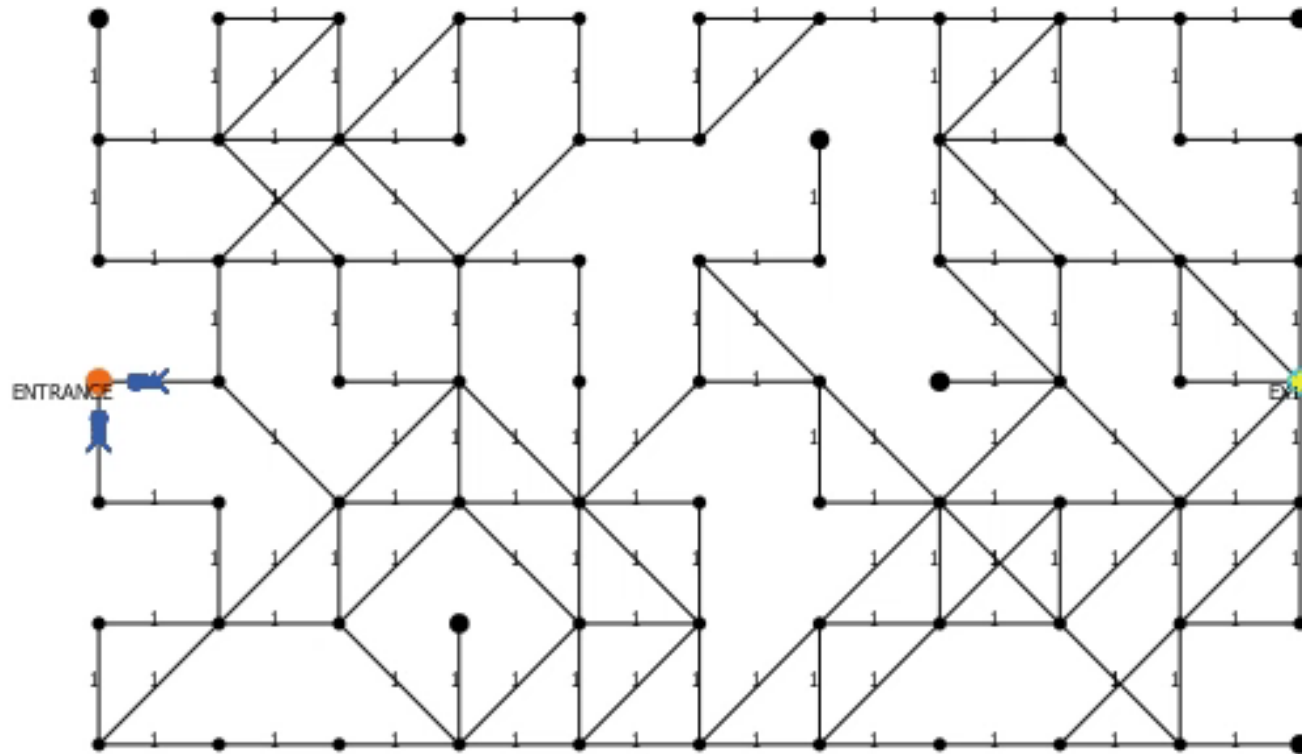
$$\tau_{ij}(t+1) = (1 - \alpha) \cdot \tau_{ij}(t) + \Delta\tau_{ij}^k(t)$$

- τ_{ij} pheromone intensity the path (i,j) ,
- $\alpha = \beta = \eta_{ij} = 1$
- J_i^k set of allowed links.



THE MODEL – OPTIMIZATION STRATEGIES

An agent-based model to study the effects of two different optimization strategies (cooperative and competitive) implemented through a modified ACO algorithm for solving a dynamic labyrinth.



