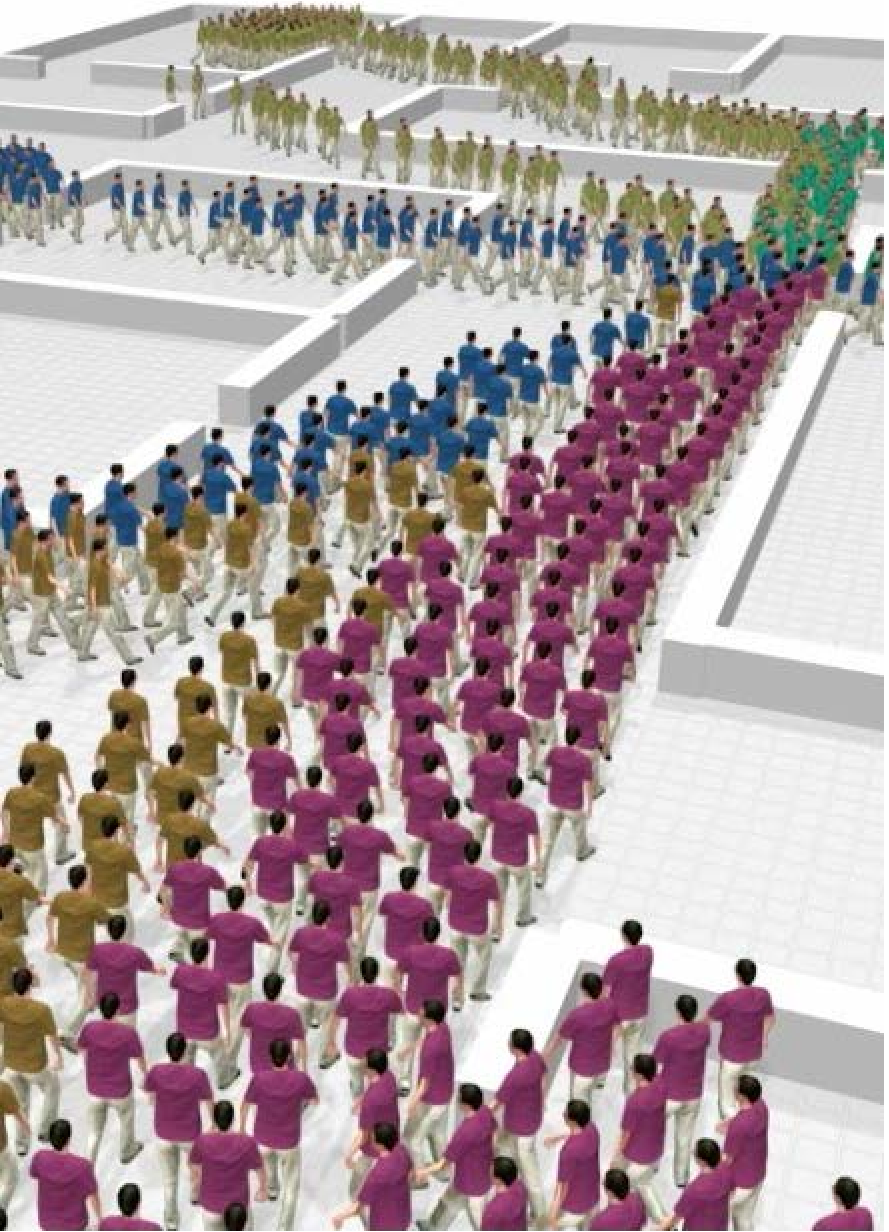

Data-driven macroscopic modelling of Crowd Dynamics via Convolutional Neural Networks

