TRAFFIC4CAST

Measuring Traffic through Sparse and Partially Biased Observations: Learnings from Floating Car Data

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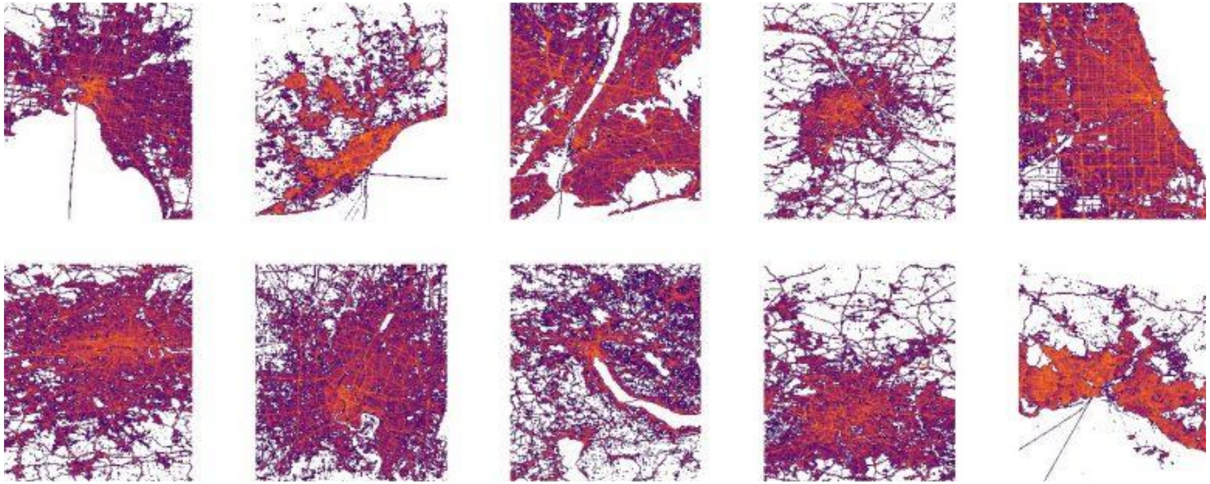
Overview

- Traffic4cast Data and Prediction Task
- Traffic4cast 2021: Tackling Domain Shift
- Big Picture: Spatio-Temporal Grid as General Framework towards Traffic Simulation
- Predicting Speeds from Sparse Loop Counter Data

Why traffic4cast?

Data driven traffic modelling

- Humans can "see" traffic from coarse data
  → Leverage recent deep learning advances
- Model traffic understanding in "purely data-driven" way
  → Benefit from industry-scale dataset derived from GPS (provided by HERE Technologies)



What does traffic4cast leverage?

Working towards a learned "digital twin" of city traffic

1. Modelling traffic evolution
   a. Traffic now-casting / short term prediction (aka "a better traffic map")
   b. Transferability of learned geo-spatial processes (see also Weather4cast)
2. Unblocking and liberating traffic based services
   a. Usage of alternative data sources
   b. Fast, cheap and accurate prediction of travel times (ETA) for fleet and delivery
   c. Traffic prediction for specific transport modes (e.g. 2-wheeler or trucks)
3. City and traffic planning
   a. Learned digital twin also encodes traffic rules an expert would not know of (bias)
   b. "multi-modal" in the sense that it just depends on the data (moving entities)

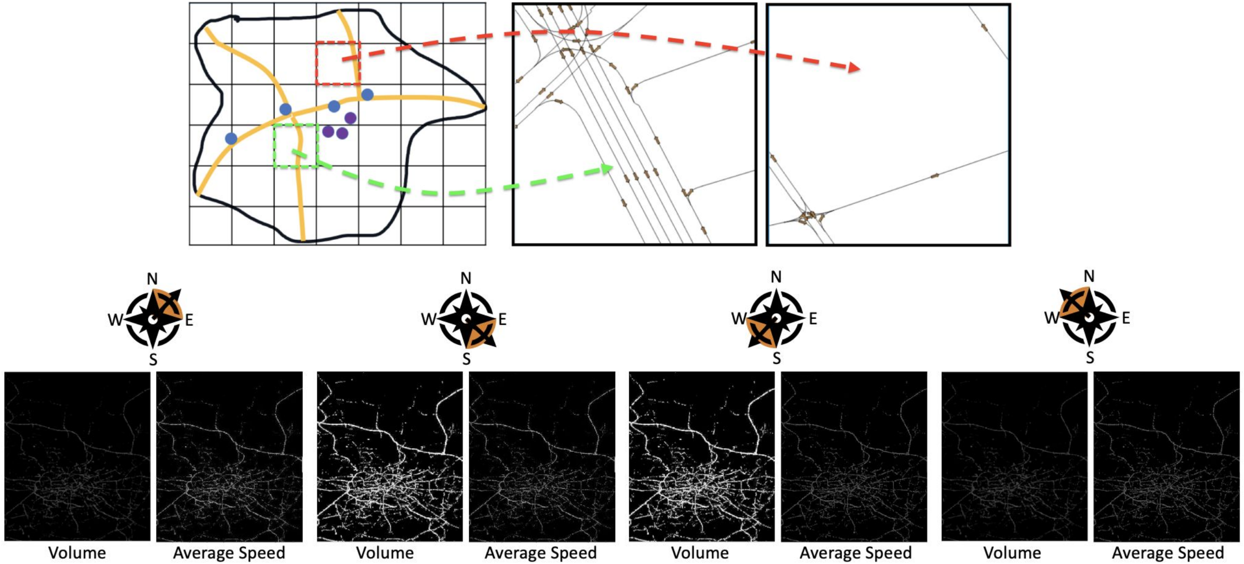
Traffic Data Sources

Category	Source	Data	Spatial res.	Spatial cov.	Temp. res.	Temp. cov.	Bias
Floating Car/Vehicle Data (FCV/FVD)	GPS probes	density/flow/speed	High to Mid (5-100m)	Full (apart from tunnels?)	High to Mid (1-5min)	Full	Fleets (delivery, working hours, loading / hop-off)
	Mobile Phone	general density / flow	Low (100m-2km)	Full	High	Full	
Stationary Sensors	Loop-counters and other sensors	density/flow/speed	High	Sparse (100-4K / city)	High to Mid (1-60min)	Full	–
	Traffic cameras	density/flow/speed	High	Sparse	High	Full	–
	Pollution sensors	proxy for density					
Overhead	Satellite imagery	density/flow/speed	High (1m) to Mid (100m)	Inverse corr. temp. cov.	Low	Low (max every 4h)	–
	UAV / Drones	density/flow/speed	High (0.1-1m)	Sparse	High	Sparse	–
	Radar	density/flow/speed	High (25cm)	Inverse corr. temp. cov.	Low	Low (max every 4h)	–
	Geo-stationary satellites	RGB/IR, proxy for density	Low (500m-2km)	Full?	Mid (~2min)	Full	–
Synthetic	Simulators	All	High	Full	High	Full	Synthetic (Imitiation Learning / PoC)

Source: own, unpublished.

