Learning Multi-sensory Fusion for Road Traffic Prediction on Resource-limited Devices

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Outline

- Road traffic congestion
- Road traffic control basics
- Learning multisensory fusion for road traffic prediction
    - Basic principle
    - Neuronal learning and fusion
    - Inference
- Real-world example on limited resources devices
- Conclusions

Road traffic congestion

Year 2018 in Berlin

- **Total of 1.5 million Km jam**
- **Total of 154 h time lost/driver**

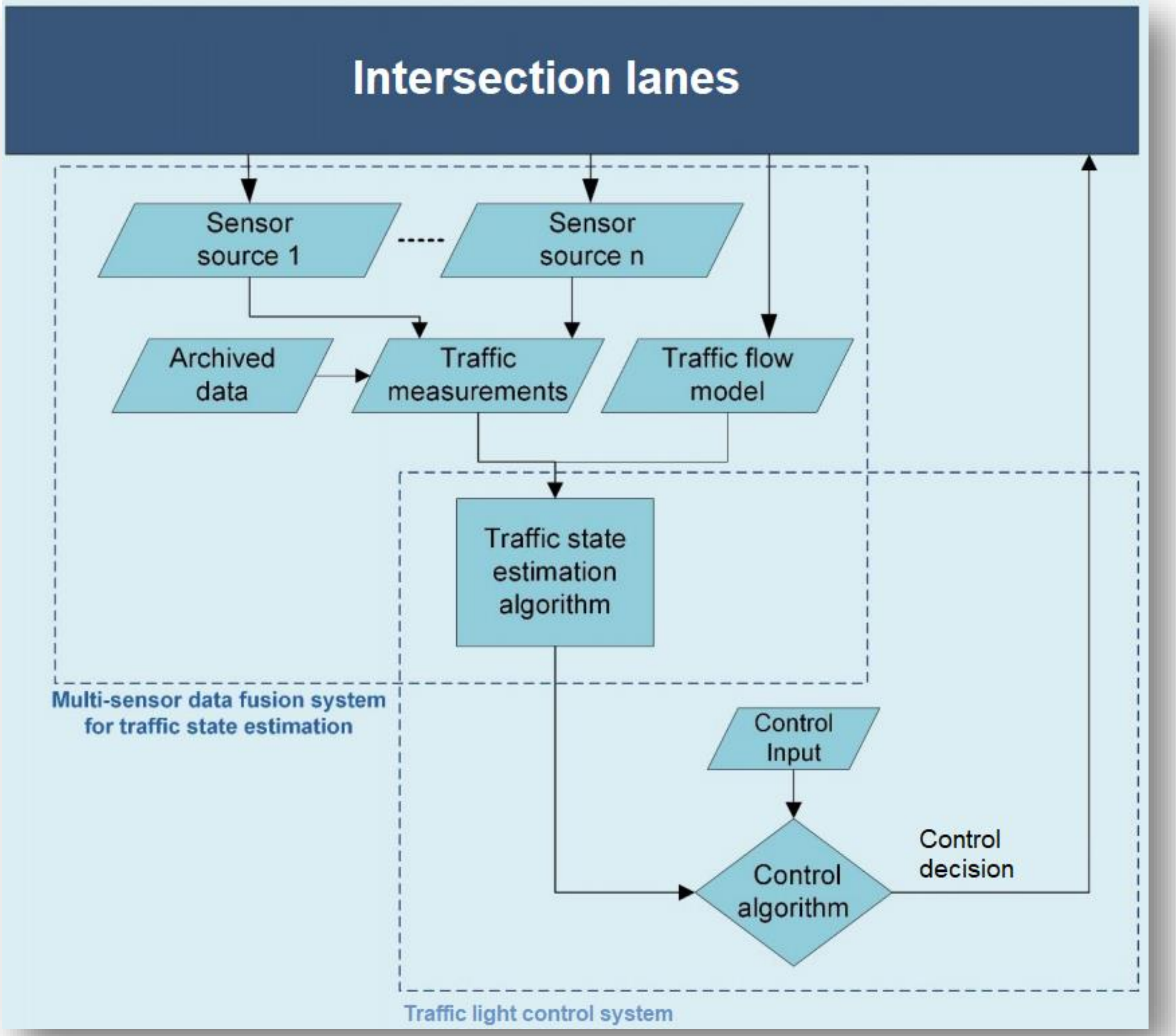
Year 2018 in Germany

- **Average 120 h time lost/driver**
- **Economic loss 1,052 €/driver**

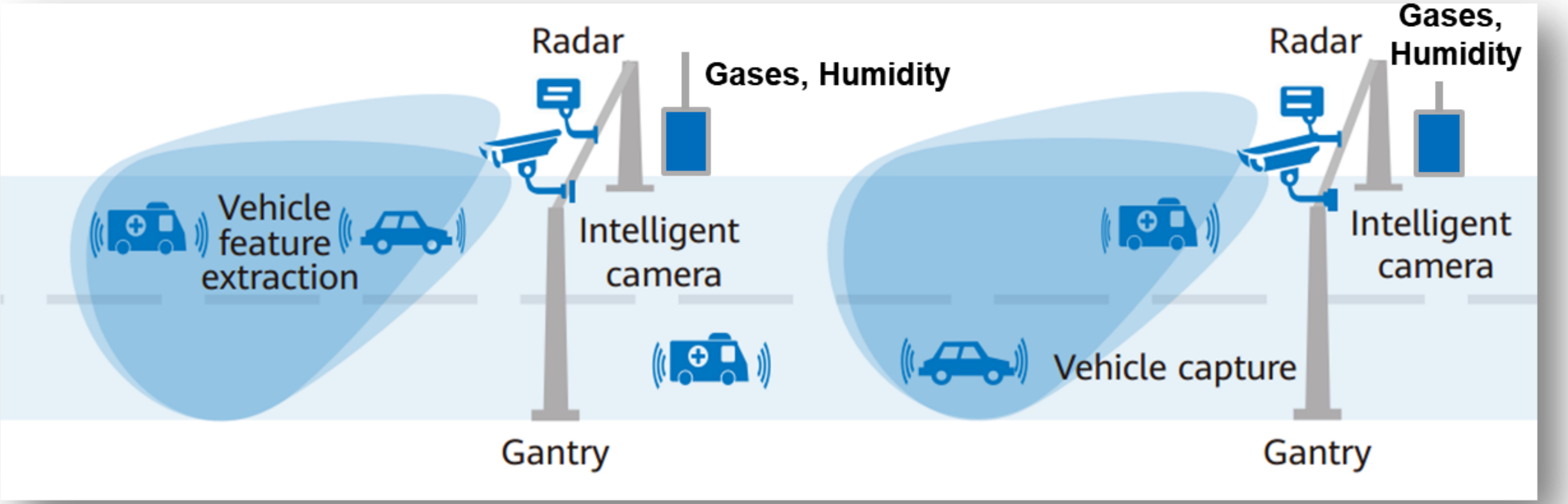
ADAC

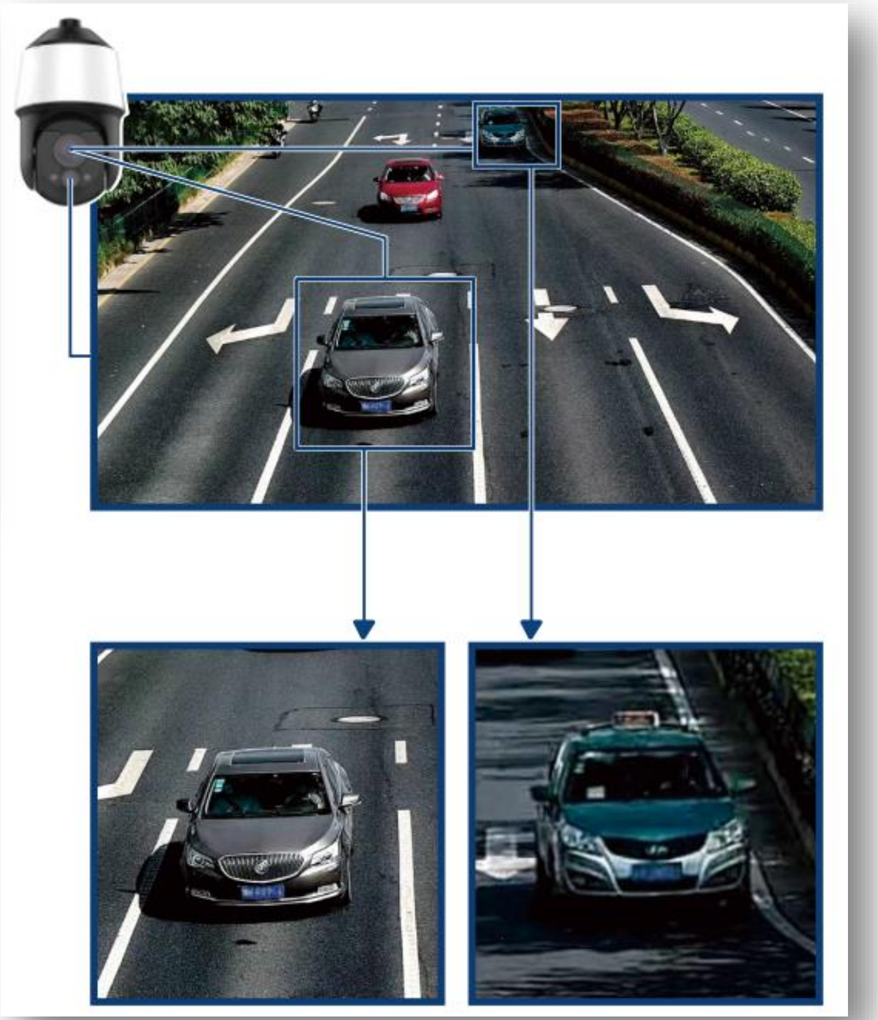
Source: https://www.thelocal.de/20190213/traffic-jams/

