SIMULTECH 2025
15th International Conference on Simulation and Modeling Methodologies, Technologies and Applications
Bilbao, Spain 11 - 13 June, 2025

Modeling and Simulation of Dense Crowds Dynamics at the Intersection of Agent-based and Deep-Learning Models: Predict and Understand

Benoit GAUDOU (University Toulouse Capitole, IRIT lab.)

Keynote Presentation - Friday, June 13th, 2025

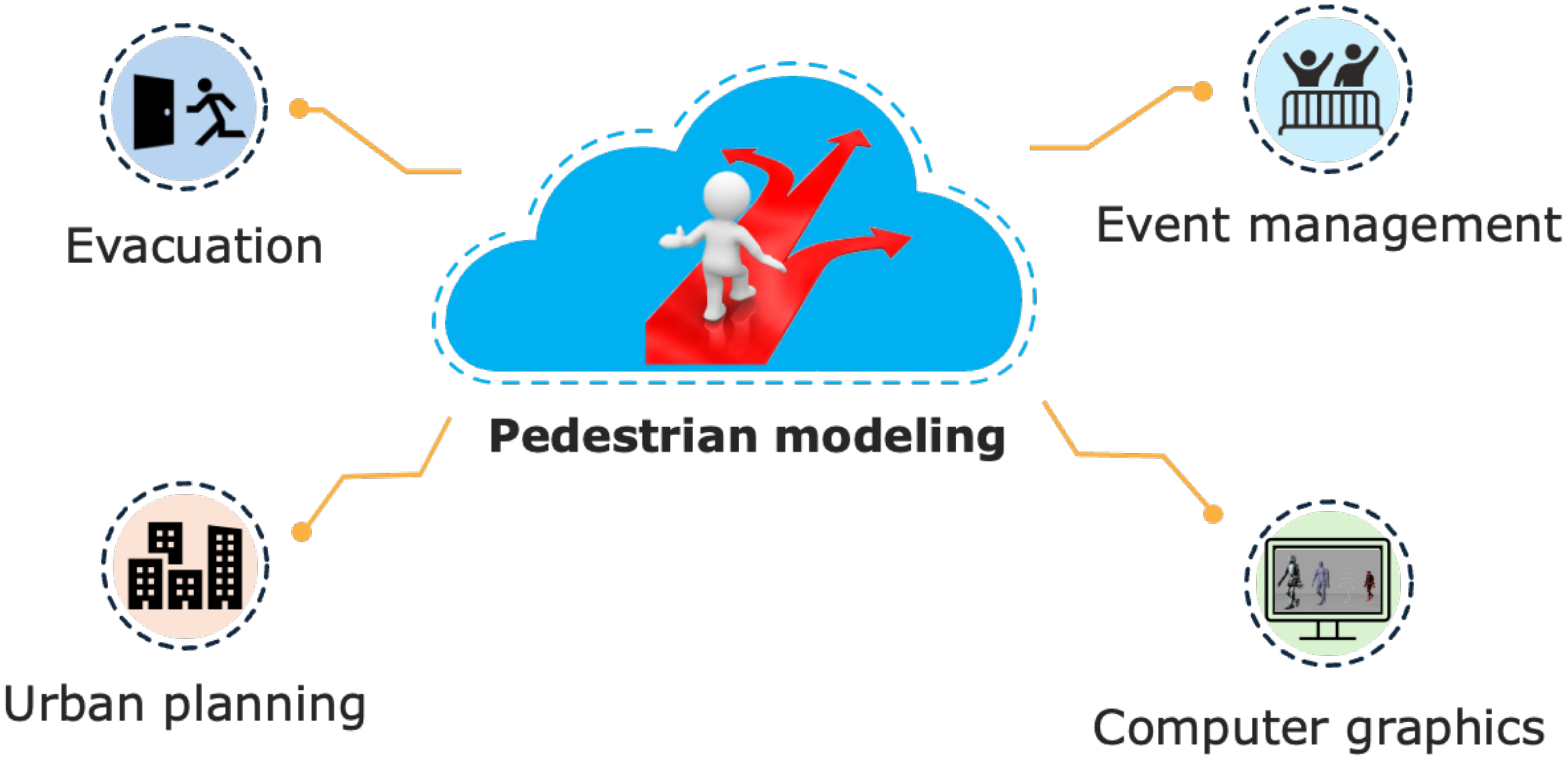
ETH/UCY dataset

[1] Pellegrini, Stefano, et al. “You’ll never walk alone: Modeling social behavior for multi-target tracking.” 2009 IEEE 12th international conference on computer vision. IEEE, 2009. https://ieeexplore.ieee.org/document/5459260

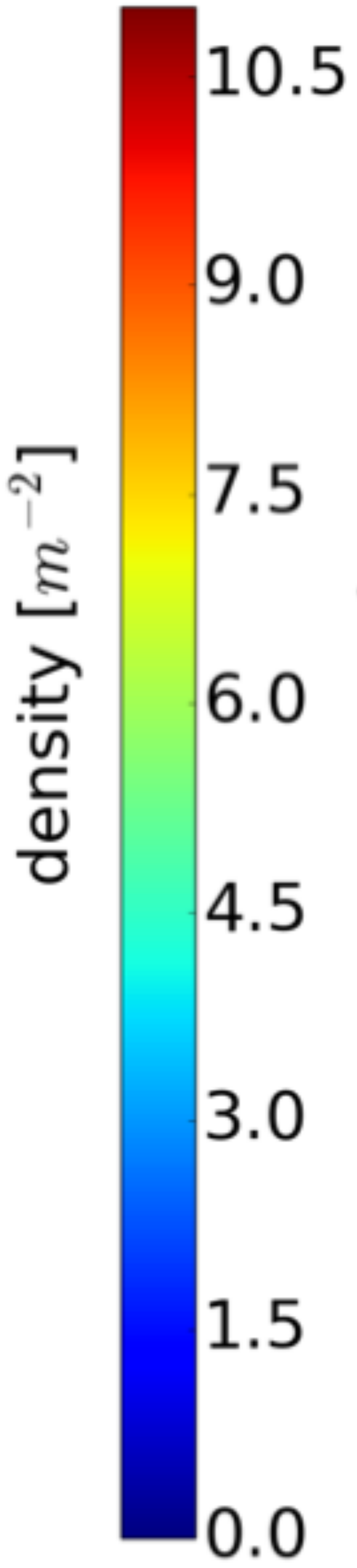
https://www.cs.cmu.edu/~csd-phd-blog/2024/t2fpv/

Hajj (Mecca), https://www.mehdimoussaid.com/a-propos/

Predict and understand crowd dynamics



Density is an important factor that directly influences pedestrian movements



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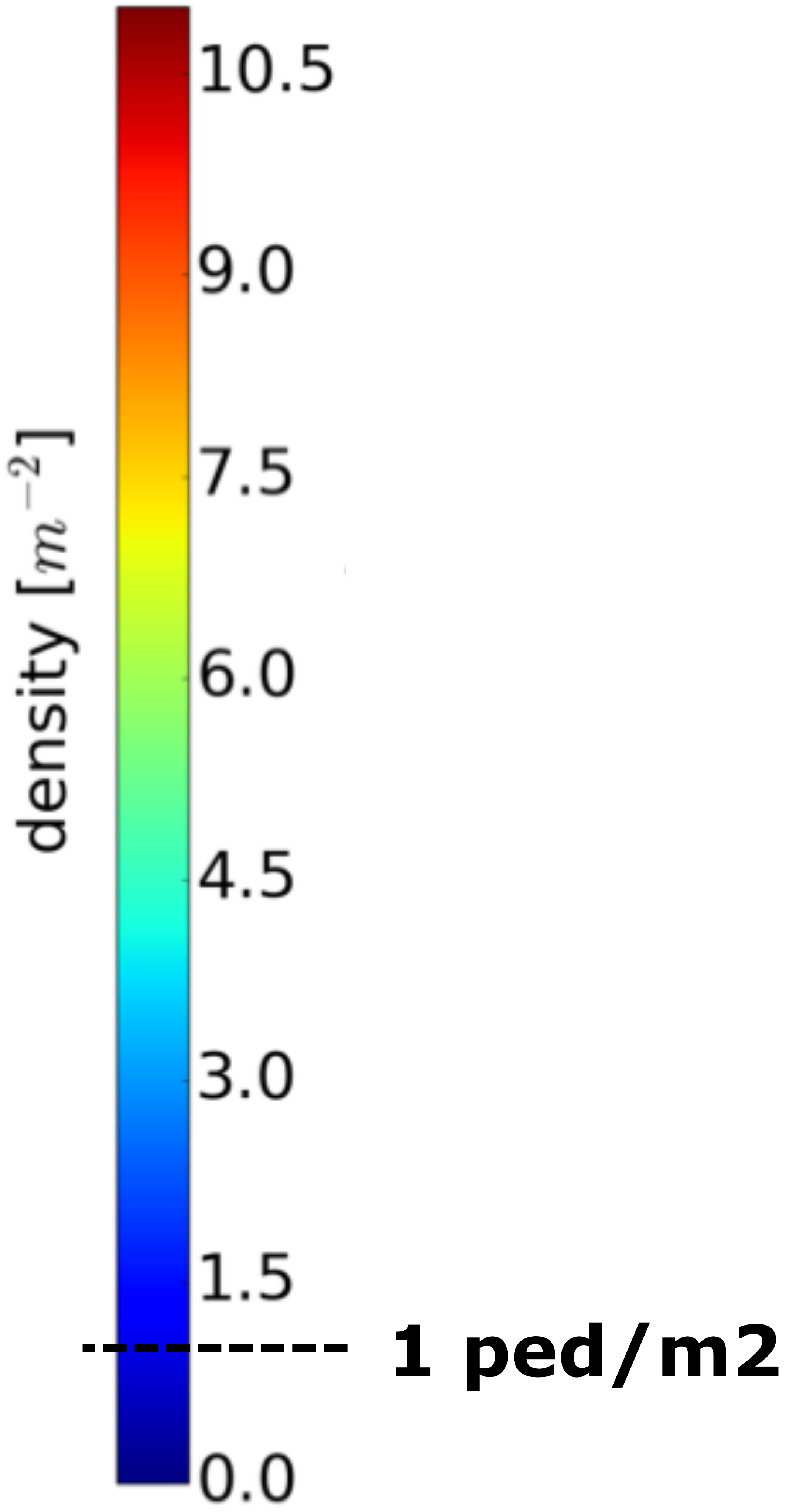
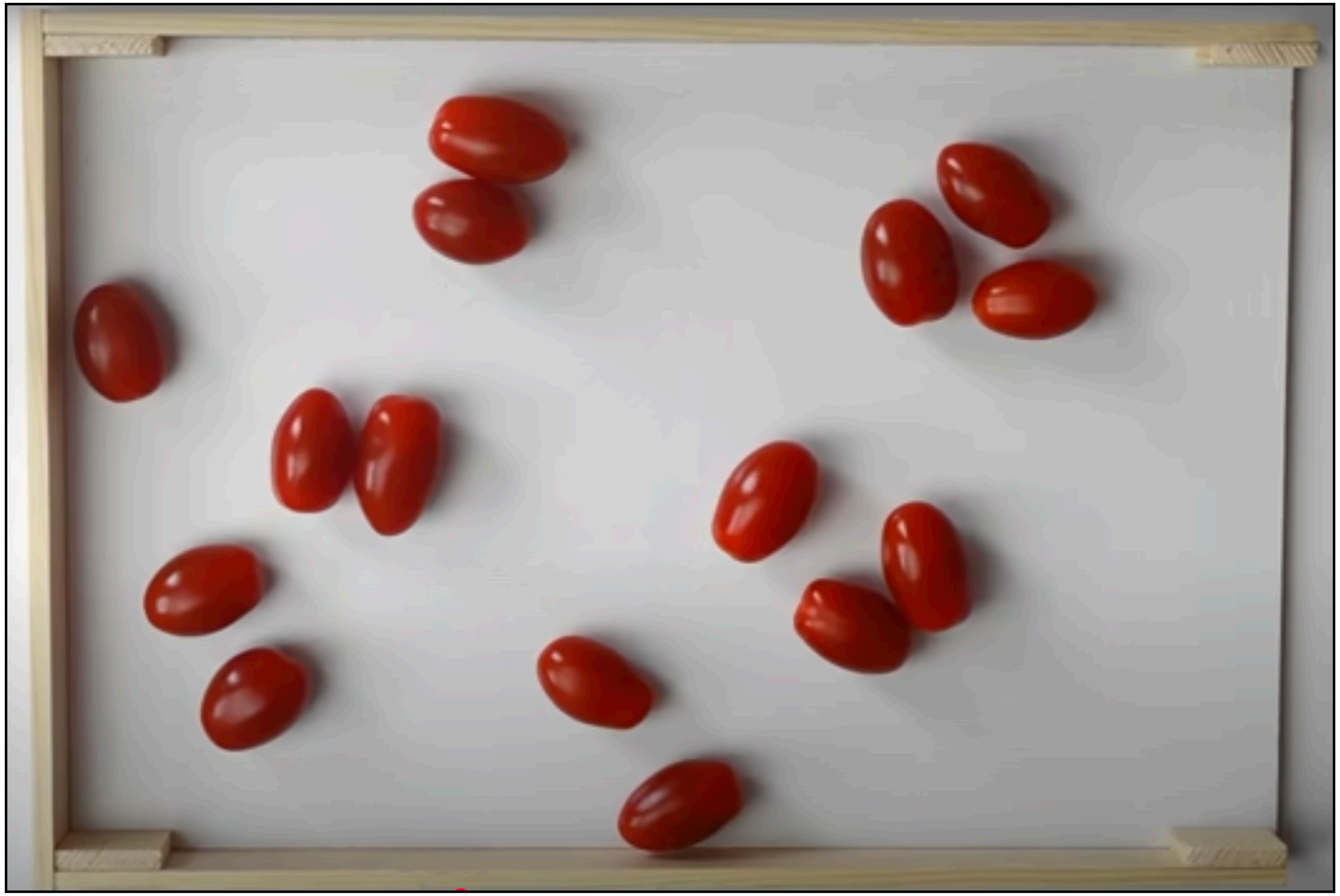
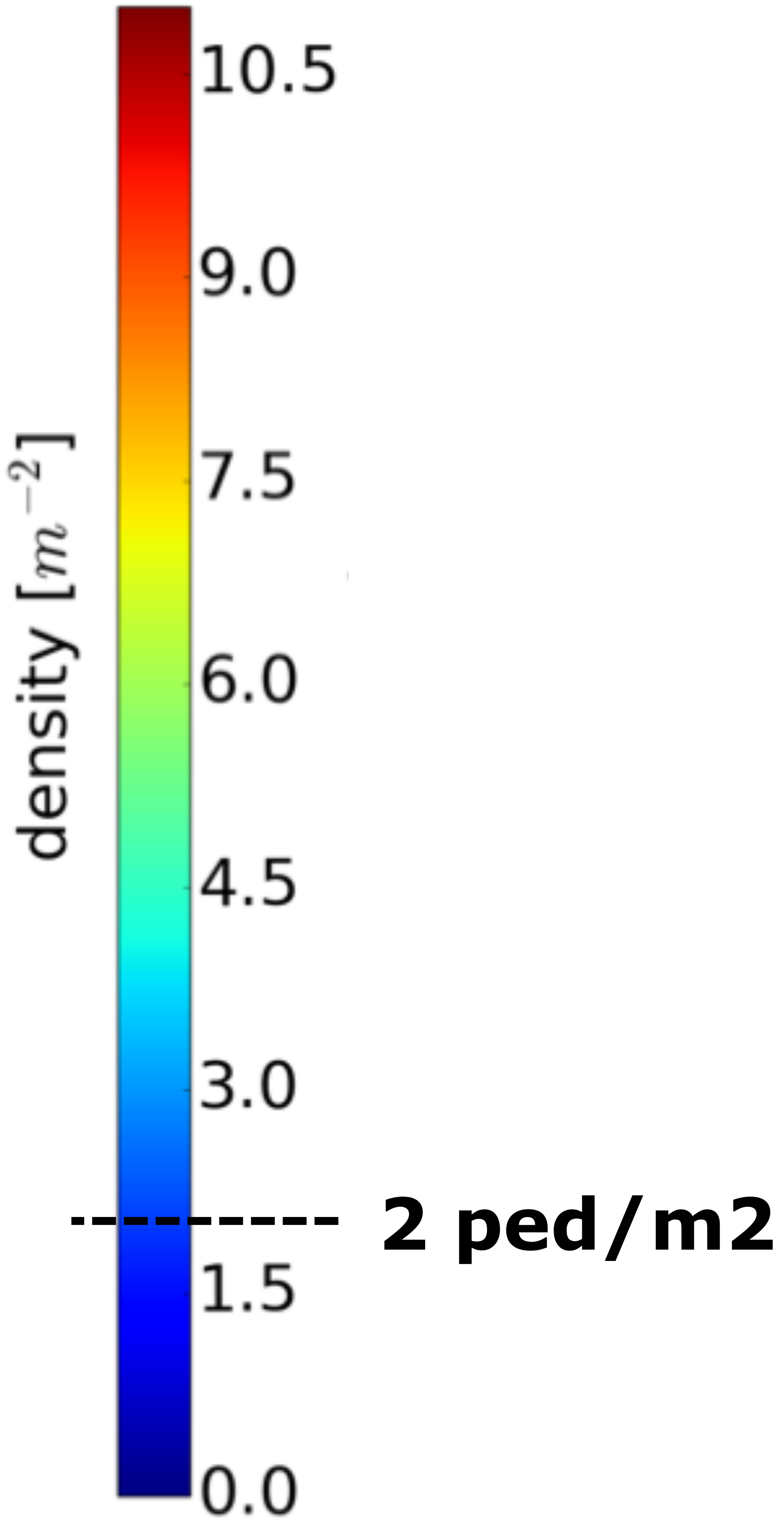


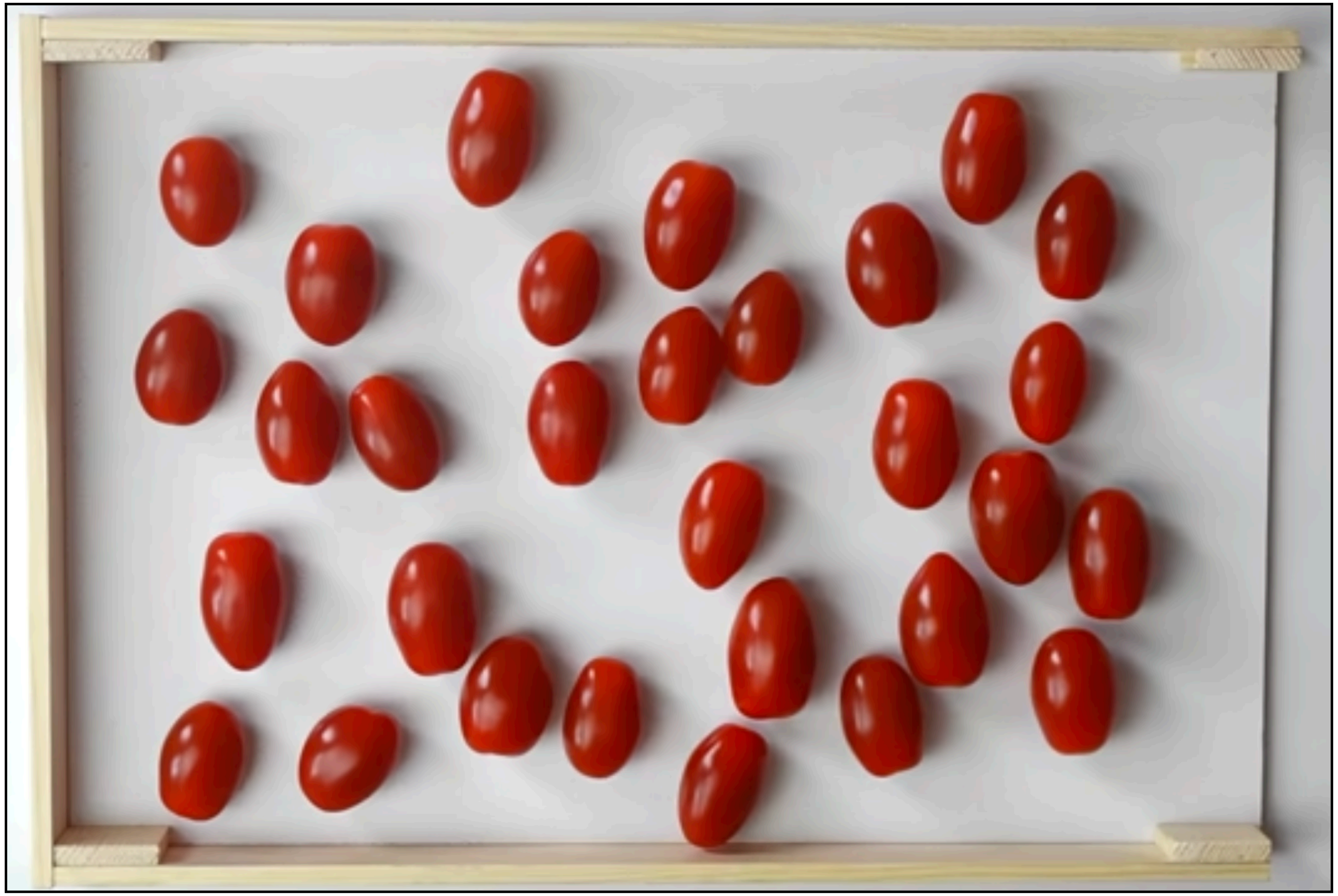


Example: shopping street Saturday afternoon

Moussaid, Mehdi - Fouloscopie - 10 niveaux de foule expliqués avec des tomates
https://www.youtube.com/watch?v=Eh7I4Gvx054&ab_channel=Fouloscopie

Density is an important factor that directly influences pedestrian movements





Comfort distance not respected. Comfort speed halved

Moussaid, Mehdi - Fouloscopie - 10 niveaux de foule expliqués avec des tomates
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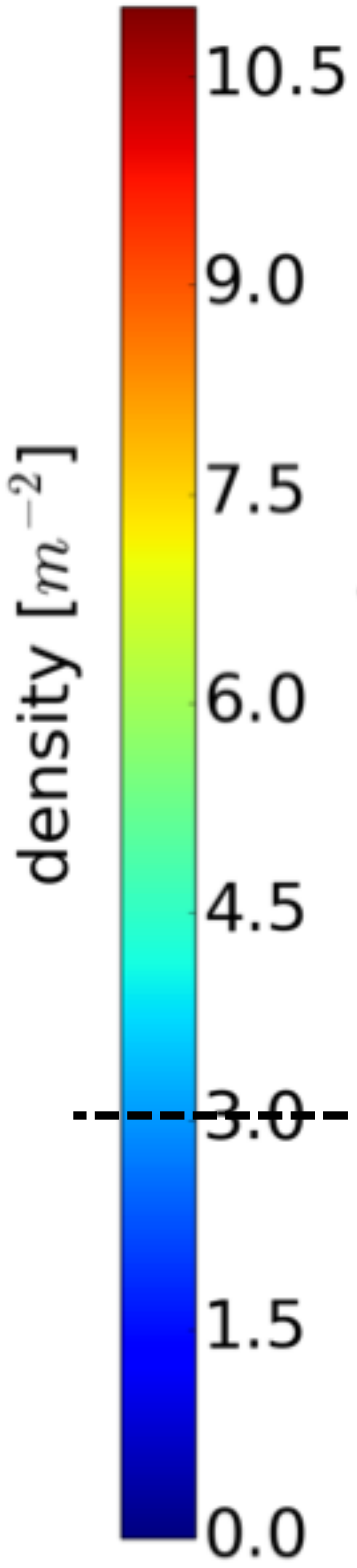


3 ped/m2

Example: An underground train on a Monday morning. **Shockwaves**.

Moussaid, Mehdi - Fouloscopie - 10 niveaux de foule expliqués avec des tomates
https://www.youtube.com/watch?v=Eh7I4Gvx054&ab_channel=Fouloscopie

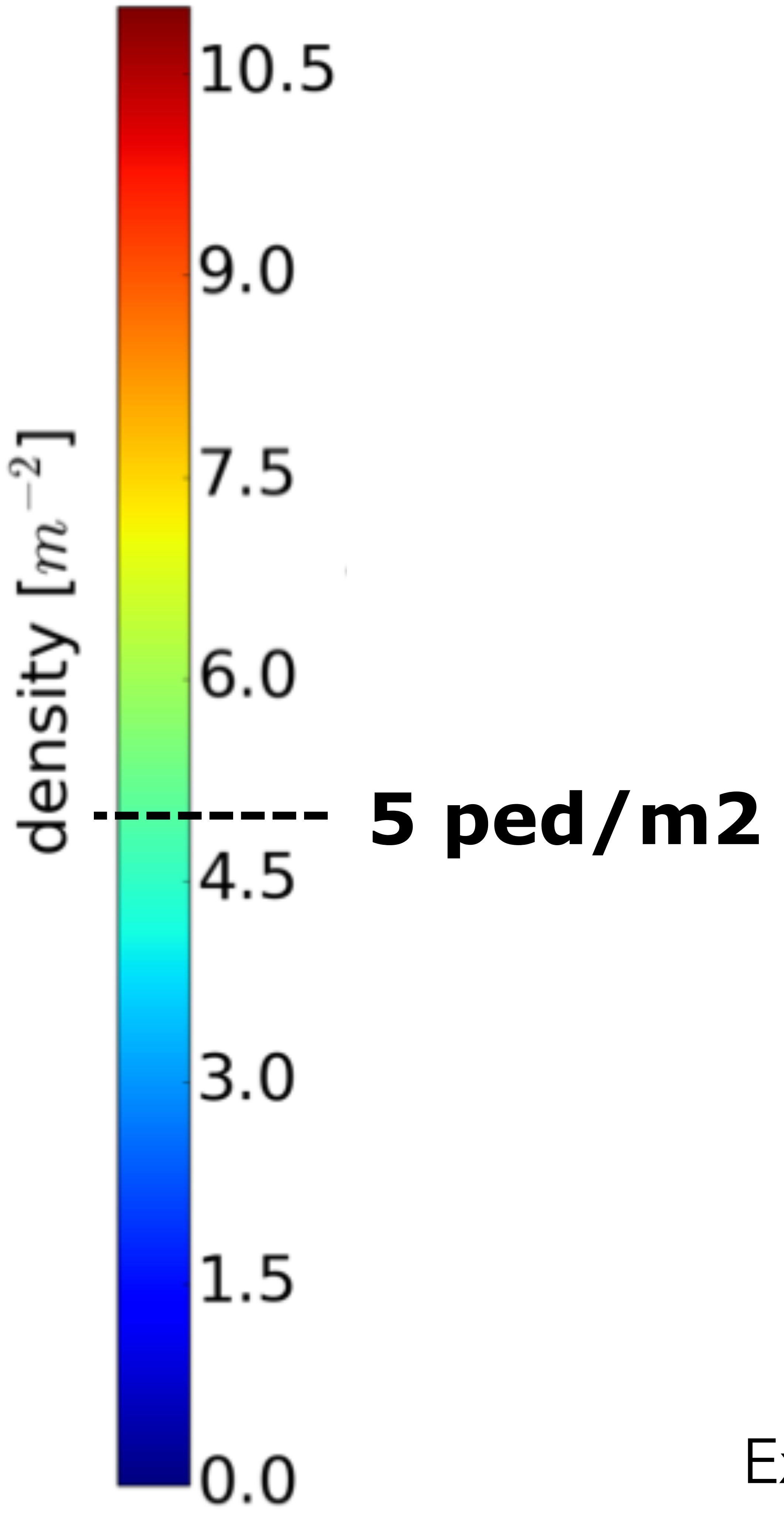
https://www.youtube.com/watch?v=Suugn-p5C1M

Shockwaves

Example: An underground train on a Monday morning. **Shockwaves**.

From a GAMA model

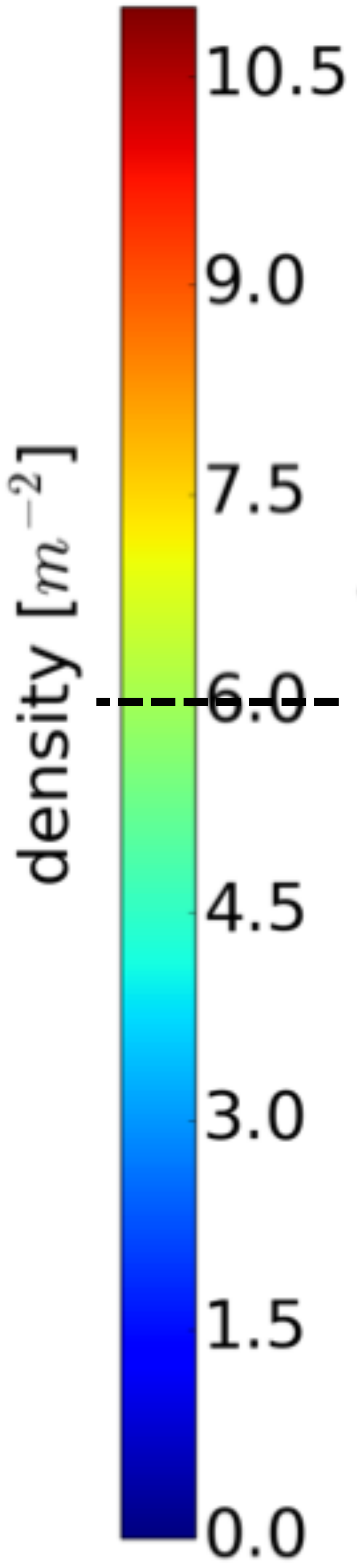
Density is an important factor that directly influences pedestrian movements



Example: An underground train on a strike day. **Congestion**. Limit of **danger** (limit to absorb pression).

Moussaid, Mehdi - Fouloscopie - 10 niveaux de foule expliqués avec des tomates
https://www.youtube.com/watch?v=Eh7I4Gvx054&ab_channel=Fouloscopie

Density is an important factor that directly influences pedestrian movements



6 ped/m2

Example: Huge concert, in front of the stage. **Turbulence** (cannot absorb pression). Should not be exceeded.

