

# Conflict solution in cellular models

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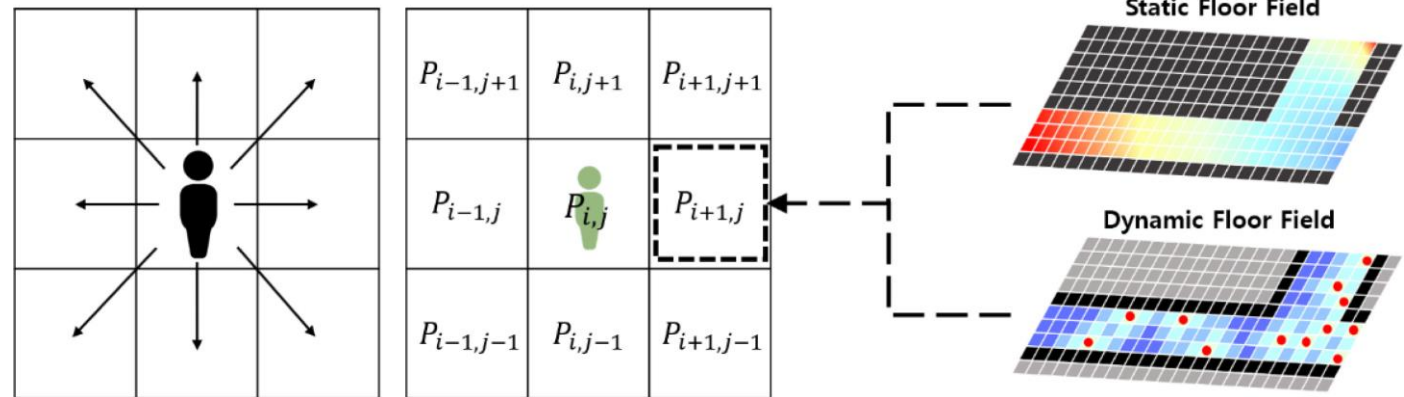


# Overview

- Floor-field model
- Proposed strategies
- Choice of cell
- Implementation
- Simulations
- Sensitivity analysis

# Floor field model

- Uncoordinated as optimal solutions are not the goal
- Sensitivity parameters:
  - **kS** – static potential
  - **kO** – occupancy
  - **kD** – diagonal movement
- Global friction parameter  $\mu$



# Proposed strategies

- The movement of agents depends on:
  - a) who wins the conflict
  - b) who participates in the conflict
- Choice of parameters means everything
  - Meaningful parameter range
  - Understand the relations between parameters
- Total evacuation time as the only observed value?
  - Formation of structures
  - Local flow

# Proposed strategies

Who wins the conflict?

Strategy A

Strategy B

- Aggressivity introduced by Hrabák and Bukáček
  - $\gamma$  in range  $[0, 1]$
- Agent/s with highest  $\gamma$  can win the conflict
  - friction  $\mu$  creates stochastic blocking occasions
  - conflicts are desired but sometimes **jamming** happens when it shouldn't
- None of the agents enter the cell with  $P = \mu(1 - \gamma)$

# Proposed strategies

Who wins the conflict?

Strategy A

Strategy B

- Agents with same low  $\gamma$  create irrelevant blockings near the exit
- Solution: **all** agents enter the conflict
  - Probability  $P_i$  is proportional

$$P_i = \frac{\gamma_i}{\sum_{j \in k} \gamma_j}$$

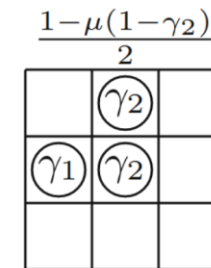
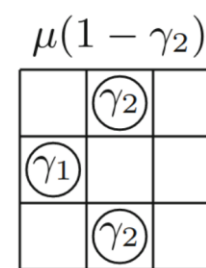
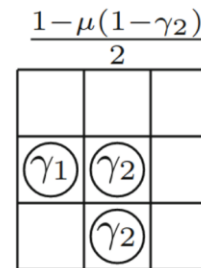
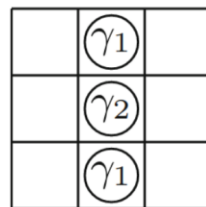
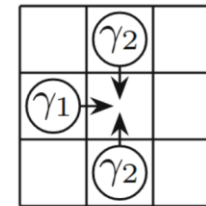
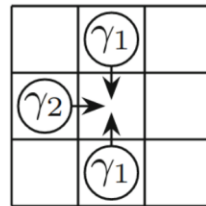
# Proposed strategies

Who wins the conflict?

