



# AI in Pedestrian Dynamics

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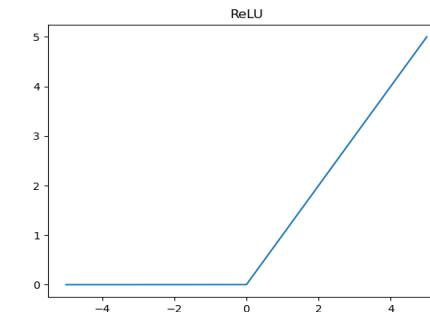
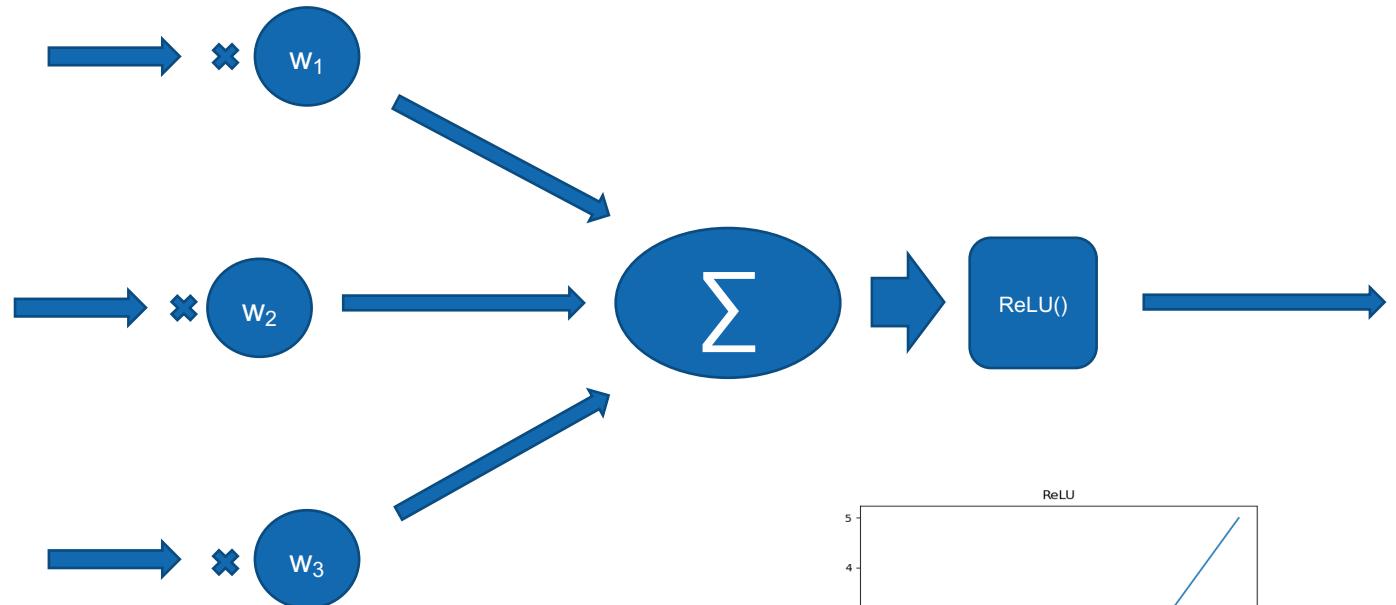


# What are Neurons?

Simply:

$$f: \mathbb{R}^n \rightarrow \mathbb{R}$$

- $n$  inputs get multiplied with weights
- Everything gets summed up
- Non-linearity applied

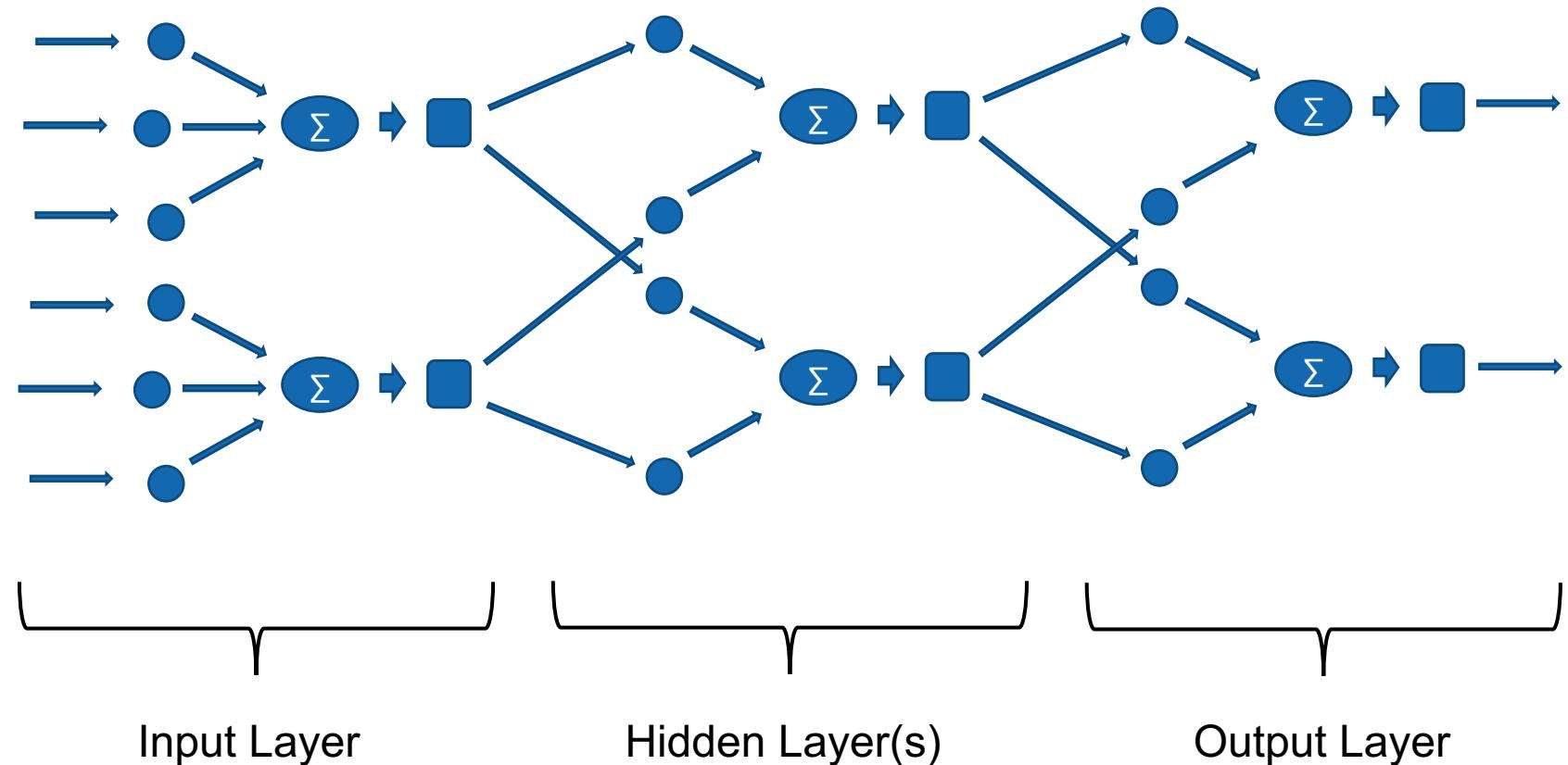


# How to make networks out of them?

More complex function:

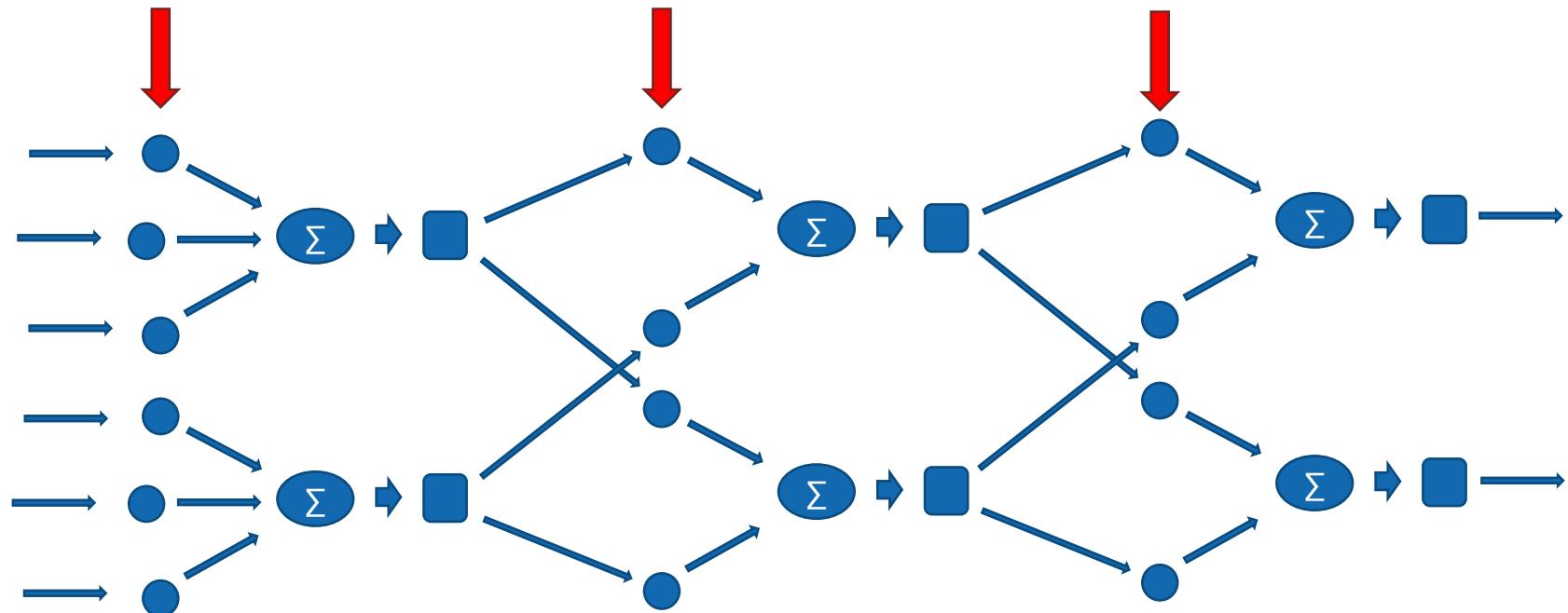
$$f: \mathbb{R}^n \rightarrow \mathbb{R}^m$$

- “Universal approximation theorem”
- They come in all shapes and sizes:  
Feed Forward, RNN,  
CNN
- They can be trained!