Moussaid, Mehdi - Fouloscopie - 10 niveaux de foule expliqués avec des tomates
https://www.youtube.com/watch?v=Eh7I4Gvx054&ab_channel=Fouloscopie

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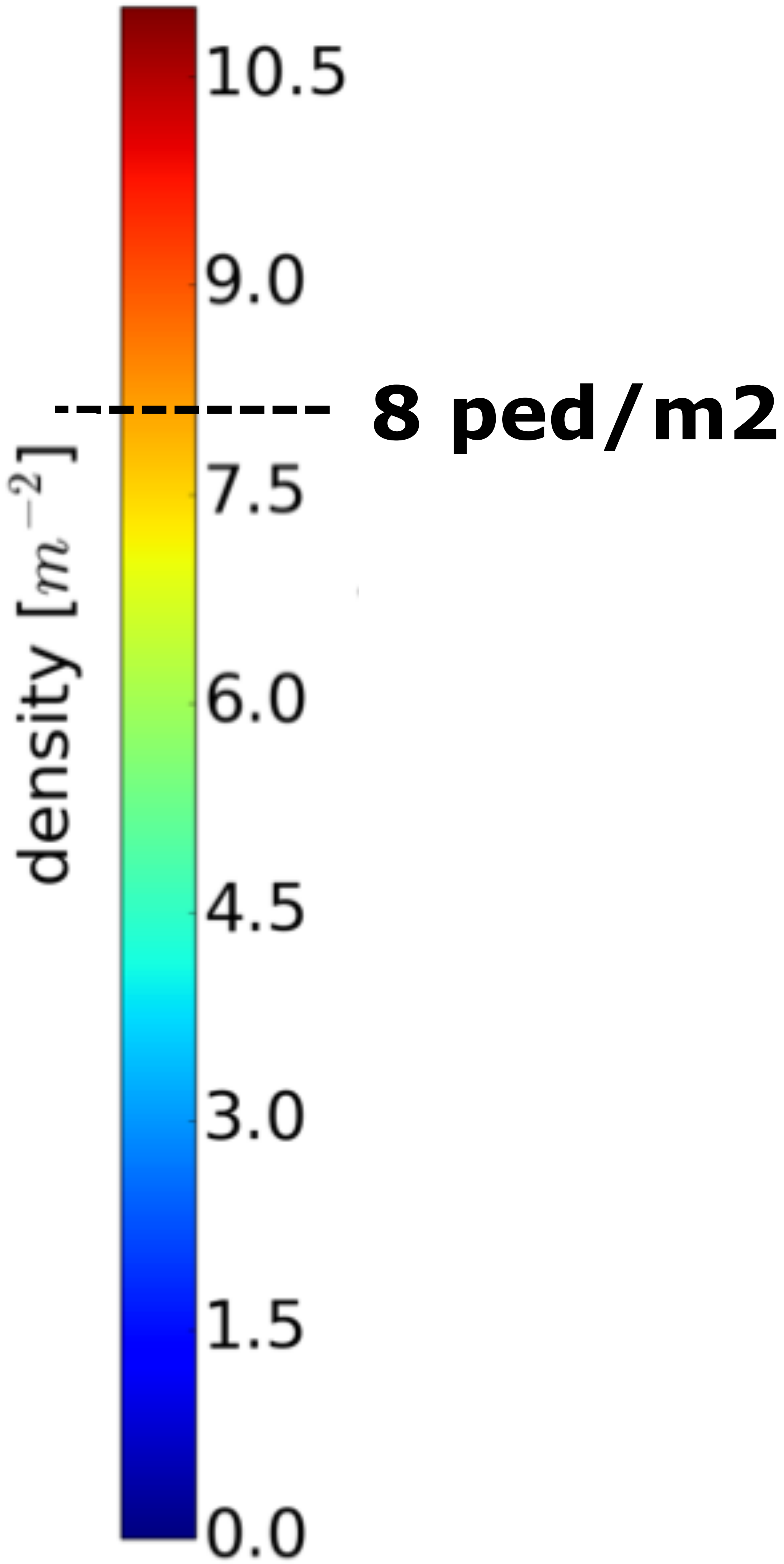

Strong contacts, possibilities of body damages. **Love Parade (Germany, 2010)**

Moussaid, Mehdi - Fouloscopie - 10 niveaux de foule expliqués avec des tomates
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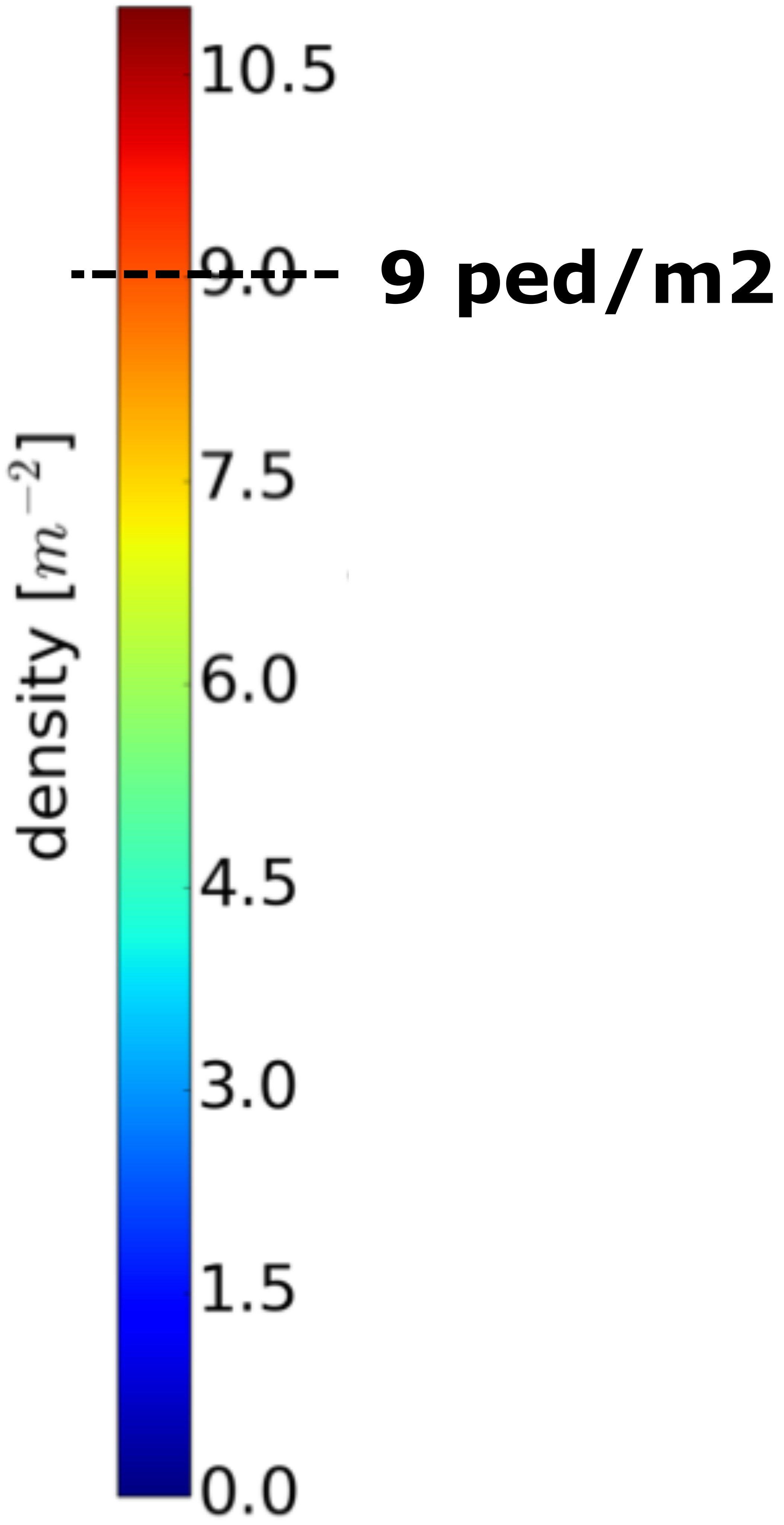
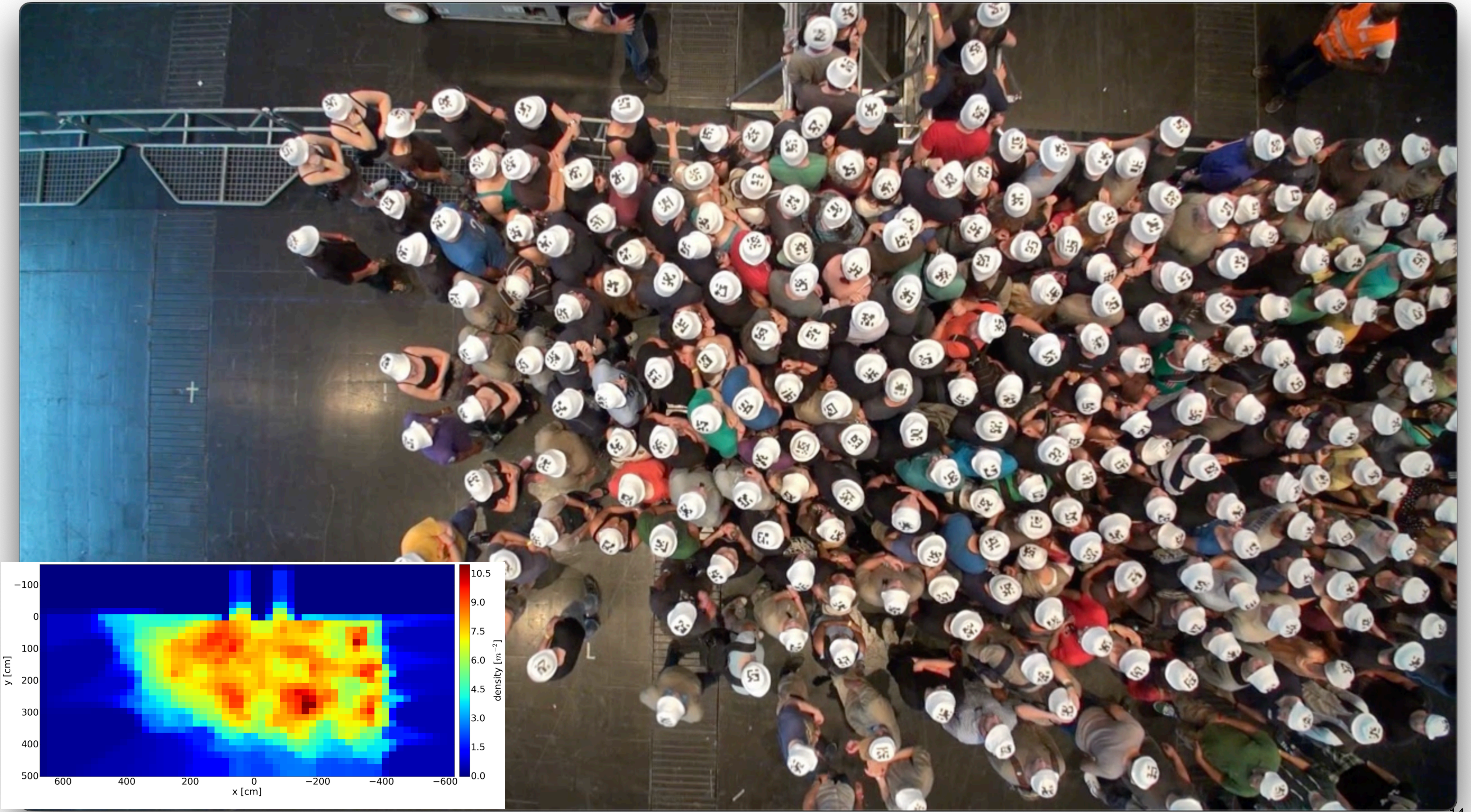


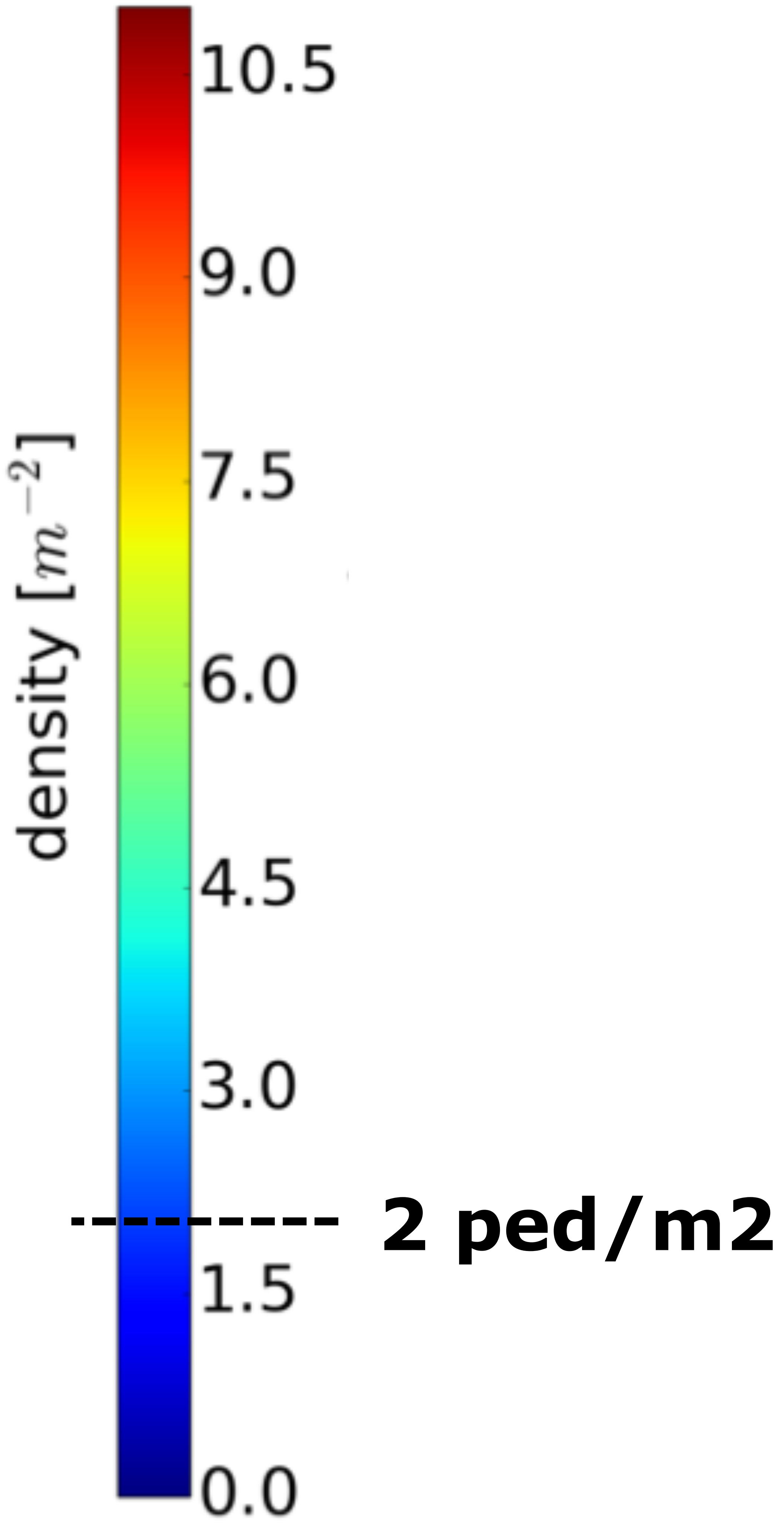
Lack of space to breath. **Hajj, Mecca pilgrimage (Mecca, 2006)**

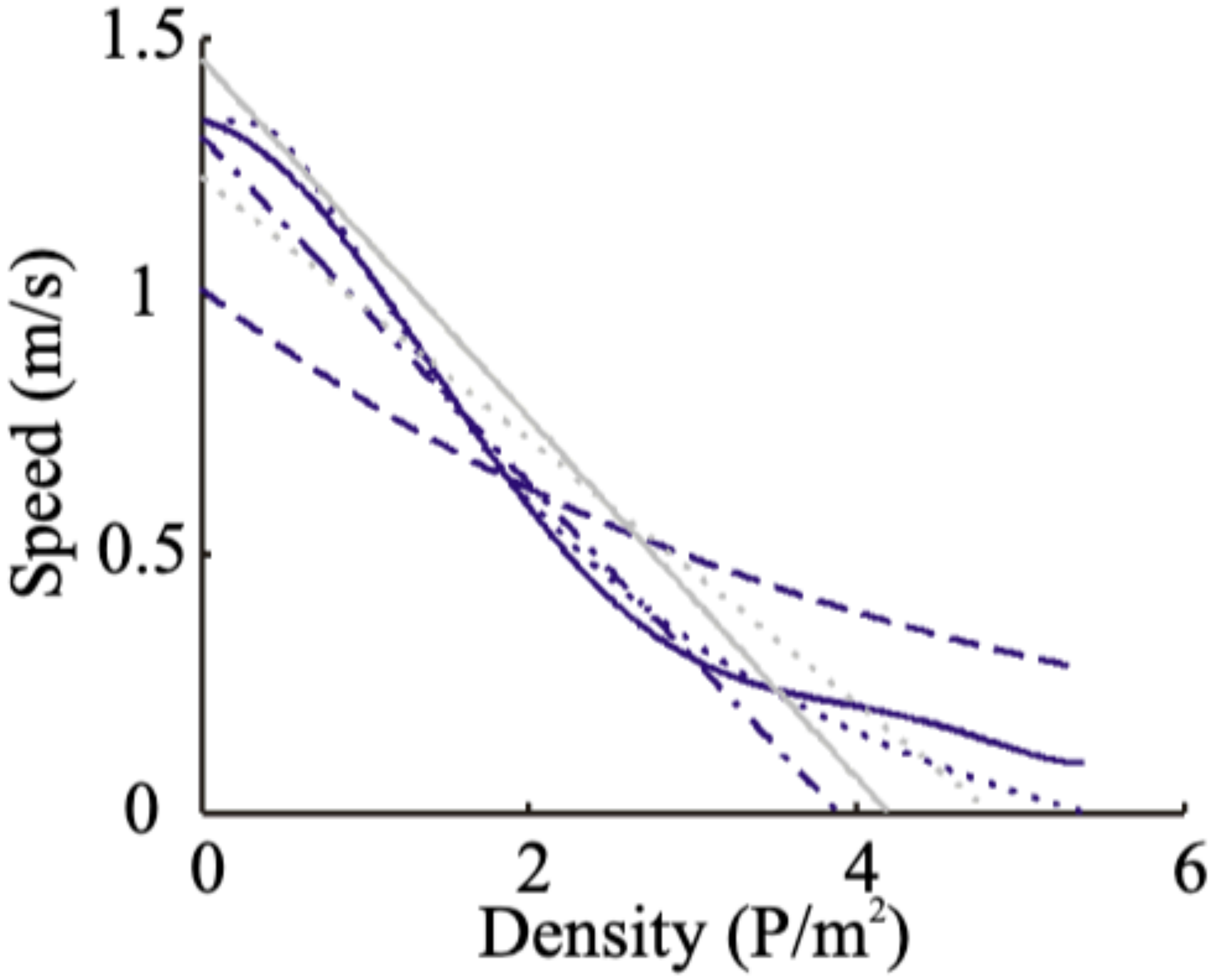
Moussaid, Mehdi - Fouloscopie - 10 niveaux de foule expliqués avec des tomates
https://www.youtube.com/watch?v=Eh7I4Gvx054&ab_channel=Fouloscopie

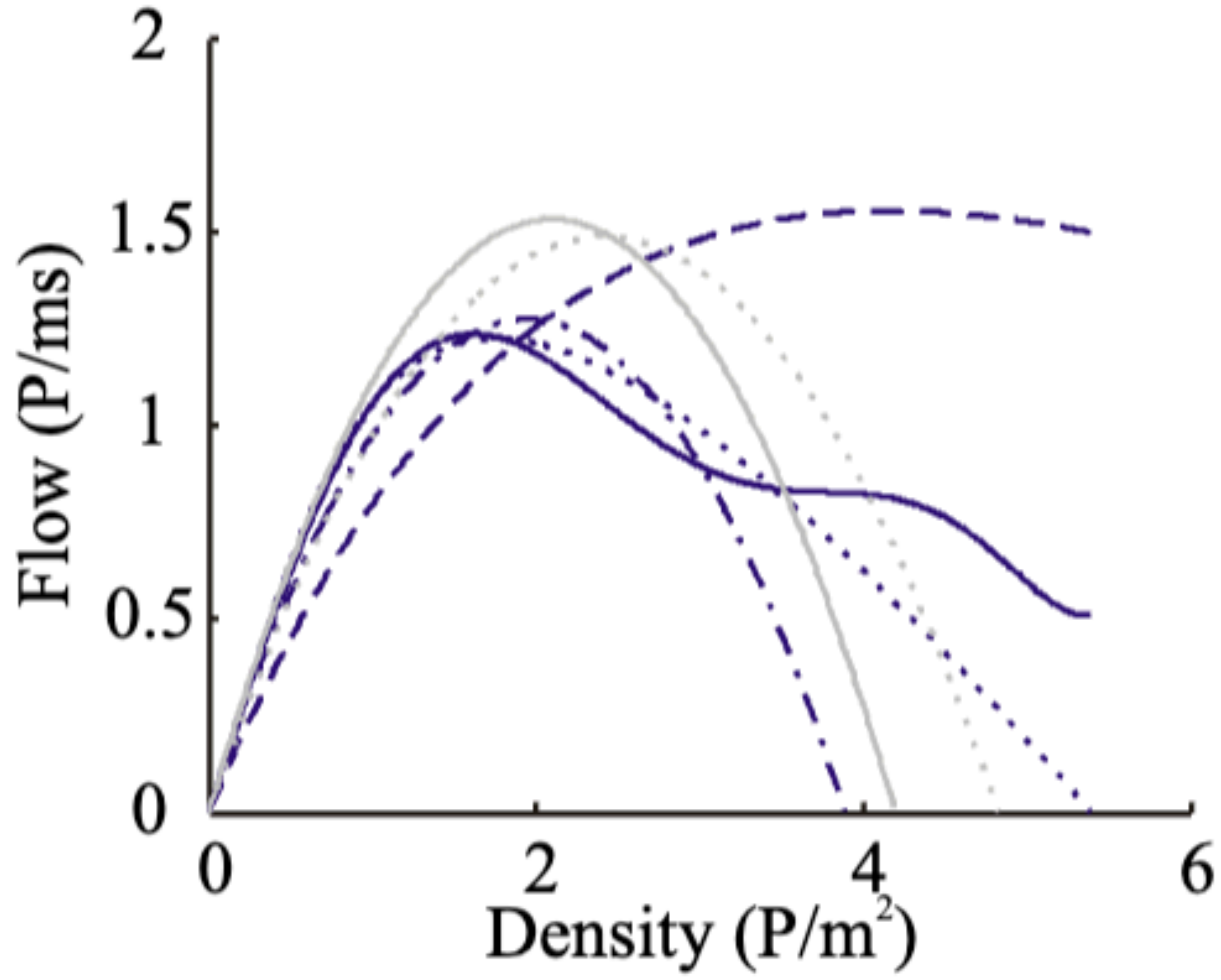


Sieben, A., Schumann, J., & Seyfried, A. (2017). Collective phenomena in crowds—Where pedestrian dynamics need social psychology. *PLoS one*, *12*(6), e0177328.

We were interested in pedestrians mobility in high-density situations (> 2 ped/m2)

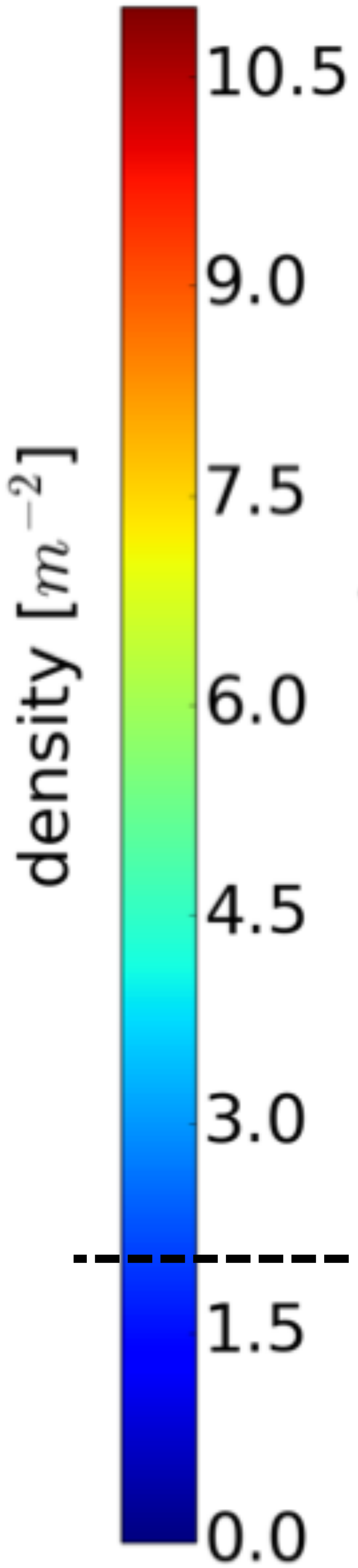




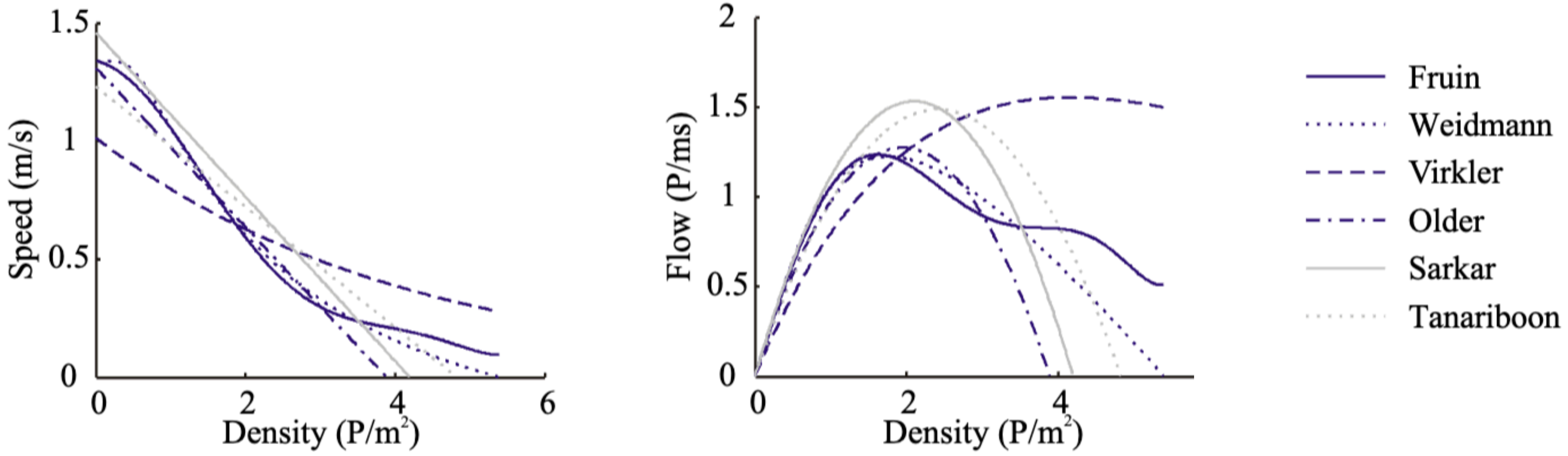


Daamen W, Hoogendoorn SP, Bovy PHL (2005). First-Order Pedestrian Traffic Flow Theory. Transportation Research Record: Journal of the Transportation Research Board, No. 1934, pp. 43-52.

We were interested in pedestrians mobility in high-density situations (> 2 ped/m2)



2 ped/m2



- Challenges in modeling **high-density** situations (> 2 ped/m^2):
  - Complex behaviors and interactions.
  - Known limitations of many models.

Daamen W, Hoogendoorn SP, Bovy PHL (2005). First-Order Pedestrian Traffic Flow Theory. Transportation Research Record: Journal of the Transportation Research Board, No. 1934, pp. 43-52.

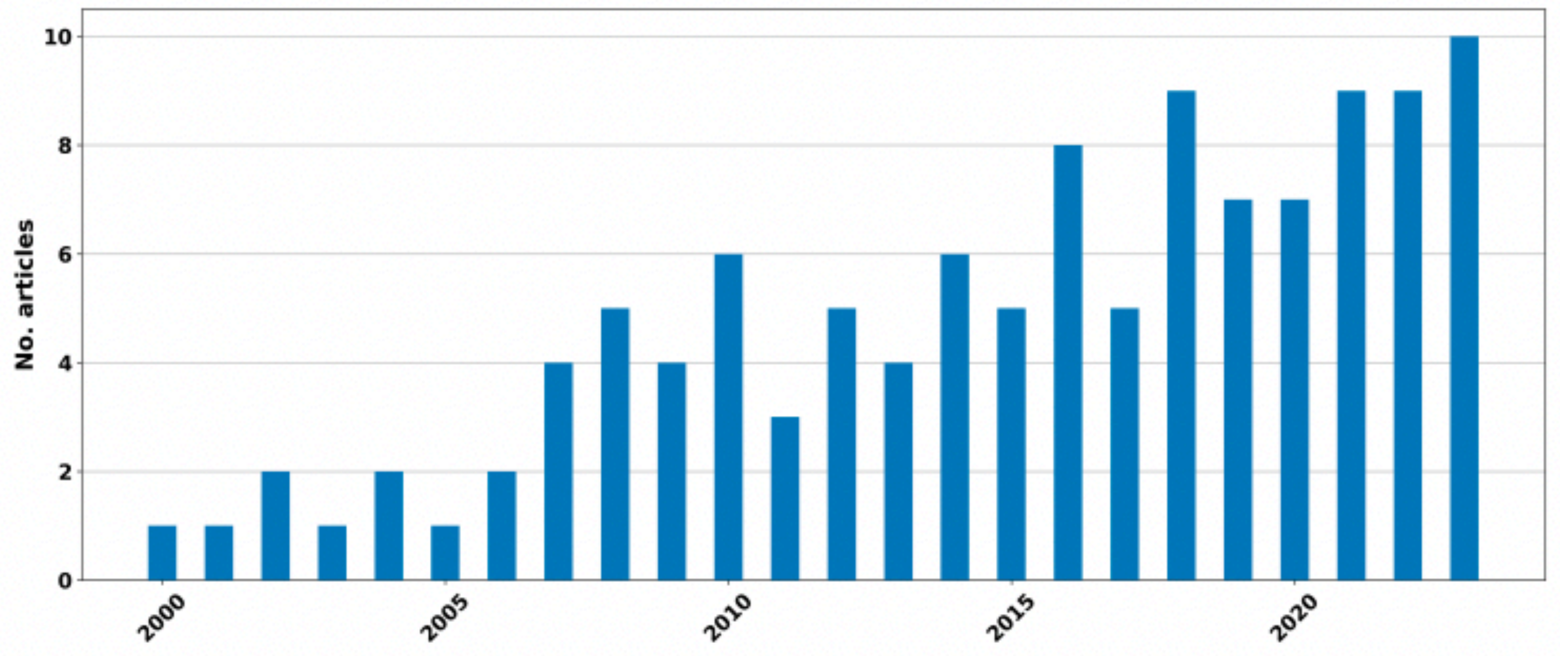
Main insights from A literature review of dense crowd models and simulation.