Strategy A

Strategy B

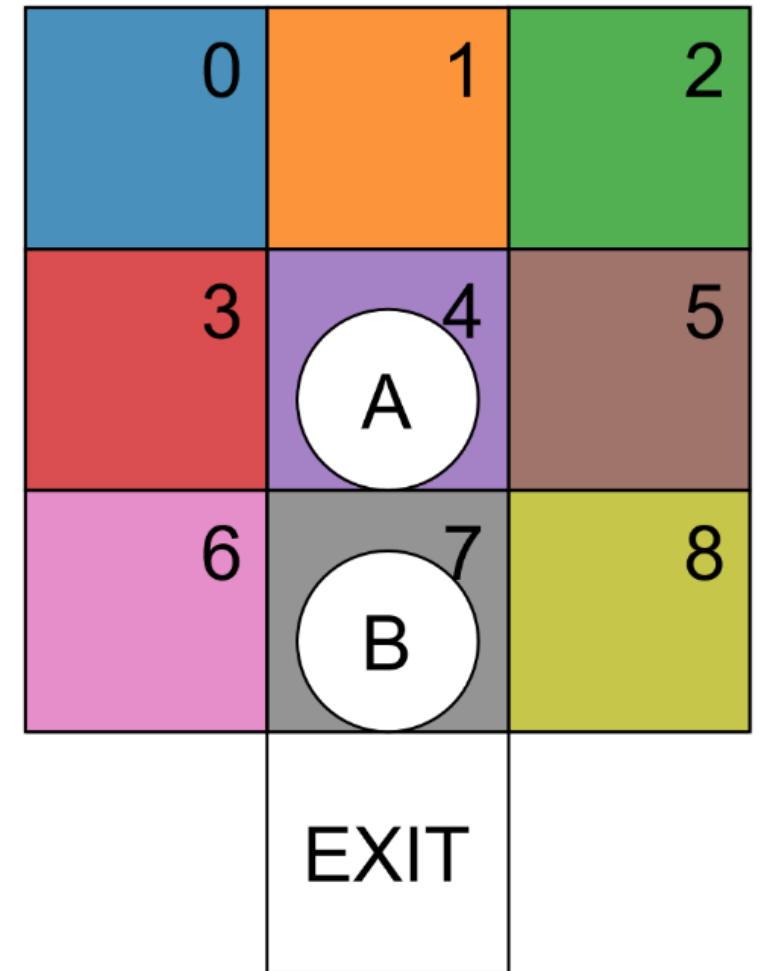
- Drawback is that blocking occasion still depends on highest  $\gamma$ 
  - $P = \mu(1-\gamma)$
- Strategy did not bring improvement
- Proportional probabilities are a valid approach



# Proposed strategies

Who participates?

- Selection of destination cell is crucial
- Is the influence of parameters predictable?
  - we need to adjust the model to our liking
- How to measure the influence?





# Proposed strategies

Who participates?

Strategy A

Strategy B

- Proposed by Pavel Hrabák and Marek Bukáček
- Probability  $\mathbf{P}$  of agent, who is in cell  $\mathbf{x}$ , moving to adjacent cell  $\mathbf{y} \in \mathbf{N}$
- Attractivity (nominator) of cells is normalized  $\rightarrow$  probability
- Only  $\mathbf{kS} \in \mathbf{R}$ , high influence

$$P(y \leftarrow x \mid N) = \frac{\exp(-k_S S(y))(1 - k_O O(y))(1 - k_D D(y))}{\sum_{z \in N} \exp(-k_S S(z))(1 - k_O O(z))(1 - k_D D(z))}$$

# Proposed strategies

Who participates?

Strategy A

Strategy B

- Focuses on the sensitivity to the occupancy of cells  $k_O$

$$P(y \leftarrow x \mid N) = k_O P_O(y) + (1 - k_O) P_S(y)$$

- $P_S$  takes into account the static potential
  - Agent moves in correct direction
- $P_O$  focuses on occupancy
- Individual attractivities are more predictable, easier to interpret

# Proposed strategies

Who participates?