Road traffic control



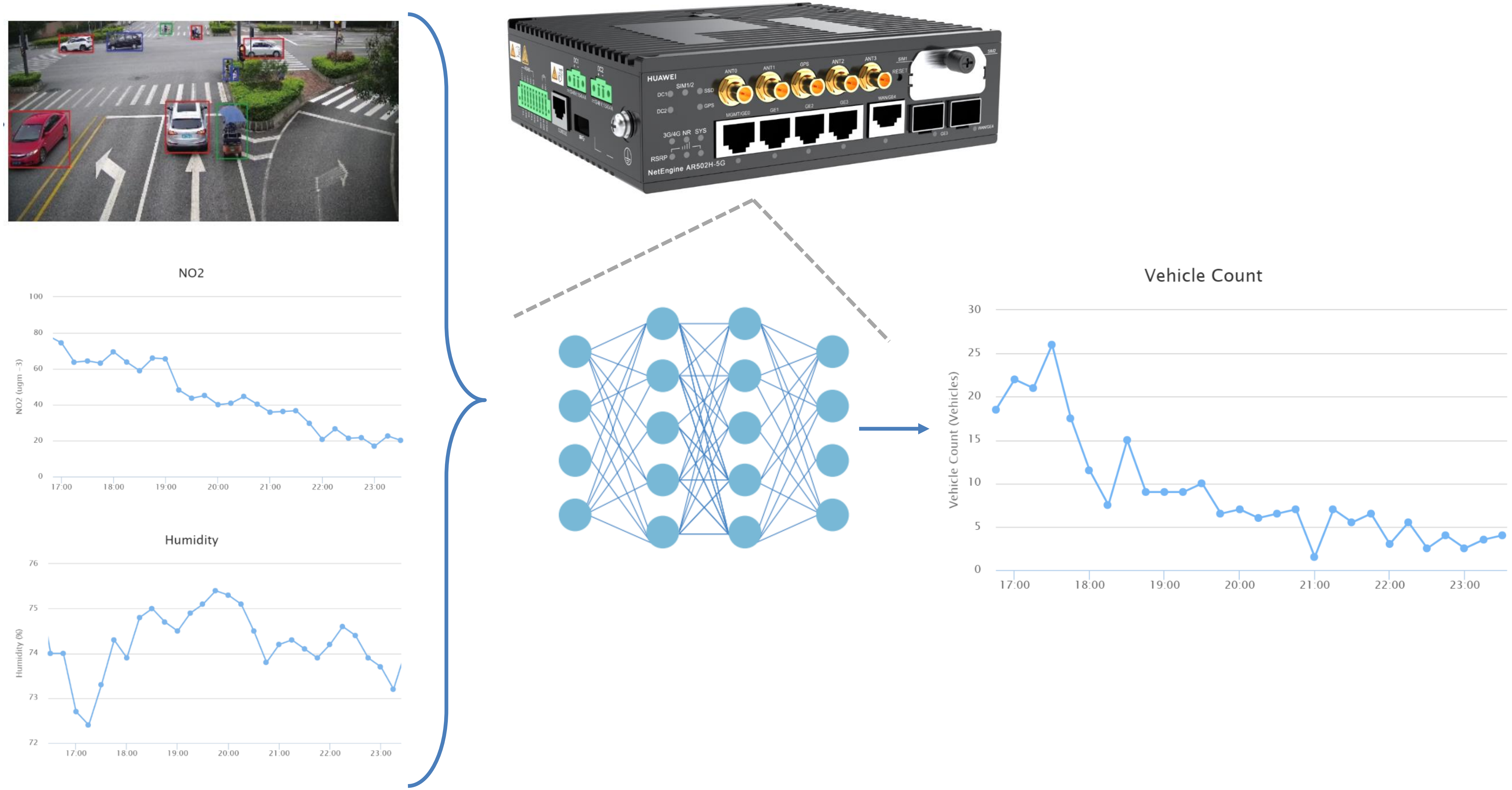
Road traffic control





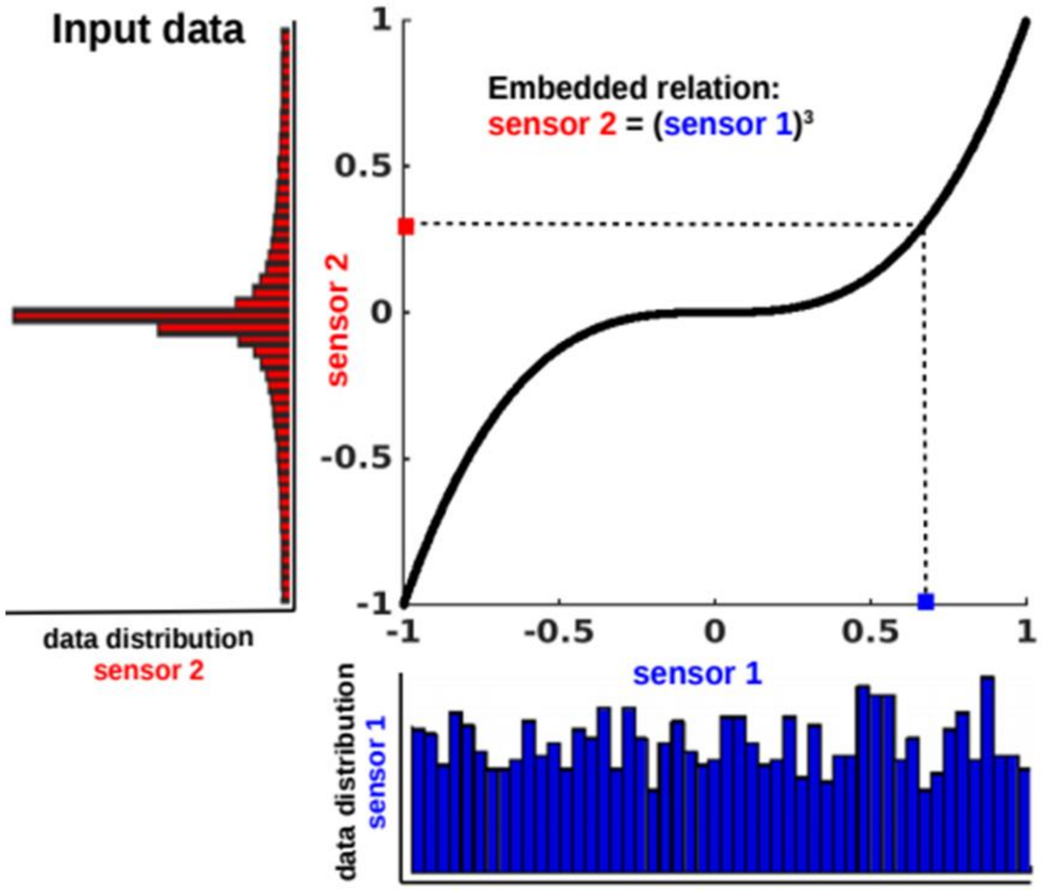
From: https://support.huawei.com/enterprise/en/doc/EDOC1100172551