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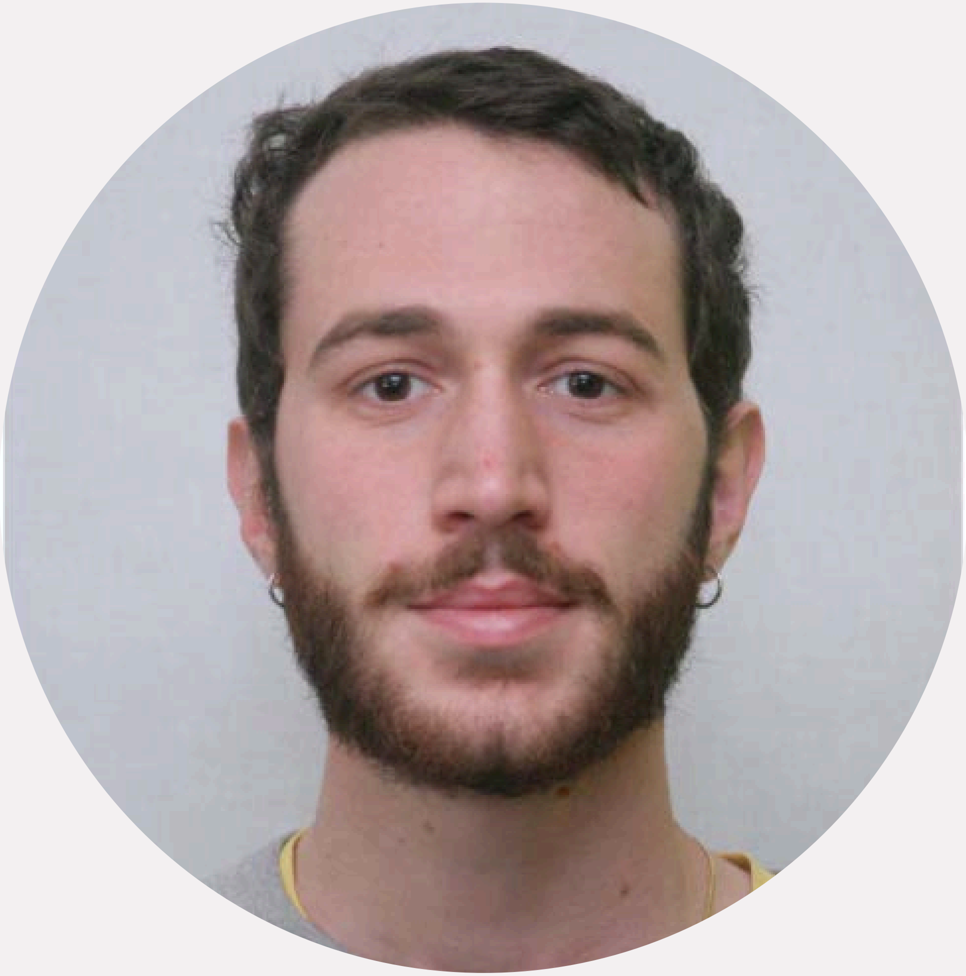

Self-Introduction

Gianmaria Viola

Bachelor's degree in Ingegneria dell'Automazione

Master's degree in Ingegneria dell'Automazione

Interested in Machine Learning, Crowd Dynamics, PDE Learning/Discovery

Crowd Dynamics

Understand and predict emergent and potentially dangerous behaviors

Mitigate Risks:

- Bottleneck
- Jamming
- Disorder

Our objective

To obtain macroscopic black box model from data to describe large crowds in big scenarios and for long time

Where data come from?

Macroscopic simulation

We aim to obtain a model that can be less computationally heavy. Aming to learn PDE in a Black-Box (BB) model to solve new IVPs.

Microscopic simulation

Bridge the gap between micro and macro scale for multidimensional problems. Use data with physics to obtain macro-description.

Empirical data

Learn from the true dynamics.

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Macroscopic-Scale

From hydro-dynamic mechanics

ρ: mean density in the infinitesimal volume

ξ: mean velocity

Second-Order

$$\begin{cases} \frac{\partial \rho}{\partial t} + \nabla_{\boldsymbol{x}} \cdot (\rho\, \boldsymbol{\xi}) = 0, \\ \frac{\partial \xi}{\partial t} + \boldsymbol{\xi} \cdot \nabla_{\boldsymbol{x}} \xi = \boldsymbol{A}[\rho, \xi, \boldsymbol{\beta}]. \end{cases}$$

Navier-Stokes Framework

First-Order

$$\frac{\partial \rho}{\partial t} + \nabla_{\boldsymbol{x}} \cdot (\rho\, \boldsymbol{\xi}(\rho)) = 0.$$

Non-linear Mass Conservation Law

Hughes Model

Continuity equation applied to pedestrian density coupled with the Eikonal equation

A continuum theory for the flow of pedestrians - Roger L. Hughes

$$\begin{cases} \frac{\partial \rho}{\partial t} - \frac{\partial}{\partial x}\left(\rho f(\rho) \frac{\partial \phi}{\partial x} \frac{1}{\|\nabla \phi\|}\right) - \left(\rho f(\rho) \frac{\partial \phi}{\partial y} \frac{1}{\|\nabla \phi\|}\right) = 0, \\ \|\nabla \phi\| = \frac{1}{f(\rho) g(\rho)}, \end{cases}$$

$$\begin{cases} \rho(x,y,0) = \rho_0(x,y) & \text{in} & \Omega \times \{0\}, \\ \left(\rho f(\rho) \frac{\frac{\partial \phi}{\partial y}}{\|\nabla \phi\|}\right) \cdot \hat{n}(x,y) = 0 & \text{on} & \Gamma_w \times \{0,T\}, \\ \rho(L,y,t) = \rho(0,y,t) & \text{on} & \Gamma_{ex} \times \{0,T\}, \\ \rho(0,y,t) = \rho(L,y,t) & \text{on} & \Gamma_{en} \times \{0,T\}. \end{cases}$$