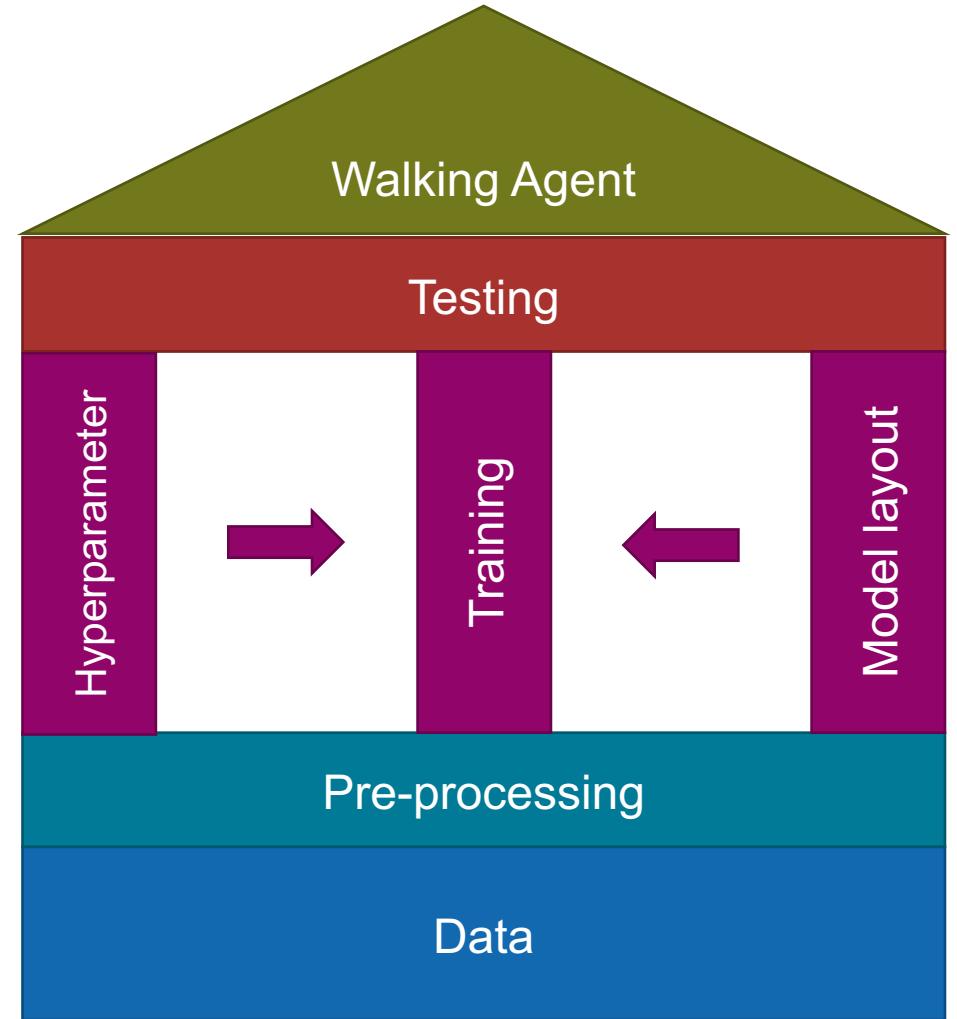
# Training a computer?

- Training modifies the weights
- Minimizing the difference between output and “solution”
- The difference is called *Loss*
- Benefit: Network decides what is important and what is not



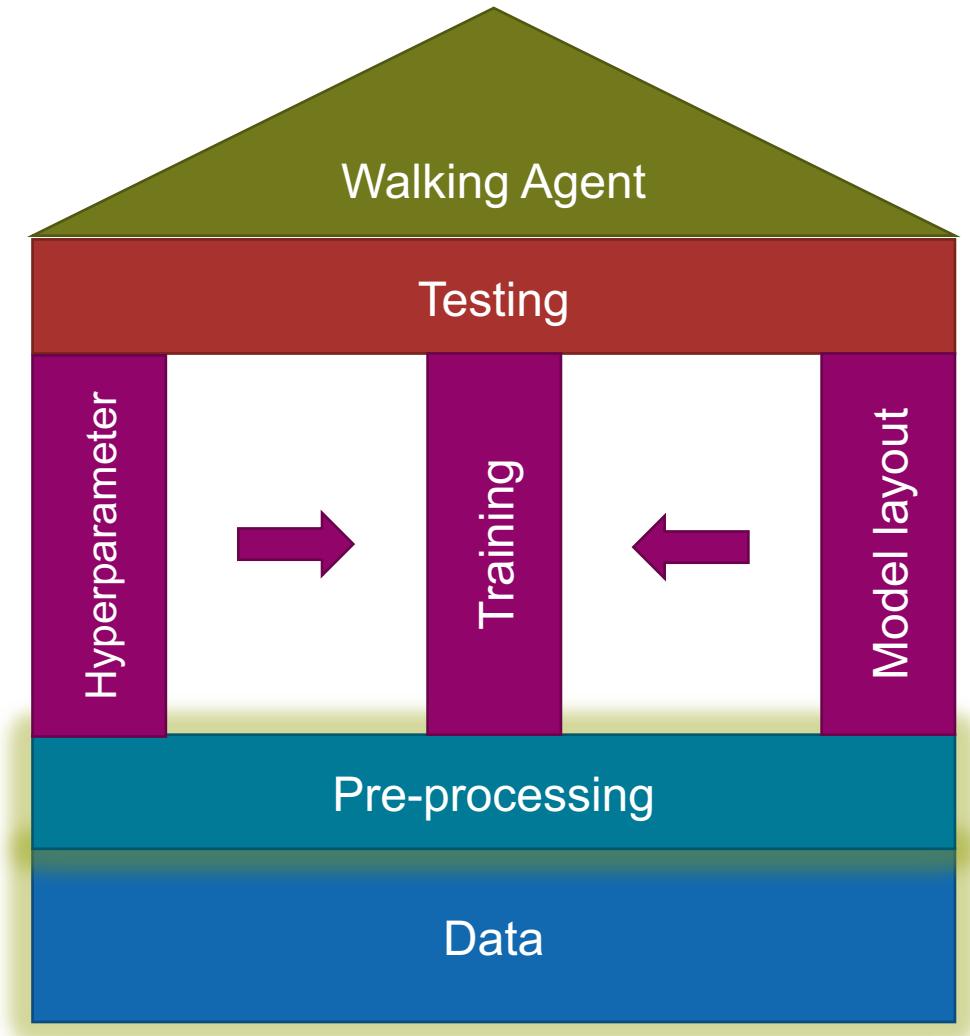
# Methode

Overview



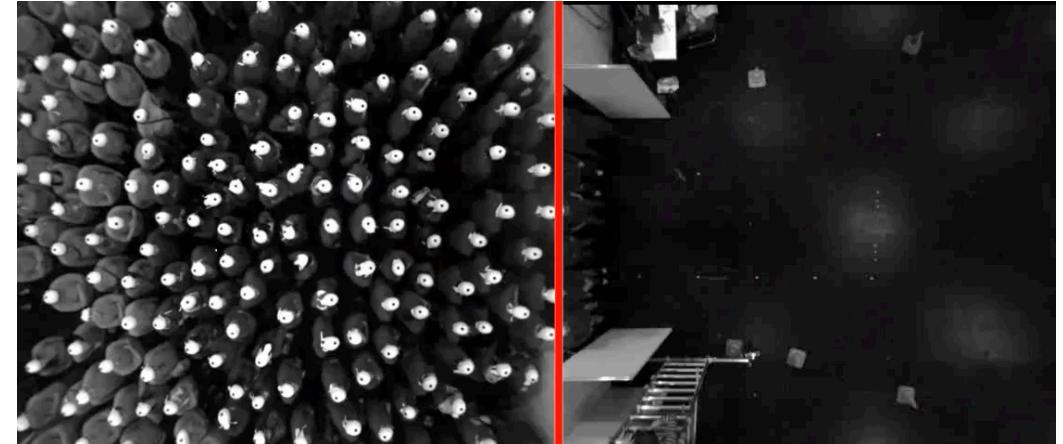
# Methode

Data & Pre-processing



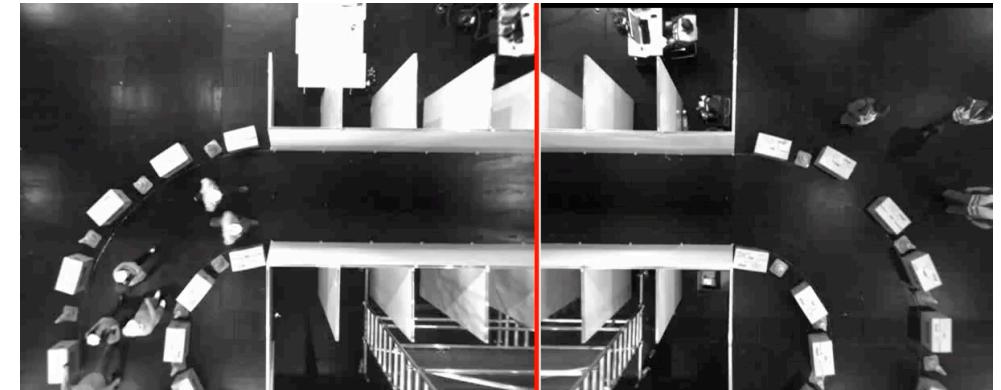
# Methode - Data

- Civil Safety Research, Forschungszentrum Jülich, <https://ped.fz-juelich.de/database/doku.php>
- Trajectories generated from tracked video
- Experimental Situation
- Instruction : leave in ordered fashion
- Advantages:
  - Pre tracked
  - Experimental setup well documented
  - Different situations



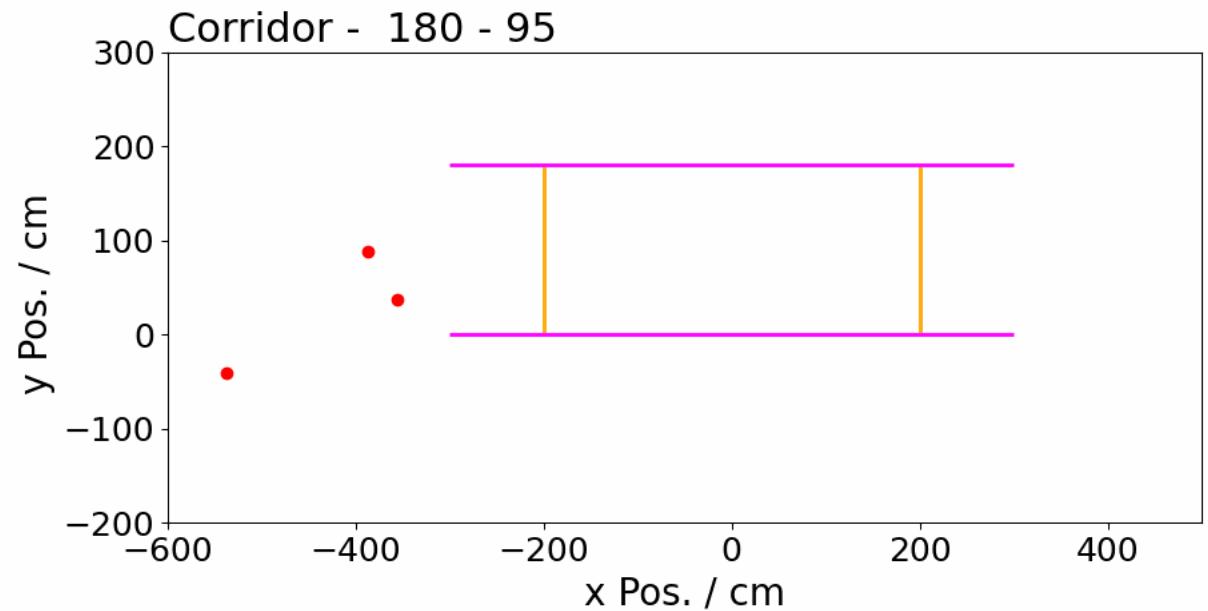
# Methode - Data

Video: 16 FPS



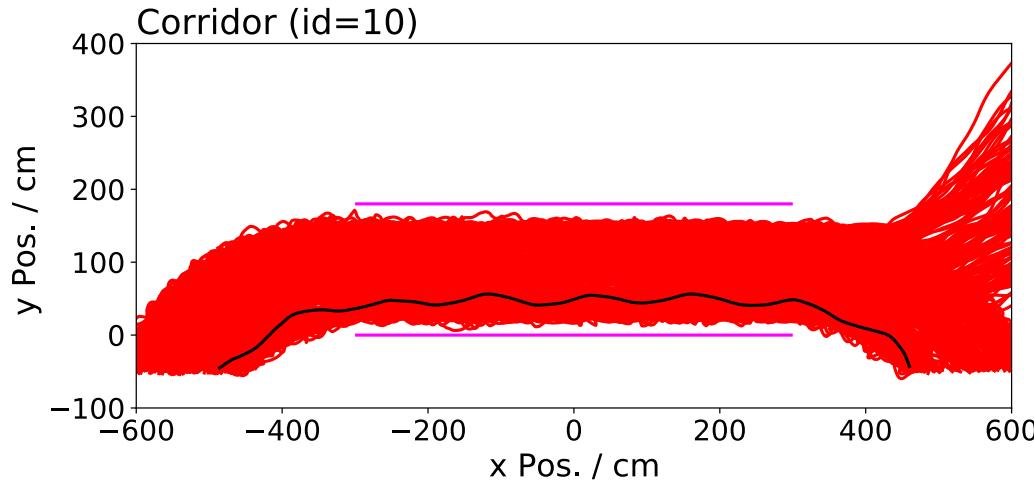
Trajectories:

- Encode geometry



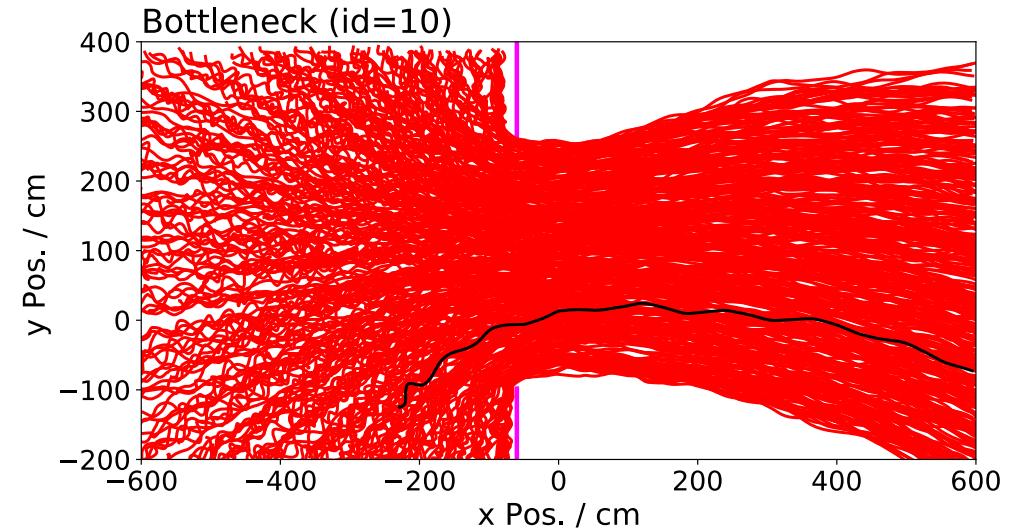
# Methode - Data

Corridor



- Width: 180 cm
- Length: 600cm
- People: 15-230
- ~2000 – 40'000 steps for Training

