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Real-time calibration of the ALICE TPC and ML traffic predictions

ESR10

SMARTHEP Yearly Meeting 2024

Lund University

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Overview

- Past year
  - Ximantis
  - Parental leave
  - Physics
- Summary

Currently

- Teaching C++/ROOT
- Started a new physics analysis in Run3 with O2Physics
  - Mostly software related currently
- Courses

Parental leave

Input data

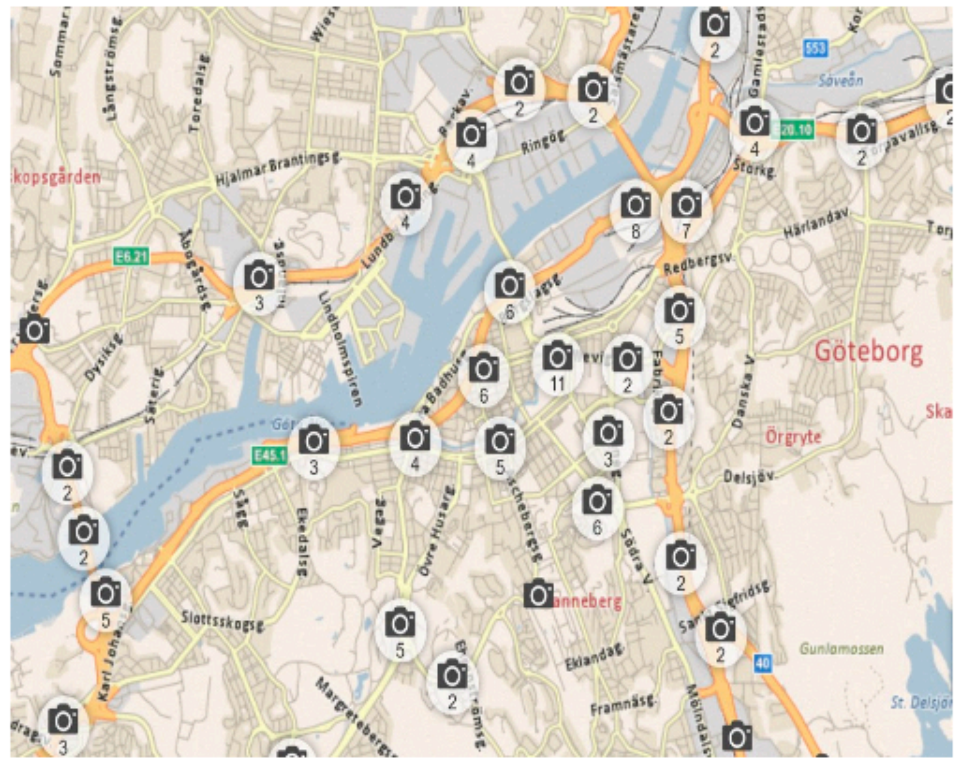


Fig. 1. A section of the Goteborg traffic network with multiple cameras indicated along each road each collecting images every minute. Data provided by the Swedish traffic authoridy: Trafikverket.

Sopasakis, A. (2019)

One cam example →

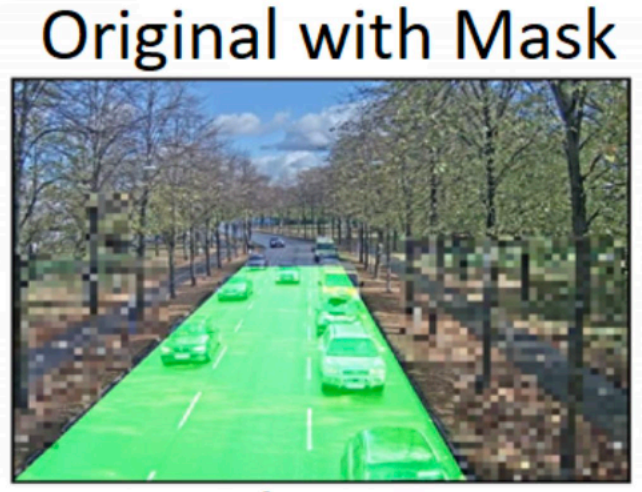
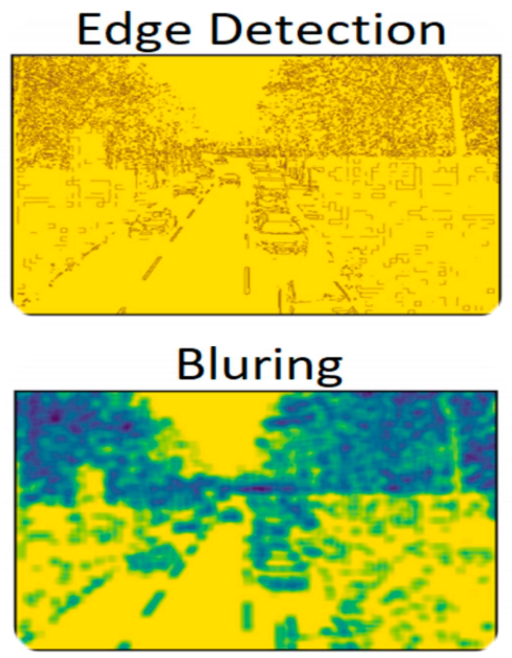


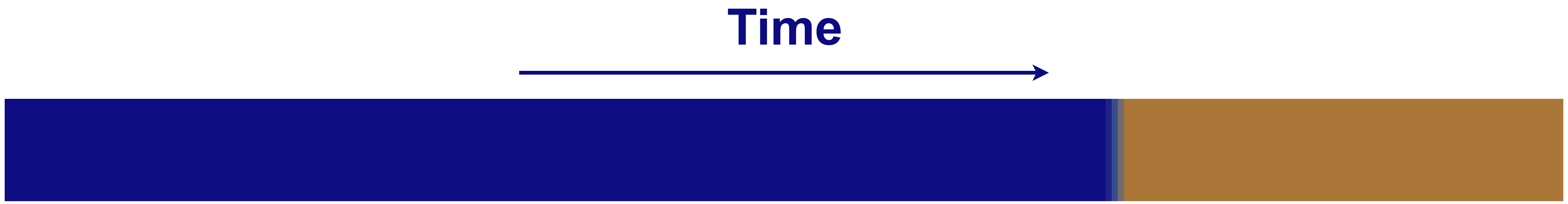
Fig. 2. Original image with superimposed mask on the region of interest.