Hypothesis 1. The speed at which pedestrians walk is determined solely by the density of thesurrounding pedestrian flow and the behavioral characteristics of the pedestrians.

$$f(\rho) = v_f \left(1 - \frac{\rho}{\rho_m}\right)$$

Hypothesis 2. Pedestrians have a common sense of the task (called potential) they face to reach their common destination such that any two individuals at different locations having the samepotential would see no advantage to either of exchanging places.

$$\hat{\phi}_x = \frac{-\frac{\partial \phi}{\partial x}}{\sqrt{\left(\frac{\partial \phi}{\partial x}\right)^2 + \left(\frac{\partial \phi}{\partial y}\right)^2}}, \qquad \hat{\phi}_y = \frac{-\frac{\partial \phi}{\partial y}}{\sqrt{\left(\frac{\partial \phi}{\partial x}\right)^2 + \left(\frac{\partial \phi}{\partial y}\right)^2}},$$

Hypothesis 3. Pedestrians seek to minimize their (accurately) estimated travel time, but temper this behavior to avoid extremely high densities.

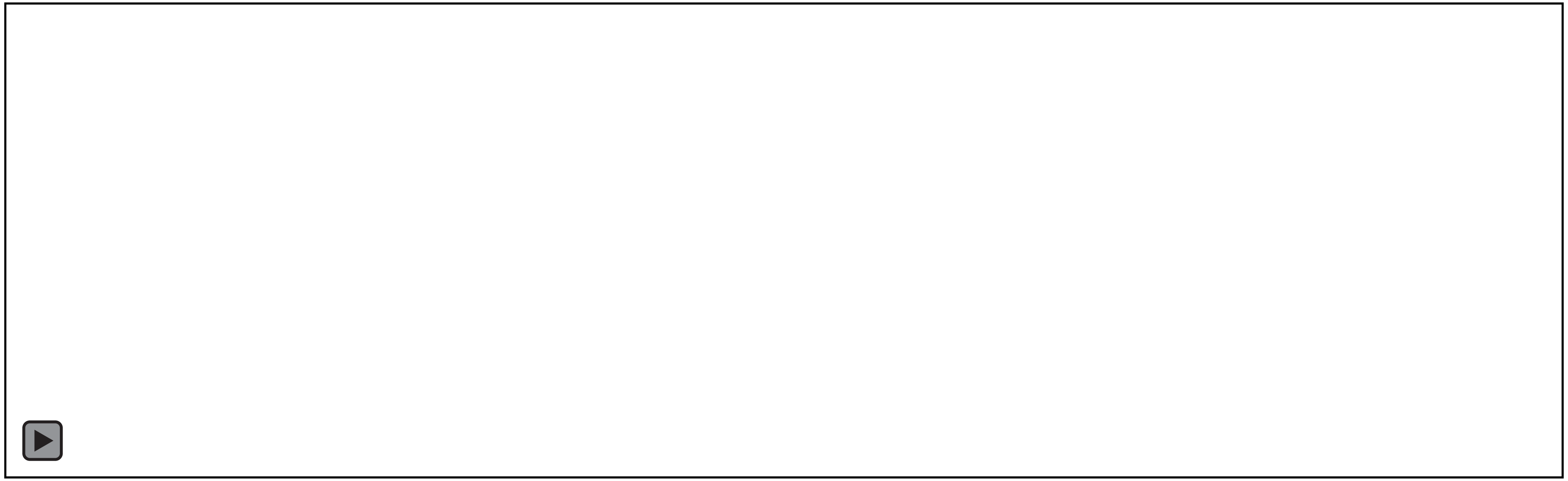
Numerical Simulation

Godunov scheme for continuity:

