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An agent-based model to investigate different behaviors in a crowd simulation

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TALK OUTLINE

- INTRODUCTION
- THE MODEL
- EXPERIMENTS AND RESULTS
- CONCLUSIONS AND FUTURE WORKS

INTRODUCTION

Studying crowd behaviour has become one of the most challenging topics of the last few years because of its applications in different fields:

Emergency management	Social science	Architecture	Entertainment industry
			
It is crucial to know in advance how people would behave to establish efficient escape plans [1].	To understand and outline different psychological aspects of human behaviors [2].	To establish where to put the exits of a building to have maximum flow, or where to realize corridors to avoid bottlenecks [3].	To create battle scenes and crowd movements in movies and video games [4].

1. Peng, Y., Li, S.W., Hu, Z.Z.: A self-learning dynamic path planning method for evacuation in large public buildings based on neural networks. Neurocomputing **365**, 71–85 (2019). https://doi.org/10.1016/j.neucom.2019.06.099
2. Varghese, E.B., Thampi, S.M.: Towards the cognitive and psychological perspectives of crowd behaviour: a vision-based analysis. Connection Science **33**(2), 380–405 (2021)
3. Shi, X., Ye, Z., Shiwakoti, N., Tang, D., Lin, J.: Examining effect of architectural adjustment on pedestrian crowd flow at bottleneck. Physica A: Statistical Mechanics and its Applications **522**, 350–364 (2019). https://doi.org/10.1016/j.physa.2019.01.086
4. Yucel, F., Surer, E.: Implementation of a generic framework on crowd simulation: a new environment to model crowd behavior and design video games. Mugla Journal of Science and Technology **6**, 69–78 (2020). https://doi.org/10.22531/muglajsci.706841

INTRODUCTION

Lack of real data

It is not easy to take data from real events.

Data inaccuracy

In experiments people know that they are not in danger.

Etich issuess[5]

It is not ethical to put people in danger just to observe how they act and react.

Costs

It can be expansive realize real word experiments.

Simulations

A valid tool to recreate, in a controlled environment, different kinds of situations otherwise difficult or impossible to analyze.

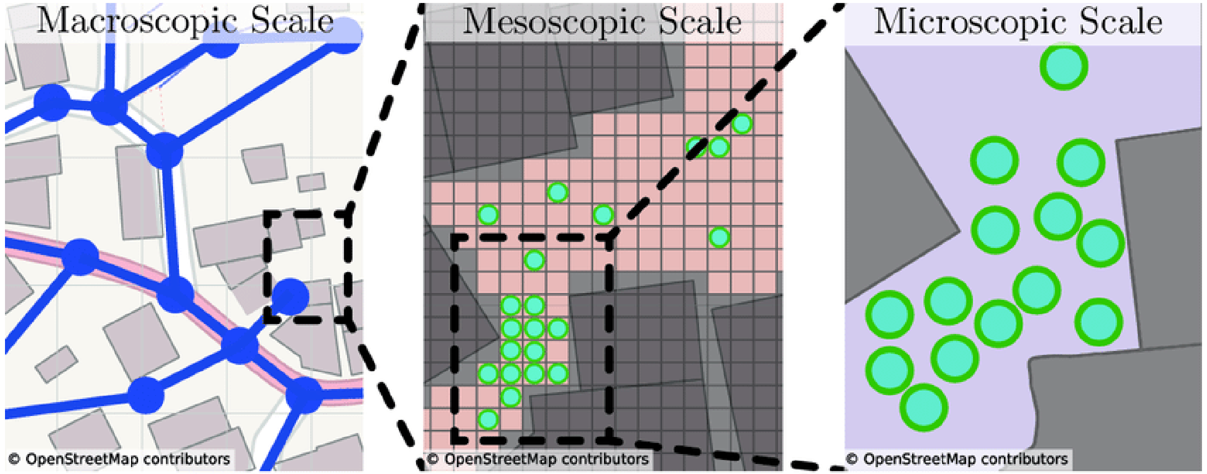
5. Drury, J., Cocking, C., Reicher, S., Burton, A., Schofield, D., Hardwick, A., Graham, D., Langston, P.: Cooperation versus competition in a mass emergency evacuation: A new laboratory simulation and a new theoretical model. Behavior research methods 41, 957–970 (09 2009). https://doi.org/10.3758/BRM.41.3.957

INTRODUCTION

Crowds' models can be very different from one to another and this depends on what one wants to focus on and on the framework used[6].

There are:

- **MACROSCOPIC MODELS:** pedestrians are represented in a collective manner as a homogenous flow. They are efficient in representing large-scale scenarios but fails to explain emergent behaviours.
- **MICROSCOPIC MODELS:** consider individual pedestrians' behaviour and the interactions among individuals. They are efficient in representing individual decision-making but need of intensive computational processes.
- **MESOSCOPIC/HYBDRID MODELS:** combination of both macro and micro techniques



Multiscale view on pedestrian dynamic simulations: the macroscopic, mesoscopic and microscopic scale

6. Siyam, N., Alqaryouti, O., Abdallah, S.: Research issues in agent-based simulation for pedestrians evacuation. IEEE Access **8**, 134435–134455 (2020). https://doi.org/10.1109/ACCESS.2019.2956880

THE MODEL

WHAT

- A mesoscopic crowd model in which we have merged different techniques:
  - ACO (swarm intelligence);
  - agent-based approach (microscopic models).

WHY

- To investigate how different agents' behaviour affect each other and the crowd.

HOW

- An agent-based model with two different kinds of agents. Collaborators and defectors that must exit from a virtual environment.

THE MODEL

WHAT

- A mesoscopic crowd model in which we have merged different techniques:
  - ACO (swarm intelligence);
  - agent-based approach (microscopic models).