→ **Image Analysis** →



→ **"Flow"** →

- Input data of Network
- Done for every available camera



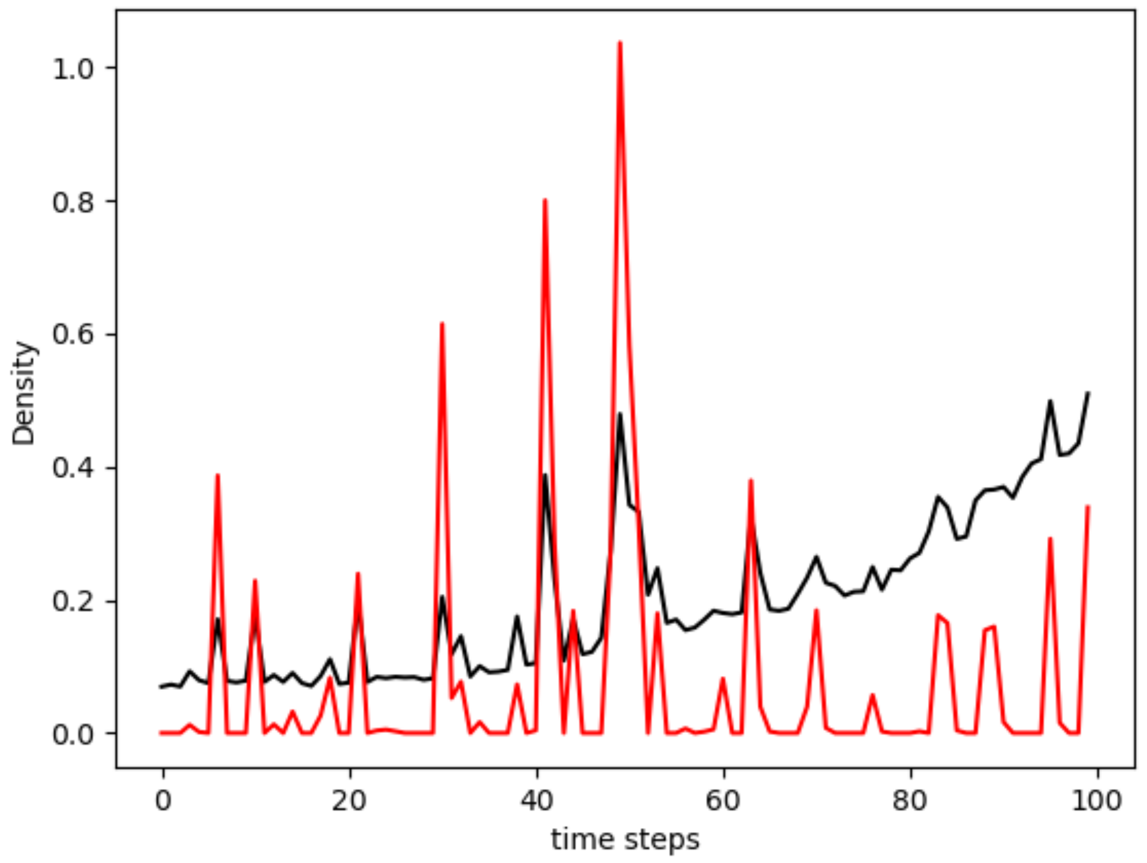
Time

Training

Validation

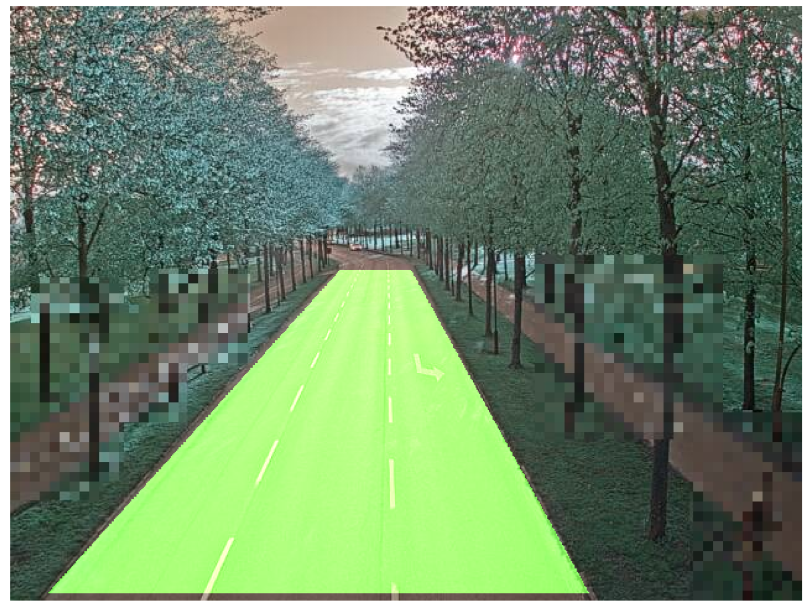
“Background” density

- Systematic shift during the day (black)
- Remade density estimation



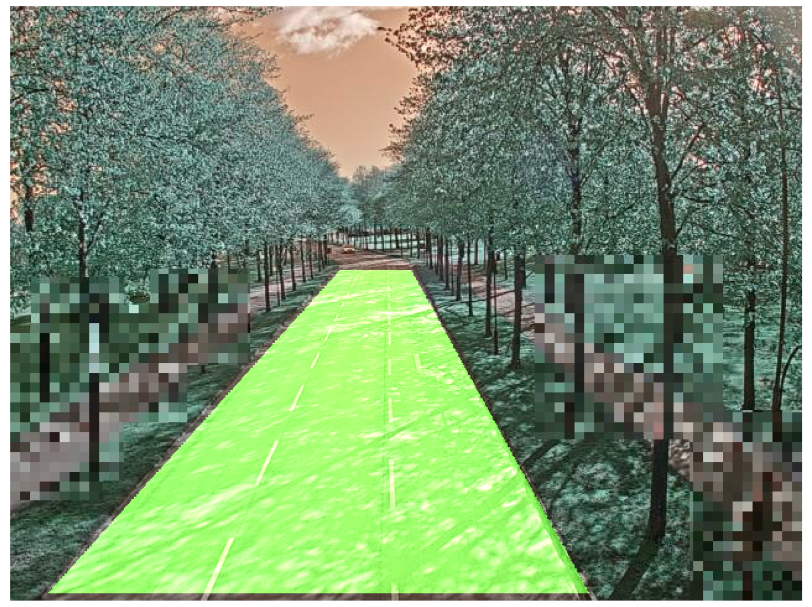
Morning

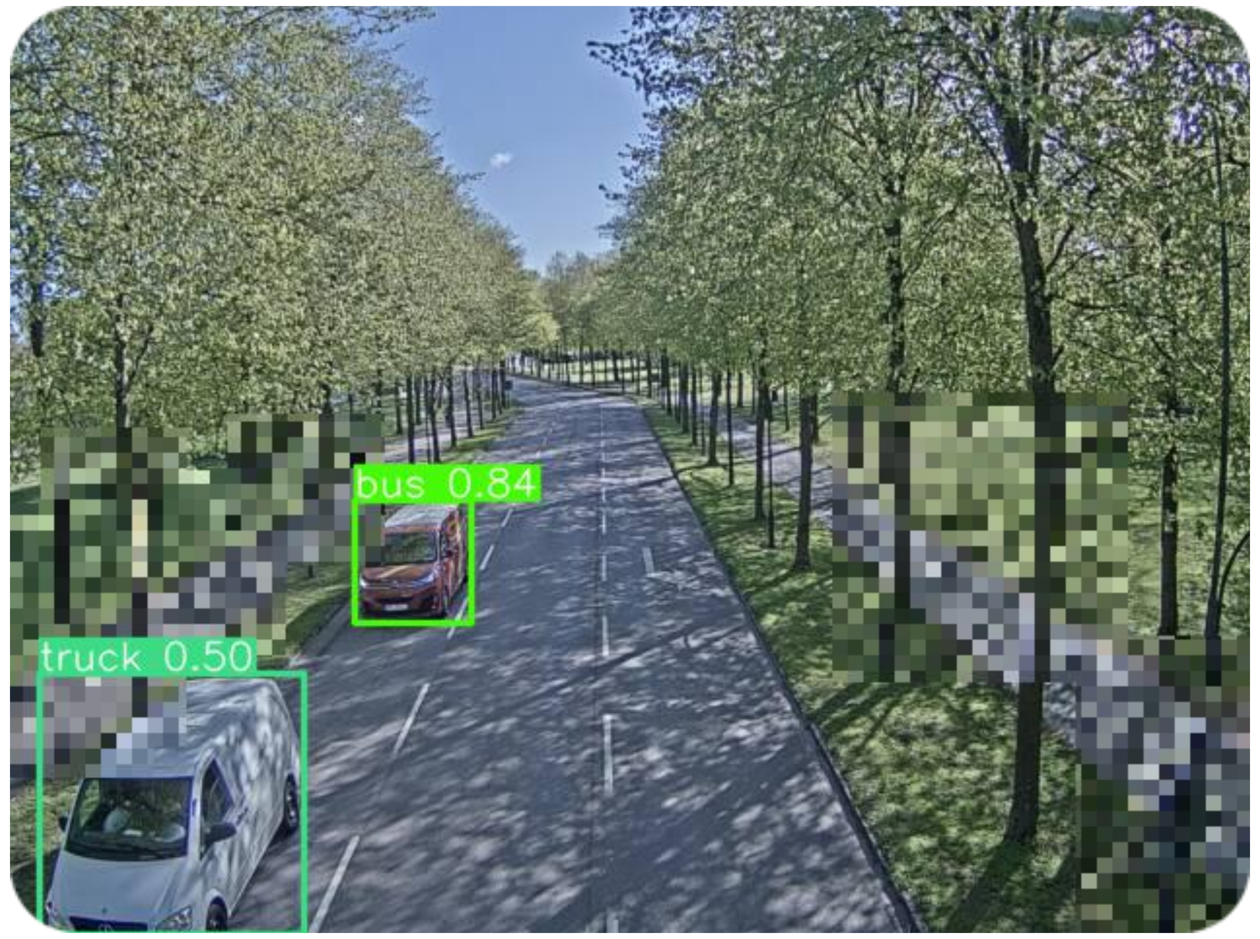
Density: 6.9596842838350215%



Afternoon

Density: 40.47357424746576%

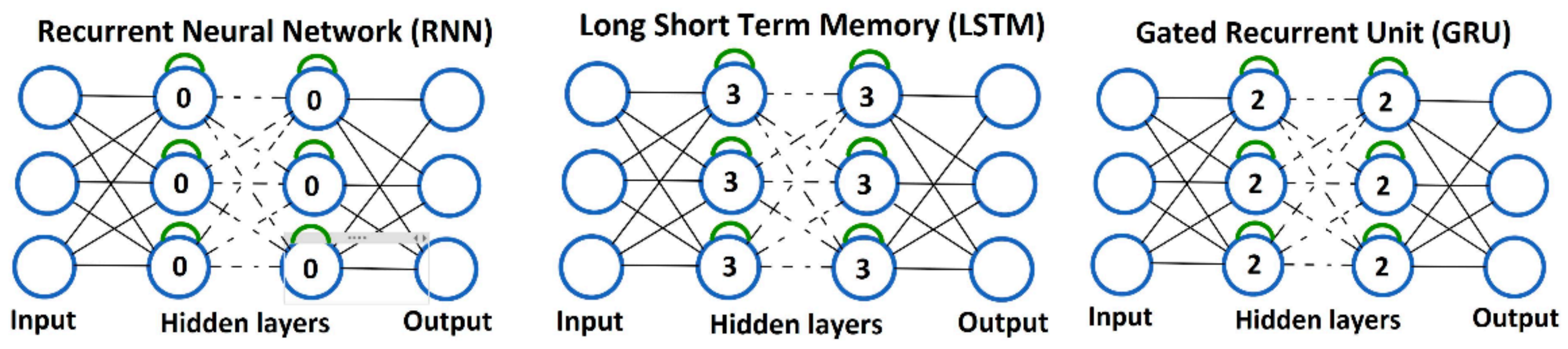