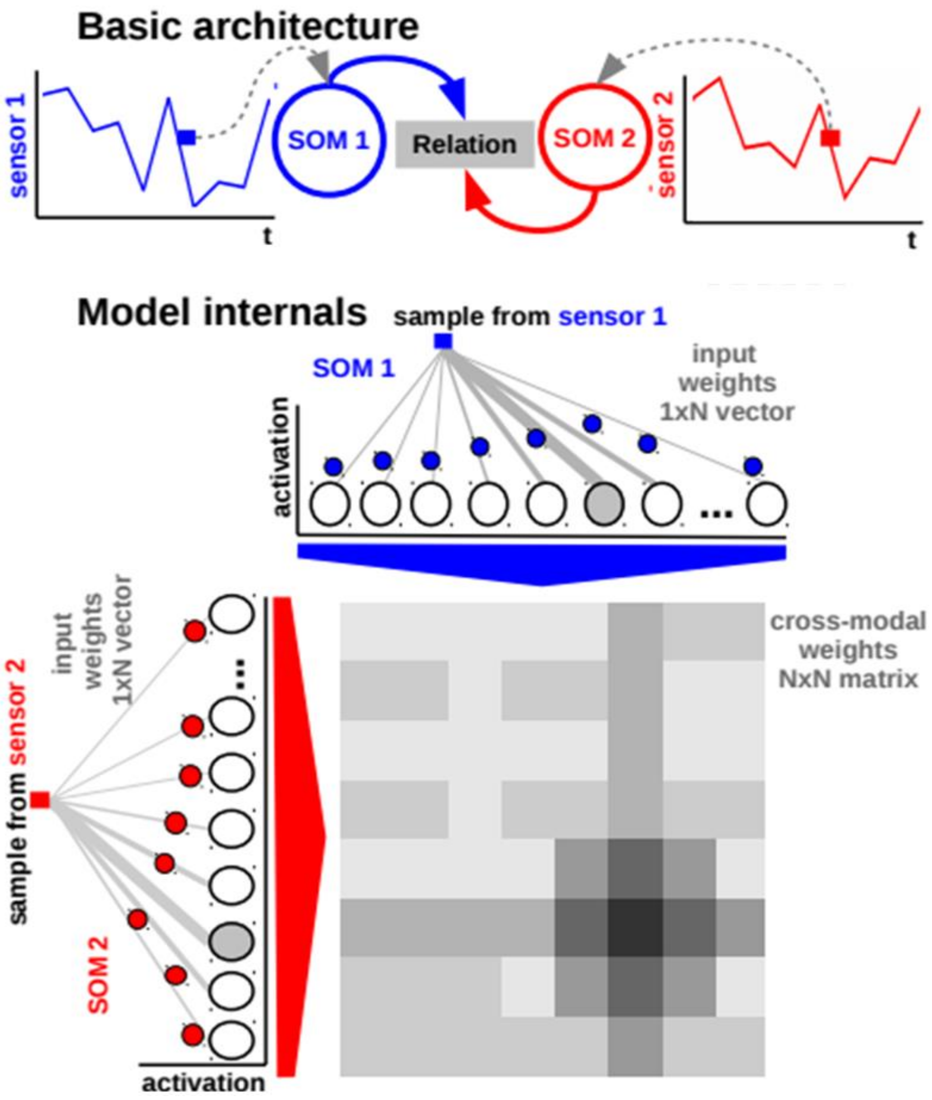
Learning multisensory fusion for road traffic prediction



Learning multisensory fusion for road traffic prediction

Basic principle [1]