Swarm intelligence algorithms, are used not only to solve optimization problems[7] but also to model the dynamics of a crowd[8,9]. Both ants in a colony and people in a crowd share some characteristics and behave following unwritten social rules:

- **local interaction;**
- **absence of centralized decisions.**

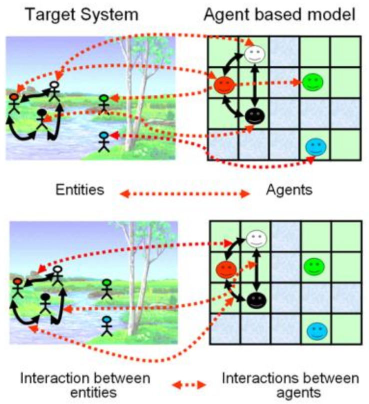
Ants in a colony

They can find the shortest path from their anthill to a source of food and communicate indirectly with one another through chemical signals (pheromones).

People in a crowd

They can optimize their decisions following or avoiding what their neighbours do, directly by communicating with one other or indirectly by seeing what others do.

Agent-based models



Is one of the most powerful technique to model individual decision-making and investigate emergent behaviours.

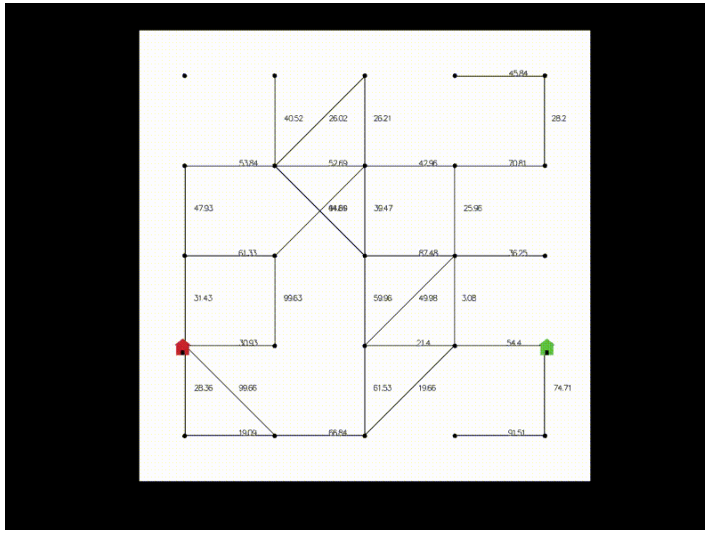
7. Carolina Crespi, Georgia Fargetta, Mario Pavone, Rocco A. Scollo "How a Different Ant Behavior Affects on the Performances of the Whole Colony", In 14th Metaheuristics International Conference (MIC2022), Di Gaspero Luca, Festa Paola, Nakib Amir and Pavone Mario (editors), Lecture Notes in Computer Science, vol. 12438, Springer, Cham, 2022 (in press).
8. Zhi-Min Huang, Wei-Neng Chen, Qing Li, Xiao-Nan Luo, Hua-Qiang Yuan, and Jun Zhang. Ant colony evacuation planner: An ant colony system with incremental flow assignment for multipath crowd evacuation. IEEE Transactions on Cybernetics, 51(11):5559–5572, 2021.
9. Carolina Crespi, Georgia Fargetta, Mario Pavone, Rocco A. Scollo and Laura Scrimali, "A Game Theory Approach for Crowd Evacuation Modelling", In Bioinspired Optimization Methods and Their Applications (BIOMA2020), Filipi˘c Bogdan, Minisci Edmondo and Vasile Massimiliano (editors), Lecture Notes in Computer Science, vol. 12438, Springer, Cham, pp. 228–239, 2020

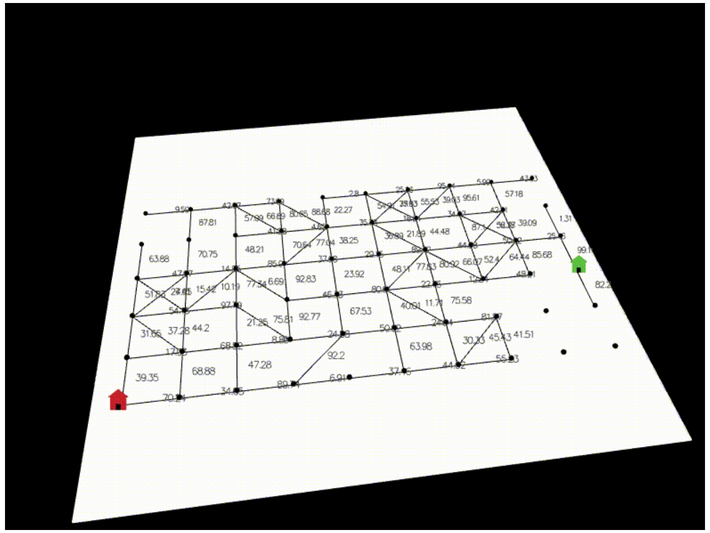
THE MODEL

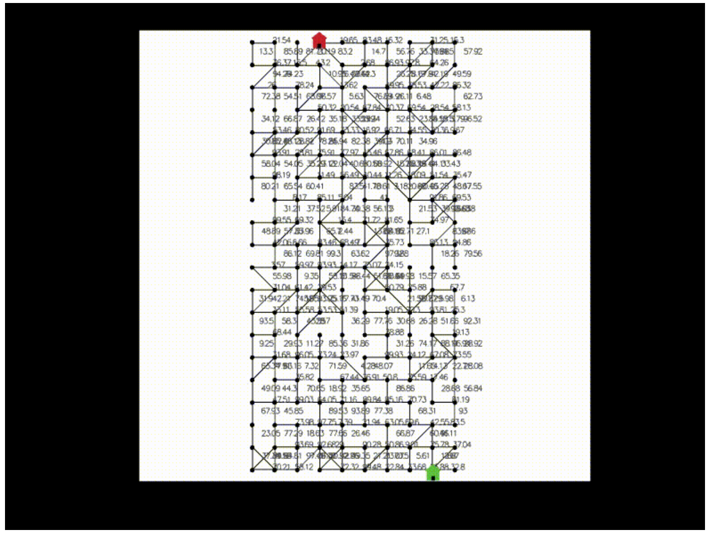
The environment is represented as a **weighted undirected graph** $G(E, V, w)$ where:

- V is the set of vertices;
- $E \subseteq V \times V$ the set of edges;
- $w: V \times V \to \mathbb{R}^+$ is a weighted function that assigns to each edge a positive cost.