Strategy A

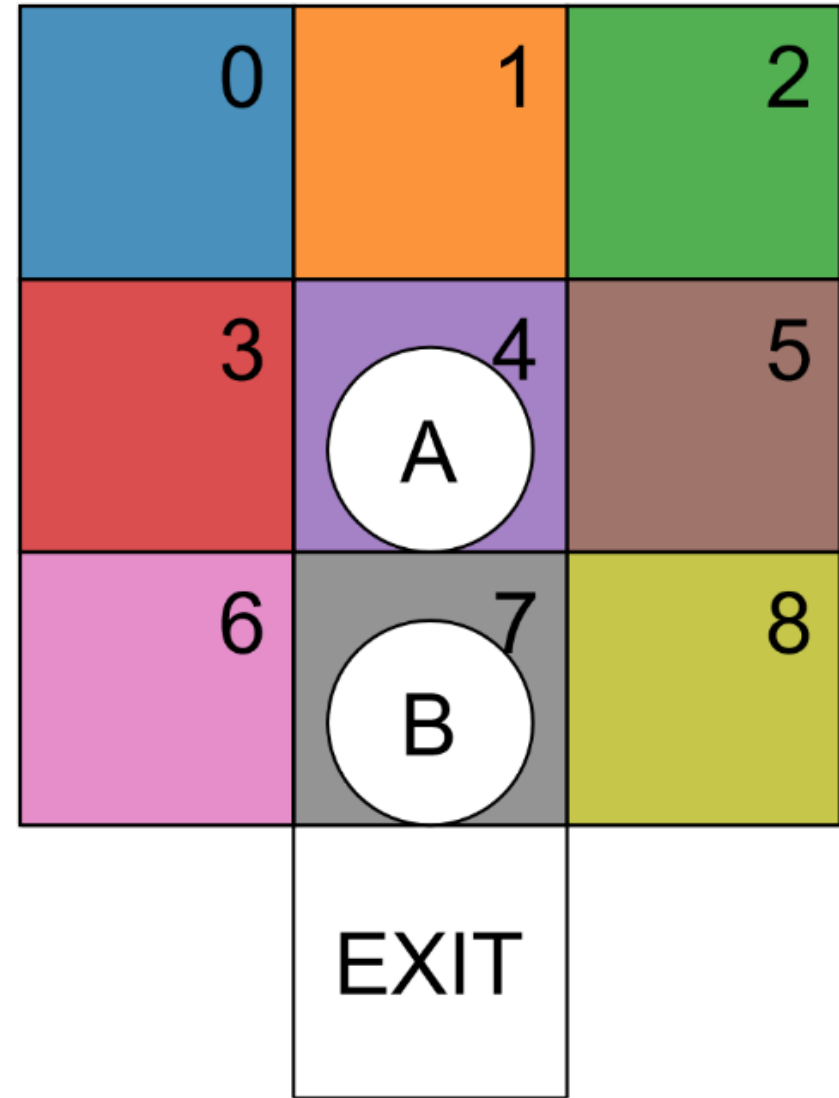
Strategy B

- **P<sub>O</sub>** doesn't use the **k<sub>O</sub>** parameter

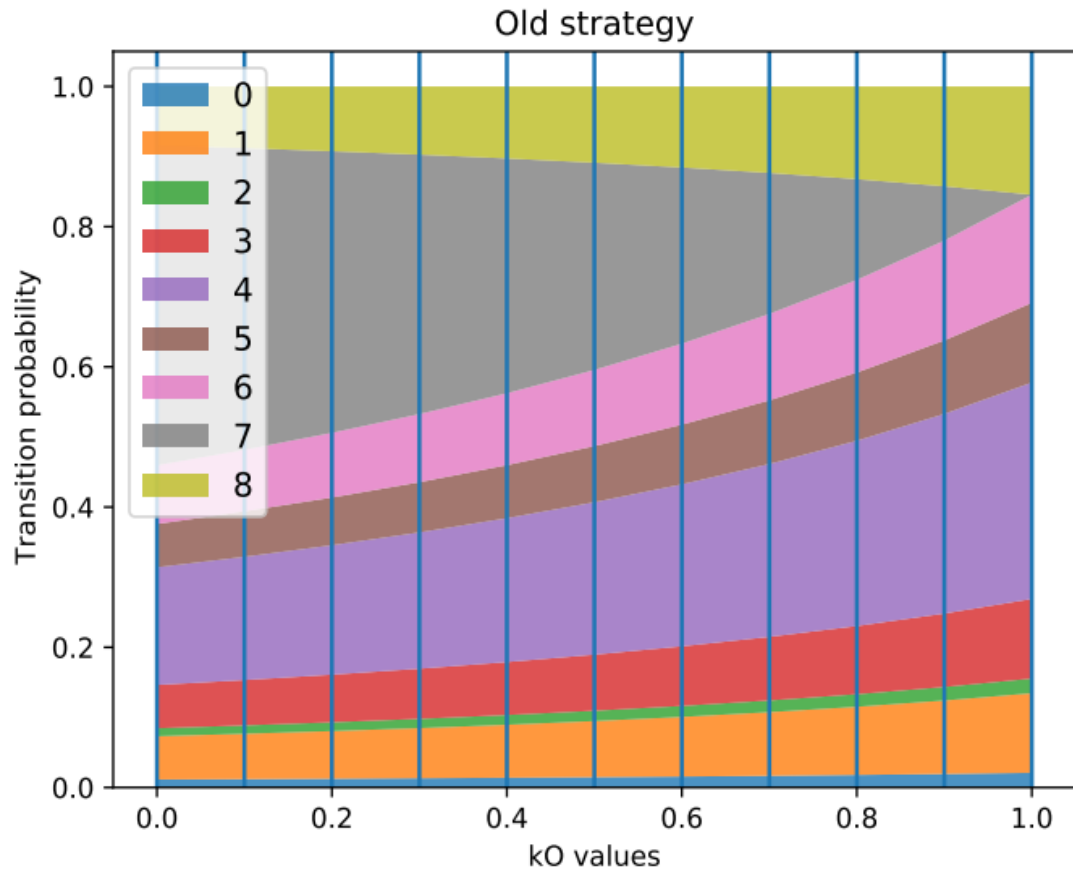
$$P_O(y) = \frac{\exp(-k_S S(y))(1 - O(y))(1 - k_D D(y))}{\sum_{z \in N} \exp(-k_S S(z))(1 - O(z))(1 - k_D D(z))}$$