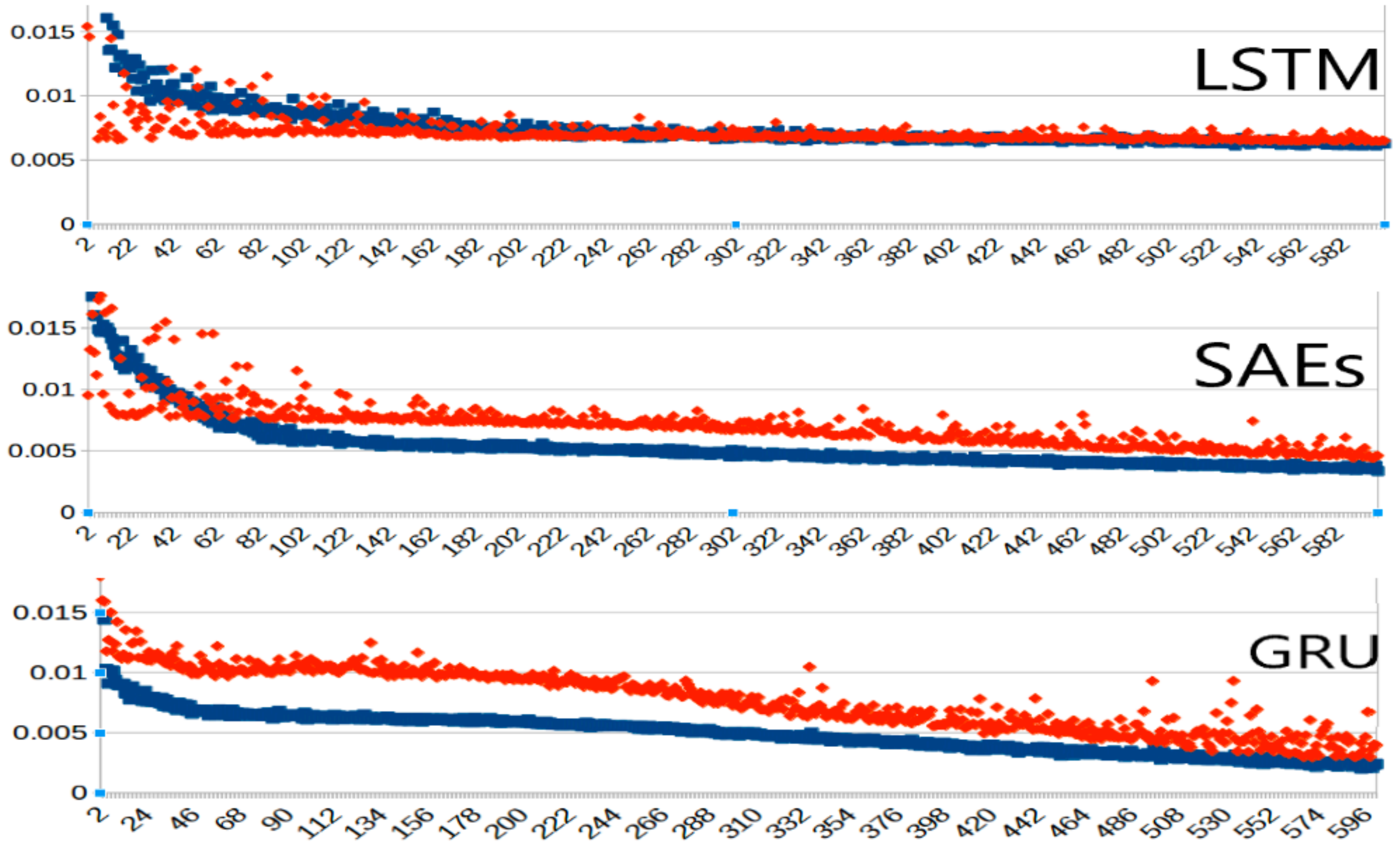


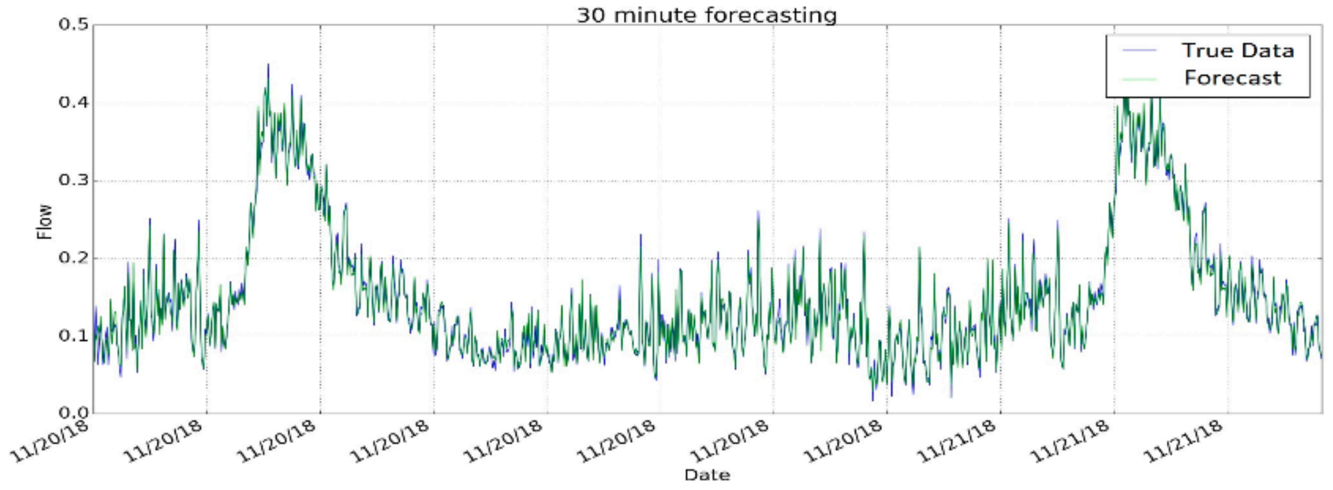
- Used YOLO pre-trained on coco
- Specifically made for real-time detection

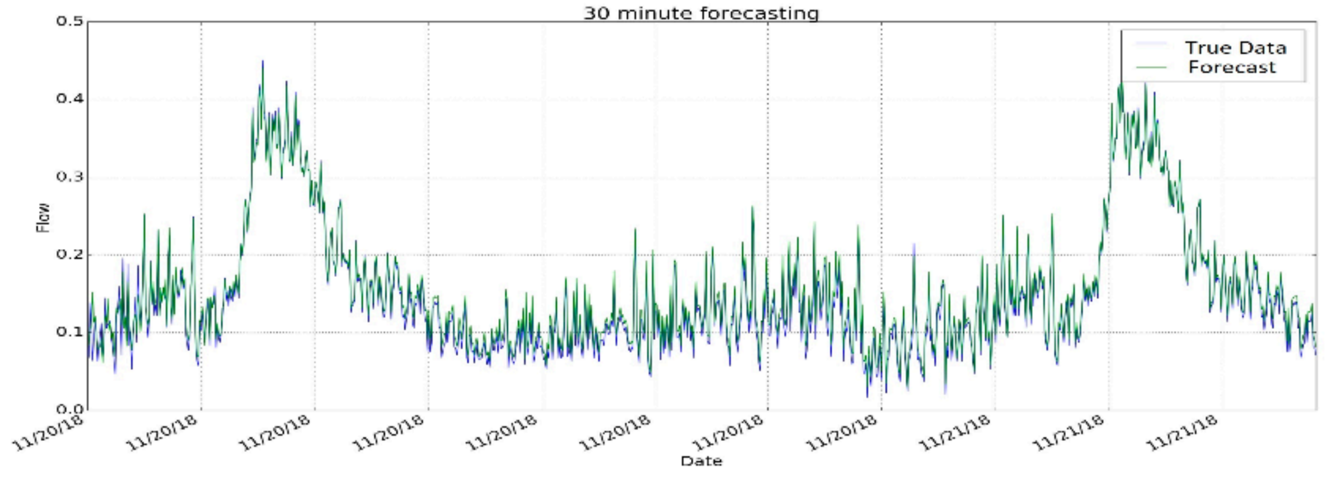
Previous work

- Traffic forecasting using different approaches…
- Works well, but can be improved
- Only temporal information
- Hard to benchmark (density algorithm)


Recurrent Neural Network (RNN)
Input
Hidden layers
Output
0
Long Short Term Memory (LSTM)
Input
Hidden layers
Output
3
Gated Recurrent Unit (GRU)
Input
Hidden layers
Output
2