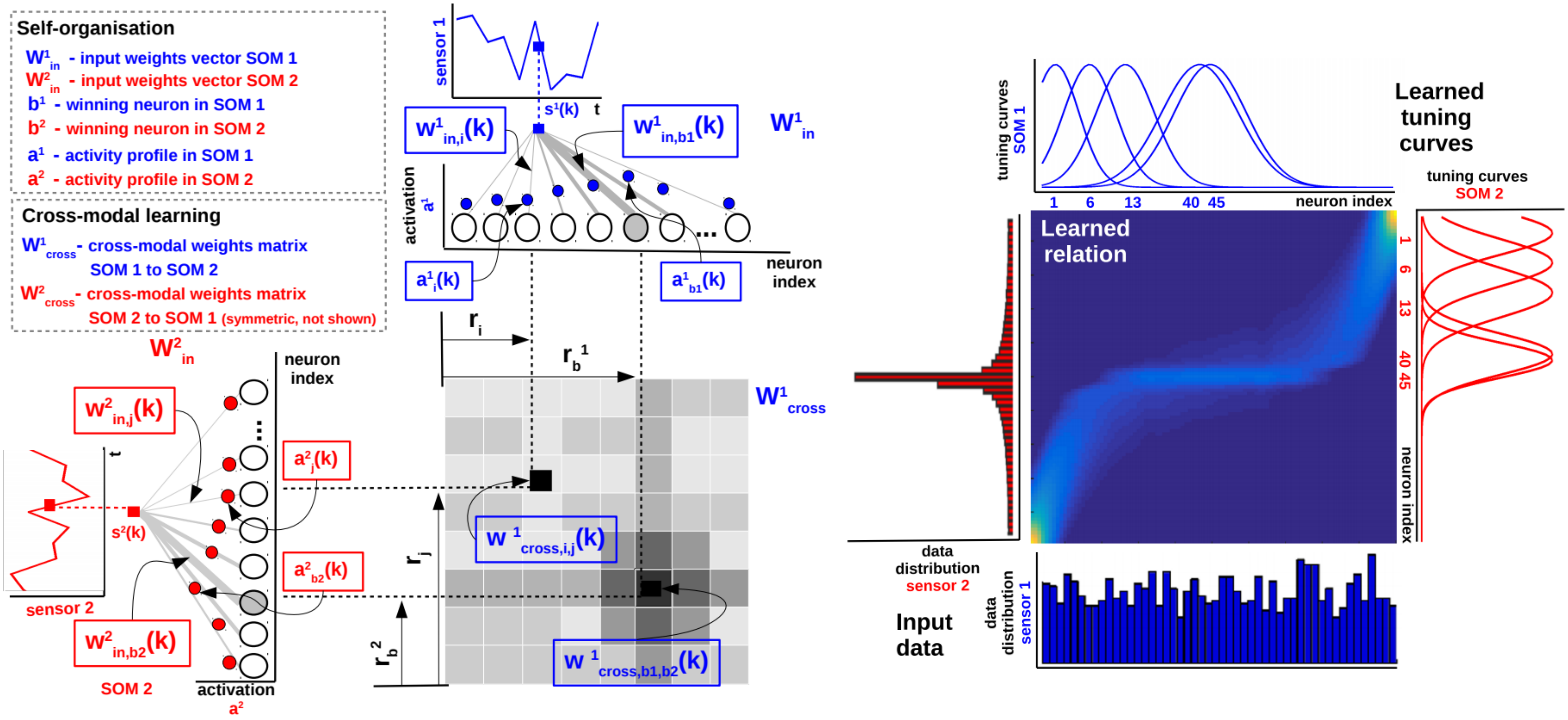


The underlying **neural networks:**

- **Self Organizing Maps (SOM) [2]** to **encode the input data** into **efficient** sparse **representation**
- **Hebbian Learning [3]** to **extract the temporal co-activation patterns** encoding the function

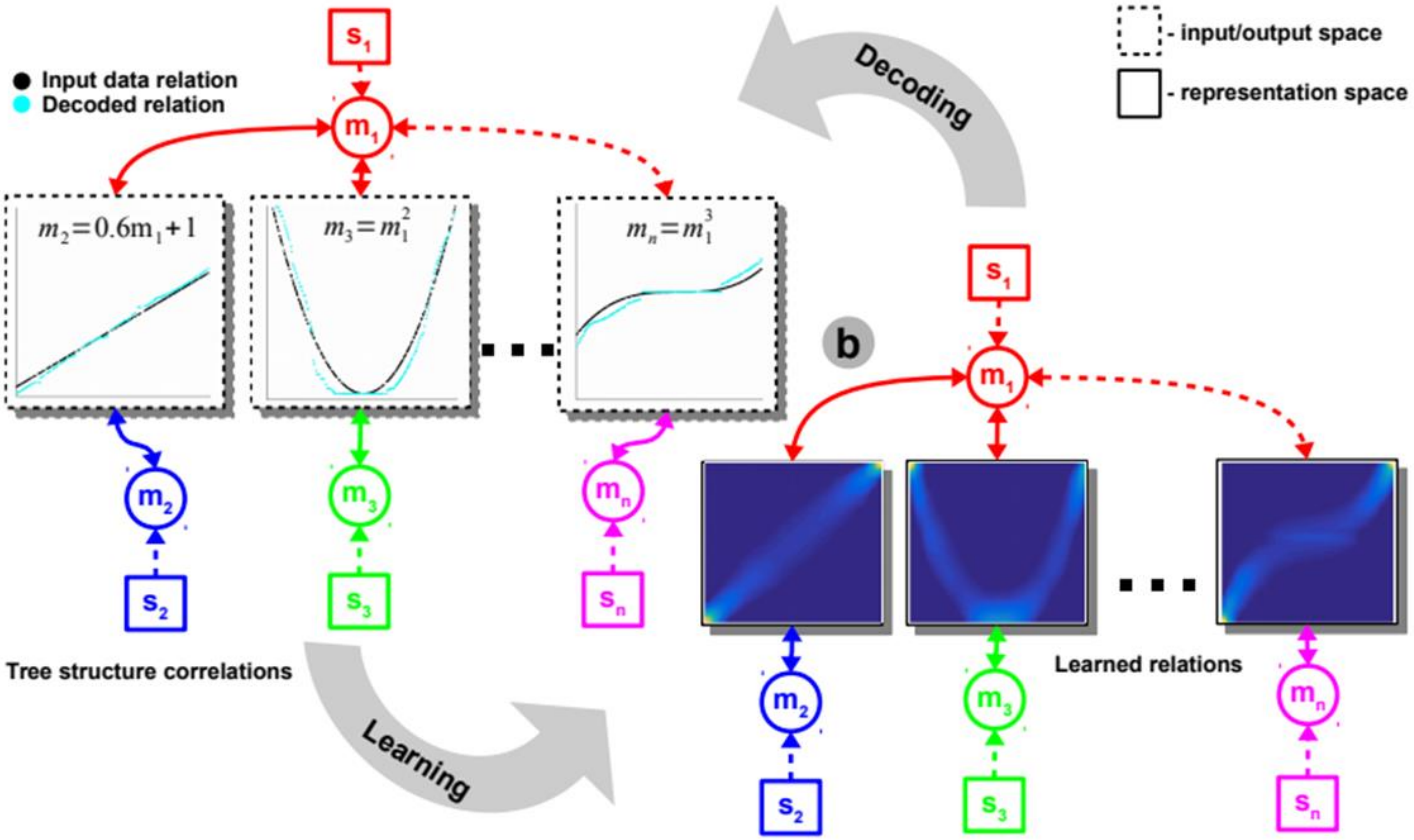
Learning multisensory fusion for road traffic prediction