It highlights how difficult is crossing a edge.





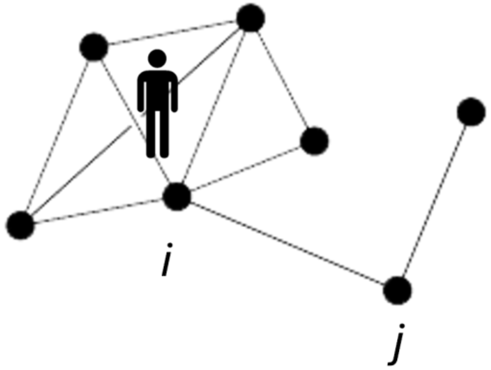


Examples

THE MODEL

Each agent *k* on a node *i* choses to visit an edge $(i,j) \in E$ at a timestamp *t* with a probability $p_{ij}^k(t)$ defined by the following **transition rule**:

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



Where:

- $\boldsymbol{\tau_{ij}(t)}$ is the **trace intensity** on the edge (i,j) at a given time *t*;
  - **the agents leave it unintentionally after each movement and manifest how many times and edge has been crossed;**
  - after each movement is increased by a constant quantity *K* following the **reinforcement rule** $\tau_{ij}(t+1) = \tau_{ij}(t) + K$;
  - every T ticks* decays following the **global updating rule** $\tau_{ij}(t+T) = (1-\rho) \cdot \tau_{ij}(t)$ with ρ evaporation rate;
- $\boldsymbol{\eta_{ij}(t) = 1/w_{ij}(t)}$ is the **desirability** of the edge (i,j) at a given time *t;*
  - information not known a priory **released intentionally by an agent** on a vertex after crossing an edge;
- **$\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are parameters that determine the importance of trace intensity with respect to the desirability of an edge**;
- $J_i^k = A_i \backslash \{\pi_t^k\}$ are all the possible displacements of the agent *k* from vertex *i;*
- $A_i = \{j \in V : (i,j) \in E\}$ is the set of vertices adjacent to vertex *i;*
- $\pi^k(t) = (\pi_1, \pi_2, \dots, \pi_t)$ is the set of vertices visited by the agent *k* at the timestamp *t.*

*The time unit used that corresponds to a single movement of all agents.

THE MODEL

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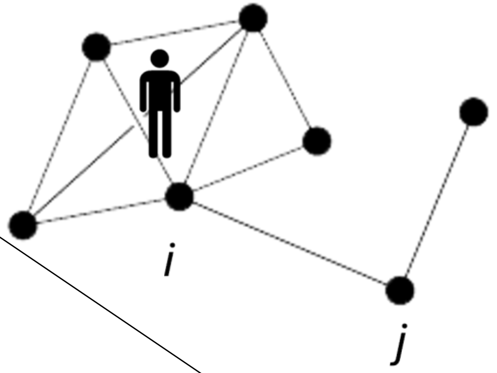
ACO RULES



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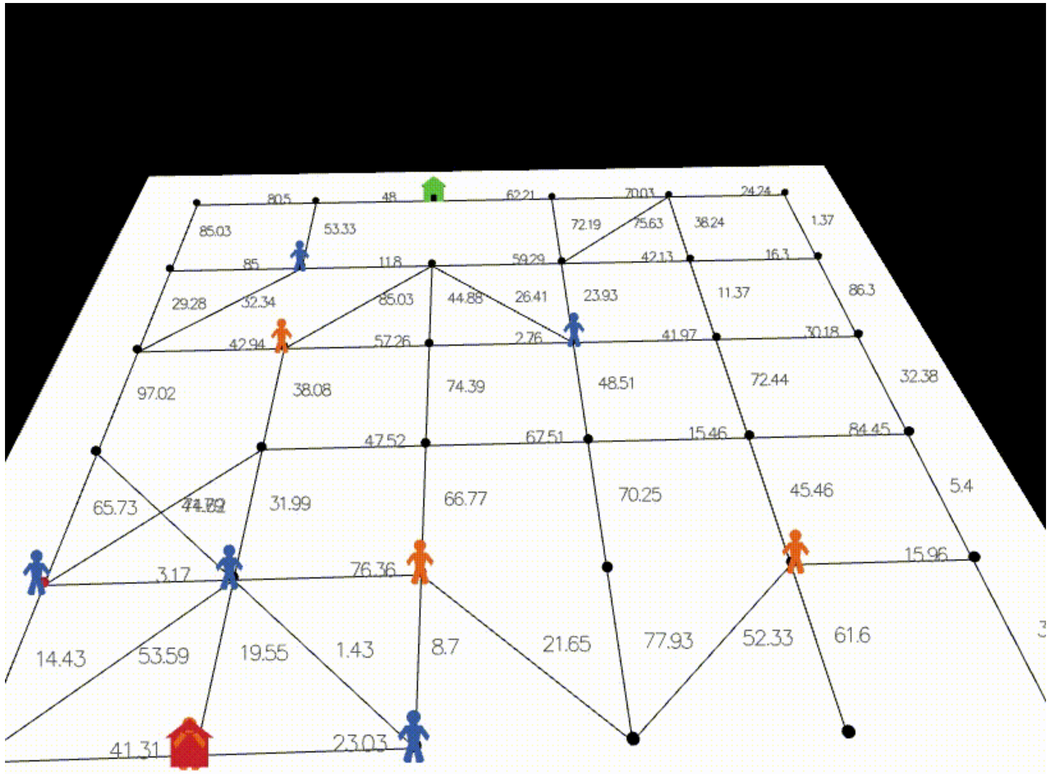
*The time unit used that corresponds to a single movement of all agents.