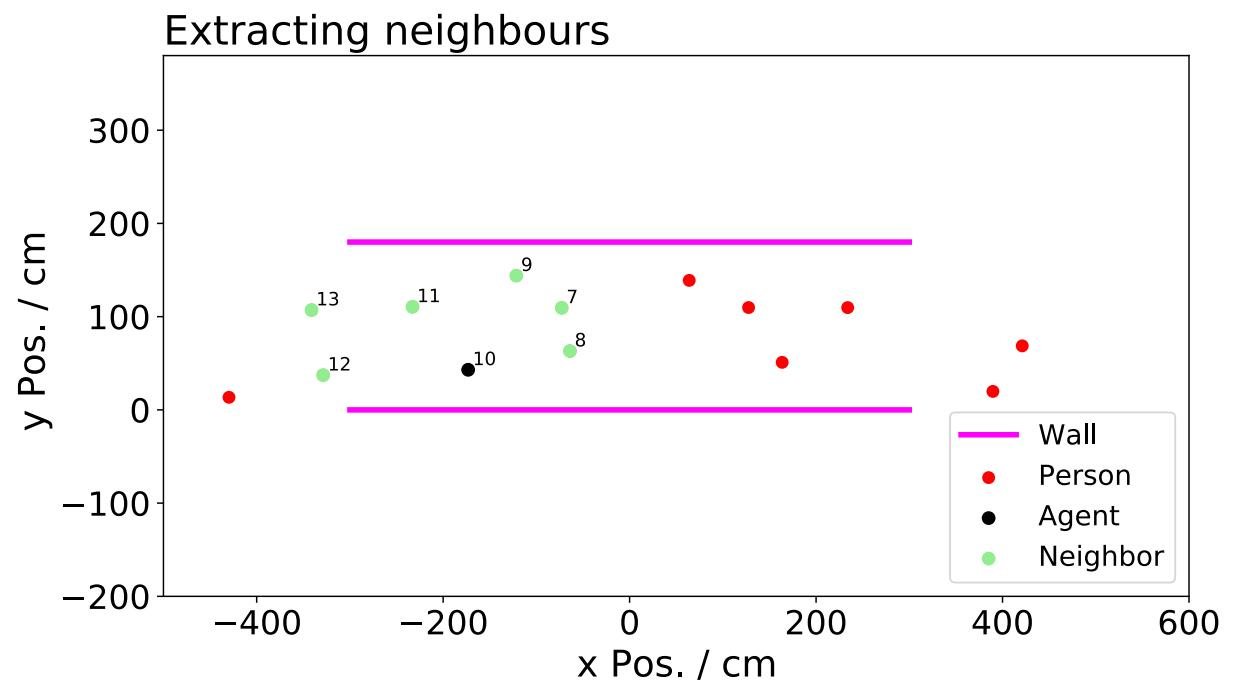
Bottleneck



- Width: 360 cm
- People: 400
- ~20'000 steps for Training

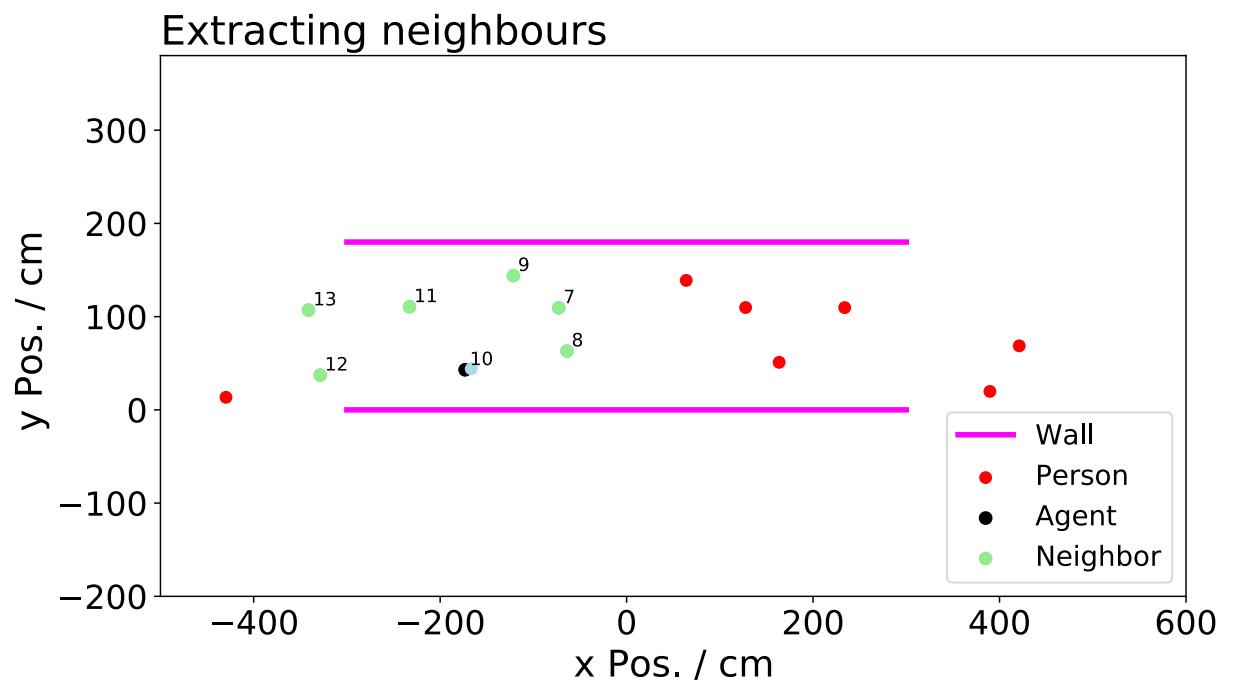
# Methode - Data

- Truth extracting
  - Nearest Neighbours



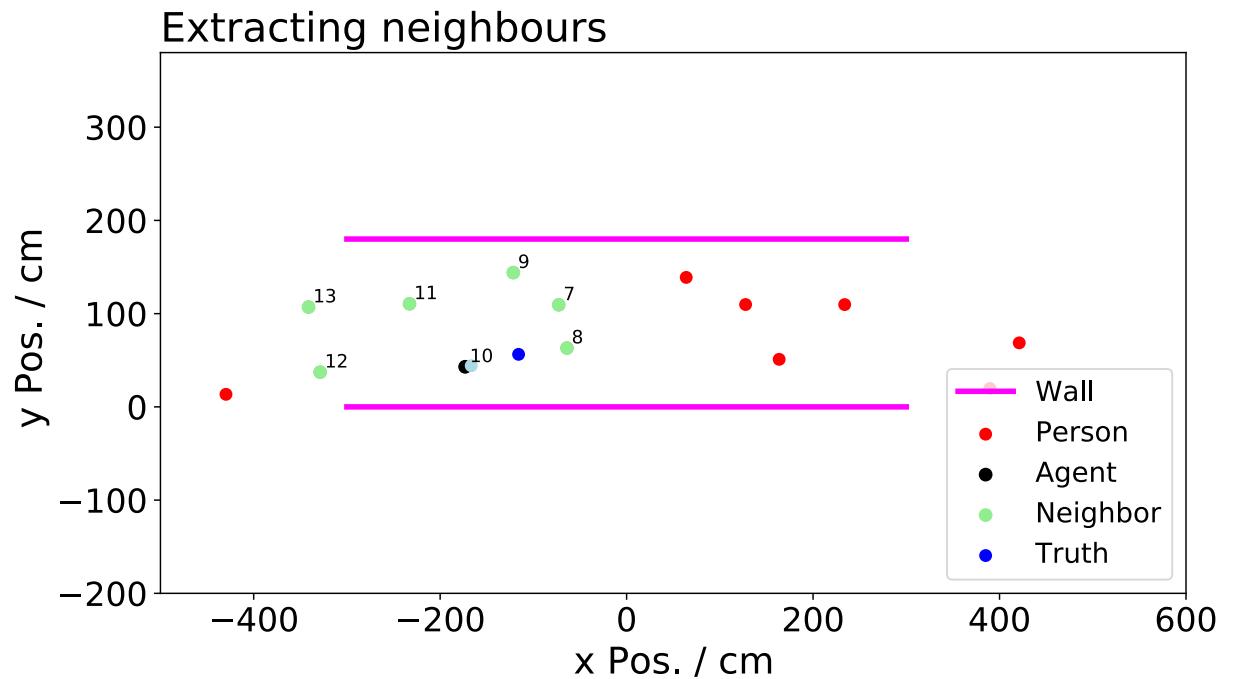
# Methode - Data

- Truth extracting
  - Nearest Neighbours
  - Next Frame



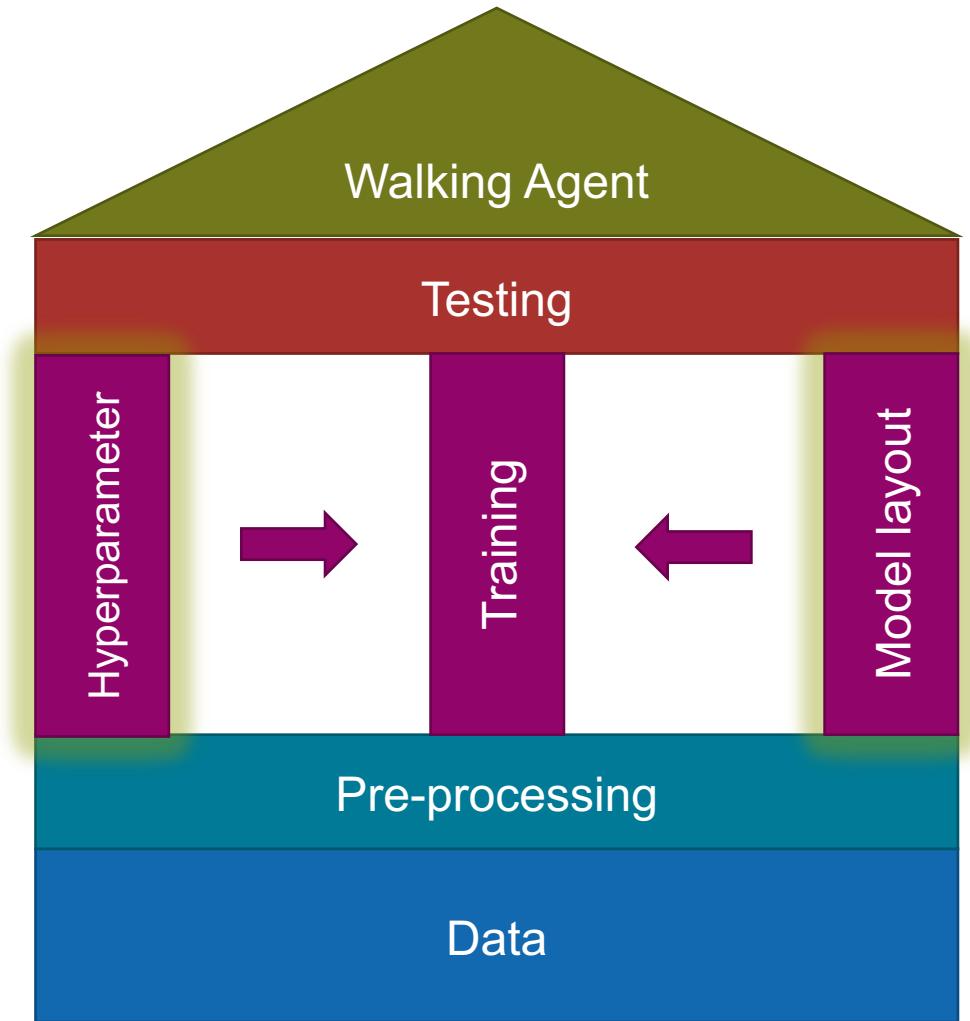
# Methode - Data

- Truth extracting
  - Nearest Neighbours
  - Next Frame
- Down sampling -> 2FPS
- Wrapping



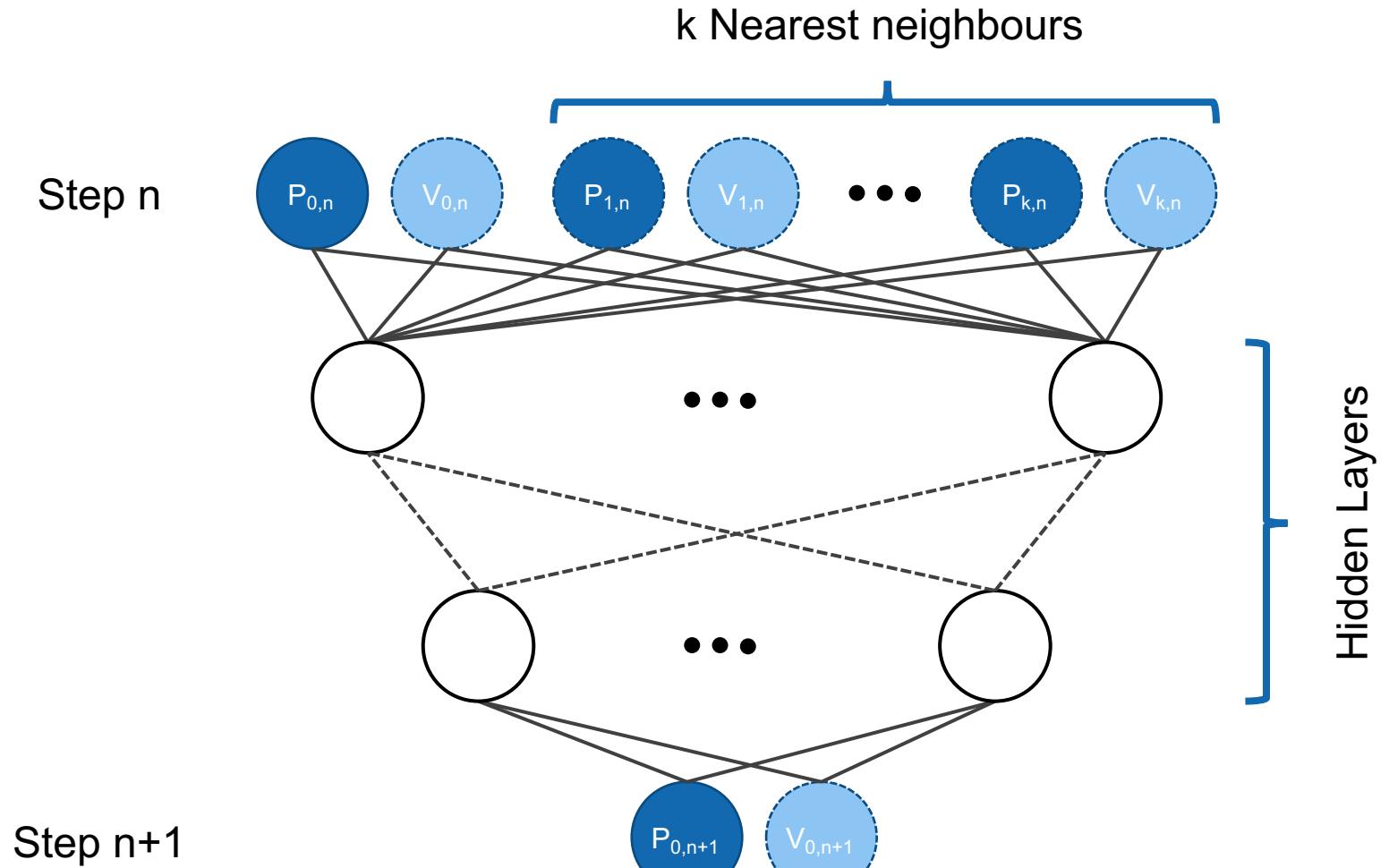
# Methode

Model – Feed Forward



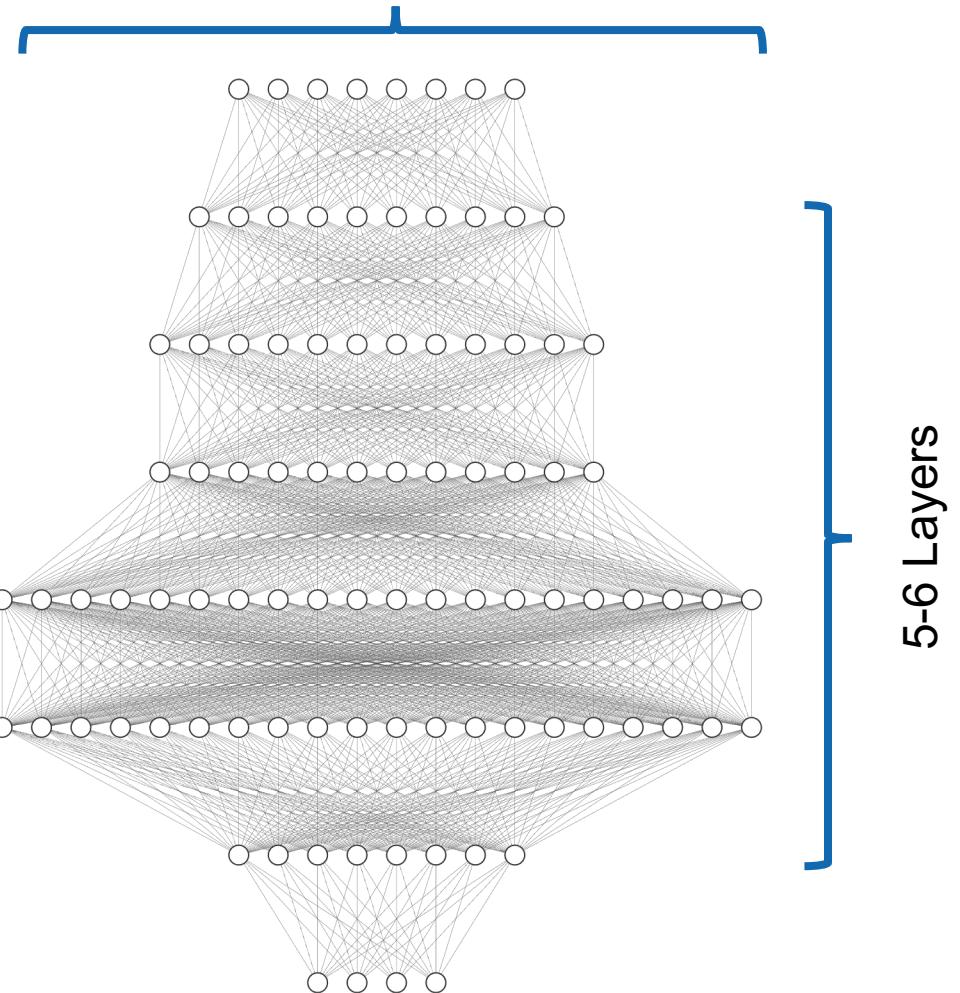
# Methode - Model

- Input:
  - Number of neighbours
  - Use velocities
  - Use past steps
- Output:
  - Position
  - Velocities