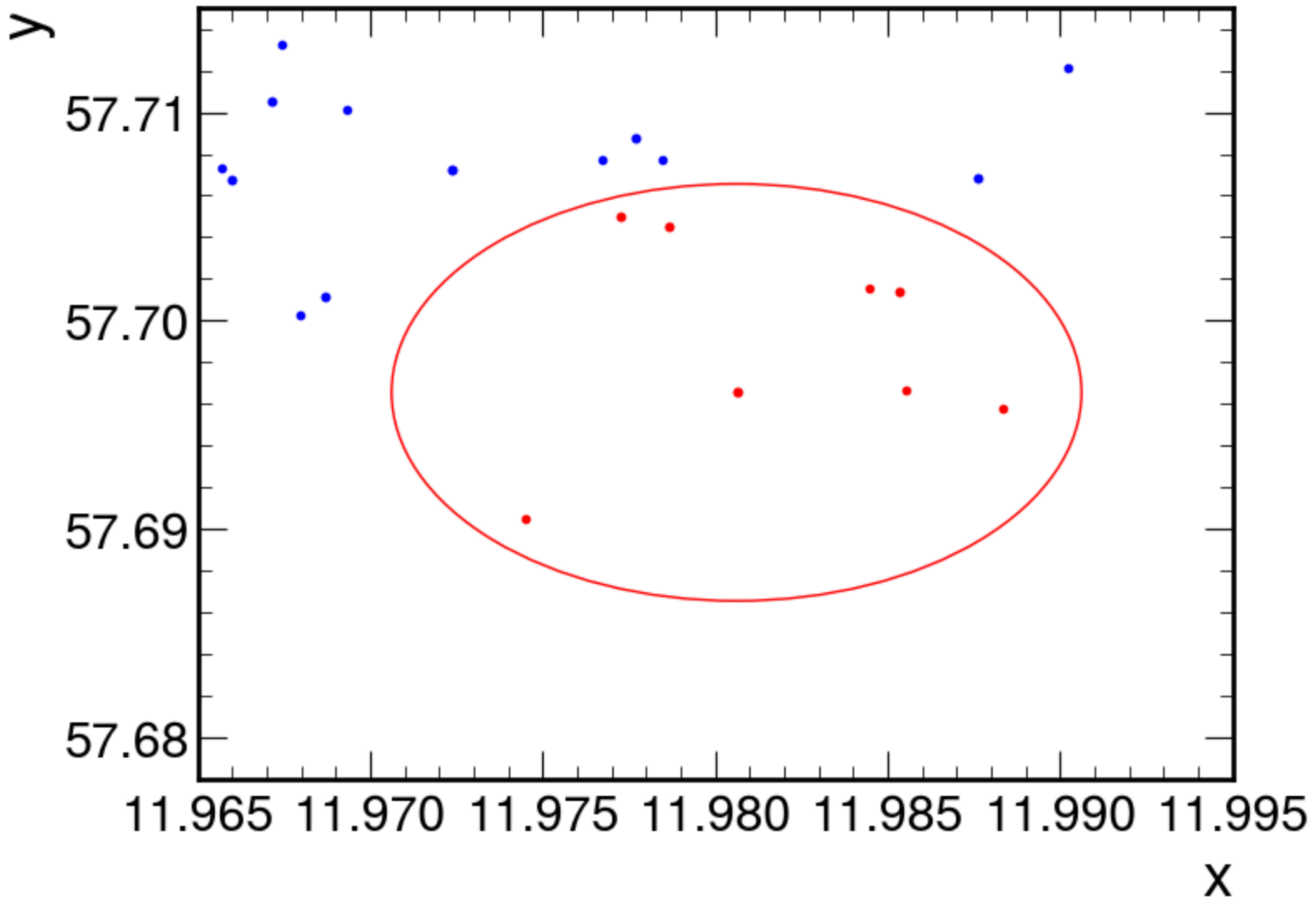


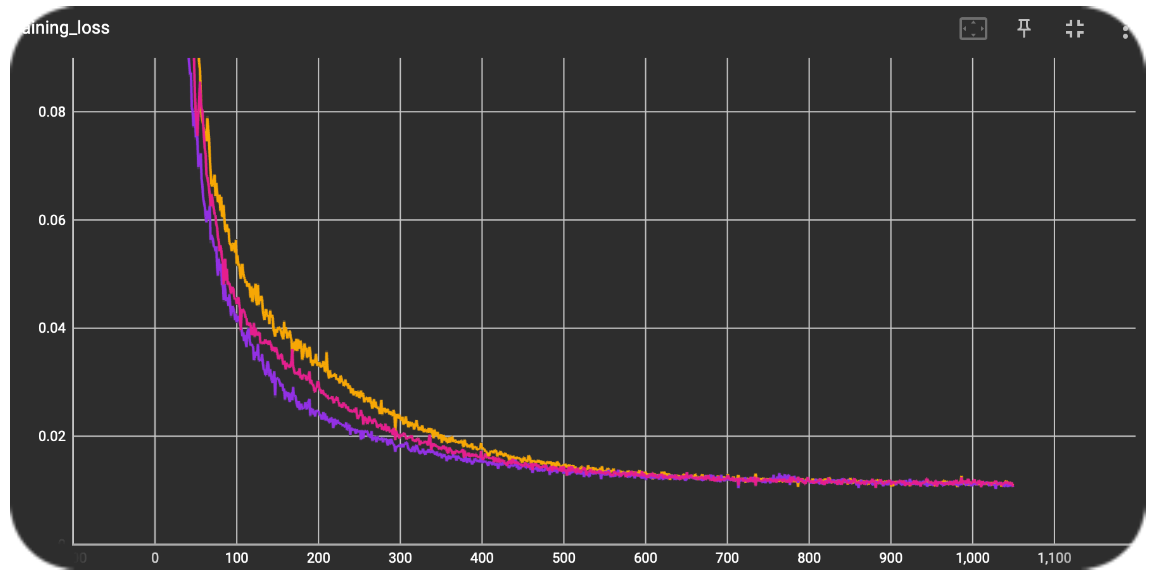




Reminding you..

- We want to use both the temporal and the spatial information
- Initially naïve assumptions:
    - Create the (symmetric) adjacency matrix based on some D_{min}
    - Cameras will use nearby nodes as spatial information