$$P_S(y) = \frac{\exp(-k_S S(y))(1 - k_D D(y))}{\sum_{z \in N} \exp(-k_S S(z))(1 - k_D D(z))}$$

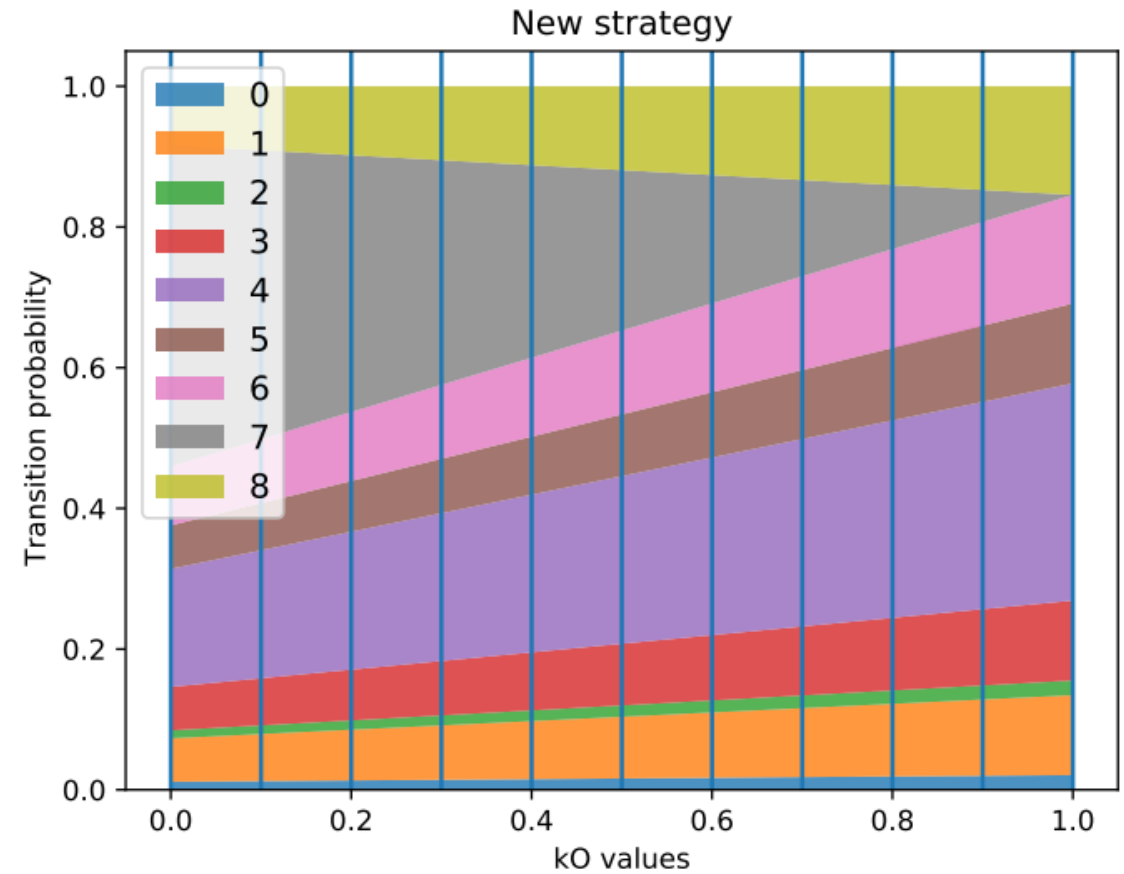
1. Agent A wants to get closer to exit.
2. He is aware of agent B in front of him.
3. He calculates attractions of all neighborhood cells.
4. Stochastic selection chooses one cell.
5. In case of conflict, stochastic process selects a winner.