Traffic4cast Data and Prediction Task

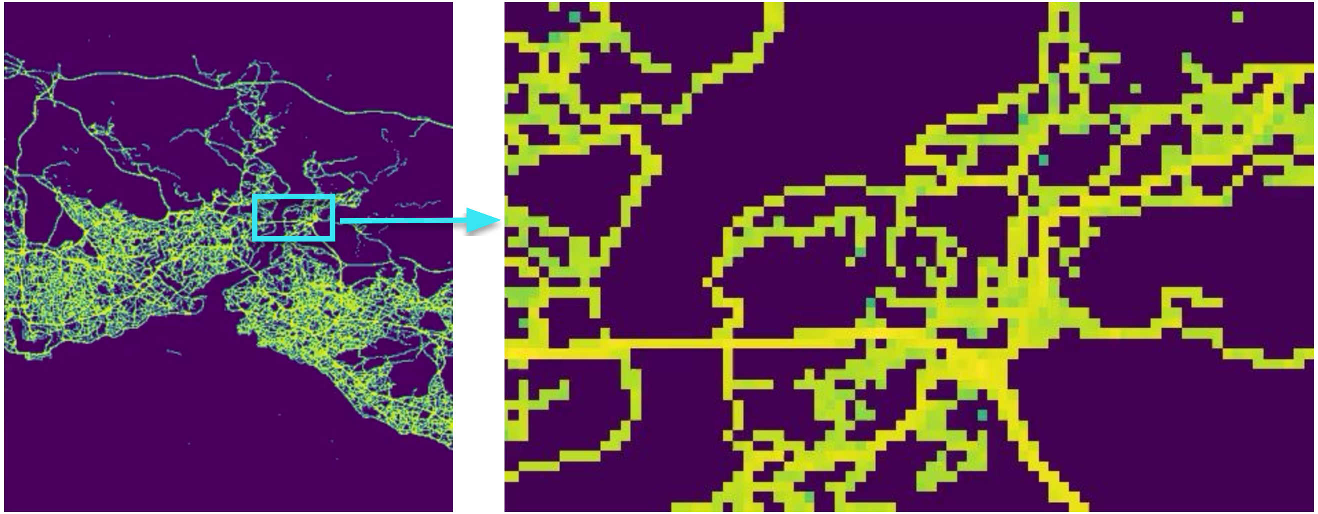
Dynamic Data Encoding



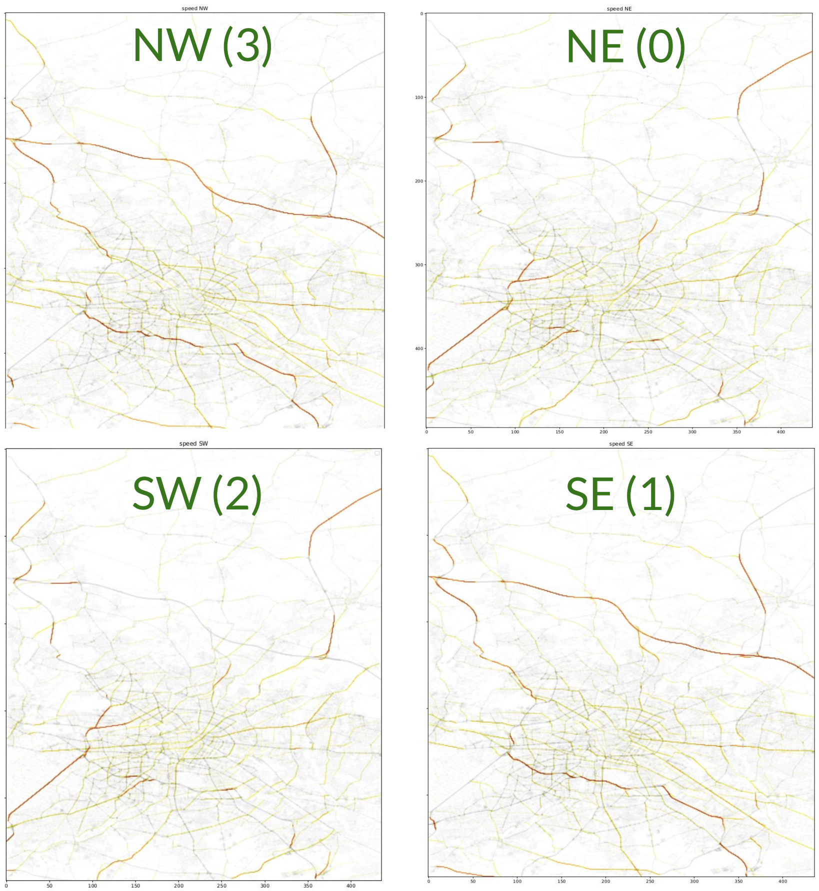
- GPS Probe data (provided by HERE Technologies)
- Aggregated into Traffic Map Movies (288 frames per day, volume and speed per main heading)

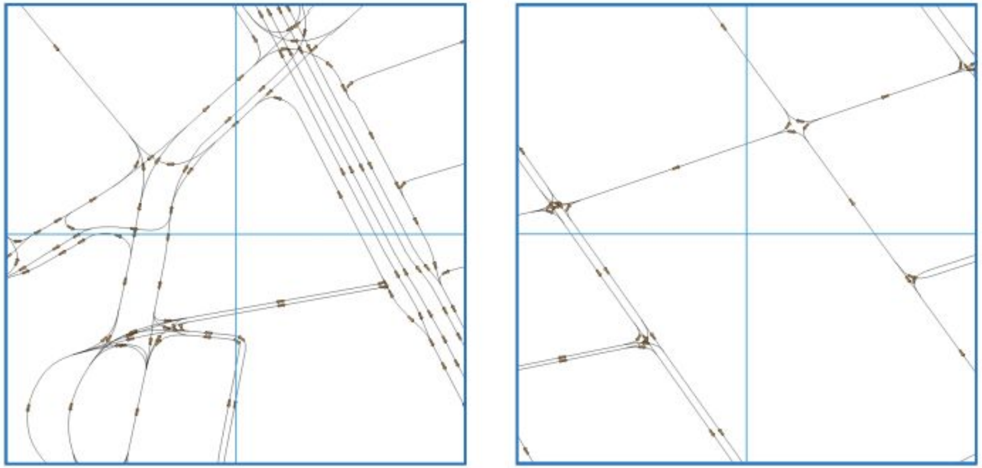
IARAI Source: Neun, Eichenberger et al. T4c at NeurIPS 2021 Competition Design and Data – Supplementary Reference Material. arXiv 2022, forthc.

Traffic Map Movie



What’s in a Cell?