LABYRINTH

- **Entrance** and **Exit** are randomly generated.
- The labels on the links represent the amount of pheromone on that path.
- **Smaller** dots are visitable nodes.
- **Bigger** dots are not visitable nodes.
- **Fires** are damaged nodes

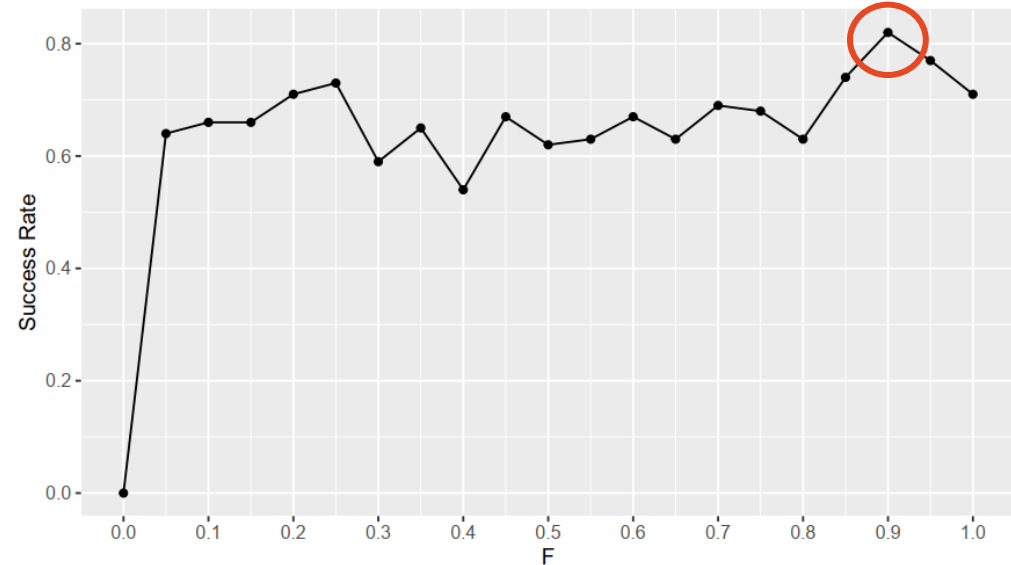
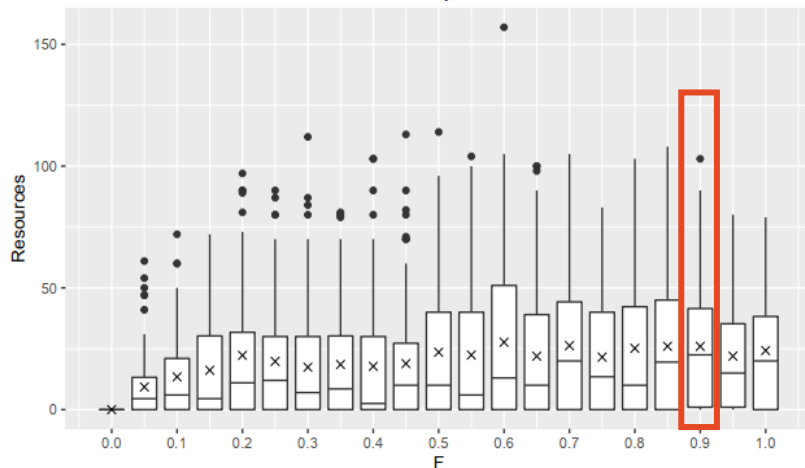
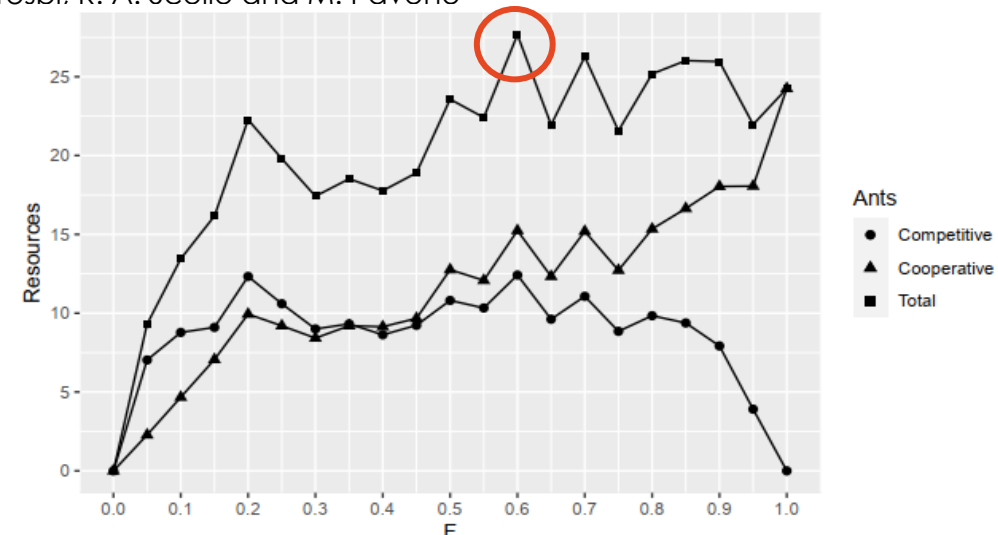
ANTS