$Nx = 321,\ Ny = 80,\ Lx = 40,\ Ly = 10$

$Dx = 0.125,\ Dy = 0.125,\ Dt = 0.01$

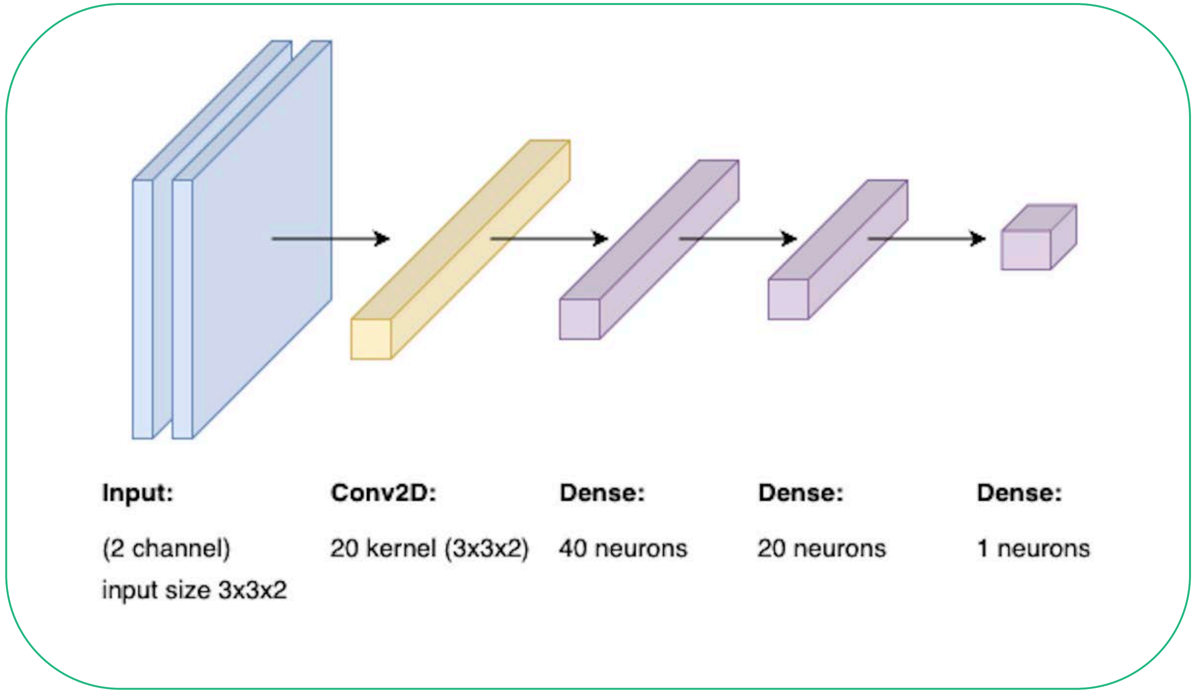
Fast Marching Algorithm for Eikonal equation



CNN-based PDE learning workflow

The model takes the variables ρ and φ in input, and gives the time-derivative ∂ρ/∂t in output, thus learning the evolution operator of the Hughes mode

Input: 3x3 neighborhood of a point in (x,y) for ρ and φ



Output: time-derivative ∂ρ/∂t of the population density in (x,y)

Data-driven black-box model based on the CNN

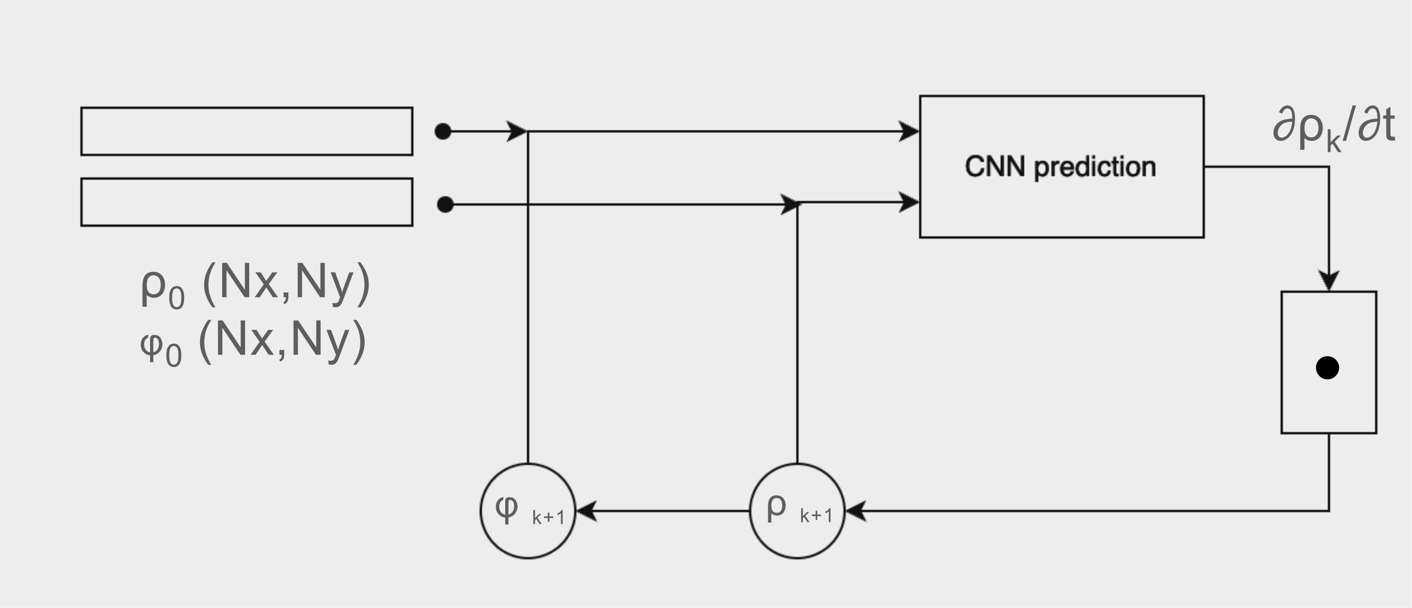
1. Select a new (unseen) initial condition for the density ρ, which is represented as an
$N_x \times N_y$ matrix;