Neuronal learning and fusion



Neuronal multisensory fusion for road traffic prediction

Inference



Real-world example on limited resource devices

Multisensory fusion for road traffic prediction

urban observatory

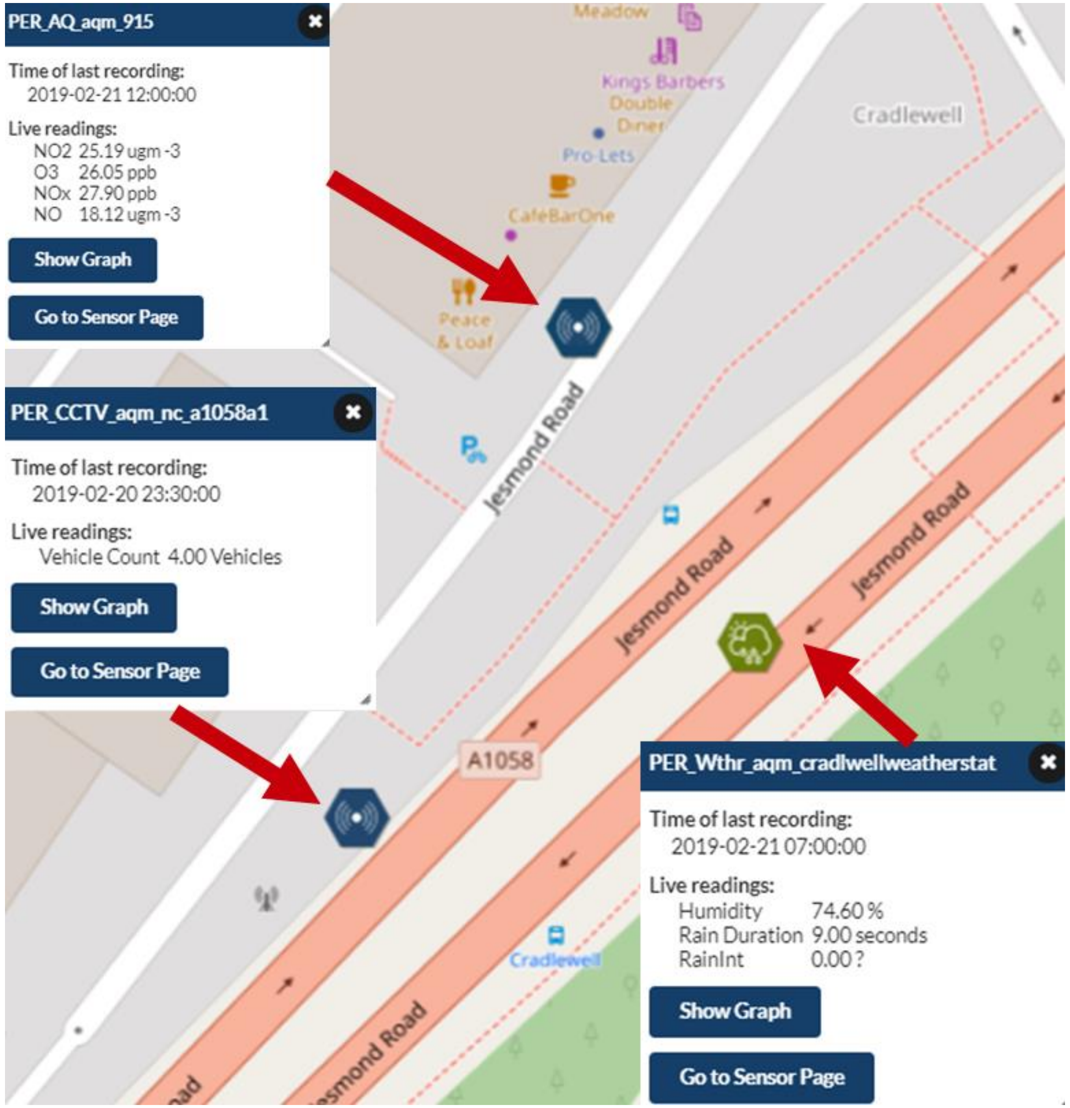
EPSRC Engineering and Physical Sciences Research Council

UKCRIC

Newcastle University

In a traffic scenario we propose to **learn the correlation** between **Environment parameters** (e.g. NO, O3, **NO2**, NOx), **Weather** (e.g. **Humidity**, Rain) and the **Traffic Flow** (i.e. number of vehicles) at a site.

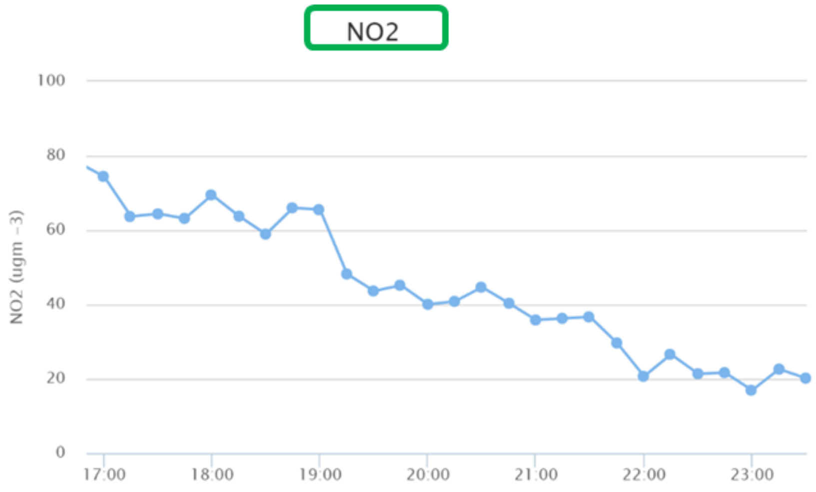
Once **learnt the correlation** we can use it to **infer traffic flow** in regions where **we do not have traffic sensors** installed but **all other sensors** are present.