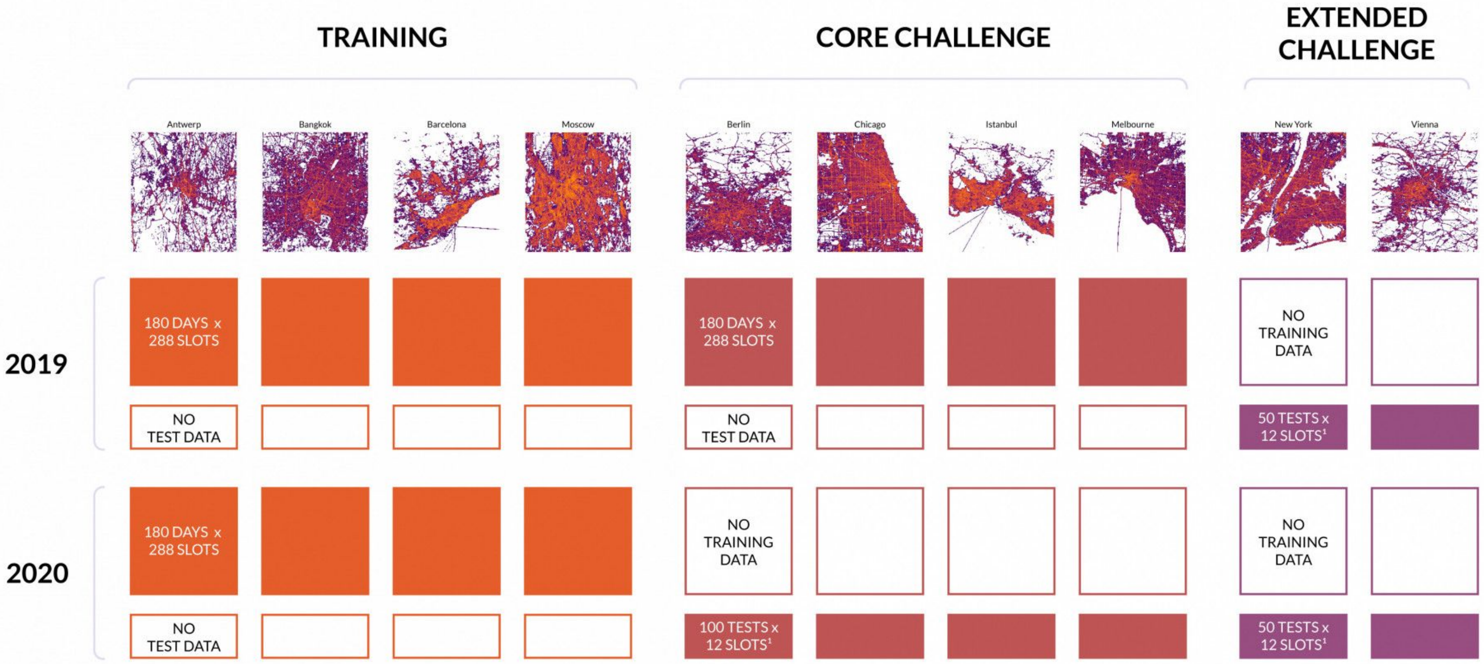




Source: Neun, Eichenberger et al. T4c at NeurIPS 2021 Competition Design and Data – Supplementary Reference Material. arXiv 2022, forthc.

Traffic4cast 2021: Tackling Domain Shifts

Traffic Map Movie Forecasting NeurIPS 2021



[1]Given one hour of data in 12 slots of 5min, predict the next 5, 10, 15, 30, 45 and 60 lead times.

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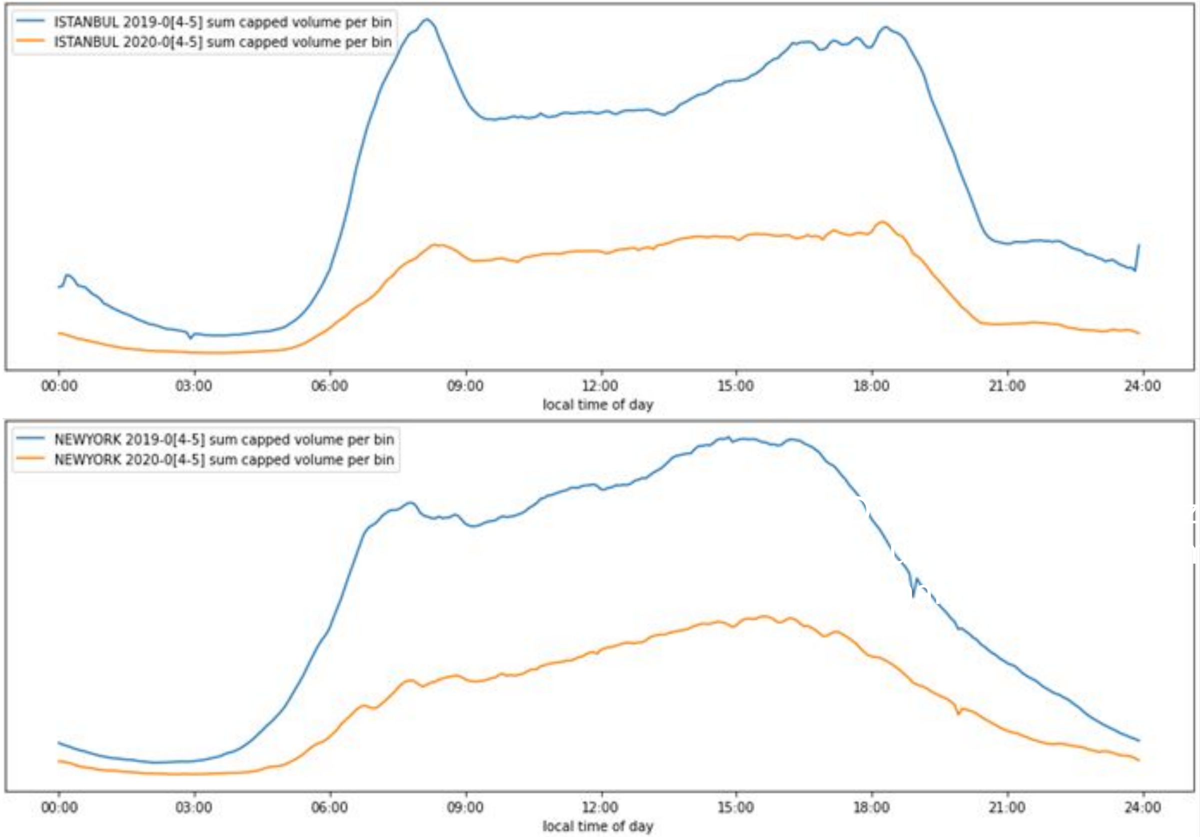
Source: Eichenberger, Neun et al. Proceedings of the NeurIPS 2021 Competition Track. PMLR, 2022 (forthcoming).