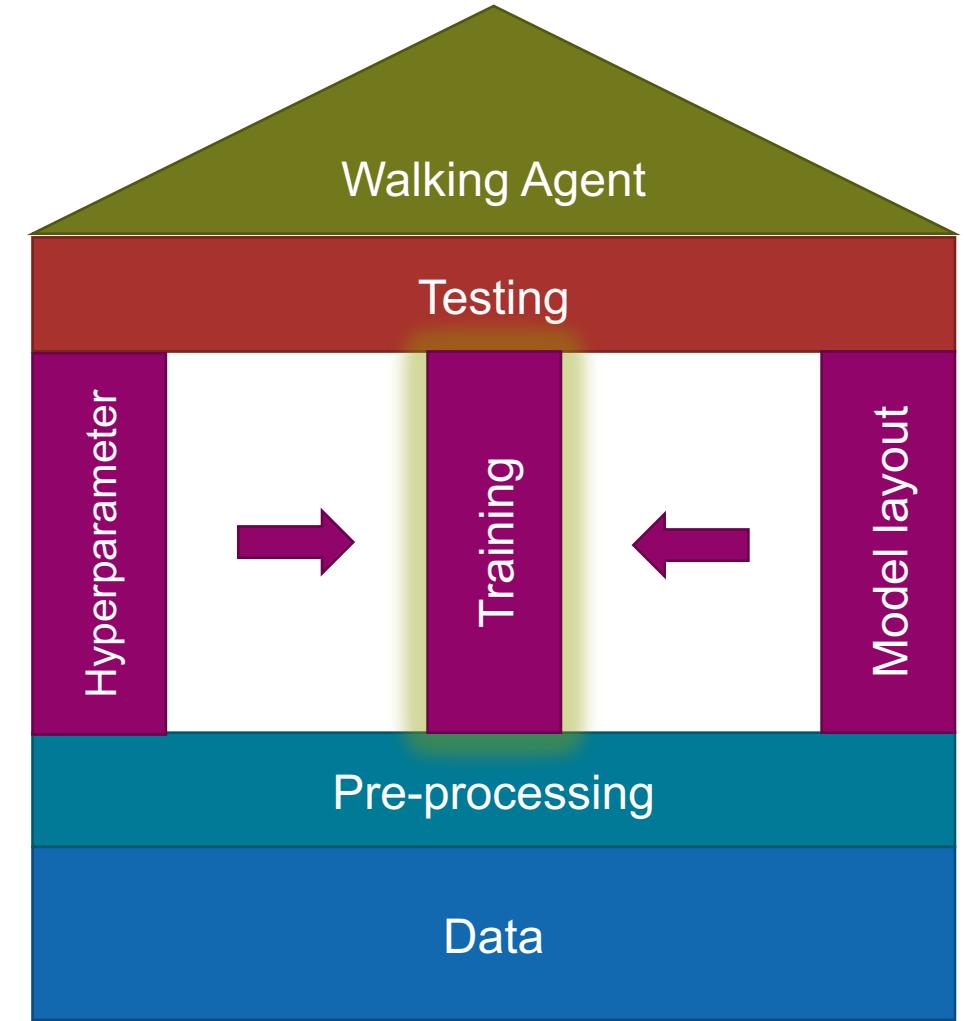
# Methode - Model

- Hidden Layers:
    - 5-6 Layers (shallow)
    - Approx. 30-120 Nodes per layer
    - Literature: Vehicle prediction network<sup>[1]</sup>
  - Current Network :
    - Input: 6 Neighbours with velocities (28)
    - Hidden layers : (32, 32 ,64, 128, 128, 40 )
    - Output: Position & Velocities (4)
  - Bottleneck: Hidden Layer: (50, 20, 50)
- 
- [1] Feed-forwards meet recurrent networks in vehicle trajectory prediction, M. Bahari, A. Alahi, EPFL
  - [2] Visualize Architecture of Neural Network, <http://alexlenail.me/NN-SVG/index.html>



# Methode

Training



# Training the Neural Network

```
y_pred = model(x)
```



```
loss = loss_fn(y_pred, y)
```

Prediction

Loss

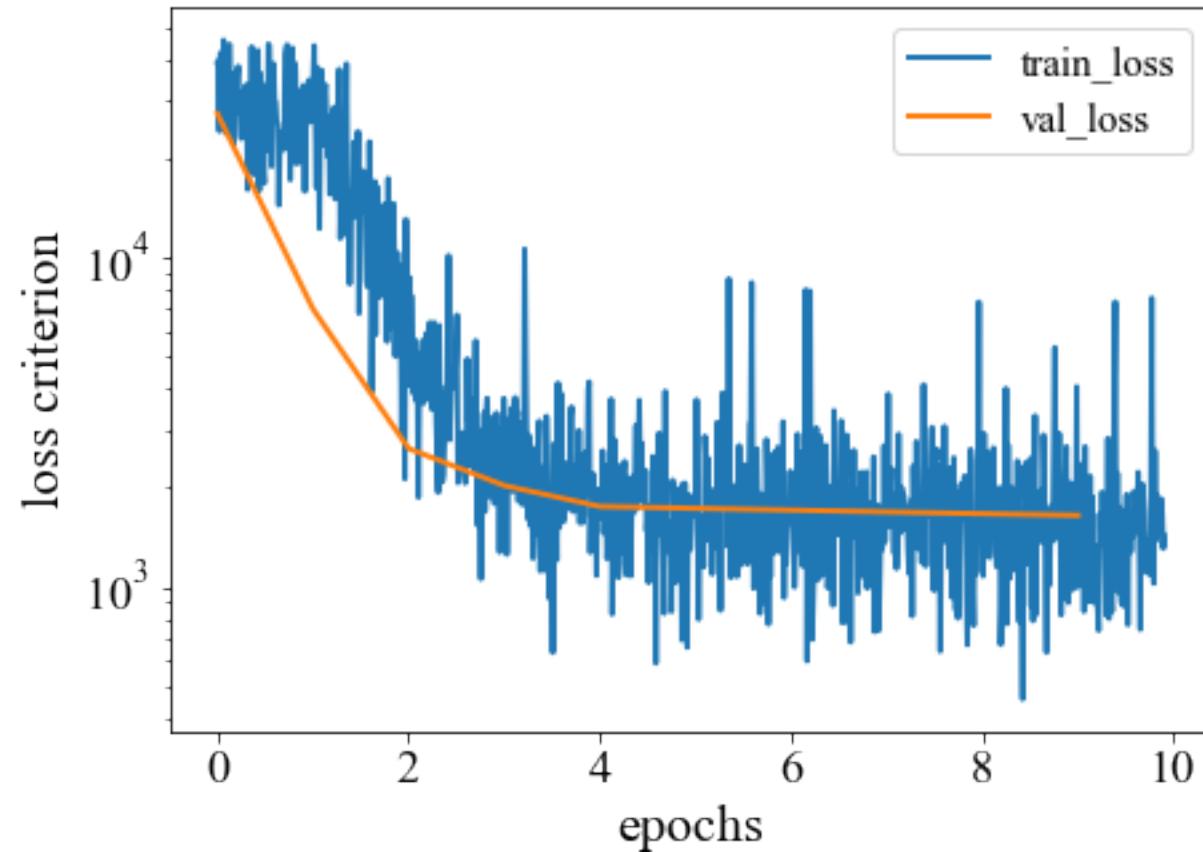


```
optimizer.step()
```

Refinements:

- Batching
- Adaptive Learning Rate

# Training the Neural Network



# Working process

1

Preparation  
- Data sets  
- Papers  
- Pytorch

2

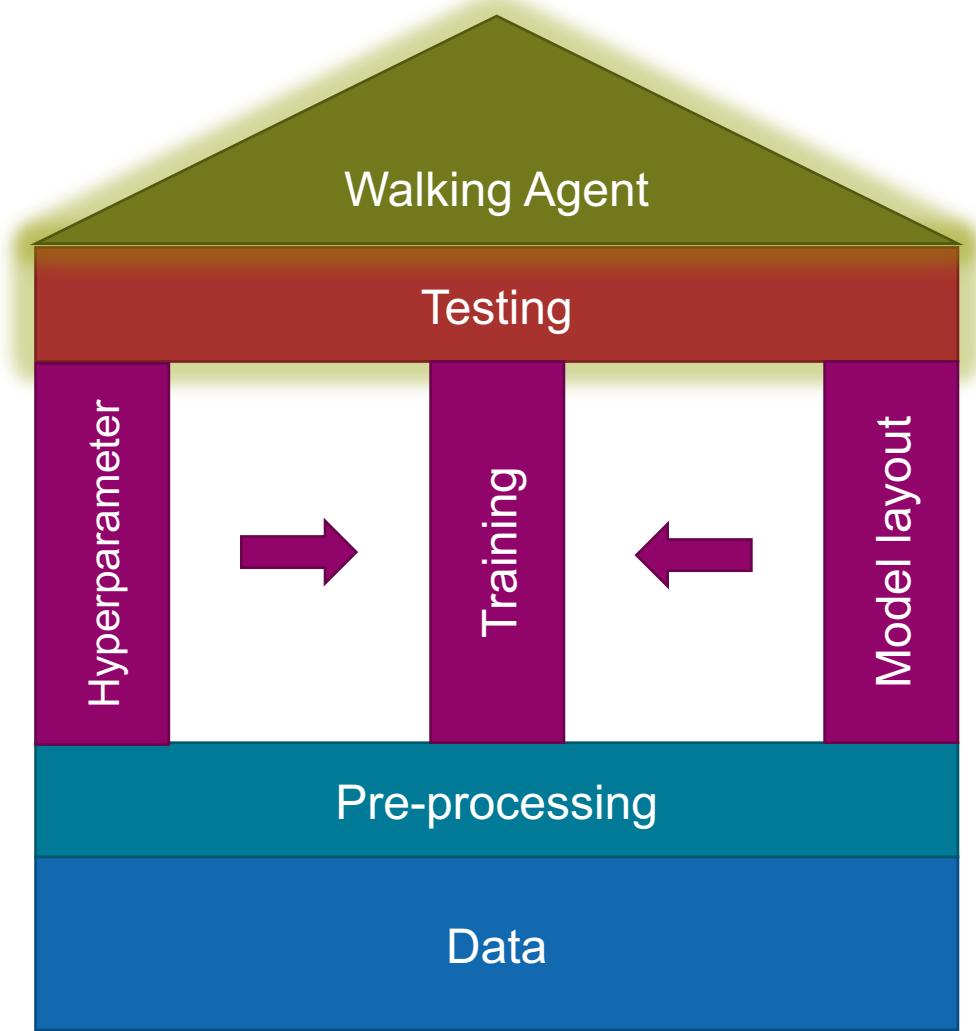
Implementation  
- Auxiliary libraries  
- Various neural networks