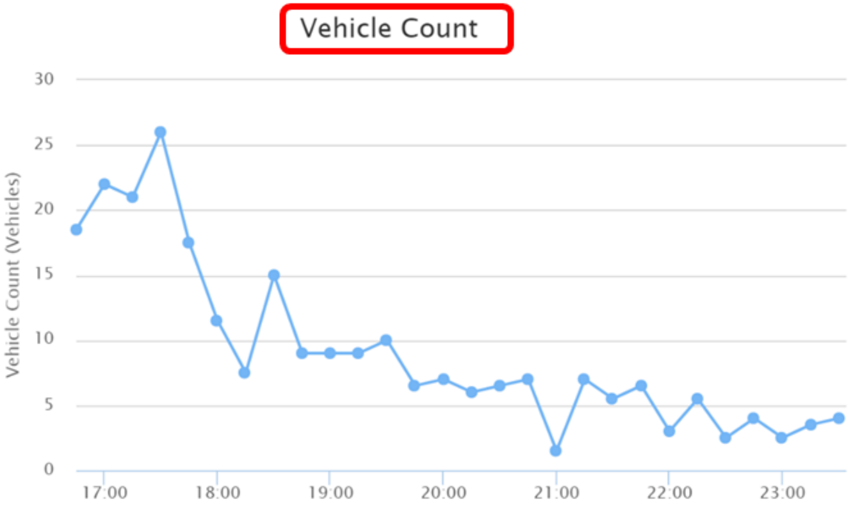


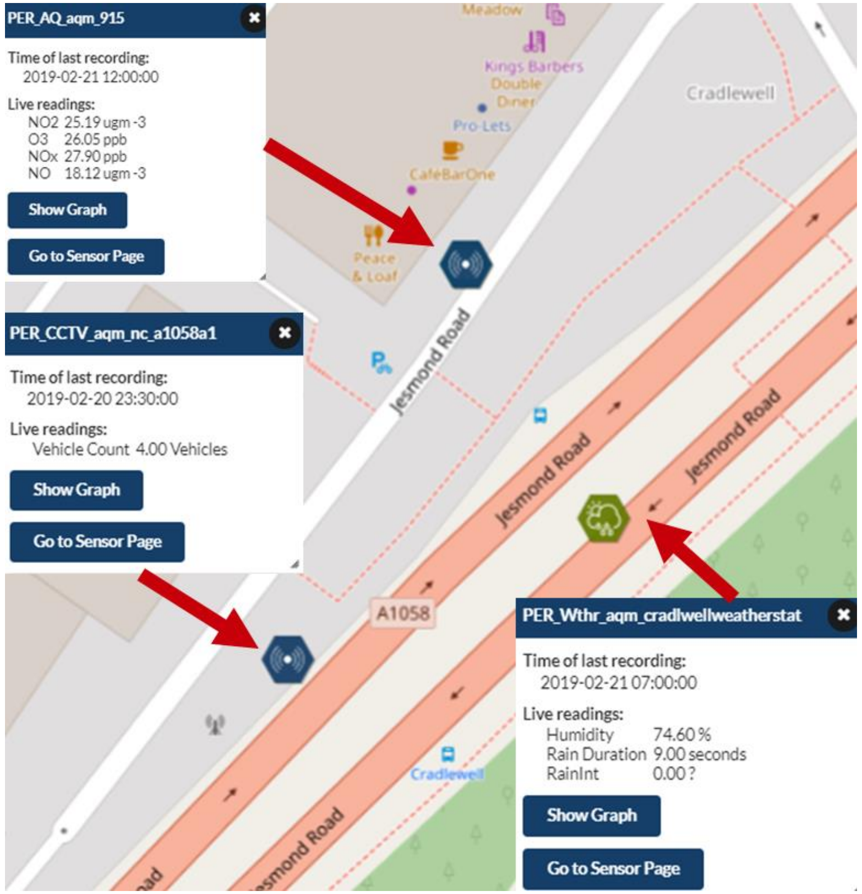
https://newcastle.urbanobservatory.ac.uk/