Core Challenge: Robustness during Paradigm Change



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Strategies for Temporal and Spatio-Temporal Domain-Shift

T*: data from all training cities
C*: training data from all core competition cities

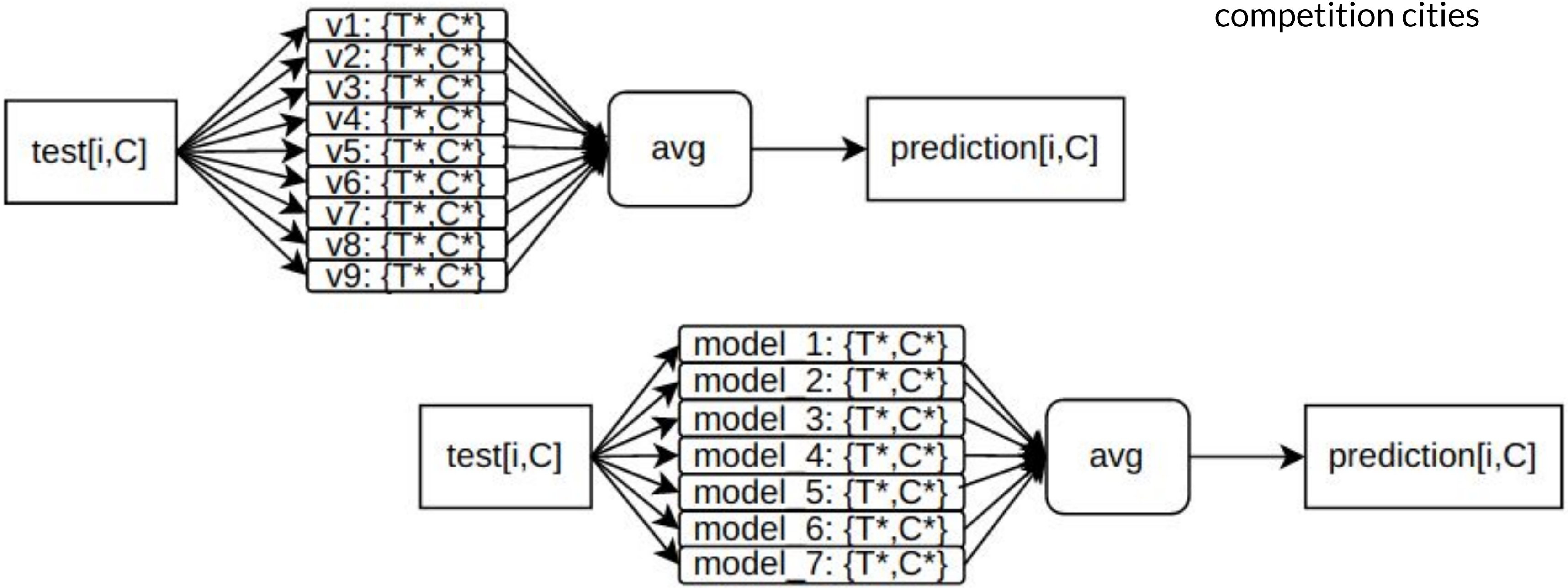

Figure 2: Inference oahciy (Lu, 2021) (left: core competition, right: extended competition).

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Source: Eichenberger, Neun et al. Proceedings of the NeurIPS 2021 Competition Track. PMLR, 2022 (forthcoming).

Strategies for Temporal and Spatio-Temporal Domain-Shift

Team, rank (core/ext), approach	road graph, time-of-day, day-of-week[a]	models trained p. city[b]	#models trained[c]	Training datasets[d]	$\sum$ #params core / ext [e]	mask[f]
oahciy (1/2) U-Net + multi-task learning (Lu, 2021)	road graph (concat)	no	9 / 7	(9/7)×{T*,C*}	1710.2M / 17.1M	–
sungbin (2/1) U-Net Ensemble (Choi, 2021)	road graph (concat)	in two U-Nets	16/4	2×{C[1-4]}; {T1,C[1-4]}; 4× {T*,C*} / 4× {T*,C*}	123.6M / 33.9M	–
sevakon (3/–) U-Net with Temporal Domain Adaptation (Konyakhin et al., 2021)	no	yes	11/–	3×{C1}; 2×{C2}; 3×{C3}; 3×{C4}	342.0M / –	city (train/test data)
nina (6/3) U-Net++ on patches (Wiedemann and Raubal, 2021)	no	no	1=1	{T*,C*}	36.7M / 36.7M	–
ai4ex (4/6) SWIN-Transformer (Bojesomo et al., 2021)	no	no	1=1	{C*}	141.9M / 141.9M	–
dninja (7/4) Graph-based U-Net (Hermes et al., 2022)	road graph, time-of-day, day-of-week	no	1=1	{T*,C*}	5.8M / 5.8M	by GNN
resuly (5/–) 3DResNet, Sparse-UNet (Wang et al., 2021a)	road graph	no	1/1	{T*, C*}	17.3M / 43k	test (test data)
jaysantokhi (8/5) Dual-Encoding U-Net (Santokhi et al., 2021)	no	after pre-training	4/4	{T*,C[1-4]}	1.0M / 0.3M	city (test data)

Source: Eichenberger, Neun et al. Proceedings of the NeurIPS 2021 Competition Track. PMLR, 2022 (forthcoming).

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Where was the Competition Won?