2. solve the Eikonal equation to determine
the corresponding φ distribution;

3. Padding operation to implement BCs;

4. Reshape of data and evaluation of the evolution operator;

5. Integration of the evolution operator to advance in time.

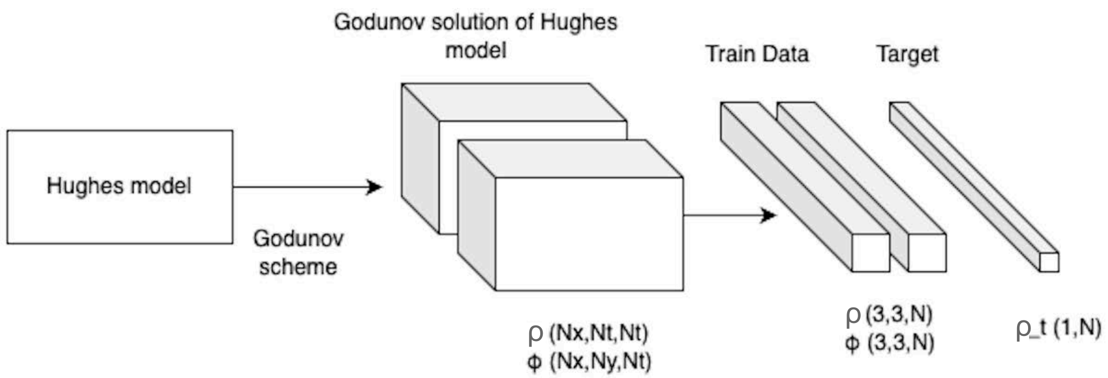


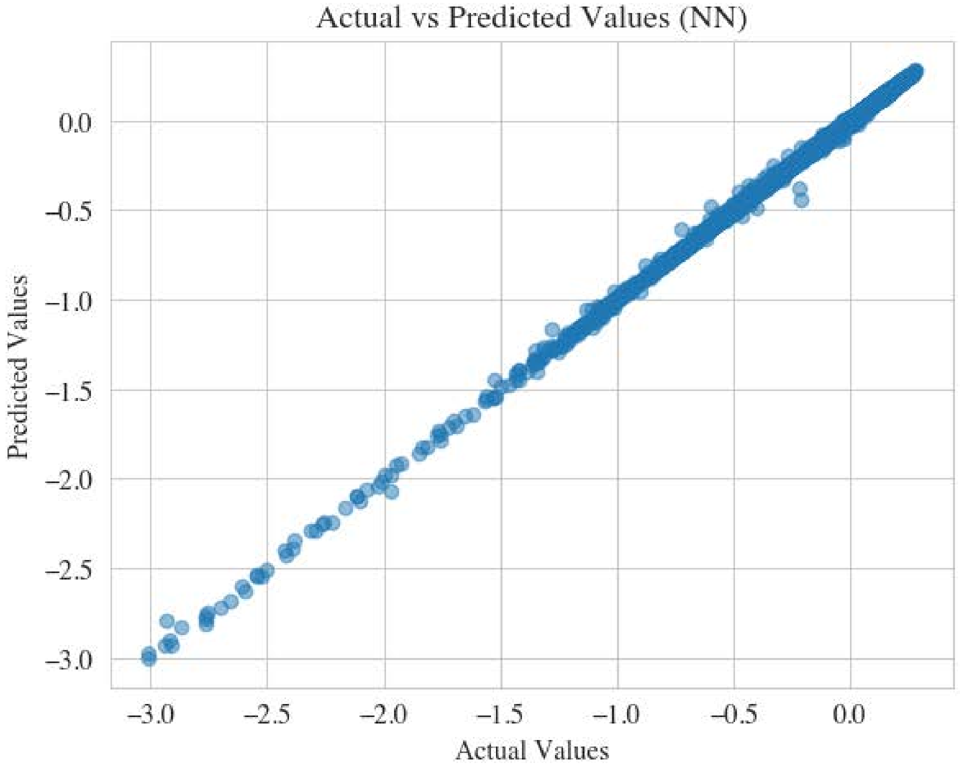
CNN training/testing

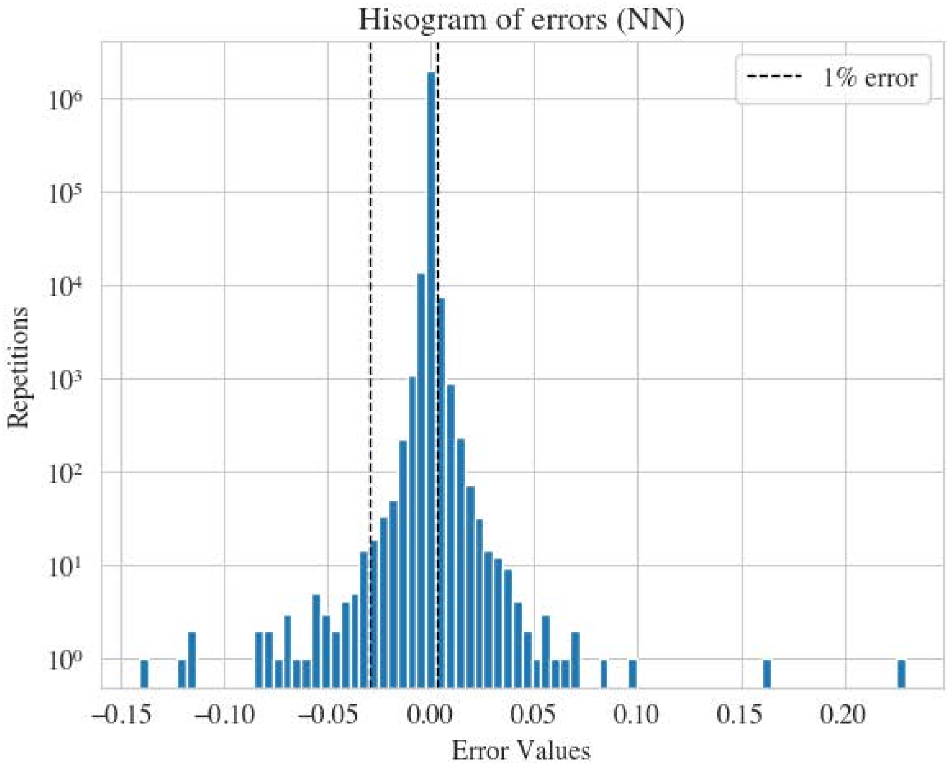
Training dataset: 1 simulation of 40s (321,81,4000)