Real-world example on limited resource devices

Multisensory fusion for road traffic prediction







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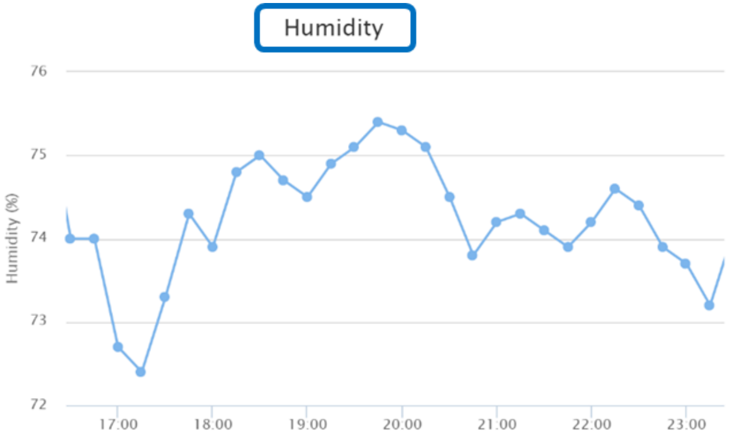
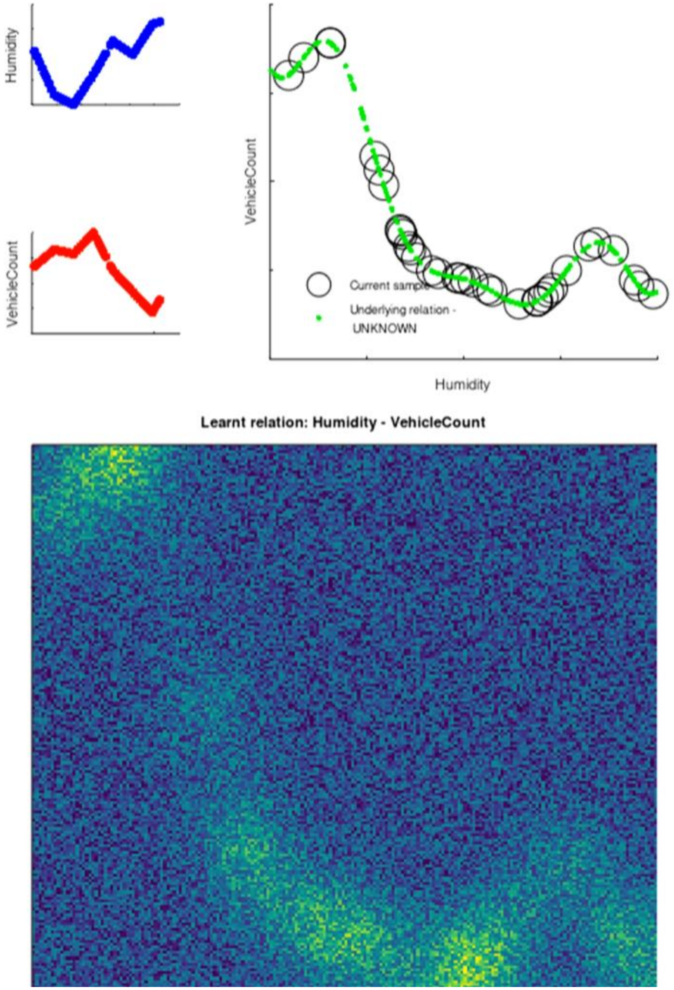
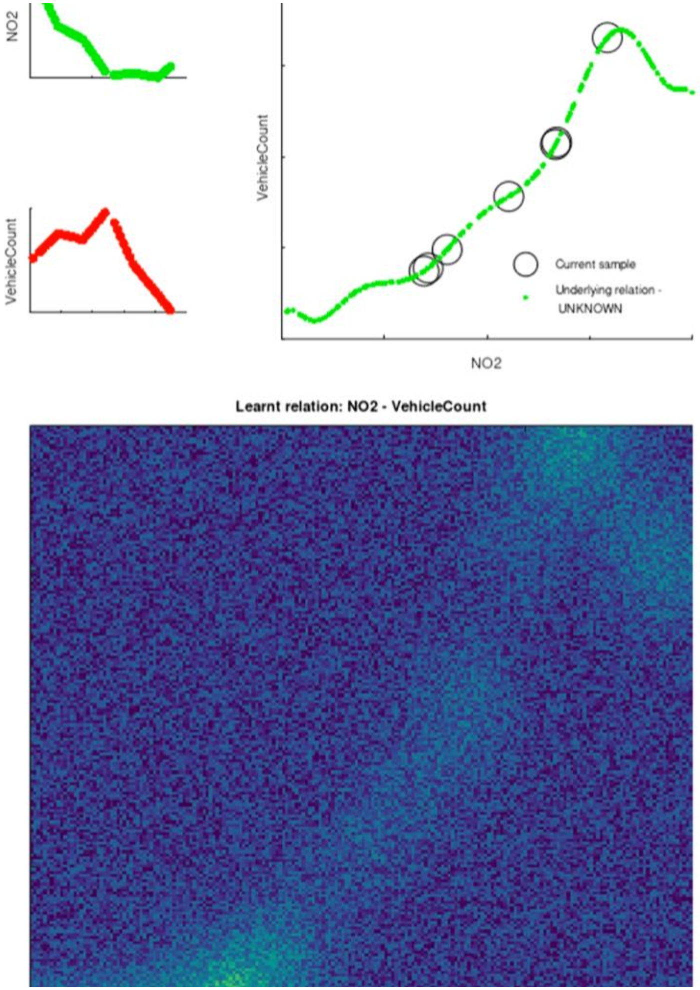
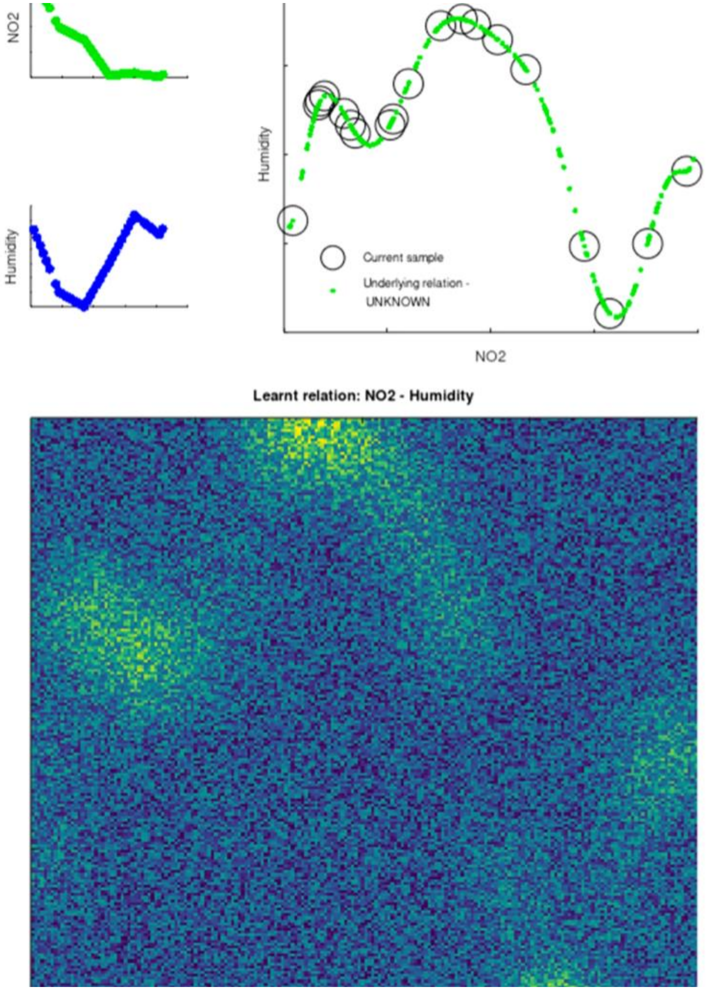


Real-world example on limited resource devices

Multisensory fusion for road traffic prediction (live-demo)