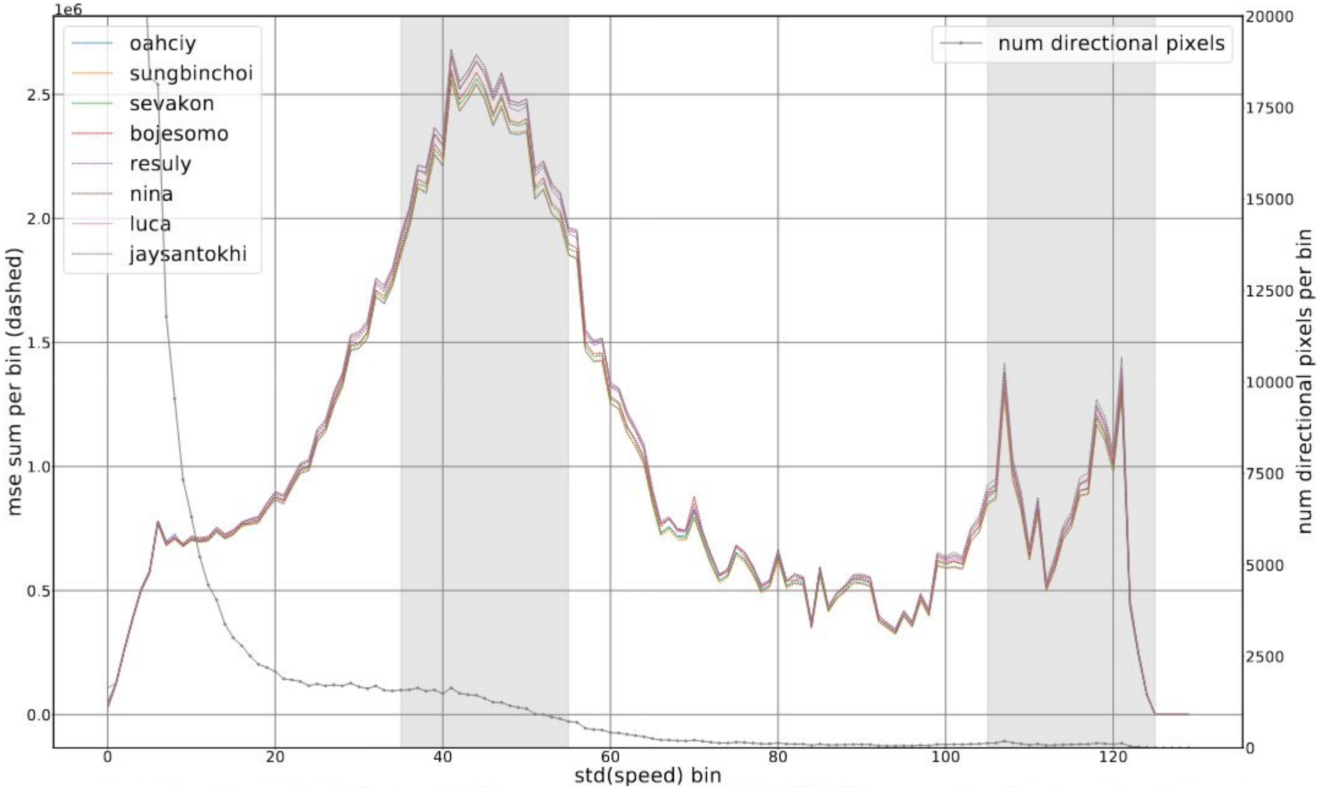

Figure 9: Relating MSE to std for speeds in BERLIN core: distribution of std among oriented pixels and average MSE (top); summed MSE and cumulated summed MSE (bottom). The shaded gray areas highlights the two critical speed std ranges.

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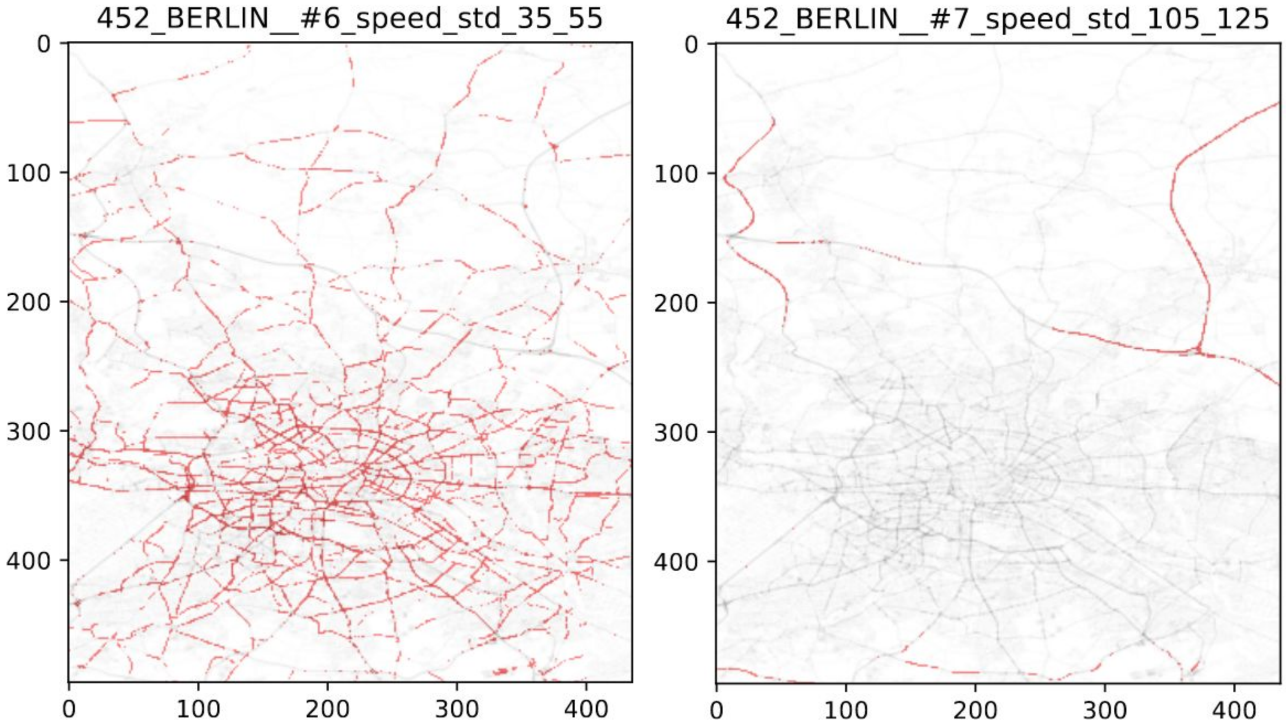

Figure 18: Locations (red) of the 35–55 (left) and 105–125 (right) speed std bands

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Source: Eichenberger, Neun et al. Proceedings of the NeurIPS 2021 Competition Track. PMLR, 2022 (forthcoming).

Big Picture: Spatio-Temporal Grid as General Framework towards Traffic Simulation

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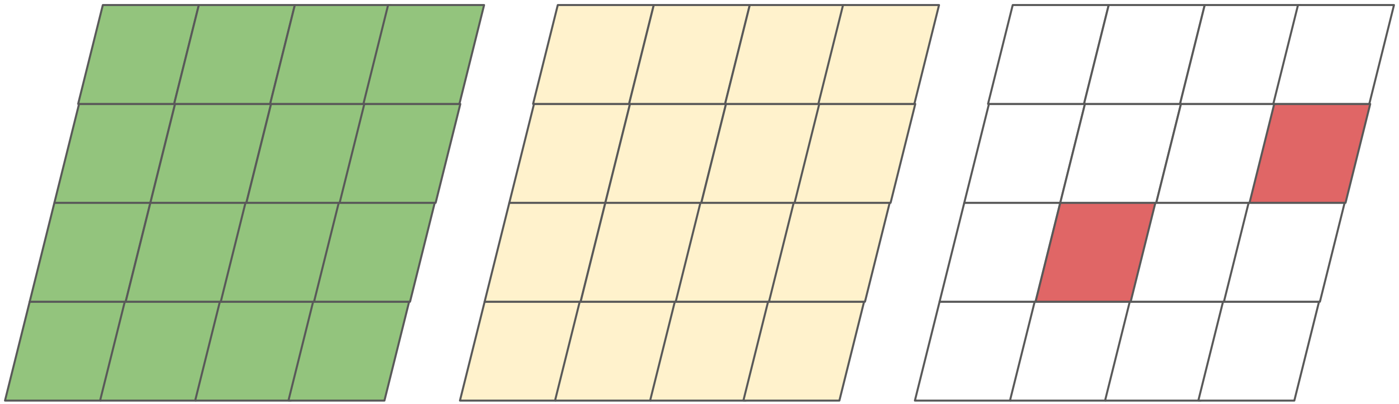
Source: own, unpublished.