- **Competitive:** When they arrive at the exit they damage (fire) a random node of their path;
- **Cooperative:** If they find a damaged node near their path, they repair it

THE MODEL – OPTIMIZATION STRATEGIES

Effects of Different Dynamics in an Ant Colony Optimization Algorithm⁷

C. Crespi, R. A. Scollo and M. Pavone



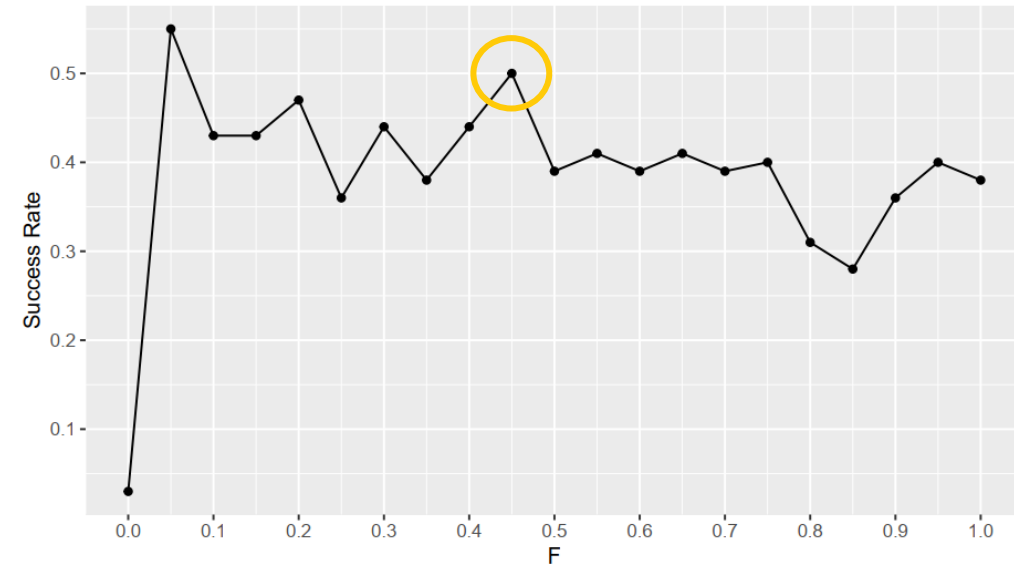
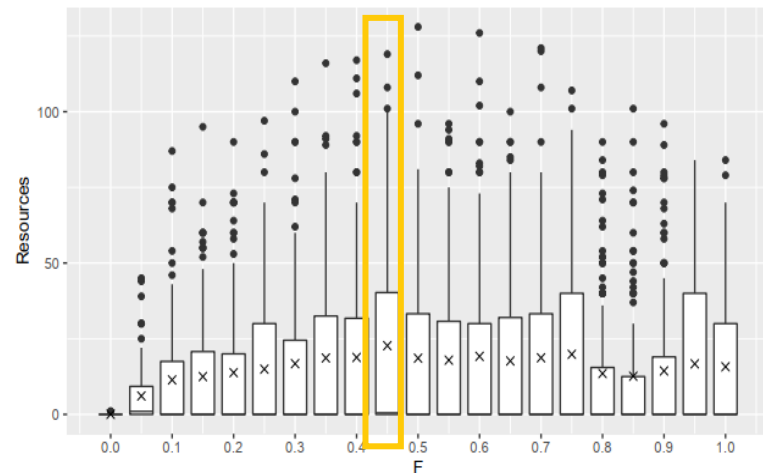
Scenario A