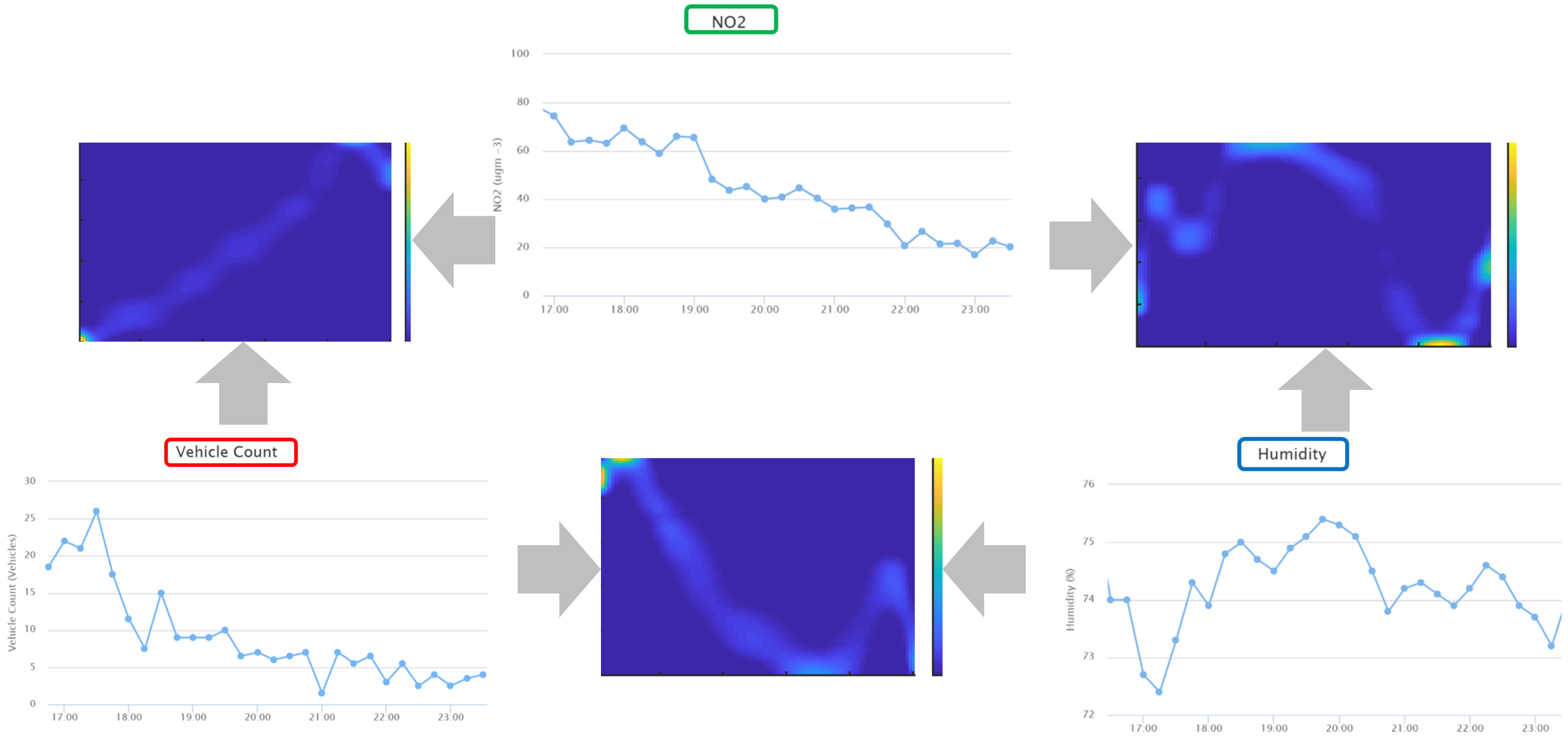






Real-world example on limited resource devices

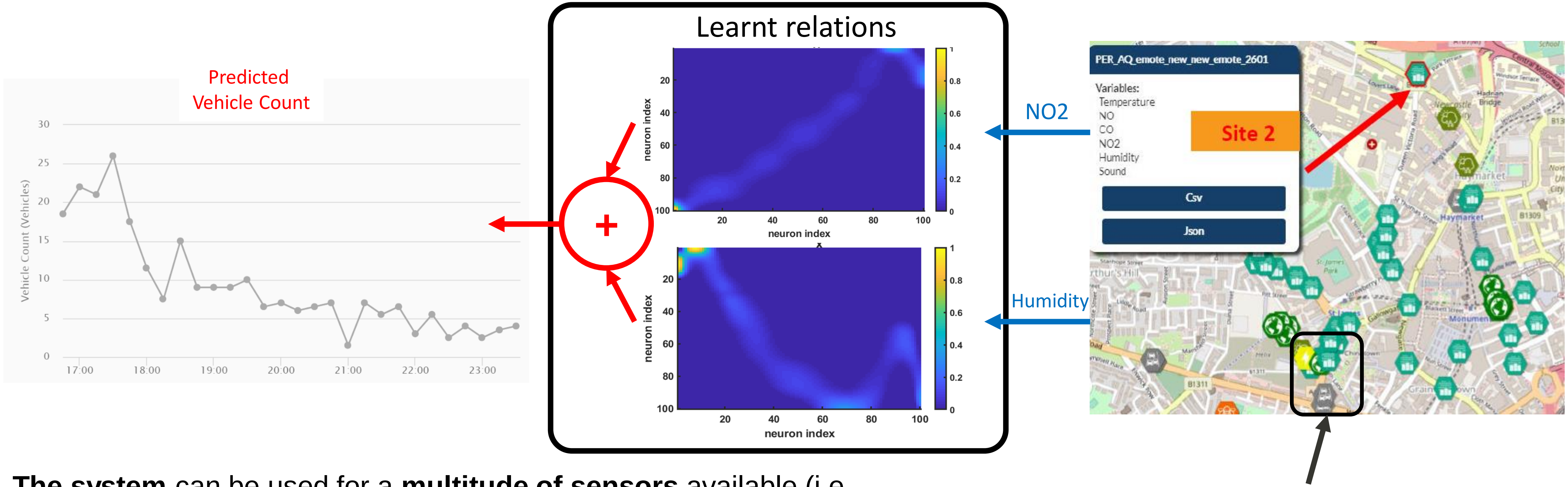
Multisensory fusion for road traffic prediction



Real-world example on limited resource devices

Multisensory fusion for road traffic prediction

Once **learnt the correlation** we can use it to **infer traffic flow** in regions where **we do not have traffic sensors** (i.e. **cameras**) installed but **all other sensors** are present (e.g. Humidity and NO2).



The system can be used for a **multitude of sensors** available (i.e. **mobility data [4]**: *GSM user cell switches overlaid on geospatial motion parameters*; *ranges of high-intensity sound mounted on streets*; *particle count sensors for high-range exhaust gas*).

If the **traffic sensor is failing / defect**, the system uses previously learnt relations to infer a plausible prediction.

Real-world example on limited resource devices
Performance analysis

Number of crossroads	Number of sensors	Data aggregation	Learning time (s)*	Inference time (s)*
1	3	1 min	54.819	0.004
	10	5 min	298.452	0.031
5	3	1 min	232.270	0.021
	10	5 min	1880.212	0.084
10	3	1 min	673.583	0.044
	10	5 min	4136.521	0.102
15	3	1 min	1300.781	0.075
	10	5 min	11093.250	0.534

Specifications
Huawei Ascend 310 Processor, 8 GB RAM (DDR4), 32 GB SSD, 50W
1000 neurons/sensor
3 Days data (72 h)
1 min aggregation - 4320 samples/sensor
5 min aggregation - 864 samples/sensor

*** Average values per 100 experiments**

Conclusions

Multisensory fusion for road traffic prediction

- **Real-time traffic prediction** needs **multisensory fusion** to better understand **traffic dynamics**

- Deployment on limited-resources **devices** needs **lightweight learning systems** for fusion

- **Neural networks** can be key for **multisensory fusion** and **prediction**

- There is an **alternative to deep neural networks** for **sensor fusion** which is **versatile**, **simple**, **adaptive** and **lightweight**

- Such a system is **easily deployable**, **transferrable**, and **fault-tolerant**

Bibliography

[1] C. Axenie, Synthesis of Distributed Cognitive Systems: Interacting Computational Maps for Multisensory Fusion, https://mediatum.ub.tum.de/1284085

[2] Kohonen, T. (1991). Self-organizing maps: optimization approaches. In *Artificial neural networks* (pp. 981-990). North-Holland.

[3] Gerstner, W., & Kistler, W. M. (2002). Mathematical formulations of Hebbian learning. *Biological cybernetics*, *87*(5), 404-415.

[4] El Faouzi, N. E. (2004). Data fusion in road traffic engineering: An overview. *Multisensor, Multisource Information Fusion: Architectures, Algorithms, and Applications 2004*, *5434*, 360-371.

Video lecture and Example code

Youtube lecture

in Produktion, verfügbar vor Montag 9.05.2022

GitHub codebase