## Old strategy A



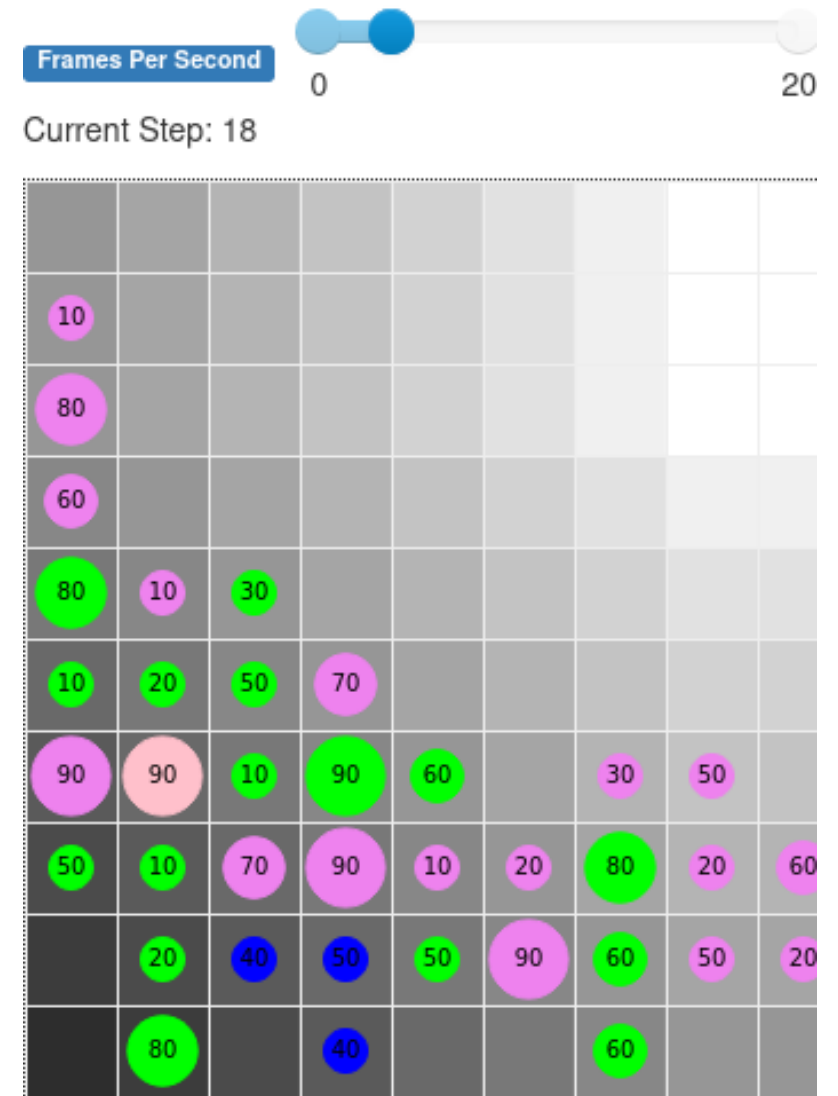
## New strategy B

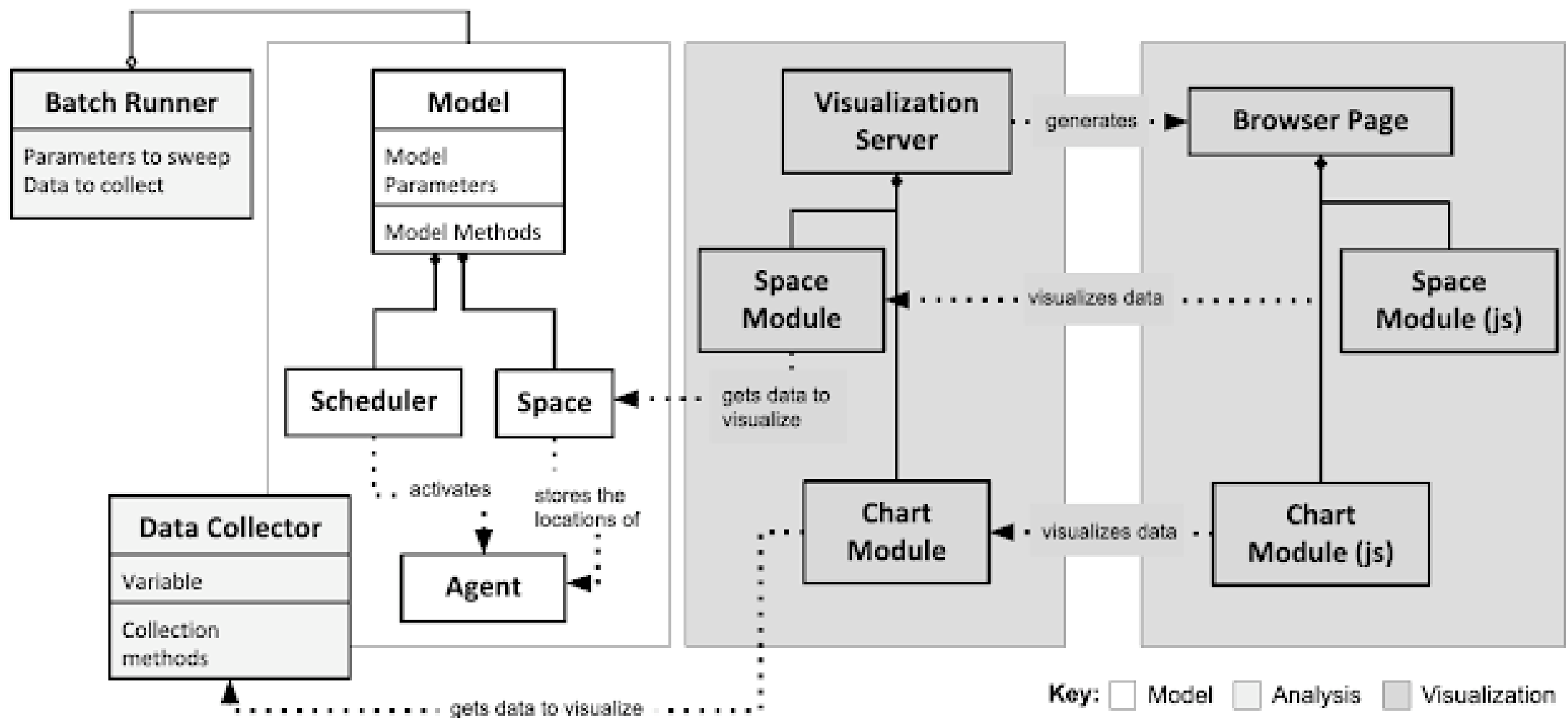


Increasing **kO**, the influence on attractivity of cells.

# Implementation

- Python
- Mesa ABM framework
  - Modularity and data-analysis
  - Graphic output
- Pseudo RNG for stochastic selection
- Non-cooperative agents

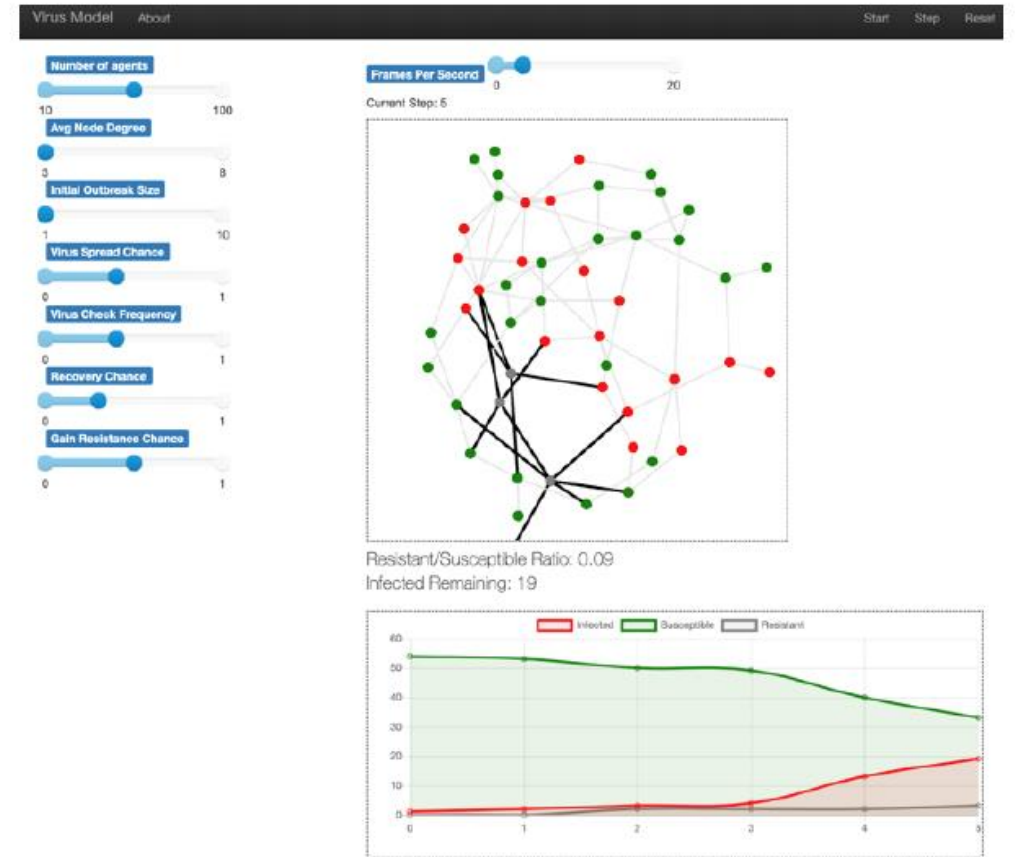




Taken from:  
[gisagents.org/2020/05/utilizing-python-for-agent-based.html](https://gisagents.org/2020/05/utilizing-python-for-agent-based.html)