Dang, H. T., Gaudou, B., & Verstaevel, N. (2024). A literature review of dense crowd simulation. *Simulation Modelling Practice and Theory*, 102955.

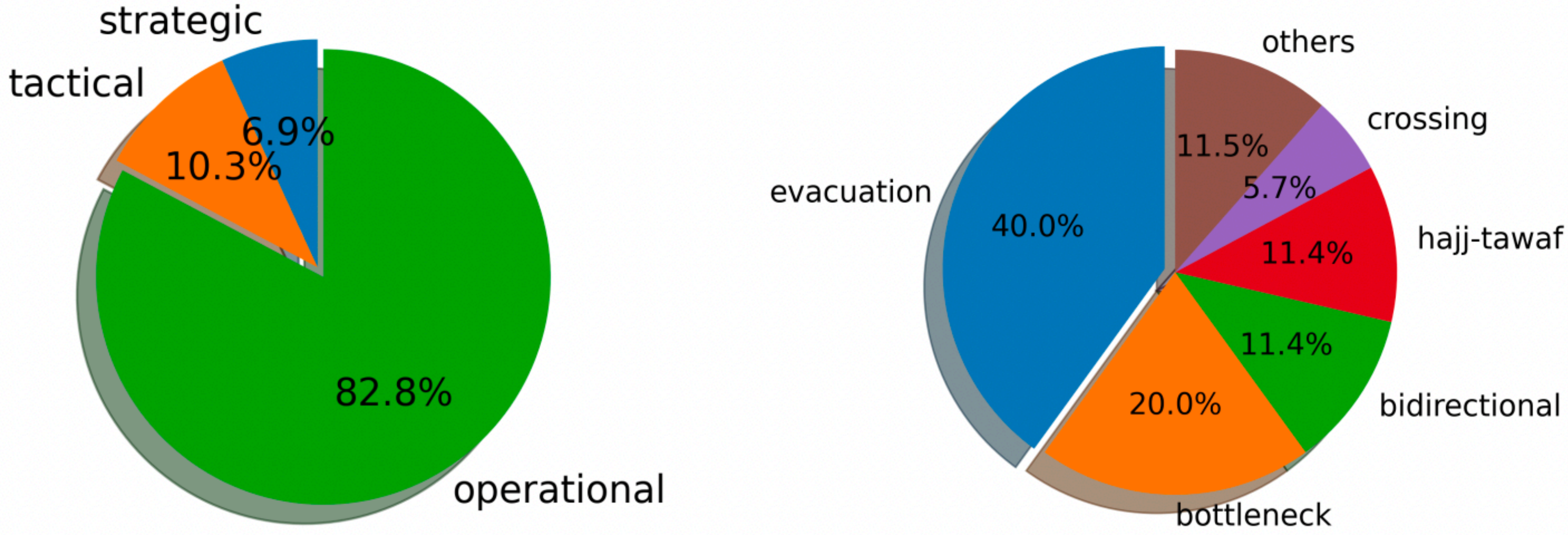
Korbmacher, R., & Tordeux, A. (2022). Review of pedestrian trajectory prediction methods: Comparing deep learning and knowledge-based approaches. *IEEE Transactions on Intelligent Transportation Systems.*

Quantitative results

- From 2000 to 2023: 116 papers selected



(d) Number of yearly publications.



(a) Classification of paper contributions to three levels of modeling [31].

(b) Classification by experiment types.

Serge Hoogendoorn, P.H.L. Bovy, and Winnie Daamen. "Microscopic pedestrian wayfinding and dynamics modelling". In: Pedestrian and Evacuation Dynamics (Jan. 2002), pp. 123–155.

Qualitative results

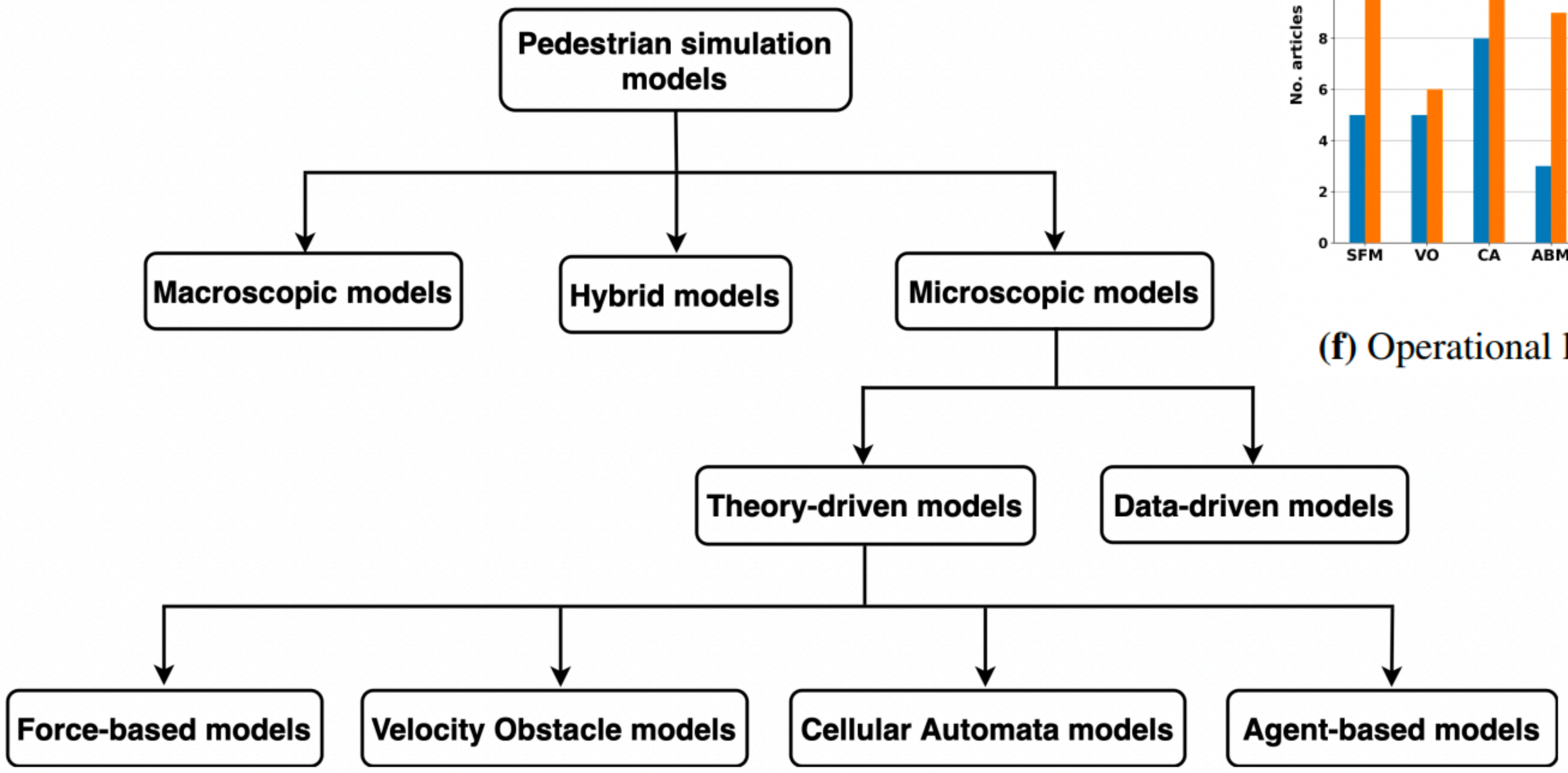
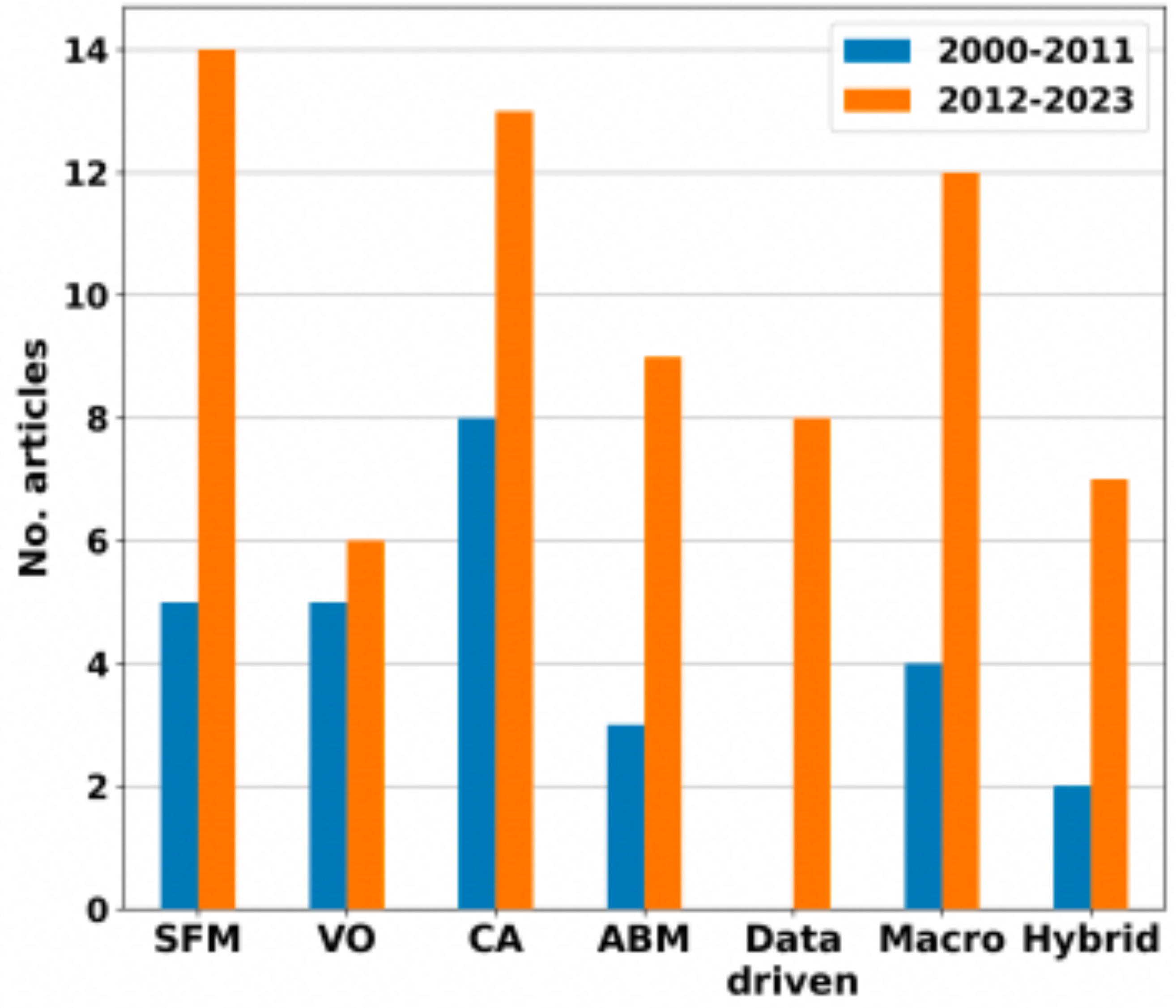


Figure 5: Hierarchical classification of operational level models.



(f) Operational level models.

Qualitative results

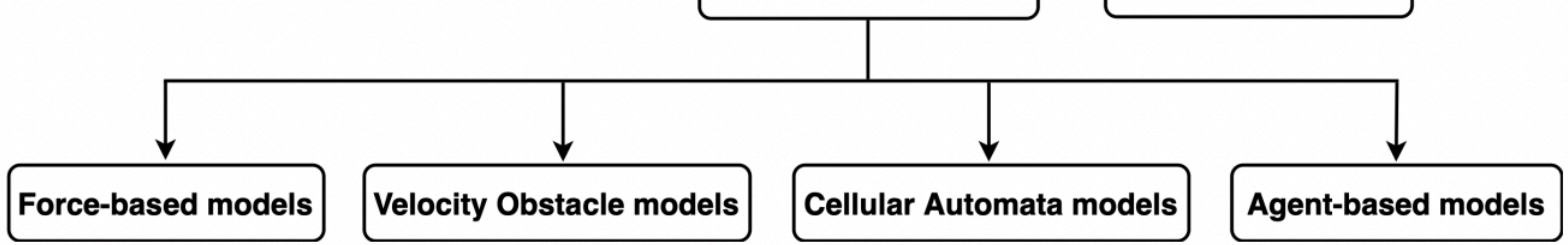
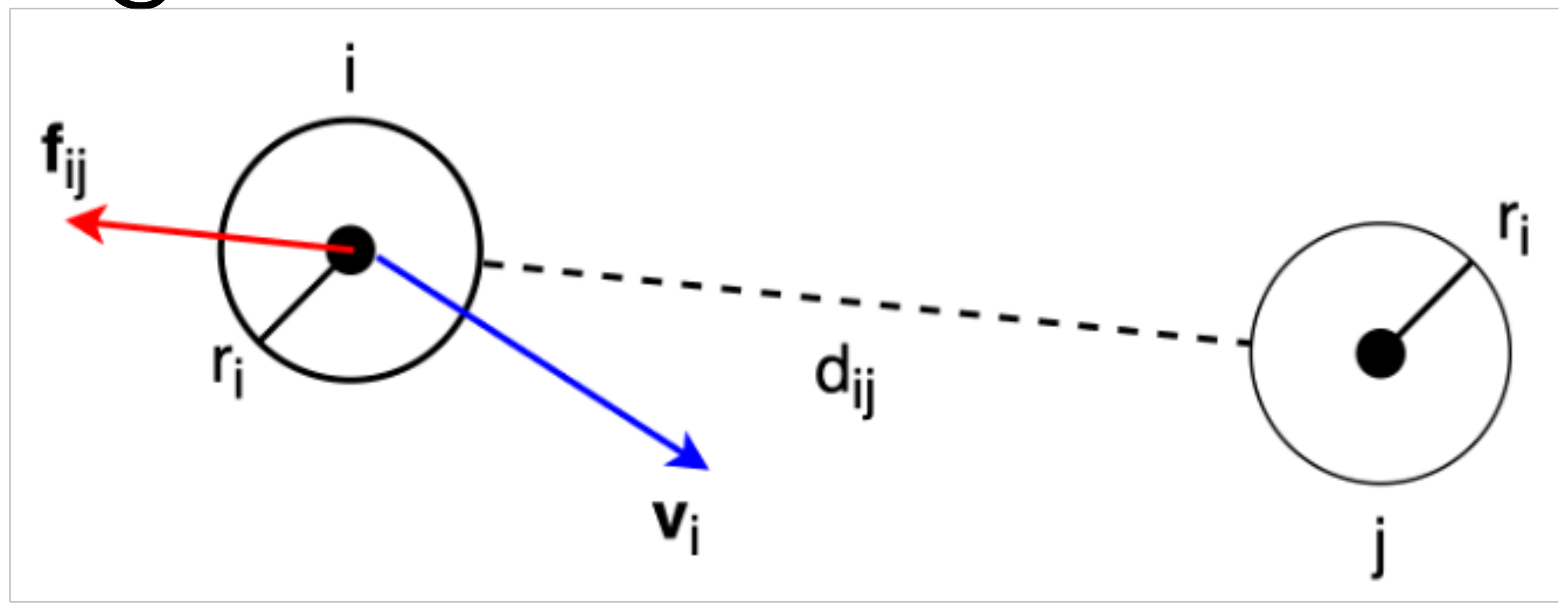


Figure 5: Hierarchical classification of operational level models.

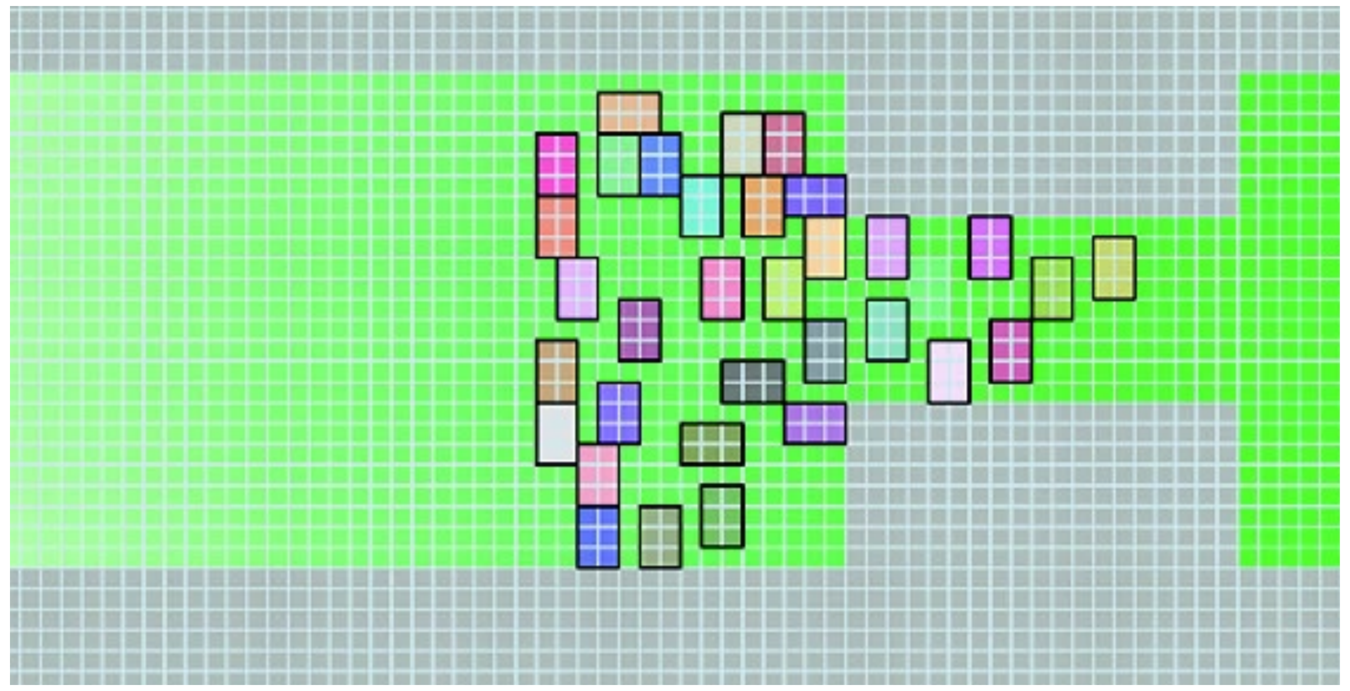
- **Microscopic models:**
  each pedestrian is represented individually, its behavior described by a set of rules.

- **Social Force model**
  [Helbing et al., 2000]:



Helbing, D., Farkas, I., & Vicsek, T. (2000). Simulating dynamical features of escape panic. *Nature*, *407*(6803), 487-490.

- **Cellular Automata**



Bazior, G., Pałka, D., & Wąs, J. (2020, June). Using cellular automata to model high density pedestrian dynamics. In *International Conference on Computational Science* (pp. 486-498). Cham: Springer International Publishing.

Model evaluation

- **Evaluation criteria:**
  - Behavior capability
  - Model performance
  - « Validity »
  - Multi-level modeling

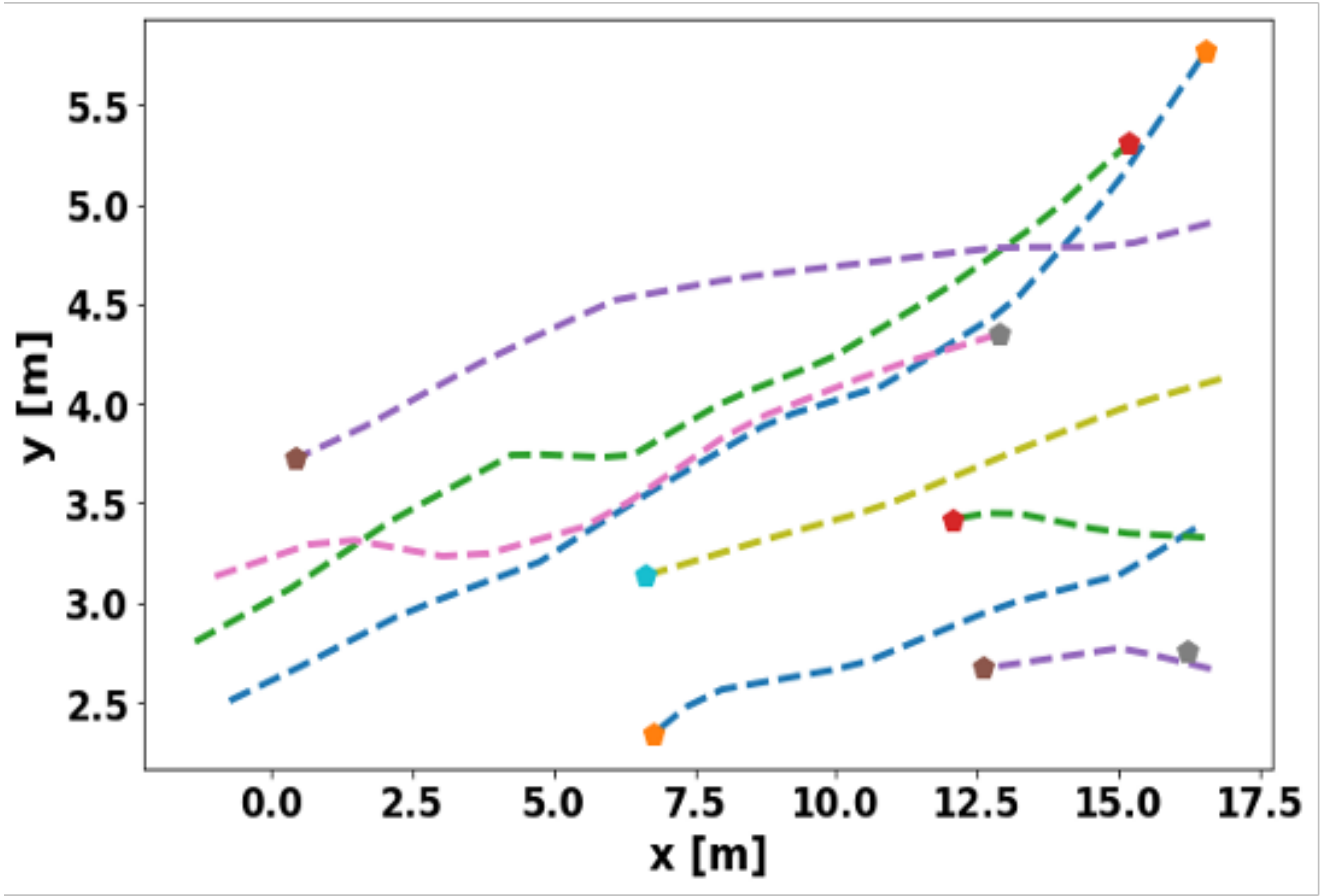
- **Example on SFM:**
  - Stable with time step 0.01 – 0.1s.
  - Density up to 6 ped/m2
  - Small – medium scale < 5K agents.

Table 4: The assessments, advantages, and disadvantages of operational level models (PI: Physical Interaction, GB: Group behavior, F: Following, R: Replan, TSA: Time step adaptivity, D: Density, SS: Simulation speed, S: Scalability, IHM: Integration of high-level modeling, AHM: Ability of high-level modeling).

Models	Behavior Capability				Model performance				Multi-level	
	PI	GB	F	R	TSA	D	SS	S	IHM	AHM
SFMs	++	++	++	+	−	+	+	−	−−	++
Advantages	Easy implementation by adding new types of forces to Newton's second equation [1] to describe new behavior				Stable with the time step of 0.01 - 0.1s; Medium high density (2 - 6) $\mathrm{ped/m^2}$; Small scale (100 - 500 agents) and medium scale (500 - 5K agents) simulations				Easy to be integrated with high-level modeling technique	
Disadvantages	Need parameter calibration to avoid unrealistic behavior at high densities				Sensitive by large time step 0.2s - 0.4s; Computational with large-scale simulation					

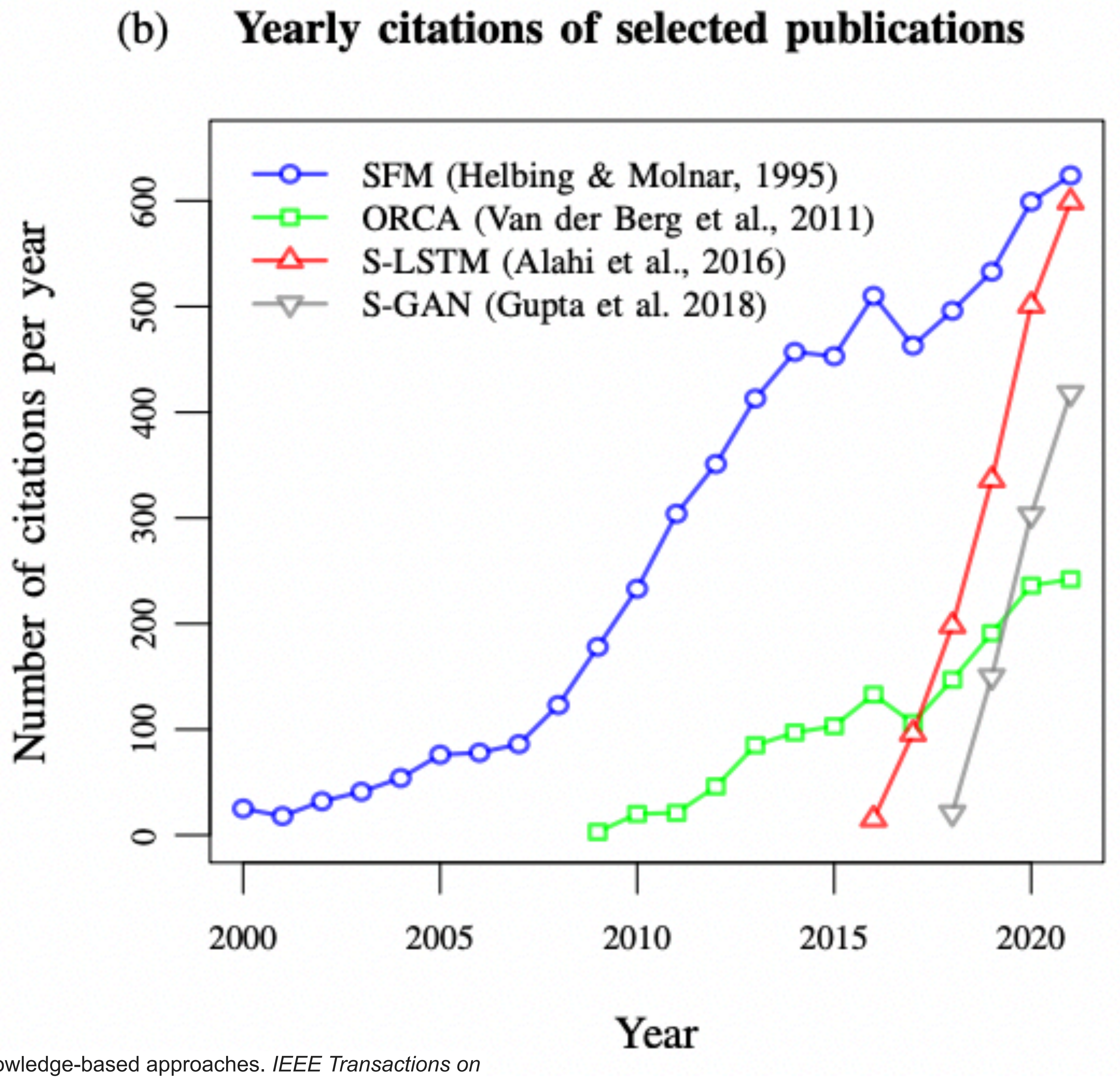
Data-driven approaches: Machine learning for predicting trajectories

- **DL model** to predict the trajectory of **one** pedestrian given:
  - **historical trajectory** (e.g. with LSTM)
  - **Historical trajectory** and **neighbors information** (e.g. Social LSTM [Alahi et al., 2016])



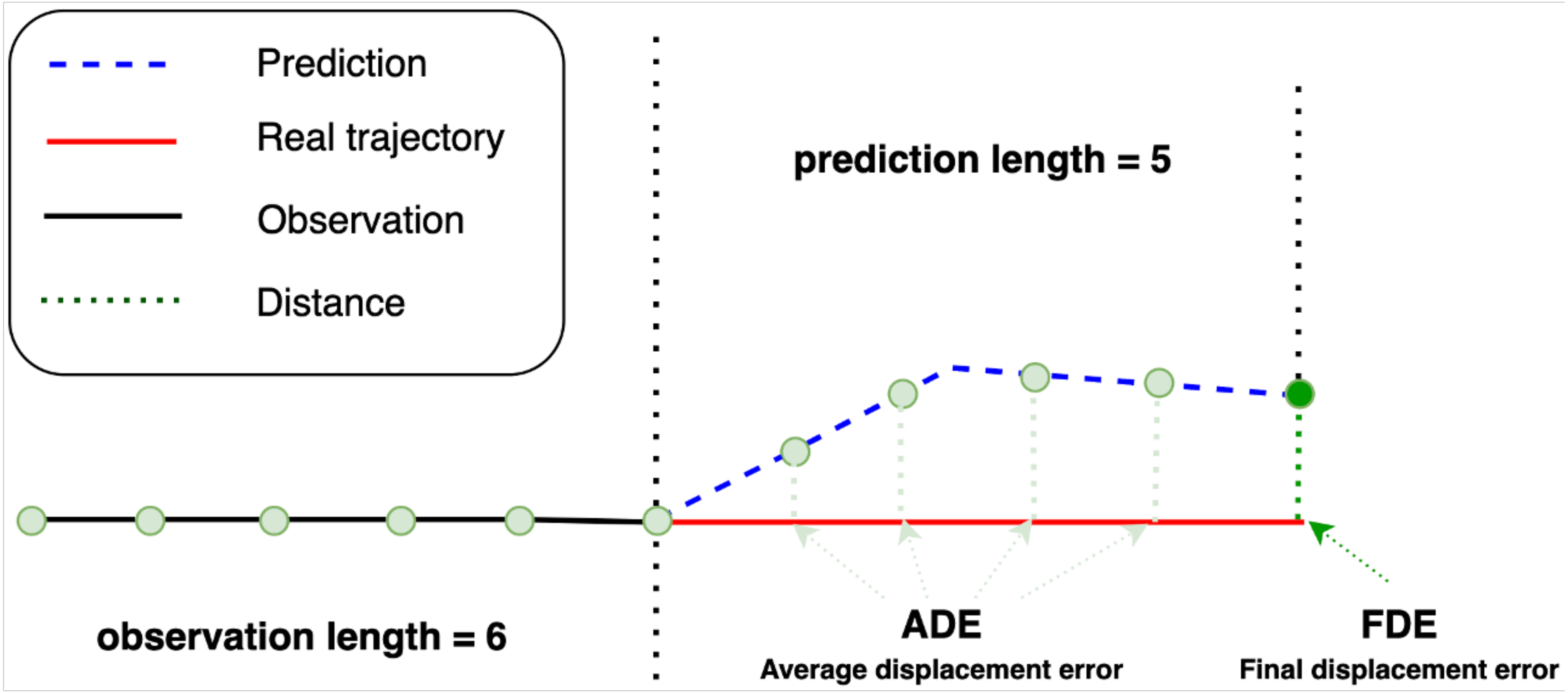
Data-driven approaches: Machine learning for predicting trajectories

- Review has shown the **growing importance of ML/DL** model in pedestrian modeling.