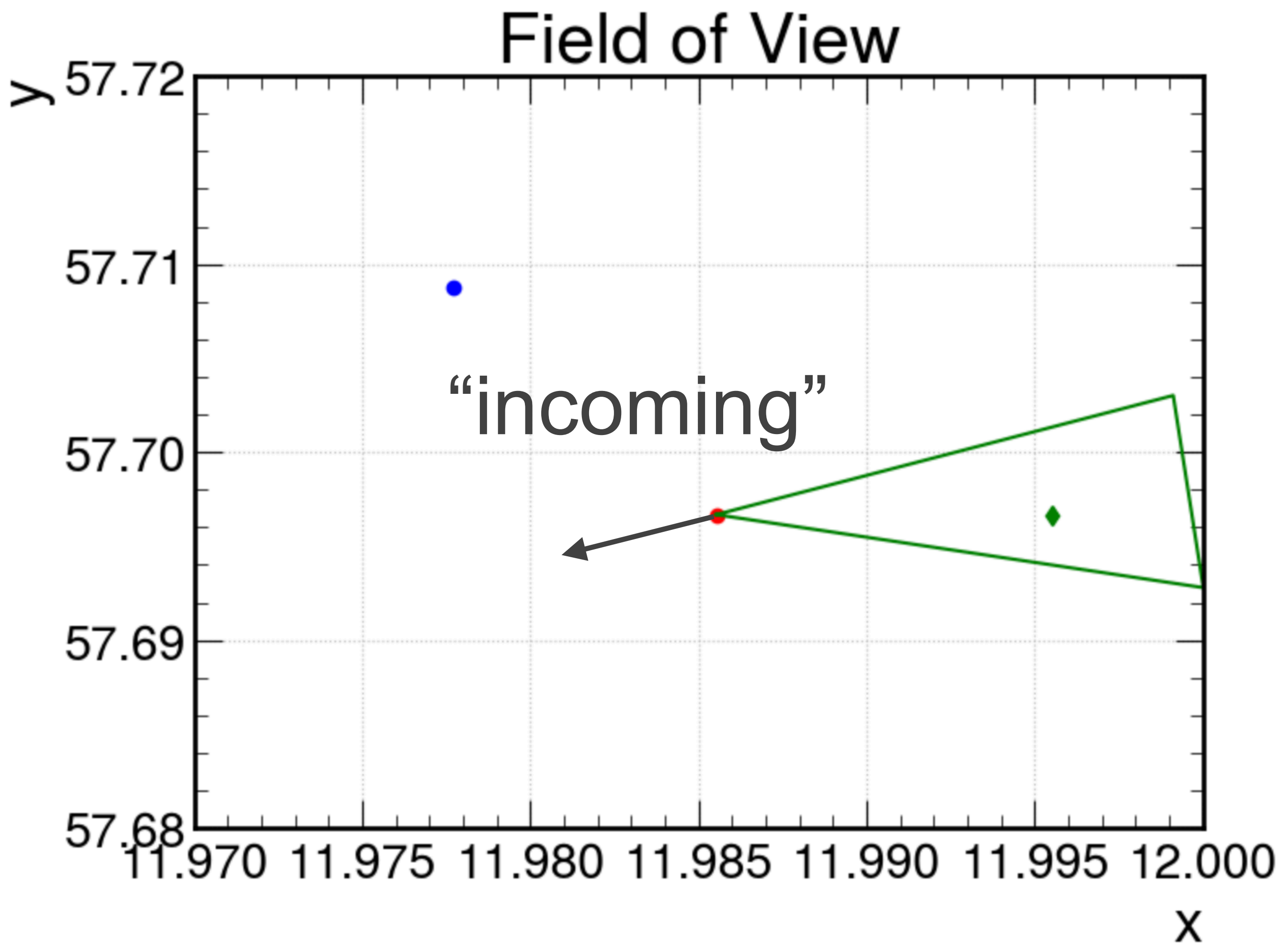


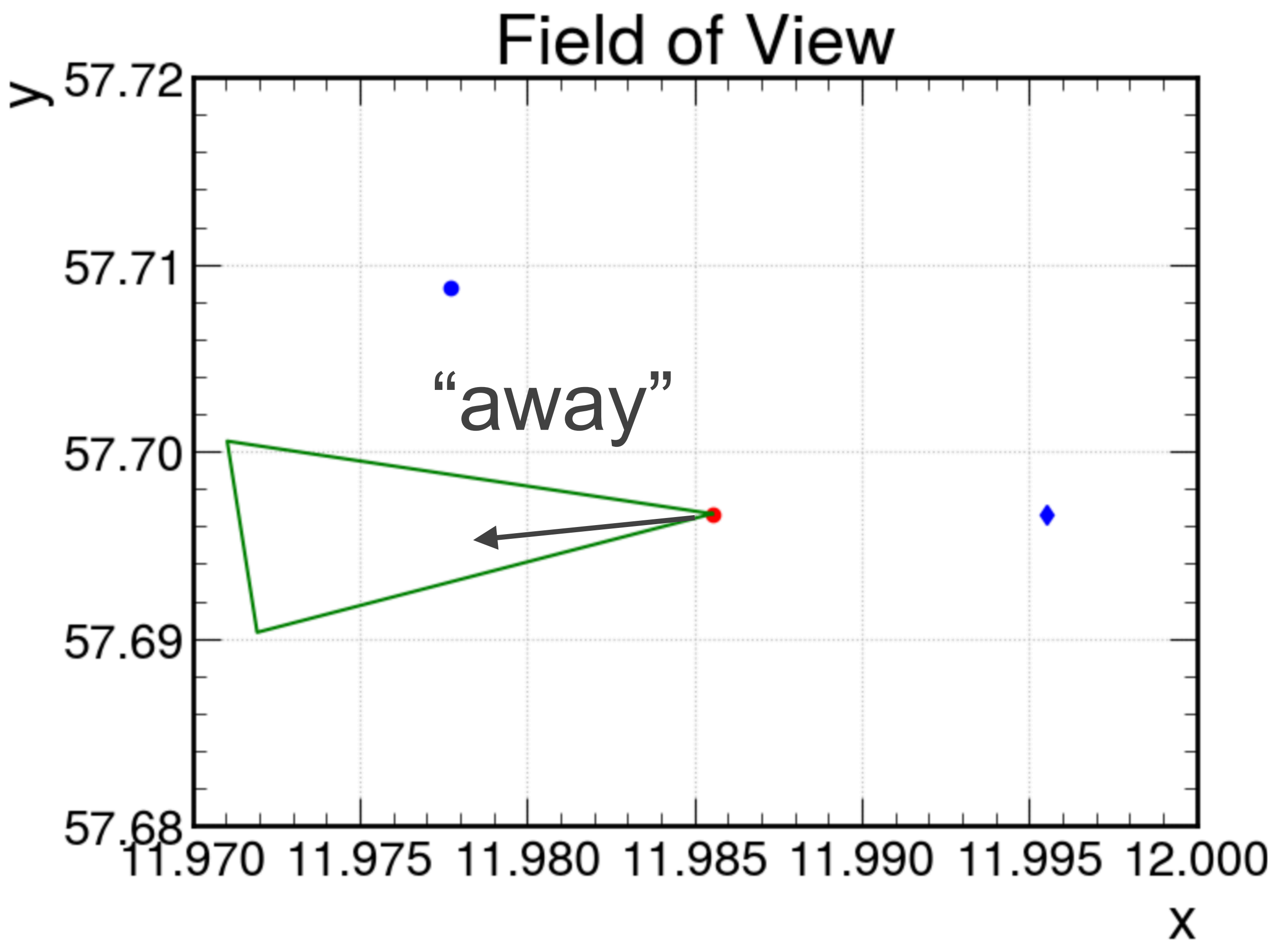


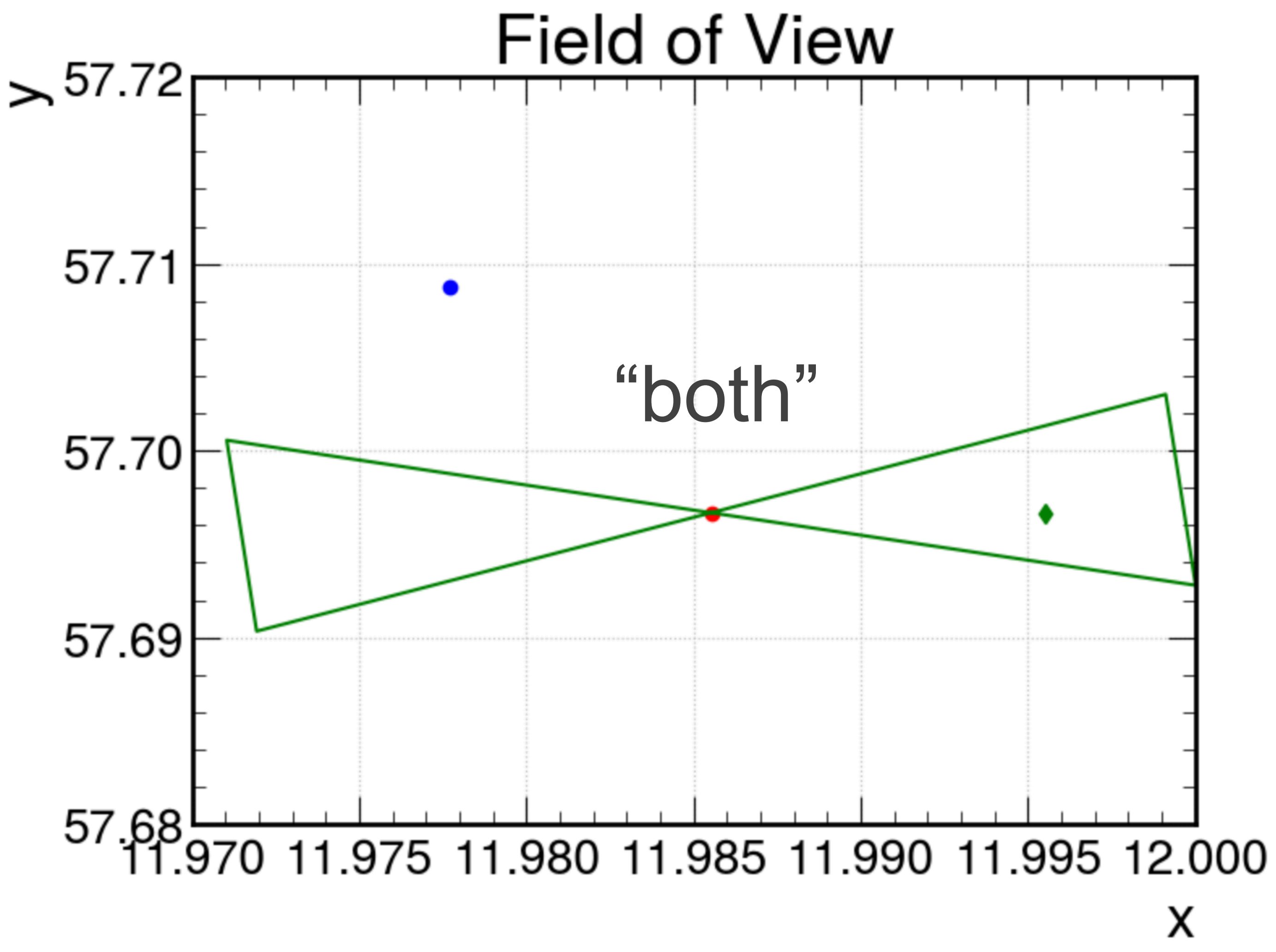
Göteborg
Örgryte

Adjacency modified

- Categorize directional traffic based on the cameras as either:
  - Incoming
  - Away
  - Both
- In short
  - Cameras gets a constrained FoV with a view cone
  - Increases spatial accuracy