- $F = 0.60 \rightarrow$ best value (27.70) of earned resources on average.
 - $F = 0.90 \rightarrow$ best success rate (82%).
 - $F = 0.90 \rightarrow$ median and mean value very close.
- $F = 0.90$ best compromise value of the cooperation factor

THE MODEL – OPTIMIZATION STRATEGIES

Effects of Different Dynamics in an Ant Colony Optimization Algorithm⁷

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Scenario B

- $F = 0.45 \rightarrow$ best value (22.70) of earned resources on average.
 - $F = 0.05 \rightarrow$ best success rate (55%).
 - $F = 0.45 \rightarrow$ median value equal to zero for all the values of F^*
- $F = 0.45$ best compromise value of the cooperation factor

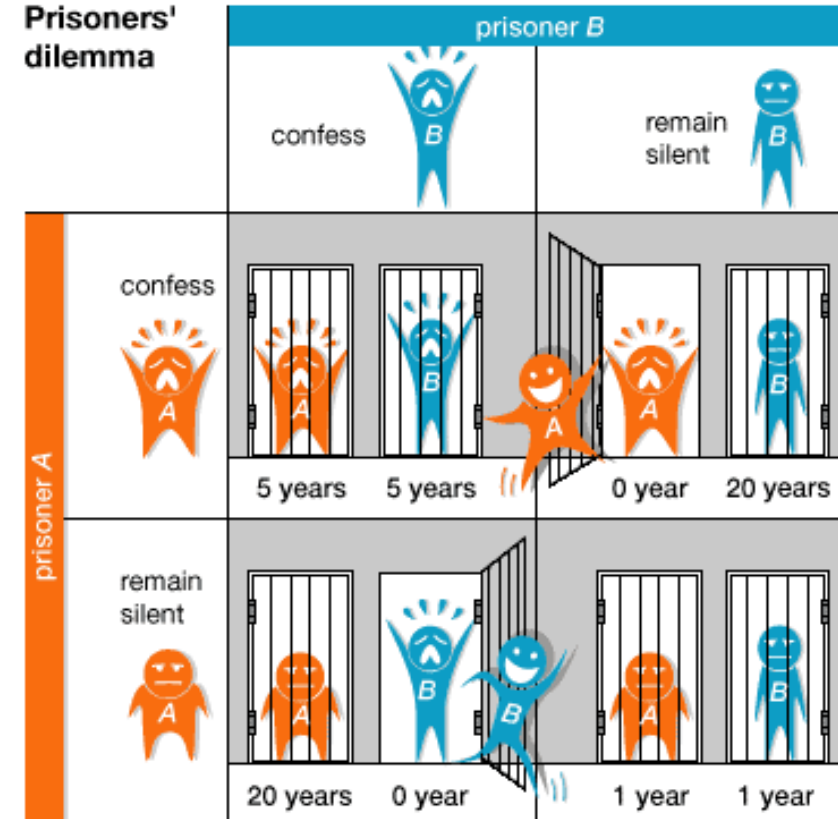
A GAME THEORY APPROACH



A GAME THEORY APPROACH

Game theory is a theoretical framework to study social situations among players and produce optimal decision-making of independent players in a strategic setting. It is often applied to biological, economic and social systems. But also for pedestrian and for evacuation and panic situations, where people tend to assume different and unpredictable behaviours. Some terms commonly used in Game Theory are:

- **Game:** Any set of circumstances that has a result dependent on the actions of two or more players
- **Players:** A strategic decision-maker within the context of the game
- **Strategy:** A complete plan of action a player will take given the set of circumstances that might arise within the game
- **Payoff:** The payout a player receives from arriving at a particular outcome
- **Information set:** The information available at a given point in the game
- **Equilibrium:** The point in a game where both players have made their decisions and an outcome is reached



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THE MODEL – CROWD EVACUATION MODELLING

A Game Theory Approach for Crowd Evacuation Modelling⁸

Carolina Crespi, Georgia Fargetta, Mario Pavone, Rocco A. Scollo and Laura Scrimali

ACO and Game Theory

- **common features:** both ants and people in panic perform simple actions (indirect and local interactions with other ants or humans) and simple social rules in absence of centralized decisions;
- **similar behaviour:** people are attracted to go through routes that are most crossed by other people, like ants who follow pheromones traces;



8. C. Crespi, G. Fargetta, M. Pavone, R. A. Scollo, L. Scrimali (2020) "A Game Theory Approach for Crowd Evacuation Modelling" In: Filipič B., Minisci E., Vasile M. (eds) Bioinspired Optimization Methods and Their Applications. BIOMA 2020. Lecture Notes in Computer Science, vol 12438. Springer, Cham. https://doi.org/10.1007/978-3-030-63710-1_18.

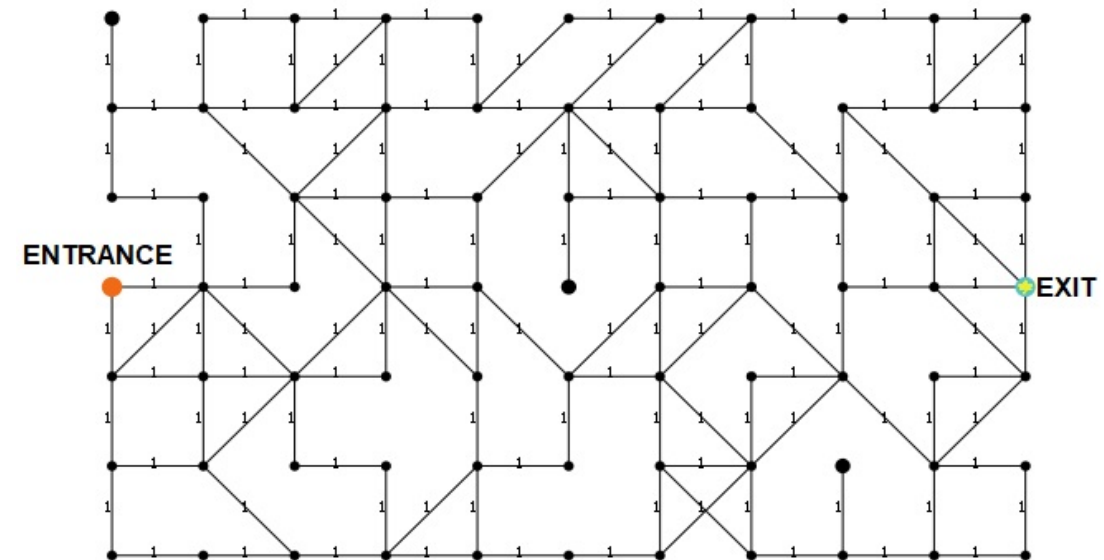
THE MODEL – CROWD EVACUATION MODELLING

A Game Theory Approach for Crowd Evacuation Modelling⁸

Carolina Crespi, Georgia Fargetta, Mario Pavone, Rocco A. Scollo and Laura Scrimali

We have imagined a city like a planar graph whose topology is unknown: a labyrinth. A group of agents must find the exit from a certain entrance as soon as possible to survive. Most disasters and emergencies (earthquakes, explosions, terrorist attacks) that involve humans happen in cities that become unknown for people in panic: they hardly understand how and where to move, just following the others in the crowd to maximize their probability to get safe. The escape situation is like a game in which every ant (agent) can adopt two different strategies to exit from the labyrinth.