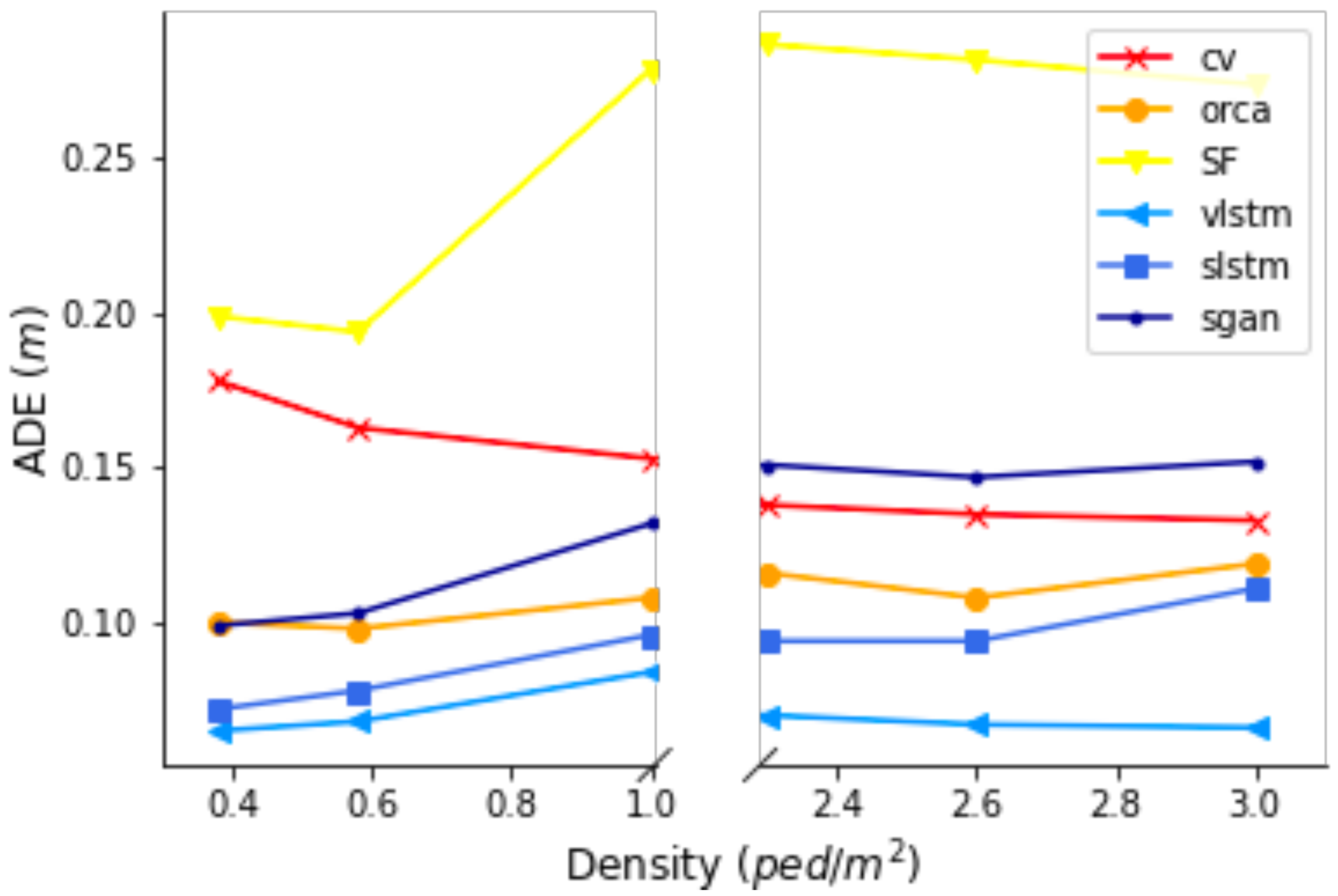
Korbmacher, R., & Tordeux, A. (2022). Review of pedestrian trajectory prediction methods: Comparing deep learning and knowledge-based approaches. *IEEE Transactions on Intelligent Transportation Systems*.

Deep learning to predict trajectories: indicators



Limitations of DL for predicting trajectories in high dense situations

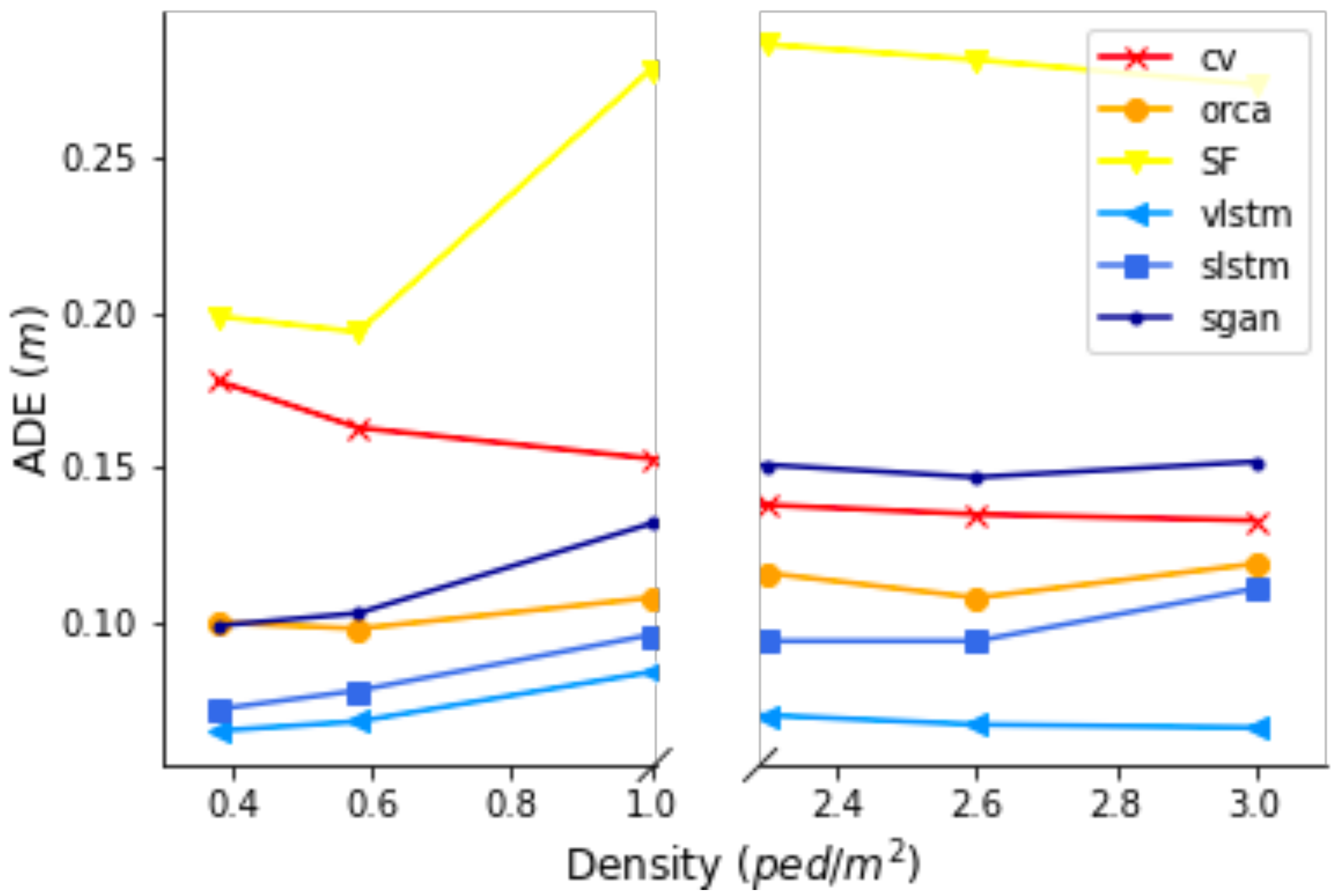
- We have shown that, whereas ML/DL are much better on **distance errors indicators**
  (Tests on an existing dataset: from Julich Center, di-directional flow)

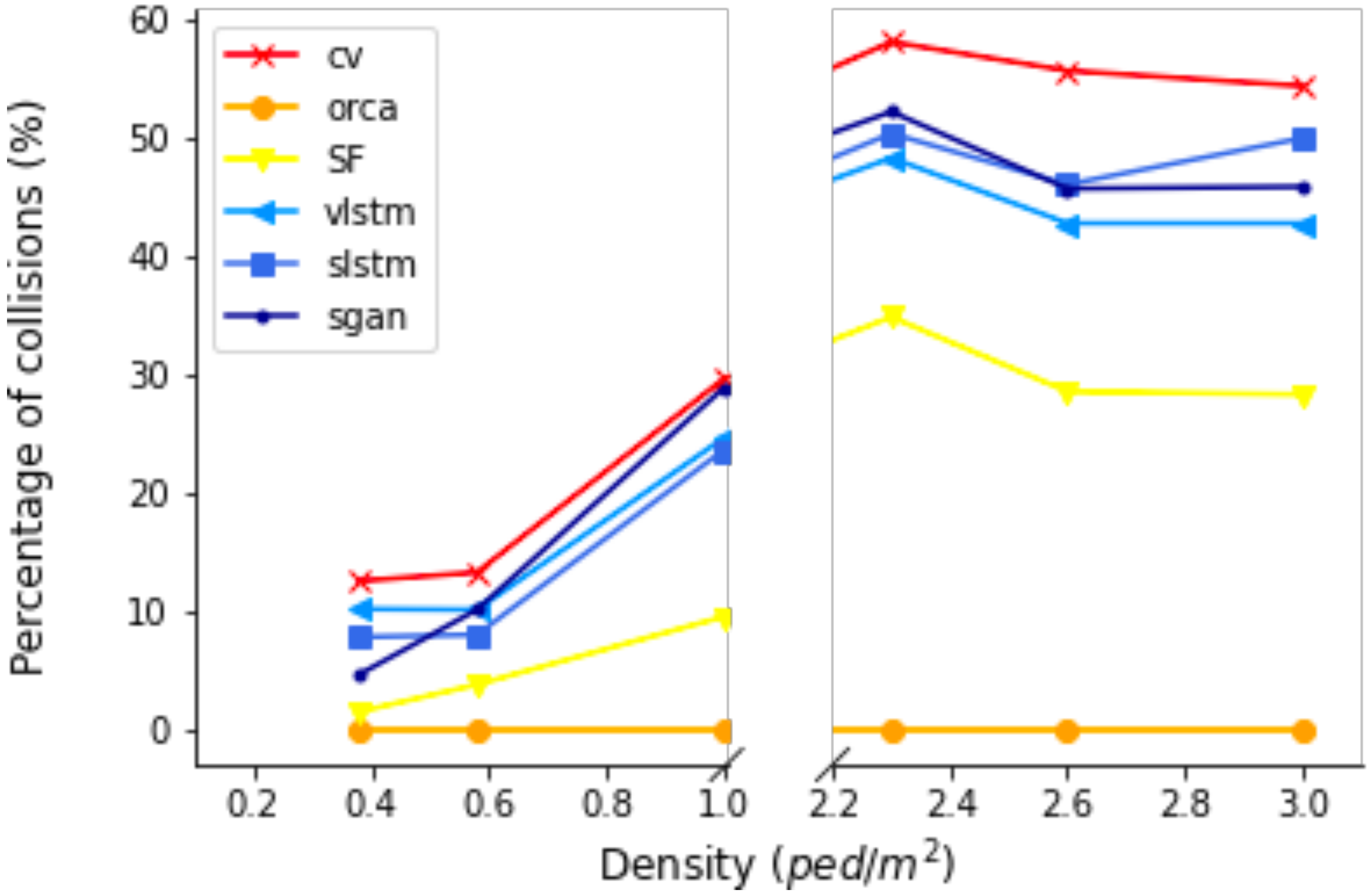


Korbmacher, R., Dang, H.-T., Tordeux, A., Gaudou, B. & Verstaevel, N. Differences in pedestrian trajectory predictions for high- and low-density situations. Traffic and Granular Flow 2022 (TGF22), 15 – 17 October 2022, IIT Delhi, India. Abstract; Slides.

Limitations of DL for predicting trajectories in high dense situations

- We have shown that, whereas ML/DL are much better on distance errors indicators, **results are not so good on collision metrics**
(Tests on an existing dataset: from Julich Center, di-directional flow)





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Key findings

- **Research gaps:**
  - Lack of models that can simulate all density levels.
  - Data-driven models: best distance accuracy, but many collisions.
  - Calibration/validation challenges: limited high-density datasets, in particular for real case-studies.

- **Objectives**
  - Collect high-density data for calibration and validation of these models.
  - Investigate the use of density-related factors in hybrid approaches:
    - To develop a **hybrid framework for coupling models (agent-based model).**
    - To enhance deep learning models for predicting pedestrian trajectories.

- **2 leading ideas:**
  - Develop new approaches of coupling various models depending on density
  - Use of the **time-to-collision** to improve collision avoidance

Application case: The Festival of Lights (Lyon)

Grand Mix au Musée des Beaux-Arts de Lyon © Brice Robert

The Festival of Lights (Lyon, 2022)

Festival of Lights (2022)

- ~30 illuminated spots

- more than 2 millions people over 4 days

Most crowded spots:

- Place des Terreaux (150 000 p/night)

- Place Saint-Jean (80 000 p/night)

https://www.le-tout-lyon.fr/fete-des-lumieres-2-millions-de-visiteurs-les-trois-spots-qui-ont-attire-le-plus-de-spectateurs-117634.html#:~:text=La%20Ville%20de%20Lyon%20a,trois%20lieux%20de%20pr%C3%A9dilection%20identifi%C3%A9s.

Organisation of the crowd around the Place des Terreaux

- 1 single entrance
- 3 streets as exit
- 7 minutes show
- After a show, a break of 7min to let people go
- Exit is free (but we observe waves during the breaks)
- Entrance is regulated depending on the density in the square.

Projection areas on buildings

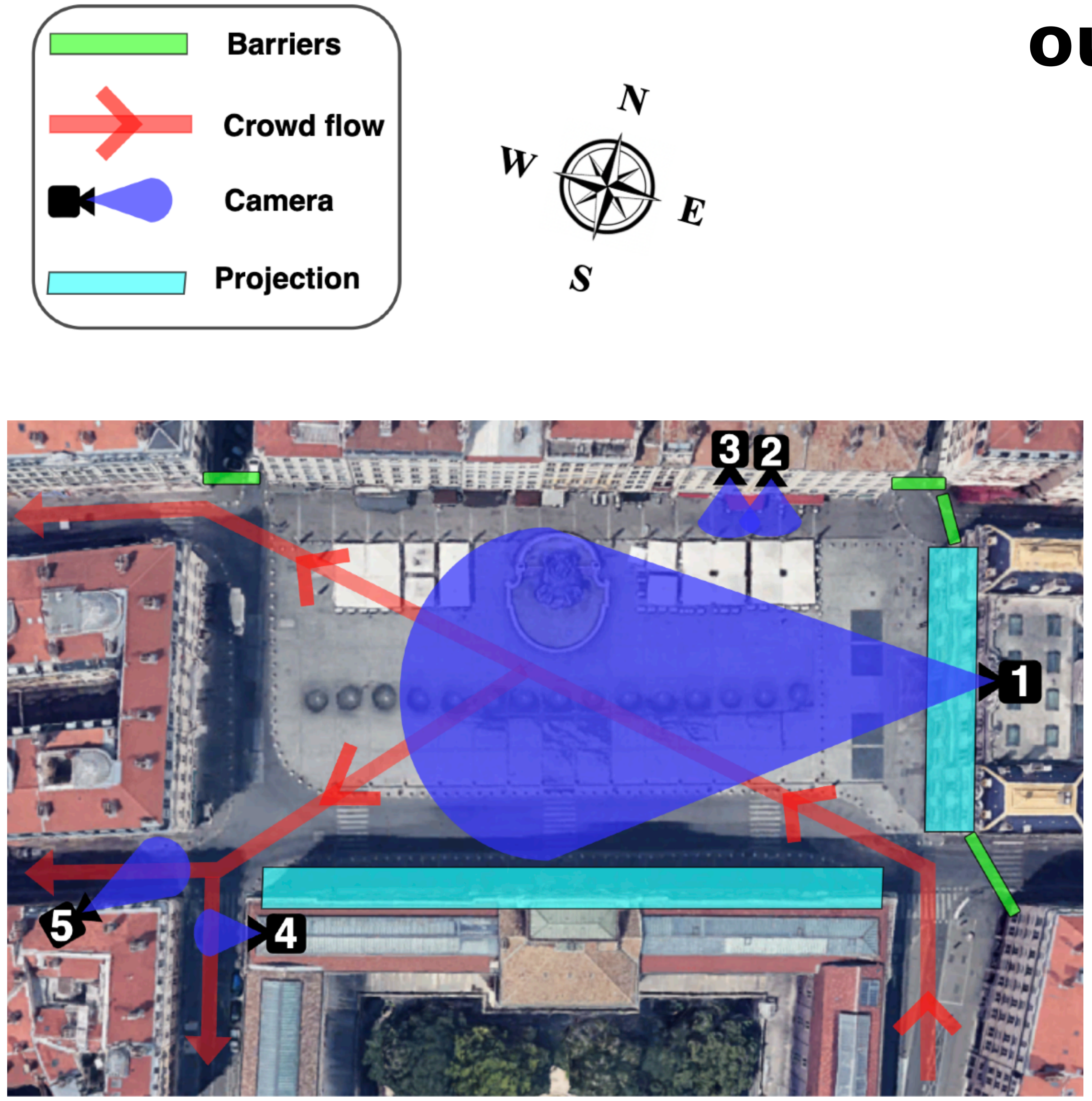
Blocked roads

Regulation points

Direction of pedestrians' flow

CCTV recording of the Place des Terreaux

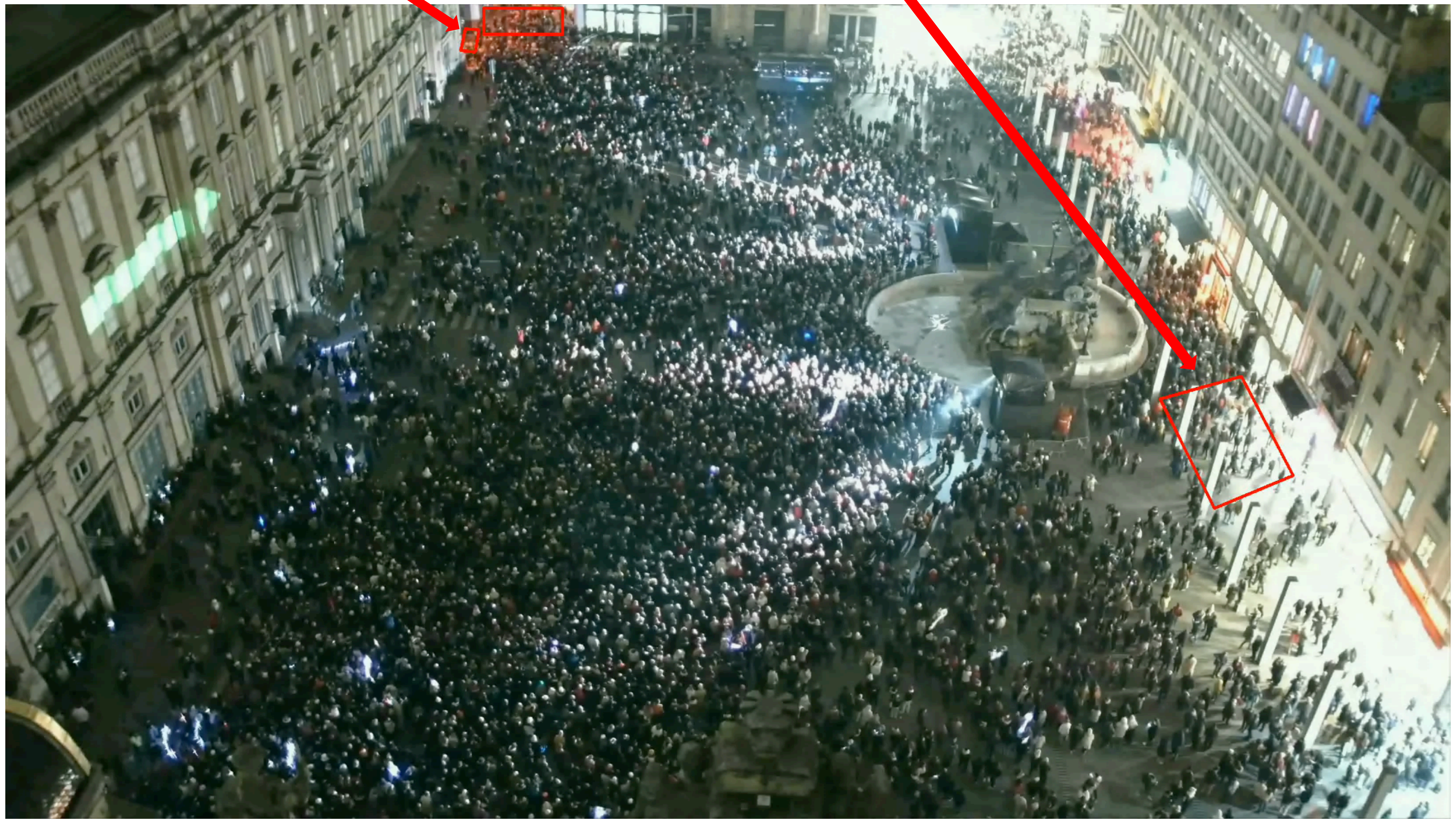
Experiment



Large view

outflows
camera 5
camera 4

trajectories
camera 2, 3



Toward a multi-scale dataset of crowd dynamics

Global ("macroscopic") view

- Street map of crowd flows
- Origins and destinations of flows on Place des Terreaux
- Composition of the crowd

"Mesoscopic" scale

- Distribution of the crowd on Place des Terreaux
- Local fundamental diagrams
- Statistics of physical contacts

Detailed ("microscopic") scale

- Full trajectories in zones (of ~10 m linear size) on Place des Terreaux
- 'Initial' positions on the whole square

Sample of full GPS tracks

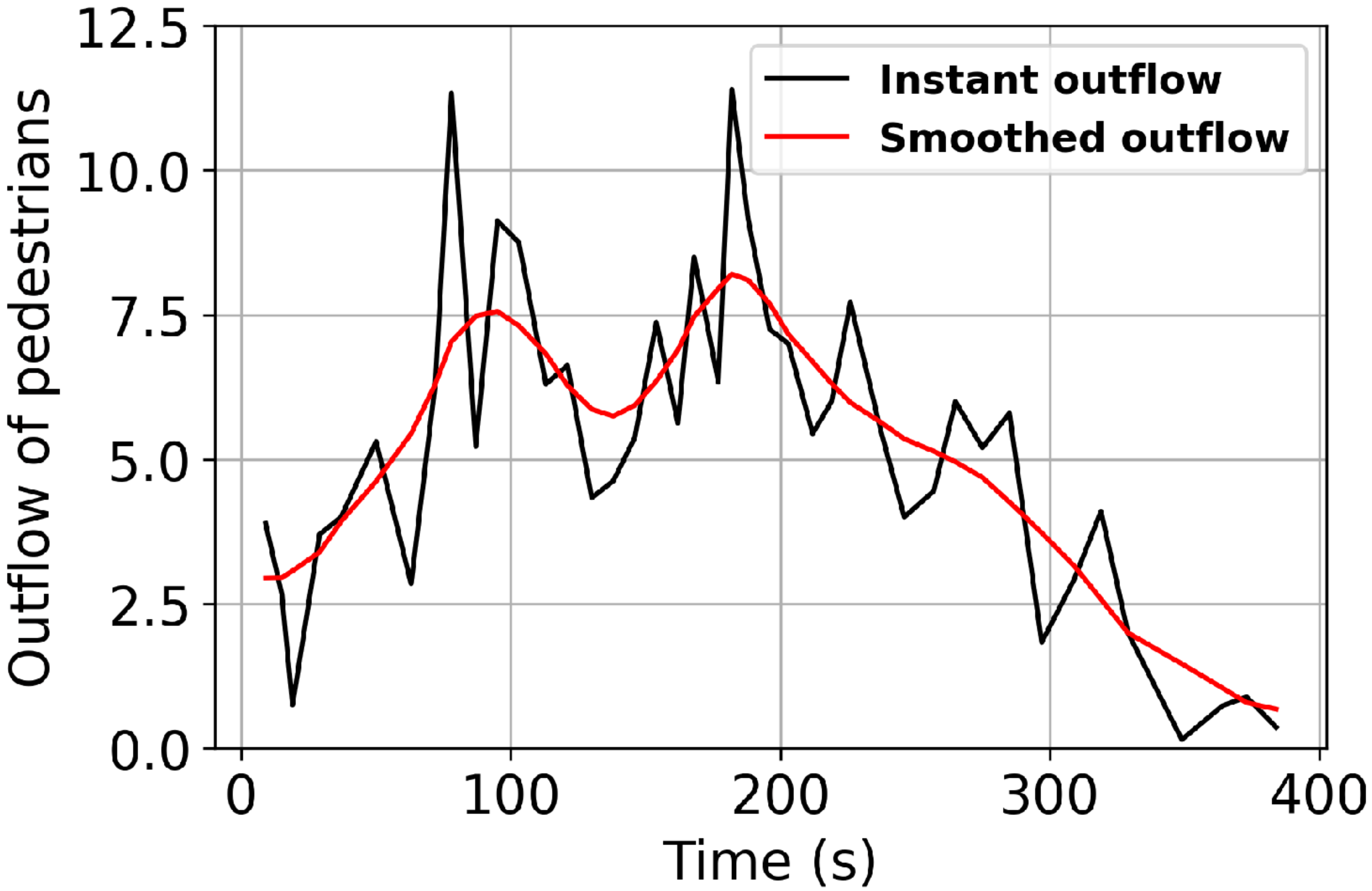
Dufour, O., Dang, H. T., Cordes, J., Korbmacher, R., Chraibi, M., Gaudou, B., ... & Tordeux, A. (2025). Dense Crowd Dynamics and Pedestrian Trajectories: A Multiscale Field Dataset from the Festival of Lights in Lyon. *Scientific Data*, *12*(1), 718.

CCTV recording of the Place des Terreaux

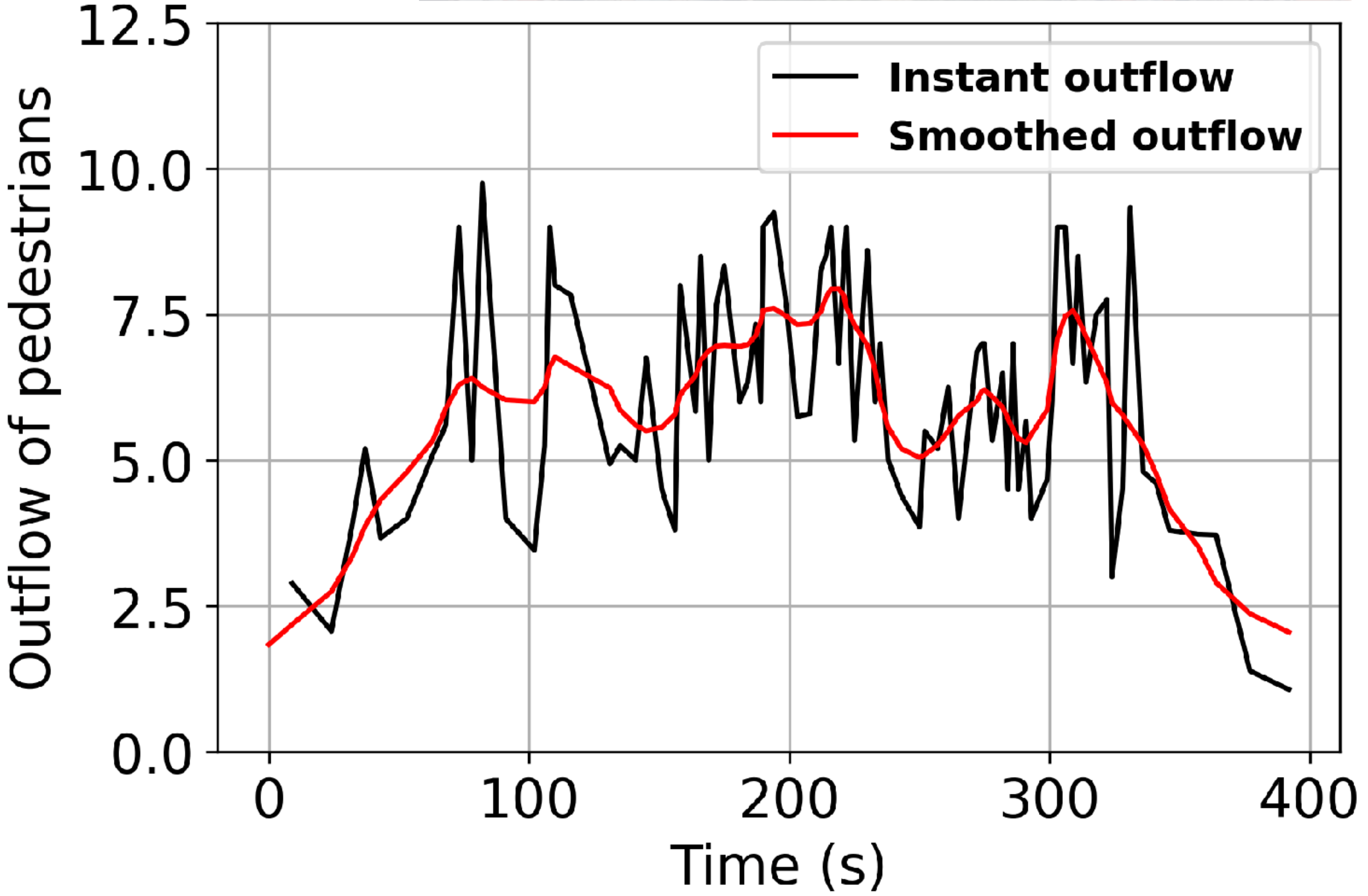
Area of interest: corridor-like area

Data collection: Outflow of pedestrians

(a) The outflow of Constantine Road (1803 p.)
(b) The outflow of Chenavard Road (2030 p.)