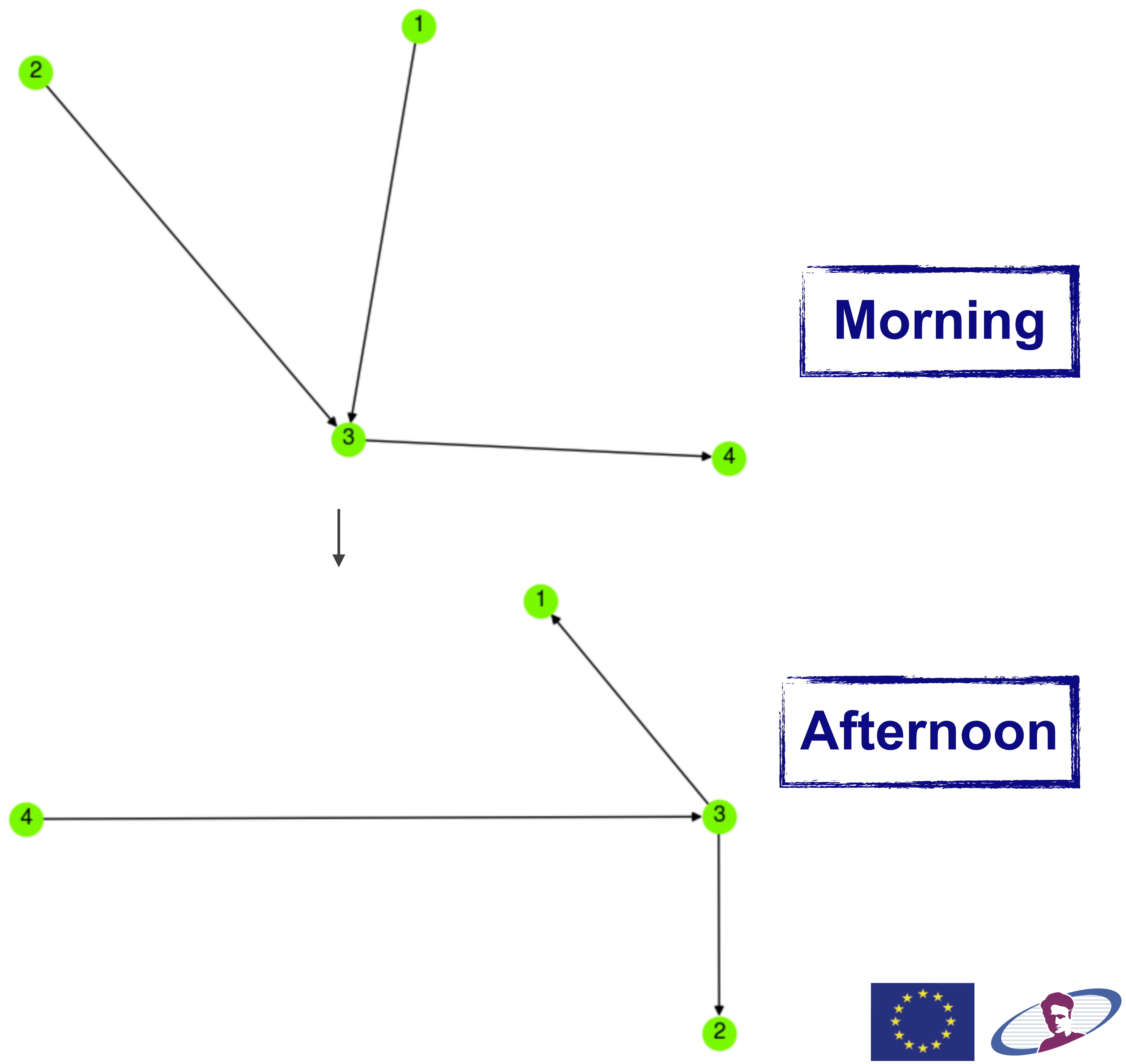






Time-dependent Laplacian

- In principle the traffic varies a lot by hour and day
- We wanted to create the adjacency matrix as a function of time of day
    - Dynamically using a neural network
    - Using input “flow” as a means to estimate it