THE MODEL

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

Cooperators

- Leave a constant trace *K* after crossing an edge (i, j)
- Leave an information $\eta_{ij}(t) = 1/w_{ij}(t)$ on the endpoint after crossing an edge (i, j)
- Repair, with a certain probability $0.0 \leq \rho_{e,v} \leq 1.0$, a damaged edge (i, j) and/or a vertex *i*



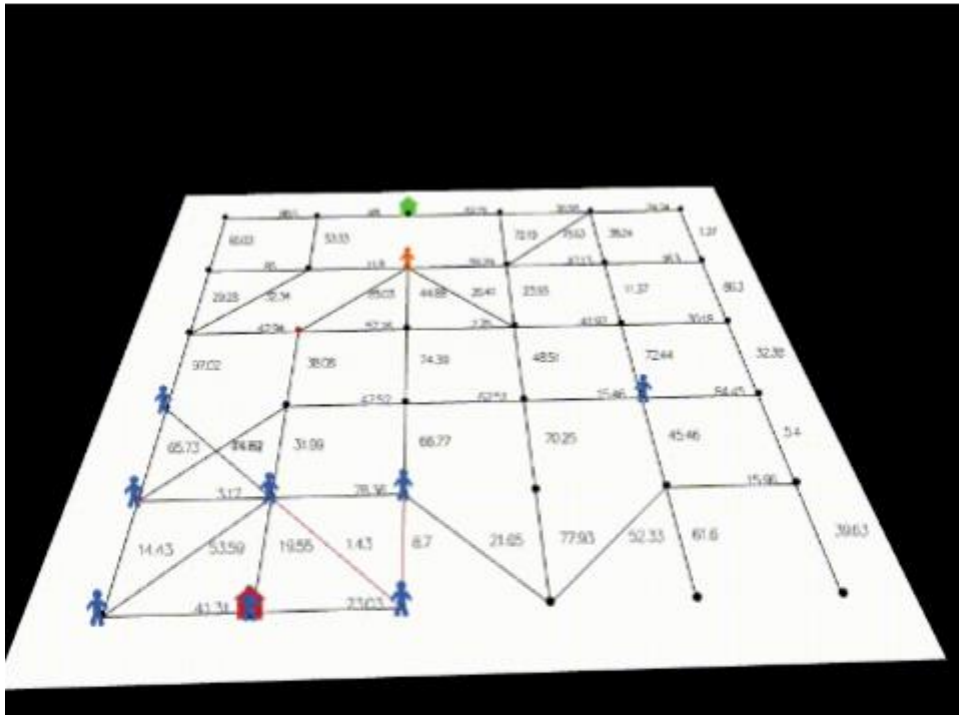
Defectors

- Leave a constant trace *K* after crossing an edge (i, j)
- Don’t Leave an information on the endpoint after crossing an edge (i, j)
- Destroy, with a certain probability $0.0 \leq \rho_{e,v} \leq 1.0$, an edge (i, j) and/or a vertex *i*

THE MODEL

To evaluate how these two behaviours influence the performance of agents, we have conducted our analysis by comparing **simultaneously** three evaluation metrics:

1. the **number of agents** that successfully reach the exit;
2. the **exit time;**
3. the **path cost** $\sum_{i=1}^{t-1} w(\pi_i, \pi_{i+1})$ with
    1. π_1 is the starting point;
    2. π_t is the safe location;
    3. $\pi^k(t) = (\pi_1, \pi_2, \dots, \pi_t)$ is the path of an agent k.



Using these metrics, the best expected performances are the ones for which the number of outgoing agents is the highest possible, while the exit time and the path cost are the lowest possible.

EXPERIMENTS AND RESULTS

We have performed the simulations by using two different scenarios:

- **Scenario A**: rows = 10, columns =10, (|V|=100) vertices and (|E|=213) edges;
- **Scenario B**: rows = 15, columns =15, (|V|= 225) vertices and (|E|=348) edge;