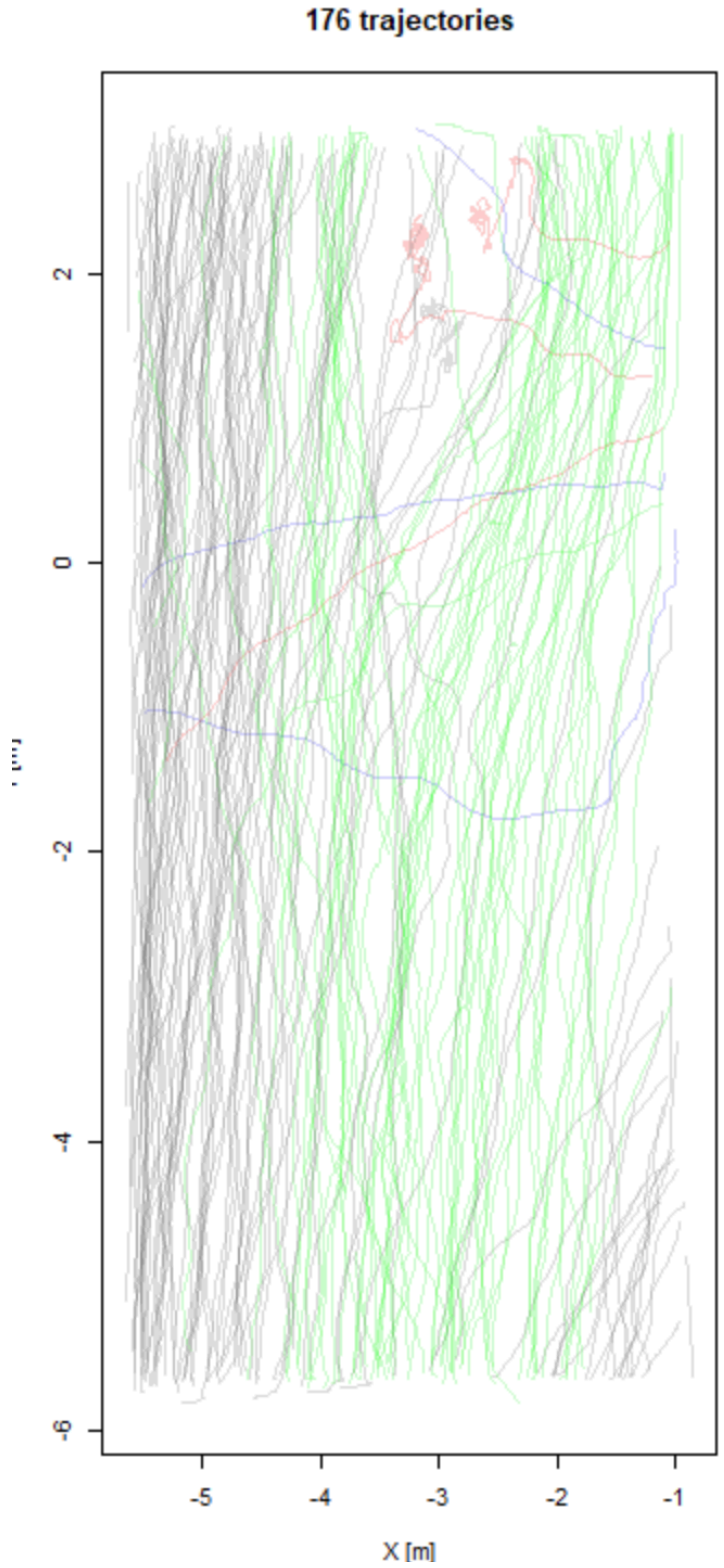
(a)



(b)

Data Collection: Trajectories extraction

- 5269 trajectories using PeTrack.
- mono-, bi-, multi-directional flows, with immobile pedestrians.
- Up to 2+ ped./m2
- Average speed between 0.33 to 1 m/s
- Validation: manual cross-checking.



[1]https://www.fz-juelich.de/en/ias/ias-7/services/software/petrack

Dataset in open-access, with an web app to explore data

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Dense Crowd Dynamics and Pedestrian Trajectories: A Multiscale Field Dataset from the Festival of Lights in Lyon

Oscar Dufour, Huu-Tu Dang, Jakob Cordes, Raphael Korbmacher, Mohcine Chraibi, Benoit Gaudou, Alexandre Nicolas & Antoine Tordeux

Scientific Data **12**, Article number: 718 (2025) | Cite this article

Abstract

The dynamics of dense crowds have received considerable attention from researchers seeking fundamental understanding or aiming to develop data-driven algorithms to predict pedestrian trajectories. However, current research mainly relies on data collected in controlled settings. We present one of the first comprehensive field datasets describing dense pedestrian dynamics at different scales, from contextualized macroscopic crowd flows

https://zenodo.org/records/13830435

https://github.com/MADRAS-crowds/madras-data-app

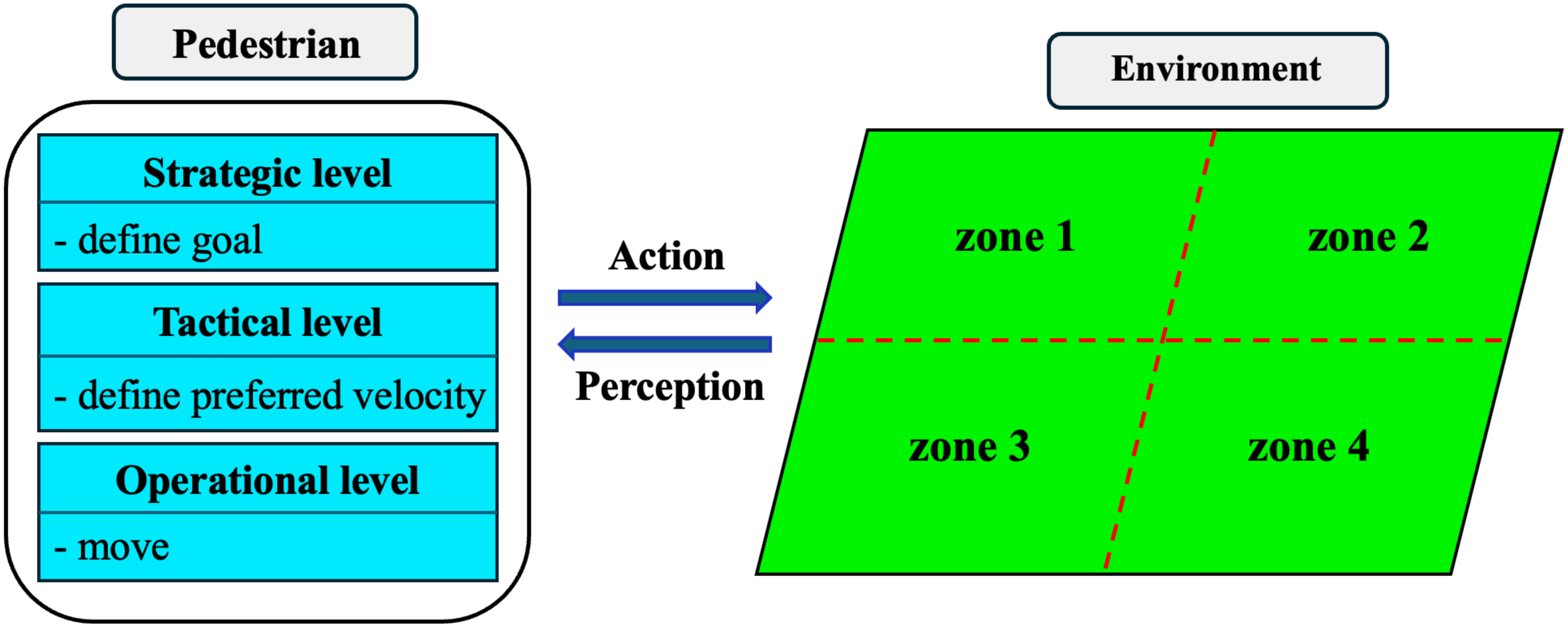
madras-data-app.streamlit.app/

HyPedSim: A Hybrid Crowd-Simulation Framework

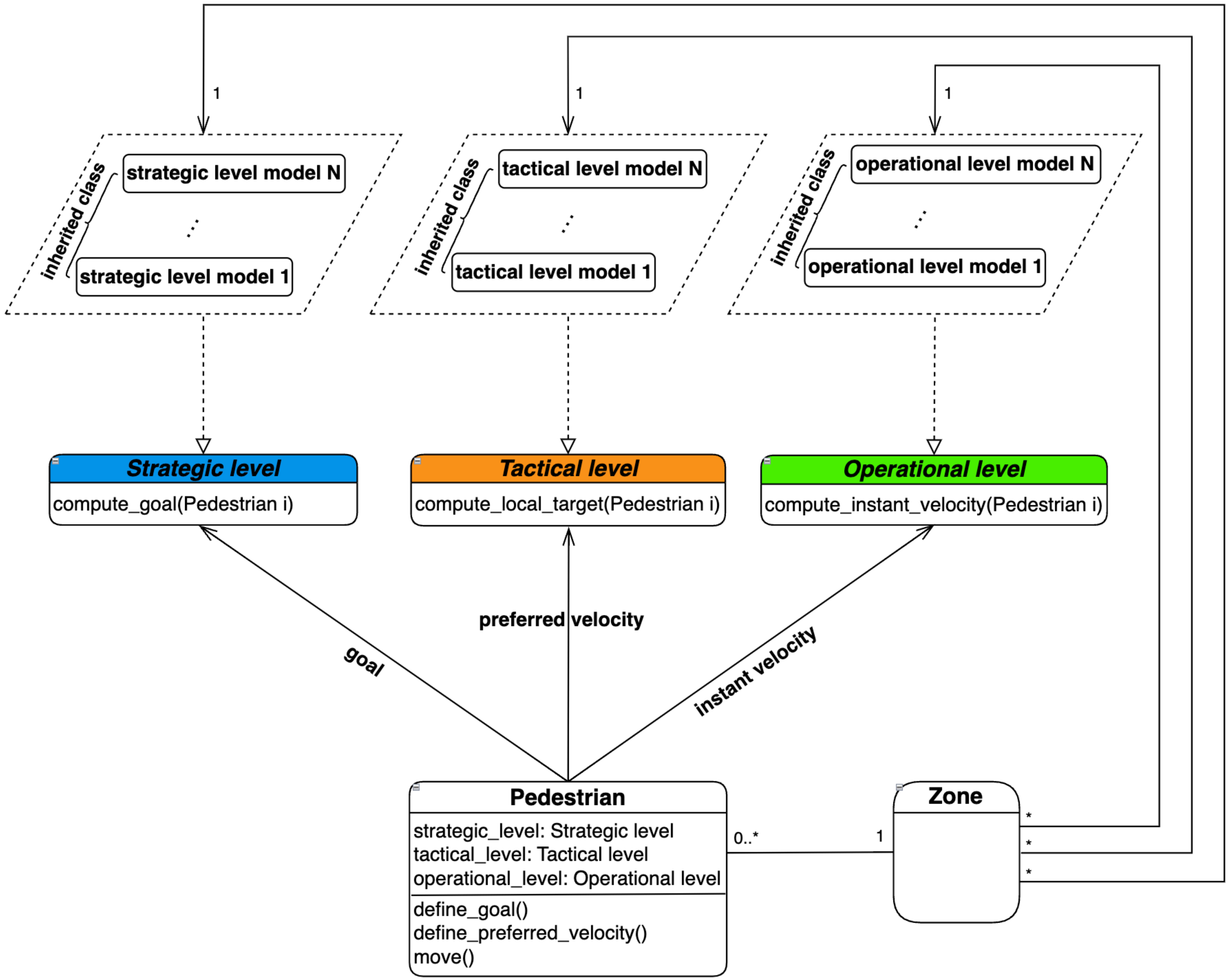
Dang, H. T., Gaudou, B., & Verstaevel, N. (2024). HyPedSim: A Multi-Level Crowd-Simulation Framework—Methodology, Calibration, and Validation. *Sensors*, *24*(5), 1639.

HyPedSim's architecture

- General idea: coupling models based on zones.



HyPedSim's architecture

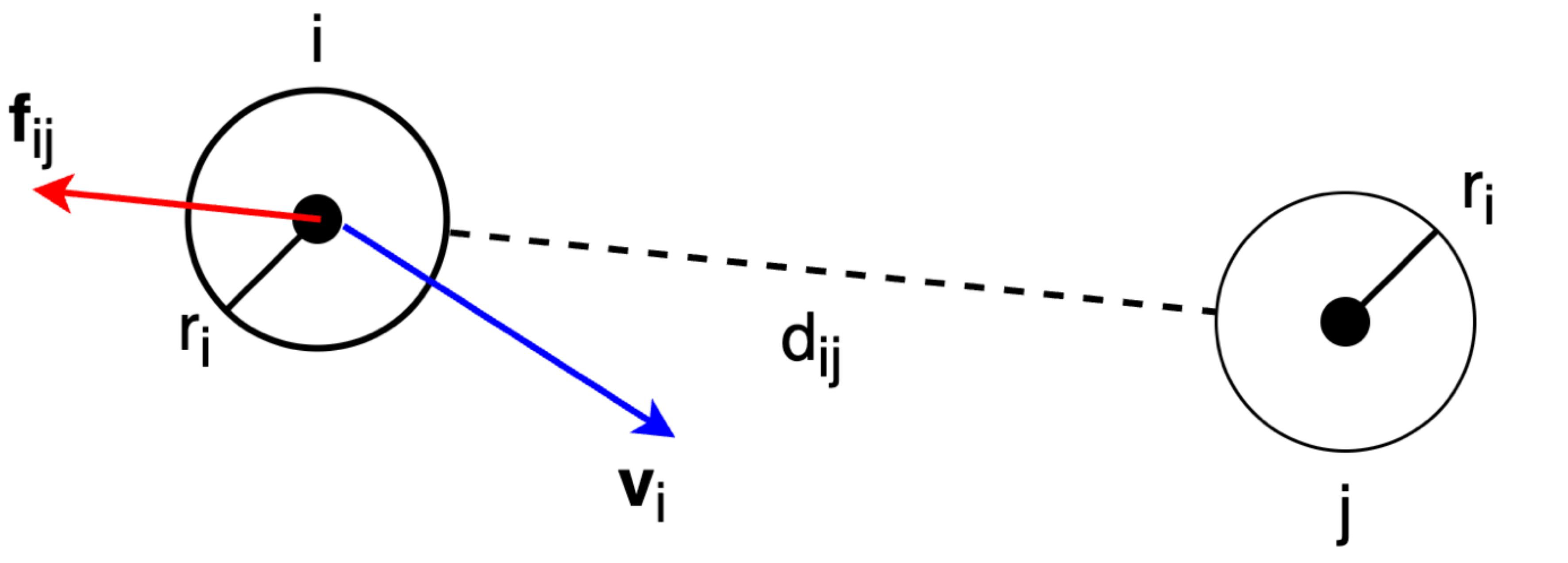


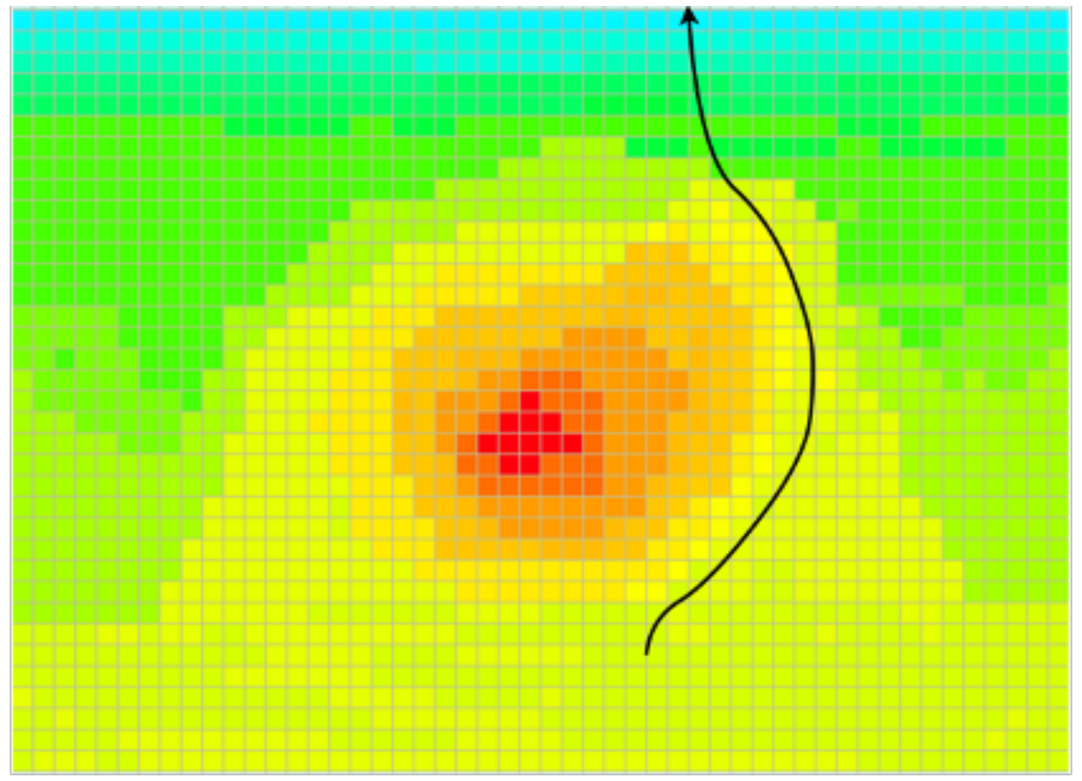
HyPedSim's architecture

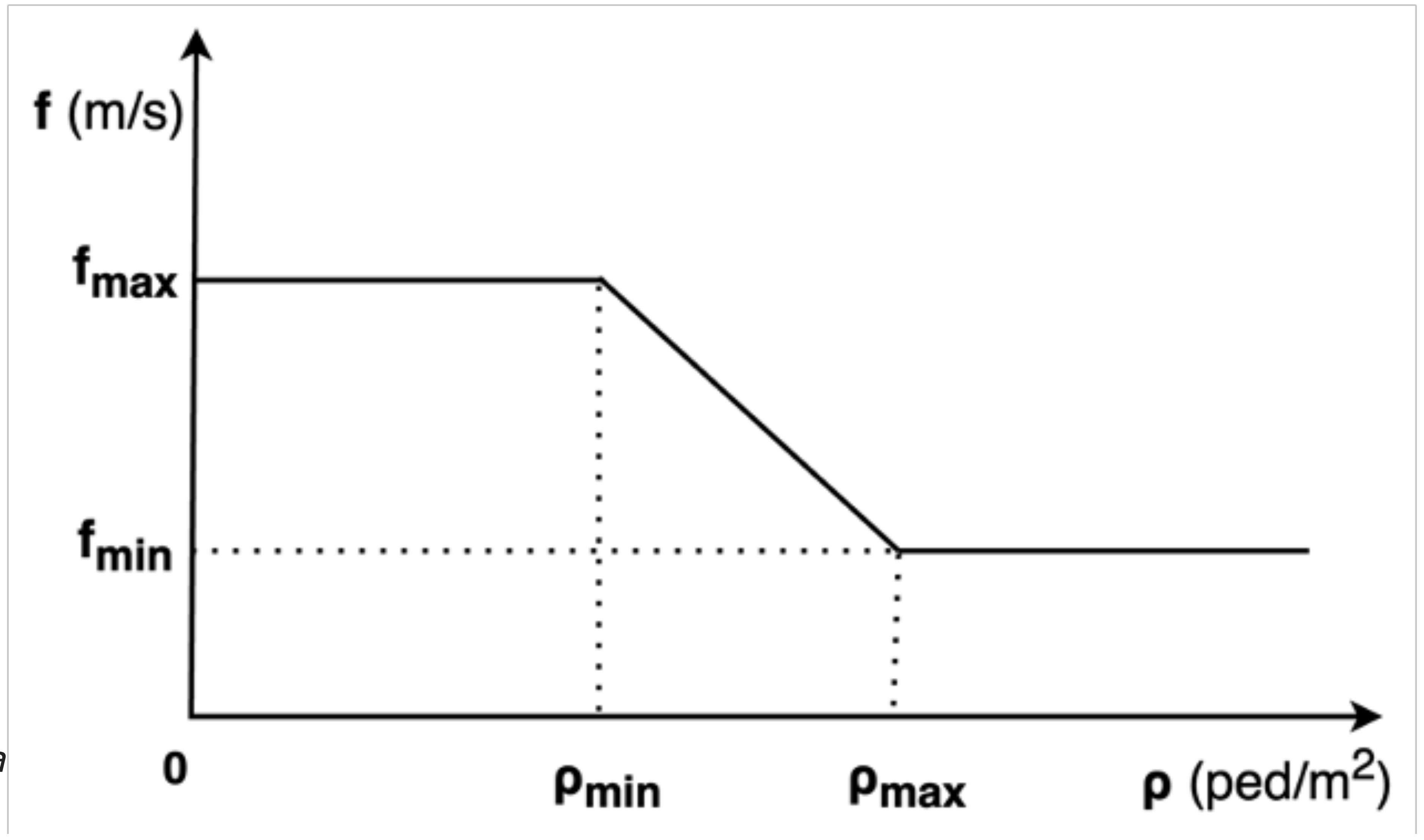
Pedestrian simulation models proof of concept

- Focus on the operational level.
  - Implemented on **GAMA platform** [Taillandier et al., 2019].

- As a proof of concept, **2 operational-level models have been implemented:**
  - **Social Force Model** for **low-density areas**
  - **Continuum Crowd model** [Treuille et al., 2006], for **high-density areas**



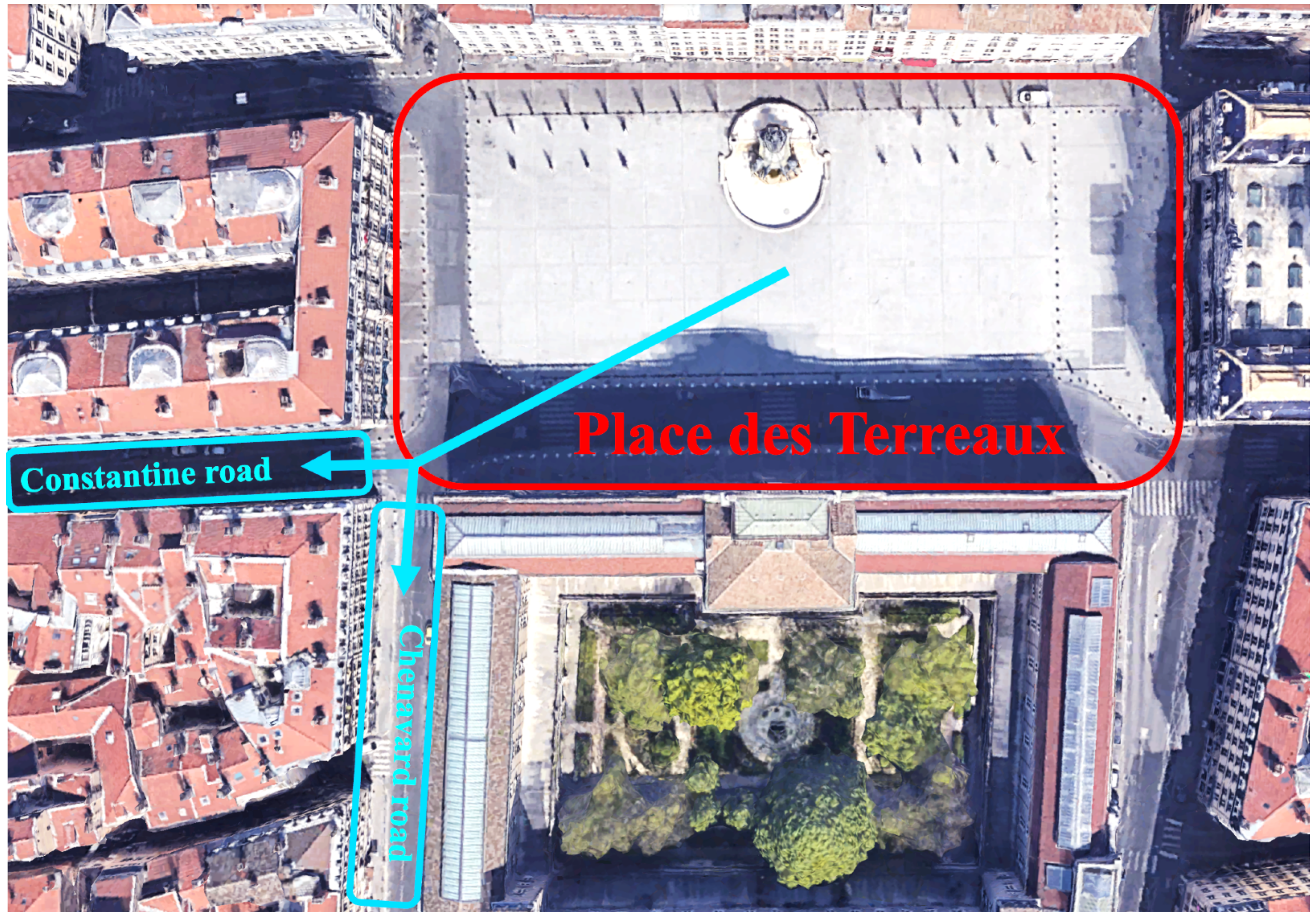




Taillandier, Patrick, et al. "Building, composing and experimenting complex spatial models with the GAMA platform." *GeoInforma*
Helbing, D., Farkas, I., & Vicsek, T. (2000). Simulating dynamical features of escape panic. *Nature*, *407*(6803), 487-490.
Treuille, A., Cooper, S., & Popović, Z. (2006). Continuum crowds. *ACM Transactions on Graphics (TOG)*, *25*(3), 1160-1168.

Applications to Festival of Lights

- Simulation scenario:
  - Start: 3833 agents uniformly distributed in the plaza.
  - End: all agents reach the end of the exit roads.



Hybrid model

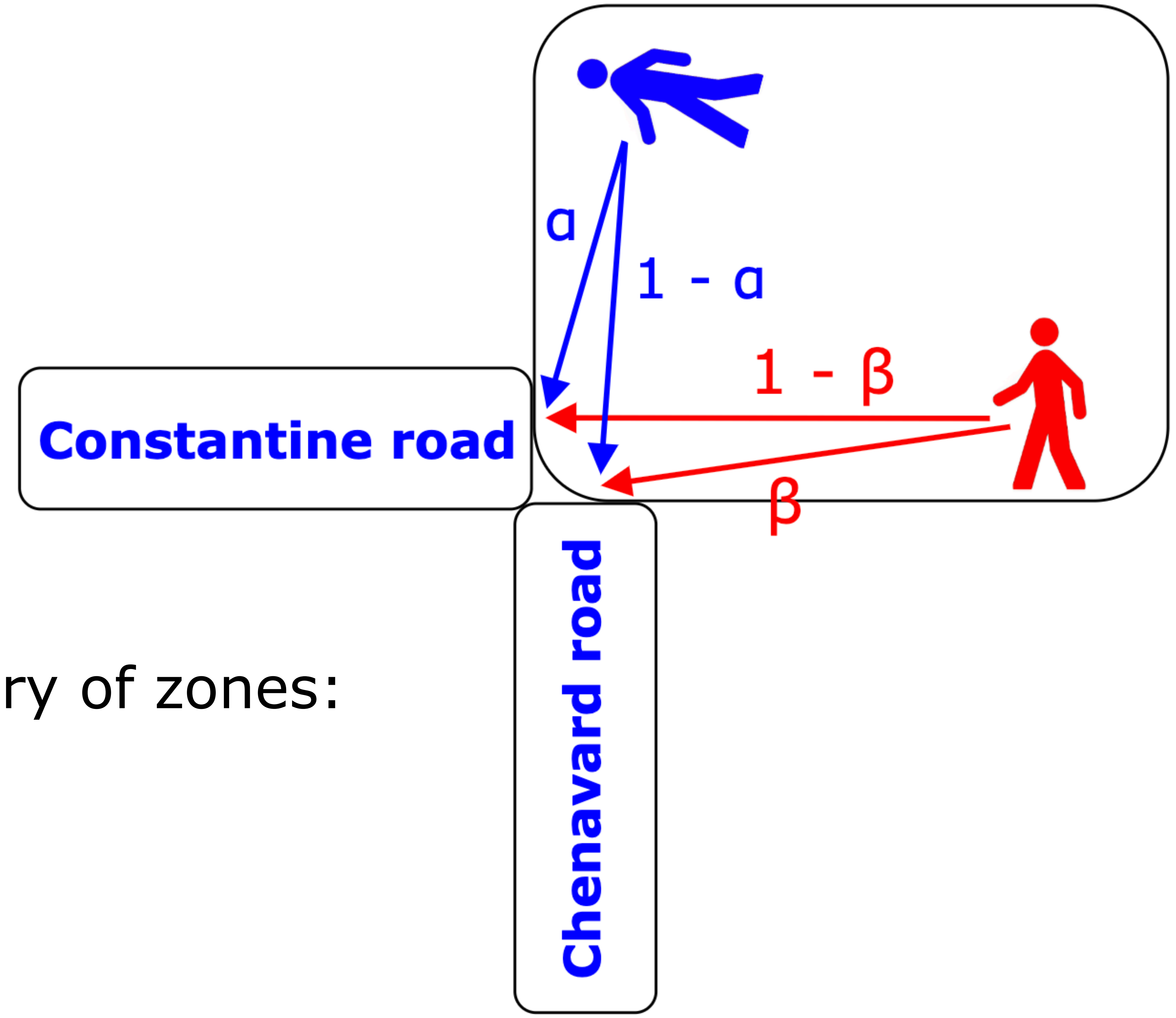
- Specification of models:
  - High-density zone: CC model.
  - Low-density zones: SFM.

- Pedestrians switch models (CC → SFM) at the boundary of zones:
  - t_{delay} ← controlling factor for outflow.