3

Wrapping Up  
- Comparing results in pedestrian dynamics context

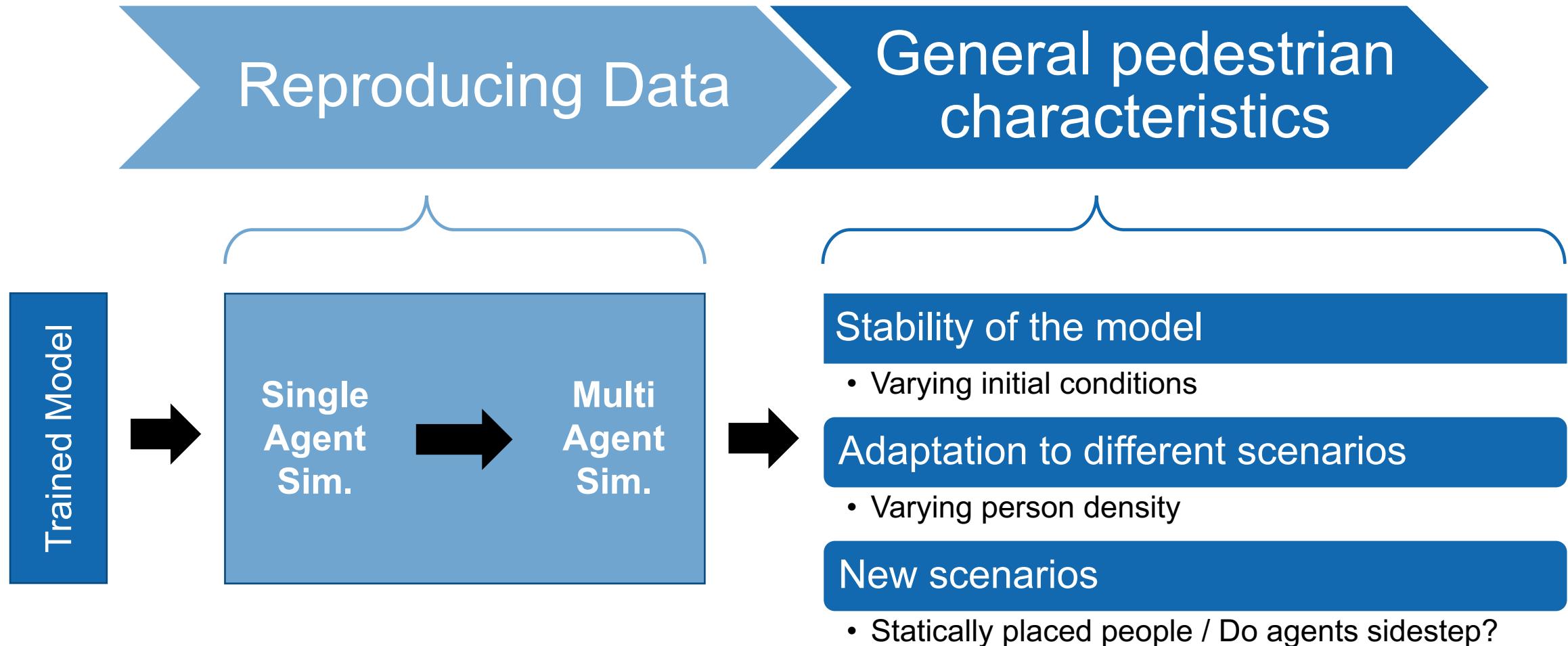
# Methode

Walking Agent(s)



# Results: Overview

How good does our trained model capture the behavior of a pedestrian?



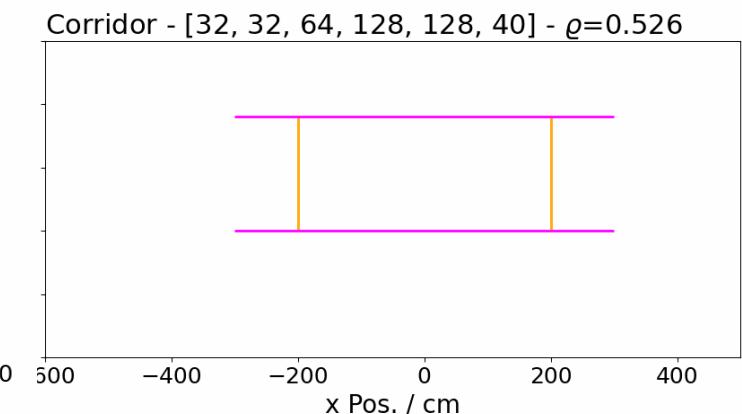
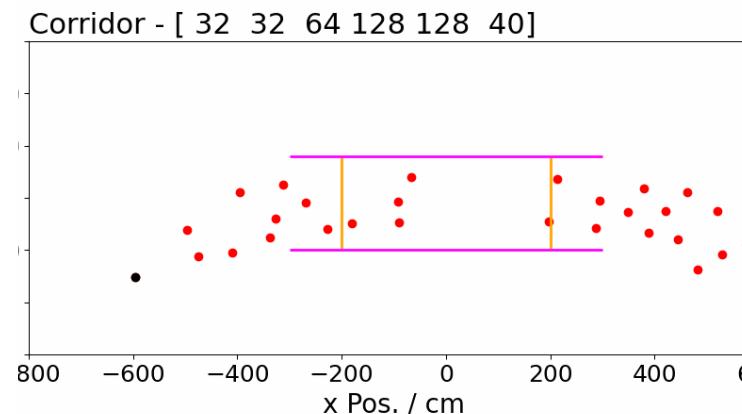
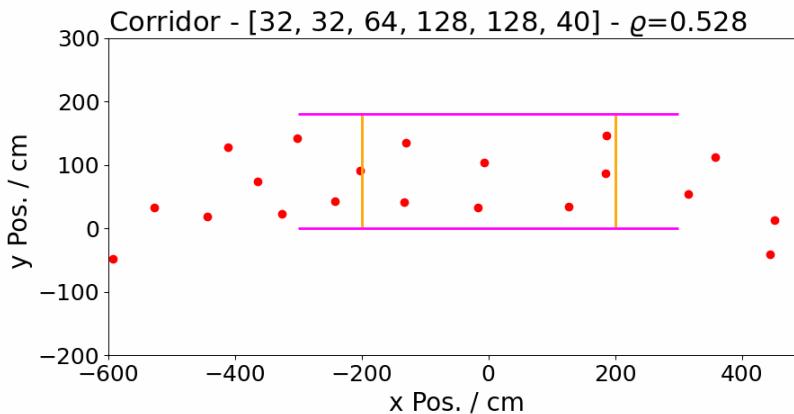
# Results: Reproducing Data

Raw data

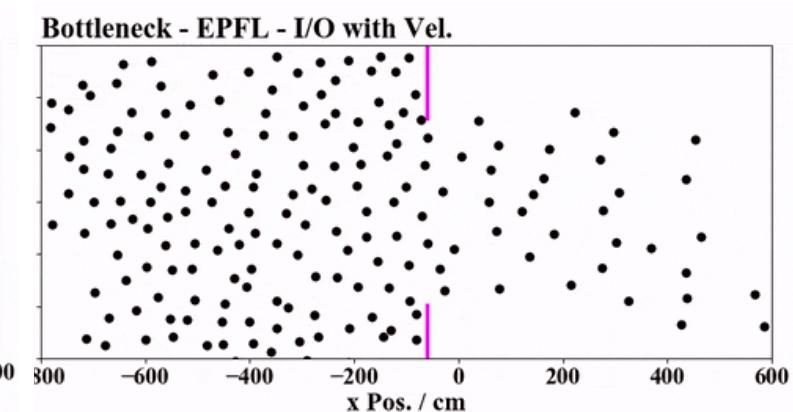
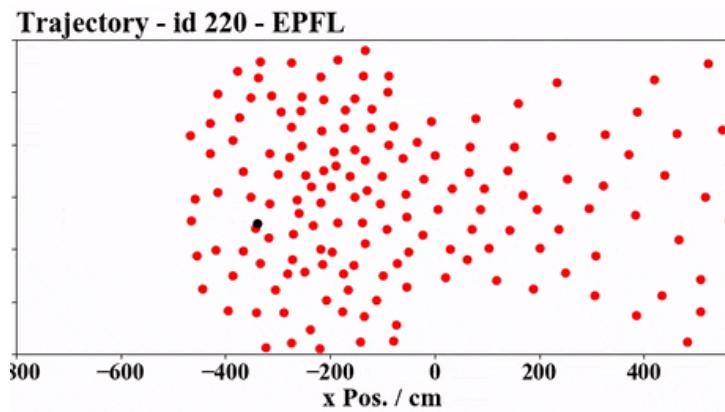
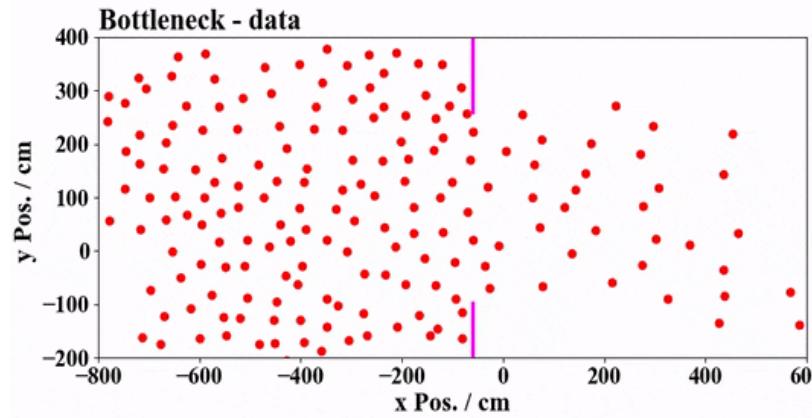
Single Agent

All Agents

Corridor



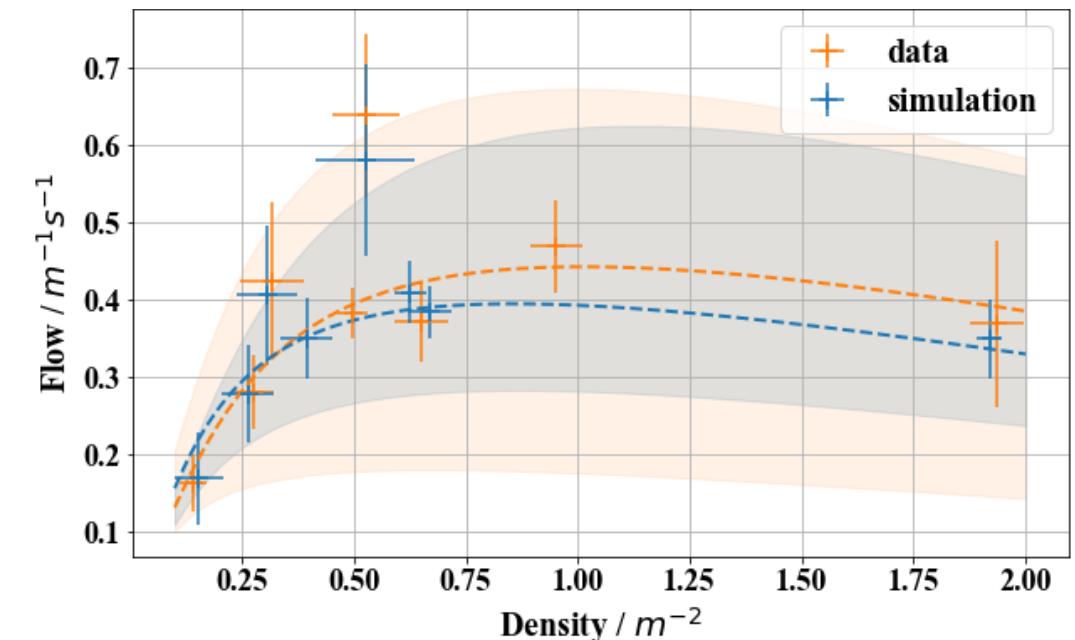
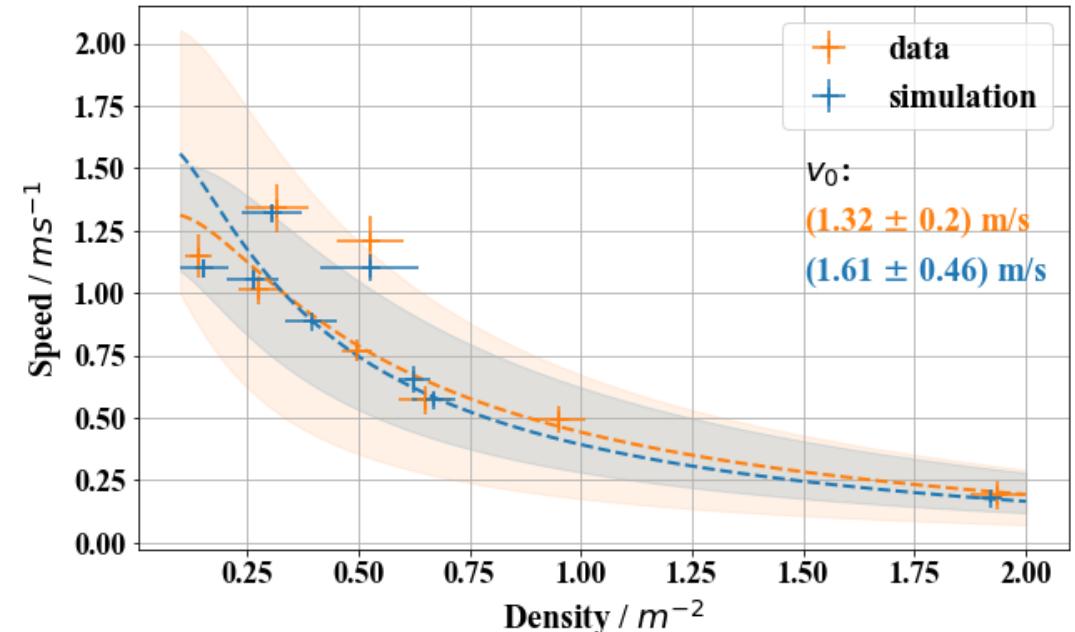
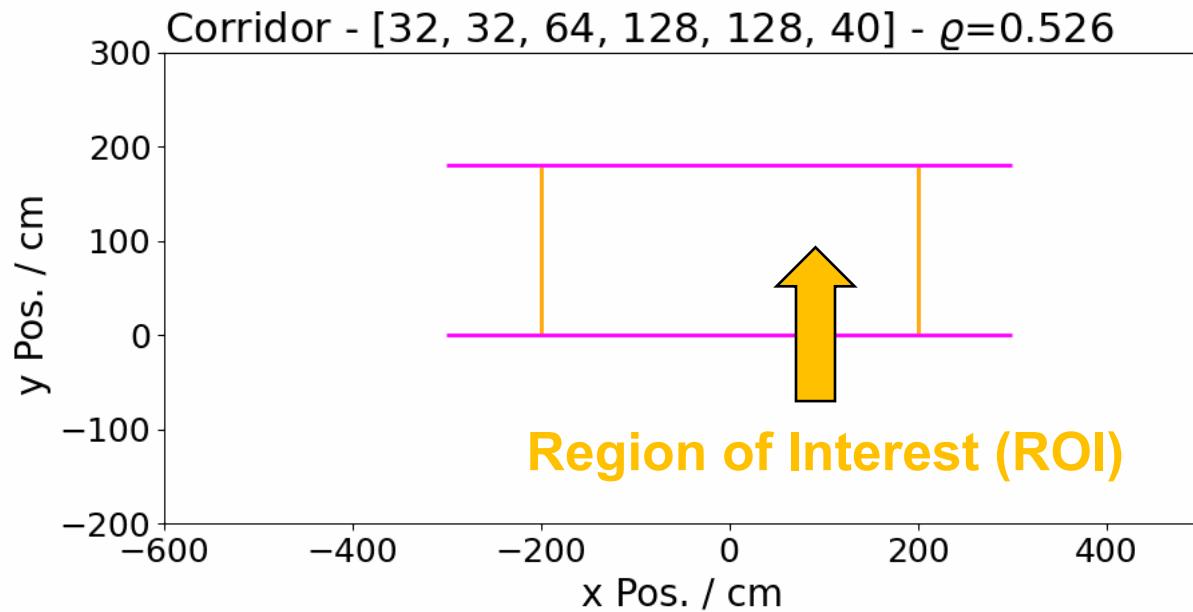
Bottleneck