A



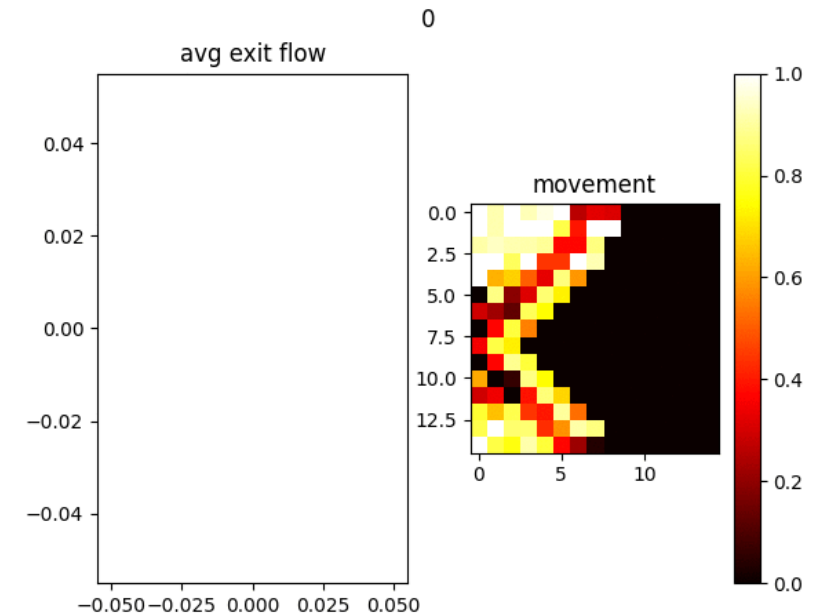
B

Taken from:  
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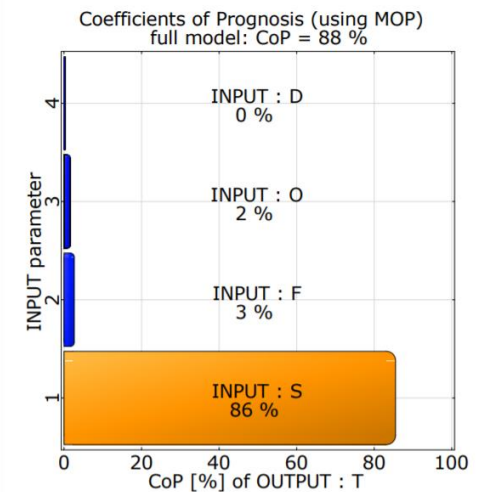
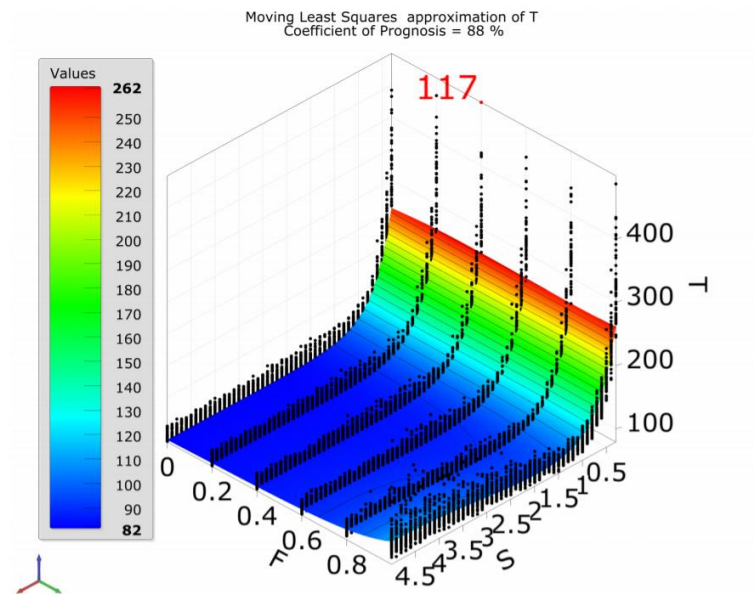
# Analysis of the model

- PRNG allow parallel batch running with varied parameters
- **Quantitative analysis**
- Contribution of individual parameters to the variance in observed values
  - Total evacuation time  $T$
  - $k_S, k_O, k_D, \mu$
- **Qualitative analysis**
- Number of agents
- Formation of structures
- Heterogeneity