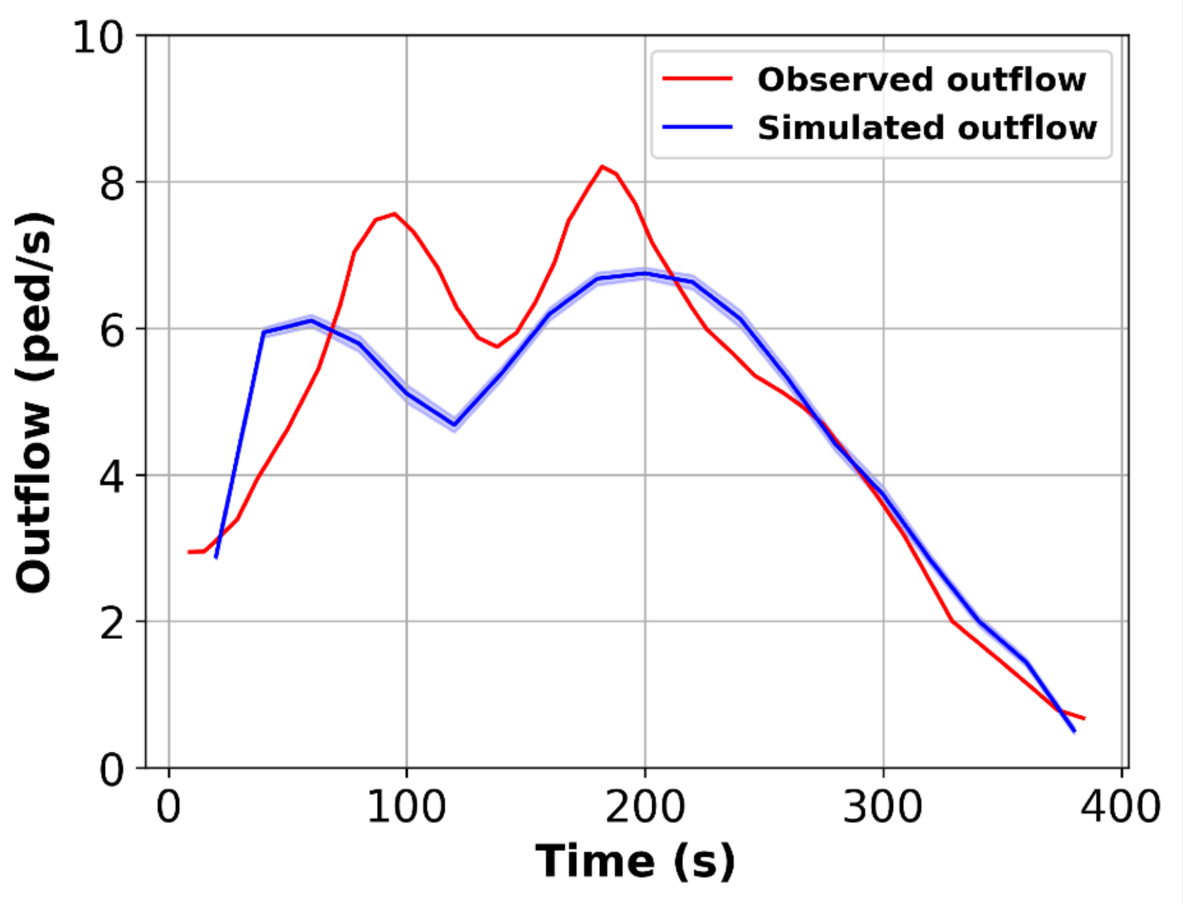
- Exit choice behaviour: nearest exit with a probability.

- Parameters: t_{delay} , α , β.

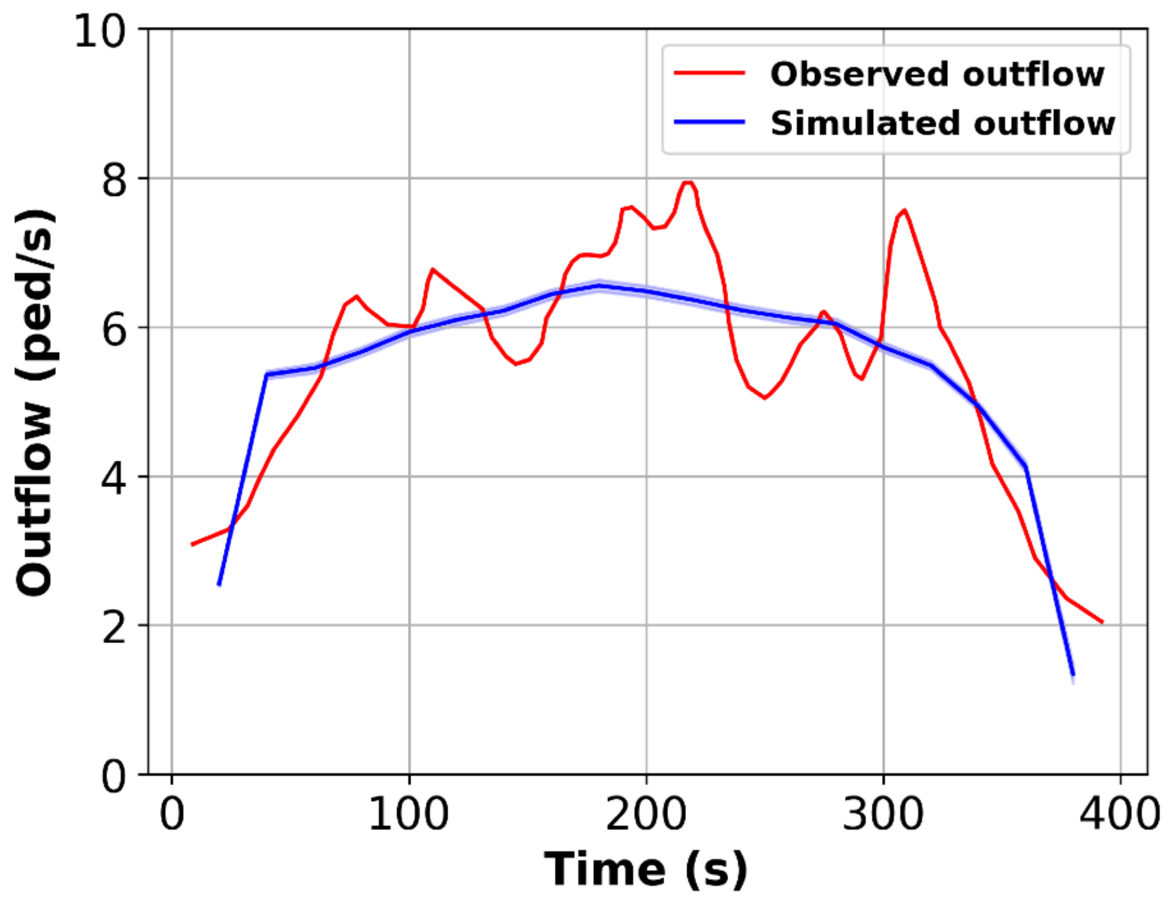
- Model **calibrated** on outflow data (11 parameters) by genetic algorithm.
  Sensitivity analysis (One-at-a-time around the best parameter values)



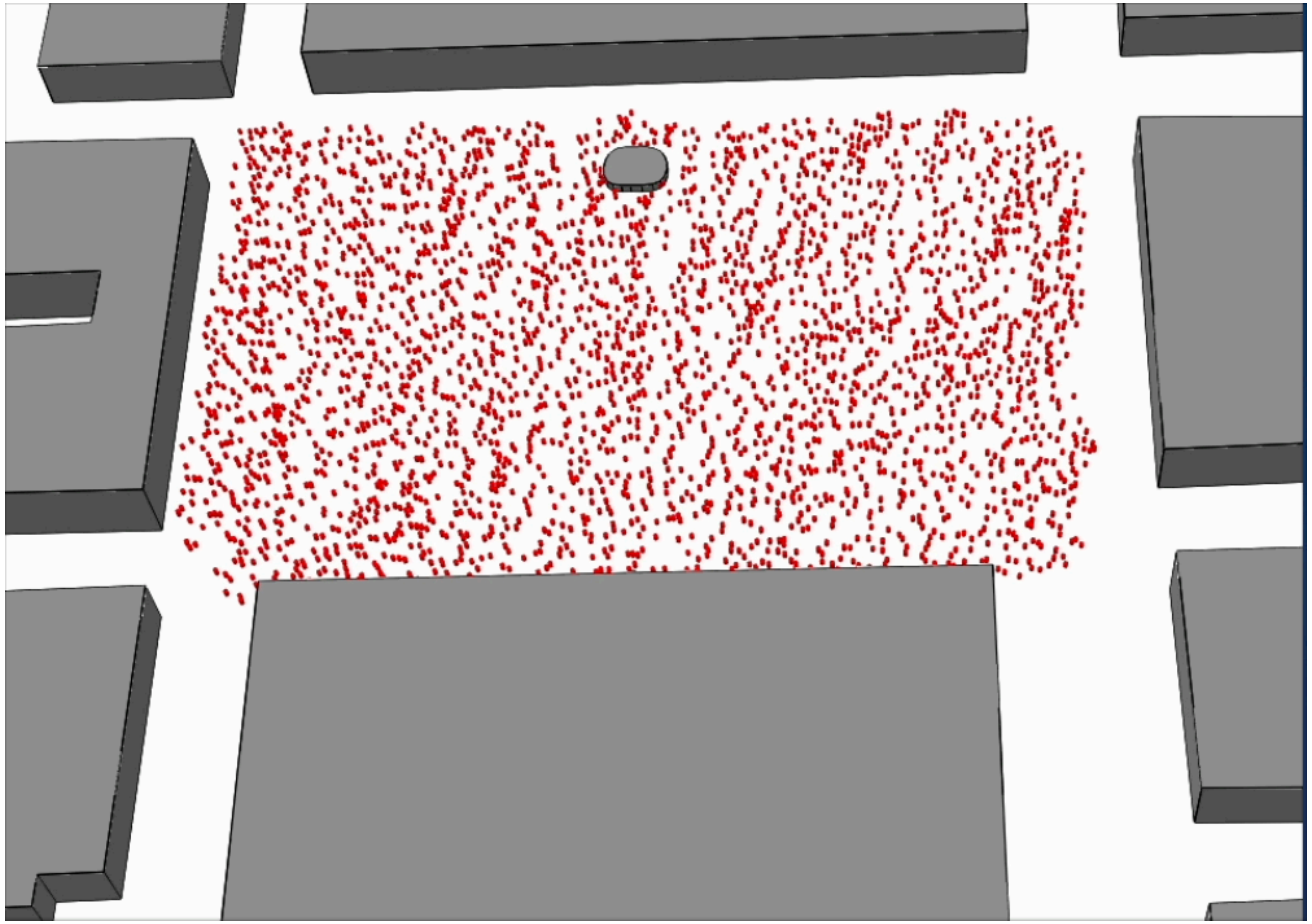
Evaluation



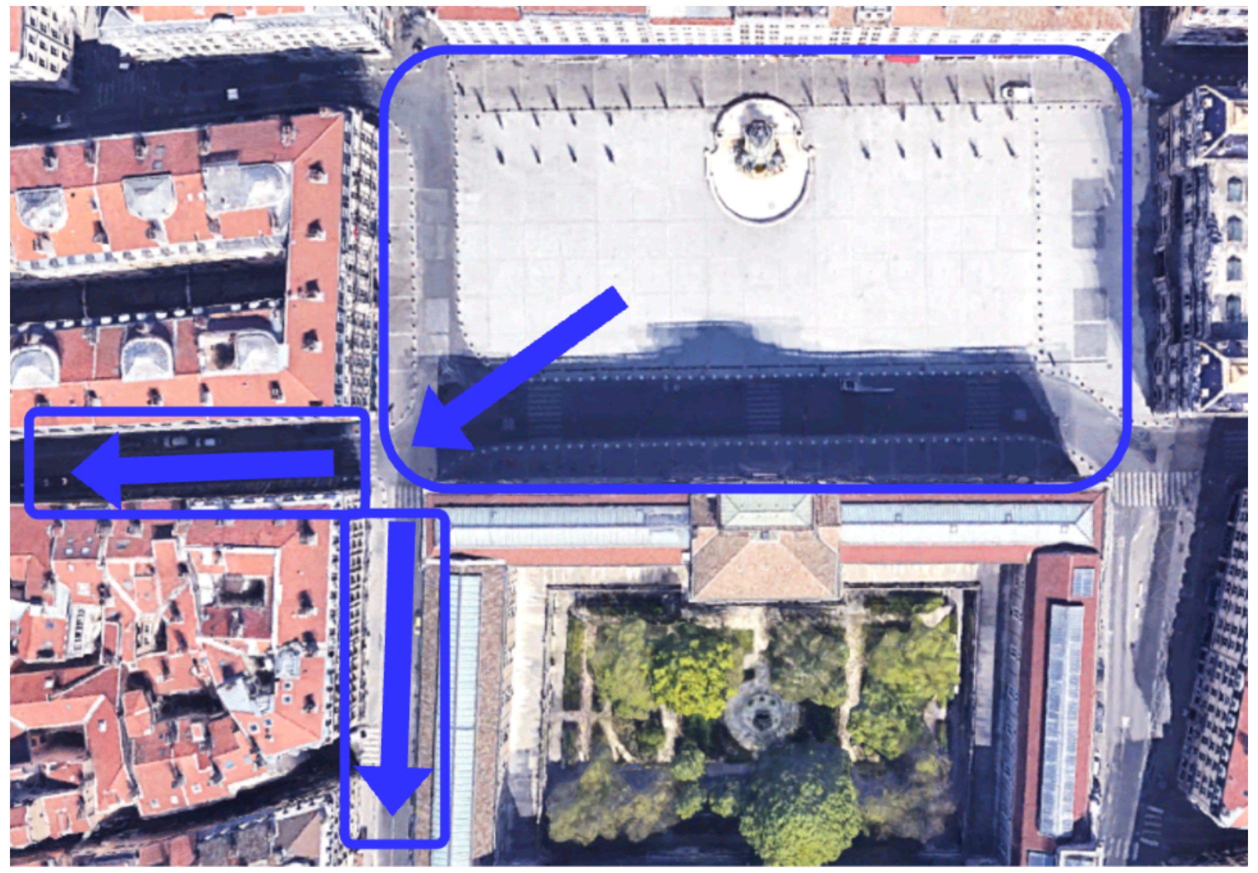
a) Constantine road



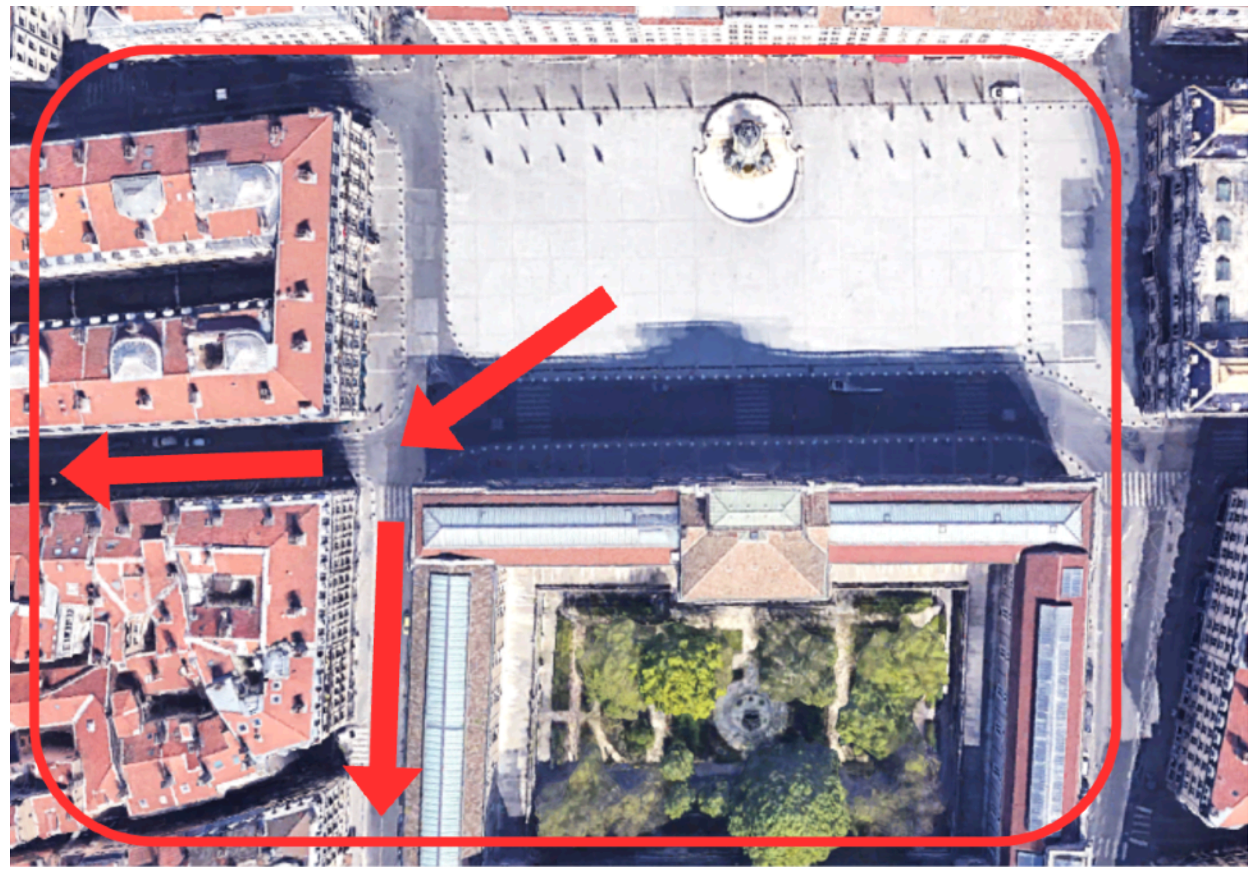
b) Chenavard road



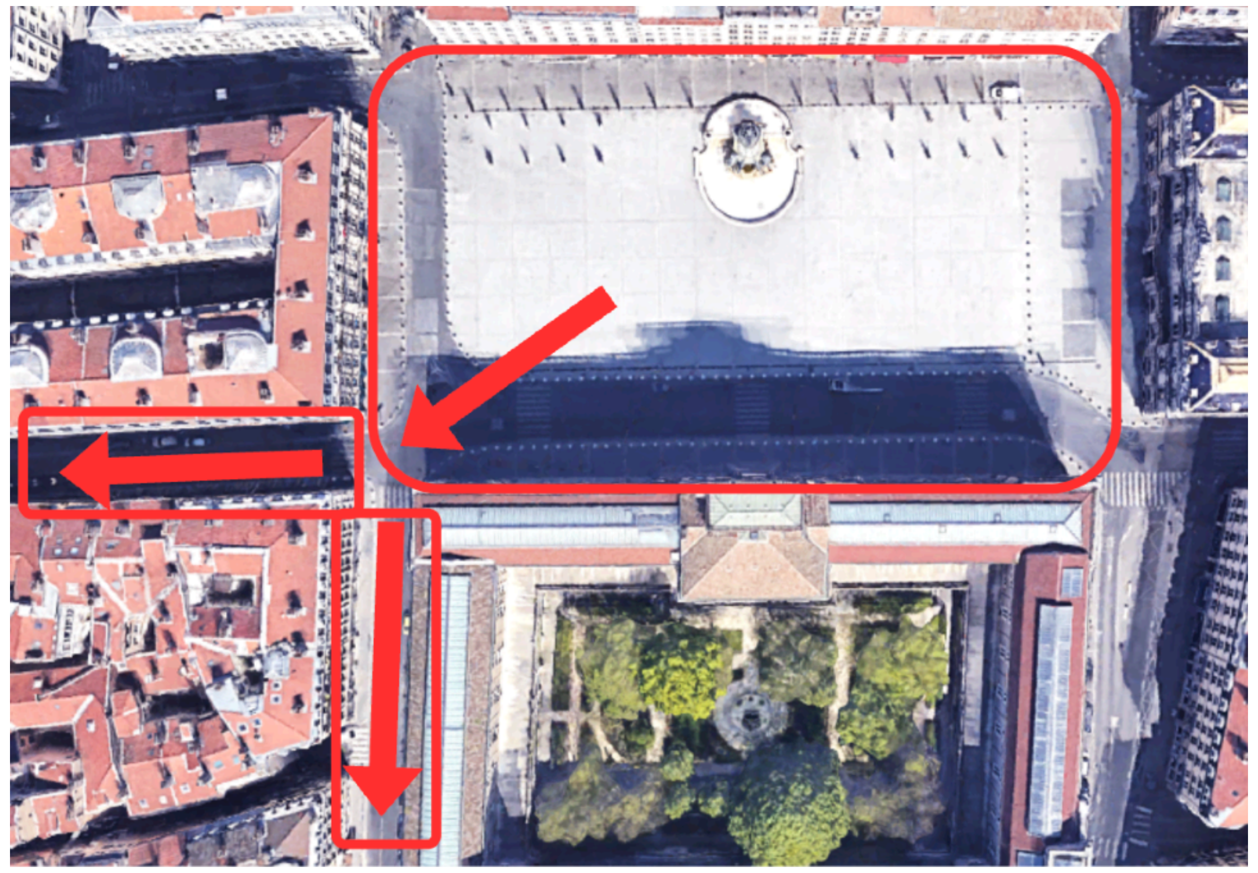
Hybrid vs other combinations



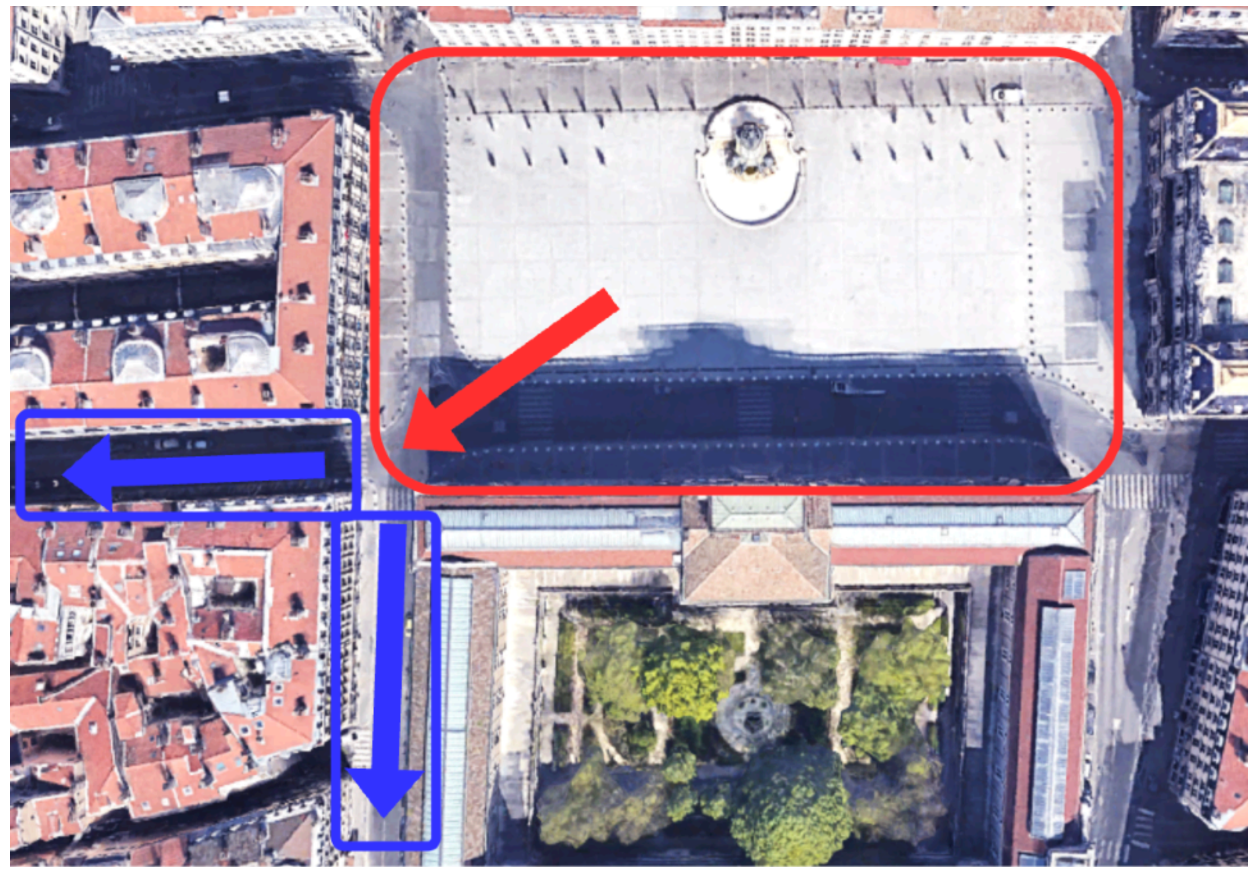
SFM-only



1-CC-2



3-CC-1



Hybrid model

Simulated by SFM

Simulated by CC

Comparison:

- Density map
- Computation time

Results (1)

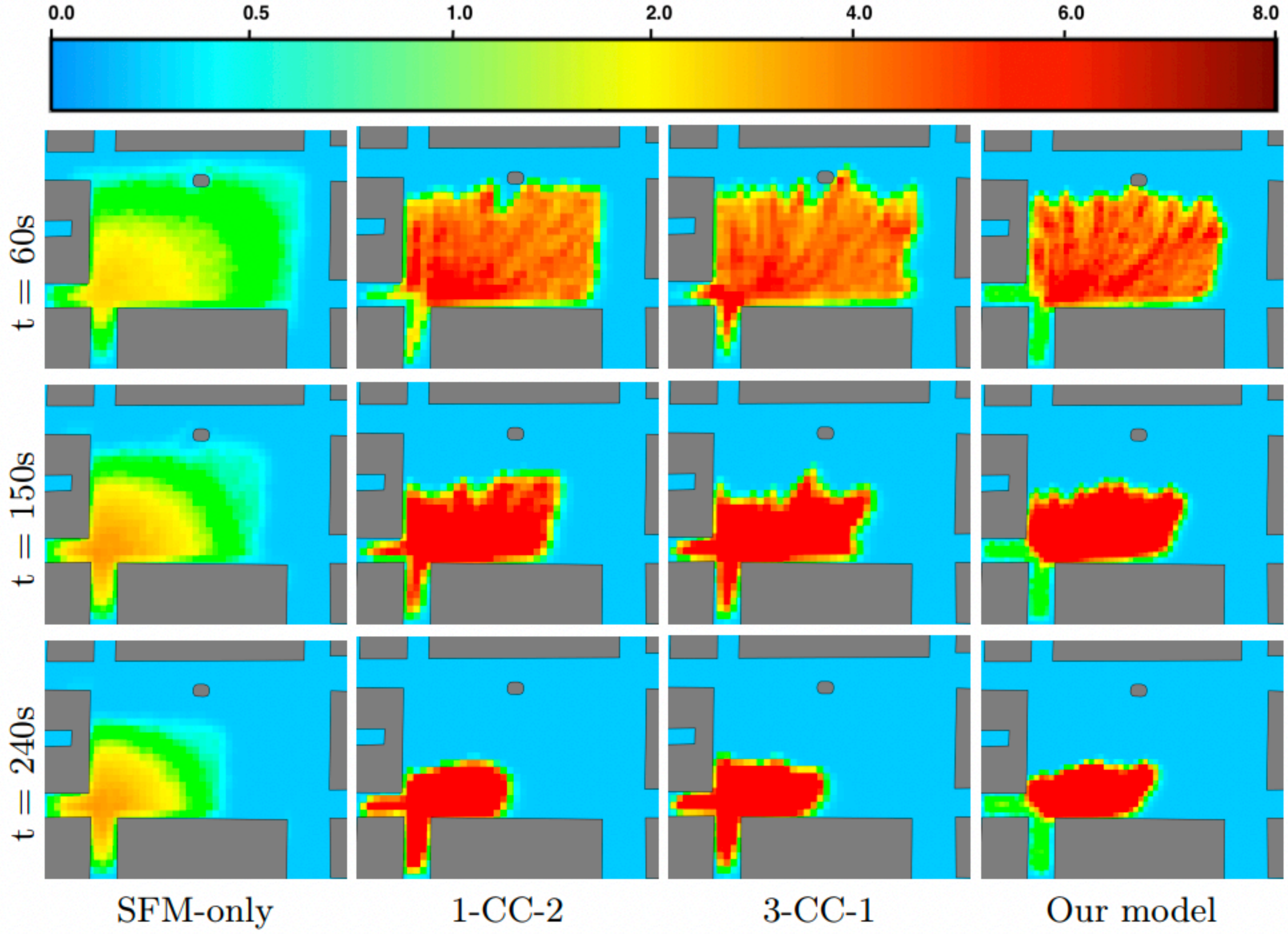
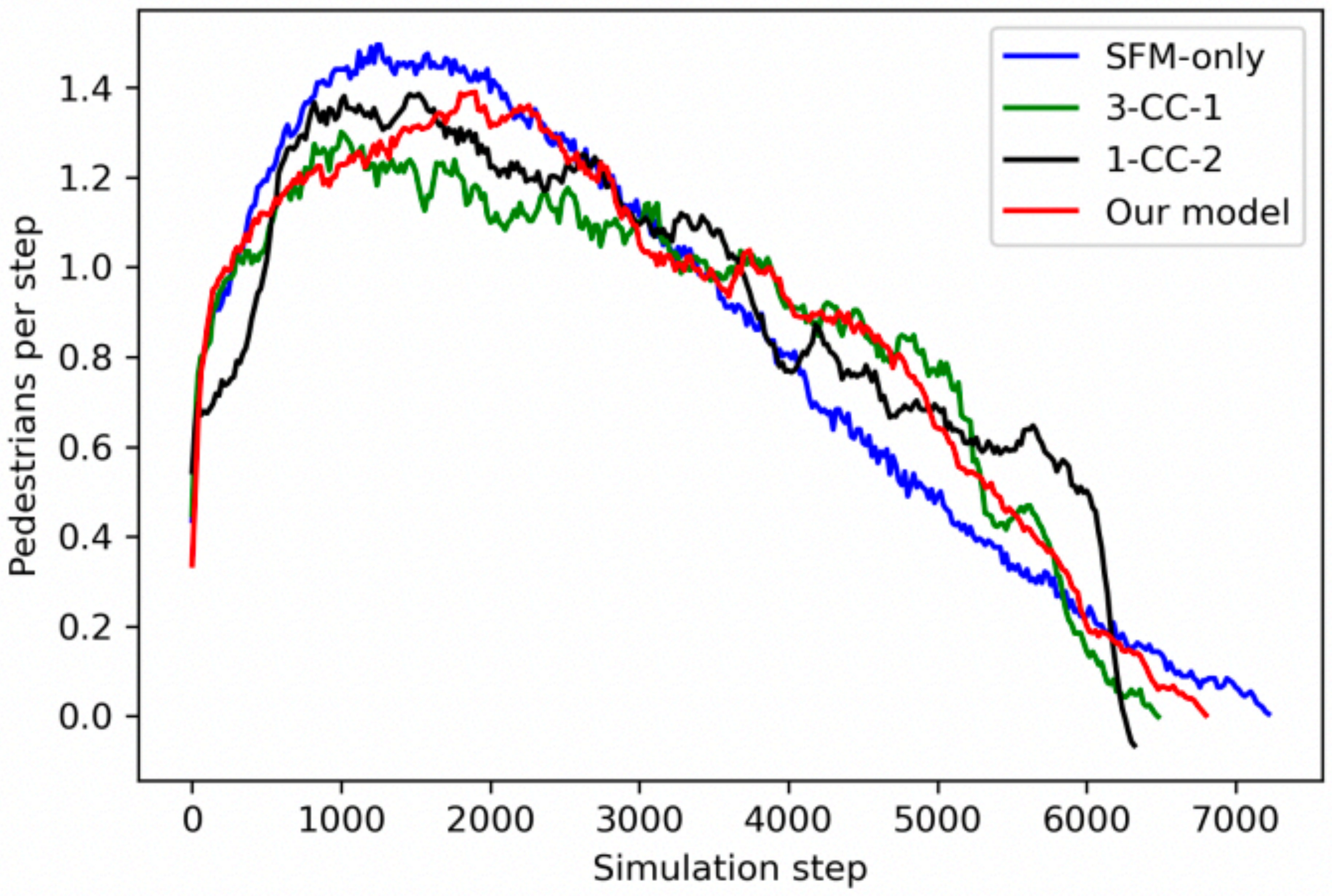
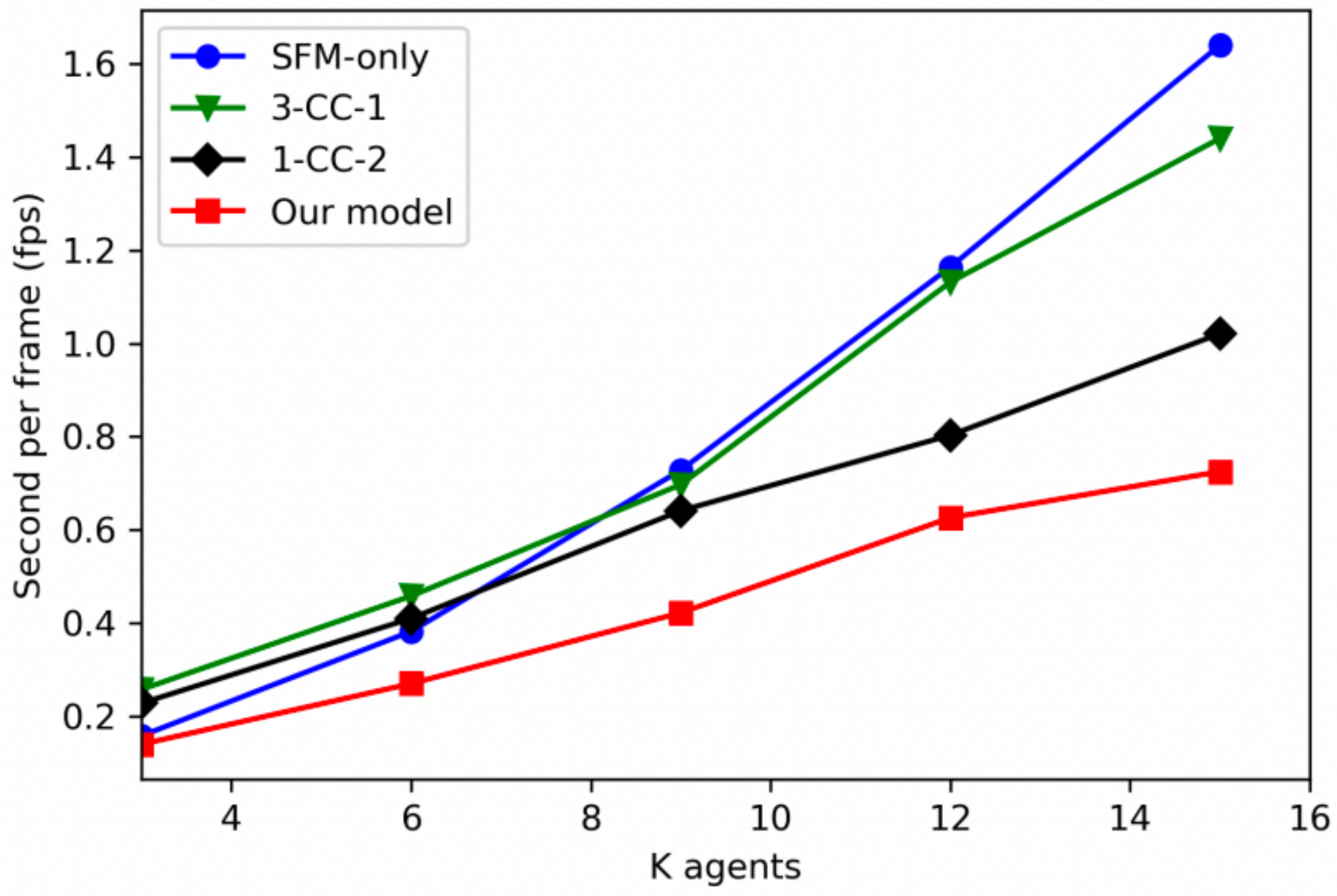