Spatio-Temporal Grid as a General Framework



Satellite or UAV counts
→ temporally sparse

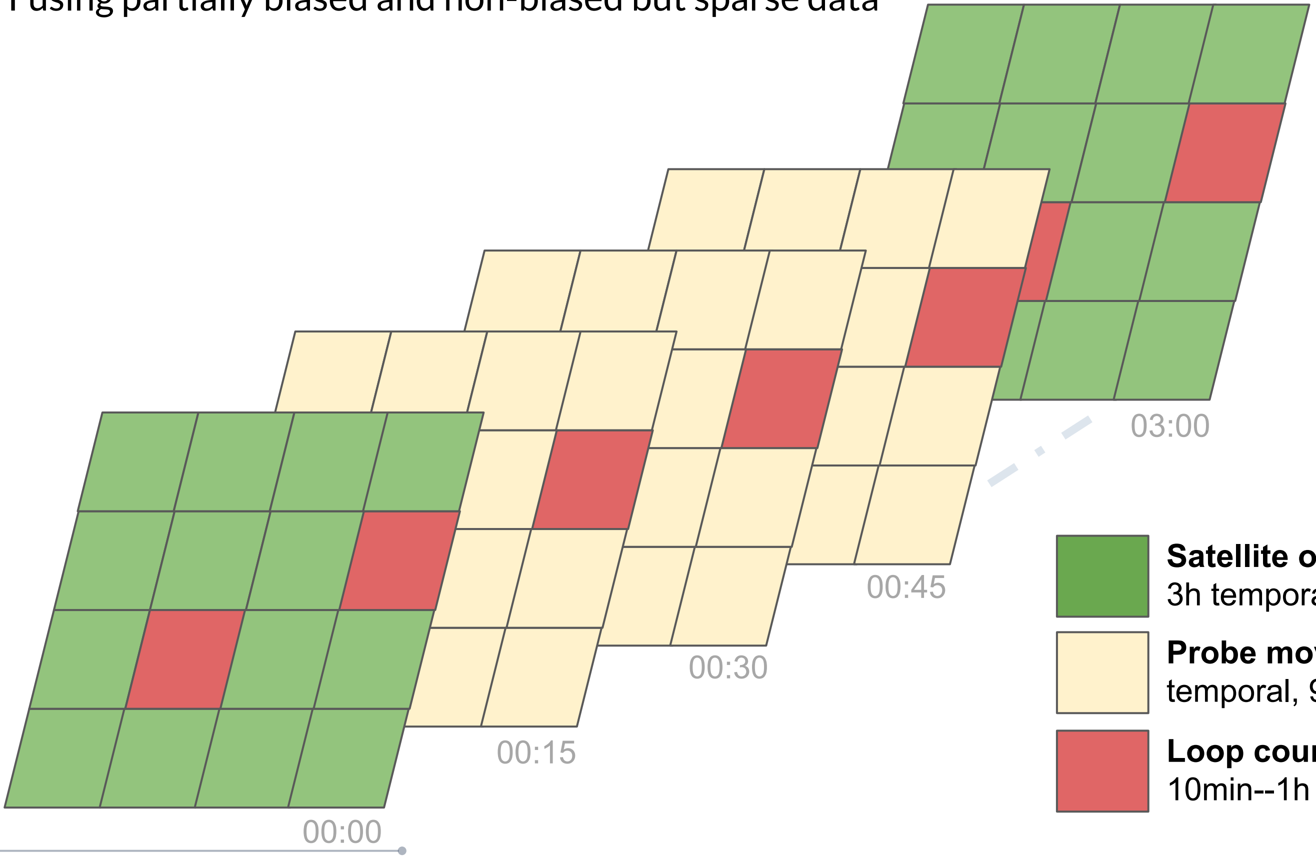
Probe movies
→ volume sparse

Loop counter or camera
→ spatially sparse

Source: own, unpublished.

Spatio-Temporal Grid as a General Framework

Fusing partially biased and non-biased but sparse data



“Completion game” combining traffic state information from satellite/UAV, loop-counter and floating vehicle data

Satellite or UAV counts (100% volume, 3h temporal, 99% spatial cells)

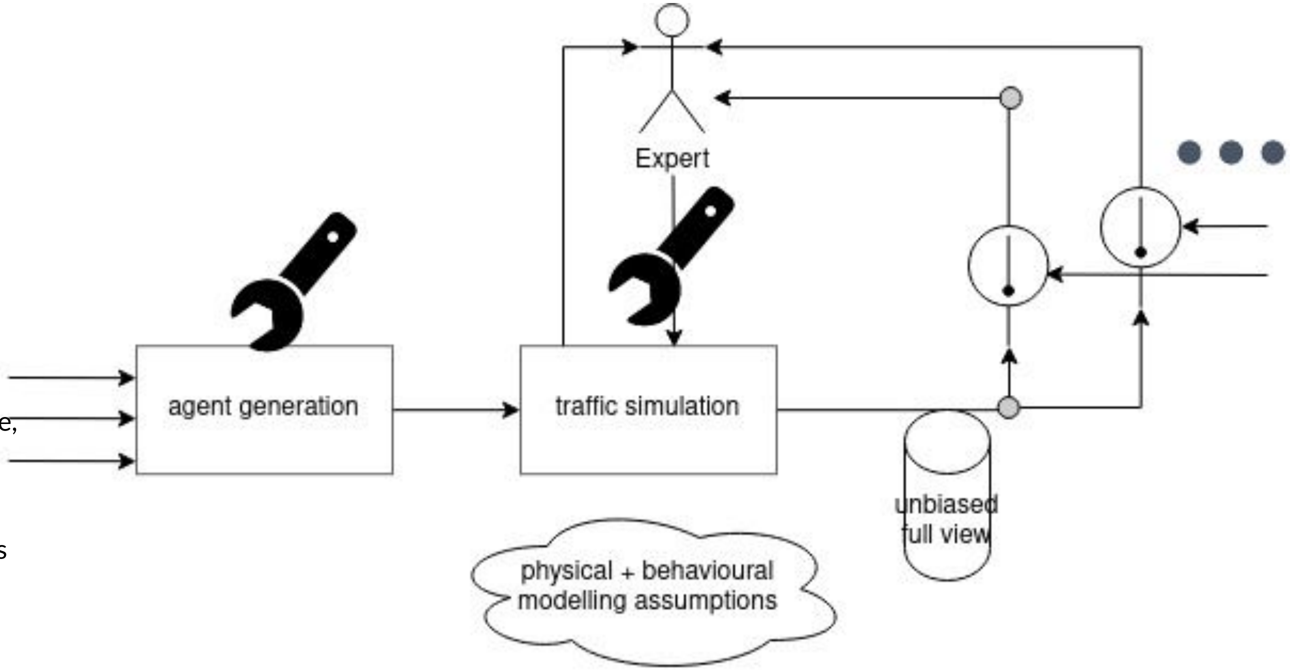
Probe movies (0.1-2% volume, 5min temporal, 99% spatial cells)

Loop counter or camera (100% volume, 10min--1h temporal, 0.1% spatial cells)

Source: own, unpublished.