# Sensitivity analysis

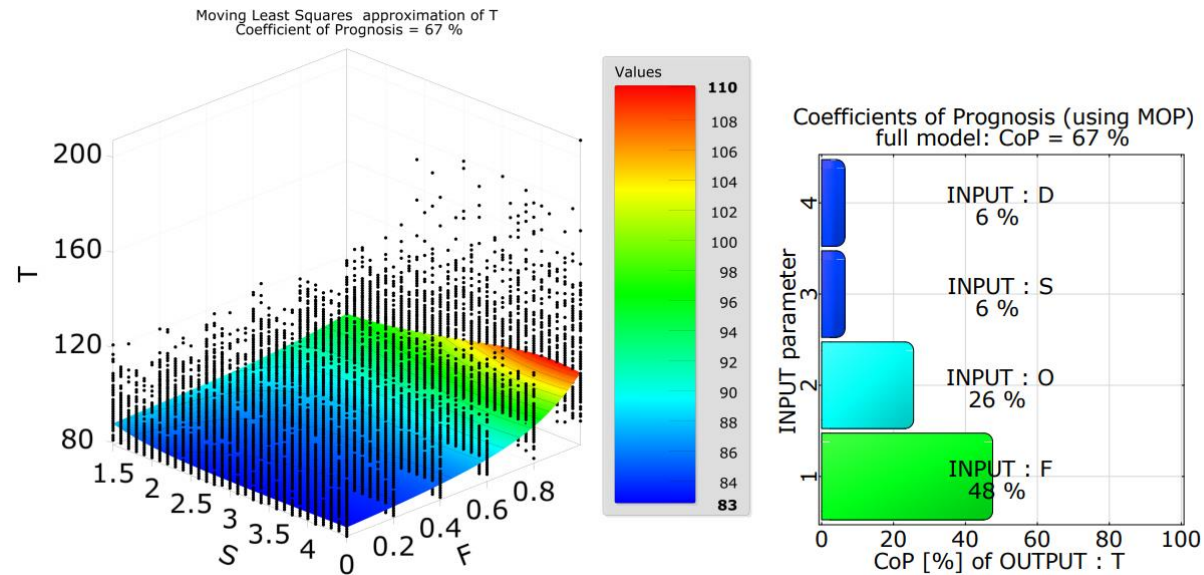
- OptiSLang by Dynardo GmbH
- How much variance in  $T$  can be attributed to parameter  $x$ ?
- Analysis brought additional result:  
Interval of  $kS$  should be limited to approx. [1.5, 4.5]



# Sensitivity analysis

COP, variable kS

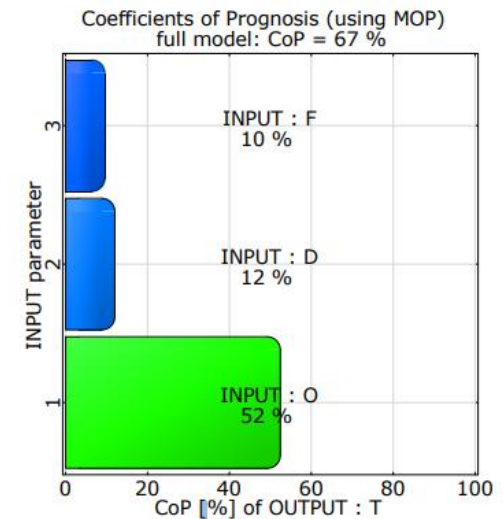
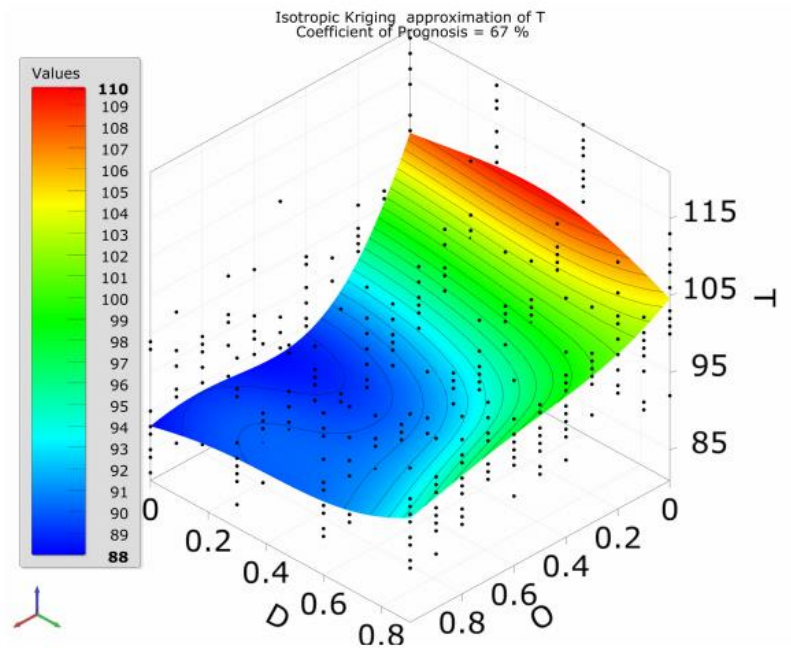
- COP graph, on the right, show the total sum of parameters contribution is higher than total COP
  - $67 \neq 6+6+26+48$
  - Parameters affect each other
  - **kD** influence is low



# Sensitivity analysis

constant  $kS=1.5$   
microscopic influence

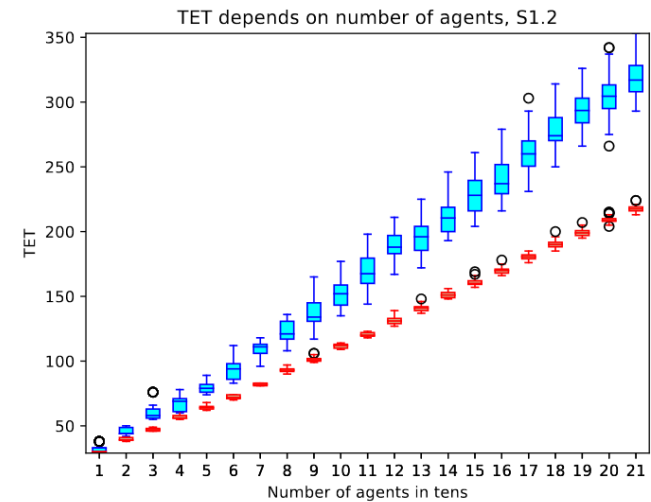
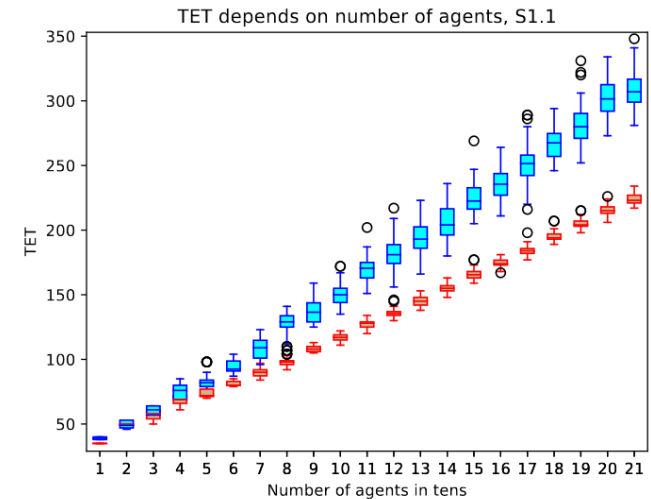
- low  $kS = 1.5$  allows other parameters to influence the process
- Microscopic behavior affected by  $kD$ , but  $T$  not so much
  - COP is 12%, 8%, 5% for  $kS \in \{1.5, 3.0, 4.5\}$  in order
  - agents can overtake the queue more often