Fig. 6: Density maps among different models with 6000 simulated agents.

Results (2)



(a) The outflow over the simulation time.



(b) Model performance.

Fig. 7: Comparison results of different models.

Summary and discussion

- Summary:
  - HyPedSim: a hybrid framework to couple different simulation models.
  - A hybrid model (SFM + CC) to simulate crowd exit at the FoL.
  - Calibration and validation of the hybrid model.
  - Different combinations of models for different scenarios.
  - Key takeways: coupling proper models

    → equilibrium of speed + accuracy.

HyPedSim

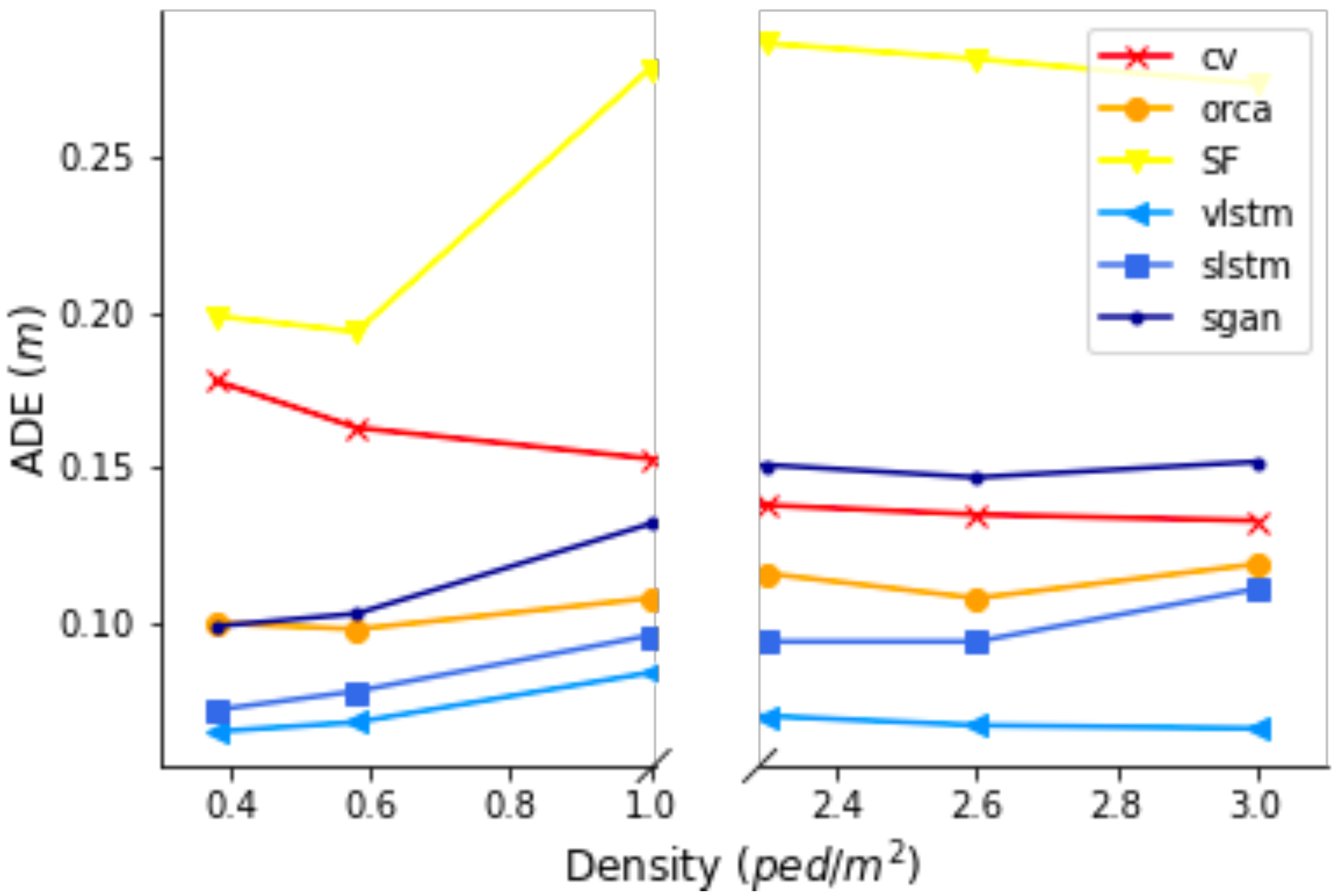
- Limitations:
  - Fixed zones.
  - Initial density estimation.

- Future works:
  - Dynamic zones → density-based clustering.
  - Each zone → dynamic switching of models depending on density.

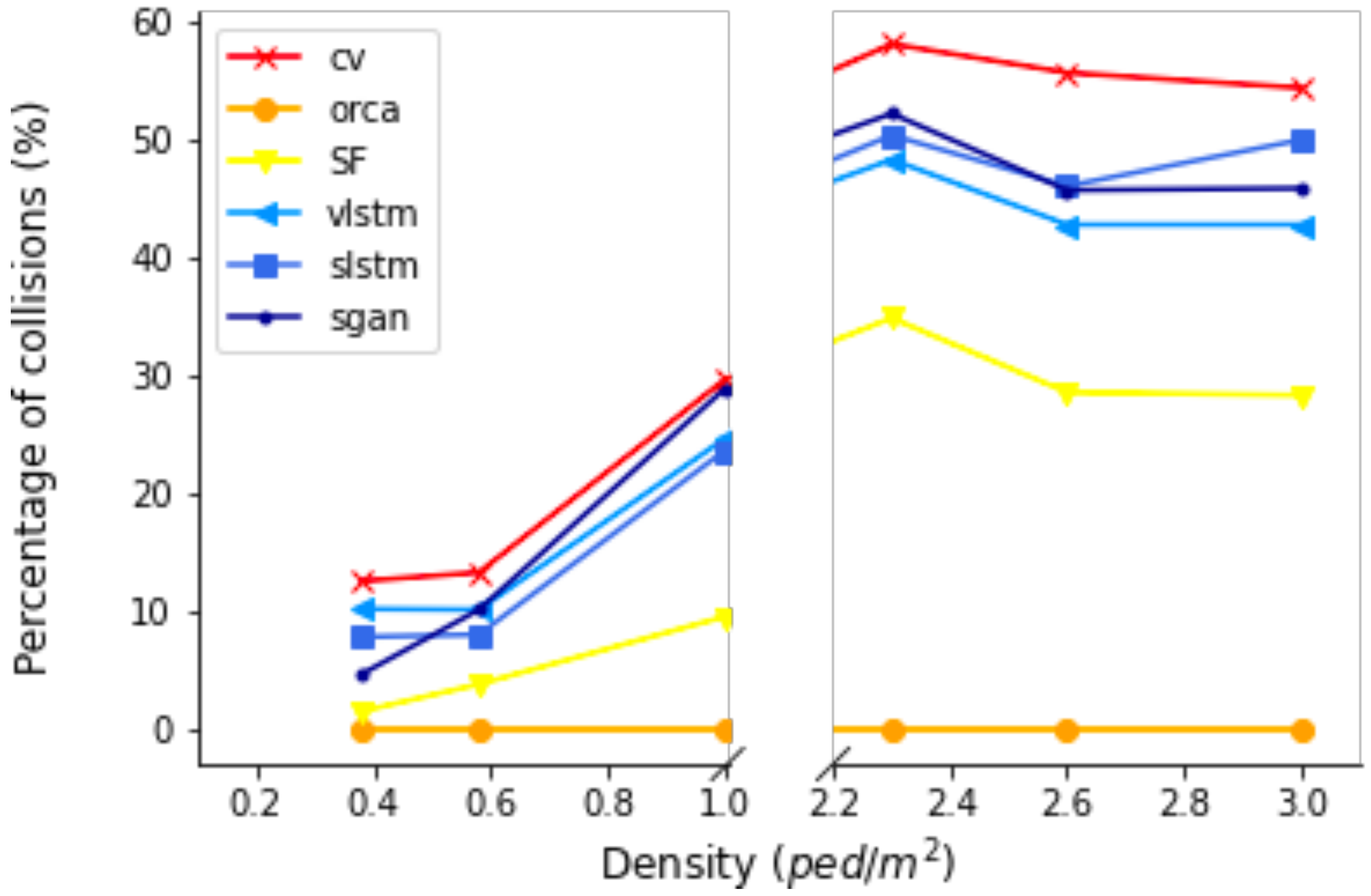
Using Deep-learning to predict human trajectory

Limitations of DL for predicting trajectories in high dense situations

- We have shown that, whereas ML/DL are much better on **distance errors indicators**, results are **not so good on collision metrics**
  (Tests on an existing dataset: from Julich Center, di-directional flow)



Results of distance error-metric (ADE).



Results of collision metric

Korbmacher, R., Dang, H.-T., Tordeux, A., Gaudou, B. & Verstaevel, N. Differences in pedestrian trajectory predictions for high- and low-density situations. Traffic and Granular Flow 2022 (TGF22), 15 – 17 October 2022, IIT Delhi, India. Abstract; Slides.

Machine learning for predicting trajectories

- 2 directions of improvement:

  - Improvment of the **loss function** of the model by introducing **Time-To-Collision**
  - **Study in terms of feature selection**: Relative distance, Relative velocity, Mean space, Frontal effect, Distance to wall, Preferred speed, Time-to-collision…..

Improvement of the model by introducing Time-To-Collision in the loss function

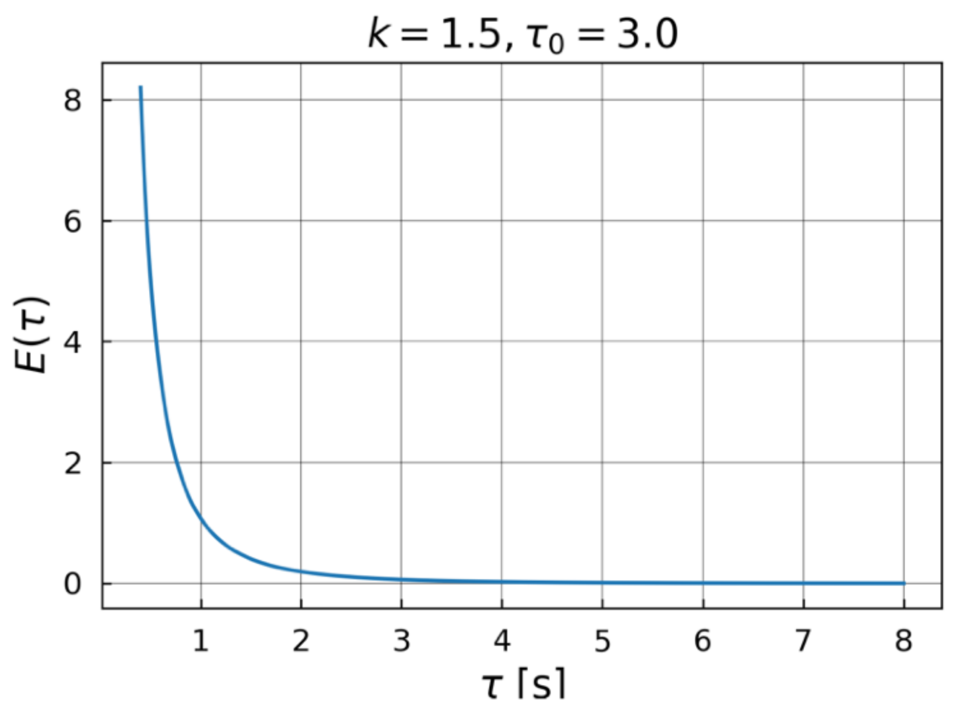
- Idea :

$$\mathrm{L}_i = \sum_{t=1}^{T_{pred}} \|x_i(t) - \hat{x}_i(t)\| + \lambda * \text{Collision term} \rightarrow \min$$

- **Time-to-collision (TTC)**: estimated time for 2 pedestrians to collide with each other if they keep moving at their current velocities [Karamouzas et al., 2014].

- Collision term: based on TTC energy [Karamouzas et al., 2014]:

$$E_{ij} = E(\tau_{ij}) = \frac{k}{\tau_{ij}^2} e^{-\tau_{ij}/\tau_0}$$



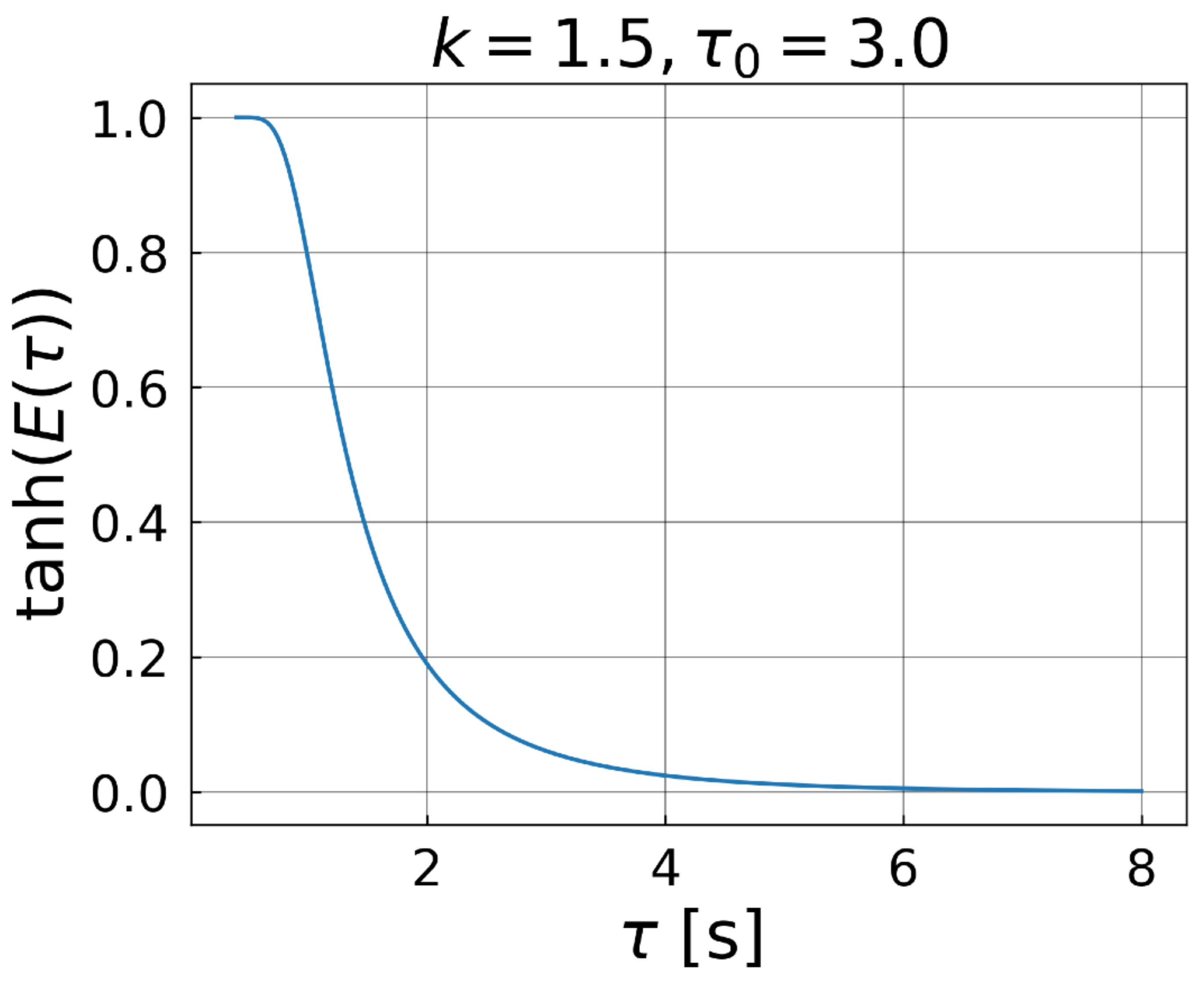
Karamouzas, I., Skinner, B., & Guy, S. J. (2014). Universal power law governing pedestrian interactions. *Physical review letters*, *113*(23), 238701.

Improvement of the model by introducing Time-To-Collision in the loss function

- Proposed loss:

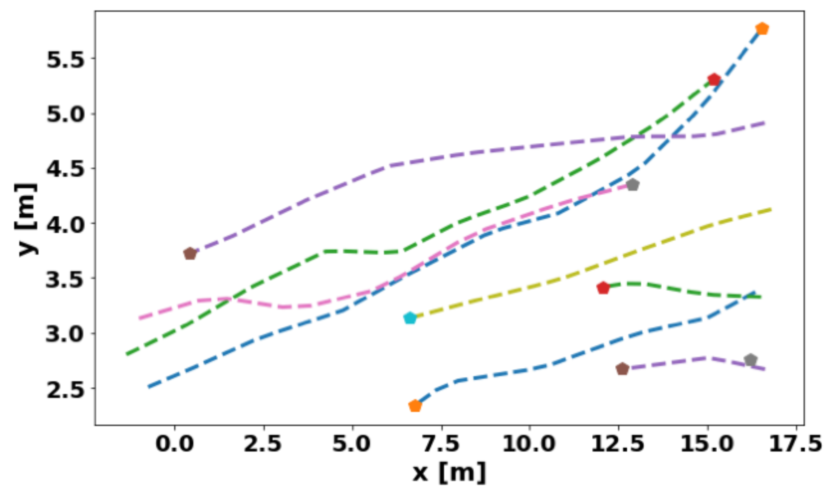
$$\mathrm{L}_i = \sum_{t=1}^{T_{pred}} \|x_i(t) - \hat{x}_i(t)\| + \lambda * \frac{\mathbf{1}}{\mathbf{T_{pred}}} \sum_{\mathbf{t=1}}^{\mathbf{T_{pred}}} \sum_{\mathbf{j \neq i}} \mathrm{tanh}(\mathbf{E_{ij}})$$