# Results: Corridor

- **Apply one Model to different scenarios**  
vary people density
- Measure mean density and speed in **ROI**
- Average over frames

Problematic:  
Inhomogeneous raw data (fluctuations in speed)

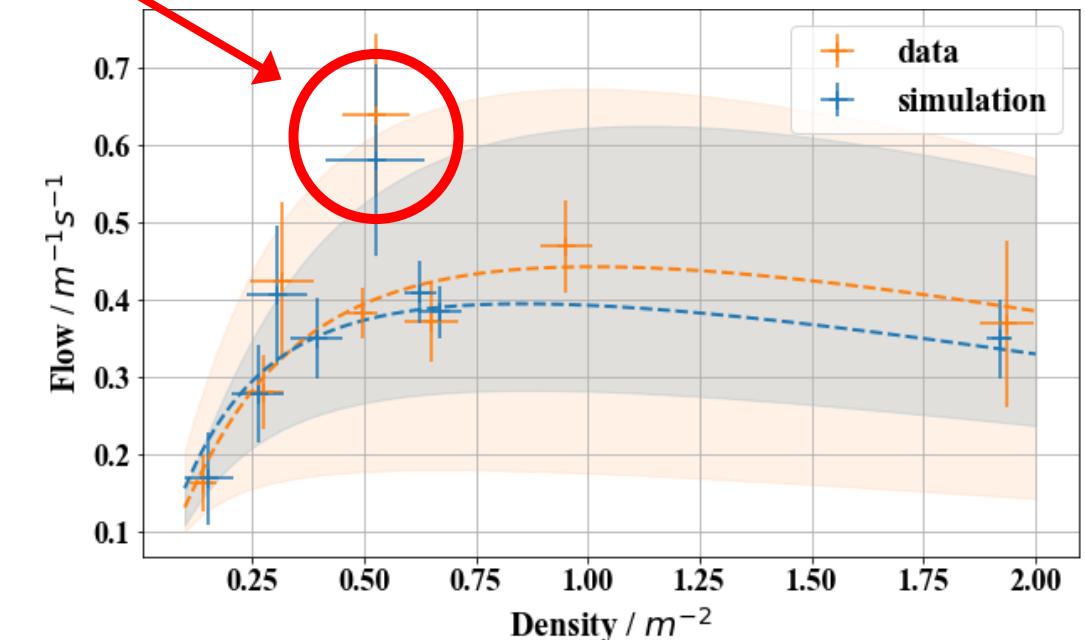
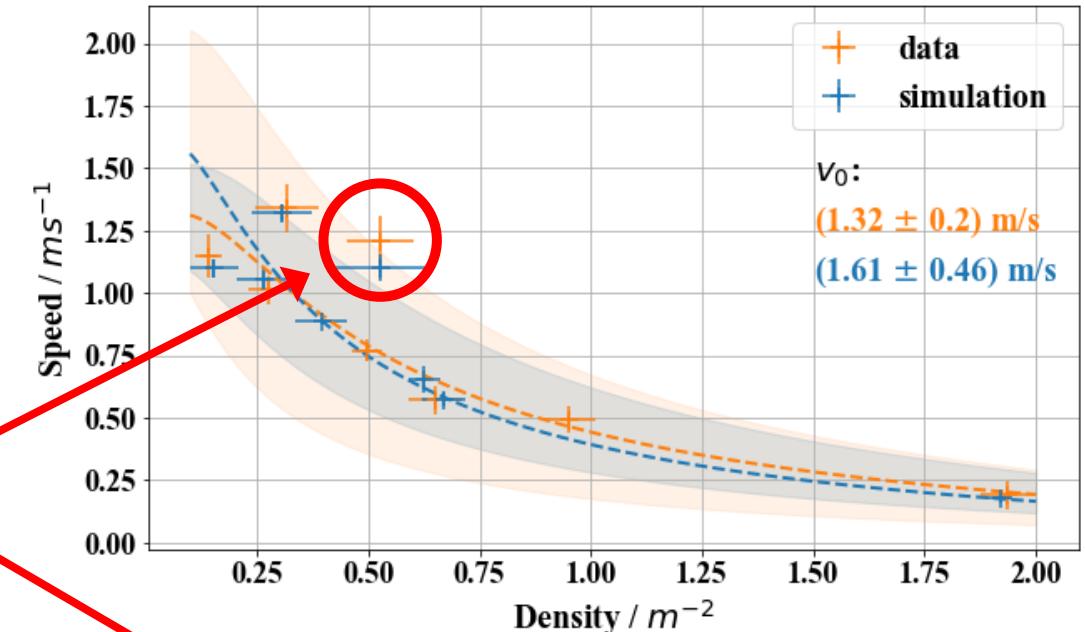
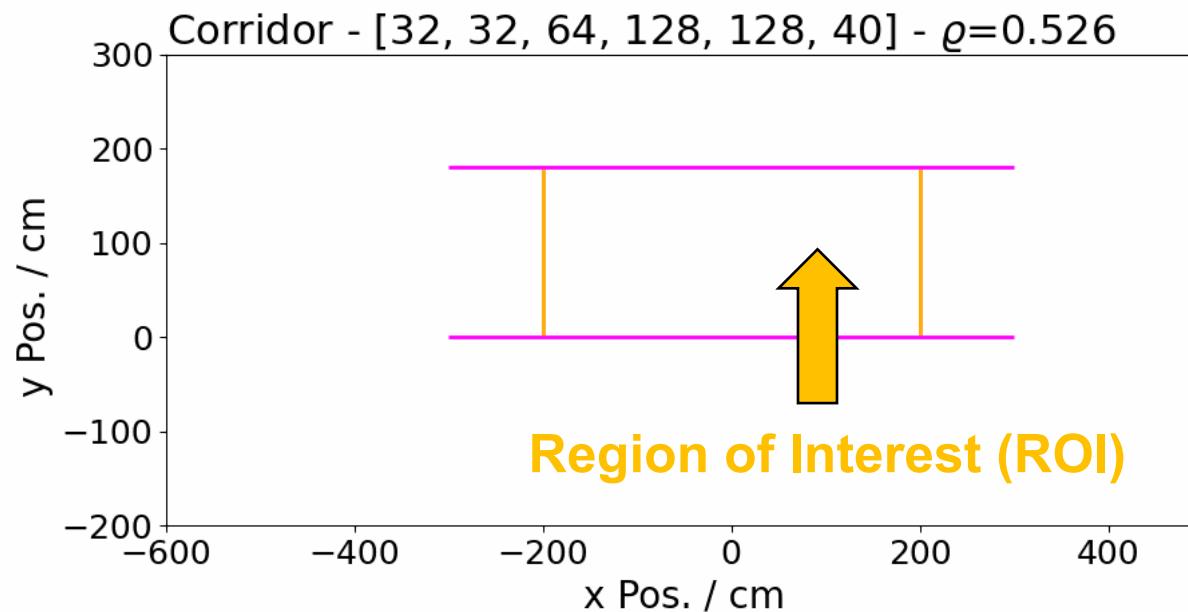


# Results: Corridor

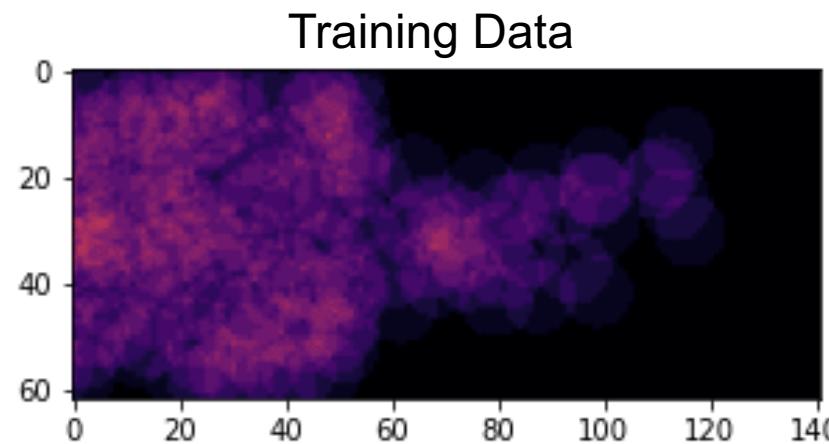
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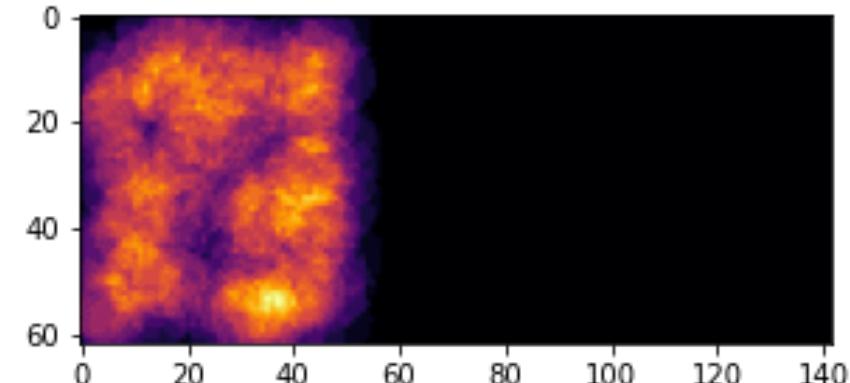
Inhomogeneous raw data (fluctuations in speed)