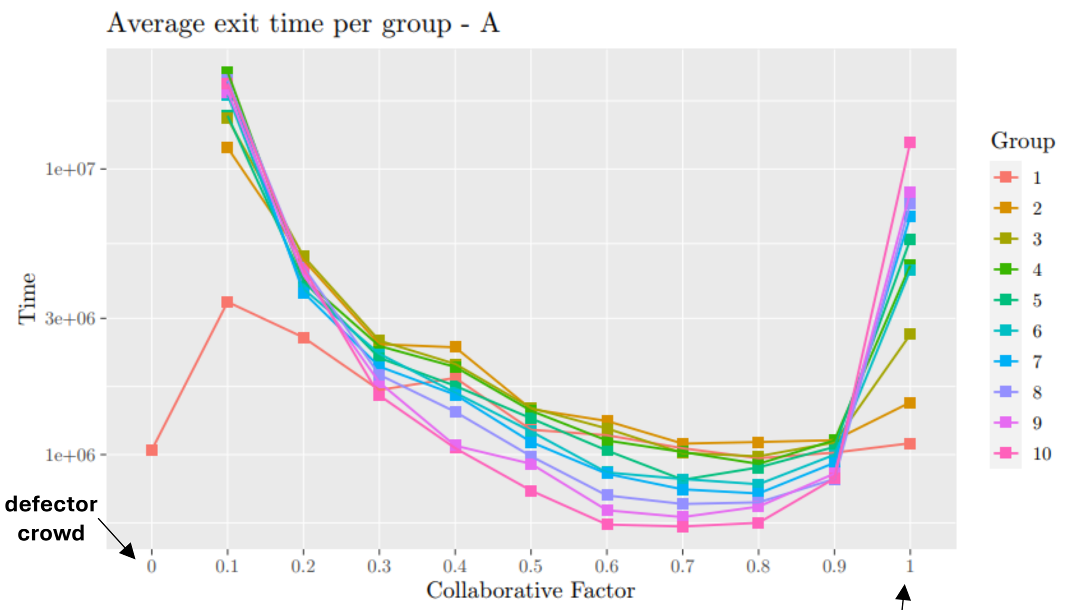
and the following value parameters

- $N = 1000$ agents;
- $\Gamma = 10$ groups of 100 agents;
- $T_e = |V|$ (start interval);
    - **each group begins its exploration after an amount of time** (T_e ticks) from the previous group;
- $T_{max} = 2 \times \Gamma \times T_e$ (max time);
    - **all the agents have a limited time to find the exit**. The first groups have more time to explore the environment compared to the last;
- $K = 1$;
- $\rho_e, \rho_v = 0.02$;
- $\rho = 0.10$;
- $\alpha, \beta = 1.0$;
- $\mathbf{0.0 \leq f \leq 1.0}$ **collaborative factor to define the proportion of collaborative agents with respect to the group**. Once it is defined, the other agents will act in a defector way;
- $s = 100$ independent simulations for every value of f.

*Plots normalized with respect to the exit rate (percentage of agents that successfully reach the exit point for each group)