Model-Driven (Expert) Calibration/Simulation

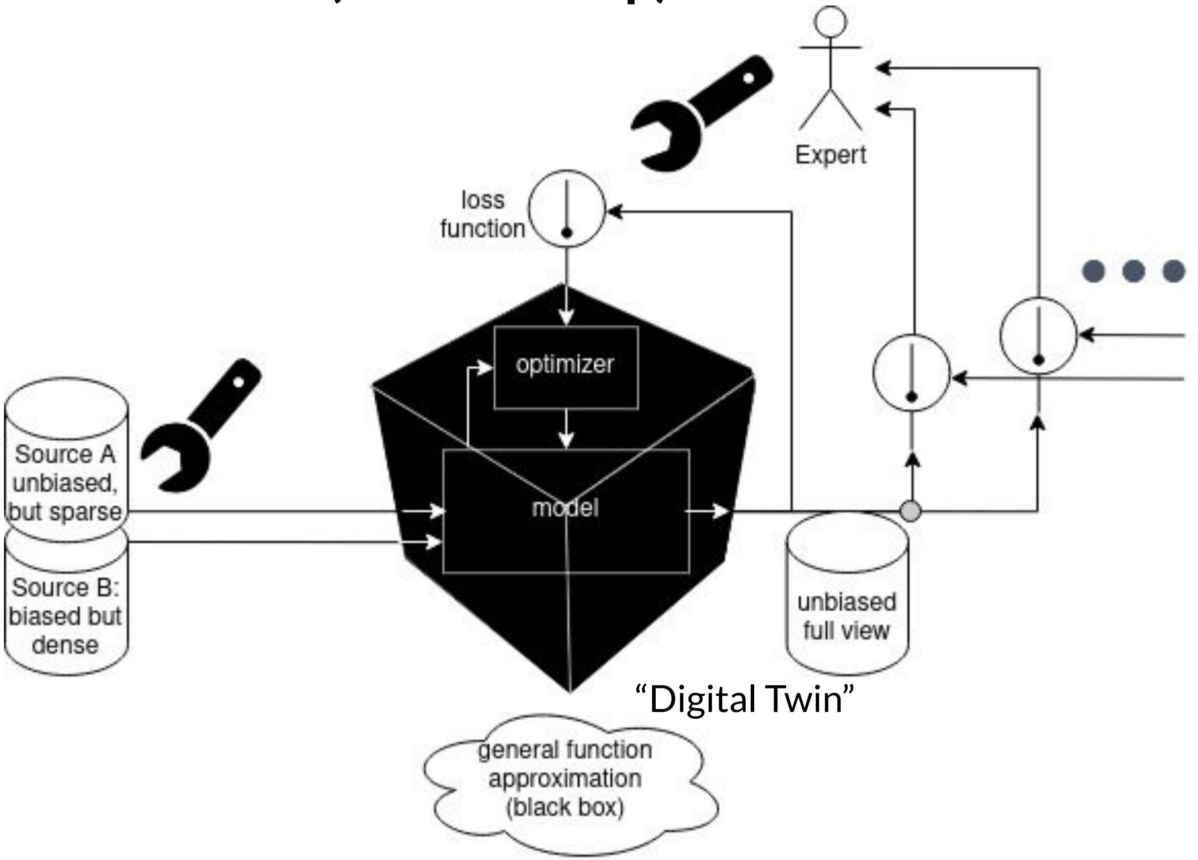
- census data
- activity locations (work, leisure, mobility)
- street map data
- pt timetables
- survey data



domain stats:
- traffic counters (hourly mean and individual stations)
- mode shares
- trip stats like
  - beeline distances
  - duration
  - departure time distributions,
  - shares of activity types

Source: own, unpublished.

Data-Driven (Closed-Loop) Calibration/Simulation



- Cross-process:
  - traffic counters
  - satellite…
- Domain stats
  - speed distribution
  - traffic state classification?
  - mode shares?
  - ETAs?
  - trip-based distributions?

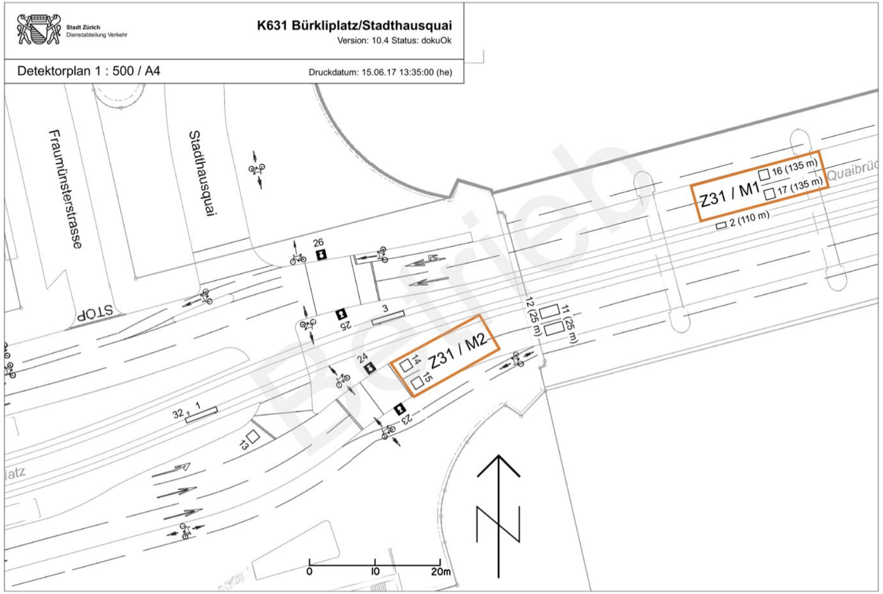
Standard catalogue like https://www.climdex.org/learn/indices/ for climate research?

Source: own, unpublished.