# Qualitative analysis

T depends on number of agents

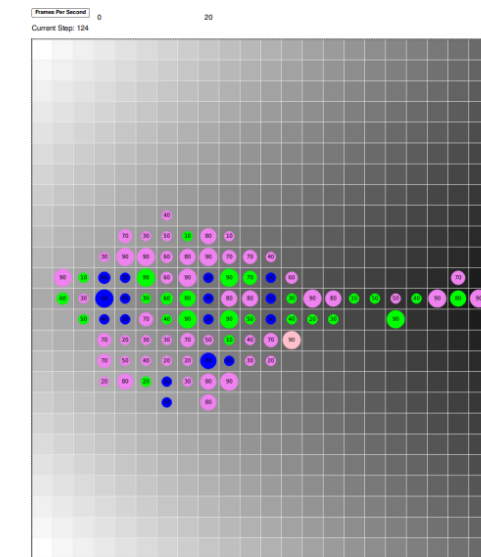
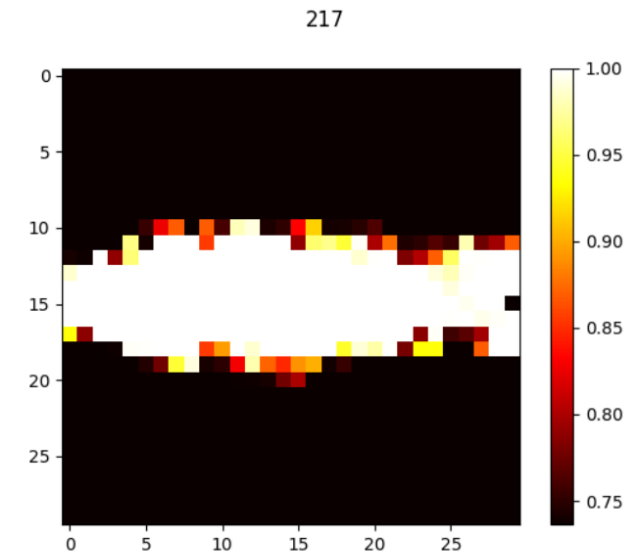
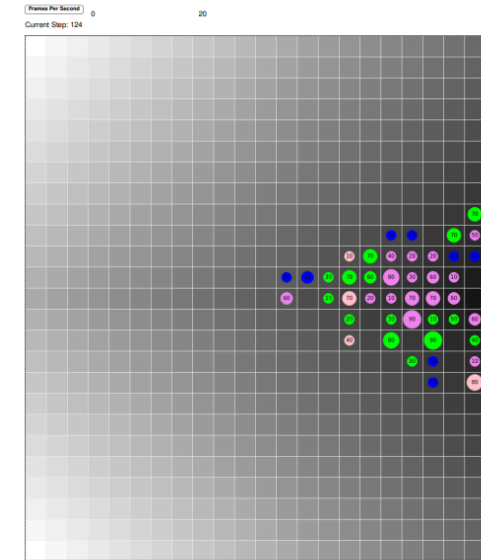
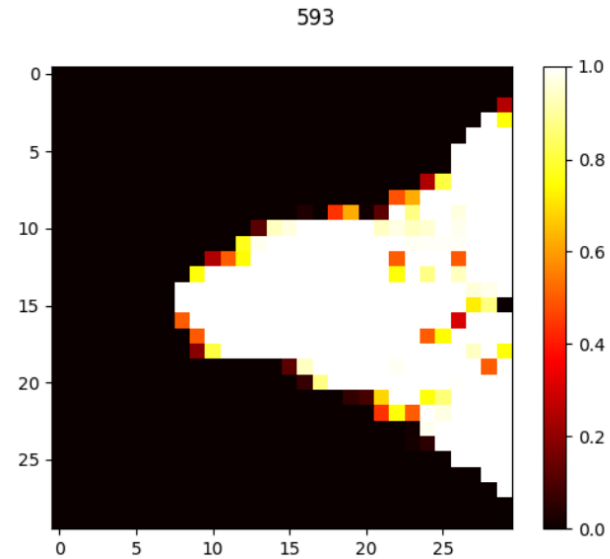
- With increasing number of agents, T increases **linearly**
- Red boxplots are simulations with low friction
- Blue boxplots are simulations with high friction
- Top:  $kS=1.5$
- Bottom:  $kS=1.5$



# Influence of $kO$ on macroscopic structures

Top: high  $kO$  allows agents to form cones

Bottom: low  $kO$  forms a queue



Thank you for  
your attention.