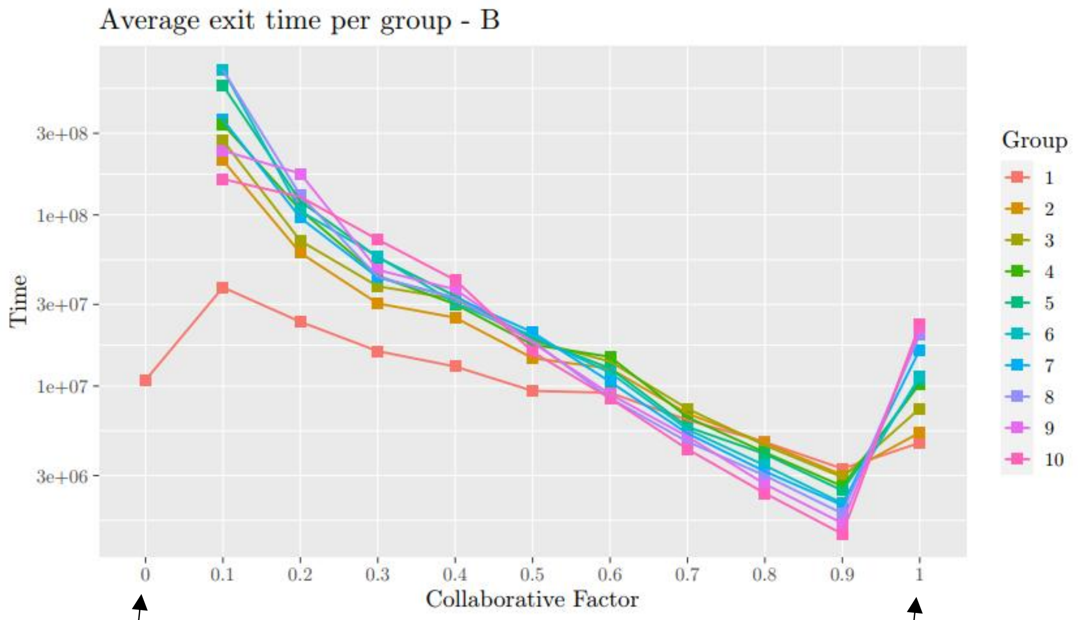
EXPERIMENTS AND RESULTS

GROUPS ANALYSIS



defector crowd

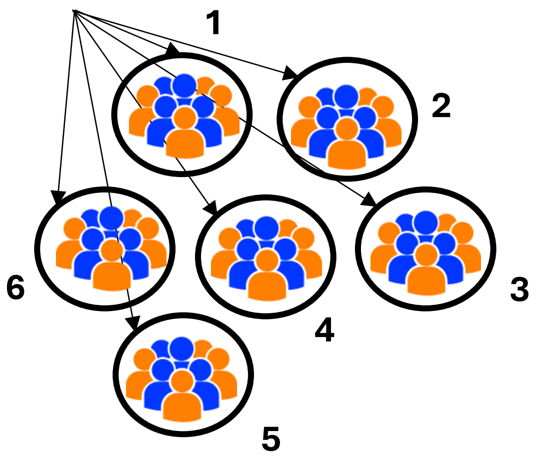
collaborative crowd



defector crowd

collaborative crowd

Groups

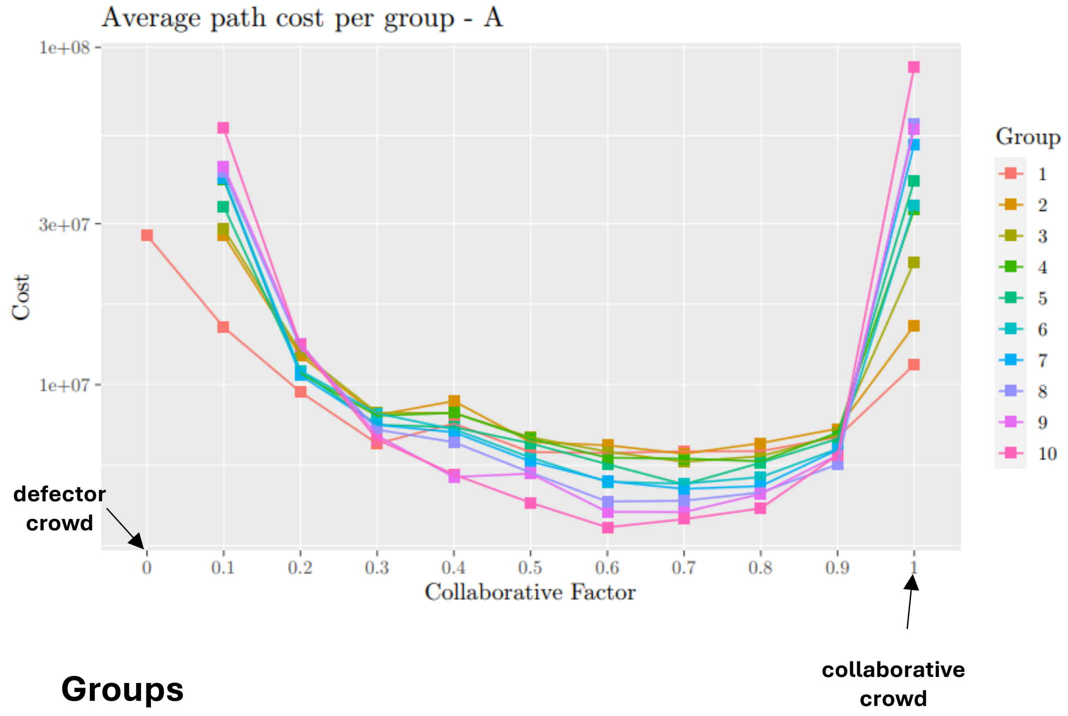


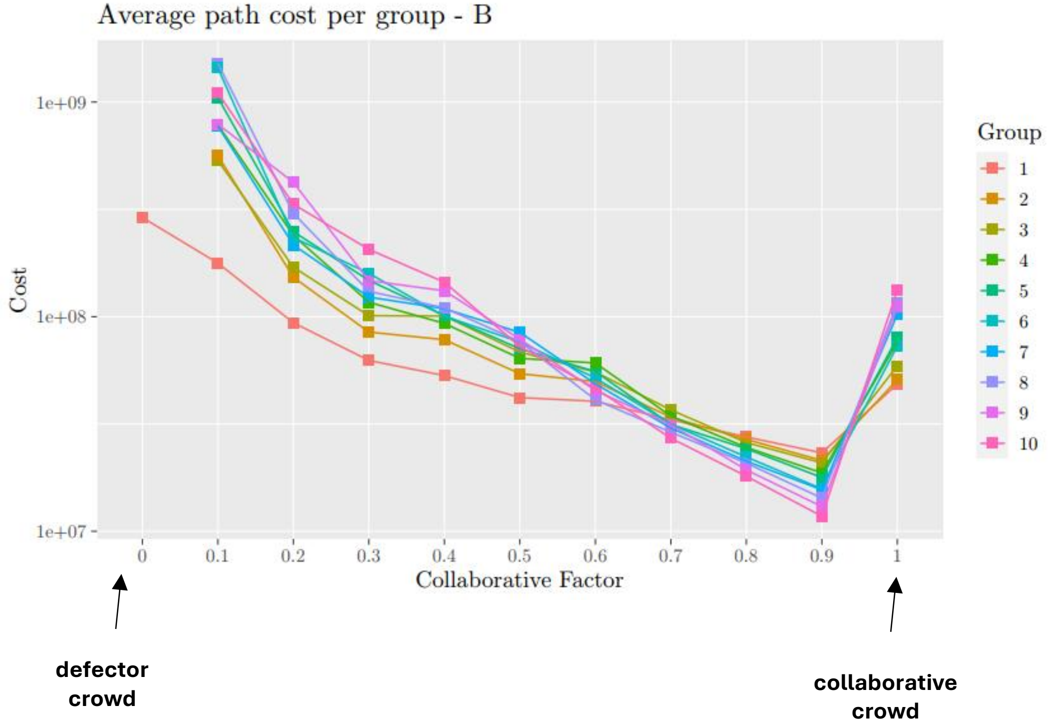
THE EXIT TIME

- **Decreases** with respect to the collaborative factor *f* and worse when *f*=1.0.
  - Each group perform better when it is mainly but not totally collaborative.
- **Decreases** with respect to the group number;
  - the groups that start to explore the environment later exploit the information left by the ones that start first.
  - group 1 <u>seems</u> to be the one that perform better than the others especially when *f*<0.5.