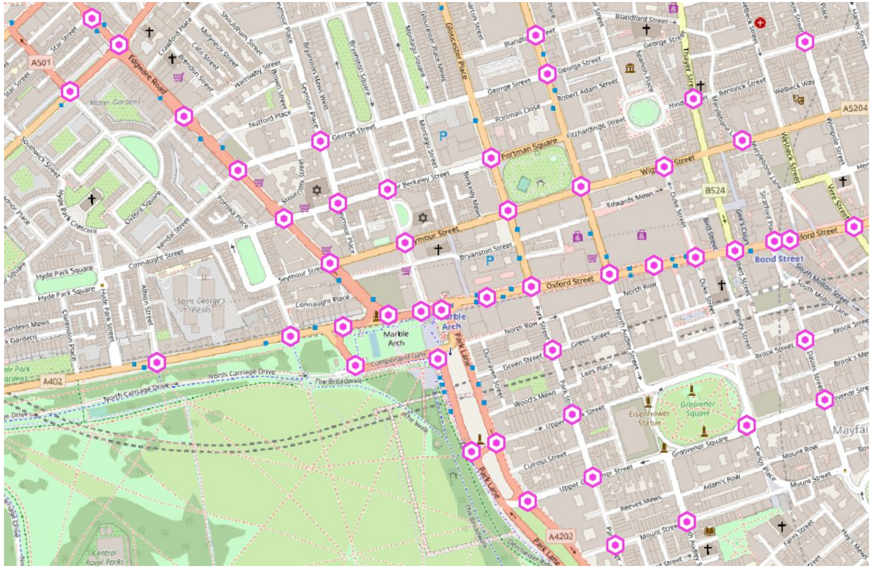
Predicting Speed from Sparse Loop Counter Data

Loop Counter Data

Traffic sensors in roads



Typical sensor placement (Zurich)



Distribution of a large sensor network (London)

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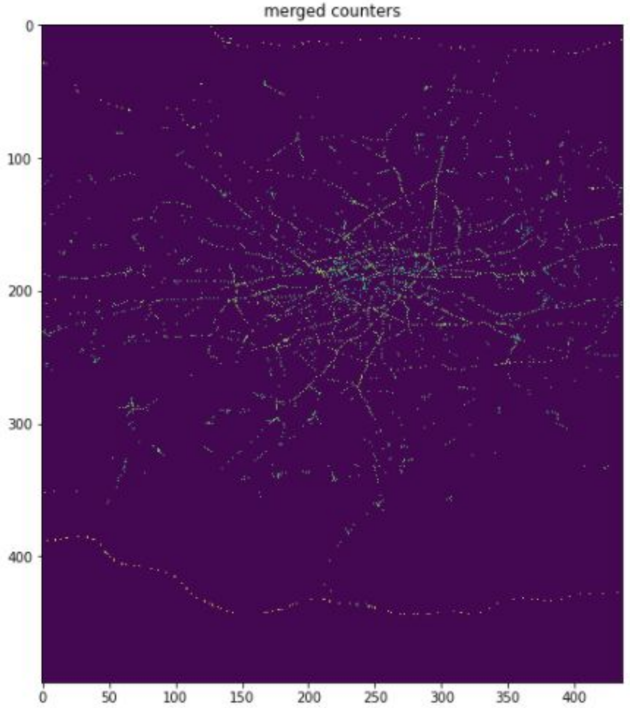
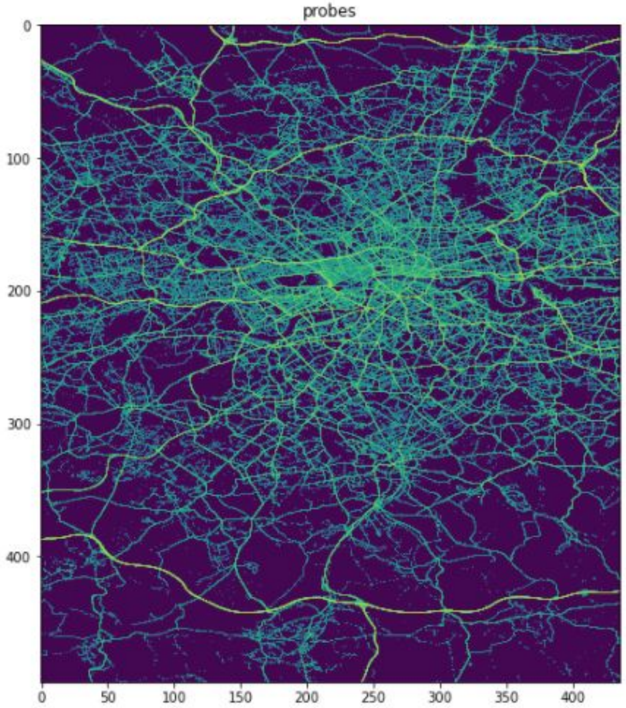
Source: City of Zurich.

Source: TFL/OpenStreetMap.

Loop Counter Data

From sparse but real-time traffic counts to a full speed prediction

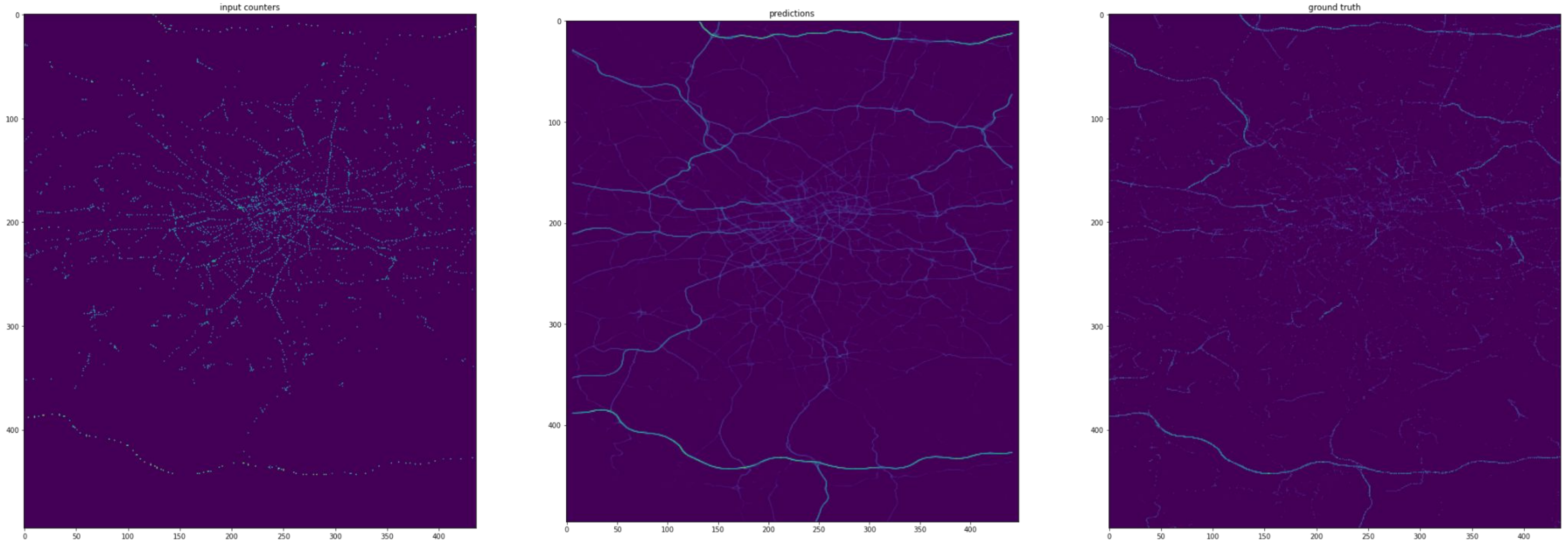




Source: own, unpublished.

Loop Counter Data

From sparse but real-time traffic counts to a full speed prediction



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Thank you!
Questions?

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