Test dataset: 1 simulation of 25s from a new IC

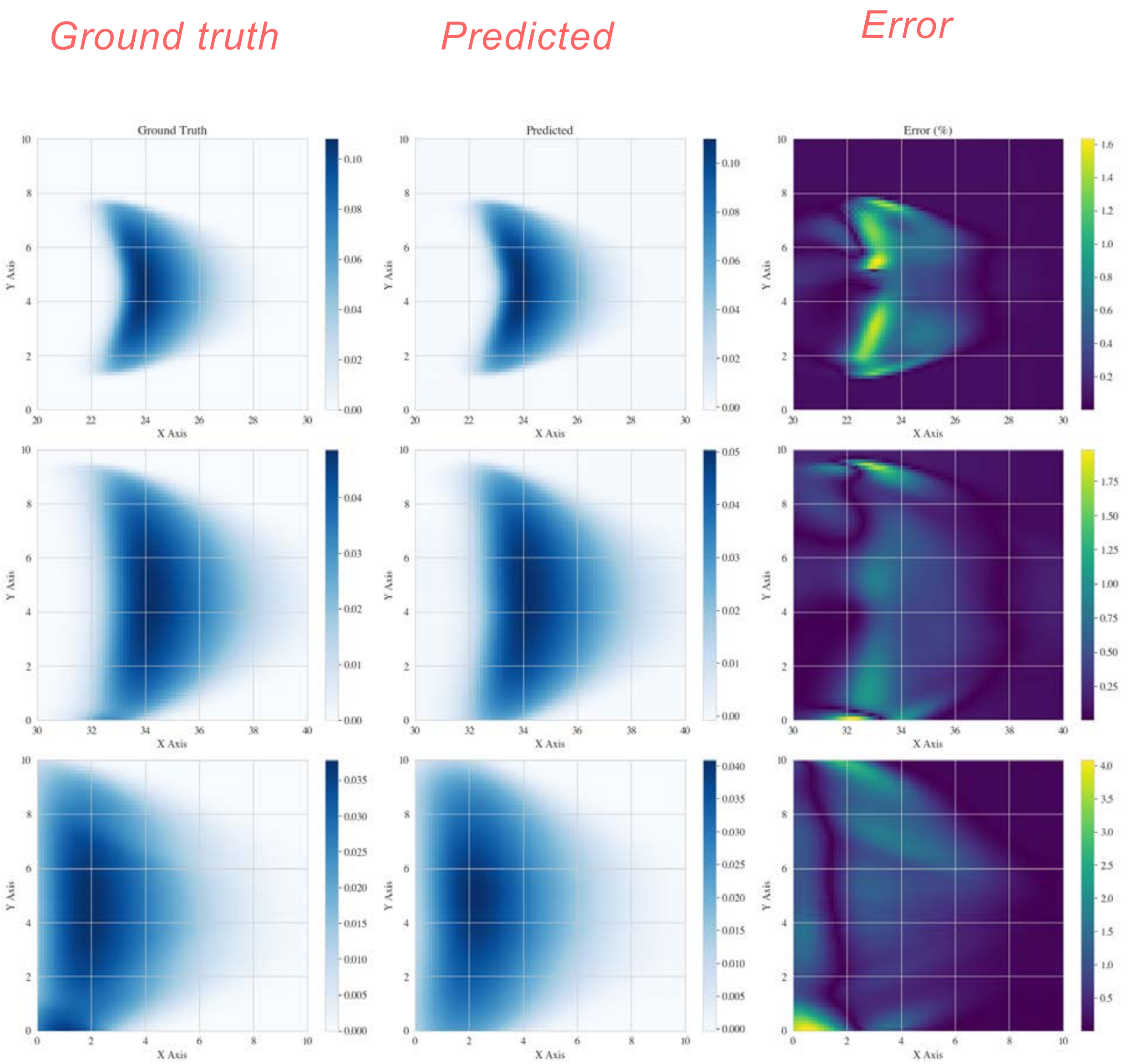
Training parameters: 3000 epochs, Adamax, lr = 1e-3