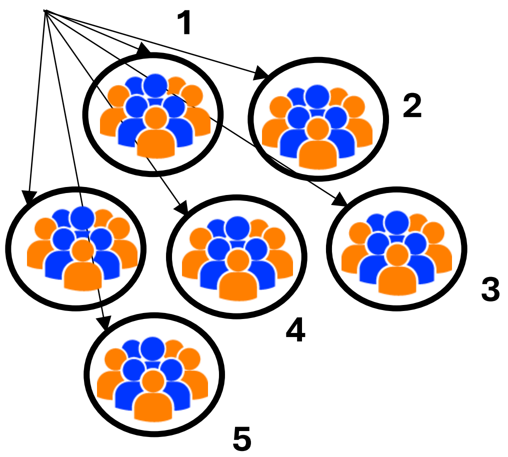
EXPERIMENTS AND RESULTS

GROUPS ANALYSIS





Groups



THE PATH COST

- **Decreases** with respect to the collaborative factor *f* and worse when *f*=1.0.
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  - the groups that start to explore the environment later exploit the information left by the ones that start first.
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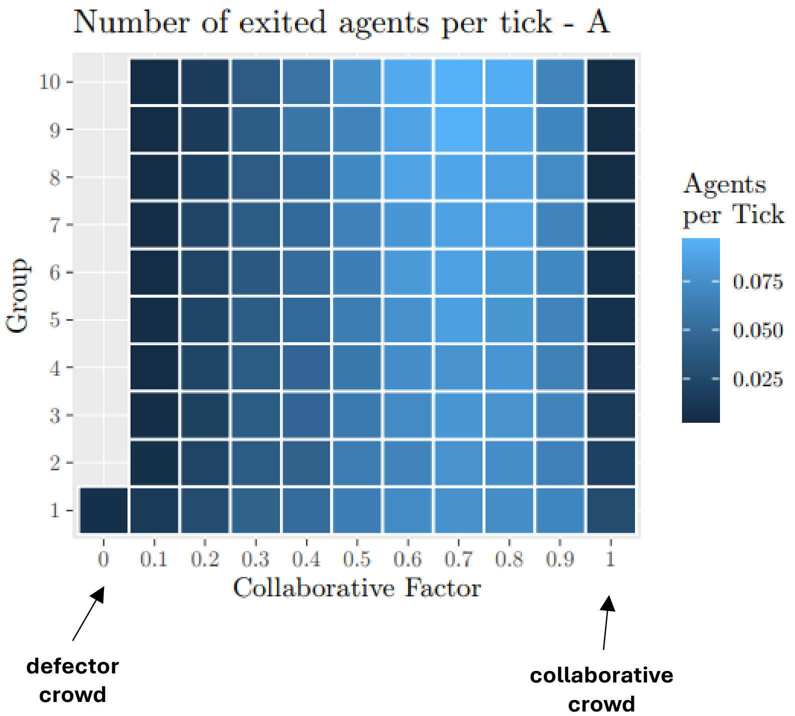
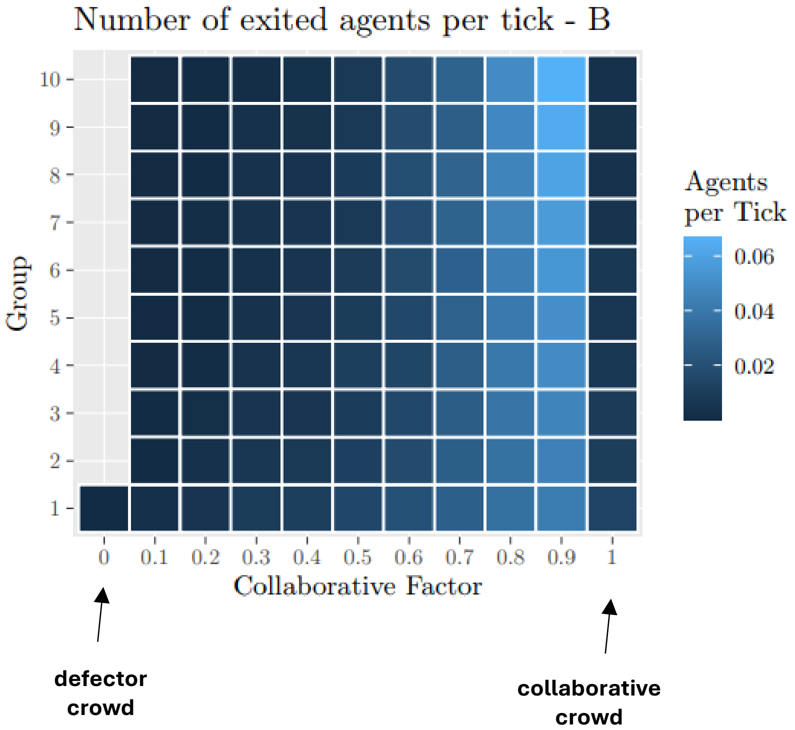
EXPERIMENTS AND RESULTS

GROUPS ANALYSIS

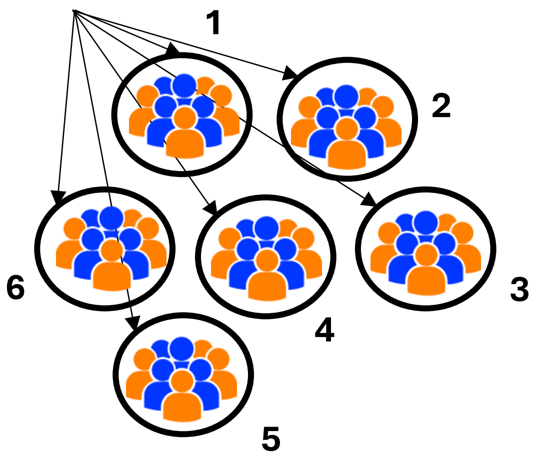
Heat map plots

- *x-axis:* collaborative factor
- *y-axis*: groups
- *legend*: the lighter the blue is the higher the value of the number of agents is, and vice versa.
- absence of colour: no agents have reached the exit.