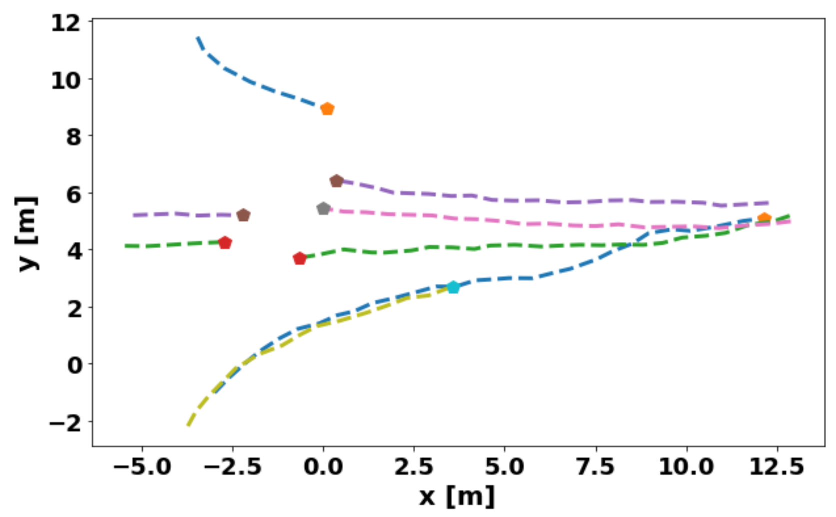
Collision weight

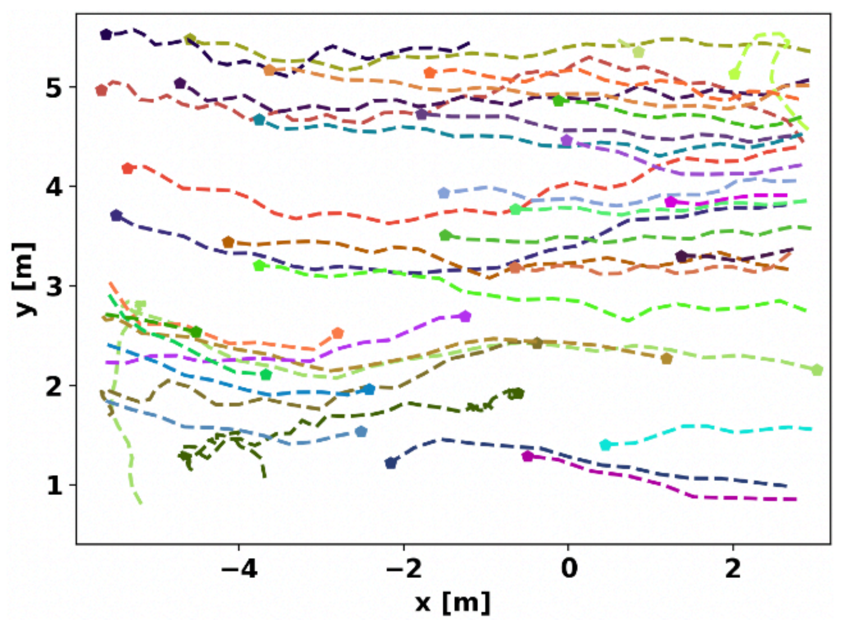


Experiment

TTC-SLSTM with **λ = 0.0, 0.1, 0.25, …, 2.0**







low-density

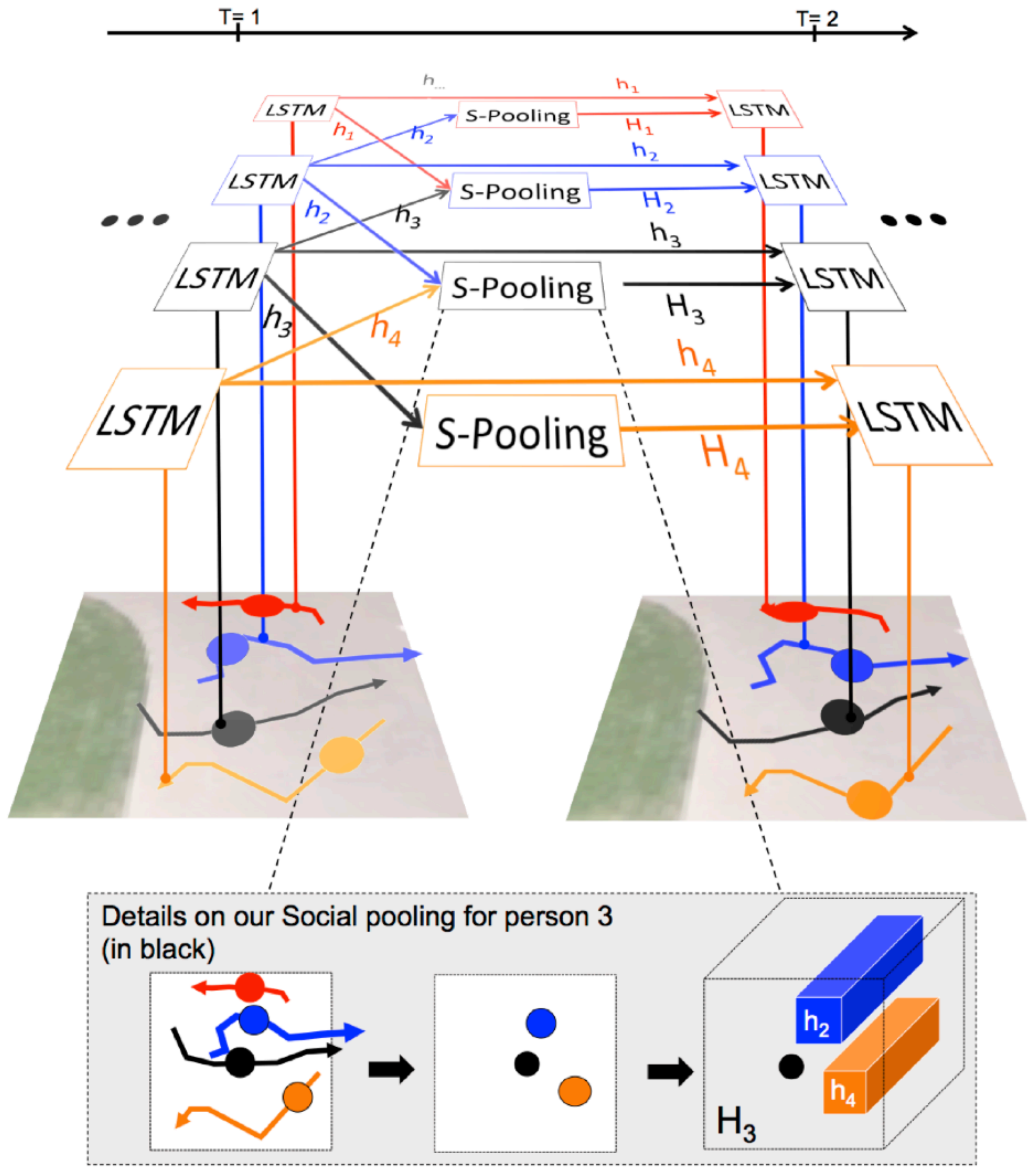
UCY

ETH

MADRAS

high-density

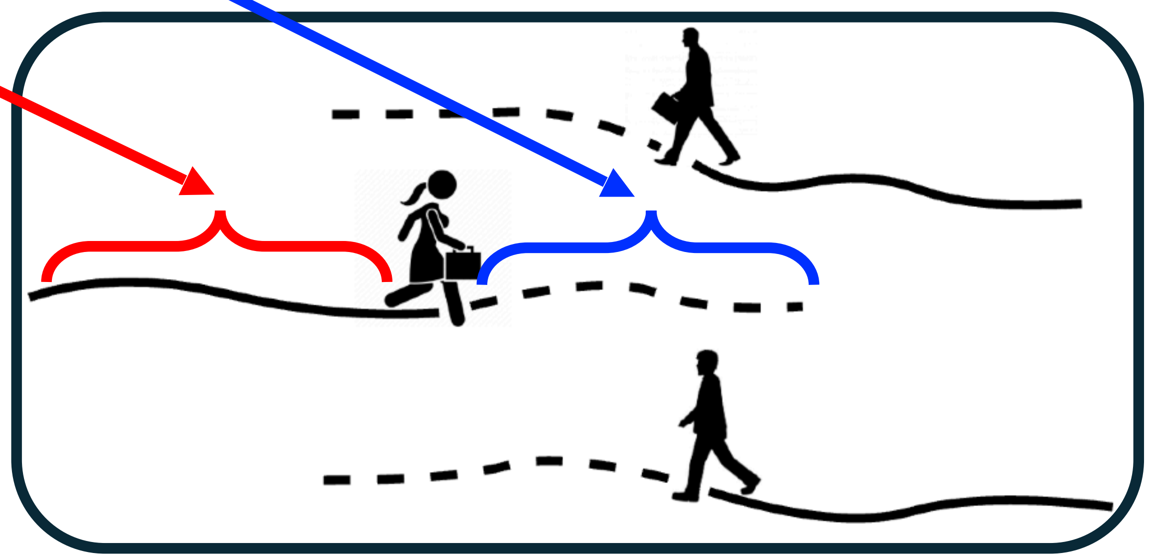
training



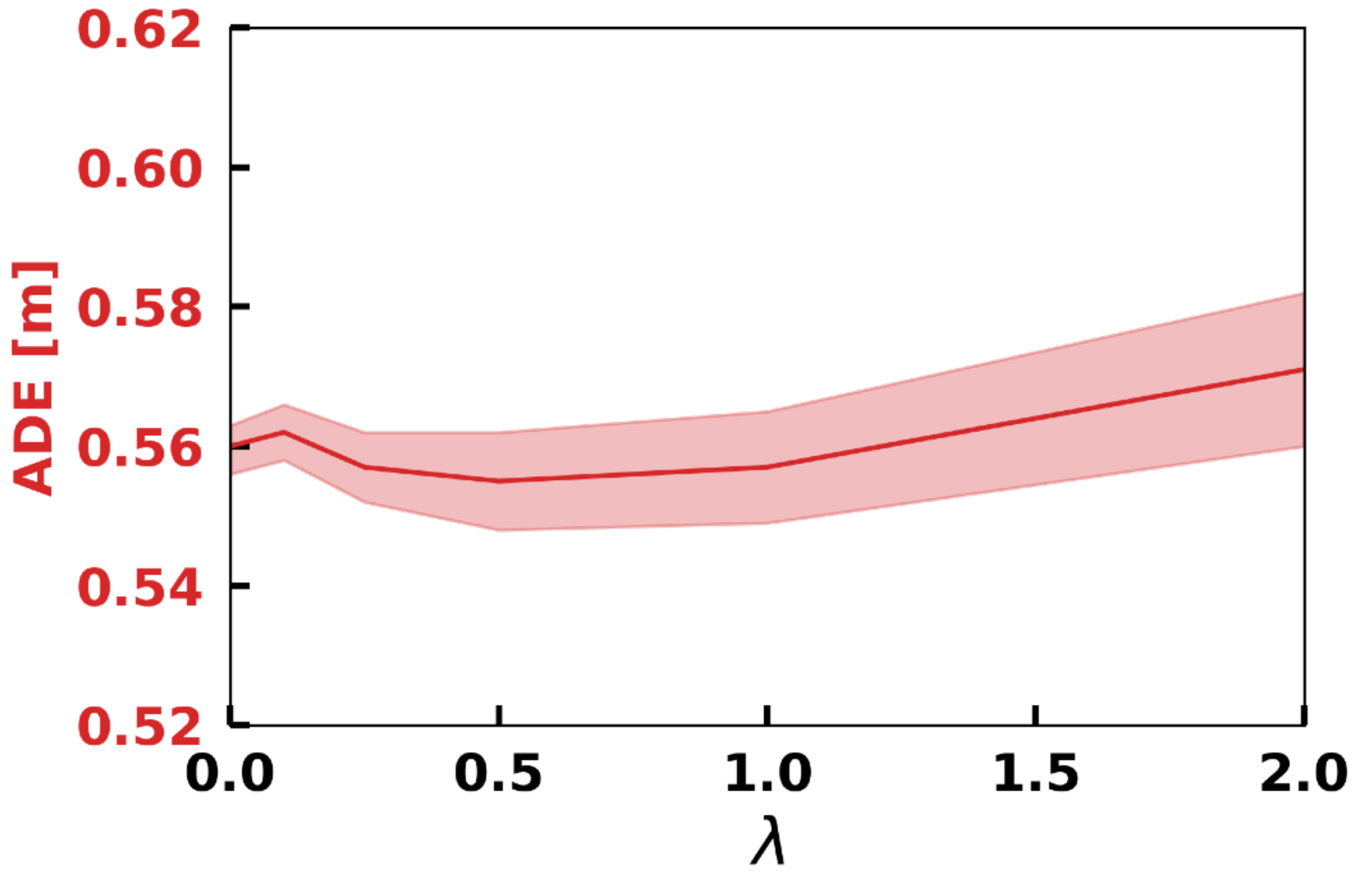
prediction

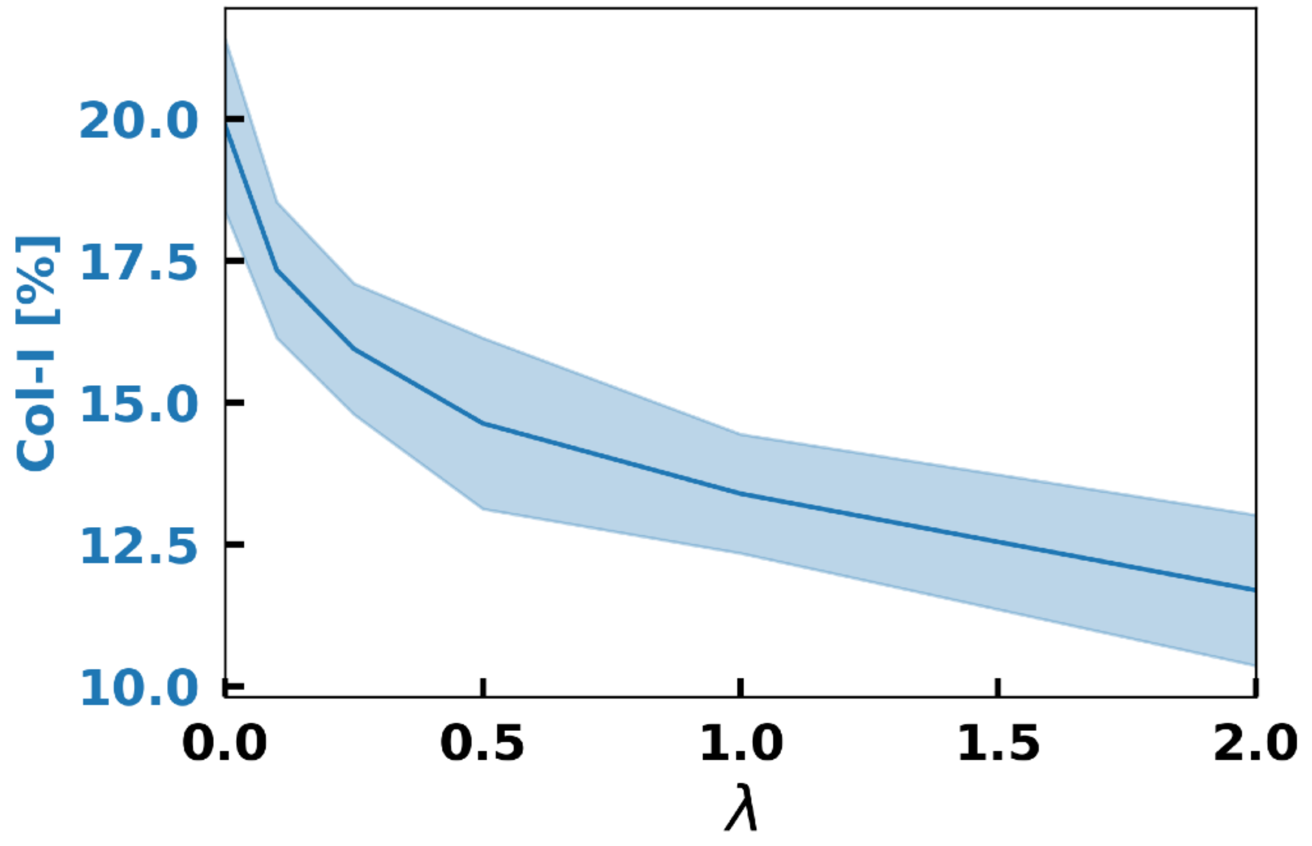
T_{pred} = 12 (≈4.8s)

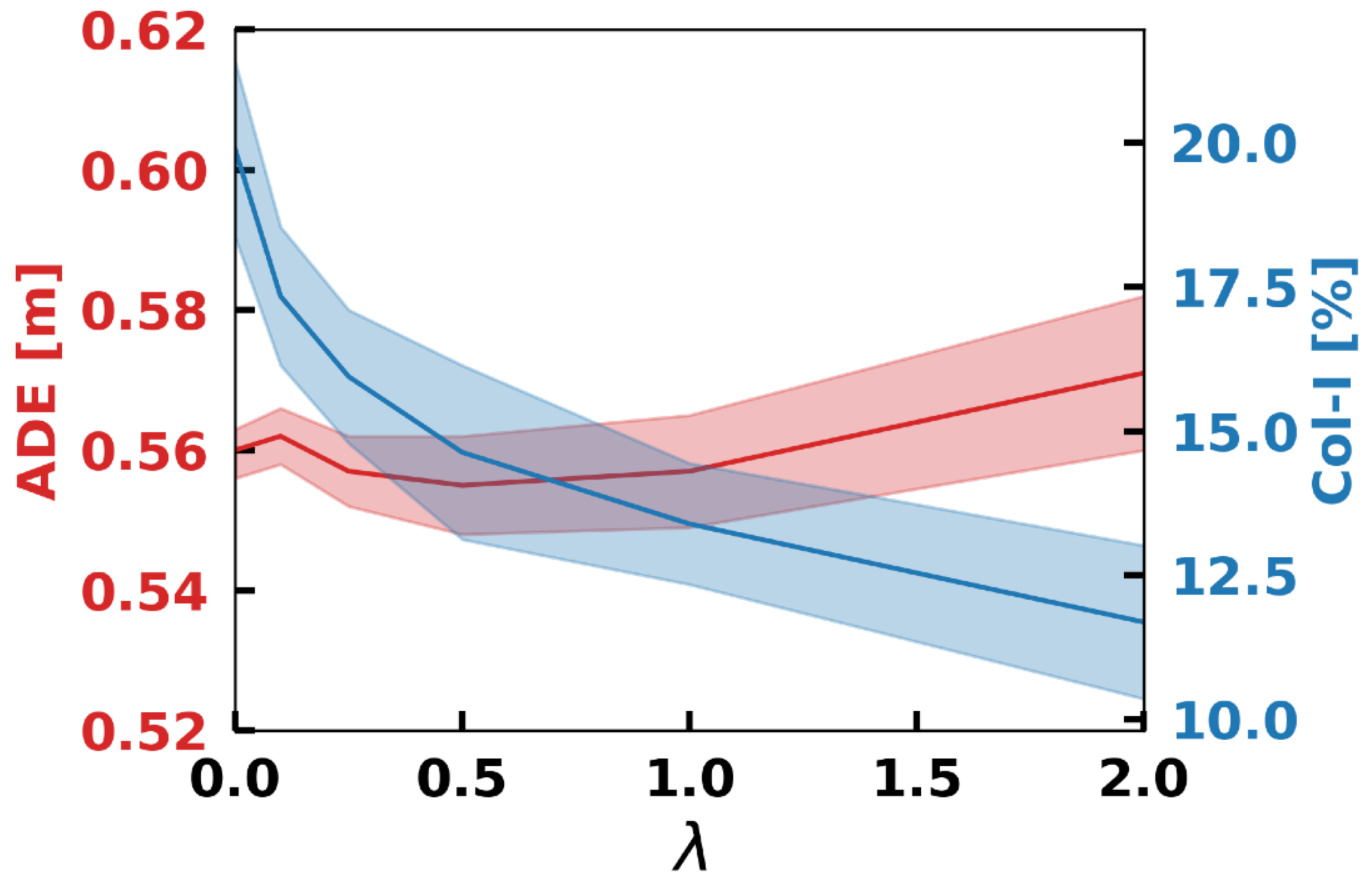
T_{obs} = 9 (≈3.6s)



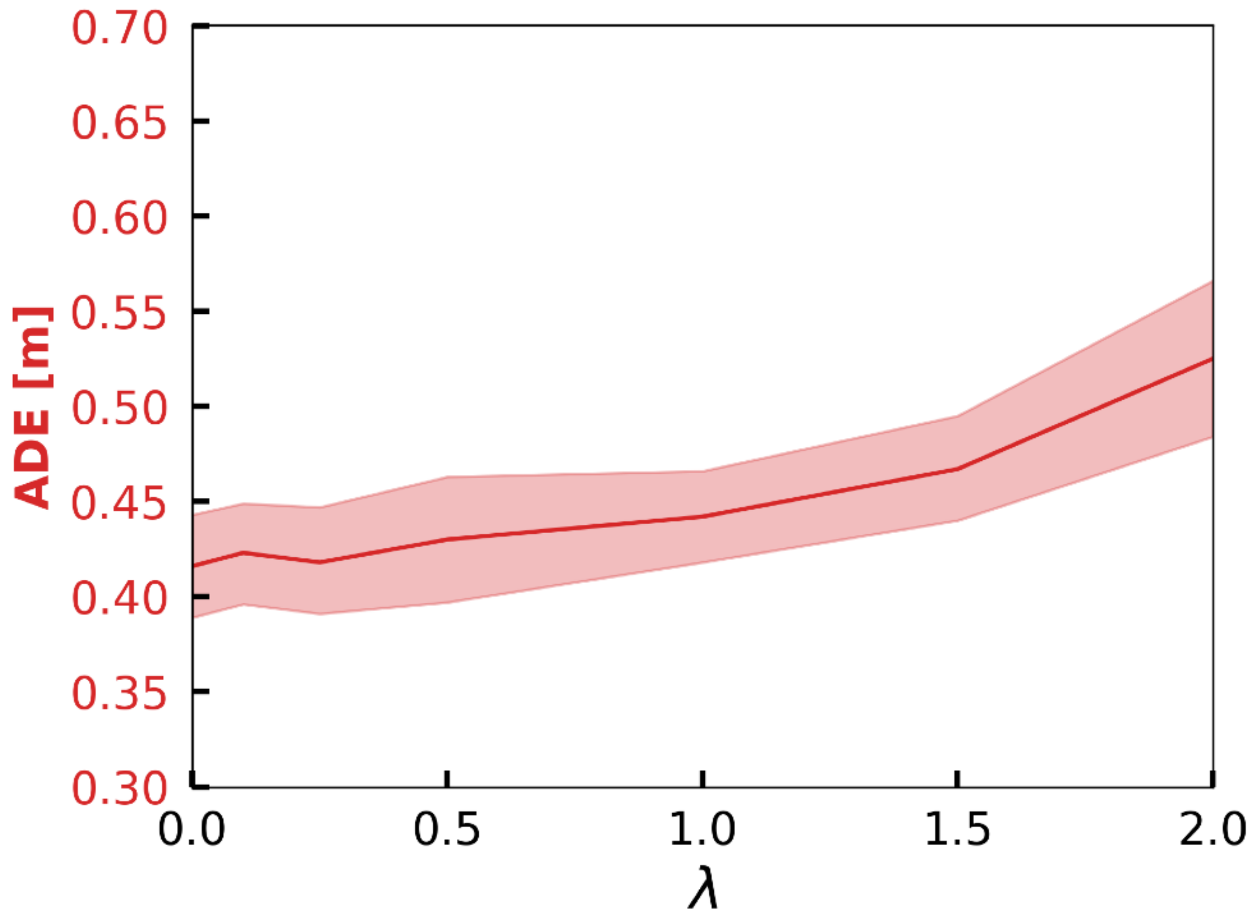
Results

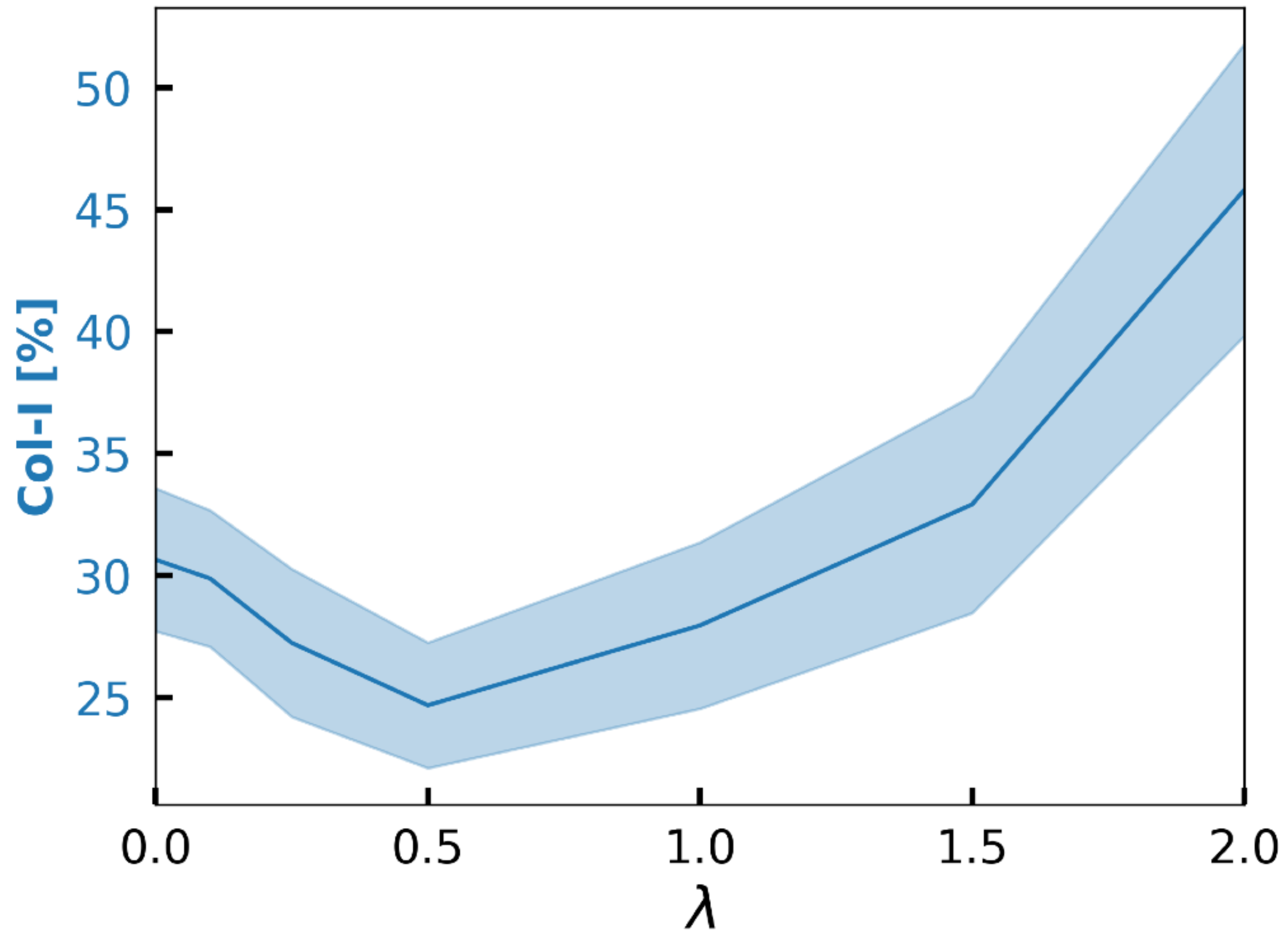


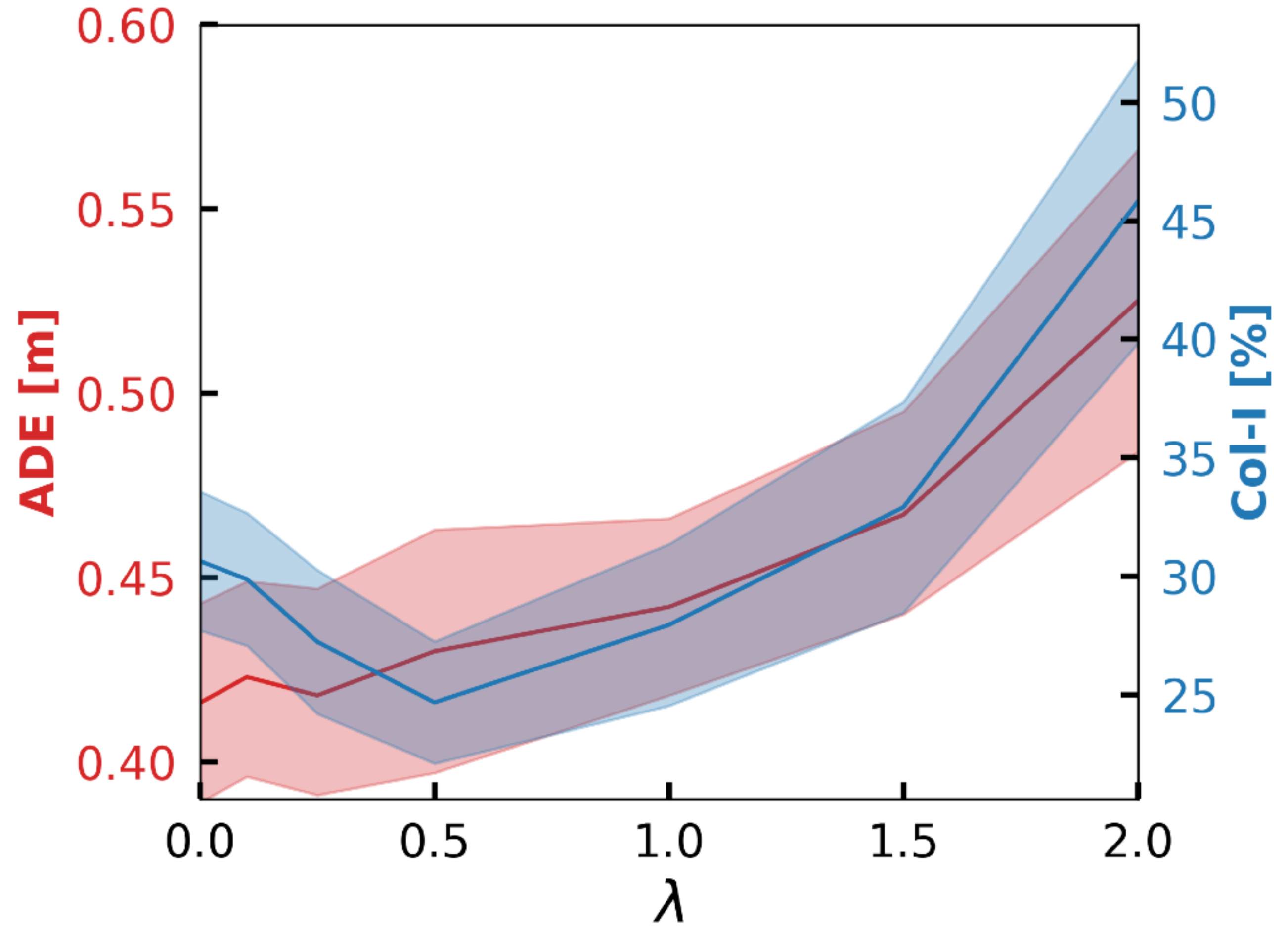




Low-density dataset





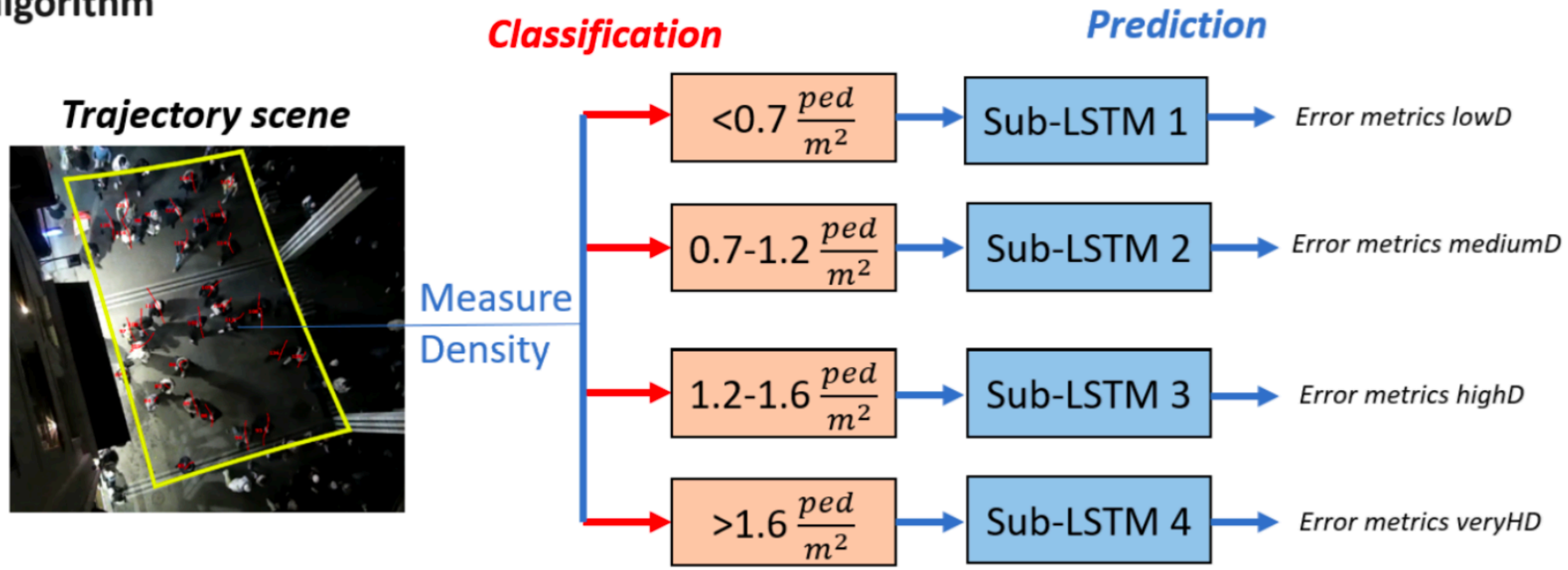


High-density dataset

- Note: λ=0 is the SLTSM

Toward better pedestrian trajectory predictions: the role of density and time-to-collision in hybrid deep-learning algorithms

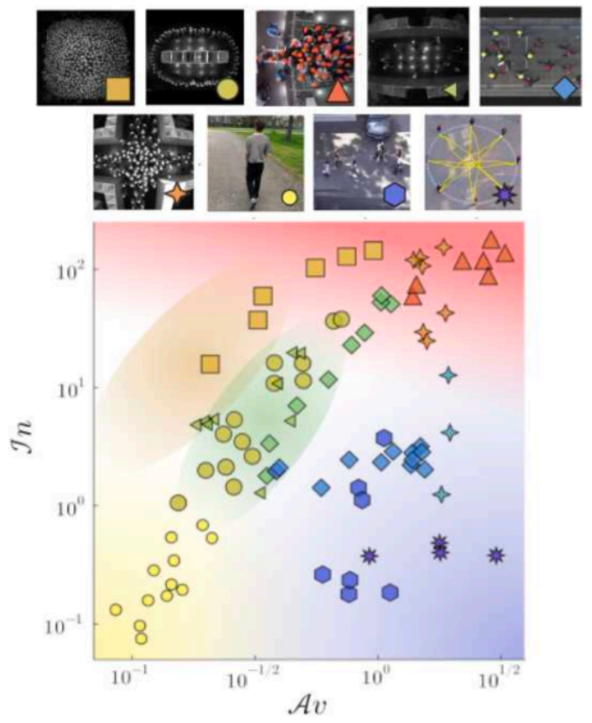
2-stage algorithm



Model	LowD		MediumD		HighD		VeryHD	
	ADE/FDE	COL	ADE/FDE	COL	ADE/FDE	COL	ADE/FDE	COL
CV	0.71/0.97	54.76	0.85/0.98	45.73	0.53/0.8	62.35	0.44/0.67	81.74
SFM [5]	0.78/1.33	**24.4**	0.55/0.89	31.16	0.5/0.82	36.43	0.36/0.63	54.78
VLSTM	0.5/0.99	31.55	0.33/0.63	37.69	0.29/0.52	36.43	**0.24/0.41**	63.8
SLSTM [1]	0.53/1.02	57.74	0.37/0.73	59.3	0.41/0.78	64.26	0.35/0.66	75.37
SGAN [4]	0.53/0.99	31.36	0.39/0.72	32.16	0.36/0.61	**32.33**	0.25/0.41	55.94
Our 2stg. SLSTM	**0.48/0.93**	30.95	**0.3/0.63**	36.18	**0.26/0.4**	42.02	**0.24/0.41**	**52.23**
Our 2stg. TTC-SLSTM	**0.39/0.73**	29.17	**0.3/0.62**	**22.61**	**0.23/0.36**	36.29	**0.24/0.41**	**52.23**

Raphael Korbmacher and Antoine Tordeux. Toward better pedestrian trajectory predictions: the role of density and time-to-collision in hybrid deep-learning algorithms. Sensors, 24(7):2356, 2024.

Perspectives



- Open of new research directions
  - Improvment DL model, by adding new features or other combinations linked to density
  - Explore regime characterization in crowds using dimensionless numbers to select more appropriate models.
- More knowledge and study from the open-access dataset.
- **Bridge the gap between ABM and DL**
  - Hypedsim provides a way to integrate any operational model in a pedestrian agents, so toward the integration of DL model
  - Study how to increase prediction time horizon of DL model and/or how to use in large-scale simulations.

Thank you for your attention !

Questions ?

https://zenodo.org/records/13830435

https://github.com/MADRAS-crowds/madras-data-app

MADRAS project: https://www.madras-crowds.eu/

Special thanks to: Dang H.T., N. Verstaevel (UTCapitole), J. Cordes, M. Chraibi (Julich), O. Dufour, A. Nicolas, D. Roney (ILM, Lyon), R. Korbmacher, A. Tordeux (Univ. Wuppertal)