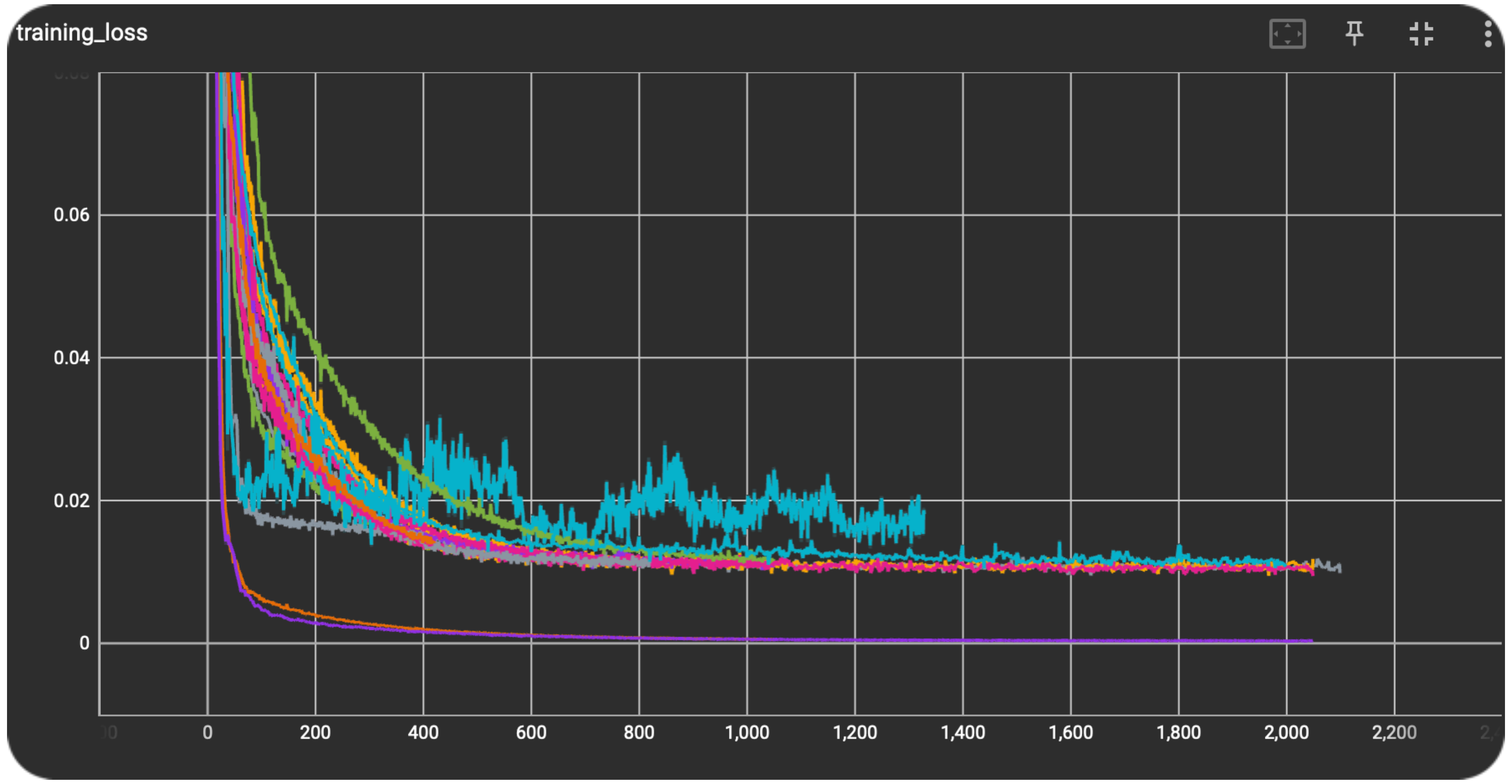
Data

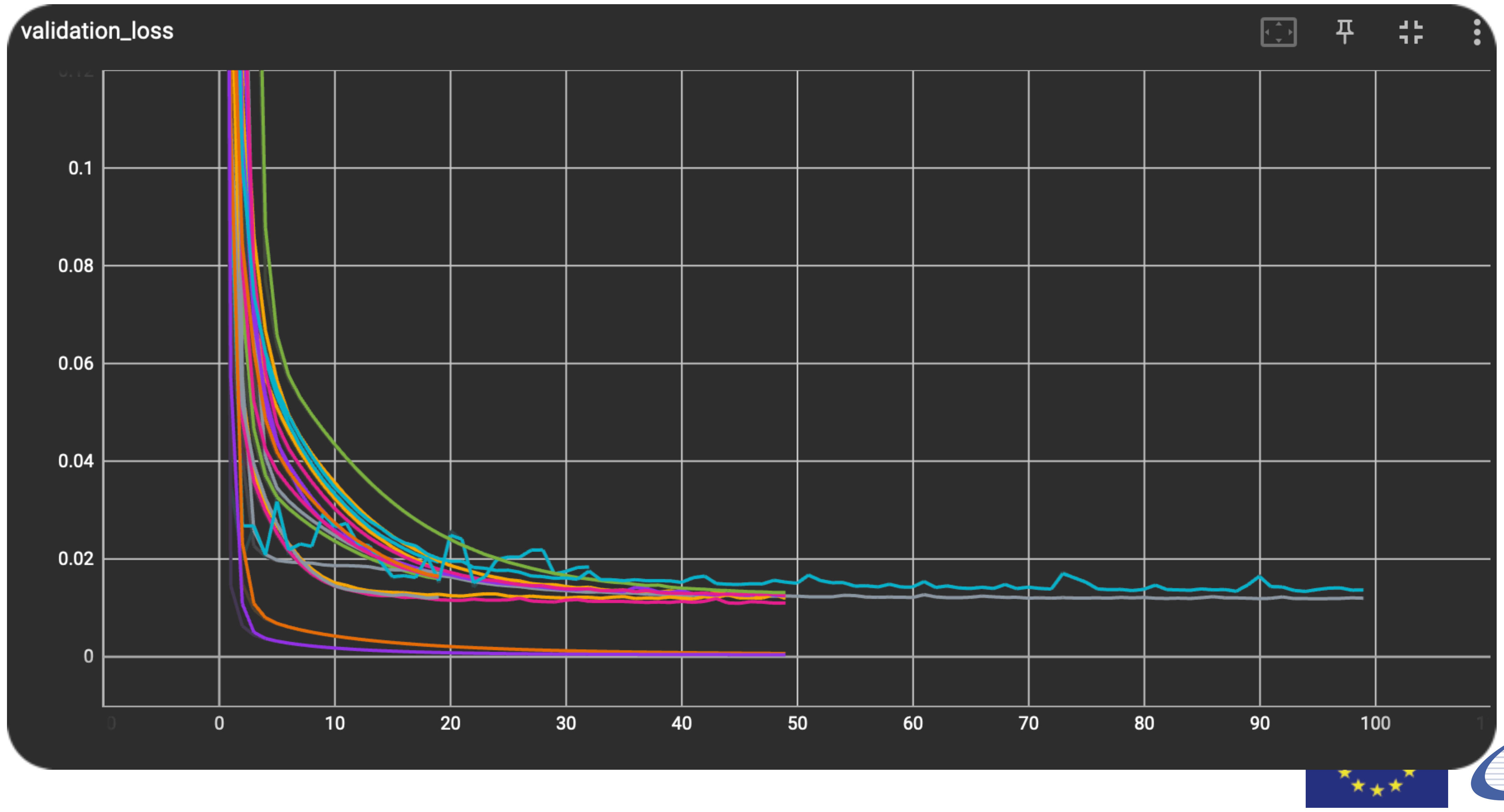
- We end up wth data from each camera and a relation between cameras
- Laplacian
  - (Dynamical one was still a WiP)
- Input data
  - [B,N,F,T] : Batch, Node, Feature, Time-step
  - Feature = 2 (3)
    - Density, time embedding

- Use 1 hour input to predict next hour
  - Several approaches

Learning anything?

- Short answer: yes
- Are the results good?





Results

- **Select few** results
- Randomly selected network
- Small scale prediction is not excellent, but does follow trend on larger scales
- Improved time-embedding and increased data size could improve results
- Similar to what was privously obtained

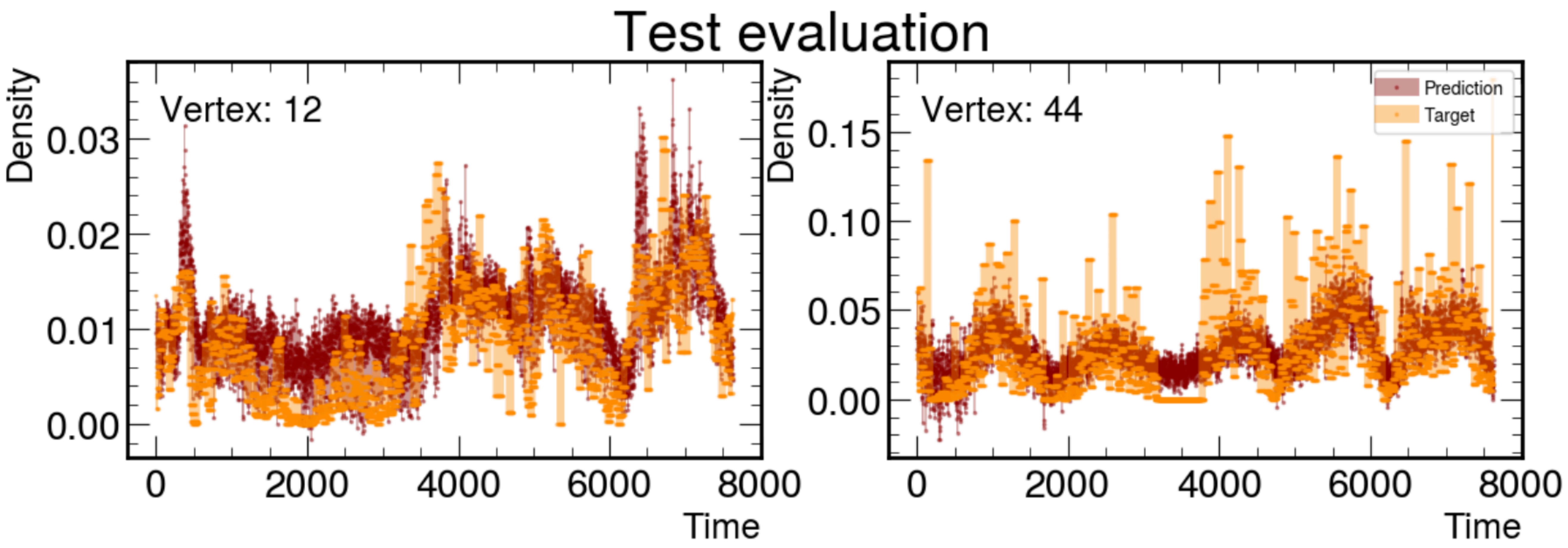
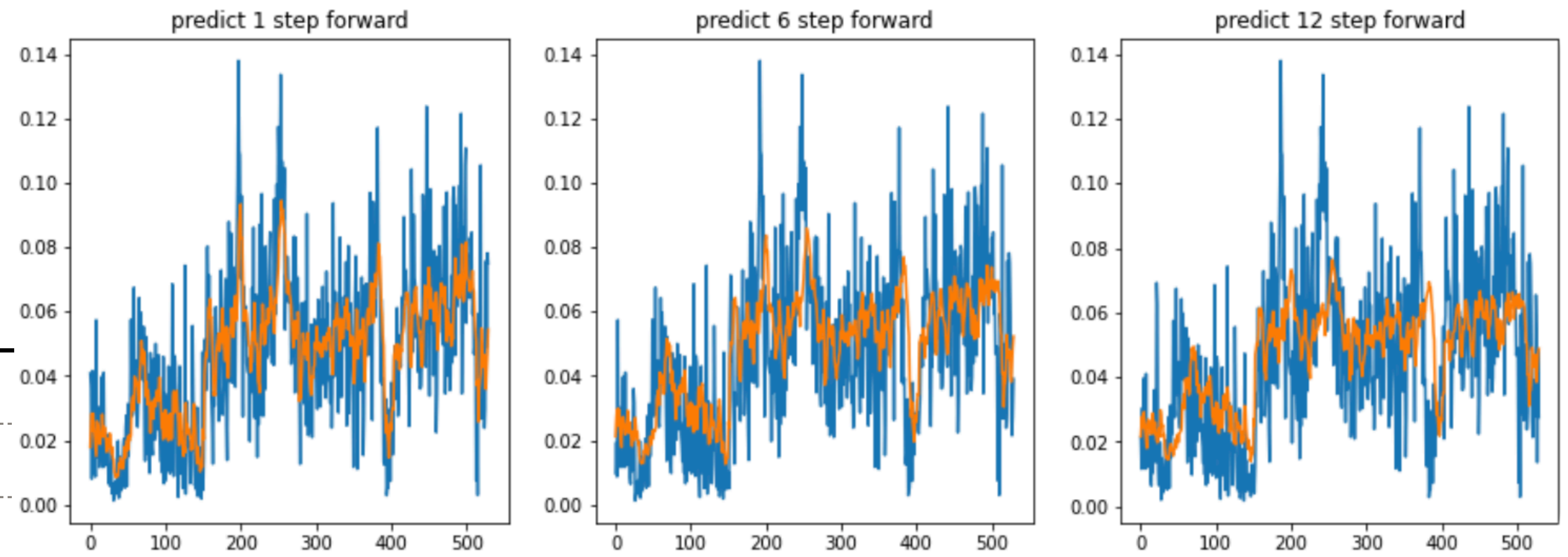