Groups

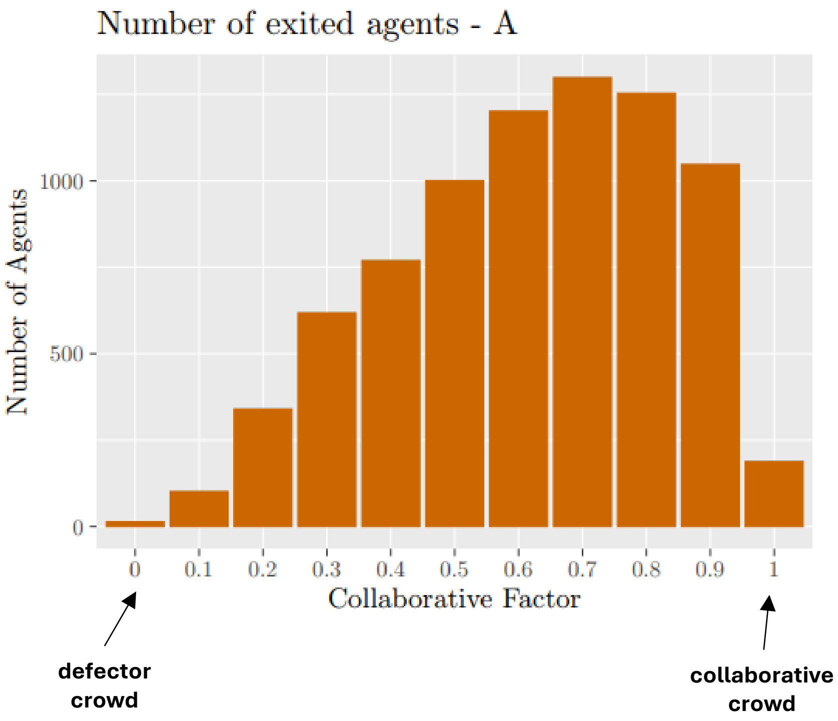


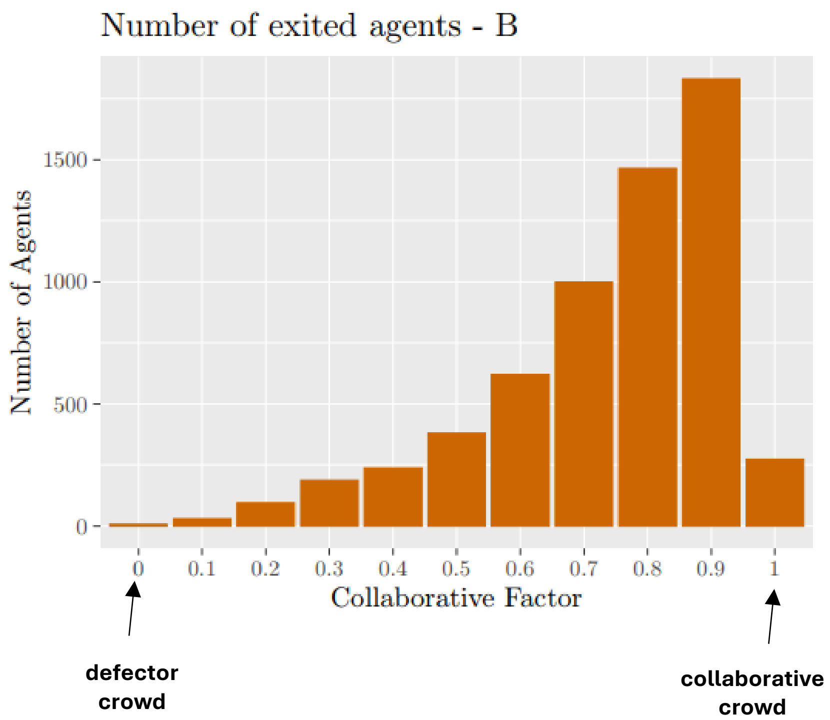
THE NUMBER OF EXITED AGENTS PER TICK

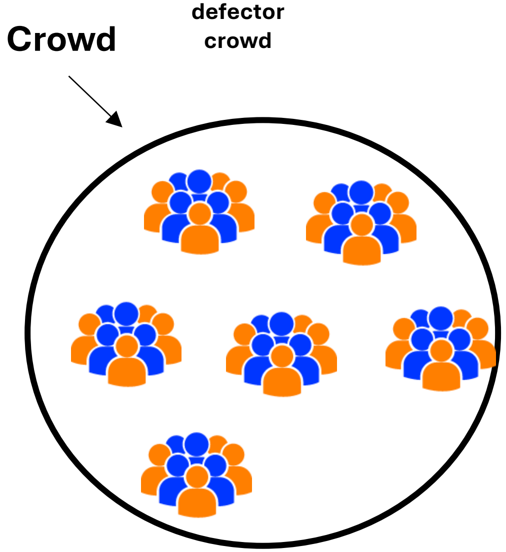
- **Increases** with respect to the collaborative factor *f* and worse when *f*=1.0;
- **Increase** with respect to the group number;
  - the groups that start to explore the environment later exploit the information left by the ones that start first.
  - **only few agents of group 1 exit** and **when *f*=0.0 and no agents of the other groups**.

EXPERIMENTS AND RESULTS

OVERALL ANALYSIS







THE OVERALL NUMBER OF EXITED AGENTS

- **Increases** with respect to the collaborative factor *f* and worsen when *f*=1.0;
  - The crowd perform better when it is mainly but not totally collaborative.

CONCLUSIONS AND FUTURE WORKS

From the results presented we can conclude that:

Collaborators

- **drive the dynamic**;
  - *they share information*;
- are forced by defectors to adapt to different changes in the environment;
- a completely collaborative crowd has bad performance.

Defectors

- **improve the dynamic**;
  - *they reduce the complexity of the environment;*
- exploit the information shared by collaborators;
- a completely defector crowd has bad performance.

Mixed crowd
(mostly collaborative)

- A **mixed crowd** exploit the best features of both behaviours:
  - drive\improve the dynamic;
  - share\reduce information\complexity.
- **Exit more agents, faster and by cheaper paths**.

CONCLUSIONS AND FUTURE WORKS

From the results presented we can conclude that:

Mixed crowd
(mostly collaborative)

- A **mixed crowd** exploit the best features of both behaviours:
  - drive\improve the dynamic;
  - share\reduce information\complexity.
- **Exit more agents, faster and by cheaper paths**.

Future works include but are not limited to…

- *Randomizing the composition of each group;*
  - *Number of groups;*
  - *Number of agents in each group;*
  - *Number of collaborators and defector in each group;*
- *Dynamic behaviours;*
  - *The agents may change their behaviours during a simulation.*

THANKS FOR YOUR ATTENTION

ANY QUESTIONS?

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