- **Non-Cooperative:** damage a random node of their path.
- **Cooperative:** if they find a damaged node close to their path, they repair it. This strategy tries to model a realistic case in which some people try to help other people to reach safe locations, while others think only of saving themselves and, due to panic, can damage a route, making it impossible to be crossed. Cooperatives, to save themselves, must make it crossable again.



THE MODEL – CROWD EVACUATION MODELLING

A Game Theory Approach for Crowd Evacuation Modelling⁸

Carolina Crespi, Georgia Fargetta, Mario Pavone, Rocco A. Scollo and Laura Scrimali

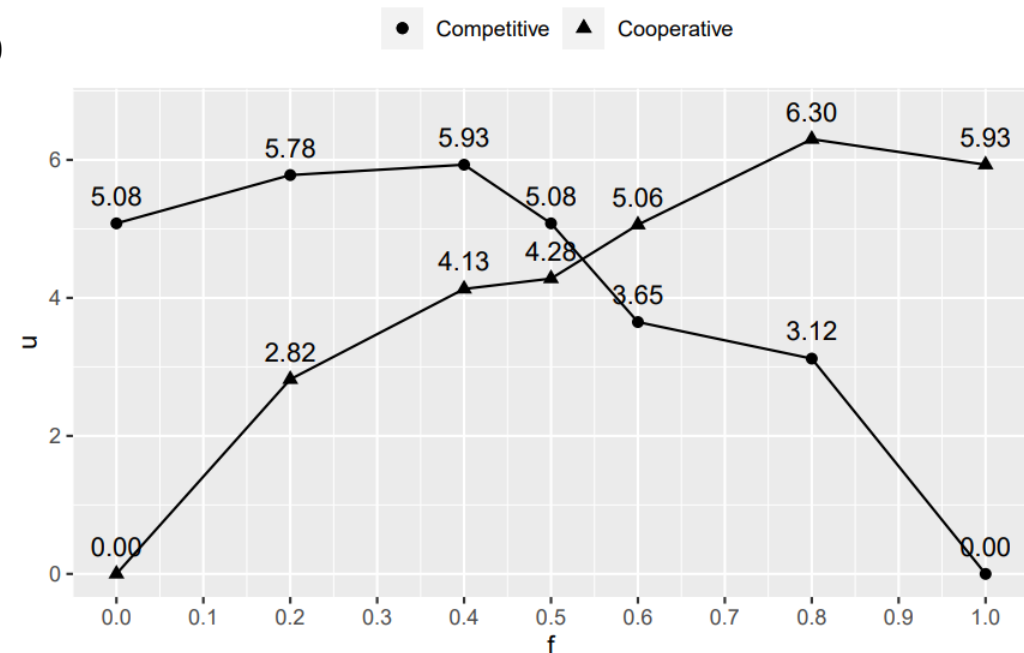
Via a game theory approach, we have investigated how these two strategies affect the final payoff of each typology. We have denoted with $G = (V ; L)$ the graph associated with the game, where V is the set of vertices and L the set of links. The game is a N -players game ($N \geq 2$) that can be cooperative or not cooperative and each player start from the entrance. The goal is to reach the exit using the minimum path. The exit is the shelter that has a capacity K represented by the prizes on it. We have choose a set of $n = 10$ agents and performed 10 different simulations for different values of f , starting from $f = 0.00$ to $f = 1.00$ and increasing f at a regular interval of 0.20.