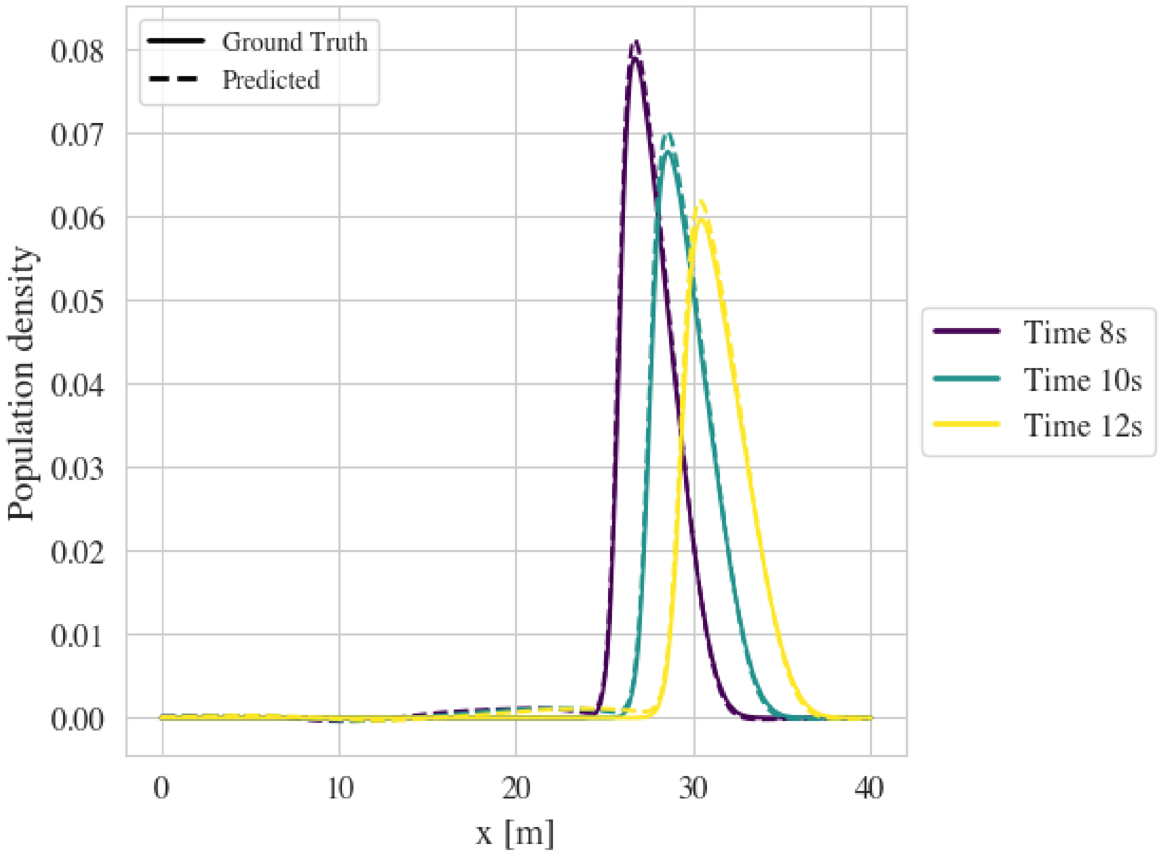


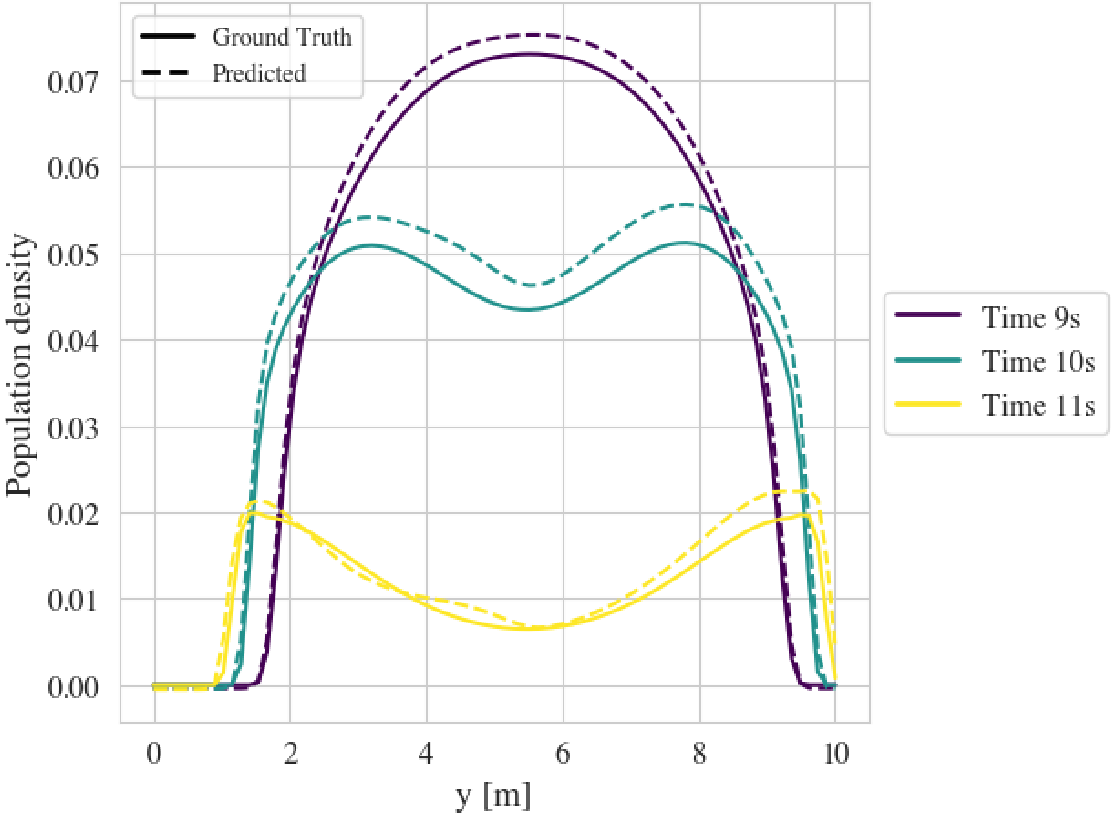


Results


Ground truth
Predicted
Error
Ground Truth
Predicted
Error (%)
X Axis
Y Axis

Comparison between ground truth and predicted simulation





Conclusions

Learn macroscopic dynamics from data

Develop a full data-driven CNN-based learning procedure to simulate realistically a crowd at macroscopic scale.

We want to **extend this approach to more realistic scenarios** (presence of obstacles) **and to different kind of data** (coming from microscopic simulations and/or experiments)

Faster surrogate model for PDE

Time to compute a solution of the Hughes model with Godunov scheme: **20min** Time to compute a solution from the same IC with the CNN model: **6min**