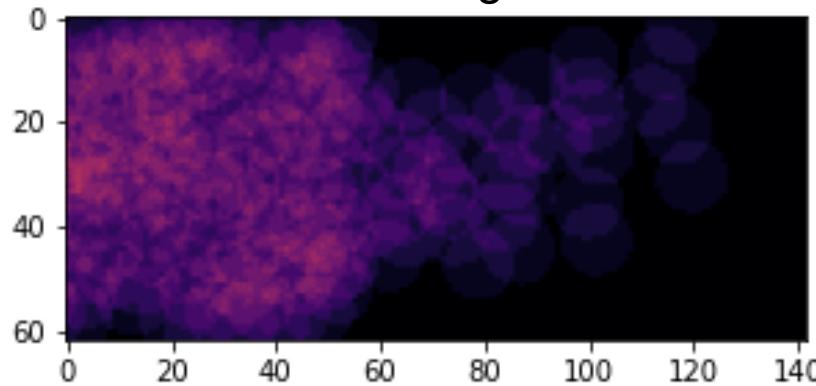
# Results - Bottleneck



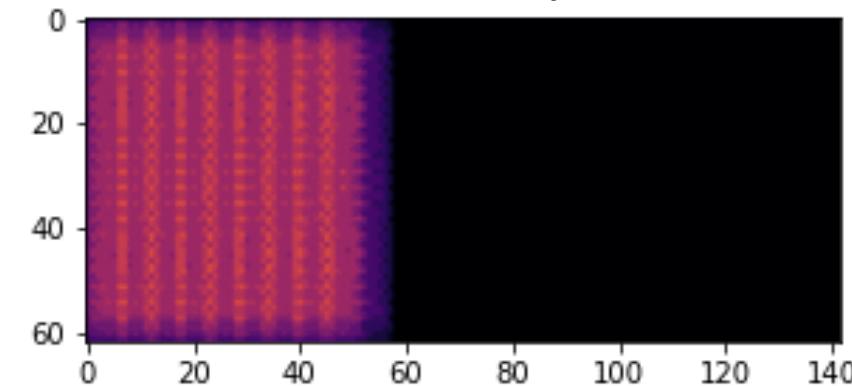
Simulation with random initial positions



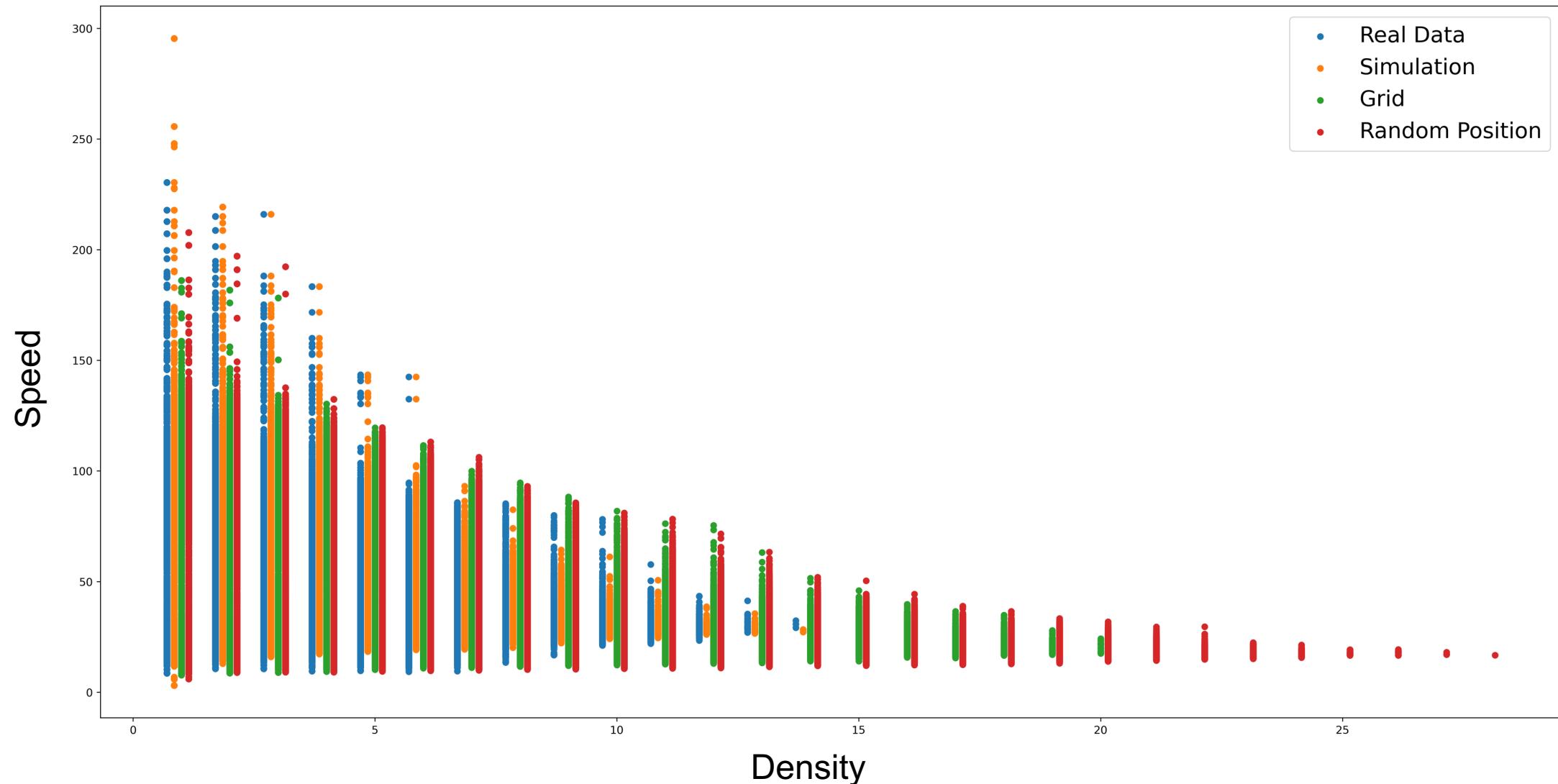
Simulation with initial positions  
from training data



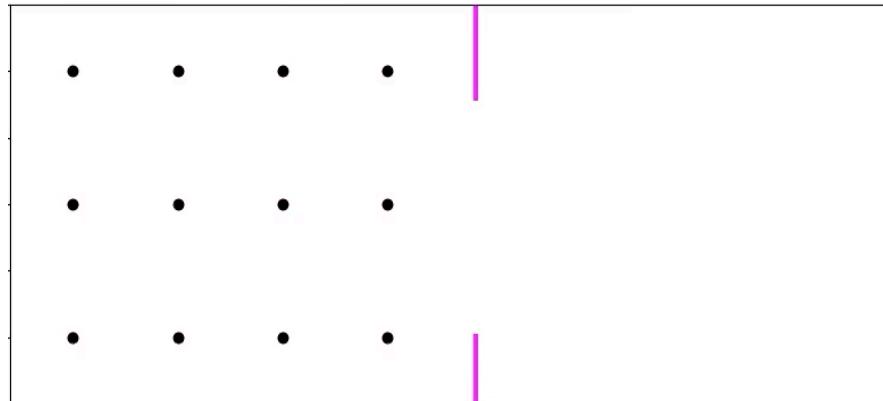
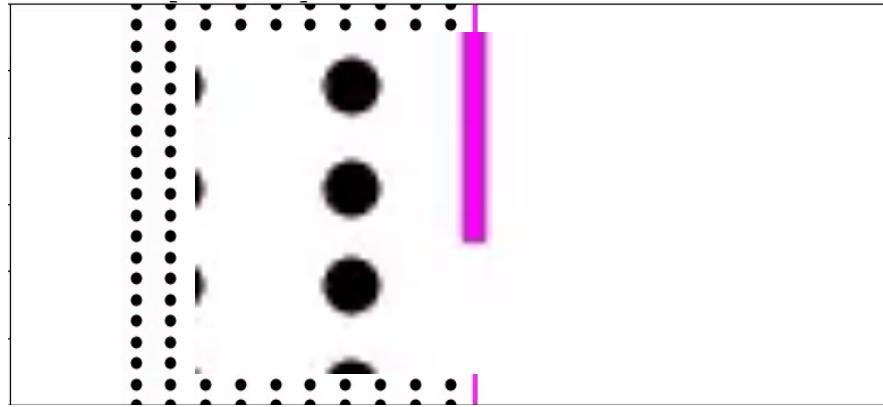
Simulation with homogenously  
distributed initial positions



# Results - Bottleneck

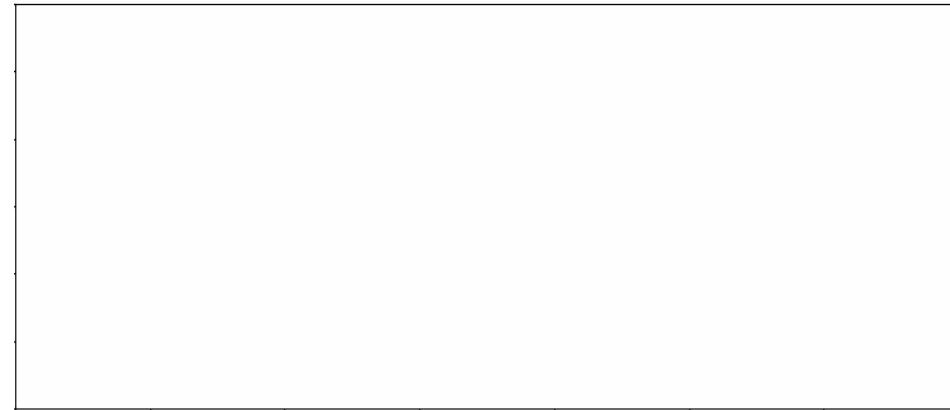


# Limitations of our approach



- Geometry of problem learnt on a data-driven basis
  - Difficult to adapt to new environment
  - Agents not forced to respect the geometry of the Problem
- Agents adhere less to the geometry at low densities
- Does not simulate fundamental changes in human behaviour such as panicking

# Outlook



## Possible Future Approaches

- Modify the architecture to ensure geometry compatibility
  - Hard-code geometry into network architecture
  - LSTMs?
  - Generative Adversarial Networks?
- Apply same method to similar problems
  - Bidirectional Flow, Intersections, ...
  - Different Agents such as cars, animals, ...
  - 3D setups such as stairs, hills, roads,...