Test evaluation

Table 1

Data length (days)	Test MAPE
3	1.5206
7	1.1028
14	0.9926



Summary and outlook

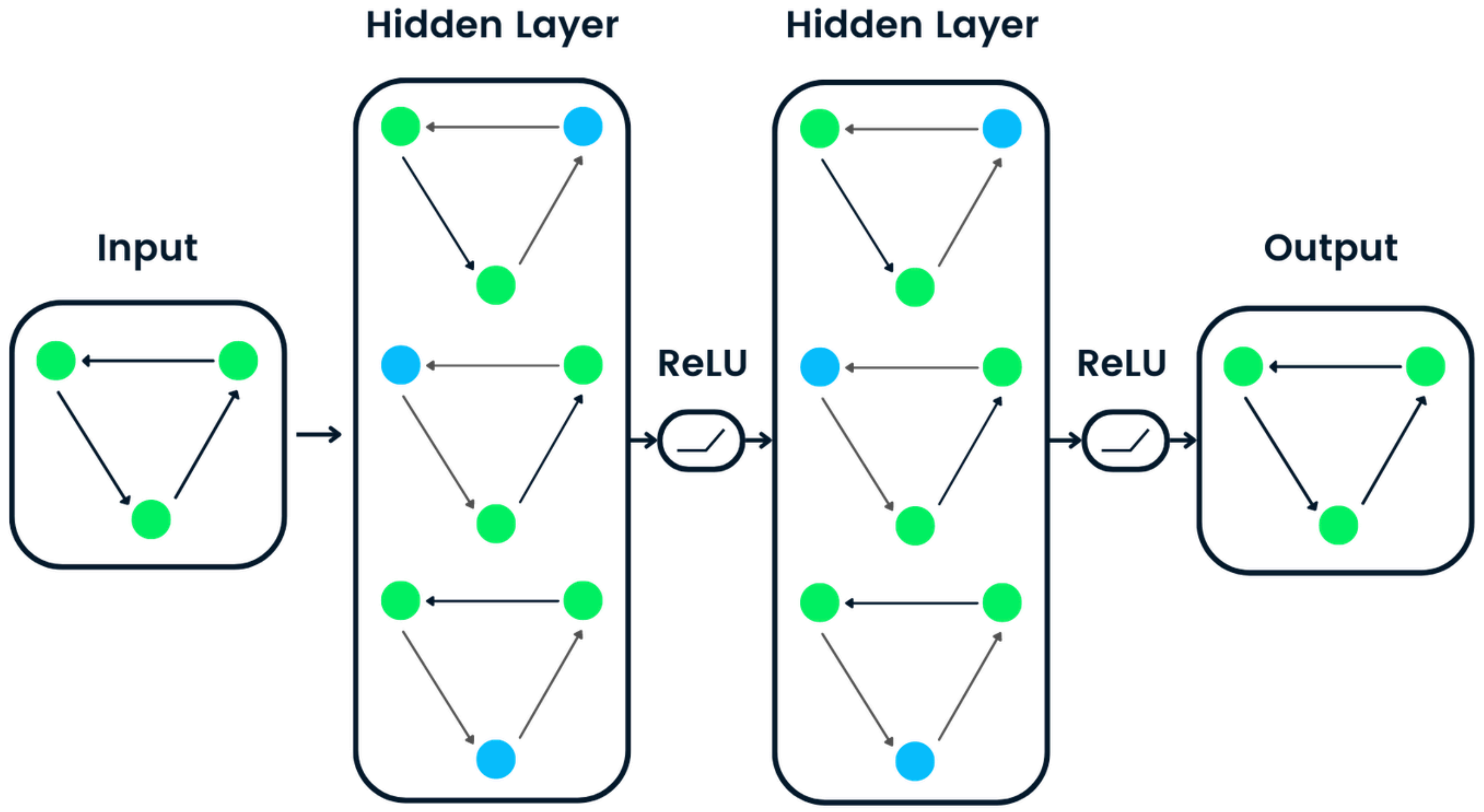
- Generalized density algorithm
- Improved Laplacian
- Used several GNNs to do traffic predictions
    - Comparing to baseline
    - Data not following daily pattern
        - Confusing

- Next?
    - Continue my jet analysis
    - Courses

Backup

.. short on GNN

- Real world data does not (always) live on a **grid**
- $G = (V, E)$
  - V: Vertices (nodes)
  - E: Edges (links)
    - Directional (non-directional)
- We use 5 different architectures
- More focus on the spatial information of the cameras



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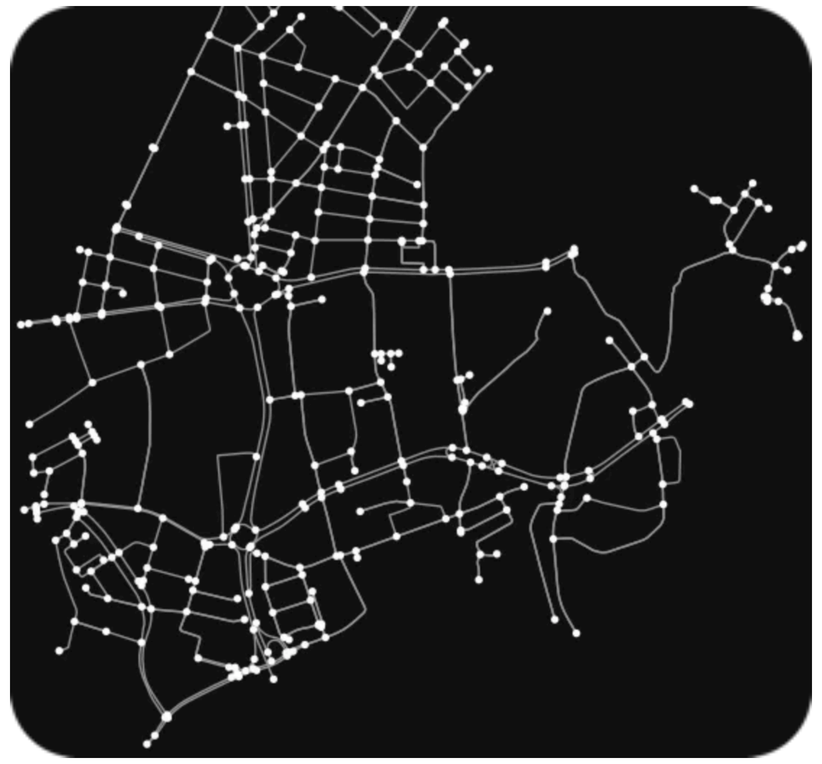

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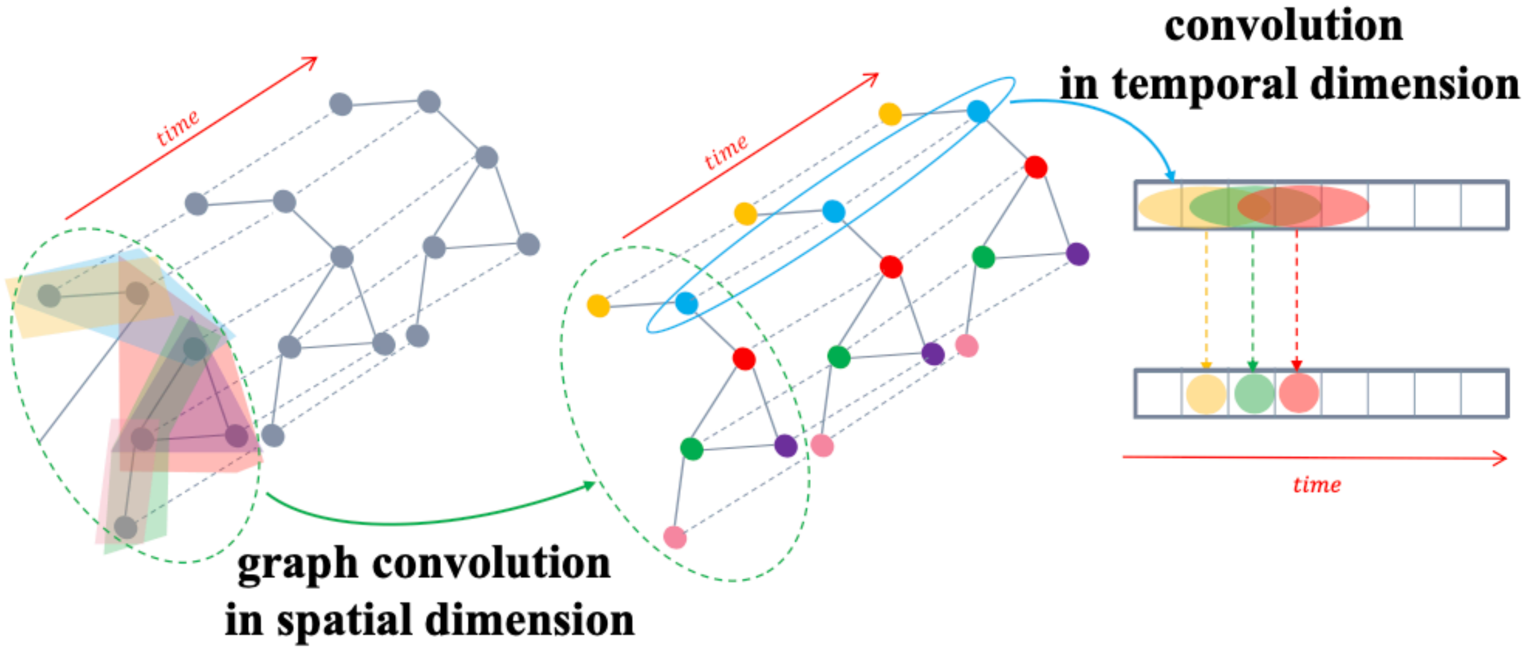
convolution
in temporal dimension
time
time
time
graph convolution
in spatial dimension