Payoff function of cooperative agents

$$u^C = f \cdot \sum_{i,j} \tau_{i,j} \quad 0 < f \leq 1$$

Payoff function of non-cooperative agents

$$u^{NC} = (1 - f) \cdot \sum_{i,j} \tau_{i,j} \quad 0 \leq f < 1$$



8. C. Crespi, G. Fargetta, M. Pavone, R. A. Scollo, L. Scrimali (2020) "A Game Theory Approach for Crowd Evacuation Modelling" In: Filipič B., Minisci E., Vasile M. (eds) Bioinspired Optimization Methods and Their Applications. BIOMA 2020. Lecture Notes in Computer Science, vol 12438. Springer, Cham. https://doi.org/10.1007/978-3-030-63710-1_18.

CONCLUSIONS AND FUTURE AIMS

From the data analysis of both models it seems that:

- a small fraction of competitive agents can be useful and advantageous for the entire colony.
- The colony reaches better results not when it is composed of just one kind of agent (the cooperative ones) but when some agents act differently.
- The payoff of the cooperative agents is higher when the colony is heterogeneous.

Counterintuitive result!

It is a counterintuitive result but a possible explanation is that when a competitive ant reaches the exit it blocks a node of the path and this action can be useful because it forces the rest of the colony to change its behaviour and to search for other paths.

The best solution is obtained thanks to a mixed strategy.

Competition is the manifestation of emergent behaviour.

There is no one that commands and coordinates the group.

The mixed strategy is a good strategy.



**COMPETITION AS AN OPTIMIZATION
STRATEGY?**

MAYBE YES!

CONCLUSIONS AND FUTURE AIMS

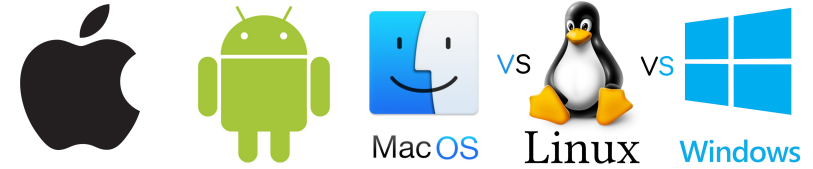
Literature shows us that we are not the only ones that are enjoying these unusual research methodologies.

- Borji A. (2007) A New Global Optimization Algorithm Inspired by Parliamentary Political Competitions. In: Gelbukh A., Kuri Morales Á.F. (eds) MICAI 2007: Advances in Artificial Intelligence. MICAI 2007. Lecture Notes in Computer Science, vol 4827. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-76631-5_7
- Wusi Yang, Li Chen, Yi Wang, Maosheng Zhang, "Multi/Many-Objective Particle Swarm Optimization Algorithm Based on Competition Mechanism", *Computational Intelligence and Neuroscience*, vol. 2020, Article ID 5132803, 26 pages, 2020. <https://doi.org/10.1155/2020/5132803>
- E. Atashpaz-Gargari and C. Lucas, "Imperialist competitive algorithm: An algorithm for optimization inspired by imperialistic competition," *2007 IEEE Congress on Evolutionary Computation*, Singapore, 2007, pp. 4661-4667, doi: 10.1109/CEC.2007.4425083.
- Chen, H., Feng, X. & Yu, H. Group competition-cooperation optimization algorithm. *Appl Intell* (2020). <https://doi.org/10.1007/s10489-020-01913-y>
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- ZHANG, Y., XUE, S., & ZENG, J. (2015, February). Cooperative and competitive coordination in swarm robotic search for multiple targets. In *Robots* (Vol. 37, pp. 142-151).

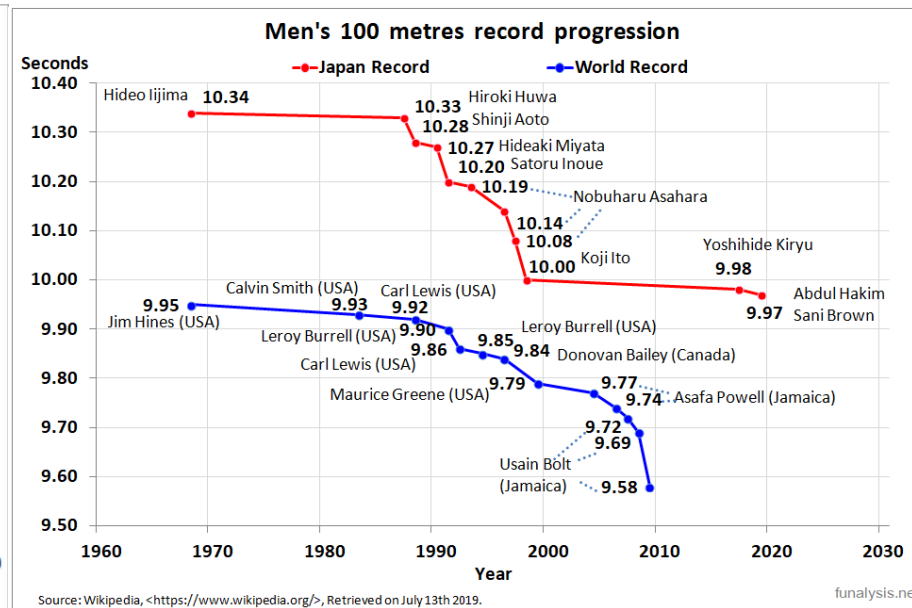
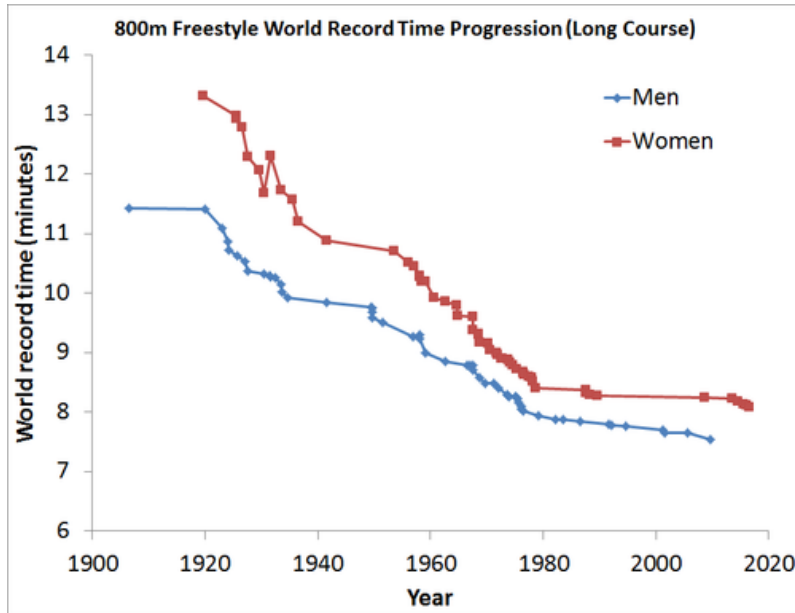
CONCLUSIONS AND FUTURE AIMS

Society shows us that we are in the right path.

COMPETITION IN TECHNOLOGY → OPTIMIZATION OF DEVICE'S FEATURE



COMPETITION IN SPORT → OPTIMIZATION OF CHALLENGES TIMES



COMPETITION IN ENTERTAINMENT
→ OPTIMIZATION OF USER EXPERIENCE



CONCLUSIONS AND FUTURE AIMS

In the next future, our aims are:

- Consider a dynamic labyrinth with appearing and disappearing edge and nodes;
- Add weight on links to search not only the shortest path but also the cheapest one;
- Improve our results performing other simulations;
- Model other critical or panic situations present in literature;
- Consider a evolutionary game theory approach in which ants (agents) can change their strategy over time;
- Investigate the research about the role of competition in the field of the natural computation with agent-based models.



THANKS ANY QUESTION?

CONTACT ME

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